

Filmuniversität Babelsberg KONRAD WOLF

Algorithms and Producers

An Evidence-Based Approach to Target Audience
Definition and Revenue Prediction for Feature Film
Producers

by
Jannis Funk

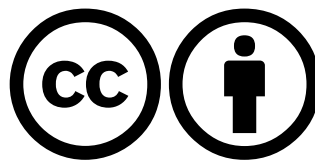
Dissertation submitted
in partial fulfillment of the requirements for the degree
of Doctor of Philosophy (Dr. phil.)

Fakultät I
Fachgebiet Medienwissenschaften

January 2021

Advisor Prof. Dr. Susanne Stürmer
Second Reviewer Prof. Dr. Daniela Schlütz

Note: This published version of the thesis is identical to the examined version except for a numerical mistake in [subsection 4.6.3](#) that has been corrected.



Some rights reserved: This work is published under a Creative Commons Attribution 4.0 International License (CC-BY). The full text of the license agreement may be found here:

<https://creativecommons.org/licenses/by/4.0/>

Abstract

With the rise of streaming platforms and direct-to-consumer business models, big data and audience analytics have emerged as powerful new ways to define target audiences and predict movie revenues in the film industry's public discourse. Yet while major studios have since launched proprietary internal data science efforts, the role such technologies could play for the practice of independent producers remains unclear.

In an effort to close that gap, this dissertation examines how the way feature film producers define their target audience and forecast box office revenues might be improved upon by the use of large sets of individual user data and digital methods of modeling movie preferences.

Drawing from the productions studies approach, we establish in an exploratory qualitative study that German independent feature film producers mostly base their target audience definitions on vague, anecdotal evidence, and use intuitive box office forecasts mainly to win over financiers.

We then take a look at scientific studies on target audience definition and revenue prediction for feature films and identify reasons for why their results have not been more widely adopted among practitioners.

Subsequently, we propose an approach to evidence-based target audience definitions building on recommender algorithms and movie preference modeling at the individual level. Using several datasets on German moviegoers ($n = 2,374$, $n = 6,564$, and $n = 700$, respectively), we confirm that past movie choices indeed provide reliable information on future behavior that can be exploited for efficient targeting. Targeting by as few as three past movie choices also is on average more efficient than targeting by demographic proxies (gender and age). The increase in targeting efficiency as compared to targeting by gender is statistically significant.

Outlining a possible practical application, we go on to show that it is possible to develop clusters of similar viewers based on such data, and that such clusters can be used efficiently for target audience definition.

Concerning revenue prediction, we utilize a large open dataset on individual users' movie preferences to compute movie similarities for a sample of 1,093 movies released in the United States between 2004 and 2015 and show that regression models trained on sub-samples of similar movies only lead to better revenue prediction results than models built on the entire dataset.

Finally, we address some critical concerns and lay out an agenda for further research on the road to practical implementation of our insights.

Zusammenfassung

Mit dem Aufkommen von Streaming-Plattformen und Direct-to-Consumer-Geschäftsmodellen haben Big Data und Audience Analytics als potentiell chancenreiche neue Methoden zur Definition von Zielgruppen und zur Prognose von Einspielergebnissen in den öffentlichen Diskurs der Filmindustrie Einzug gehalten. Doch während die großen Studios interne Data-Science-Abteilungen aufbauen, bleibt unklar, welche Rolle solche Technologien für die Praxis unabhängiger Produzent:innen spielen könnten.

Um diese Lücke zu schließen, untersucht diese Dissertation, ob die Art und Weise, wie Spielfilmproduzent:innen ihr Zielpublikum definieren und die Umsätze an der Kinokasse prognostizieren, durch die Verwendung großer Mengen individueller Nutzer:innendaten und digitaler Methoden zur Modellierung von Filmpräferenzen verbessert werden könnte.

Ausgehend vom Ansatz der Production Studies stellen wir in einer explorativen qualitativen Studie fest, dass deutsche unabhängige Spielfilmproduzent:innen ihre Zielgruppendefinitionen meist nur auf anekdotische Evidenz stützen und intuitive Box-Office-Prognosen vor allem nutzen, um Geldgeber:innen zu überzeugen.

Anschließend werfen wir einen Blick auf wissenschaftliche Studien zur Zielgruppendefinition und Einspielergebnisprognose für Spielfilme und identifizieren Gründe, warum deren Ergebnisse in der Praxis nicht weiter verbreitet sind. Darauf aufbauend schlagen wir einen Ansatz für evidenzbasierte Zielgruppendefinitionen vor, der auf Empfehlungsalgorithmen und der Modellierung von Filmpräferenzen auf individueller Ebene beruht. Anhand verschiedener Datensätze zu deutschen Kinobesucher:innen ($n = 2.374$, $n = 6.564$ bzw. $n = 700$) bestätigen wir, dass vergangene Kinobesuchsentscheidungen und Filmbewertungen tatsächlich zuverlässige Informationen über zukünftiges Verhalten liefern, die für ein effizientes Targeting genutzt werden können. Wir stellen fest, dass bereits drei vergangene Kinobesuchsentscheidungen pro Zuschauer:in mehr Aufschluss über deren Präferenzen geben als demographische Parameter (Geschlecht und Alter, wobei lediglich die Verbesserung der Targeting-Effizienz gegenüber Gender-Targeting statistisch signifikant ist).

In einem Ausblick auf eine mögliche praktische Anwendung zeigen wir, dass es möglich ist, auf Basis solcher Daten Segmente ähnlicher Zuschauer:innen zu entwickeln, und dass diese Cluster effizient für die Definition von Zielgruppen genutzt werden können.

Im Hinblick auf Umsatzvorhersagen verwenden wir einen großen offenen Datensatz zu den Filmpräferenzen einzelner Nutzer:innen, um Filmähnlichkeiten für eine Stichprobe von 1.093 Filmen zu berechnen, die zwischen 2004 und 2015 in den USA veröffentlicht wurden. Wir zeigen auf dieser Grundlage, dass Regressionsmodelle, die auf Teilstichproben ähnlicher Filme geschätzt wurden, zu genaueren Umsatzvorhersagen führen als Modelle, die den gesamten Datensatz zur Grundlage nehmen. Abschließend gehen wir auf kritische Erwägungen ein und skizzieren eine Agenda für die weitere Forschung auf dem Weg zu einer praktischen Anwendbarkeit der gewonnenen Erkenntnisse.

Acknowledgement

This work would not have been possible without the generous support of many researchers, practitioners, and friends. I would like to begin by thanking my advisor Susanne Stürmer, for encouraging me to undertake the endeavor of writing a PhD dissertation in the first place, and the many opportunities offered along the way.

Daniela Schlütz has agreed to provide the second review and I want to thank her as well for her time, her commitment, and the interest in my work.

The "Big Data, Big Movies" conference in 2016 was an early formative experience for me in the context of this dissertation, as it allowed me to get in touch with many of the relevant voices from both industry and academia. I would like to extend my special thanks to Nadja Radojevic and the staff of the Erich Pommer Institut for organizing the event, and of course to Thorsten Hennig-Thurau, Susanne Stürmer, and Benjamin Benedict for co-chairing the conference with me.

My research stay at the UCLA School of Theater, Film, and Television in Los Angeles 2016-17 provided me with an entirely different "Hollywood" perspective on my topic. I would like to thank Ben Harris for facilitating the opportunity in the first place, and offer my special thanks to my advisor Denise Mann for the invitation and her insightful guidance during the stay. In addition to that, I am very grateful to John Caldwell for introducing me to the Production Studies approach in his UCLA graduate course and inspiring me to empirically assess German producers' audience conceptions upon my return.

I wish to thank the anonymous producers who took the time and participated in the interviews and Martina Berger-Haseloff for conducting some of the interviews with me. Also I want to acknowledge the support provided by Mahelia Thurow and the staff of the participating cinemas in carrying out the offline survey 2017-18. It was great to collaborate with Joel Schumacher and

Nora Pähler vor der Holte of the Marketing Center Münster for the online survey in early 2017.

I also would like to express my appreciation for Thorsten Hennig-Thurau for inviting me to co-chair the "20th Annual Mullen Scholars and Practitioners Conference in Filmed Entertainment Economics" in 2018, and I am especially thankful for the working group that was formed during that conference with whom I went on to co-author the paper on "Leveraging analytics to produce compelling and profitable film content", namely Ronny Behrens, Natasha Zhang Foutz, Michael Franklin, Fernanda Gutierrez-Navratil, Julian Hofmann, and Ulrike Leibfried.

Invaluable advice was provided by Allègre Hadida, who invited me for a research stay in Cambridge and pointed me to the Evidence-Based Management approach, which served as a framework for the entire dissertation.

A large part of my journey during these last few years was the founding and scaling of Cinuru Research, the company in which we applied many of the concepts discussed herein to industry practice. I would like to express my gratitude to my co-founders Martina Berger-Haseloff, Tobias Lohse, Paulo Ruhrländer, and Jean-David Herld who went through many challenges with me and also served as the primary sounding board for many of the conceptual ideas explored in this dissertation.

This dissertation would not have been possible without the generous financial support of the German Academic Scholarship foundation (Studienstiftung des deutschen Volkes) and the Fulbright Commission.

Finally, I would like to extend my special thanks to my family and friends for their continued love and support.

Contents

List of Figures	XI
List of Tables	XIV
1 Introduction	1
1.1 Relevance	1
1.2 Perspective	4
1.3 Outline	6
2 The Practice of Target Audience Definition and Revenue	
Prediction	8
2.1 Theoretical Considerations	8
2.2 Empirical Exploration	14
2.2.1 Target Audience Definition Criteria	15
2.2.1.1 Demographics	16
2.2.1.2 Film Taste	17
2.2.1.3 Lifestyle and Interest	18
2.2.1.4 Behavior	19
2.2.2 Revenue Prediction in Practice	20
2.2.3 Audience-Producer Relationships	21
2.3 Intermediate Discussion	23
3 Scientific Approaches to Target Audience Definition and	
Revenue Prediction	25
3.1 Branches of Research	25
3.2 The Psychological Approach	26
3.2.1 Overview	26
3.2.2 Moviegoing Motives	27
3.2.3 Consumer Decision-Making	35
3.2.4 Audience Segmentation	44

Contents

3.3	The Economic Approach	47
3.3.1	Modeling Techniques and Purposes	47
3.3.2	Movie Traits	49
3.3.3	Third-Party Information	65
3.3.4	Market Environment	69
3.3.5	Industry Applications	72
3.4	Intermediate Discussion	75
4 Evidence-Based Target Audience Definitions and Revenue		
	Prediction	77
4.1	Digital Representations of Movie Preferences	77
4.1.1	Overview	77
4.1.2	Content-Based Recommendation	79
4.1.3	Collaborative Filtering	81
4.1.4	Recommender Algorithms Used for Targeting	88
4.2	Targeting by Preferences Learned from Behavioral Data	90
4.2.1	Hypotheses	90
4.2.2	Survey Design	91
4.2.3	Data	91
4.2.4	Analysis	95
4.3	Profile Depth and Targeting Efficiency	107
4.3.1	Hypotheses	107
4.3.2	Survey Design	107
4.3.3	Data	111
4.3.4	Analysis	116
4.4	Targeting by Preferences Learned from Movie Ratings	123
4.4.1	Hypotheses	123
4.4.2	Survey Design	124
4.4.3	Data	129
4.4.4	Analysis	137
4.5	Building Movie Preference Clusters	153
4.5.1	Hypotheses	153
4.5.2	Data and Analysis	153
4.6	Revenue Prediction	163
4.6.1	Research Objective	163
4.6.2	Data	165
4.6.3	Analysis	168

Contents

5 Conclusion and Outlook	181
5.1 Summary of Findings	181
5.2 Managerial Implications	184
5.3 Directions for Further Research	186
5.4 Critical Considerations	188
A Offline Questionnaire	192
B Online Questionnaire	193
Bibliography	205

List of Figures

2.1	Stages of production and exploitation of a typical feature film	10
4.1	One-dimensional representation of movies and users	84
4.2	Ratings matrix of users and movies (1D embedding)	85
4.3	Two-dimensional representation of movies and users.	85
4.4	Ratings matrix of users and movies (2D embedding)	86
4.5	Schematic illustration of Matrix Factorization (2D embedding)	87
4.6	Age distribution of target users	92
4.7	Gender distribution of target users	93
4.8	Histogram of visitor numbers for films among responses	94
4.9	Lift chart of age-based targeting vs. random and perfect model	102
4.10	Lift chart of age-based targeting vs. gender-based targeting	103
4.11	Lift chart of all targeting methods for THOR: TAG DER ENTSCHEIDUNG	103
4.12	Cinuru: Screenshot of movie detail page	108
4.13	Cinuru: Screenshot of post-trailer dialog	109
4.14	Cinuru: Screenshot of digital bonus card	110
4.15	Cinuru: Screenshot of movie-rating dialog.	110
4.16	Distribution of interactions per movie.	112
4.17	Releases per week	113
4.18	Distribution of number of genres among movies in dataset	115
4.19	Active weeks per user	115
4.20	Distribution of moviegoing frequencies among app users	117
4.21	Mean lift for genre-based targeting across all target movies by profile depth of eligible users	122
4.22	Median threshold value across all movies for the <i>mean_genre_overlap</i> similarity measure required from a user to be included in a movie's target audience	122
4.23	Screenshot of fictitious cinema program in online survey	125
4.24	Awareness screening at the beginning of the online questionnaire	126
4.25	Rating page in online survey	127

List of Figures

4.26 Sources of awareness rating in online questionnaire	128
4.27 Genre Frequency Page in Online Survey	128
4.28 Demographics page in online questionnaire	129
4.29 Age distribution of target users	130
4.30 Gender distribution of target users	131
4.31 Income distribution of target users	131
4.32 Home city size distribution of target users	132
4.33 Moviegoing frequencies of target users	133
4.34 Favorite genres of target users	134
4.35 Histogram of rated movies per target user	134
4.36 Histogram of mean ratings per target user	135
4.37 Histogram for share of satisfactory movies	135
4.38 Histogram for ratings per movie	136
4.39 Movie selections of target users	138
4.40 Movie selections of target users in training sample	139
4.41 Movie selections of target users in test sample	139
4.42 Lift of MF-targeting by k past movie ratings	145
4.43 Lift of MF-targeting for GHOST IN THE SHELL	147
4.44 Lift of MF-targeting for SMURFS: THE LOST VILLAGE	147
4.45 Lift of MF-targeting for POWER RANGERS	148
4.46 Lift of MF-targeting for FREE FIRE	148
4.47 Lift of MF-targeting for THE FOUNDER	149
4.48 Lift of MF-targeting for LOMMBOCK	149
4.49 Lift of MF-targeting for HEAVEN WILL WAIT	150
4.50 Lift of MF-targeting for TIGER GIRL	150
4.51 Movie clusters based on preferential data (1/3)	156
4.52 Movie clusters based on preferential data (2/3)	157
4.53 Movie clusters based on preferential data (3/3)	158
4.54 Lift for different numbers of clusters	161
4.55 Distribution of revenues	167
4.56 Distribution of budgets	168
4.57 Distribution of Google Trends popularity values (Cast)	169
4.58 Distribution of Google Trends popularity values (Director)	169
4.59 Distribution of genres	170
4.60 Distribution of age ratings	170
4.61 RMSE for different number of similar movies k	176
4.62 RMdSE for different number of similar movies k	176
4.63 MAPE for different number of similar movies k	177
4.64 MdAPE for different number of similar movies k	177

List of Figures

4.65 Distribution of movies by optimal k	178
A.1 Questionnaire as handed out to moviegoers in participating cin- emas	192
B.1 Online Survey, page 1	194
B.2 Online Survey, page 2	194
B.3 Online Survey, page 3	195
B.4 Online Survey, page 4	195
B.5 Online Survey, page 5	196
B.6 Online Survey, page 6 (repeated multiple times)	196
B.7 Online Survey, page 7	196
B.8 Online Survey, page 8	197
B.9 Online Survey, page 9	197
B.10 Online Survey, page 10	198
B.11 Online Survey, page 11	198
B.12 Online Survey, page 12 (repeated multiple times)	199
B.13 Online Survey, page 13	199
B.14 Online Survey, page 14	200
B.15 Online Survey, page 15	200
B.16 Online Survey, page 16	201
B.17 Online Survey, page 17	201
B.18 Online Survey, page 18	202
B.19 Online Survey, page 19	202
B.20 Online Survey, page 20	203
B.21 Online Survey, page 21 (repeated multiple times)	203
B.22 Online Survey, page 22	203
B.23 Online Survey, page 23	204

List of Tables

2.1	Overview of categories as inferred from producer interviews . . .	16
2.2	Occurences of main categories in producer interviews	16
2.3	Occurences of socio-demographic categories in producer interviews	17
2.4	Occurences of categories of film taste in producer interviews . . .	18
2.5	Occurences of lifestyle categories in producer interviews	19
2.6	Occurences of behavioral categories in producer interviews . . .	19
2.7	Categories of box office forecasting techniques in producer inter- views	21
2.8	Categories of box office forecasting motivation in producer inter- views	21
2.9	Occurences of categories of audience-producer interactions in producer interviews	22
2.10	Occurences of categories describing the audience-producer rela- tionship in producer interviews	23
3.1	Average Metascore ratings for films based on different kinds of source material	51
4.1	Fictitious database of movie ratings	82
4.2	Similarity between users	83
4.3	Target movies in the dataset	95
4.4	Logistic regression results for movie consumption predicted by the scores of different targeting models	100
4.5	Median lift values for different targeting methods across all 17 films	104
4.6	Lift values for different targeting methods (targeting 10% of respondents in the test set)	105
4.7	Distribution of interaction types	111
4.8	Movies with most interactions	111
4.9	Genre occurences among movies in observation period	114
4.10	Most watched movies in dataset	118

List of Tables

4.11 Logistic regression results for watching behavior explained by mean similarity of past movie interactions	119
4.12 Linear regression results for mean lift across all movies explained by the number of active weeks per user before release (profile depth d)	123
4.13 Movies to be selected from in fictitious cinema program	125
4.14 Distribution of ratings for films watched in cinemas and at home	137
4.15 Lift values for different demographic targeting methods	140
4.16 Genres assigned to target movies on TMDb	141
4.17 Lift values for genre targeting method	141
4.18 Lift values for matrix factorization targeting, using $k = 30$ past movie ratings	144
4.19 Linear regression results for lift explained by number of past rated movies k	146
4.20 Similar movies to target movies	152
4.21 Number of respondents per cluster	160
4.22 Lift values for cluster targeting method, $n = 20$	160
4.23 Lift values for cluster-based targeting vs. genre-based targeting	161
4.24 Mean and median lift values for different targeting methods . .	162
4.25 Regression results for the entire dataset of 1,093 films	172
4.26 Similar Movies for FANTASTIC MR. FOX	173
4.27 Similar Movies for THE TWILIGHT SAGA: BREAKING DAWN - PART 1"	174
4.28 Optimal values for k according to different error measures . . .	175
4.29 Two models based on niches of 100 similar films each for FANTASTIC MR. FOX and THE TWILIGHT SAGA: BREAKING DAWN - PART 1, side-by-side	179

1 Introduction

1.1 Relevance

*"For a really long time, we have been disintermediated from our customer base, because we sell to exhibitors. We had been flying blind."
Stacey Snider¹, CEO, 20th Century Fox*

The meteoric rise of online streaming platforms has substantially transformed the movie industry in recent years. When it comes to attracting talent and winning prestigious awards, technology companies have proven capable of competing at eye level with established networks and studios. At times, Netflix's market capitalization has even surpassed Disney's, making it the highest-valued media company in the world (Kim 2018).

In the wake of Netflix's success, the traditional entertainment powerhouses such as Disney and Warner Bros. hurried to build their own streaming services, aiming to build one-on-one relationships with their audience members, and thus gradually switching to a direct-to-consumer business model as well (Ball 2016b).

These increasingly direct consumer relations have introduced one particular novel weapon into the permanent fight for audience time, attention, and spendings: individual-level user data.

In the case of Netflix's first-ever series, "House of Cards", executives signed off on a nine-figure commitment for a drama series without having seen a pilot before, simply because they trusted their user data and were sure that people would like to see this (Smith & Telang 2016, Carr 2013). At least as far as known to the public, this marked the first time that large-scale individual user data were used in the greenlighting decision of a major fictional production. At the Sundance Film Festival 2015, Netflix's Head of Content Ted Sarandos participated in a panel called "The Beauty of Big Data or: How I Learned to Stop

¹ Lang (2017)

1 Introduction

Worrying and Love the Algorithm", attributing 70 per cent of the company's greenlighting decision-making to data, 30 per cent to human judgement (Wu 2015). Netflix founder and CEO Reed Hastings went so far as to profess that he viewed "consumer science" as the cornerstone of his "legacy" (Eyal & Biddle 2018).

Large streaming services have access to data on the entertainment preferences of millions of viewers world-wide – and, equally important, they have the ability to distill the relevant information from these data. The key to that distillation process is algorithms. As streaming platforms have tapped into the possibilities of algorithmically mediated audience relationships, they have successfully challenged the formerly prevalent "Nobody knows anything" paradigm in Hollywood, which holds that movie success is fundamentally unpredictable².

The new-found technological grasp on consumer preferences has quickly captured the imagination of the higher echelons in corporate Hollywood (Napoli 2016). As venture capitalist and entertainment industry futurist Matthew Ball (2019) puts it, "Through Disney+, The Walt Disney Company will be able to know, for the first time, each of its customers individually, which content and character they like, and how much. This should in turn allow the company to make more informed decisions about which content and merchandise to produce, increase the efficacy of its marketing and promotion, and sell more Disney-related products and experiences to Disney fans."

Yet while large media conglomerates increasingly turn (or integrate) into technology corporations, the greenlighting decisions and project selection processes of independent producers, i.e. production companies not vertically integrated with distribution, still mainly rely on gut feeling (Rimscha 2010, Bassett 2015).

Accurately predicting who and how many consumers will go watch a certain movie could prevent film producers from two common mistakes (Eliashberg, Elberse & Leenders 2006): producing flops (type one error) and missing out on potential hits (type two error). Given that a majority of individual film

² The adage goes back to screenwriter William Goldman who famously stated: "Not a single person in the entire motion picture field knows for a certainty what's going to work." (Goldman 1983, 39).

1 Introduction

projects fail economically³, "Murphy's law"⁴ states that 20 per cent of the films generate 80 per cent of box office revenues (De Vany & Walls 1996). Reliably mitigating those risks should sound like an intriguing proposition to producers of all sizes.

Over the last years, many studies on box office prediction have been published (Hadida 2009). Yet practical implementation of their findings is apparently nowhere to be found among the more than 300 production companies in Germany that depend on the theatrical success of motion pictures (Castendyk & Goldhammer 2012). Why is that?

Production studies have shown that practitioners in the movie business conceive of themselves as being privy to certain insights into "how the industry works, what it means, and what 'really' goes on 'behind the scenes'" (Caldwell 2008, 10), which outsiders – such as scientists – would be simply unable to comprehend. Hennig-Thurau & Houston (2018, 16) suspect that this "myth" is at the root of the gap between science and practice.

People who are in the film business tend to see themselves as artists, enjoying an amount of freedom that would be impossible in most other branches of trade. Especially German production companies are producers of niche products in an economy dominated by American films (Kumb 2017). Their task is perceived a cultural one, it exceeds and transcends simply earning money. Thus producers may be hesitant about taking any steps that could lead to what the marketing scientist Hennig-Thurau calls a "demystification" of the industry⁵: They might fear that their beloved profession might be reduced to soulless number crunching, resulting in an impoverished motion picture landscape of uniformity.

But while a certain disdain for "mathematical wannabe wizards", as Tom Cruise puts it (Beier & Evers 2005), does indeed exist among the movie industry, this work is going to argue that scientific models for predicting feature film audiences have not been readily implementable for independent producers in the past.

3 Of course, not all projects are created equal: Follows (2019) takes a specific look at independent films, i.e. movies not released by one of the major studios. Of all independent movies produced, he finds 90% not to be released theatrically at all, which likely means they remain unprofitable. Of the independent movies that do get a theatrical release between 1999 and 2018, about 60% fail to recoup their budget.

4 Named after the famous trade press journalist Arthur D. Murphy

5 Original German (Hennig-Thurau 2011, 18): "Demystifizierung der Branche"

1 Introduction

We will look at practical and scientific approaches of a) target audience definition (i.e. *who* is going to watch a certain film?), and b) revenue prediction (*how many?*). We will find that the two processes have been mostly treated separately by scientific approaches, while they are inherently linked in producers' practices.

While tackling the issues separately in academic works has been warranted by limited data availability in the past, we suspect that the recent abundance of individual-level consumer data will help reconcile approaches from communication studies, marketing science, and computer science into a coherent model of target audience definition and revenue prediction.

Drawing on the possibilities of individual-level data analytics as demonstrated by the large streaming services, we will furthermore examine how such a reconciliation of heretofore separate scientific approaches might spark the development of concrete tools, which could in turn enable independent producers to make more informed decisions about their projects in the future.

1.2 Perspective

The dissertation at hand builds and expands on the earlier, unpublished diploma thesis by the same author⁶. Applying data analytics at the level of individual viewers to better understand and predict movie consumption has been a long-standing interest of the author – an interest that was developed during film school, on track to becoming one of those independent producers whose perspective is taken here.

Correspondingly, this work is naturally inclined to constantly ground its research in industry practice. While it certainly constitutes a respectable goal for academic research to develop knowledge for knowledge's sake only (Huff 2000, Van Aken 2005), we see our work more in line with research conducted at professional schools such as business schools, and thus add relevance as a second criterion next to validity. Van Aken (2005) calls such "Mode 2 Knowledge Production" processes "solution-oriented", an attribute which consciously circumnavigates the dogmatic pitfalls associated with either "prescriptive" or "normative".

6 Text fragments from that thesis have been reproduced in an updated form as parts of [section 2.1](#) and [chapter 3](#).

1 Introduction

The epistemological positioning of this work may best be described as "engaged scholarship" (Van de Ven 2007). In such a model of knowledge production, practitioners are not simply conceived as passive recipients of research results, who may then go on to apply those in their respective field, but "enter into modes of collaboration" (Schön 1983, 328) with researchers, engage in the formulation of problems, reveal the thought processes underlying their practices, and implement research results into their own "reflection-in-action" (Schön 1983, 328).

Taking that conception of research as its intellectual vantage point, this dissertation is consequently heavily influenced by the ideas of evidence-based management and design science.

As we will examine further in [chapter 2](#), the practice of producing movies can be well described as a management practice. Evidence-based management (EBMgt), according to Rousseau (2012, 2), "is the systematic, evidence-informed practice of management, incorporating scientific knowledge in the content and process of making decisions." It is a practice modeled after the success of evidence-based medicine (Pfeffer & Sutton 2006) and, in order to function, needs the support of three distinct constituencies: "(1) the managers, consultants, and others who practice EBMgt and the (2) educators and (3) scholars who provide it critical support" (Rousseau 2012, 2).

It is important to note that the scholars' input into this process is not superior to that of the practitioners: Whereas in a pure technical rationality model, an "applied-science" approach, "professional practice largely boils down to instrumental problem solving on the basis of explicit knowledge, made rigorous by applying scientific theory and technique" (Van Aken & Romme 2012), an evidence-based management approach takes into account that "professionals use rich repertoires of explicit and tacit knowledge in a creative process of reflection in action" (Van Aken & Romme 2012, 3).

Nobel laureate Herbert Simon (1996, 111) put forward the idea that management research is a science of design, which he defines as devising "courses of action aimed at changing existing situations into preferred ones." According to Simon (1996, 111), design is "the principal mark that distinguishes the professions from the sciences. Schools of engineering, as well as schools of architecture, business, education, law, and medicine, are all centrally concerned with the process of design."

Certainly, the process of producing a movie is also a design practice in this sense.

1 Introduction

Thus research aimed at improving the practice of producing can be understood as design science. According to Van Aken & Romme (2012, 4), "the iconic research product" of such design science research "is a well-tested solution concept, that is, a generic intervention to solve a generic field problem, tested in the laboratory and in the field of its intended use."

While arriving at a specific, implementable solution for the problems of target audience definition and revenue prediction will be beyond the scope of this project, we aim to at least provide a reasonable outline of how a better practice could be crafted and prove the validity of the underlying mechanism proposed.

A useful framework to structure such a design-science endeavour is provided by the so-called CIMO logic (Denyer, Tranfield & Van Aken 2008), which breaks down design propositions into four parts: Context (C), Interventions (I), Mechanisms (M), and Outcome (O).

A fully-developed, evidence-based model of defining target audiences and predicting revenues which could be implemented by independent producers into their practice would need to cover all four components. Over the course of this dissertation, we will aim to lay the groundwork for such a solution by analyzing the context (C) of target audience definition and revenue prediction in practice and discussing a possible mechanism (M) which a meaningful intervention (I) could use to produce a favorable outcome (O) of the target audience definition and revenue prediction processes.

1.3 Outline

In line with the CIMO logic as explicated in [section 1.2](#), we will first examine the context of the problem at hand and take a look at target audience definition and revenue prediction in practice ([chapter 2](#)). From a general discussion of the producer's role in the film production process, we will infer the motivations, expectations, and importance of both defining target audiences (asking: who?) and predicting revenues (asking: how many?).

To empirically enrich our grasp on the status quo of target audience definition and revenue prediction, we will then conduct interviews with working independent German feature film producers and use the methodology of qualitative content analysis (QCA) to examine in which dimensions these producers think about audiences; if, how, and why they forecast the economic success of

1 Introduction

their works; and how they characterize their relationships with their audiences themselves.

Having established the context, we will then take a look at scientific approaches to target audience definition and revenue prediction by means of an extensive literature review in [chapter 3](#) and try to find reasons for why the practical implementation of these approaches has been negligible in the past. We will also derive possible forms which a successful, implementable target audience definition and revenue prediction practice might take on (the intervention part of the CIMO logic).

From there, we will go on to discuss a technological approach to target audience definition and revenue prediction which we envision to be at the heart of any future evidence-based model: the combination of individual-level user data and recommender algorithms as pioneered by streaming services ([section 4.1](#)). In the CIMO framework, this constitutes the mechanism.

In the subsequent sections of [chapter 4](#), the empirical core of the work at hand, we will then zoom in on this mechanism and validate its functioning in an industry context. To test its target audience definition capabilities, we will employ individual-level user data from two different customer surveys conducted with German moviegoers in 2017 ([section 4.2](#) through [section 4.5](#)). In each of the four analytic scenarios, we will formulate clear hypotheses on what results we expect the algorithmic approach to deliver and test these using various methods of statistical inference.

Finally, to investigate the applicability of the proposed approach to revenue prediction, we will take advantage of the open MovieLens dataset on mostly American moviegoers (Harper & Konstan 2015) and publicly available box office information ([section 4.6](#)).

In [chapter 5](#), we will wrap up by discussing our results: We will outline how they might be consolidated into a fully-developed, evidence-based model of predicting audiences by further research, and what implications our findings may bear for managerial practice today.

2 The Practice of Target Audience Definition and Revenue Prediction

2.1 Theoretical Considerations

The following considerations refer specifically to German feature film producers. The focus on Germany was chosen due to accessibility of research subjects. While it is important to differentiate between producers of different countries, because their economic environment and incentives differ substantially, many of the findings in subsequent sections can probably be generalized and apply to other European countries and independent US producers as well.

We will first take a look at the producers' economic role in the wider context of the film industry, then turn to their specific role within a production.

Similar to an entrepreneur starting a company, producers initiate films and take responsibility for their success. In theory, producers decide what screenplay they produce, who is going to direct, who will star in the movie, and how it will be sold¹. From a business model perspective, producers buy intellectual property rights from people and companies involved in the production of a film and go on to sell or license exploitation and usage rights to third parties at a profit. Their own contribution mainly consists in the composition of the package, i.e.

1 In practice, many more people have a say in those decisions. This is because film is a collaborative endeavour, and a producer usually needs to sell rights before the film is even produced. Thus the early financiers and their interests will influence the film's production significantly. In a European context, the co-producing TV commissioning editors are the most influential party. In a US context, studios function as the main financiers.

2 The Practice of Target Audience Definition and Revenue Prediction

the decision what rights to obtain from whom. Their work is protected as a standalone intellectual property right by German law².

The production of a film undergoes several stages (see [Figure 2.1](#)). It all starts with an idea, may this be an original one or the filming rights to some previously existing work (a novel, a comic book, another film, etc.). This idea is taken on by a producer who develops it together with the screenwriter (Gates 1999). At the same time, the producer will start packaging, i.e. bringing together core elements of the aspired production (Rimscha 2010), most importantly key cast and crew members as well as budget. Only if the budget can be secured, the project will be realized. Otherwise, the producer has to either change elements of the package or abandon the project.

As soon as the film is green-lit, production may start, which in itself consists of three phases (Wendling 2008): pre-production, principal photography and post-production. It ends with the delivery of one hard copy of the finished film (this has been called the "negative" in the analog world, therefore all costs accrued up to that date are still being referred to as "negative costs").

The producer's main work is typically³ done with delivery of the final film. Then, exploitation starts, typically employing a windowing strategy, i.e. entering different markets at different times, moving from those with the highest price per unit and least number of customers (cinema) to broader ones at a reduced rate (home video, pay TV, free TV)⁴. As Ball (2016a) poignantly observed, windowing can be thought of as a price discrimination strategy, bluntly mediated by the business-to-business nature of the market, and might be substituted by other, more fine-grained price discrimination strategies in the future, building off the current shift to direct-to-consumer models which

2 The American copyright is intended to protect investments in the creative process, thus the producer is actually the owner of a film's copyright (unless they sell it to someone else). In Germany, the producer obtains an ancillary copyright ("Leistungsschutzrecht", cf. §94 UrhG).

3 These explanations refer to a classical division of work, where the producer is no longer involved in the exploitation process after delivery of the first copy. Yet over the last years, conventional boundaries between producer and distributor have been blurred. On the one hand, the Internet as a marketing instrument and the availability of relatively inexpensive digital copies have partly democratized distribution, empowering independent filmmakers to market their own films (Reiss 2010). On the other hand, sales agencies and broadcasters increasingly expect producers to deliver additional material to feed the new channels with content.

4 The optimization of this distribution strategy has been subject to scientific research – cf. Frank (1994), Lehmann & Weinberg (2000) and Hennig-Thurau, Henning, Sattler, Eggers & Houston (2007), respectively – and causes ongoing public debate in Germany, since movies funded by state subsidies have to stick with rather conservative windowing timeframes defined by German film funding legislation (cf. §20 FFG).

2 The Practice of Target Audience Definition and Revenue Prediction

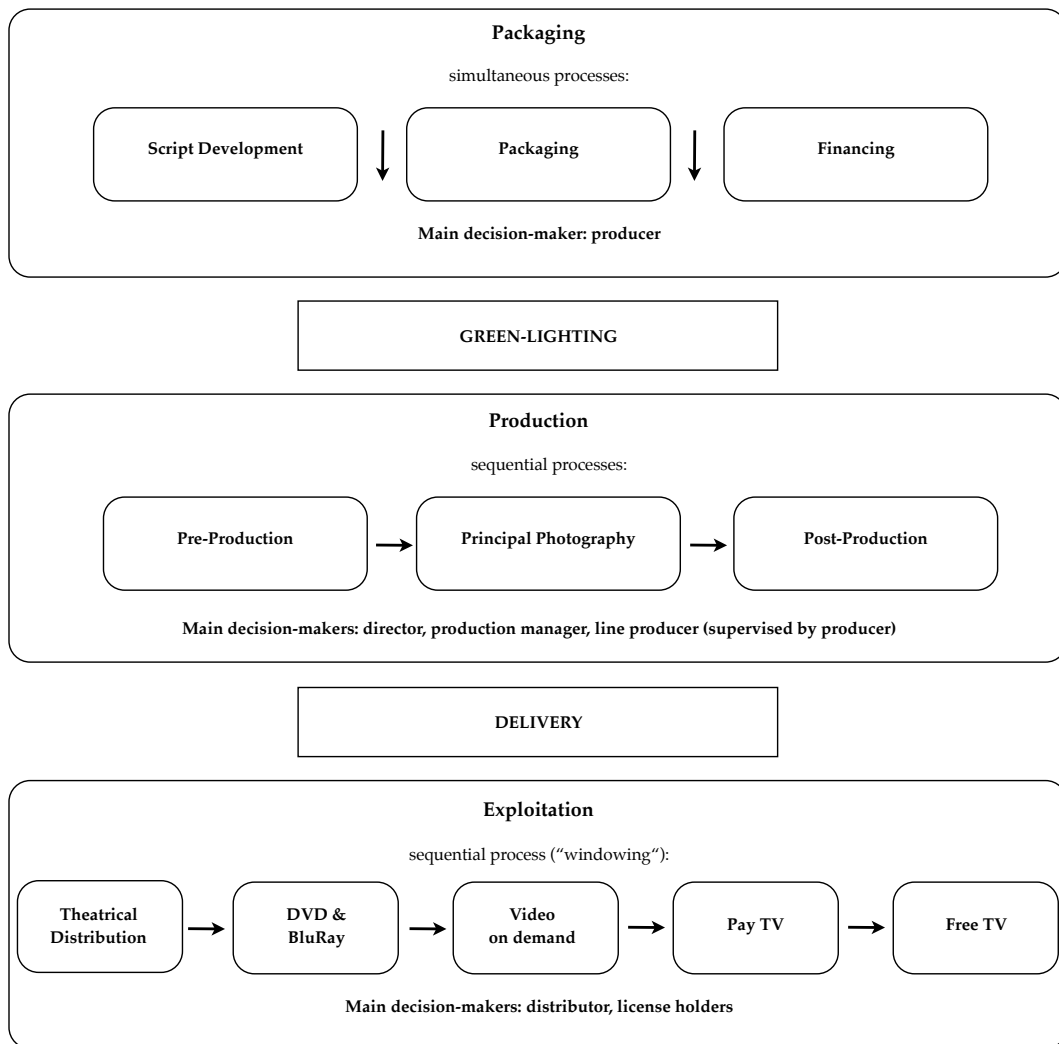


Figure 2.1: Stages of production and exploitation of a typical feature film, own illustration, also reproduced in Behrens et al. (2020)

2 *The Practice of Target Audience Definition and Revenue Prediction*

is also at the heart of the new technological models discussed in the work at hand.

As Björn von Rimscha points out in his study on risk management among German film producers, the producers' main risk in this process is their development risk, i.e. the risk to develop a screenplay for production which subsequently fails to secure funding and has to be abandoned (Rimscha 2010).

The actual consumption risk is of more imminent concern to the distributor⁵ and less threatening to the producer. This can be explained by the typical financing structure of a German feature film: In general, there are four distinct sources of film funding: equity, debt, pre-sales, and so-called soft money, i.e. public subsidies. While likening the film producer to an entrepreneur might evoke the impression of equity and debt being major funding sources, the typical funding of a German feature film is to a large degree enabled by public subsidies, with soft money accounting for 43 per cent (Castendyk & Goldhammer 2012) of the budget on average (the legal maximum being 50 per cent)⁶. Only 5 per cent are usually provided by the producers themselves (the legal minimum at which films are still eligible for public subsidies⁷).

With so little funds of their own, producers usually sell most – if not all – valuable exploitation rights to third parties before production even starts in order to use the licensing fees or advances on future licensing fees as a contribution to the budget. After selling most of the rights beforehand, they only participate in revenues if earnings exceed certain thresholds.

At the same time, the producer is legally entitled to include general expenses (7 per cent) and a producer's fee (2.5 per cent) in their budget (Zwirner 2011). This quasi-salary is often the only money the producer will earn, as in most cases the thresholds for profit participation will not be met⁸.

5 Storm (2000) explains how the distributor's guarantee emerged as the most important funding source for German feature films after WWII, because distributors were able to recover their financial basis quicker than producers (by distributing foreign films). In some years, there were even deals in which producers only managed the production, with distributors providing 100 per cent of the funding.

6 For a breakdown of the budget of European fiction films, cf. Kanzler (2019).

7 cf. Section 63 of the German Film Promotion Act (§63 Filmförderungsgesetz).

8 Numbers on individual films are usually not disclosed, but the German federal public funding body (Filmförderungsanstalt, FFA) hands out production subsidies as conditionally repayable loans that need to be paid back pro rata with the producers' exploitation revenues (cf. Section 71 of the German Film Promotion Act, §71 Filmförderungsgesetz). From the FFA's annual report it can be seen that only 17% of films pay back any money; just 3% of movies are able to repay the loan completely; thus most films never reach a point where the producer substantially participates in revenues (FFA 2020b).

2 The Practice of Target Audience Definition and Revenue Prediction

That dynamic has a significant impact on the producer's incentives: Of course they do not want to produce flops, but often they do not reasonably expect to participate in profits, either. Thus the producer's main focus in their daily work is arguably on fundraising and the business-to-business market of pre-sales, less on the consumer market.

The main private financiers on the other hand (studios, broadcasters, distribution companies) are much more incentivized to reach a large audience than the producers themselves. So it comes as no surprise that these players have historically been the progenitors of consumer research within the industry (Prommer 1997). As Jenke (2018) details for the producer-broadcaster relationship, this results in a knowledge asymmetry that producers perceive as disadvantageous.

In the production process itself, producers take on a role of creative management at the intersection of art and business. As Ryan (1992) notes: "The legitimacy of creative management depends partly on their ability to exercise artistic leadership, a form of talent possessed by some as an element of their charismatic personality. It entails a substantive contribution to the search for originality through any of a number of means; it may involve creating designs and interpretations which are themselves original and exciting, perhaps being able to recognise talent in others, or being able to inspire performers to great heights of achievement. It may be the ability to direct transcription in novel and imaginative ways. For some it may mean sensing changing taste communities and producing originals which consistently bring popular and/or critical acclaim with various audiences." While many of the points raised apply to the feature film producer, the last one is of particular interest here, as it suggests that producers are also specifically tasked with anticipating public taste and making cultural products that appeal to audiences.

The contrast between the actual business model and the assumed function of the producers leads to an interesting question: If producers' direct customers are rather film distributors and TV commissioning editors than the actual viewers, how do they think about those remote consumers that will eventually watch their films?

Our analysis of the producer's role here would suggest that target audience definition and revenue prediction, i.e. the process of predicting who and how many viewers will be interested to watch a certain new movie, mainly serve the purpose of convincing financiers to fund a new project. In an explanatory breakdown of film financing for potential new film investors, Brown (2015, 8)

2 The Practice of Target Audience Definition and Revenue Prediction

cites the importance of "a solid business plan that lays out how financiers get their money back based on the film's capital structure and a realistic assessment of audience demand" when looking for equity investments. For a few years now, governmental film funding institutions in Germany have been demanding marketing concepts from producers along with their subsidy applications for production funding (Backen 2009). These concepts typically contain a rough forecast of sales as well. And while the buyers in a pre-sale of rights, be it distributors, broadcasters, or world sales agencies, will typically run their own forecast and profitability assessment before entering a deal, producers obviously engage in some form of demand forecast to convince buyers how those buyers' audiences (i.e. their subscriber base, regional moviegoer audience, etc.) are aligned with the target audience of the film. In subsequent sections, we will conduct an exploratory examination of the reasoning behind these practices of target audience definition and revenue forecasting.

Research on producers' concrete audience conceptions is scarce both in US and European contexts. According to McQuail (1997, 113), "those who occupy the more autonomous and creative of mass communication production roles are likely to be the least yielding to some 'target group' defined by audience research or imposed by management. The integrity of artistic creation does not really allow compromise of the highest standards [...]. Nevertheless, they also need some conception of their audience, and a practical solution is to pay special attention to the reactions and views of personal contacts, friends, and relatives". Zafirau (2009, 200) sheds some light on the relationship between Hollywood executives and their audiences, pointing out how "micro-level social phenomena (...) inform producers' common sense understandings of what sorts of products will 'work' with audiences". According to Zafirau (2009, 192), producers inhabit a "liminal space (or gray area)", being neither completely "removed producers" looking at their audiences from afar, nor real "audience members" themselves. He maintains they "depend on their own hunches" as much as on audience research (Zafirau 2009, 190). Production Studies have focused mainly on the Anglo-American media industries in the past (Krauß & Loist 2018), so an equivalent study for German producers does not exist as of now. It will be interesting to examine if and how the insights on American producers transfer to German producers as well.

2.2 Empirical Exploration

As argued, German feature film producers find themselves in a position where their economic success is largely dependent on their success with business-to-business clients, while they are at the same time tasked with anticipating the desires of consumer audiences.

How they define and think about audiences has to the author's best knowledge not been researched before and will be the focal point of the next sections.

To examine producers' audience conceptions and producer-audience relationships, a qualitative approach was pursued and eight interviews with German feature film producers were conducted by two interviewers over the course of eight months in 2016 and 2017. The interviewees were sourced by personal contacts at first and then by referrals of the first interviewees.

The interviews were semi-structured with slightly differing questionnaires, but all producers were asked to think of a recent or current film of theirs and describe who the audience of that film was. All interviewees were working producers who had at least completed one widely-distributed feature film, with their experience ranging from first-timers to veteran producers of Academy-Award-winning films.

The interviews were conducted in various environments as was most suitable to the respective interviewee: producers' offices, coffee shops, and co-working spaces. Seven out of eight interviews were conducted in person, one over telephone.

One important note on the author's perspective: The author and his colleague themselves are young producers and film school graduates, so the interviewees would see them mainly as younger colleagues and talk quite openly, referencing mutual acquaintances and experiences from practice as well as issues from the current public discourse among German film producers. Therefore the research set-up was similar, but slightly different from what Ortner (2009) describes as "studying sideways". The interviewees were made aware of the fact that the material would be used to develop tools to assist producers with data analytics, and specifically for the PhD dissertation of the author. To maintain the informal character of the conversations, the interviews were only recorded in written notes and the interviewer drew up a selective, comprehensive transcript right after the interview.

2 *The Practice of Target Audience Definition and Revenue Prediction*

The interviews were analyzed using qualitative research analysis and the focus of the analysis was on audience definitions, producers' attempts to forecast economic success, and their descriptions of the audience-producer relationship. The study's nature is explorative, so inductive category formation was chosen as the appropriate mode of analysis. The goal was to identify relevant categories from the text (Mayring 2014).

Following the procedure described by Mayring (2014), three research questions were defined from the research interest before coding.

Research Question 1: By what criteria do producers define their audiences?

Research Question 2: How can and do producers forecast box office revenues?

Research Question 3: What kind of relationship do producers have with their audience?

Then, for each research question, a selection criterion for categories as well as a level of abstraction was defined (Mayring 2014). Subsequently, the text was coded and categories were identified. After analyzing 50 per cent of the corpus, the categories were revised; afterwards the complete corpus was coded (Mayring 2014). Upon coding, the identified categories were grouped into main categories. The complete analysis was performed using the free software QCAmap⁹. Relevant quotes were translated into English for this text by the author.

2.2.1 Target Audience Definition Criteria

Categories were defined before coding as "qualities of the audience" and the level of abstraction specified as "concrete qualities, described in a form that can occur in other interviews as well (no idiosyncratic formulations)".

Subsequently, 17 categories were identified, which were then grouped into four main categories: demographics, film taste, lifestyle & interest, and behavior. [Table 2.1](#) shows the clustered categories.

[Table 2.2](#) gives an overview of how often the main categories occurred among the eight cases. All categories are discussed briefly below.

⁹ QCAmap has been developed specifically for qualitative content analysis, cf. Mayring (2014).

2 The Practice of Target Audience Definition and Revenue Prediction

Main Category	Categories
Demographics	Age
	Gender
	Nationality
	Geographical area
Film Taste	Affinity to similar films
	Affinity to a director
	Affinity to an actor
	Affinity to a production technology
Lifestyle and Interest	Cultural Capital
	Affinity to a topic
	Distinct lifestyle
	Gratifications sought
Behavior	Biographical background
	Media consumption

Table 2.1: Overview of categories as inferred from producer interviews

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Demographics	0	4	6	3	1	6	3	1
Film Taste	0	8	1	2	1	1	1	1
Lifestyle and Interest	1	5	3	8	1	2	2	2
Behavior	1	0	0	0	0	0	0	0

Table 2.2: Occurrences of main categories in producer interviews

2.2.1.1 Demographics

Age and Gender were very commonly used by producers to describe their audience. Five producers referred to their spectators' age, three of them also to the prevalent gender among that age group.

The descriptions varied in specificity, ranging from "kids from 9 to 12" to "best agers" and "older than 35, maybe 40". Producers were aware of the fact that a film never exclusively appeals to one gender and mostly used relative terms such as "more female".

Four producers referred to their audience's nationality, but mostly negatively, i.e. to deny that category's importance, citing their film's "international potential", "international appeal", and "international target group". Only one producer, whose film was based on a true story, stated their protagonist was "only known in Eastern Germany". In general, producers tended to regard nationality mostly as a potentially limiting factor to their film's reception, less as a defining trait of their audience.

2 The Practice of Target Audience Definition and Revenue Prediction

Two producers used a geographical area to describe their audience: In both cases they distinguished between rural and urban areas, speaking of an "urban audience" and people "from the metropolitan areas". Education was just mentioned once: The producer simply labeled their audience as "educated".

Overall, demographics were almost always brought up in one way or another, but the description did not follow a comprehensive framework and no producer referenced all identified demographic criteria.

Table 2.3 shows the occurrences of the categories among the 8 cases.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Age	0	2	4	1	0	2	3	0
Gender	0	0	2	1	0	2	0	0
Nationality	0	0	0	0	1	2	0	1
Geographical Area	0	1	0	1	0	0	0	0
Education	0	1	0	0	0	0	0	0

Table 2.3: Occurrences of socio-demographic categories in producer interviews

2.2.1.2 Film Taste

Descriptions of film taste were just as common as demographic categories in the producers' audience conceptions, with seven out of eight producers using such categories to describe their audience.

The most common way to capture film taste was to bring up the viewers' affinity to similar movies (or TV series). Three producers explicitly mentioned other audiovisual works in their audience descriptions, referring to a "50 SHADES OF GREY-type" audience, "fans of GAME OF THRONES' and THE REVENANT and such things", or the spectators of their own "previous films". Notably only one or two other works were mentioned in each case, all of the examples were American and globally successful blockbusters, coming from a budget level that none of the interviewed producers operated at themselves.

Two producers described their audience by their affinity to a certain director, either as "fans of" the specific director of their own film or referencing a seminal director's fanbase: "the audience that Wajda had".

2 The Practice of Target Audience Definition and Revenue Prediction

Affinity to a certain actor was cited twice by one producer, and affinity to a certain genre ("family entertainment") occurred once. At one point, a producer negatively mentioned affinity to a production technology when talking about people's "fear of the glasses", referring to the typical spectacles used for stereoscopic screenings.

Overall, descriptions of film taste seemed rather vague and randomly defined. Established genres and formats were rarely mentioned and similar films chosen without a systematic approach.

Table 2.4 shows the occurrences of the categories among the 8 cases.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Affinity to similar films	0	0	1	1	1	1	0	1
Affinity to a director	0	4	0	0	0	0	1	0
Affinity to an actor	0	2	0	0	0	0	0	0
Affinity to a genre	0	1	0	1	0	0	0	0
Affinity to a production technology	0	1	0	0	0	0	0	0

Table 2.4: Occurrences of categories of film taste in producer interviews

2.2.1.3 Lifestyle and Interest

The categories in this main category revolve around the question of why people go to the movies.

Five producers cited their audience's cultural capital, describing them as a "feuilleton audience", as coming from "the artsy-fartsy Cannes-arthouse corner", simply as "arthouse", or "classic arthouse", "large arthouse", or "mainstream". The arthouse-mainstream divide seemed like the most basic definition of audiences that everything else built on.

Four producers assumed their audience was interested in the specific theme of the movie, i.e. they referred to rather obvious topics of the film: "contemporary dance theater audiences", "people interested in India and Pakistan", "migration" or "the culinary aspects", "people interested in cooking and love", "people interested in the topic of culture clash". Less obvious topics like specific characters, conflicts, or narrative structures were not referenced by the producers.

In two cases, producers tried to capture a complete lifestyle of their spectators with a catchphrase: "stay-at-home-moms" and "eco-millennials". A specific

2 The Practice of Target Audience Definition and Revenue Prediction

biographical background was only referred to once: The respective producer speculated that their upcoming film might particularly resonate with migrants and people who were familiar with that "search for a home" from their own experience.

One producer specifically cited gratifications audiences might seek from a movie: for their own film, they were looking for "people who take two hours to be moved, emotionally and intellectually", dismissing other audiences' "expectant attitude: cinema has to be fun" as well as some audiences' longing for an "uplifting" ending.

The descriptions of lifestyle, interests, and motivations seemed to evoke rather vivid images in the producer's heads, but no underlying system to structure these audience definitions was recognizable.

Table 2.5 maps the occurrences of the categories across the 8 cases.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Cultural capital	0	3	0	1	0	2	2	1
Affinity to a topic	0	2	2	4	0	0	0	1
Distinct lifestyle	0	0	1	0	1	0	0	0
Gratifications sought	0	0	0	3	0	0	0	0
Biographical background	1	0	0	0	0	0	0	0

Table 2.5: Occurrences of lifestyle categories in producer interviews

2.2.1.4 Behavior

Only one producer at one point referred to a specific behavior of their audience: reading newspapers. This came to the producer's mind almost by accident, during the interview, because they were explaining their target audience by likening them to a real person: "people like my father – well, he would have to read about it in a newspaper".

It seems like behavior is an additional category that producers almost completely neglected. The single occurrence can be seen in **Table 2.6**.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Media consumption	1	0	0	0	0	0	0	0

Table 2.6: Occurrences of behavioral categories in producer interviews

2.2.2 Revenue Prediction in Practice

Categories were defined before coding as "techniques and approaches of forecasting, forecasting context, and assessments of their forecasting abilities", the level of abstraction was specified as "concrete techniques and motivations, in a form that could occur in other interviews as well (no idiosyncratic formulations)".

Six categories were found which were subsequently grouped into two main categories: box office forecasting methods and box office forecasting motivations. Because they were not explicitly asked for their forecasting methods, not all producers referred to this in their descriptions of the audience relationship.

Concerning forecasting methods, three producers claimed to predict box office success based on so-called comparables, i.e. using similar movies as a benchmark for theirs. One said: "We mostly look up comparables by topic", another one explained "I mostly look at comparables and research at IMDb Pro for similar budgets and genres within the last eight years – everything else is not meaningful anyway." The third one provided some insights on the motivations behind that: "I choose comparables by topic and director. One must keep in mind that they are not only a forecasting instrument, but a sales argument. It is not about being 100 per cent accurate in the prognosis, but about plausibility." This angle was reinforced by several producers when they talked about the context of their forecasting efforts, as described in more detail below.

One producer stated to rely only on their own experience with past movies when it comes to box office forecasting: "For 90 per cent of our films, I know who the audience is, thus I also know the potential." And one other producer mentioned using a specific box office forecasting software ("Cinelytic") to predict revenues¹⁰.

[Table 2.7](#) maps the occurrences of the categories across the 8 cases.

When it comes to motivations, we already touched upon the comparable films' purpose to serve as a sales argument for the producer during fundraising and negotiations with their business clients, i.e. distributors, co-producers, and buyers of rights.

¹⁰ For a description of Cinelytic, cf. Bastian (2017).

2 The Practice of Target Audience Definition and Revenue Prediction

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Forecasting by comparables	0	0	1	0	1	1	0	0
Forecasting based on own experience	0	0	0	0	0	0	0	3
Using a box office forecasting tool	0	0	1	0	0	0	0	0

Table 2.7: Categories of box office forecasting techniques in producer interviews

The same is true for the estimated numbers: Box office forecasts are mainly a funding tool, a part of the pitch, as four of the producers explain in the interviews. On the same note, the estimates are usually deliberately inflated. "In most cases, we estimate a slightly too optimistic number – at least that way we can get the necessary budget in Germany." Producers refer to this as a common industry practice: "Everybody always writes in these applications: We aim for 250,000 admissions and a premiere at an A festival." One producer comments: "It is always a game", admitting on the same note: "Yet it would be more satisfying not to have to play."

Table 2.8 shows how occurrences of the categories were distributed among the cases.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Forecast as a funding tool	0	1	0	1	0	2	0	1
Forecast as deliberately inflated	0	1	0	1	0	1	0	1

Table 2.8: Categories of box office forecasting motivation in producer interviews

2.2.3 Audience-Producer Relationships

Categories were defined before coding as "descriptions of the relationship or interactions with the recipients of their movies" and the level of abstraction was specified as "high-level description of the interaction, which could be found in other interviews as well (no idiosyncratic formulations)".

Nine categories were identified, which were then grouped into two main categories: audience-producer interactions and descriptions of the audience-producer relationship.

Most interactions between producers and audiences happen rather late in the production process. Four producers mention test screenings, which they do mainly for creative purposes, i.e. when the edit is mostly done, but feedback

2 The Practice of Target Audience Definition and Revenue Prediction

can still be incorporated. The producers used the term "test screening" not only to describe large, conventional test screenings with several hundred spectators, but also for showings to invited people in the editing room. One producer mentioned hosting "up to 50 test screenings" with just a few people each for one film. Another one described picking "5 to 8 people consciously". Others had a specialized market research company recruit the audience for a test screening which was facilitated by the production company. The purpose was usually to evaluate the narrative structure and overall impact of the film. One producer specifically mentioned the audience's ability to pinpoint critical issues: "They are all professionals, because they watch TV for two hours every day."

One producer described two more forms of audience interactions at a later stage of the film's lifecycle: getting first reactions at a premiere and meeting the audience on a cinema tour. At the latter occasion, this particular producer learned some surprising facts about who their audience was. The same producer also mentioned "looking into the audience of comparables" as an early way to learn more about one's recipients, but did not elaborate on how exactly this was done. Another producer tried a more direct form of early audience interaction: "I did a concept test once, in fact a project of mine was performed as a table read at a [...] festival."

Table 2.9 gives an overview of the occurrence and frequency of the categories among the eight cases.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Test screenings	2	1	0	0	0	1	0	2
Premieres	0	1	0	0	0	0	0	0
Cinema tours	0	1	0	0	0	0	0	0
Concept tests	0	0	0	0	1	0	0	0

Table 2.9: Occurrences of categories of audience-producer interactions in producer interviews

One producer described the relationship to the audience as "mediated". They called it "indirect" and regarded the current technological change as a "large chance to eliminate the middlemen, go for the consumers directly. That would make distributors and world sales obsolete." As in regards to their own position relative to the audience, producers perceived themselves either as a part of their audience – "I make films for people like me" – or as different people whose taste they cater to: "[the topic of the movie] was never really my

thing".

Interestingly, one producer also voiced concrete expectations: "My audience should value originality." The remark points to an audience concept of a "model spectator", that, like Umberto Eco's "model reader" is imagined and demanded to be competent enough "to deal interpretatively with the expressions in the same way as the author deals generatively with them" (Eco 1984).

Table 2.10 provides an overview of the occurrence and frequency of the categories among the interviews.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
The relationship as mediated	0	0	0	3	0	0	0	0
The producer as part of their audience	0	1	0	0	0	0	0	0
The audience as distinct from producer	0	1	0	2	0	0	0	0
The producer demanding from the audience	0	0	0	1	0	0	0	0

Table 2.10: Occurrences of categories describing the audience-producer relationship in producer interviews

2.3 Intermediate Discussion

Over the course of this chapter, we have systematically assessed current audience conceptions and relationships of German feature film producers, both from a conceptual point of view and by means of an empirical exploration.

Target audience definition and box office forecasts are mainly used for fundraising purposes by producers. In order to convince financiers of a project's viability, producers aim more for plausibility than accuracy and predictions are often deliberately optimistic. The prevalent forecasting method is using comparable films ("comps") as a benchmark.

Our findings also show how producers use very different categories to define their audiences and how the level of detail varies significantly. Although demographics, taste, lifestyle, and behavior are all mentioned by producers, no audience description in our interviews covered all these categories. Target audience definitions do not follow a structured approach and rely heavily on intuition and anecdotal evidence.

The producer-audience relationship is perceived as indirect, intermediated both by the producers' business partners (distributors, broadcasters) and third

2 The Practice of Target Audience Definition and Revenue Prediction

parties (critics). Direct interactions with the audience occur only relatively late in the production process, when the editing is finished or about to be finished. Earlier audience interactions like concept tests are rare exceptions. The empirical value of such audience interactions is doubtful, as the viewers of test screenings and premieres are likely not representative of the film's actual target audience.

In line with previous research (Ang 1991, Jenke 2018), producers' current audience conceptions may be characterized as anecdotal: based on few, episodic interactions with the audience, they lack structure, focus on demographics, and are supplemented with seemingly arbitrary categories of film taste.

We will now take a look at scientific findings on movie audiences and revenue forecasting before trying to lay out a more evidence-based approach in [chapter 4](#).

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

3.1 Branches of Research

Scientific studies on movie audiences either try to link movie properties and external factors such as favorable critical reviews or the competitive environment directly to aggregate numbers of admissions and revenues – or they stay at the individual level and have a deeper look at the viewers' decision-making process itself. This consideration leads naturally to the common differentiation between the "economic" and the "psychological" approach (Eliashberg et al. 2006) in movie performance research.

The psychological or "communication theory approach" (Hadida 2009, 300) examines the movie consumption behavior of individual viewers, their motivations, and decision-making processes. Surveys and experiments are the main research tools, here. The goal is to find out what kinds of people watch what kinds of films – and why. This approach draws from psychology, cultural studies, and sociology. While it shares a lot of film-specific variables with the economic approach, it also looks at expectations, gratification experiences, and psychological traits, as well as sources of awareness and circumstances of movie attendance. The definition of distinct audience segments is a practice based on insights from the psychological approach.

The economic approach on the other hand asks: How many spectators will a certain film attract? As Hadida (2009) points out, such modeling is not industry-specific, but builds on several economic theories such as the resource-based view, the dynamic capabilities view, and industrial organization economics. Movie traits discussed in such studies include genre, existence and success of underlying source material, screenplay quality, track record and interplay of

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

key personnel like cast and director, economic factors such as budget, advertisement spendings and branding power of the distributor, movie runtime, artistic and technical skills like music and special effects, as well as circumstances of the movie's market entry, such as age restriction (MPAA or FSK rating), ticket price, and release date. Although derived from a different theoretical framework, third-party information sources are usually incorporated as factors in the same models, as if e.g. the average rating by critics was a feature of the film itself¹.

As Sochay (1994) states, the industry itself prefers the psychological approach, which is exemplified by the prevalence of studies funded by the German Federal Film Board (FFA), that indeed concentrate on the individual spectator's film selection process². We will briefly address how both streams of research have been received by practitioners in subsequent sections.

Of course both approaches are complimentary: They may (and should) be combined, since they just offer different terminology to talk about the same phenomena and it depends on the context which one is most suitable.

3.2 The Psychological Approach

3.2.1 Overview

What has been dubbed the "psychological approach" within movie marketing research is concerned with the motivational aspect of motion picture consumption: Who watches feature films and why?

Entertainment products, such as feature films, are distinguished from other products by some unique characteristics (Hennig-Thurau & Houston 2018). Since (at least) Aristotle it has been established that human behavior can largely be explained by a general tendency to seek pleasure and avoid pain. While many everyday consumption decisions are instrumental to reaching some separate, pleasurable goal for the consumer, a mode which is called "utilitarian consumption" (Alba & Williams 2013), entertainment products are typically

1 Hadida (2009) coins the term "information theory approach" for the theoretical framework from which these factors originate. According to her, one may respectively classify such factors as "expert-based" (critical reviews), "non-expert based" (word of mouth), and "peer-based" (awards) sources of information.

2 This holds true both for their funding of scientific studies like Blothner (2000), Blothner (2001), Blothner (2003), Blothner (2004), FFA (2006), and Neckermann & Blothner (2001), and their annual publications on audience statistics (FFA 2020c).

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

consumed in a mode of "hedonic consumption", i.e. "it is the consumption of the product itself that provides the consumer with gratification" (Hennig-Thurau & Houston 2018, 63).

Different psychological theories have been proposed as to why such entertainment consumption experiences are perceived as enjoyable. We will take a more detailed look at some of these approaches in [subsection 3.2.2](#). The suggested explanations originate from a variety of academic backgrounds within psychology, communication sciences, and sociology.

These underlying motives then lead to concrete consumption decisions. Again, different theories have been put forward regarding how these decisions are eventually being made, mostly in a broader media context. Researchers have employed different methods to put these theories to the empirical test, ranging from consumer surveys and self-introspection to unobtrusive observational studies and laboratory experiments. We will take a closer look at some of those frameworks in [subsection 3.2.3](#) and discuss their applicability in the context of theatrical feature film consumption.

3.2.2 Moviegoing Motives

Why do people go to the cinema and watch films? In the early days of cinema, motion picture producers famously tried to lure in audiences with sensational images of moon landings³, approaching trains⁴, and erotic striptease⁵. Gunning (1997) described the aesthetics of the time as a "cinema of attractions", building on a term developed by Eisenstein (1974, 78), who defined an attraction as any element "that subjects the spectator to a sensual or psychological impact". Early audiences explicitly sought out these attractions, attending motion picture shows like fairgrounds. To the day, such sensation-seeking is still among the motives for movie consumption, although the nature of the images and scenes that may provide such sensual impact has certainly evolved. Researchers have defined sensation-seeking as a personality trait that describes the "generalized tendency to seek diverse, novel, complex, and intense sensations and experiences, possibly through taking physical risks for the sake of these experiences" (Knobloch-Westerwick 2015, 40). Zuckerman & Litle (1986, 55) have empirically established that consumers that score high on a

3 A TRIP TO THE MOON, France 1902, directed by Georges Méliès

4 THE ARRIVAL OF A TRAIN AT LA CIOTAT STATION, France 1895, directed by Auguste und Louis Lumière

5 BEDTIME FOR THE BRIDE, France 1896, directed by Léar

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

sensation-seeking scale "like scenarios that are relatively novel and arousing", referring in particular to consumers' interest in depictions of sexuality and graphic violence.

But while such sensation-seeking certainly contributes to contemporary moviegoing motivations (Eliashberg & Sawhney 1994), it is hardly sufficient to explain consumers' desires for a variety of different movies with more or less complex narrative structures.

Another consumption motive which has been widely discussed not only in academic circles, but also among practitioners and in the general public, is escapism. As Vorderer (1996, 311) defines it, at its core, "escapism means that most people have, due to unsatisfying life circumstances, again and again cause to 'leave' the reality in which they live in a cognitive and emotional way"⁶. A first empirical study of escapism was conducted by Pearlin (1959) asking television viewers about their stress levels and viewing behavior, and escapist motives have been empirically linked to feature film consumption for different genres (Hirschman 1987). Notably, within the framework of escapism, it is not so much the experience of watching a film itself that is pleasant, but the temporary relief from one's psycho-social surroundings. The notion of movies as a refuge can also be observed in moviegoers' own descriptions of their behavior: Stempel (2001) surveyed 158 moviegoers about their moviegoing experiences, providing a unique collection of insights into consumers' motivations, emotions, and memories associated with going to the cinema. We will repeatedly turn to this compilation to illustrate how some of the media consumption motives discussed throughout this section may apply to moviegoing in particular. One of his respondents professed that in his adolescence, films "became a way to forget. Through junior and high school I cut class on a weekly basis to disappear into dark movie houses" (Stempel 2001).

As Knobloch-Westerwick (2015) notes, escapism is rather vaguely defined, since one cannot truly "leave" reality, and thus escapist media consumption might be better described as a special case of coping, a broader psychological concept which encompasses all "thinking, feeling, or acting so as to preserve a satisfied psychological state when it is threatened" (Snyder 2001, 4)⁷. For the media consumption context specifically, coping behavior has been conceptualized in the mood management approach.

⁶ Translation taken from Henning & Vorderer (2001, 101)

⁷ Quoted in Knobloch-Westerwick (2015, 36).

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

Mood management theory maintains that "the consumption of messages [...] is capable of altering prevailing mood states" (Zillmann 1988, 327) and thus consumers choose media messages (which encompasses entertainment content as well) that are likely to either preserve a pleasant hedonic state or terminate an unpleasant one, "without stipulating that individuals necessarily comprehend the utility of their choices" (cf. the "selective exposure" paradigm in [subsection 3.2.3](#)). Zillmann (1988) proposes four different mechanisms by which media messages can impact consumers' mood: their excitatory potential (bored people will seek out exciting content, stressed people will look for soothing media fare), their absorption potential (the more cognitively absorbing a message, the greater its potential to alter the consumer's mood), the semantic affinity between mood and message (if someone seeks to terminate a state of anger, they should not seek out content concerned with other people's anger), and the message's hedonic valence (pleasant messages are more likely to improve the consumer's mood than unpleasant ones).

Mood management theory has been supported for television usage by experimental studies (Bryant & Zillmann 1984) and field observations (Anderson, Collins, Schmitt & Jacobvitz 1996). Yet the application to theatrical feature film consumption is less obvious: A trip to the cinema is in most cases planned well before the actual day of consumption (Stradella Road 2010): The consumer does not even know which mood they will be in at the time of consumption. Also the voluntary exposure to movies which produce negative emotions, such as tragedies or horror films, presents a challenge to the mood management approach.

Viewers immediate emotional reactions to movies go beyond mere excitement and can take on a variety of different, nuanced emotional states. According to the affective-disposition approach, these reactions are largely facilitated by empathy: If a viewer develops a positive affective disposition (i.e. they like a certain character, care for the character, approve of their actions), they will hope for a good outcome and will feel empathy with all the character's emotions – whereas, if they develop a negative affective disposition (i.e. they dislike the character, resent them, disapprove of their actions), they will hope for a negative outcome, and feel counter-empathetic emotions (Zillmann 1991, Zillmann 1994)⁸. So why would consumers seek out experiences like watching a tragedy, where characters to whom they maintain a positive affective disposition will suffer? Oliver (1993) presents a solution from the framework of meta-

8 Zillmann (1994) suggests that "empathy" is a more useful mechanism to explain our emotional reactions than the widely used Freudian term "identification".

3 *Scientific Approaches to Target Audience Definition and Revenue Prediction*

emotions: Building on a concept by Mayer & Gaschke (1988), she observes "that a mood or emotion can be experienced at two levels: at a direct level (analogous to Zillmann's use of the concept) and at a reflective level that consists of impressions and feelings about the mood (a metaexperience of mood)" (Oliver 1993, 318). In this view, consumer's appraisal of their own emotional reactions to a movie play a crucial role in their overall valuation of the viewing experiences. In an empirical study of sad film consumption, Oliver (1993, 336) concludes that "feelings of sadness elicited from viewing tearjerkers can be interpreted as pleasurable sensations among many viewers" and that "ratings of enjoyment for sad films were positively correlated with ratings of sadness" as an emotion itself. Rather than just escape from an unpleasant reality, according to this approach, movie viewers may explicitly seek out emotional experiences beyond their everyday life. Again, Stempel (2001) provides a fitting account for this as one of Stempel's respondents recounts a screening of John Cassavetes' *HUSBANDS* (1970): "The theatre was packed, the energy was good, and on came the film. Cassavetes brings you into very personal portraits of his family and friends. [...] I laughed my lungs off and also understood something about my father. This was my definition of 'an experience,' because I felt a lot of different feelings and had interesting thoughts of marriage, men and women. I knew it was all right to be a shambles emotionally and to take off and see other things than the usual" (Stempel 2001, 215). The statement that it was "all right" to "be a shambles emotionally" illustrates perfectly the process of appraisal of one's emotions. The respondent's reference to "understanding something" also characterizes the viewing experience as profound and insightful, which Oliver (2008) links to the Aristotelian concept of "eudaimonia": "under some circumstances, individuals may choose to view entertainment for reasons that may not be best described as driven by hedonic motivations but rather as driven by eudaimonic motivations: greater insight, self reflection, or contemplations of poignancy or meaningfulness" (Oliver 2008, 42). Building on her idea, Knobloch-Westerwick, Gong, Hagner & Kerbeykian (2012) show using an experimental study that watching a tragedy can indeed lead to more reflection on one's own life and one's close relationships, and raises overall life happiness, which results in the enjoyment of the activity.

Apart from the emotional reactions they elicit, movies have cognitive effects on their viewers which may also contribute to a pleasant or unpleasant consumption experience. One basic cognitive motivation for watching movies is epistemic curiosity, "a desire for knowledge, going beyond concrete sensory stimulation", that "is characteristic of humans" (Knobloch-Westerwick 2015, 34).

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

Curiosity is certainly a driving force behind the attendance of documentaries, but also e.g. historical films. In addition to that, curiosity contributes to the viewing experience in yet another way: While the movie might not convey knowledge applicable to the world outside, after starting to watch a movie many spectators will be curious as to how the story may end. This has been conceptualized in screenplay theories, e.g. McKee (2010) differentiates between emotional "concern" and cognitive "interest", which the filmmakers both try to elicit in their audiences. According to this framework, the more suspenseful a movie is (i.e. the more curiosity it evokes over the course of the plot), the more enjoyable.

Hennig-Thurau & Houston (2018) identify three closely related, potentially desirable cognitive states that consumers of entertainment products experience: transportation, immersion, and flow. All three are facilitated by "imagery", the mental process by which inner images are created; the term "images" herein not only pertains to visual images, but entails all representations of sensory perceptions in our brains' working memory (Hennig-Thurau & Houston 2018). When a medium provides strong stimuli for a viewer's imagery, they may get "immersed" into the world of the medium. Immersion thus is a state which describes their "sensory impression of being surrounded by an alternate (often virtual) world" (Hennig-Thurau & Houston 2018, 267). Whereas immersion can pertain to a variety of different media, which need not tell a story, "narrative transportation" specifically describes a state of "immersion or absorption into a narrative world" (Green & Brock 200, 704). Green (2008, 5170) holds that "this experience is a key mechanism underlying the influence of stories or narratives on individuals' attitudes and beliefs", and Green, Brock & Kaufman (2004) have shown the level of narrative transportation while reading a short story to be highly correlated with participants' self-reported enjoyment of the story. Stempel (2001) provides an example for transportation in the context of movies, when one of his respondents describes getting "so involved in the movie I am watching that I will talk back to the actors when danger approaches, or I will advise them regarding what is the best thing for them to do. Sometimes I even argue with them for the stupid thing they did or did not do, and on several occasions, I have embarrassed my peers by getting up from my seat in an effort to influence their actions" (Stempel 2001, 222). The state of "narrative transportation" closely resembles so-called "flow" states, in which individuals "act with total involvement" (Csikszentmihalyi 1975, 136), get totally absorbed by an activity and often feel a deep sense of enjoyment, a state they experience "as a unified flowing from one moment to the next, in

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

which we feel in control of our actions, and in which there is little distinction between self and environment; between stimulus and response; or between past, present, and future" (Csikszentmihalyi 1975, 137). Flow states can be experienced during a wide variety of activities and are most notably associated with situations where an individual's skills are well-matched with a challenge at hand, preventing both feelings of boredom and anxiety (Csikszentmihalyi & Csikszentmihalyi 2000). For games, which match this description perfectly, flow states have been repeatedly shown to correlate with enjoyment (Hennig-Thurau & Houston 2018). As a presumably more passive form of entertainment, movies seem not to lend themselves equally well to providing flow experiences, yet the obvious similarities between flow states and movie consumption experiences as described above suggest that the inner process of immersing oneself into a narrative world may require enough "competence" on the viewer's behalf to elicit similar (and similarly pleasant) mental states of "total involvement" (Csikszentmihalyi 1975, 136), which contribute to viewers' motivations to watch movies. This notion of competence in entertainment consumption has been examined explicitly: Groeben & Vorderer (1988) hold that readers of literary texts prefer texts that pose a challenge to them, provided that they are still capable of overcoming the challenge. As Vorderer, Steen & Chan (2006, n.p.) conclude: "In sum, entertainment has almost always been described as an activity where there is rather little challenge, or only as much challenge as the media user can still handle successfully. This, of course, would be the optimal challenge, the level that allows people to feel the greatest sense of competence." Competence has been identified by Ryan & Deci (2000) as one of three main drivers of intrinsic motivation, along with autonomy and relatedness. Since entertainment consumers are usually entertained voluntarily, the activity may also be regarded as autonomous, and oftentimes entertainment can also provide a sense of relatedness, as "research shows that media users do not sense that they are alone. They usually feel connected and related to characters in movies, shows, novels, and even video games" (Vorderer et al. 2006, n.p.). Therefore entertainment consumption perfectly fits the description of an intrinsically motivated behavior. Vorderer et al. (2006) go a step further and link this to evolutionary psychology: Interpreting the cognitive activity involved in the consumption of entertainment as a form of simulation (Oatley 1994), they argue that "biology would favor, through natural selection, cognitive adaptations supporting the capacity for and proclivity towards simulation" of "high-stakes adversarial encounters" like predation (Vorderer et al. 2006, n.p.). A similar explanation has been suggested for the enjoyability of emotional responses as well: Arguing from an evolutionary psychology perspective and building

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

on an idea by Tooby & Cosmides (2001), Tan (2008) theorizes that while the proximal cause of engaging in activities that create an emotional response may be non-utilitarian intrinsic enjoyment of that response, a distal cause can be conceived wherein the "the emotional reactions to the content of imagination [...] help train people's adaptive capacities". He elaborates that "[t]raining one's adaptive skills consists in part in envisioning alternative courses of events and actions, and adaptive learning has taken place once various outcomes associated with different courses of action have been interpreted by the emotion system [. . .]. When a similar situation is met in the future, the individual will be ready to decide more efficiently how to act" (Tan 2008, 28). Although this might have been the original evolutionary reason for the enjoyability of entertainment, this does not mean that today's entertainment products actually facilitate any such learning (Vorderer et al. 2006), just as sexual experiences may be perceived as enjoyable without serving the purpose of procreation. While this perspective shines an interesting light on why aesthetic experiences might be perceived as pleasurable in the first place, it makes no predictions as to what content might be sought out by what consumers under what circumstances (Knobloch-Westerwick 2015).

Additional, motivational drivers for media consumption have been suggested by sociology and social psychology. Audiences' consumption choices may not only be influenced by the people they consume entertainment with directly, but also the "mental representations of others", wherein these can be "either actually known in person or merely constructed as the social environment" (Knobloch-Westerwick 2015, 41).

Consumers may acquire as well as express membership in certain stratified, social groups by specific media choices, so-called "taste cultures", which are defined by their shared aesthetic values and preferences (ranging from "high culture" to "low culture"). Gans (2010) argues that most consumers choose the majority of their content from one or two of these taste cultures, but occasionally "straddle" either "upward", e.g. to seek higher status or to increase their children's chance of upward social mobility, or "downward", for "relief from the cultural routine" (Gans 2010, n.p.). While such distinctive behavior may be mostly habitual (Bourdieu 1984), individuals can also take intentional actions to reinforce their "social identity", which has been identified by Tajfel (1978, 63) as "that part of an individual's self-concept that derives from his (sic!) knowledge of his (sic!) membership of a social group (or groups) together with the value and emotional significance attached to that membership". This concept is more flexible than that of taste cultures, as various in-groups and

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

out-groups can be defined and value be assigned to respective membership almost arbitrarily. Knobloch-Westerwick (2015) argue that social identity is especially salient for minority groups and can make members of such groups seek out content that reinforces that membership, as has been shown for news content (Knobloch-Westerwick, Sharma, Hansen & Alter 2005). For feature films, it has been argued in the context of recent discussions about greater on-screen diversity (Hunt, Ramón & Tran 2019), that minority audiences have an under-served desire for members of their communities to be portrayed on screen (Burkert & Kelly n.d.).

Lastly, another influential concept is the idea of "para-social interactions" or "para-social relationships". The term was coined by Horton & Wohl (1956) to describe the "seeming face-to-face relationship between spectator and performer" (Horton & Wohl 1956, 215) in a mass media context, originally mainly television, which is facilitated by the "frequent and consistent appearance of a realistic persona" (Rubin & Perse 1987, 248). The basic idea is that over time, consumers forge a relationship with on-screen personae, comparable to friendships in real life, and will repeatedly seek out programs to spend time with their relationships. While initially referring mostly to anchormen and -women, i.e. actual human beings, the term has subsequently been applied to fictitious characters as well (Perse & Rubin 1988) and it is now widely accepted that parasocial relationships can be formed between spectators and both actors and the characters they portray. Several studies have looked at para-social relationships between viewers and characters for soap operas (Rubin & Perse 1987, Perse & Rubin 1988) and the concept has also been proposed as a mechanism of emotional involvement for motion pictures; here it seems to be particularly applicable to movie sequels, where audiences have had a chance to form relationships with characters before they enter the cinema, by consuming previous installments of the franchise. The existence of such relationships has been indicated by empirical works, e.g. for the popular Star Wars movies (Hall 2019).

All heretofore discussed motivational factors pertain to watching movies in general – yet moviegoing, i.e. watching a movie in a theatrical setting, involves additional considerations. Several respondents in Stempel (2001) recall, when asked about their most memorable cinema visits, not as much the respective movie as the interactions with or observations of other audience members. In their study of cinema audiences, Cuadrado & Frassetto (1999) find several forms of external, social utility ("Be with friends", "Have something to talk about", "Share an interest", "Be with my partner") to be important to moviegoers and to contribute to their moviegoing decisions.

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

While this overview cannot cover the entirety of theoretical approaches, we have now touched upon the most influential frameworks. As we have seen, consuming a movie in a cinema is a complex activity, instigated by the interplay of a variety of different motivational factors. In [subsection 3.2.3](#) we will now turn to the decision-making process itself: We will discuss consumer preferences and choices, and examine what scientific approaches so far may contribute to our understanding of why specific consumers choose to go watch specific movies in specific situations.

3.2.3 Consumer Decision-Making

When we look at concrete movie consumption decisions, it is important to differentiate between two terms: "preferences" and "choices". According to Knobloch-Westerwick (2015, 11), a choice "is executed by an individual media user at a specific time, when he or she selects to attend to a media message", whereas a preference describes "a general tendency of an individual to favor a specific kind of media content", materializing as "repeated choices of the same kind" (Knobloch-Westerwick 2015, 14). Thus preferences are an abstraction from concrete choices, an underlying pattern, "an intangible but measurable concept" (Knobloch-Westerwick 2015, 14). Usually we assume that choices do reveal preferences over time, although it has been argued that the level of preference-choice congruence can vary substantially (Garlin & McGuiggan 2002). Two major paradigms have been proposed as to how media preferences are formed and individual media consumption choices being made: The selective exposure theory and the uses-and-gratifications approach. As Knobloch-Westerwick (2015, 18) notes, these "theoretical approaches intersect but are nevertheless associated with different levels of assumed awareness of this learning process and how spontaneous versus planned the subsequently enacted behavior is". We will discuss the main ideas of both approaches and then look at how they may be applied.

Selective exposure starts from the observation that the audience composition of any specific media content is not necessarily representative of the overall population, but often systematically biased (Sears & Freedman 1967) – and conversely, the media intake of any given individual is not an unbiased sample of all available media content. The term was developed early on in the context of political communication, where Lazarsfeld, Berelson & Gaudet (1948, 89) observed in their study of American voters that "actual exposure does not parallel availability"; rather, recipients subject themselves predominantly to

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

communication that reinforces their pre-existing beliefs. Festinger (1957) and his theory of cognitive dissonance later provided the theoretical explanation for such systematic avoidance of information that is inconsistent with a consumer's worldview⁹. Later, the concept of selective exposure was applied more broadly, expanding the meaning of the term to not only denote avoidance, but also intentional exposure to specific, preferable content, and from a focus on informational content to encompassing entertainment as well (Zillmann, Hezel & Medoff 1980).

When it comes to explaining individual consumers' selective behavior, Zillmann & Bryant (1985, n.p.) stipulate that choices are largely situational: "Instead of accepting the idea that taste, as a trait of unknown origin, governs entertainment choices throughout all conceivable emotions", they "attempt to show that the choice behavior in question grows from a situational context and that affective and emotional states and reactions play a key role in the formation of rather stable content preferences". They go on to describe how such preference formation may be conceived: From the assumption, that individuals at any given time strive to "terminate noxious, aversive stimulation" and "perpetuate and increase the intensity of gratifying, pleasurable experiential states", they conclude that consumers will be "inclined to arrange and rearrange their exposure" to entertainment content (Zillmann & Bryant 1985, n.p.) to meet those needs. Building on the concept of operant conditioning (Skinner 1969, Thorndike 1932), they further theorize that initially incidental responses by consumers to certain situations lead to certain outcomes which leave a memory trace in the individual (Zillmann & Bryant 1985), establishing a „perceived response-outcome relation" (Knobloch-Westerwick 2015, 15): If the consumer's action (i.e. exposure to a certain type of entertainment) is successful in terminating a negative affective state or perpetuating a positive state, the behavior will be reinforced, forming a behavioural tendency, whereas when it leads to unfavourable consequences, such behavior will be discouraged in similar situations in the future (Zillmann & Bryant 1985). Drawing from their past entertainment exposure experiences, consumers will over time develop relatively stable preferences which inform their future choices (McQuail 1997). Zillmann & Bryant (1985, n.p.) do not assume this process to involve conscious cognition to any significant degree: "Although some individuals may well recognize that their environment-altering actions and selections influence their moods and emotions, even that they seek to attain particular effects dependent on particular moods and emotions, it is considered the rule that persons have poor comprehension both of the causes of their

9 Such behaviour is today often described in terms of confirmation bias (Knobloch-Westerwick 2015).

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

choices and of the ends that these choices serve." Consequently, studies from the selective exposure approach typically do not rely on introspective accounts by media users, but try to observe consumer behavior in preferably unobtrusive experimental settings (Knobloch-Westerwick 2015).

The uses-and-gratifications approach takes a different approach in modeling consumer behavior: "The core assumption [...] is that audience members are active, and their selection and use of media is purposive, goal directed and motivated to satisfy their social and psychological needs or desires" (Weiyan 2015, 77). Many of the early works in uses-and-gratifications research have tried to map these needs and desires and cluster them into types of gratifications that consumers seek and obtain in their media use (Katz, Blumler & Gurevitch 1973). Researchers within the uses-and-gratifications tradition put an emphasis on cognition and have introduced expectancy-value models into media research (Galloway & Meek 1981, Palmgreen & Rayburn 1982, Leuven 1981). Audience "expectations concerning the characteristics of the media and potential gratifications to be obtained" (Rayburn & Palmgreen 1984, 538) play a central role in all uses-and-gratifications studies, and the expectancy-value model provides a useful conceptualization of the term. While there are several approaches to expectancy-value theory, they all build on a concept of expectancy – the probability that a certain behavior will lead to a specific outcome – and a concept of value, i.e. the subjective attractiveness of said outcome. In the case of entertainment consumption, the relevant outcomes translate to the gratifications obtained by the consumption of specific content. In the determination of behavior, expectancy and value are assumed to combine multiplicatively (Galloway & Meek 1981): An individual will not necessarily choose the behavior associated with the highest value outcome, if the expectancy of attaining that outcome is substantially lower than the perceived likelihood of another, less attractive, yet more attainable outcome. Applying this to media consumption behavior, Palmgreen & Rayburn (1982) define gratifications sought by a consumer as:

$$GS_i = b_i e_i,$$

where GS_i denotes the i^{th} gratification sought from a specific media content, b_i is the belief (= subjective probability) that the consumption of this content will lead to a specific outcome, and e_i is the subjective, affective evaluation of this outcome. As any media consumption behavior may serve several needs, i.e. produce several distinct outcomes, such beliefs and value assessments are held by the consumer about all pertinent outcomes concurrently. Therefore in order to arrive at a valuation that is indicative of the consumer's generalized

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

tendency to seek gratifications from specific media content, one needs to sum the products over different gratifications sought:

$$\sum_{i=1}^n GS_i = \sum_{i=1}^n b_i e_i.$$

The theory thus predicts that media users will choose to consume that medium and that content which is associated with the highest expected value (gratifications sought) as per the formula above. This decision-making concept explains their choices – and in repeated choices the underlying preferences of the consumer are revealed, because the way in which they believe certain outcomes to be attainable and the value they ascribe to those outcomes differs from person to person. In stark methodological contrast to the selective exposure theory, the uses-and-gratifications approach typically assumes that "the goals of mass media use can be derived from data supplied by individual audience members themselves — i.e., people are sufficiently self-aware to be able to report their interests and motives in particular cases, or at least to recognize them when confronted with them in an intelligible and familiar verbal formulation" (Katz et al. 1973, 511).

Having discussed two general paradigms of entertainment consumption decision-making at the consumer level, we can now discuss how these apply to the context of deciding whether to watch a movie in a cinema. Whereas many empirical studies have successfully used the selective exposure paradigm for media such as television (Bryant & Zillmann 1984) and recorded music (Knobloch & Zillmann 2002), few attempts have been made to explain moviegoing behavior in terms of selective exposure: Stroud (2007) found that viewers with more negative views toward then-US president George W. Bush were more likely to intend to watch the political documentary *FAHRENHEIT 9/11*, Valenzuela (2015) provide strong evidence for partisan selective exposure of Chilean audiences to the political historical drama *NO*, and Castle & Stepp (2018) find political sorting among audiences among partisan lines for a variety of different films, both documentaries and fictional movies. Yet all these works have focused on politically charged content and subsequent avoidance or reinforcement respectively based on viewers' social identity; an attempt to empirically assess from a selective exposure perspective why moviegoers choose to watch different films beyond their political inclinations has yet to be undertaken.

Within the uses-and-gratifications approach, a number of concrete gratification categories that movies may provide have been suggested, drawing on many of

3 *Scientific Approaches to Target Audience Definition and Revenue Prediction*

the research findings detailed in [subsection 3.2.2](#) Austin (1986), using 70 different motivational items from earlier uses-and-gratifications research he deemed potentially pertinent to moviegoing, performed a factor analysis on survey results from 493 college students who were asked to rate each item on a scale ranging from 1 ("not at all") to 5 ("exactly like my reason"). He subsequently identified seven distinct factors of moviegoing motivation, which he labeled 1) "learning & information", 2) "forget & get away/escape", 3) "enjoyable & pleasant activity", 4) "pass time", 5) "relieve loneliness", 6) "behavioral resources", 7) "learning about self" (Austin 1986, 121). He further divided his sample into infrequent, occasional, and frequent moviegoers (as per the respondents' accounts), and found significant differences among those admission frequency groups regarding four of the seven motivational factors ("learning & information", "forget & get away/escape", "enjoyable & pleasant activity", "learning about self"): Participants who went to the movie theater more frequently scored significantly higher for the respective motivational factor, i.e. expressed stronger agreement with the individual moviegoing reasons presented to them. While this study points to motivational differences between moviegoers, it treats all moviegoing as equal: No distinctions between different (kinds of) films are being made.

Palmgreen, Cook, Harvill & Helm (1988) had 205 respondents write essays on motivations for cinema attendance or avoidance and subsequently performed a content analysis to derive 70 items which they presented to 486 students for rating on a 7-point scale of importance, along with questions about their moviegoing behavior. A factor analysis of the replies led to ten distinct factors (in order of importance): "general learning" (e.g. learning about other cultures, times, or historical events), "mood control/enhancement" (e.g. to relax, change mood, forget about problems), "social utility" (to do something social, go on a date), "medium characteristics" (e.g. large screen, good sound, dark auditorium), "personal identity" (e.g. to identify with characters, to learn for one's own life), "entertainment" (e.g. pleasure, have a good time), "social facilitation" (e.g. enjoy other people's reactions), "communication avoidance" (e.g. not having to talk on a first date), "communication utility" (e.g. to be in the know about a hot topic), "great expectations" (e.g. to see a specific actor or to compare a literature adaptation to the book).

Using a sample of 241 respondents (age 18-44), Bracken & Lombard (2001) found cinema to rank highest among all investigated media (books, cinema, radio, television, and newspapers) as being able to fulfill the needs "to be entertained", "to re-experience events in which I was involved", "to experience beauty", "to escape

3 *Scientific Approaches to Target Audience Definition and Revenue Prediction*

from the reality of everyday life", "to spend time with the family", "to participate in the discussion with my friends", "to learn how to behave among others", "to spend time with friends", and to "participate in the experience of other people". Like Austin (1986) and Palmgreen et al. (1988), Bracken & Lombard (2001) did not look at differences between movies.

Tefertille (2017) sought to understand why consumers still choose to watch films in the cinema after the emergence of numerous video-on-demand streaming services, using a uses-and-gratifications approach. He found affective gratification expectations ("have a good time", "be affected emotionally", "exciting visuals & sounds") to exert the largest influence on theatrical attendance across different types of movies, suggesting that "audiences are increasingly selective about the types of films they choose to view in the theater, favouring exciting, visually enticing films" (Tefertille 2017, 27)¹⁰.

Henkel, James & Croce (2016) investigated a similar problem comparing the motivations for legal and illegal online streaming opportunities vis-à-vis cinema visits among Australian students. Also employing a uses-and-gratifications approach, they found moviegoers to put a premium on the social gathering provided by theatrical consumption with family, friends, and significant others. As another uniquely gratifying feature of moviegoing they identified the "escape" function and an "opportunity to immerse themselves in the cinematic experience" (Henkel et al. 2016, 6). Because cinema is more expensive than home video, cinema was often regarded by the students as something special, like a reward. The researchers also asked students if they had experienced any life events in a movie theater, and of 81 respondents, 54% had spent a birthday in the cinema, about 25% had had their "first kiss" in a movie theater, 62% answered "midnight screening", 60% "first date", and 20% "anniversary" (Henkel et al. 2016, 6)¹¹. This provides further evidence for the cinema as a place for potentially significant social events.

In an attempt at market segmentation, Cuadrado & Frasquet (1999) identify three distinct clusters of moviegoers based on differing gratifications sought, which they label "social", "apathetic", and "cinema buff" respectively: the social cluster goes to the cinema "mainly to enjoy themselves and cultivate social relations" (Cuadrado & Frasquet 1999, 261); the cinema buff cluster puts e.g. more emphasis on following specific directors and less on social aspects of

10 Reeves, Lang, Kim & Tatar (1999) have shown that larger screens correlate with greater levels of arousal.

11 All numbers have been rounded to full percentage points, here.

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

moviegoing like having a good time; the apathetic cluster evaluates all gratifications associated with moviegoing less favorable than the social cluster, but emphasizes "boredom", "friends", "partner", "good time" and "laugh" more than the cinema buffs. Of the three clusters, the members of the cinema buff group are the most avid moviegoers.

Yet little has been found out about motives to attend specific films at the cinema so far. From the producer's perspective, film choice is of course the central question pertaining to moviegoing decision-making. Möller & Karppinen (1983) performed a factor analysis on responses by 228 Finnish moviegoers, who each rated the relevance of 15 motivational factors, identifying four primary motivations of cinema attendance: "interest and information", "relax and change", "social relationships", and "aesthetics and art" (Möller & Karppinen 1983). The motivations varied substantially between moviegoers and the researchers went on to relate the individuals' motivations to their concrete movie choices (respondents were recruited in the cinema while consuming a specific film); they found that the "adventure/thriller" audience scored low for "interest and information" as well as "aesthetics and art" and high on "relax/change", while the opposite was true for "human/social drama" viewers. Education and, to a lesser degree, age, also were found to correlate with specific moviegoing motivations. The sub-groups also valued different movie attributes. In a discriminant analysis, both motivational factors and the evaluation of specific movie attributes were found predictive of respondents' movie choices.

In a very similar study, Tesser, Millar & Wu (1988) also employed factor analysis to analyze 100 college students' evaluation of 15 statements pertaining to their moviegoing decisions; they identified three factors: "self-escape", "self-development", and "entertainment". When relating those factors to explicitly stated movie preferences for 40 recent releases (on a 1-9 point scale), different motivational factors were clearly correlated to different movies.

Using almost the same methodology on German moviegoers, Baum (2003) identifies four factors: "sociability", "escapism", "utilitarianism" (linked to the two motives "to do something for my education" and "to watch a specific film"), and "fun and recreation"¹². He finds high valuations of "sociability" to correlate negatively with age and education, suggesting that younger people are more likely to go to the cinema for social reasons. The reverse was true for "utilitarianism". While young moviegoers scored higher for "escapism", "fun and recreation" was not significantly correlated with any demographic

¹² translated by the author; German: "Geselligkeit", "Eskapismus", "Utilitarismus", "Spaß und Erholung"

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

variables. The study went on to predict genre preferences from gratification ratings by means of regression analyses and found (somewhat in line with stereotypical industry assumptions) that (young) age and "sociability" predict a preference for the horror genre, gender (female) and "utilitarianism" predict a genre preference for drama, an action preference can be explained by gender (male) and "escapism", and "utilitarianism" and education predict the preference for socially critical movies.

Benesch (2004) explicitly differentiates between the decision to go to the cinema and the choice of a specific film. She determines seven factors underlying the motives for moviegoing in general, of which she finds only "relaxation/escapism"¹³ to have a significant influence on moviegoing frequency. Regarding film choice, respondents rated the importance of 15 concrete film traits (story, genre, and cast obtained the highest scores) and 23 abstract film qualities¹⁴, but the study did not correlate these with one another or look at specific film choices.

Neemaligham & Jain (1999) conducted a lab experiment wherein they captured participants' expectations regarding three as-of-yet unreleased films in three dimensions: expectations of emotional stimulation (funny, appealing, interesting, exciting, fascinating), core product attributes (story, cast), and peripheral product attributes (sets, costumes, music, effects). Afterwards, respondents could choose one of the three films and would be gifted a voucher to attend a cinema screening. Looking at the chosen films, the researchers found that only the expectations of emotional stimulation significantly influenced subsequent choices.

As can be inferred from these short summaries, studies have employed the uses-and-gratifications approach more prolifically in the explanation of movie attendance than the selective exposure paradigm so far. This might have to do with certain characteristics pertaining to moviegoing decision-making that differ from other media choices: First, there is very little repeat consumption in the cinema. Movie theaters mostly show recently released movies and most audience members only go see a specific film once. Thus compared to other media like music or television, there is a lot less habitualized consumption. Consumers do not know what to expect before they see a movie and have to actively seek out information in order to evaluate what experience to expect: Hennig-Thurau,

13 German: "Entspannung/Alltagsflucht"

14 Respondents were asked to complete the sentence "A film I like should ..." (German: „Ein Film, der mir gefällt, sollte ...“) and could choose from options such as "deal with interesting topics", "have beautiful pictures", "be witty", "move me", etc.

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

Walsh & Wruck (2001) differentiate between "experience qualities" on the one hand, movie traits audiences "can only comprehend after watching it", and "quasi-search qualities", i.e. "factors that moviegoers can comprehend before watching a movie", on the other hand. While the movie's distributor will typically foreground quasi-search qualities like cast members and genre, film critics and friends — potentially more trusted sources for other moviegoers — try to convey experience qualities more directly in their assessments (Hennig-Thurau et al. 2001). According to a 2010 study in the US (Stradella Road 2010), 78% of moviegoers often or very often seek details on what the movie is about, 70% research the genre, 57% want to know the stars, and 44% mention friends' opinion as an important source of information. The movie's trailer is a key source of influence for 74% (Stradella Road 2010). Often, moviegoers decide well in advance that they want to see a specific movie (Hand 2002); Stradella Road (2010) reports that in 29% of cases, consumers decided to watch a film more than a month before their visit, and 58% know which film to watch before they decide on a specific cinema.

Such extensive information-seeking suggests that the moviegoing decision-making process is indeed akin to planned behavior as the uses-and-gratifications approach purports. While it would be a stretch to assume that moviegoers are always able to pinpoint what exactly intrigues them about a "story", or what it is that "entertains" them, at least some amount of cognitive processing is involved. There are several reasons for this: Compared to other media, a fairly high amount of activity (Palmgreen et al. 1988) is required (finding convenient show-times, potentially finding company, actually leaving the house), and also there is a greater monetary risk involved (Hennig-Thurau, Houston & Walsh 2006). These circumstances favor the application of uses-and-gratifications approaches as frameworks to model moviegoing decisions. At the same time, it seems likely that movie preferences are formed by some form of operant conditioning (as suggested by the selected exposure paradigm) where consumers learn in a largely unconscious process which (kinds of) films provide them with what gratifications. Then, when confronted with a specific choice about going or not going to watch a movie at the cinema, they make a rather deliberate decision, looking for cues such as trailers, posters, critical reviews, etc. as to decide whether a specific film is likely to provide them with an experience similar to the ones they have evaluated and found gratifying before (as theorized by the expectancy-value approach).

A final aspect to be considered for moviegoer decision-making is the fact that moviegoers usually watch films in groups. No more than 12% of tickets in Ger-

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

many 2019 have been bought by sole attendants (FFA 2020c)¹⁵. Stradella Road (2010, 54) list "someone else wanted to see it" as the second most important reason moviegoers cited for a specific visit. To model how consumers' individual preferences combine in a group consumption context is a non-trivial problem (Rao & Steckel 1991, Arora & Allenby 1999, Aribarg, Arora & Kang 2010, Adamowicz, Hanemann, Swait, Johnson, Layton, Regenwetter, Reimer & Sorkin 2005, Hennig-Thurau, Marchand & Marx 2012). Cinema-specific findings by Baum (2003) suggest that there is a smaller sub-group within moviegoers that wields outsized influence on film choices. Yet, as there are still more basic challenges to overcome in understanding film choices, we will neglect the problem of group decision-making in our further discussion and regard group preferences as a function of the individual preferences.

Thus far, we have seen that there is a variety of different (emotional, cognitive, social) motivational factors for cinema attendance, which motivate different consumers to varying degrees. Repeated satisfaction or frustration of these motivational factors as experienced during the consumption of specific movies leads the viewers to form movie preferences, be it by operant conditioning or more conscious cognitive processing. These preferences in turn guide consumers' concrete choices: They will seek out content, i.e. movies, which they (consciously or unconsciously) deem likely to provide a favorable experience. A consumer may hold different preferences for different configurations of situational factors (company, mood) that will lead to different choices. These findings have informed market research in the film industry and attempts at audience analysis and segmentation (see [subsection 3.2.4](#)).

3.2.4 Audience Segmentation

Most of the market research conducted in the film industry is conceptually closer to the psychological approach than to the economic approach in academia as defined here¹⁶. A historical review of industry research on cinema audiences may be found in Austin (1983), a comprehensive update and application to the German market is provided by Prommer (1997) and Prommer (2010). In addition to concept tests, positioning studies, and focus groups, several systems for audience segmentation have been proposed (Backen 2009).

15 This number even includes those tickets for which respondents did not specify the number of people in their company.

16 Jenke (2018) notes that qualitative studies are perceived as less anonymous and therefore evaluated as preferable by producers.

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

Segmentation, understood as „the process of partitioning markets into groups of potential customers with similar needs and/or characteristics who are likely to exhibit similar purchase behavior" (Weinstein 2004, 4), provides a way to simplify the process of target audience definition: Instead of having to come up with a novel definition for every new project from the ground up, well-researched, pre-defined audience segments allow practitioners to define target audiences with considerably less effort and still implement the insights into moviegoers' motivations as discussed in the previous sections. Backen (2009) lists three main approaches to such segmentation for the movie industry: socio-demographic, marketing-oriented (i.e. behavioral), and qualitative segmentation.

The socio-demographic approach uses segmentation parameters such as age, sex, education, and income to divide the population into target audiences. Such target audience definitions have been used in the industry since systematic research on audiences started back in the 1940s (Eliashberg et al. 2006). Hollywood traditionally aspires to produce "four-quadrant movies" that appeal to all four segments of the market, i.e. both males and females, both under and above the age of 25 (Vogel 2004). The German Federal Film Board (FFA) publishes annual reports on the socio-demographic composition of moviegoers. Building on a fairly simple model of personal motivational development over lifetime, Blothner (2000) tries to link these findings to psychological traits of the individual viewers. Collins & Hand (2005) use a classification system for UK households to predict moviegoing probability and find substantial differences between neighborhoods of different socio-demographic make-up. To the best of the author's knowledge, Redondo & Holbrook (2010) are the only ones that have explicitly implemented target segments into an econometric model. Their starting point is a Spanish study on the composition of cinema audiences for specific films. Using canonical correlation analysis, they link socio-demographic segments to particular content, without having to determine the groups beforehand.

The marketing-oriented studies divide people into segments in terms of different consumption behaviors: How often do they attend cinemas? How much money do they spend there? A public German study by the FFA (2006) pursued this approach, asking different viewer groups why they do or do not attend theatrical screenings, examining how their attendance frequency could be increased, etc.

Qualitative segmentation tries to sort viewers up into clusters according to

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

qualitative traits such as psychological profiles, motivations, values, etc. The lifestyle concept has been of particular importance in recent decades. The underlying assumption is that our society can be divided into distinct cultural segments (Schulze 1992) that follow specific ways of life and seek specific experiences. From a media marketing researcher's view, these segments have more explanatory power than a simple clustering by age and sex, because they are based directly on what these people envision as a good life and desirable experiences, including media consumption. The lifestyle approach has been successfully applied to television (Buß & Neuwöhner 1999), radio (Egger & Windgasse 2007), and print media. The German public broadcaster ARD has developed specific media user typologies¹⁷, which do indeed predict television watching preferences quite well (Hartmann & Neuwöhner 1999, Hartmann & Höhne 2007).

Applications are considerably more advanced in television (Murschetz & Schlütz 2018, GfK 2015), probably because the advertisement-based business model of television naturally requires more specific knowledge about the audience's composition in order to effectively sell their attention to marketers — in a way, television audiences can be conceived of as the networks' actual product (McQuail 1997, Kosterich & Napoli 2015, Nelson 2016).

Yet the development of a similar qualitative typology is conceivable for cinema audiences as well. Zuta (2007) suggests to simply use the media user typologies from television and link them to distinct kinds of films¹⁸, but moviegoers represent only about 38 per cent of the overall population (FFA 2020c), so in order to meaningfully discriminate between different films, a framework clustering the entire population into 10 groups (Oehmichen 2007) is hardly sufficiently fine-grained: It might well predict who goes to the cinema at all, but it will likely fail to capture the comparatively subtle differences between moviegoers. Cuadrado & Frasquet (1999, 256) specifically address cinema audience segmentation and partition viewers into clusters according to "benefits sought", building on the uses and gratifications approach. Neckermann & Blothner (2001) use generalized "leisure orientations"¹⁹ to establish six distinct segments based on fundamental recreational demands. While this seems like a pragmatic alternative to full-blown lifestyle models, the approach has not been adopted by the industry to date.

17 German: MedienNutzerTypologien (MNT)

18 His concept does not use traditional genres, but rather groups films by psychological experience patterns according to Blothner (1999).

19 German: "Freizeitorientierungen"

3 *Scientific Approaches to Target Audience Definition and Revenue Prediction*

Overall, despite only limited implementations to date, audience segmentation by "gratification sets" (McQuail 1997) appears to be a straight-forward application of scientific findings on audience motivations and behavior. Providing producers with an evidence-based segmentation framework that actually captures differences in movie preferences could serve as a meaningful intervention (as defined by the CIMO logic, cf. [section 1.2](#)) to improve on the largely intuition-based current target audience definition practices as discussed in [section 2.2](#).

3.3 The Economic Approach

3.3.1 Modeling Techniques and Purposes

The 'economic approach' tries to link a movie's performance in the market place to specific success factors. Movie success in this context usually refers to commercial success, as opposed to non-commercial indicators of success (such as awards or critical acclaim), which may be equally important for individual producers and their careers.

In modeling commercial movie success, academic models serve two distinct purposes: Either they try to deepen our understanding of what drives movie sales (explanatory models) or they attempt to actually predict a certain number (predictive models). Most scientific modeling attempts pursue the explanatory approach: Thus they do not necessarily confine the input to data which would actually be available before the movie has been released (or even before it is made), but instead regularly include data pertaining to the release pattern, distribution strategy, and advertising efforts, which are of course unavailable for any producer's predictive purposes at the greenlighting stage.

Different variables have been suggested to measure movie success, including the length of the theatrical run (Sochay 1994), as more successful films are being exhibited for a prolonged period, or profitability and return on investment (Ravid 1999, Lehmann & Weinberg 2000, Miller & Shamsie 2001, Hennig-Thurau 2004, Ravid & Basuroy 2004, Jansen 2005). The latter makes a lot of sense from a business perspective, but usually suffers from lack of granular data and obscure revenue sharing models which differ from project to project. The most widely used measure for movie success is box office revenues (either opening weekend

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

revenues or cumulative revenues over the movie's run), mostly focusing on a specific market (e.g. North America). As the distribution of box office results across films is very skewed, usually the logarithm of revenues is incorporated into the models as the actual target variable.

Regarding modeling techniques, only a few basic studies have stuck with descriptive statistics and correlation matrices, most do at least employ a linear regression. Multiple linear regression of box office is the prevailing modeling approach in the relevant literature. Some researchers prefer the conception of success categories or thresholds, turning box office modeling into a classification problem (Eliashberg, Hui & Zhang 2007), amongst others in order to avoid problems arising from the application of ordinary least squares (OLS) regression to heavy-tailed samples (Collins, Hand & Snell 2002). Unfortunately, many studies do not model interrelationships between factors, leading to questionable estimations of individual factors' influence. In the last years, this problem has been targeted by the use of more complex modeling techniques like structural equation models (Hadida 2010), path analysis (Hennig-Thurau, Houston & Walsh 2007), or partial least squares regression (Fuchs 2010)²⁰. Some machine learning models such as neural networks have recently produced impressive prediction results (Ghiassi, Lio & Moon 2015, Lash & Zhao 2016), but as these models are difficult to interpret for humans, it will be at least challenging to leverage such techniques to persuade financiers of a movie project's financial viability (Behrens et al. 2020).

A considerable part of research is concerned with box office development over time, trying to model how revenues change over the course of the theatrical run. In that context, the Bass diffusion model, that has first been introduced to describe how innovative products spread among a population (Bass 1969), has been successfully applied to motion picture admission dynamics by Boatwright, Basuroy & Kamakura (2007). Other approaches to model diffusion over time include estimating revenues as an exponential function of time after release (Lehmann & Weinberg 2000) and generalized gamma distributions (Sawhney 1996)²¹ as well as the separate estimation of weekly box office revenues (Elberse & Eliashberg 2003).

Other, more unusual mathematical models like the Yule distribution (Albert 1998) or the Einstein-Bose distribution (De Vany & Walls 1996) have been used

20 For a comparative study on several prediction techniques such as regression, decisions trees, random forests, and gradient boosting for movie revenue prediction, cf. Bruneel, Guy, Haughton, Lemercier, McLaughlin, Mentzer & Zhang (2018)

21 For an overview, cf. Clement, Fabel & Schmidt-Stolting (2006, 160).

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

by single studies to test specific theorems.

All these methods use a number of different input variables to describe the movie and its market environment, which is then related to the movie's success by the model. Such variables may refer to movie traits (everything controlled by the movie's producers and distributors, including its distribution strategy, see [subsection 3.3.2](#)), third-party information (uncontrollable, such as critical reviews, [subsection 3.3.3](#)), or structural factors of the marketplace (e.g. seasonality, see [subsection 3.3.4](#)). We will address previous research findings in the subsequent subsections and then take a look at some industry applications of such models ([subsection 3.3.5](#)).

3.3.2 Movie Traits

For the purpose of this section, movie traits will refer to all characteristics of the movie or its release that can be controlled either by the producer or the distributor, as opposed to third-party information such as critical reviews or word of mouth.

The earliest movie trait to possibly have an impact on the final film's appearance would be source material. Conventional wisdom suggests that a film project starts with the screenplay, but this is not always the case: 57 per cent of US films released between 2006 and 2010 (Dietz 2011) were based on some previous work like books, graphic novels, other films, TV series or video games. Similarly, Berauer (2007) finds a considerable 36 per cent of German films (1997-2006) to be derivative of some other work, as well.

Why are adaptations so popular with producers? Given the 30,000 spec scripts registered with the Writers' Guild of America every year (Simens 2000), shortage of supply with original ideas can hardly be the reason. Instead, producers believe derivatives to reduce risk (Lins 2000). Among the most successful films worldwide, the derivatives' market share has substantially increased over the last years (Allen 2012)²².

From a marketing theory perspective, the use of another work (just like the casting of stars) can be understood as a "brand transfer strategy" (Hennig-Thurau,

22 For the German market, Berauer (2007) shows the original movies (64 per cent of releases) to account for only 44.5 per cent of revenues. In her analysis of the top 40 films in Germany between 2000 and 2011, An der Gassen (2019) identifies as many as 72.5 per cent of these as being based on some sort of source material.

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

Houston & Walsh 2007, 71): consumers expect a movie to share at least some qualities with the (popular) work it is based upon²³.

Several modeling approaches have been conceived to test if derivatives really reduce risks. Most studies simply build a dummy variable (like "sequel yes/no") into their model and many have found a significant positive effect of this sequel variable (Litman & Kohl 1989, De Vany & Walls 1999, Collins et al. 2002, Basuroy, Chatterjee & Ravid 2003, Ainslie, Drèze & Zufryden 2005, Chang & Ki 2005, Clement, Fischer & Görke 2007, Boatwright et al. 2007, Hennig-Thurau, Houston & Heitjans 2009, Joshi & Mao 2012), while others have not (Litman 1983, Sochay 1994, Gemser, Van Oostrum & Leenders 2007, Fuchs 2010). Only one study found a negative impact (Jedidi, Krider & Weinberg 1998), but since their sample is compiled of only top five grossing films, the representativeness of that finding is questionable. The research results in general thus seem to support conventional industry wisdom. Basuroy et al. (2003) show that the previous work's impact on box office peaks in the week of release, slowly declining thereafter. Using the case of AMERICAN PIE 2, Blothner (2003) exemplifies how a film can build on its predecessor's success without appealing as much to the audience as the original, generating most revenues right after the start²⁴.

Yet many of these studies suffer from over-simplification, since nature and success of the previous work are not being accounted for in their models²⁵. Joshi & Mao (2012) show recency of book release, book success, and similarity between book and film to positively influence the box office results of literature adaptations. They state literature adaptations to be qualitatively different from sequels. On a similar note, Sood & Drèze (2006) discover a negative effect of similarity with the original film on sequels' performance. They attribute this to satiation effects²⁶.

23 Presumably another benefit of sequels and adaptations can arise from so-called "reciprocal spillover effects", i.e. increased sales of the original product around the time of the adaptation's release (Knapp, Hennig-Thurau & Mathys 2013), which is of less interest in the context of this work.

24 Moon, Bergey & Iacobucci (2010) argue similarly and expect fan bases to decrease due to such effects, leading to weaker performances of the third movies in a series.

25 Hennig-Thurau & Wruck (2000) – and Hennig-Thurau et al. (2001), concordantly – develop the concept of "symbolicity", meaning the film's capability of being classified by familiar cognitive categories. Besides being based on another work, a catchy plot and the movie's merchandising potential are included in that construct. The authors argue that there is a maximum level of symbolicity (or cultural familiarity), above which a given movie is considered boring (Hennig-Thurau et al. 2001, 7).

26 In line with that argument, a verbal title (like DAREDEVIL: TAKING IT TO THE STREETS) is found to be preferable (Sood & Drèze 2006) to just adding a number (like DAREDEVIL 2).

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

Type	Share (%)	Metascore
Based on a true story	10.6	60.5
Based on a play or musical	2.1	58.2
Based on written material (book, story, article, etc.)	24.1	57.1
Based on comic, graphic novel, or comic strip	4.1	52.3
Reboot	1.5	50.9
(ALL FILMS)	100	50.3
Based on a TV series	4.1	49.8
Original concepts	43.1	48.0
Sequel or prequel	11.8	47.9
Other*	0.7	47.8
Remake of foreign film	3.0	45.8
Remake (any type)	7.2	44.0
Remake of American film	4.2	42.8
Based on another film or film characters**	2.1	40.6
Based on a video game	1.1	30.4

*) refers to movies based on material not specified in the list (toys, radio shows, ...)

***) refers to movies that are neither remakes nor sequels, like spoofs

Table 3.1: Average ratings on Metacritic.com for films based on different kinds of source material according to Dietz (2011)

Dietz (2011) provides evidence that different kinds of source material lead to different levels of acceptance by critics and consumers alike (cf. Table 3.1). Sequels, prequels and remakes usually appeal less than original films²⁷, adaptations of literature (plays, novels, comic books), true stories, and reboots appeal more than the average original film.

The next step in a project's evolution after the source material would be the screenplay. Audiences consistently name a film's content as the single most important reason to attend a certain movie (Stradella Road 2010). The different effort and resources put into the development of screenplays in Europe and the US (Finney 1996) has been recurrently cited as one of the reasons for American films' worldwide market dominance (Hennig-Thurau & Henning 2009). Yet the relationship to financial success is non-trivial: While a good script may lead to a "good" film, a good film as judged by expert opinion is not necessarily a commercially successful one²⁸. Very few econometric studies to date include the screenplay in their considerations: Eliashberg et al. (2007) use story summaries written by viewers to identify movie topics (using a bag-of-words approach),

²⁷ Their perceived inferior quality could be the reason for sequels' significantly lower video rental revenues (Hennig-Thurau, Houston & Walsh 2006) and television spectator numbers (Fuchs 2010) – the theatrical run might just be too short-lived to suffer from negative word of mouth.

²⁸ Popular appeal and expert judgments (such as top 100 lists) have been shown to differ in taste (Holbrook 1999).

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

combine these with an evaluation questionnaire filled in by experienced script readers, and predict return-on-investment from these data using decision trees (bag-CART). Similarly, Eliashberg, Hui & Zhang (2014) extract textual information like genre and content, semantics, and bag-of-words from screenplays and use a kernel-based approach to predict box office revenues. Hunter, Smith & Singh (2016) use network text analysis and predict opening weekend box office by the size of the main component of a screenplay's text network. Yet such automated screenplay evaluation methods suffer from their lack of understandability, as results are non-interpretable for humans, and arguably machines are nowhere near as competent as human readers when it comes to picking up the nuances and complexities of a screenplay. Using human screenplay evaluation data as an input for a prediction model seems more promising: Simonton (2011) uses screenplay awards as a success factor in an ex post analysis of film success and Goetzmann, Ravid & Sverdiove (2013) report that the price paid for the script predicts a movie's box office revenues.

While the difficult conceptualization of the complex input factor screenplay has led researchers to exclude it from most models, producers consistently name screenplay evaluation as their primary tool of risk management (Rimscha 2010). In line with their self-conception, we argue that the screenplay is crucial to any kind of film, since it functions as a blueprint of the project to be made, sharing much of the final film's qualities. Goetzmann et al. (2013) indicate that producers may be able to assess such qualities, as higher screenwriter payment is correlated with more successful films, although other confounding factors may be at play here. Assessable screenplay qualities include genre and source material, as well as something vaguely perceived as screenplay quality. Yet it is questionable to capture any screenplay's quality in a single value: That undertaking is as likely to succeed as a quest for one numeric value which captures the quality of an architectural blueprint, regardless of the fact that such blueprints may refer to buildings as different as railway stations, town halls, and kindergartens. Therefore it is important to understand that we do not deal with one abstract screenplay quality, but several distinct qualities. These traits are not to be regarded as normative in and of themselves, but may only become crucial in the context of a given kind of film.

If one is willing to accept the impossibility of reducing screenplay quality to a single scale, script analysis might actually help to understand box office success. We assume the following: A screenplay contains information on the experience the film will provide to its audience. If this experience is in line with the audience's expectations, they will be gratified (Schweitzer 1996)

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

and more likely to recommend attending the film to others, thus leading to higher revenues. Additionally, there may be endogenous and self-reinforcing effects of screenplay quality on other parameters of the package, like facilitated persuasion of key personnel or investors by the mean of an obviously promising script (Simonton 2011).

Macdonald (2003) has shown professional readers to apply very different criteria in judging screenplay quality²⁹. The definition and validation of intersubjective standards could arguably rationalize readers' work. Given these considerations, the screenplay is obviously not irrelevant to the film's success. There is just no generic procedure to (quantitatively) capture the relevant screenplay features (except for genre and type of source material) as of now.

One movie trait variable that may comparably easily be distilled from the screenplay is the movie's genre. Oftentimes, the genre is probably the first thing a producer gets to know about a possible future project, as the screenwriter or their agent will usually mention it early on in the pitch. Thus if the genre could be made use of to determine the likelihood of success, this would undoubtedly be of great value. Most studies of the economic approach include genre variables, usually as dummy variables. But before we will turn to particular results, it is crucial to address two questions: What are genres? And why is a motion picture's genre supposed to influence its box office?

The term "genre" is used in a rather unreflected manner throughout most of the studies in question (Clement 2004). Such usage of genres corresponds to what Gehrau (2003) identifies as the social function of genres: We use a genre name in the hope that our counterpart will know what we are talking about. Yet in a scientific context, the social construction of the terms in use has to be reflected – and genre classifications should not be taken for granted. Especially, as the intersubjectivity of genres has been seriously doubted: different people attribute different qualities to the same genre names (Neckermann 2001a). Blothner (2003) details how different kinds of comedies, appealing to distinct audiences, may be distinguished by the kind of "fun" they promote and Hsu (2006) provides quantitative evidence for the fact that the same film goes by different genres in different databases. Most films even have several genres assigned to them in the same database (Hsu 2006, 432)³⁰.

29 Similarly, interviews by Eick (2006) show the majority of screenwriters and producers not to take the normative claims of screenplay 'gurus' seriously. For a critical discussion of prescriptive screenwriting theories, cf. also Conor (2014).

30 This holds true e.g. for IMDb, Rotten Tomatoes, Showbizdata, Hollywood Reporter and Box Office Guru. Hsu (2006) finds the average number of genres assigned to one film in one

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

Basically, genres organize expectations and reduce uncertainty. As Gehrau (2003) explains, this reduction of uncertainty can be understood from different points of view: culturally, economically, psychologically, and socially. For different reference groups and contexts, the concept of "genre" serves distinct purposes. But generally, genres provide a system to determine similar films: They are developed as production and marketing patterns (Gehrau 2003), thus expressing filmmakers' and distributors' expectations about what audiences want to see³¹. Once emerged, they affect these audience wishes, as well³². Moviegoer surveys show a film's genre to be one of the main reasons for the decision for or against seeing a particular film (Stradella Road 2010), so people seem to expect a certain kind of experience from a certain genre. Therein, expectations may refer to a film's visual (animation) or narrative form (thriller, musical) as well as content (science fiction) or setting (western). But whereas it seems quite straightforward to determine whether a film's genre affects a particular individual decision, modeling its aggregated effect on sales (i.e. numerous people with very different preferences) is much more challenging.

Most of the examined studies – glossing over the contingency of genre attribution – fail to explain why they use a certain set of genres. They use the publicly available genre names that come with the box office numbers. Thus, a multitude of different classifications is employed, with the total number of distinct genres ranging from a handful (Sochay 1994) up to as much as nineteen (Fuchs 2010). This makes them nearly impossible to compare and identify cumulative findings.

Some genres correlate with greater success, but this correlation does not seem to be causal, but presumably has to be attributed to confounding factors such as higher budgets in some genres, since in regression analysis, tendency and significance of results differ largely between studies: Sometimes, the genre of comedy is identified as particularly successful (Bagella & Becchetti 1999), sometimes drama (Lange 1999), which again has a highly significant negative impact elsewhere (Sochay 1994). Not a single genre has been consistently found to affect box office in a positive or negative way (Clement 2004). The genre variable does

database ranging from 1.71 to 2.33 among these platforms.

31 According to Maltby (2004), Hollywood's treatment of genres is cyclical: A major success in one genre leads to the production of more similar films – until the next big thing in another genre captures the industry's attention and budgets shift again.

32 Genre attributions must also not be viewed as stable, but dynamic (Hennig-Thurau 2004): Genres change over time and each film adds something to the genre's definition. Altman (1999) describes from a more theoretical point of view how genres are subject to historical change.

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

not serve its purpose as a success factor very well. Although most studies include it in their models, there are no secured findings.

Therefore another course of action seems more prolific. Hennig-Thurau & Wruck (2000) split their sample into sub-samples, segmenting by genres, thus getting a different weighting of the remaining variables for each genre and a better model fit. Hennig-Thurau (2004) returns to this approach, also getting better results for the sub-samples than for the aggregated sample. Similarly, Chen, Chen & Weinberg (2013) show the impact of individual variables to vary among genres.

This makes perfect sense keeping in mind how we defined genres in the first place: It is much more plausible to state that similar rules apply to similar films, with similarity based on consumer expectations, than to claim that similar rules applied to all films, regardless of expectations.

Unfortunately, this approach has not been pursued by many, although theoretical considerations lead to it, naturally: Genres' explanatory power cannot be reduced to a simple "more" or "less" in admissions, but genres provide a tool to cluster films by perceived similarity, thus determining the influence of every other factor. A pooled regression of all genres "fails to represent the heterogeneous influence of movie features on demographic groups" (Redondo & Holbrook 2010, 299). Therefore we must state a common shortcoming in hitherto published research: Possible effects of single factors are blurred by the prevalent indifference toward (dis-)similarity of films (Behrens et al. 2020).

Since most films may not be unambiguously linked to one genre (Hsu 2006), the corpus of the most similar films will in most cases not be identical to all films attributed to one conventional genre. Consequently, one could compile a distinct sample of most similar movies for each film. We will return to this idea in [section 4.6](#).

Obviously, the concept of genre is linked to that of the film's target audience. Since target audiences have not been included as a factor of success or segmentation criterion in previous studies, the genre variables work as proxies for the target audiences as well³³, inseparably mixing the effects.

The scientists' preference for genres over target audiences is presumably due to the better availability of data. Target audiences are even less well-defined than

³³ This is rarely formulated consciously, with the notable exceptions of Brewer, Kelley & Jozefowicz (2009) and Dellarocas, Zhang & Awad (2007).

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

genres. Given their practical importance for the packaging process (Hsu 2006, 422), the neglect of differing target audiences must be also regarded as a severe shortcoming of most heretofore published research.

A success factor that has been used as widely as any is the presence of stars. This is no wonder given movie stars' public exposure, the attention they command, and their impressive salaries. Most studies concentrate on actors and actresses, but the same basic argument holds true for all cast and crew members whose names are famous enough among the public. The term stars may thus refer to actors, directors, and well-known other crew members alike for the rest of this examination.

Stars can predict or influence a film's success in three conceivable ways:

- a) First, as a mere indicator. Stars are usually offered more projects than newcomers, so they can pick wisely (Clement 2004). Thus the stars variable would function as a proxy for outstanding projects.
- b) Second, the presence of stars can positively influence other factors of success. In the US, "Who's in it?" is often the first question asked by a studio considering a new project (Albert 1998). The attachment of stars evidently helps to secure a higher budget (Hennig-Thurau, Houston & Walsh 2007), higher advertisement spendings (Hennig-Thurau, Houston & Walsh 2006), and wider distribution (De Vany & Walls 1999). Elberse (2007) shows that the announcement of a star's attachment to a film raises expectations about that film's success³⁴. Also a positive impact on critical reviews has been measured (Hennig-Thurau, Houston & Walsh 2007)³⁵.
- c) Third, stars can of course directly increase theater attendance for several reasons: Obviously, their fans will probably watch their new film. This is commonly referred to as "drawing power" (Albert 1998). Additionally, they function as "branded ingredients" (Hennig-Thurau et al. 2001), signaling a certain level of quality: their "marking power" (Albert 1998). Finally stars add to another level of enjoyment that goes with watching a movie: As Adler (1985) points out, part of the fascination of entertainment is discussing it with others – an appeal that increases with the level of popularity. The presence of a well-known star would thus increase a film's appeal by virtue of their fame, regardless of the actual performance.

34 Her study shows the virtual stock prices on the Hollywood Stock Exchange (cf. [subsection 3.3.5](#)) to react to cast announcements prior to production.

35 Interestingly, Hennig-Thurau, Houston & Walsh (2007) find a negative impact of star power on consumer evaluations. They suggest this effect to be explained by disconfirmation theory: consumers expect more, if a star is attached, and are thus more likely to be disappointed.

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

These effects suggest star power to be a positional good (Rimscha 2010): Not the absolute quality or publicity of the star is relevant, but their relative publicity compared to other stars – the winners take it all (Gaitanides 2001). This makes ranking an obvious way to conceptualize star power: Most studies use proxy variables to code the presence or non-presence of major stars, who are defined in various different ways, e.g. based on their appearance in current industry star rankings (Ainslie et al. 2005, Elberse & Eliashberg 2003, Liu 2006, Neemalegham & Chintagunta 1999, Sawhney 1996) such as The Hollywood Reporter’s annual list, or based on awards for achievements in acting or directing (Basuroy, Desai & Talukdar 2006, Litman 1983, Ravid 1999). Other approaches try to capture differences between individual stars on a more discriminative scale: Hennig-Thurau, Houston & Walsh (2006) use the average box office revenues of a star’s three most recent films, Ainslie et al. (2005) employ the Hollywood Reporter’s list rank (as opposed to a binary coding of the mere presence on the list), and Nelson & Glotfelty (2012) use the IMDb Starmeter rank of the cast and crew members in the film’s opening week as an index for its star power³⁶. Among all abstract measures, the latter is certainly more sophisticated, since it directly measures public interest in the star at the very point of time the film is released. Unfortunately, it is not available for most non-US actors (Clement, Wu & Fischer 2014).

Regardless of conceptualization, most studies have found a positive impact of star power on box office success³⁷, which is arguably stronger for the US than for European markets (Hennig-Thurau 2004).

While stars seem to reduce the risk of failure at the box office, their employment bears arguable profitability risks, as stars can add substantially to a film’s production costs. Their participation can be regarded as licensing a brand: the more popular, the more expensive (Chisholm 2004). This is a simple price mechanism of supply and demand: Big stars get more offers and face higher opportunity costs when they commit to a certain project (Wei 2006). On the other hand, they can only be imperfectly substituted by a less popular star (Rosen 1981), increasing producers’ willingness to pay³⁸. Ravid (2002) suspects a principal-

36 According to Karniouchina (2011b), this can be regarded as a measure for the buzz surrounding the star in question.

37 This holds only true for cast members. Directors have mostly not been found to have a significant impact, but this could be due to the in-discriminative treatment of different genres: Maybe only a few select directors have a positive impact in only some genres (e.g. arthouse dramas). To the best of the author’s knowledge, this has not been tested appropriately to make a profound statement, yet.

38 Rosen (1981) compares this to patients’ willingness to pay for a surgeon with a ten per cent higher survival rate among his patients: survival is crucial – as is box office success for motion pictures.

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

agent-dilemma to be at play here: Individual producers who have hired stars are less susceptible to blame for a film's failure (they have done what they could), so this strategy helps them to boost their track records, although it might harm the production company's or studio's profitability.

De Vany & Walls (1999) use distinct proxy variables for individual stars, finally publishing a list with nineteen names whose variables have been shown to have a significant impact on box office success (two of them directors). The concreteness of this approach corresponds to the producer's concrete choice between individual stars, yet its applicability is limited and seems very susceptible to market dynamics and changing tastes. Also it requires large sample sizes to yield meaningful results for a large number of stars.

The results of published research to date are rather sobering, as they do not compare preferably to industry gut feeling: Stars do increase box office, but we know too little about how they influence it to rationally price their performance. Again, genre-specific modeling could help: Blothner (2001) shows empirically that Julia Roberts has attracted different audiences for a drama (ERIN BROCKOVICH) than for her comedies (here: PRETTY WOMAN). A star's value may be highly dependent on the nature of the planned project. Yet most research studies fail to capture such complexities: Cast and crew members are reduced to their public awareness, disregarding both a possible fit with the project and interaction effect between different creative talents attached to a project (Bagella & Becchetti 1999, Meiseberg, Ehrmann & Dormann 2008).

Another widely used movie trait in predicting and explaining box office revenues is the production budget. Feature film budgets may range from a few thousand dollars to hundreds of millions. They are not fully determined by the film's screenplay, since a film's budget can usually be divided into a below-the-line and an above-the-line budget (Moore 2007). The former is necessary to realize what is described in the screenplay, the latter is a voluntary investment by the filmmakers into the film's production value (technical skills, stars, etc.), hoping to increase the likelihood of success. Determining an appropriate and financially feasible above-the-line budget is part of the producer's creative task during packaging.

Obviously one could argue that, if expensive films would not pay back the investment in some way, they would not be made in the first place. Yet it is interesting to examine whether this return on investment comes in terms of increased box office figures or if it is non-monetary, like a gain of prestige for

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

the production company and crew members involved. In this subsection we will neglect the latter and concentrate exclusively on budget's possible impact on box office.

Of course most spectators do not look up a film's production costs in order to decide whether they attend it. Thus, the budget does not appear among their consciously stated reasons for attending films (FFA 2020c, Stradella Road 2010). Yet it has an indirect impact on their evaluation that can most easily be explained by the concept of "production value". The budget variable serves as a mean to capture qualities of the film that are not measured otherwise, but which are assumed to increase in quality according to the money that is being spent. In line with that argument, Simonton (2011) shows the budget to correlate with visual, technical, and musical quality of films (measured ex post by respective awards). Hadida (2010) finds production costs to be dependent on the team members' track record. Since budget allocation data are sparse, almost all studies use aggregated production costs.

Unsurprisingly, most studies find a positive influence of the film's budget on revenues. Simonton (2011) even attributes the highest influence of all factors to the film's budget. Evidence dates back as far as to Litman (1983). But, as Antipov & Pokryshevkaya (2011, 3) point out, estimates of budget elasticity vary significantly. In order to prove helpful for the practitioner, studies would have to show either the non-linearity or the limited generalizability of a budget effect: Obviously, revenues do not proportionally scale with budget for all movies. So what is an ideal budget (for a specific film or specific genre)? This question is addressed by far less scholars.

A few studies have clustered the films by budget size and examined the probability of success for those different classes. According to Duvvuri (2007), little differences in budget do not matter. Neighboring clusters did not yield significantly different revenues. Concordantly, if films are clustered in sub-samples by the size of release, budget becomes insignificant as well. The production costs have been found to secure opening power (i.e. they strongly influence the film's opening weekend through a high number of screens), not staying power (De Vany & Walls 1999). Basuroy et al. (2003) model the box office of all weeks during the film's run separately and show the budget's influence to become insignificant by the fourth week. Given the hitherto available evidence, the budget's influence is likely to consist mainly of its impact on distributor's decisions (advertisement spendings, number of copies) and production value.

3 *Scientific Approaches to Target Audience Definition and Revenue Prediction*

Considering profitability, Hennig-Thurau (2004) finds 50 per cent of the films produced on a budget smaller than \$5 million dollar to be profitable, while only 3.6 per cent of high-budget films (production costs > \$75 million) break even, suggesting the average profitability to decrease with budget size. Yet this surprisingly low percentage is likely due to the fact that the study did not look at all earnings over the film's lifecycle³⁹. In contrast to that, Elberse (2013) examines the portfolio of Warner Bros. and finds high-budget movies to be superior drivers of profitability: While some of them tank, some of the most profitable films fall into this category (Cassidy 1997), either – let alone these projects' importance for producers' and distributors' prestige and publicity. Often pushing the envelope for technical and visual development, such tentpole movies are also important for the industry as a whole. Whereas findings on large blockbusters are mixed, medium-budgeted films are considered unprofitable among industry insiders since the late 1990s (Cassidy 1997, Schulz 2005, Turitz 2016, Evangelista 2020).

As one would expect budgets to be more crucial for science fiction films than for documentaries, a clustering of similar films before modeling seems highly recommendable to avoid false implications about budgets as well. Models with access to budget composition data (e.g. if developed internally at a studio or network) should rather include distinct budget categories as input variables.

One thing that higher production value can afford is technical skills. Technical skills that contribute to a film's appeal include special and visual effects, cinematography, art direction, and sound. Because of their difficulty to be measured these qualities have found little entrance in econometric research on box office so far. Simonton (2011) has examined their influence in an ex-post assessment of the awards won in respective categories and finds a positive impact of these awards on box office that is even larger than that of the "dramatic" categories (acting, directing, screenplay). In terms of conceptualization for a predictive model, one would have to come up with an inter-subjective scale to estimate technical qualities in advance (since awards are obviously not available beforehand), relying for example on track records of relevant team members or expert opinion.

Another movie trait which is often used in box office models is age ratings: The American MPAA rating and its German equivalent, the FSK rating, assess a film's suitability for consumption by minors and sort it into one of several

³⁹ Follows (2016) uses a sample of internal cost and revenue data and finds about 50 per cent of all movies with budgets north of \$100 million to be profitable.

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

categories. The audience that can possibly be reached by a film classified as "R" (or "freigegeben ab 18 Jahren", respectively) is evidently smaller than that of a film with a less restrictive rating. This makes the rating an important target value for distributor policy (Epstein 2005) in order to secure a high market potential. Repeatedly, econometric studies have incorporated the rating as a variable assuming a decreasing effect of restrictive ratings on box office. Several studies find such a negative impact (De Vany & Walls 2002, Ravid 1999, Leenders & Eliashberg 2011)⁴⁰. Basuroy et al. (2003) suggest this effect to hold only true for the opening week.

All these findings on age ratings face a severe objection, that should already seem common by now: It is hardly conceivable why such a statement should generalize to all kinds of films. A simple differentiation between wide- and platform-released movies leads Boatwright et al. (2007) to observe that R-rated arthouse movies, whereas they have a smaller market potential, open wider and generate more word of mouth⁴¹. (Simonton 2011, 89) assumes that films that get an R seem more "artistic". A sophisticated model must therefore examine genre-specific impacts of the film's rating, since its importance will arguably be different, dependent on whether it is a comedy – on the edge of being suitable for families – or a horror film (Antipov & Pokryshevkaya 2011).

The number of screens on which a film debuts is not exactly a movie trait, but it is mostly treated as such when it comes to econometric modeling. All studies that examine the number of screens a film is initially shown on find it to be a strong (if not the strongest) factor of influence on cumulative revenues. Fuchs (2010) identifies four possible ways in which the number of screens may be related to sales:

- a) Screens fulfill a gatekeeper function, as they limit the availability of the film.
- b) A wide release serves as an indicator of the film's assumed quality.
- c) A large amount of copies generates additional buzz.
- d) Copies correlate with advertisement budget.

This might seem as if the producer and distributor could just define a certain number of screens: the higher, the better the outcome. For several reasons this does not hold true. First, screens are a rather scarce resource (Clement 2004).

40 While those studies concentrate on theatrical performance, Hennig-Thurau, Houston & Walsh (2006) have shown video rental revenues to increase with restrictive ratings. Accordingly, Lang, Switzer & Swartz (2011) find DVD releases of R-rated movies to be less risky.

41 They use a Bass diffusion approach to model the film's performance over time.

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

The number of films released any year has steadily increased over the last years (Follows 2017), while the number of cinemas has been fairly stable⁴². More films compete for a limited amount of slots. Theater owners today can hardly be forced to exhibit underperforming movies from the distributor's repertoire like back in the days of block booking (De Vany 2006), but they must be persuaded of the individual project's likelihood to succeed. Thus, the number of screens reflects theater owners' expectations. During a film's run, it does not stay stable, but is dynamic and subject to weekly negotiations between distributor and exhibitor (Elberse & Eliashberg 2003). Usually they agree on a weekly target number of admissions the film has to generate at a certain screen in order to be exhibited under the same conditions in the following week as well (De Vany & Walls 1996)⁴³. If the film fails to draw enough spectators, the distributor may lower the fee (Clement 2004) to increase demand among exhibitors. Still it is impossible to continuously operate at full capacity of supply, so the absolute number of screens varies (and usually decreases). Elberse & Eliashberg (2003) prove the number of screens to be an endogenous variable in box office forecasting models, as it depends on most of the factors that influence box office plus the previous week's sales. The relevant number for predictive modeling is the number of copies at the start of the film's run, as it has been incorporated in most studies⁴⁴.

Interestingly enough, the process of how this number of opening screens is determined has hardly been addressed by research so far (Zuta 2007). It is certainly dependent on the anticipated success⁴⁵ – this becomes evident by the fact that films that have proven their appeal in a foreign market are promoted and distributed more aggressively (Lange 1999). Some factors might indeed not influence sales directly, but only through their impact on exhibitors' behavior (Gemser et al. 2007).

Basically, there are two release strategies: wide release and platform release.

42 This applies to Germany (FFA 2020c, FFA 2012) and the US (MPA 2020). In other markets, especially China, there has been considerable growth in recent years regarding the number of theaters.

43 Sometimes, theaters are contracted to show a film for a minimum number of weeks regardless of its success (Eliashberg, Swami, Weinberg & Wierenga 2001).

44 Gaitanides (2001) and Lange (1999) use the maximum number of screens during a film's run, which is in most cases, but not necessarily the same as the number of opening weekend screens. But where it deviates from the opening screens number, that measure is itself highly dependent on the film's success, thus it must be regarded as unsuitable.

45 Elberse & Eliashberg (2003) successfully use Hollywood Stock Exchange data (cf. [subsection 3.3.5](#)) as a proxy for expected sales and find them to have a substantial impact on the number of opening screens. Since HSX numbers are only available for wide release movies, Clement et al. (2014) suggest the IMDb Moviemeter rank in the week prior to release as an alternative measure of industry expectations.

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

The predominant former strategy directly opens a film market-wide at as many screens as possible, concentrating all marketing efforts on the first week in order to skim as much of the market potential as possible, early in the run. The latter places a film in selected cinemas first (usually targeting major cities) in order to build word of mouth and slowly spreads through the market, often abandoning the screens of the first weeks and moving the copies to another city. While a wide release builds on a film's marketability, a platform release must rely on what industry insiders call playability⁴⁶.

The resulting sales curves can be modeled as diffusion processes, e.g. by use of the Bass diffusion model for innovations (Bass 1969): While the platform release corresponds to the classical spread of technologies by early adopters and word of mouth, the wide release depicts an extreme case where the "Bass model simplifies to a model of exponentially decreasing sales in which the innovator purchase probability measures the speed of decay of the exponential" (Boatwright et al. 2007, 415)⁴⁷. According to Clement et al. (2006), generalized gamma distributions suit the diffusion of motion pictures best.

As mentioned above, the wide release strategy is more prevalent in the marketplace: De Vany & Walls (1999) state that for 65-70 per cent of all released films⁴⁸, the first week generates more revenues than any single later week of the run. But the existence of two valid strategies implies a non-linear or non-generalizable relationship between number of opening screens and total box office, that most studies do not account for (Clement 2004).

An important factor in the release strategy is obviously the distribution company, which may also be regarded as a movie trait for modeling purposes. Distributors range from little owner-run companies with a handful of employees to global mega-corporations that are usually part of even larger media conglomerates. Distributors' economic power is crucial for the number of screens a film can find and the size of the advertisement campaign it will be backed by. Not only do majors command more resources, but they also enjoy a superior starting point in negotiations with theater owners. Unsurprisingly,

46 Elberse & Eliashberg (2003, 337): "Practitioners often use terms such as *playability*, *legs*, *longevity*, and *driven by word-of-mouth* interchangeably".

47 There may be additional peaks later in the movie's run due to seasonal market size variations. Radas & Shugan (1998) convincingly propose to model seasonality as an acceleration effect, a speeding up and down of time (since more or less units are sold over the same period) in diffusion models.

48 Using more recent numbers, Follows (2018) finds week one to be the financially most important for "just under half" of the 10,719 movies in his sample released between 1998 and 2017. However, this relationship is more pronounced for larger film: Of the top 50 films per year in the sample, 90% earn most revenues in week one.

3 *Scientific Approaches to Target Audience Definition and Revenue Prediction*

there is a strong correlation between distribution-related factors and distributor size. The distribution contract, as part of the producer's package, does certainly influence the success probability of the project.

Still it may be doubted if the distributor has any direct impact on audience behavior or just indirectly affects it through the number of opening screens and advertisement spendings. Indeed, no distributor – maybe with the exception of Disney (Eliashberg et al. 2006) – has managed to establish wide-spread brand loyalty among audiences, as the focus is rather on building movie franchises (Eliashberg et al. 2006). Due to risk diversification, the slates of the large distributors vary too much to be suitable for conventional branding. Like products of large companies in other branches, their films are just more likely to be circulated widely than competing products by no-name companies (Clement 2004). Therefore it has been argued that "independent" was a negative label, since it confines the broadness of appeal to a niche market (Zuckerman & Kim 1999). Results of econometric analysis are mixed: Sochay (1994) has found distributor identity – although highly correlated with box office – to have no significant impact in regression analysis, whereas Hsu (2006) does find such an impact.

One of the main ways in which the distributor may wield influence is arguably advertisement spendings. Advertisement throughout all channels is meant to capture the attention of the possible audience, spark their interest and desire to see the film in order to eventually make them attend cinemas. At the same time, expectations are raised⁴⁹ which the product (the film itself) may or may not be able to fulfill – thus leading to positive or negative word of mouth.

Due to very limited availability of data, few studies have incorporated advertisement as a variable, yet. Advertisement is usually paid for by the distributor. Part of the effort is contributed by cinemas, which usually play trailers without billing the distributors (Backen 2009). Like the number of opening screens, the amount of money spent is a measure of the anticipated success. The correlation between advertisement expenditures and number of screens has been shown to be as high as 0.7 (Hennig-Thurau, Houston & Walsh 2006). Also a correlation with budget has been argued for (Hennig-Thurau, Houston & Walsh 2007), which seems reasonable as the higher the budget (i.e. the risk at stake) the more will the distributor be willing to back the project promotionally. Stars, source

⁴⁹ Actually, consumers see film trailers as a possibility to gain first experience with the product, not just as advertisement (Hennig-Thurau & Wruck 2000).

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

material, and seasonality can also have an impact, as they contribute to the prestige status of a film project within the distributor's portfolio (Hennig-Thurau, Houston & Walsh 2007).

Elberse & Anand (2007, 320) argue that "studying the effect of advertising on box office receipts is confounded by the classic endogeneity problem: movies expected to be more popular also are likely to receive more advertising". Concomitantly, McKenzie (2013) proposes to model them as a dependent construct, affected by the same movie traits as the number of opening screens.

Studies have unanimously found a positive impact of overall advertisement spendings on box office revenues (Ainslie et al. 2005, Basuroy et al. 2003, Elberse & Eliashberg 2003, Lehmann & Weinberg 2000, Prag & Casavant 1994, Basuroy et al. 2006). Elberse & Anand (2007) show pre-release advertising spendings to influence sales expectations among the industry⁵⁰. For post-release advertising, results are mixed: Zufryden (1996) finds that even on a weekly basis, advertisement spendings can directly be linked to public awareness (and, consequently, box office figures). In contrast, Hennig-Thurau, Houston & Sridhar (2006) observe the long-term box office to be mainly dependent on perceived "movie quality" and the resulting word of mouth, suggesting that "if studio actions do not manage to bring people into theaters when a movie opens, they will not have any kind of effect thereafter" (Hennig-Thurau, Houston & Sridhar 2006, 217).

Most importantly, the above-mentioned blur of effects by amalgamation of genres holds true for advertisement, as well. According to the genre-specific model by Chen et al. (2013), advertisement has a much stronger effect for action and comedy movies than for dramas.

3.3.3 Third-Party Information

In addition to (quasi-)movie traits, another range of possibly influential factors for box office revenues may be described as third-party information, i.e. sources which signal movie quality to potential viewers that are independent from the makers and marketers of the respective movie, such as critical reviews, awards, and word of mouth.

According to conventional wisdom, critical reviews play at least two important roles in the creative industries, as they "are a medium for research and

⁵⁰ They use Hollywood Stock Exchange data to capture expectations, cf. [subsection 3.3.5](#)

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

development, and they provide a 'seal of approval' for the aesthetic worth of output, thereby increasing demand and/or helping in the pursuit of subsidy" (Cameron 1995, 324). Concerning the latter, their impact on demand, two ways of influence are conceivable for critics: On the one hand they function as multipliers, providing visibility and thus raising additional awareness for the movie. On the other hand they influence potential consumers' viewing intentions by their evaluation of the film.

To measure visibility, one can simply count their number or take into account the medium's circulation and even the review's size on the printed page (Gemser et al. 2007). Unfortunately the only study investigating awareness directly (Zufryden 1996) does not include weekly critical reviews in their time-dependent model. Yet a higher visibility can certainly be expected to go with higher awareness and higher box office. Substantial progress is probably prevented by the already discussed prevalent indiscriminate treatment of all films as equal in econometric research. Gemser et al. (2007) differentiate between arthouse and mainstream movies, since arthouse audiences presumably apply evaluation schemes more similar to the critics' ones, and find an effect of the provided visibility on box office for arthouse films that does not apply to mainstream movies⁵¹

Concerning the (positive or negative) content of the review, surveys suggest it to have an impact as well, but its valence is difficult to measure: Not only does one have to assign numeric values to written texts, but also a simple arithmetic mean of the ratings in all reviews is arguably neglecting differences among the reviews (regarding their circulation, placement, and the author's niche-specific prestige⁵²). Although the nature of critical reviews can hardly be captured appropriately, most studies focus on that evaluation's impact, neglecting the provided visibility and stating positive (Hennig-Thurau & Wruck 2000) or U-shaped (Wallace, Seigerman & Holbrook 1993) relationships. Occasionally, a stronger impact of negative reviews ("negativity bias") has been argued (Basuroy et al. 2003).

The correlations of box office revenues both with volume and valence of reviews might – though empirically demonstrable – still be either correlational or causal.

51 Similarly, Koschat (2012) finds an increased effect of reviews for films based on literature.

52 Hsu (2006) proves critics to develop different levels of competence for different genres. Boatwright et al. (2007) examine single critics and find that only some of them are of any importance for box office. Reinstein & Snyder (2005) assume the opinions of the two famous US film critics Roger Ebert and Gene Siskel to account for as much as twenty per cent of the opening weekend's box office.

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

Viewers repeatedly mention critical reviews as an important source of awareness (FFA 2020c), one third of the US population actively seek them out during their film choice process (Basuroy et al. 2003) and, in an experimental setting, people's pre-viewing assessment of films could be shown to depend on the evaluation by incidentally presented critical reviews (Suarez-Vásquez 2011)⁵³. On the other hand, there is support for a non-causal correlation as well, due to evident confounding factors like the presence of stars (Hennig-Thurau, Houston & Walsh 2007) or major distribution companies (Hsu 2006). To tackle the question of causality, Eliashberg & Shugan (1999) first introduced the concept of discrimination between influencers and predictors: Based on the observation that critical reviews are usually published in a film's opening week, they argue that short-term box office should be affected more heavily if any effect was determinable, since other sources of information like word of mouth should be stronger later in the run. Pursuing a different approach, Hennig-Thurau, Marchand & Hiller (2012) try to separate critical reviews from consumer quality perceptions⁵⁴ and find them to influence long-term, but not short-term box office. They base their interpretation of these results on the change in the demographic structure over a film's run (Epstein 2012), with older people generally being more receptive to influence by critical reviews than teenagers. As arthouse audiences are significantly older (Neckermann 2001b), this could provide further evidence for the widely held conviction that critical reviews are really critical in this market segment. Genre- or niche-specific modeling could help to overcome some of the emerging modeling difficulties.

Given the current state of research, critical reviews must be seen at least as an important multiplier whose influence is primarily based on additional awareness. Critics receive special treatment by producers and distributors (Hennig-Thurau et al. 2001) and are constantly being persuaded "to write about [a] movie in the first place" (Gemser et al. 2007, 57), because of the awareness any kind of review raises⁵⁵.

Apart from critics, awards indubitably play an important role in the film in-

53 Similarly, Burzynski & Baker (1977) conducted an experiment employing fake conversations between apparently leaving moviegoers that were intended to be overheard by the entering customers. Negative statements about a film prior to film consumption led to lower ratings thereafter. Thus our opinion may already be shaped by the influence of others (critics and peers, alike) before we actually see a film.

54 They do so by an auxiliary regression, regressing critics' evaluations (Metascore averages) on ordinary moviegoers' ratings (Netflix/Yahoo average ratings), using the residuals of the regression as the critical review variable (Hennig-Thurau, Marchand & Hiller 2012).

55 Accordingly, Wyatt & Badger (1990) find in an experimental setting, that the amount of information in a review is more relevant to the reader's resulting interest in the film than the evaluation.

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

dustry as third-party signals of movie quality. Awards can boost careers and company track records. Some films are intentionally made for winning awards. But within the scope of this work our main interest is to determine whether winning an award actually affects revenues.

Such an impact has been repeatedly assumed in the scientific literature. Most studies concentrate on the Academy Awards ("Oscars")⁵⁶. Of course, no producer can know at greenlighting that they are going to win an Oscar. Certainly it makes no sense to plan with winning an Academy Award – very few films get nominated, still fewer win, and even fewer are still in the cinemas at the time of the ceremony to reap any potential box office benefits. So chances for positive box office effects are rather slim⁵⁷.

But if a win seems within reach – is a large lobbying and advertisement campaign worth the effort (commercially)? According to Deuchert, Adjamah & Pauly (2005, 159), "Universal Pictures spent \$15 million to promote 'A Beautiful Mind' with the 5,739 voting Academy members". On the one hand, research supports the idea of a direct commercial impact of Oscar wins and nominations (Sochay 1994). According to Jedidi et al. (1998), nominations occur only for films whose sales follow successful revenue decline patterns after their release. Yet a win is considered more valuable than a mere nomination (Hennig-Thurau & Wruck 2000). Hennig-Thurau, Houston & Walsh (2007) even find Oscar wins to affect profitability more than all other variables. All these findings are put into perspective by Clement et al. (2007) who model a random experiment ex post by using propensity score matching, building a control sample by assigning a similar non-winning partner movie to all Oscar-winning films. In this quasi-experimental setting, awards have no significant impact at all. Thus the effect of awards in past models may instead be attributable to inherent movie quality which may not be captured otherwise by the respective models.

Obviously, spectators talk to each other about their experience of watching a

⁵⁶ According to Simonton (2011) the seven prominent organizations Academy of Motion Picture Arts and Sciences (AMPAS), Hollywood Foreign Press Association (HFPA), British Academy of Film and Television Arts (BAFTA), New York Film Critics Circle (NYFCC), National Society of Film Critics (NSFC) and Los Angeles Film Critics Organization (LAFCA) tend to agree in their evaluation of filmmakers' accomplishments. Among all those awards, the Oscars are statistically nearest to consensual opinion and, additionally, match the also famous guilds' prizes best. Thus they are the most reasonable measure of merit in the film industry as evaluated by peer filmmakers.

⁵⁷ It has been argued that a reverse relationship could hold true: high revenues will increase a film's chances to be nominated (Hadida 2009). Over the course of recent years, some research has been put into the question how to determine factors influencing Academy Awards as well (Pardoe 2005).

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

film and influence each other's intention to attend or not to attend it. Surveys show peer recommendations to rank among the most important sources of awareness (FFA 2020c), thus word of mouth constitutes another potentially large third-party information factor for movie success. The omnipresence of word of mouth for movies is probably rooted in many people's high level of involvement (Hennig-Thurau & Wruck 2000) and has led many to regard it as the most important factor of success (Zuta 2007), at least in the long run⁵⁸. But the "long run" (De Vany & Walls 1999, 308) is not the key to success it used to be (with the exception of platform-release movies), since most films rely on their marketability rather than playability today (Clement 2004). The relative importance of word of mouth might be smaller than usually assumed. Yet word of mouth plays an essential role in the development of demand for all entertainment goods (Eliashberg et al. 2006) and is well worth investigation.

Hennig-Thurau, Houston & Walsh (2006) make use of the Cinemascore service that provides weekly aggregated audience opinions from surveys conducted right at the exit of North American cinemas. According to their study, a significant positive impact of audience opinions on box office revenues is observable. So-called "word of mouse" or "electronic word of mouth" ("eWOM"), i.e. consumer evaluations and recommendations on the Internet, have also been found to contribute to film success⁵⁹; Dellarocas et al. (2007) prove volume, valence, and dispersion (variation of the recommending users in gender and age) to be all significantly impacting box office in a positive way. Liu (2006) as well as Kim, Namkee & Park (2013) find an effect for volume or frequency, but not for valence. The findings of Asur & Huberman (2010) about the ratio of positive and negative mentions on Twitter point in the same direction.

3.3.4 Market Environment

Apart from inherent movie traits and third-party information, structural factors may also be at play when it comes to determining a film's box office performance, such as the economic environment, seasonality, and competition.

58 Such an argument is also repeatedly used to emphasize the commercial relevance of the screenplay: Its evident importance for people's opinions (Stradella Road 2010) make its quality a likely cause (and predictor) of buzz.

59 Similarly to classical market research institutes, the advertisement industry has already seen a surge of companies specialized on such online monitoring like Nielsen Buzzmetrics, Cymphony, MotiveQuest etc., cf. Dellarocas et al. (2007).

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

The general idea is that the same film performs differently dependent on its release date. The choice of the release date is usually made by the distributor⁶⁰ and cannot be changed at short notice without causing costs (Caves 2000)⁶¹. In order to determine by what criteria this decision should be made, we have to discuss how the release date can influence the film's success. Two reasons seem conceivable:

- a) There are more or less potential viewers at the respective date.
- b) There is more or less competition for a given audience's attention at the respective date.

Obviously the willingness of the population to spend time in movie theaters can vary over time. Again this may happen in two ways: As an overall market trend (long-term) or on a yearly basis (seasonality).

Considering long-term development, market size variations have not been explained well, yet. For Germany, admissions vary by as much as 19 per cent year over year (Rimscha 2010)⁶². Conventional industry wisdom has long suggested motion picture ticket sales to evolve in a counter-cyclical way compared to the overall economy (Nardone 1982)⁶³, which may be explained by a shift toward low-cost and local leisure activities during recession (Vogel 2004). Yet newer research by Orme & Vogel (2020) shows that recessions do indeed harm the motion-picture industry as well.

In an attempt to forecast cinemas' overall market potential ten years into the future, Neckermann & Blothner (2001) link box office to the demographic structure, since young adults are the most frequent moviegoers. Lange (1999) identifies gross domestic income, the share of 14-39-year old people in the population, and ticket prices to be significant predictors of a country's per capita admission frequency, thus contradicting the common notion of counter-cyclical sales. By autoregression one can obtain a range in which admissions will probably vary for the next years (Hand 2002), but these models are of little explanatory power. Technically, one would have to control for other factors like technological inventions as well – home entertainment products (Cameron 1988), to name an

60 The distributor's incentives can be different from the producer's ones if several films of the distributor compete with each other.

61 Einav & Ravid (2009) show changes of already publicly announced release dates to negatively influence the distribution company's stock price.

62 The even sharper decline in revenues from 2019 to 2020 because of the Covid-19 pandemic must be considered an outlier.

63 Again, this only pertains to usual ups and downs of economic development, not to external shocks: The 2020 Covid-19 pandemic hit the movie industry just as hard as the rest of the economy.

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

important example – which can hardly be captured comprehensively in a model (Nelson & Glotfelty 2012). In his essay on prediction validity, Silver (2012) believes such macro-economic forecasts to be able to foresee a few months at best. Rimscha (2013) concludes that possible effects of the overall economy on cinema ticket demand are completely obscured by the impact of individual films.

This leaves us with seasonality. There is lots of evidence for variation of admissions over the year: In the US, every theater owner knows about the importance of the summer vacation and the time between Thanksgiving and Christmas. Other national holidays (Easter, Independence Day) have a noticeable impact on sales as well. Basuroy et al. (2003) incorporate seasonal variation data from Vogel (2004) into their econometric model, scaled to a value between 0 and 1, and do not find a significant influence. That should not be too surprising: Weekly admissions are subject to large variations between one year and another. The simpler conceptualization of using a dummy variable which indicates whether a film was released at a conventionally "high season" weekend⁶⁴ yields superior results and has already revealed a significant positive impact of seasonality (Hennig-Thurau, Houston & Walsh 2006).

While scheduling their releases, distributors not only try to avoid seasonal, non-film entertainment competition like major sports events, but also specifically films which compete for the same target audiences. Simonton (2011, 73) even states: "Because the timing of release is such a gamble, box office returns may reflect more the merits of competing films than the quality of the film itself." In spite of the methodological difficulty, several researchers have tried to model competition in their studies. Although all films vie for a limited screening capacity (Vogel 2004), obviously not all films compete in the same way: Calantone, Yenyurt, Townsend & Schmidt (2010) distinguish four kinds of competition for motion pictures: films of the same genre that have been released before, newly released films of the same genre, films of other genres that have been released before, and newly released films of other genres (Calantone et al. 2010). They find a significant negative influence of all competitive threats on a given film's performance.

Instead of measuring competition simply by the number of other films, Sochay (1994) assumes that the presence of especially threatening competition (i.e. blockbusters) in the market can be indicated by a higher share of overall

⁶⁴ For the US, that is the summer vacation and the holiday season between Thanksgiving and Christmas. For Germany, it is less clear, but the week around Christmas has traditionally seen the strongest box office performances.

3 *Scientific Approaches to Target Audience Definition and Revenue Prediction*

weekly ticket sales that the top ten movies of the respective week account for. Consequently, he takes this share as the competition variable and indeed finds a significant negative impact on movie success. Also, competition from similar films is more threatening to a movie's box office potential than competition from films that target different audiences (Gutierrez-Navratil, Fernandez-Blanco, Orea & Prieto-Rodriguez 2012) or offer different gratifications (Foutz 2016).

While they may be difficult to foresee and model, it can be assumed with certainty at this point that structural market environment factors do indeed influence any film's box office performance.

3.3.5 Industry Applications

Compared to the psychological approach and the audience segmentation models it has inspired, application of ideas from the economic approach in the industry has traditionally been very sparse. As Eliashberg et al. (2006, 641) state: "While maximizing the greenlighting success rate is extremely challenging, it is staggering to discover how little science usually goes into the process."

Large distribution companies in the US employ prediction models internally. As an executive at Fox 2000 states, all projects' box office potential is assessed – and if it looks too risky, "they just don't do it" (Rimscha 2010, 195). The data breach at Sony Studios in 2014 has revealed some of these internal models⁶⁵.

In the Sony documents, it can be seen that the studio used different regression models for different movie clusters to predict revenues based on pre-release awareness levels as measured by tracking surveys (Troy Research 2008).

Tracking surveys are a very common tool of market research in the motion picture industry (Prommer 1997). Such studies monitor the population's awareness and intention to see a specific film. For a wide release, market leader NRG (National Research Group) aims at a total awareness level of 40 per cent at release date, 30 per cent one week prior, and 25 per cent two weeks before

⁶⁵ For a discussion of the ethics of using the leaked documents from the Sony hack for research, cf. Connor (2015).

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

opening day (Prommer 1997). If these goals are not met, the distributor is advised to put more effort into advertising the film.

Data from tracking surveys are hard to obtain for scientists, thus they have been used by only few scientific models. Zufryden (1996) collaborated with a studio and shed some light on how awareness and intention influence box office (for the French market). He modeled weekly admissions, using advertisement, awareness, and intention, as well as box office data on a weekly basis. Awareness demonstrably impacts intention and intention demonstrably impacts admissions. Additionally, he shows advertisement spendings in one week to influence awareness in the following week⁶⁶.

Given the rise of online user data, such tracking could become widely available to smaller companies as well. Google and Youtube search queries (Panaligan & Chen 2013), film-related activity on Wikipedia (Mestyan, Yasseri & Kertész 2013) and Twitter (Asur & Huberman 2010) have been found to be highly predictive of box office success and could certainly be made use of by distributors who cannot afford tracking surveys beforehand, since at least the data from Wikipedia are freely available from the Wikimedia servers (Mestyan et al. 2013).

While Elberse & Anand (2007, 327) state that "once advertising budgets have been allocated and expenditures allocated across media outlets, studio executives have very limited flexibility in adjusting a movie's advertising campaign in the weeks leading up to the release", we will certainly witness an increasing flexibility and reaction capability in marketing campaigns due to the abundant availability of real-time audience data.

In another internal Sony model, the studio's analysts use North American box office numbers to predict revenues in other markets for the same film (Troy Research n.d.) — a relationship that has been well-established and explored in detail by researchers as well (Hennig-Thurau, Walsh & Bode 2004, Craig, Greene & Douglas 2005).

In recent years, some third party services have emerged that offer statistical revenue prediction to producers, such as Goldmedia (Goldmedia 2010), Cinelytics (Bastian 2017), Epagogix (Gladwell 2006), Vault (Stiff 2019), Greenlight Essentials (Calvario 2016), Largo Ai (Goodfellow 2020), Scriptbook (Buder 2017), and Slated (Slated 2016). Some of the companies claim to use advanced machine

⁶⁶ Similarly, Chintagunta & Lee (2012) work with confidential data from DreamWorks and examine how intentions develop in the weeks leading up to a film's release.

3 Scientific Approaches to Target Audience Definition and Revenue Prediction

learning methodologies for prediction, but none have provided scientifically validated evidence of their forecast reliability, and as of now they do not seem to play a significant role in the industry.

Another, less mathematical approach to forecasting box office is expert opinion. There is a lot of consultants ("script doctors") who offer producers their services on the basis of the screenplay. Correspondent to the scarce empirical knowledge on what makes a successful script (or film), expert opinion is mostly non-scientific, but relies on the gut feeling and experience of industry insiders (Rimscha 2010). Most of them do not raise quantitative claims, but simply advise producers to the best of their knowledge⁶⁷. Regular public forecasts based on expert opinion can be found online, for example on showbizdata.com and showbuzzdaily.com for the US, or on insidekino.de for the German market. The correlation between the predicted numbers from boxofficemojo.com and the actual revenues on the opening weekend is 0.945 (Pennock, Lawrence, Giles & Nielsen 2001).

A special case of expert-based prediction is represented by the Hollywood Stock Exchange (HSX). It is an online market, where fictitious "stocks" of films and stars can be traded⁶⁸. The user behavior is efficient enough to not only predict academy award winners correctly (Pennock et al. 2001), but its correlation with actual box office numbers is 0.94 (Pennock et al. 2001). Its reliability and transparency has made HSX an interesting tool of research and its forecast has been employed as a variable in several statistical models from the economic approach (Elberse & Eliashberg 2003, Elberse & Anand 2007, Fuchs 2010, Karniouchina 2011a, Hennig-Thurau, Fuchs & Houston 2013). Yet these reliable numbers are predicted immediately before the opening weekend, with lots of information available – a situation that is decidedly different from a producer trying to convince financiers at the greenlighting stage.

Overall, it may be stated that applications of modeling as suggested by the economic approach are sparse and usually confined to the distribution, not the production side of the motion picture industry.

67 For example, script consultant Roland Zag (2005) claims to have analyzed about 200 remarkably successful or unsuccessful films to determine underlying reasons in their dramatic composition.

68 In the US, there have also been ambitions to establish a real-world stock market for trading movie derivatives. In the context of 2009 financial crisis, these plans have been scrapped, as they seem incompatible with the 2010 Wall Street Reform and Consumer Protection Act.

3.4 Intermediate Discussion

Over the course of this chapter, we have looked at scientific insights that might help to define target audiences and predict revenues of feature films. Results from the so-called "psychological" approach to movie marketing research try to explain moviegoer motivations and decision processes, while the "economic" approach links film traits and market environment factors directly to a given movie's commercial success.

Researchers have identified a number of different motivational factors for movie consumption and proposed several models for the process of how these factors contribute to an eventual consumption decision. The different interplay of these motivational factors for any given individual informs their movie preferences, which — alongside circumstantial factors — determine concrete choices. We have identified audience segmentation as an abstraction from individual preferences to assist in the definition of target audiences and looked at hitherto proposed segmentation approaches. Prevalent socio-demographic clustering techniques only capture movie preferences by broad proxies such as age and gender. Typologies that group consumers by their actual media consumption preferences are not cinema-specific (as of now) and thus insufficiently fine-grained to differentiate between the respective target audiences of different movies. Yet we have identified such a preference-based audience segmentation technique as a promising tool (or intervention, in terms of the CIMO logic, cf. [section 1.2](#)).

Results regarding revenue prediction lack consistency. There are very few cumulative findings, nothing seems certain (Duvvuri 2007, Simonton 2011) and particularly the impact of single factors has not been quantified (Clement 2004) — leading to contradictory managerial implications. Differing conceptualizations and seemingly arbitrary inclusion or exclusion of variables across different studies further exacerbate the difficulty to reproduce and compare results. Many studies fail to publish forecasting quality indices (Fuchs 2010). De Vany & Walls (1999) even assume that given the extremely skewed distribution of box office success⁶⁹, "one can forecast the mean of box office revenue since it exists and is finite, but the confidence interval of the forecast is without bounds", effectively rendering all forecasts worthless.

⁶⁹ In their 1996 paper "Bose-Einstein dynamics and adaptive contracting in the motion picture industry", De Vany and Walls model box office distribution among films by employment of the chaotic Bose-Einstein distribution (De Vany & Walls 1996, 286).

3 *Scientific Approaches to Target Audience Definition and Revenue Prediction*

Yet we have reason to believe that forecasting revenues more reliably is possible: If we assume that the allocation of movie budgets is, among other things, also an indicator of the producers' expectations about how much revenues can be generated by a movie, the predictive power of the budget variable in most econometric models (see [subsection 3.3.2](#)) suggests that the industry as a whole does have a good intuition about what revenues may be expected. This is further corroborated by the predictive power of the virtual film stock prices on the Hollywood Stock Exchange. Maybe, regression models are either an inferior forecasting technique or they lack sufficient input data. On a conceptual level, regression models assume that the same rules apply to all films in the sample – as we remarked earlier, this might just not be the case (Antipov & Pokryshevkaya 2011), and simply modeling interaction effects likely fails to capture the complex interplay of differing success factors in different niches. Lovallo, Clarke & Camerer (2012) suggest to use similarity-based forecasting (SBF) instead. Their approach blends the management methods of reference class forecasting (Kahneman & Tversky 1979) and case-based decision making (Gilboa & Schmeidler 1995) and more closely resembles the industry practice of using "comparables", yielding more accurate box office forecasts than a benchmark regression model. While their model relies on experts to assess the similarity of movies manually, it would seem promising to estimate the similarity systematically, based on target audience overlap. Historically, regression models built on sub-samples divided by genres have been more accurate (Hennig-Thurau & Wruck 2000).

Thus, an evidence-based approach to target audience definition and revenue prediction that is actually implementable by independent producers might reconcile the psychological and the economic approach: First, it is determined for each film who will be interested and why, using an empirically sound audience segmentation. Then, information on the film's target audience composition is used to identify similar films and use these as evidence-based comparables to predict revenues according to niche-specific patterns of success.

To prototype such an approach will be our goal in [chapter 4](#). In [section 4.1](#), we will introduce a technology from computer science which may provide the basis to learn movie preferences of individual users in order to build such a model.

4 Evidence-Based Target Audience Definitions and Revenue Prediction

4.1 Digital Representations of Movie Preferences

4.1.1 Overview

Recommender algorithms are ubiquitous in today's Internet. When we visit an online bookstore and encounter a section called "Customers Who Bought This Item Also Bought", that is a recommender system, powered by a recommender algorithm. When we open up an online video platform and the starting page is automatically compiled according to our past viewing preferences, that is a recommender system as well (Jannach, Zanker, Felfernig & Friedrich 2011).

WIRED editor Chris Anderson identified the capability of "connecting supply and demand" across many different niches as a key component of the "long tail" economy of endless shelf space he envisioned for the digital future (Anderson 2006). He cited algorithmic recommendation as a proven way to accomplish such connection between users and cultural items.

Thus originally conceived as "a specific strategy of managing abundant culture in the digital context" (Wright 2014, 146), algorithmic recommendation in the context of cultural goods like movies can also be thought of as a means of "digitalizing tastes" (Wright 2014, 144): An important trait of successful recommender systems is their ability to produce personalized recommendations as opposed to simply recommending the best-selling items to everybody. In order to do so, every such recommender system must gather information about a user and "maintain a *user model* or *user profile* that, for example, contains the user's preferences" (Jannach et al. 2011, 1). In their article on "Deconstructing

4 Evidence-Based Target Audience Definitions and Revenue Prediction

Recommender Systems", the founders of the GroupLens recommender research group ponder this thought in more detail: "Have you ever wondered what you look like to Amazon? Here is the cold, hard truth: You are a very long row of numbers in a very, very large table. This row describes everything you've looked at, everything you've clicked on, and everything you've purchased on the site; the rest of the table represents the millions of other Amazon shoppers. Your row changes every time you enter the site, and it changes again with every action you take while you're there. That information in turn affects what you see on each page you visit and what e-mail and special offers you receive from the company" (Konstan & Riedl 2012).

Information about user preferences can either be gathered implicitly, as implied in the Amazon example above, where clicks are interpreted as implicit statements of preference, or fed into the system by the user explicitly, for example by rating an item on a five-star scale or clicking on a thumbs-up icon (Jannach et al. 2011).

Regardless of whether the data were obtained implicitly or explicitly, subsequently they need to be interpreted to produce recommendations, which can be achieved by a variety of different algorithms. The two most prevalent types of systems are so-called content-based recommendation and collaborative filtering, which will be discussed in more detail throughout sections [4.1.2](#) and [4.1.3](#).

As we will see over the course of that discussion, many recommender algorithms are based on computing affinity scores for specific pairings of items and users, and then select recommendable items by means of highest predicted affinity scores. Such scores are reminiscent of the expected utility in the uses and gratifications approach as discussed in [subsection 3.2.3](#). If we assume that a) consumers make choices based on some expected utility, that b) in the case of movies that utility is determined by the viewer's film preferences, and that c) we can predict the expected utility from preferences as revealed by past behavior, we should be able not only to make recommendations for individual users, but also predict for a certain item (=movie) which consumers will be interested, i.e. define a target audience. Some technology companies have already pioneered this approach as we will address in [subsection 4.1.4](#), and that argument will also be the idea underlying our evidence-based target audience definition models as sketched in subsequent sections.

As Ricci, Rokach & Shapira (2015, vii) maintain, "development of recommender systems is a multi-disciplinary effort which involves experts from various

fields such as artificial intelligence, human computer interaction, data mining, statistics, decision support systems, marketing, and consumer behavior." We have not covered recommender algorithms as a part of the chapter on scientific approaches to target audience definition and revenue prediction, as they developed in a very different context, and although there have been important contributions from academia, the development of recommender systems was and is predominantly driven by technology companies. Notably, Netflix hosted a competition for recommender algorithms from 2006 to 2009 (Bennett & Lanning 2007), which produced many important insights and papers in the scientific community and helped to shape the field of (movie) recommender system research. The original challenge was to improve the then-current Netflix recommendation algorithm by 10%. After scientists from different countries, teams, and fields got together, they were able to achieve that goal three years after the competition was first initiated¹. Another six years later, Netflix estimates their personalization and recommendation systems to save the company more than \$1 billion per year (Gomez-Uribe & Hunt 2015), as internal experiments show users who do not receive recommendations to cancel their subscription at a higher rate.

4.1.2 Content-Based Recommendation

Content-based recommender systems select recommendable items based on item characteristics and the specific preferences of a user. For example, if a user liked fantasy movies in the past, a content-based recommender algorithm might recommend them another fantasy movie. To do so, two pieces of information have to be available to the recommender algorithm: "a description of the item characteristics and a user profile that somehow describes the (past) interests of a user" (Jannach et al. 2011, 51).

Movies come with several such observable characteristics, most prominently their genre. Genres can be coded as binary variables. In the most simple case, a film can thus be represented by a vector of m such binary dummy variables X_1, X_2, \dots, X_m which each indicate whether a certain movie attribute is present (1) or absent (0). Accordingly, every user u is represented by a vector of $m + 1$ dimensions, m of which specify the weights $\beta_{u,1}, \beta_{u,2}, \dots, \beta_{u,m}$ of

1 While the final solution performed better than the original Netflix recommender algorithm, it was never implemented, as Netflix engineers found that "the additional accuracy gains [...] did not seem to justify the engineering effort needed to bring them into a production environment" (Amatriain & Basilico 2015, 390)

4 Evidence-Based Target Audience Definitions and Revenue Prediction

the movie attributes for this particular user's probable rating. The remaining dimension represents the user's baseline rating β_0 . These weights can e.g. be obtained as coefficients in a multiple linear regression² (Marx 2011), wherein the dummy variables are taken as independent variables, user u 's rating $r_{u,i}$ of film i represents the dependent variable and $e_{u,i}$ stands for the estimation error of the regression model (Marx 2011, 38):

$$r_{u,i} = \beta_0 + \sum_{j=1}^m \beta_{u,j} X_{i,j} + e_{u,i}$$

A negative β corresponds to a dislike of the respective movie trait, a positive one points to an appeal of the trait to that particular user. The resulting vectors for users and films can be used for the prediction of ratings (Marx 2011), which are computed as the inner product of movie and user vector³:

$$r_{u,i} = \vec{u} \vec{x}_i.$$

Such analysis is of course not necessarily confined to genres, but can span all observable film traits. For example, the nature of a possible previous work (comic book, novel, film, television series, etc.), or the presence or absence of certain star provides other characteristics that can be coded likewise and exploited by content-based recommender algorithms: Users who liked films with Robert De Niro can be recommended new films starring De Niro, users who are into comic book adaptations can be recommended new such movies. Typically, such systems are mostly limited by data availability: While genre information are widely available, there is no point of reference that reliably provides data on whether a film for example has a "twist ending", although that could well be conceived of as a characteristic that could be encoded and exploited by a content-based recommender system. For the very purpose of building such a database, Netflix famously employs human viewers who go through their back catalog of movies and tag them according to some proprietary system (Grothaus 2018, Madrigal 2014).

Not requiring such extensive information on individual items is the main advantage of so-called collaborative filtering algorithms, which we will cover

2 We will concentrate on linear models for explanation purposes here. Other modeling techniques can be applied as well and may often be better suited to capture the influence of many different content traits on which too few data points exist for training a linear regression model.

3 One must include a "unity entry" at the position corresponding to β_0 for the equation to hold (Marx 2011).

in [subsection 4.1.3](#). Collaborative filtering has emerged as the de-facto standard in recommender systems (Konstan & Riedl 2012). Yet content-based recommender systems should not be disregarded altogether, as there are several ways to combine the results of content-based recommender algorithms with those obtained by collaborative filtering, and often-times hybrid models have been shown to produce the best results (Marx 2011, Marchand & Marx 2020).

4.1.3 Collaborative Filtering

The central idea of collaborative filtering is that "if users shared the same interests in the past" – in our case, if they liked the same movies – "they will also have similar tastes in the future" (Jannach et al. 2011, 2). Collaborative filtering algorithms have been used for recommender systems at least since 1992 (Konstan & Riedl 2012).

Various algorithms have been proposed and tested over the years (Jannach et al. 2011). We will describe a very basic one first and then dive into a more complex technique of which extensive use will be made throughout subsequent sections.

Collaborative filtering recommender algorithms typically require only the input of a matrix containing user-item ratings and, in the most basic cases, will output "(a) a (numerical) prediction indicating to what degree the current user will like or dislike a certain item and (b) a list of n recommended items" (Jannach et al. 2011, 13). The list of recommended items is usually created by selecting the highest predicted affinity scores among all eligible items (typically excluding items the user has already consumed before).

One simple method to arrive at such affinity score predictions is Pearson's Correlation Coefficient:

Assumed we have access to a database of movie ratings (like the ones of Moviepilot, MovieLens, or IMDb) where users rate films on a predefined scale, e.g. from 0 to 10. [Table 4.1](#) shows an example of five movies, all rated by five different users. In this case, Leia's rating of the new film shall be inferred from the four other viewers' rating. In order to do so, we have to figure out similarities in movie preferences between her and the other users. Pearson's correlation coefficient provides such a measure of similarity and is defined for

	Leia	Luke	Han	Anakin	Padme
ALIEN	3.0	7.5	5.0	2.5	6.0
LION KING	7.0	5.5	8.0	7.0	6.5
AVATAR	6.5	9.0	7.0	4.5	5.0
PRETTY WOMAN	8.0	2.5	8.5	4.0	7.5
NEW FILM	?	5.5	7.5	9.0	8.0

Table 4.1: Fictitious database of movie ratings on a typical scale; own illustration in the style of Marx (2011)

two users x and y and a set of items (=films) that has been rated by both of them $I_{xy} = \{i \in I | r_{x,i} \notin \emptyset \cap r_{y,i} \notin \emptyset\}$ ⁴ as follows:

$$sim(x, y) = \frac{\sum_{i \in I_{xy}} (r_{x,i} - \bar{r}_x)(r_{y,i} - \bar{r}_y)}{\sqrt{\sum_{i \in I_{xy}} (r_{x,i} - \bar{r}_x)^2 \sum_{i \in I_{xy}} (r_{y,i} - \bar{r}_y)^2}}$$

The coefficient can take on values between -1 and +1, where +1 means perfect positive correlation, -1 represents perfect negative correlation, and 0 denotes totally unrelated variables. In our case, Leia and Padme have a Pearson's correlation coefficient of

$$sim(Leia, Padme) = \frac{(3.0-6.125) \cdot (6.0-6.25) + (7.0-6.125) \cdot (6.5-6.25) + \dots + (8.0-6.125) \cdot (7.5-6.25)}{\sqrt{(3.0-6.125)^2 + (7.0-6.125)^2 + \dots} \sqrt{(6.0-6.25)^2 + (6.5-6.25)^2 + \dots}} = 0.42$$

The other coefficients are given in [Table 4.2](#). As one can easily see, Han's movie preferences are the most similar to Leia (0.98 is an almost perfect fit). Accordingly, it is assumed that Han's ratings bear the most information on how Leia will rate films she has not seen, yet. The opinions of all users whose similarity in preferences with Leia is below a certain threshold (e.g. +0.5) will not be used in the estimation of her rating. Alternatively, one can define a so-called neighborhood size k in advance and then take into account only Leia's k nearest neighbors among the other users (Jannach et al. 2011). The ratings of these others will be weighted according to their respective similarity (Jannach et al. 2011)⁵:

$$r_{u,i} = \bar{r}_u + l \cdot \sum_{u' \in \hat{U}} sim(u, u') \times (r_{u',i} - \bar{r}_{u'})$$

⁴ The rating of user x for film i is coded as $r_{x,i}$.

⁵ Other ways to aggregate ratings have been proposed, but the one described here is especially robust for large neighborhoods; $l = \frac{1}{\sum_{u \in \hat{U}} sim(u, u')}$ "serves as a normalization factor" (Marx 2011, 19).

4 Evidence-Based Target Audience Definitions and Revenue Prediction

	Luke	Han	Anakin	Padme
Leia	-0.58	0.98	0.61	0.42

Table 4.2: Similarity between users in our fictitious database; own illustration, in the style of Marx (2011)

In our example, this means: If we had decided to take into account the $k = 2$ nearest neighbors (Han and Anakin), the resulting rating would be:

$$\begin{aligned} r_{\text{Leia, New Film}} &= 6.125 + 0.63 \cdot [0.98 \cdot (7.5 - 7.125) + 0.61 \cdot (9 - 4.5)] \\ &= 8.1 \end{aligned}$$

This means: We expect Leia to like the new film quite a lot. In the same way, we can determine probable ratings for all other unknown films, and then recommend her the ones with the highest predicted ratings.

The main advantage of these collaborative algorithms is that they need absolutely no information about the items except for past interactions between items and users. This allows for "serendipitous recommendations" (Google 2020), where an item is being recommended only because a similar user liked it, with no obvious trait connecting it to other items previously appreciated by the same user. On the flipside, collaborative filtering works poorly on very small datasets – as similarities are inferred from past ratings, the systems tend to work the better, the more such interaction data are available.

Having illustrated the foundational ideas behind collaborative filtering, we will now turn to the specific approach we will make extensive use of over the course of [chapter 4](#): matrix factorization. During the Netflix Prize, an open competition for recommender algorithms (Bennett & Lanning 2007), recommendations based on matrix factorization proved superior to the nearest neighbors approach as described above (Koren, Bell & Volinsky 2009)⁶.

Matrix factorization techniques map the rating vectors of films and users onto a low-dimensional space and infer preferences from their proximity in that space (Koren et al. 2009).

To better understand this, we can take a look at a one-dimensional embedding first⁷: Suppose we represent each movie only by a value between -1 and

⁶ For an overview of the advantages and disadvantages of different recommender algorithms, cf. Marchand & Marx (2020).

⁷ This way to break down matrix factorization follows the excellent explanation in Google (2020).

4 Evidence-Based Target Audience Definitions and Revenue Prediction

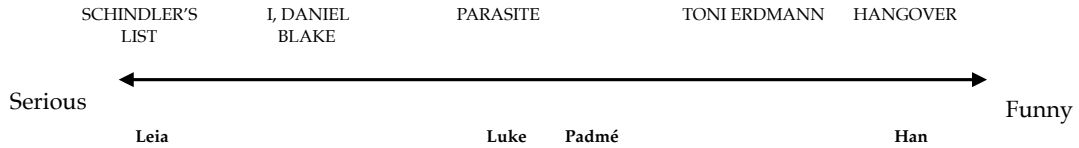


Figure 4.1: One-dimensional representation of movies and users; own illustration in the style of Google (2020)

+1, that denotes how funny it is. Additionally, we assign each user a value between -1 and 1 that represents that user's affinity to funny movies, see [Figure 4.1](#).

Table [4.2](#) shows if the users watched the movies (1 = yes, 0 = no). While the behavior of Leia and Anakin is well explained by our one-dimensional model, Luke's and Han's preferences remain elusive.

When we add a second dimension (also referred to as a *feature*) that describes whether a film leans more toward arthouse or blockbuster cinema (or whether a user prefers arthouse vs. mainstream movies), we can map the users and films as vectors onto a two-dimensional space as depicted in [Figure 4.3](#).

The dot product of a user vector and an item vector should be indicative of the user's preference for said item, being close to 1 for an item the user has watched, and close to 0 for an item they have not watched (Google 2020), as can be seen in [Figure 4.4](#).

These two dimensions seem to explain the consumption behavior of the users pretty well. While we made up the features for illustrative purposes here ourselves, the idea behind matrix factorization is to *learn* the relevant dimensions directly from the data. These dimensions, sometimes referred to as "latent factors", can correspond to obvious movie characteristics (as in the examples above), or they may be totally uninterpretable (Jannach et al. 2011).

To learn the latent factors, the original ratings matrix M is "factorized" into two matrices, a user embedding matrix U and an item embedding matrix I . The embeddings are learned such that the product UI^T approximates the original matrix M (see [Figure 4.5](#) for illustration).

Such collapsing of a high-dimensional matrix into a low-rank approximation can be achieved by matrix factorization techniques such as singular value

4 Evidence-Based Target Audience Definitions and Revenue Prediction

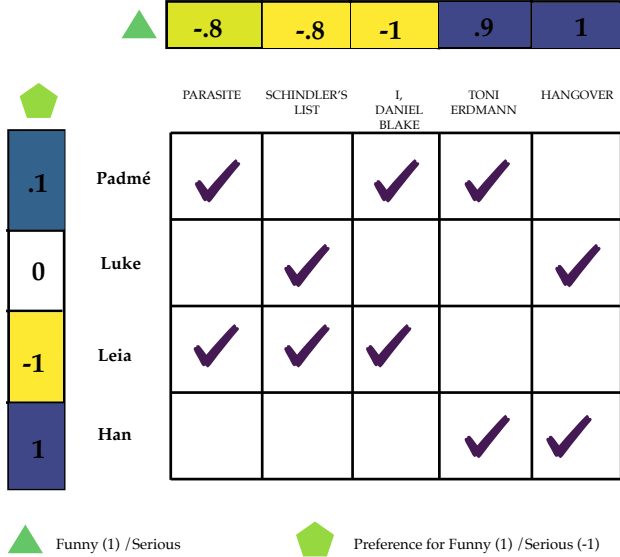


Figure 4.2: Ratings matrix of users and movies (1D embedding); own illustration in the style of Google (2020)

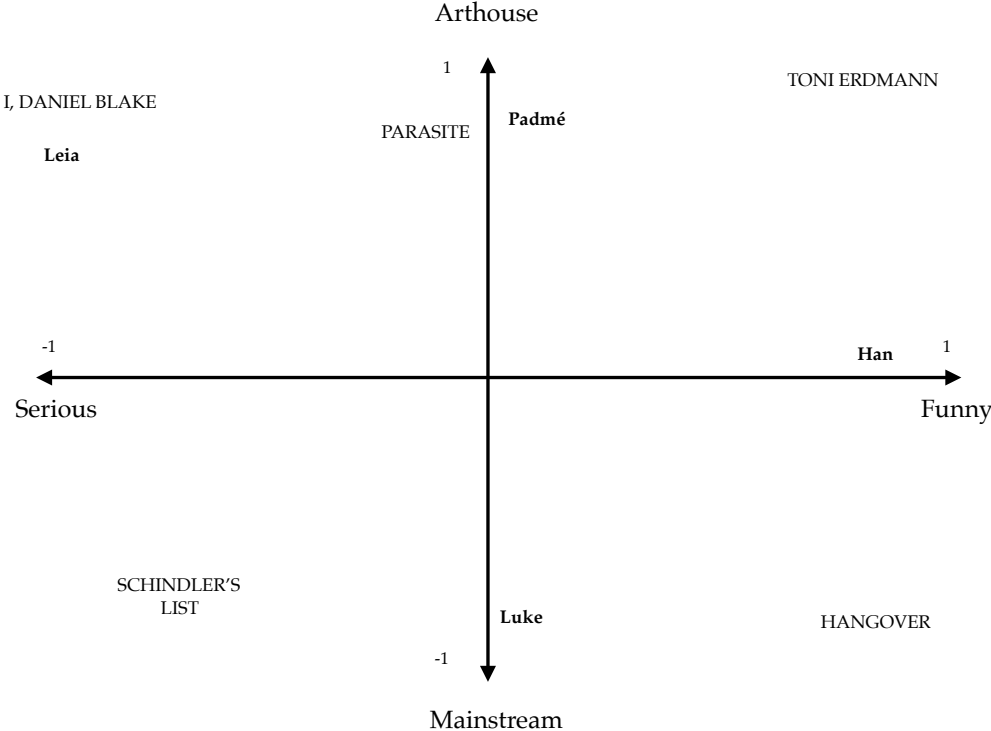


Figure 4.3: Two-dimensional representation of movies and users; own illustration in the style of Google (2020)

4 Evidence-Based Target Audience Definitions and Revenue Prediction

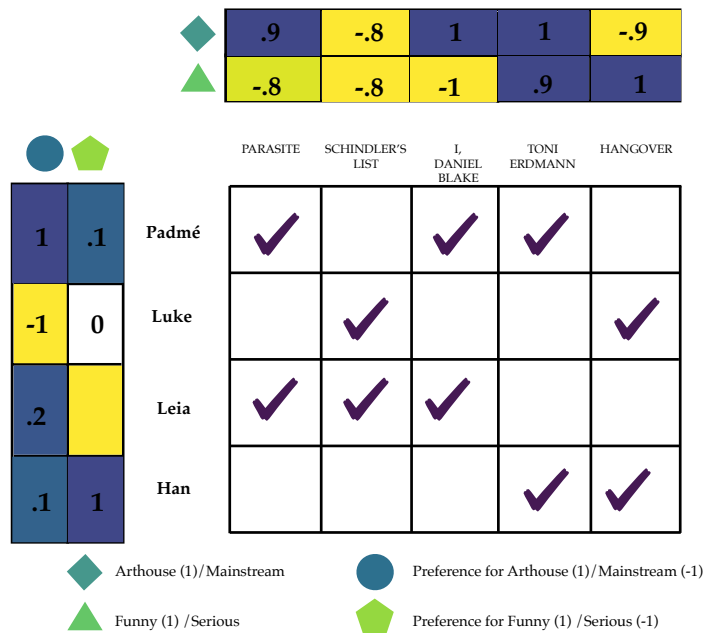


Figure 4.4: Ratings matrix of users and movies (2D embedding); own illustration in the style of Google (2020)

decomposition (Golub & Kahan 1965). Matrix factorization is conceptually equivalent to the wide-spread technique of principal component analysis, yet methodically modified to handle sparse datasets in which a majority of data is missing (Jolliffe & Cadima 2016). The mechanism has been exploited for information retrieval tasks as early as 1990 (Deerwester, Dumais, Furnas, Landauer & Harshman 1990) and various algorithms have been proposed over the years specifically for recommendation contexts (Jannach et al. 2011), using both explicit and implicit input data. One widely adopted algorithm is the so-called Alternating Least Squares (ALS) technique (Koren et al. 2009).

The number of latent factors can be chosen rather arbitrarily: The more factors, the closer the approximation of the original matrix will be, but the higher is also the likelihood of overfitting the original data in such a way that the learned latent factors will not generalize well to new items/users.

Matrix factorization is at the heart of many state-of-the-art recommender systems and will provide one of the main techniques used in subsequent sections.

4 Evidence-Based Target Audience Definitions and Revenue Prediction

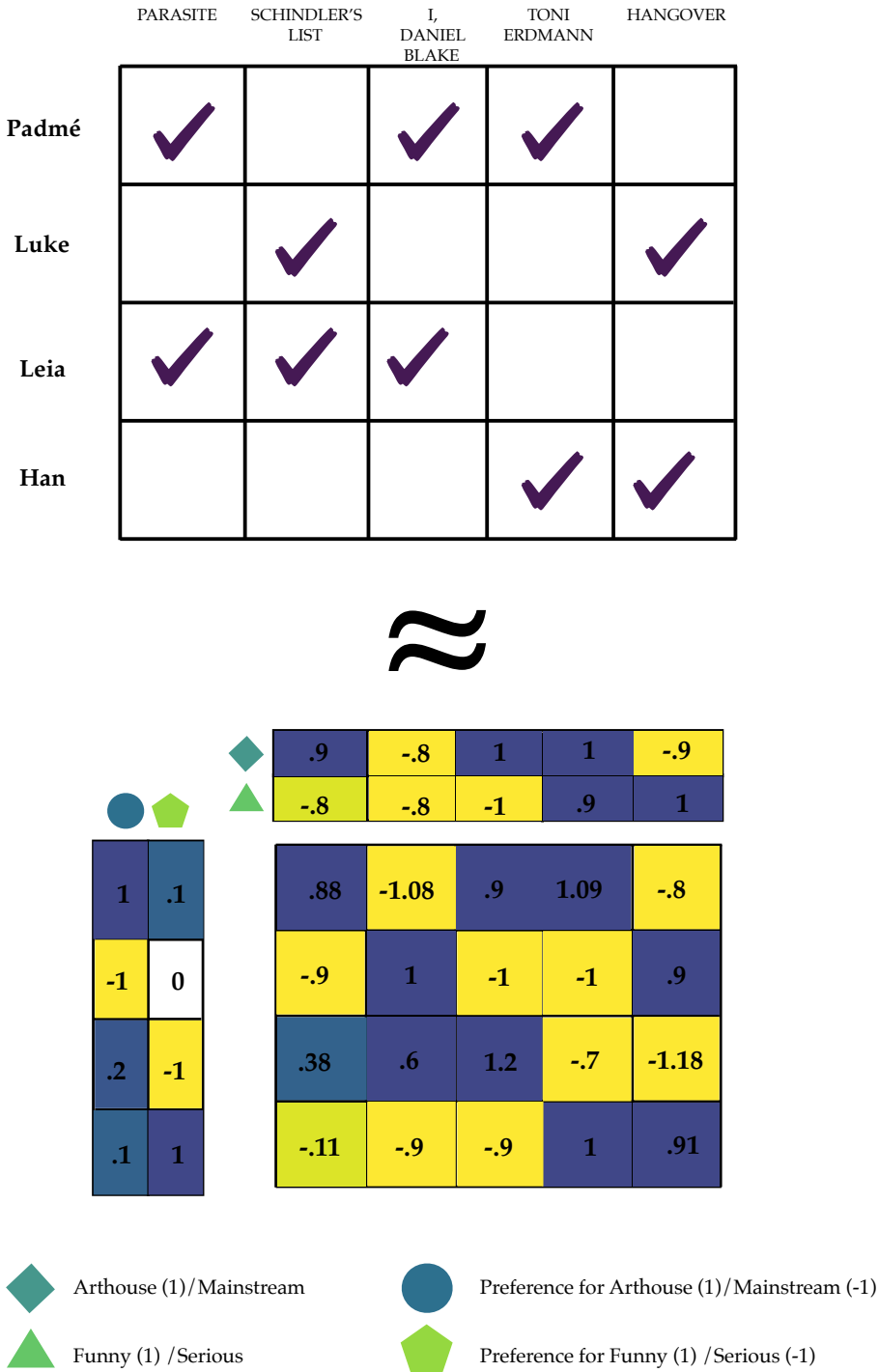


Figure 4.5: Schematic illustration of Matrix Factorization (2D emedding); own illustration in the style of Google (2020)

Yet Bell, Koren & Volinsky (2007)⁸ note that the key to to successful forecasting is actually "blending" of several methods: "Our experience is that most efforts should be concentrated in deriving substantially different approaches, rather than refining a single technique."⁹

In [section 4.2](#) and [section 4.3](#), we will use a simple content-based algorithm, in [section 4.4](#) and [section 4.5](#) we will employ matrix factorization. And in [section 4.6](#), we will use a hybrid approach and supplement matrix factorization with a content-based approach.

4.1.4 Recommender Algorithms Used for Targeting

While the main purpose of recommender algorithms has usually been to manage an abundance of product offerings and recommend the most suitable items to any particular user, it is also well conceivable to use them for the reversed process and select the most suitable users for any item, i.e. target audience definition.

Some such applications of recommender algorithms for this tasks have surfaced throughout the film industry in recent years (Behrens et al. 2020):

The movie marketing company JustWatch has successfully used recommender algorithms to help movie distributors target audiences for upcoming feature film releases more precisely by leveraging past user queries in their streaming search engine to build movie preference profiles of individual users, which can then be targeted for similar films in the future (Croyé 2017).

Cinema software provider Movio professes to be able to predict individual moviegoers' affinity toward new releases from past behavior and allows exhibitors to run targeted e-mail campaigns among their recurring customers (Palmer 2018): "[W]e're profiling every single moviegoer every single day, and working out; what is the right movie that's in-theater right now for that person to watch?"¹⁰

8 The eventual winners of the Netflix Prize, cf. [subsection 4.1.1](#).

9 In a common blending procedure, multiple algorithms are assigned weights, e.g. by linear regression: Each algorithm functions as an independent variable, being represented by a vector containing the respectively predicted ratings for all users in the test subset. The dependent variable is the vector of the actual ratings of the subset (Marx 2011). Tröscher, Jahrer & Bell (2009, 23) add that "optimizing the predictors individually is not optimal. Best blending results are achieved when the whole ensemble has the right tradeoff between diversity and accuracy".

10 Similarly, the company co-founded by the author, Cinuru Research, enables cinemas to send mobile film recommendations to the most suitable viewers among their patrons.

4 Evidence-Based Target Audience Definitions and Revenue Prediction

Even among the large Hollywood studios, there have been early applications of the technique: Campo, Hsieh, Nickens, Espinoza, Taliyan, Rieger, Ho & Sherick (2018) successfully pioneered their "Collaborative Metric Learning Recommendation System" at 20th Century Fox to predict purchase decisions on the individual level across a large moviegoer database and opine that "being able to predict audience composition in terms of past movies is important for movie studios to architect successful franchises, produce successful movies, identify optimal release windows, and execute on-target marketing campaigns" (Campo et al. 2018, 4)¹¹. Several applications by technology companies in the Chinese movie industry even go further, using a plethora of mobile ticketing user data to fuel personalized movie marketing campaigns (Fettweis 2018).

In the neighboring music industry, Spotify's Matthew Ogle, at the time in charge of the algorithmically curated "Discover Weekly" playlists, framed the potential of recommender systems from the artist's point of view: "We now have more technology than ever before to ensure that if you're the smallest, strangest musician in the world, doing something that only 20 people in the world will dig, we can now find those 20 people and connect the dots between the artist and listeners" (Pasick 2015).

All these developments can be viewed as instances of target audience definition by means of recommender algorithms and digital representations of (movie) preferences. The early traction of such applications is certainly promising. We will subsequently follow the same approach in our exploration of evidence-based target audience definition and revenue prediction. In [chapter 3](#) we identified the use of target audience segmentation as a useful intervention to support the target audience definition practices of independent producers. In this [section 4.1](#), we have identified digital representations of movie preferences as in recommender systems as a potential mechanism to arrive at meaningful segmentations that capture actual movie preferences. In the subsequent sections, we will now go on to validate this mechanism empirically.

11 Similarly, Marolda & Krigsman (2018) describe how Legendary Entertainment assigns affinity scores to millions of potential viewers on the individual level before a campaign starts to allocate marketing funds efficiently.

4.2 Targeting by Preferences Learned from Behavioral Data

4.2.1 Hypotheses

In [section 4.1](#) we have argued that past film choices contain valuable information about a consumer's movie preferences and could thus be used as a targeting criterion when selecting the target audience for an upcoming release. In this section, we will test empirically whether past film choices indeed provide a valid targeting criterion.

Our underlying assumption is that people's film preferences have a certain degree of stability over time, i.e. they will be likely to purchase cinema tickets for films in the future which are similar to films they watched theatrically in the past. Thus to target people who have watched similar films in the past should be more efficient than random targeting ([H1a](#)). Given the cold-start problem in recommender algorithm research¹² it seems reasonable to hypothesize that the more past movie choices are known about a specific consumer, the more reliably their affinity toward a new release may be predicted, thus the more efficient the targeting based upon these information ([H2a](#)-[H2b](#)). Based on anecdotal evidence from streaming services (Barrett 2016) we also maintain that targeting by similarity of past choices will prove superior to targeting by gender ([H3a](#)) and age ([H4a](#)).

This leads to the following hypotheses:

Hypothesis 1a *Targeting by similarity of past movie choices is more efficient than random targeting.*

Hypothesis 2a *Targeting by the mean similarity of two past movie choices is more efficient than targeting by one past movie choice.*

Hypothesis 2b *Targeting by the mean similarity of three past movie choices is more efficient than targeting by two past movie choices.*

Hypothesis 3a *Targeting by the mean similarity of past movie choices is more efficient than targeting by gender.*

Hypothesis 4a *Targeting by the mean similarity of past movie choices is more efficient than targeting by age.*

¹² This refers to the difficulty of predicting suitable items for users on which few previous data points are available (Jannach et al. 2011).

4 Evidence-Based Target Audience Definitions and Revenue Prediction

We will test this on a dataset from a survey conducted with actual moviegoers in German cinemas.

4.2.2 Survey Design

The survey was a collaboration between the Film University Babelsberg and Cinuru Research. Nine cinemas across Germany which at that time used the services of Cinuru Research participated and administered paper questionnaires to their customers between November 11 and December 6, 2017. Some of the theaters would hand the questionnaires and pencils to every single visitor together with the ticket at the point-of-sale, others presented them to their viewers on a table in the lobby.

The complete questionnaire can be found in [Appendix A](#). While a large part of the questions was concerned with consumers' moviegoing behavior in general and their cinema loyalty and app usage in particular, the following questions included are relevant to our hypotheses: What screening are you attending right now? What three films have you watched in the cinema most recently? Also, respondents were asked to provide their age and gender.

All questions were open-ended, i.e. respondents were able to fill in their own text.

4.2.3 Data

The initial number of questionnaires sent to each cinema was proportionate to their expected visitor numbers based on past annual figures. The response rate differed substantially among cinemas and also between different days over the course of a three-week period each.

All in all, 3105 questionnaires were collected. The handwritten answers were then manually transcribed by students and saved in a table format. Films were denoted by their TMDb ID¹³. Often, the spectators got the film title wrong or would not conform to the official title. For example, a spectator may have written "Abdul & Victoria" instead of VICTORIA AND ABDUL or "Blade Runner"

¹³ The Movie Database (<https://www.themoviedb.org>) is a large and open, community-built online database on films and TV shows that provides information among others on cast, crew, content, genres, and release dates for many movies.

4 Evidence-Based Target Audience Definitions and Revenue Prediction

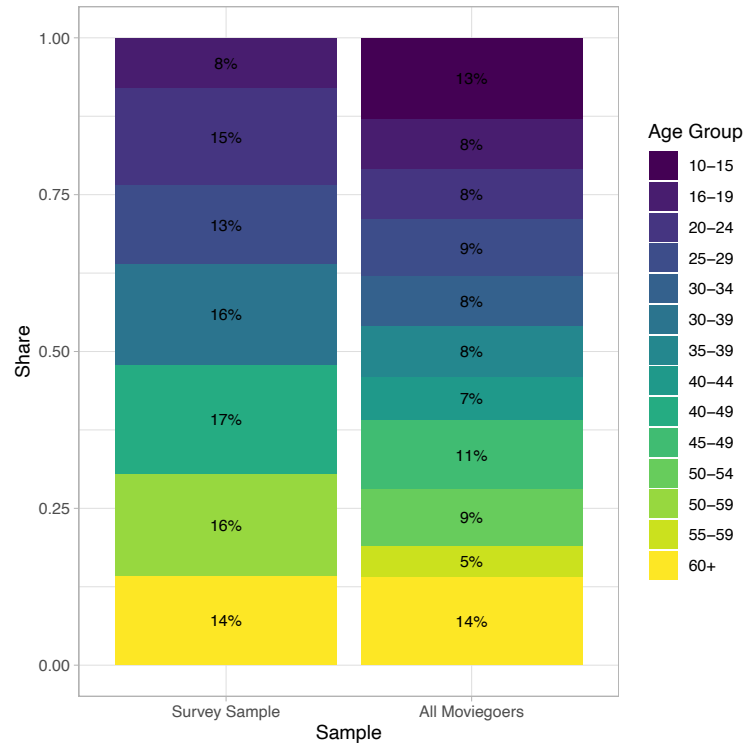


Figure 4.6: Age distribution of target users compared to age distribution among all moviegoers in Germany in 2017 as per FFA (2018)

instead of BLADE RUNNER 2049. As long as it was possible to reasonably infer the film in question from context, the transcribing students were encouraged to do so. If a film title was not identifiable at all, the field was left blank. Respondents' age was captured as an integer variable and gender as a binary dummy variable (1 for female, 0 for male).

2690 respondents reported in an intelligible way which film they watched at the day of the survey ("Current Film"), 2374 also named at least one past film, 2020 reported at least two past films, and 1424 filled in all three fields and reported three past movies each.

As an unproportionate share of the participating cinemas self-identified as arthouse cinemas, the respondents were not representative of the German moviegoing public in general: There was a strong female bias in the data and also fewer responses from young moviegoers than a representative sample would have captured (see figures [4.6](#) and [4.7](#)).

From the answers (current and recent films together), 686 different movies could be identified. For these films, genre information were retrieved from TMDb via a programming interface using the TMDb package in R (Capozio 2020, R Core Team 2020).

4 Evidence-Based Target Audience Definitions and Revenue Prediction

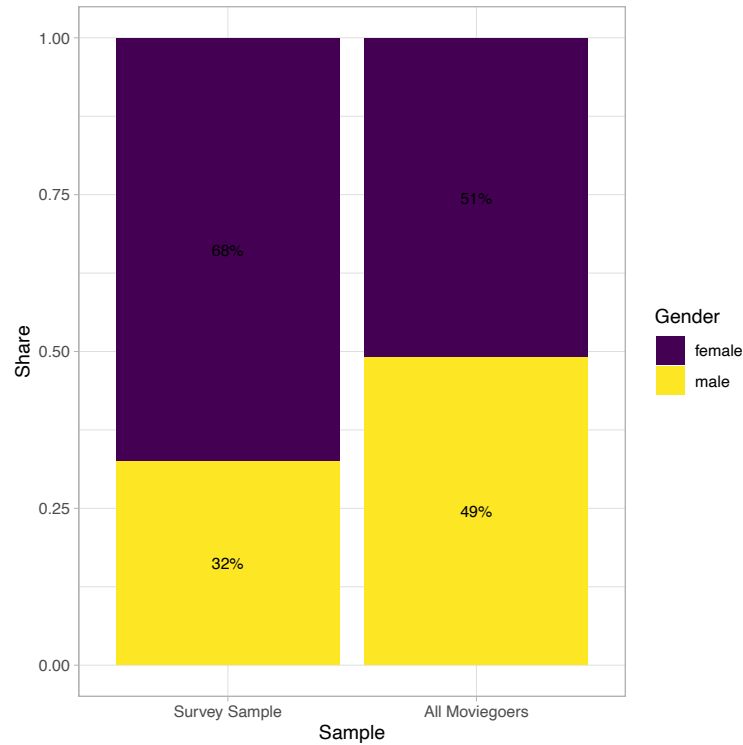


Figure 4.7: Gender distribution of target users compared to age distribution among all moviegoers in Germany in 2017 as per FFA (2018)

TMDb provides 19 different genre variables for each movie. These are dummy variables which can either be 1 (if a film has been assigned that genre) or 0 (if the film has not been assigned that genre) by the community of TMDb users. The TMDb genres are: Action, Adventure, Animation, Comedy, Crime, Documentary, Drama, Family, Fantasy, History, Horror, Musik, Mystery, Romance, Science Fiction, TV Film, Thriller, War, and Western.

During the survey period, the respondents watched 91 different movies in theaters ("Current Film"). However, as figure 4.8 shows, the attendance figures are heavily skewed: While one film (MURDER ON THE ORIENT EXPRESS) was seen by more than 500 respondents, most films had less than 10 visitors who filled in the survey.

Because we assume random effects to obscure all meaningful audience composition information for very small samples, we decide to focus on films with at least 20 visitors among the respondents who filled in all three past films. This leads to the sample of 17 movies listed in Table 4.3 for which all targeting methods could be compared¹⁴.

¹⁴ Throughout this section, the films will be referred to by the official German distribution title.

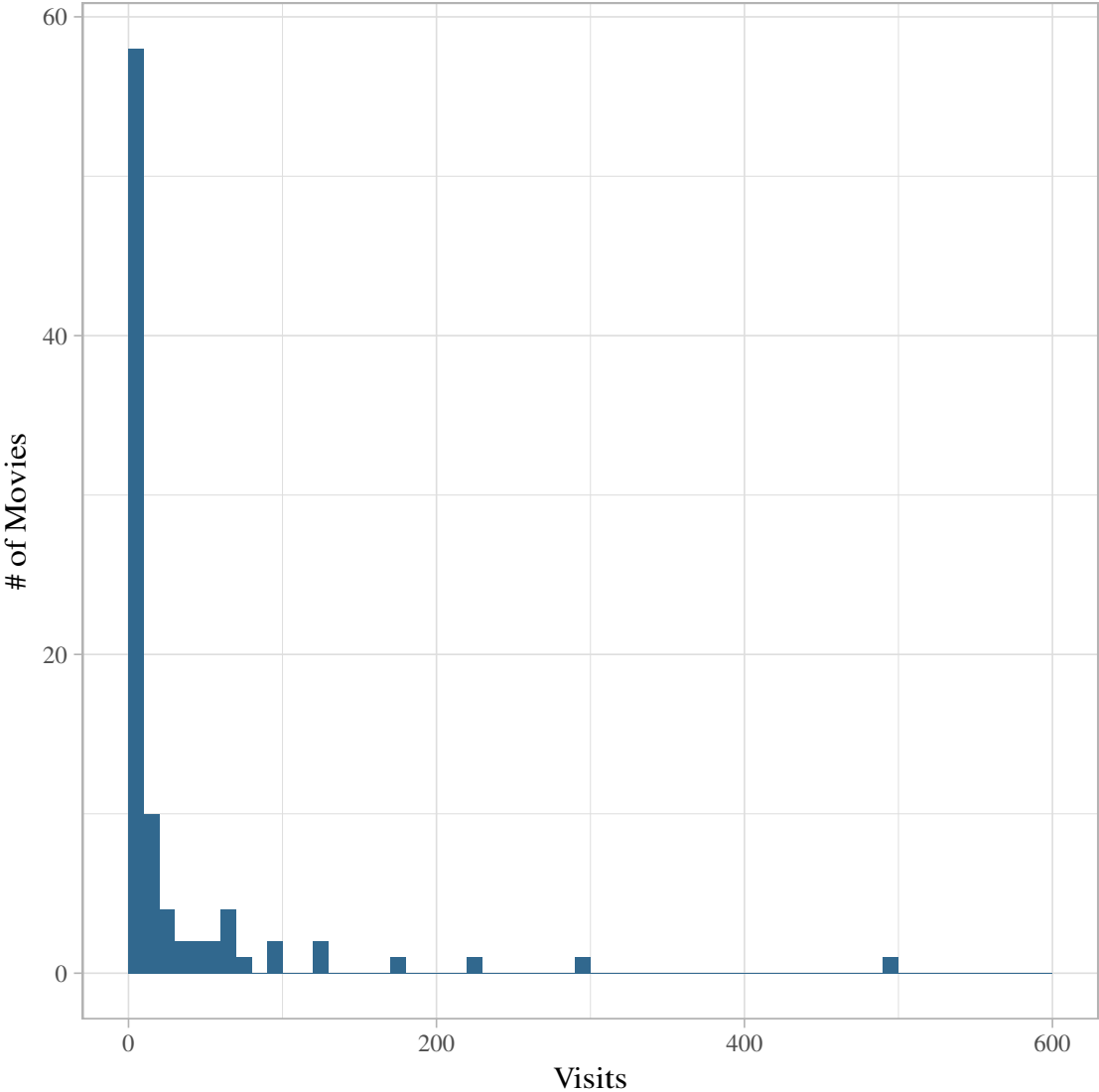


Figure 4.8: Histogram of visitor numbers for films among responses

Movie_Title	Viewers
MORD IM ORIENT-EXPRESS	305
SIMPEL	125
AUS DEM NICHTS	114
THE BIG SICK	93
FACK JU GÖHTE 3	90
BAD MOMS 2	62
FIKKEFUCHS	58
JUSTICE LEAGUE	46
SUBURBICON - WILLKOMMEN IN DER NACHBARSCHAFT	46
MAUDIE	42
THOR: TAG DER ENTSCHEIDUNG	37
DIE UNSICHTBAREN	30
WEIT. DIE GESCHICHTE VON EINEM WEG UM DIE WELT	29
GAUGUIN	28
THE SQUARE	27
BLADE RUNNER 2049	24
MANIFESTO	23

Table 4.3: Target movies in the dataset along with the number of viewers who provided all three past movie choices

4.2.4 Analysis

In general, targeting can be understood as selecting a subset of a population which will then be the "target" of a marketing message in such a way that this subset has a higher probability to react positively to the message. This process is often referred to as "response modeling" (Lo 2009). Focusing marketing efforts on a suitable subset of the population reduces waste and can help tailoring messages more specifically.

At the heart of any targeting method, there is a targeting model that decides for each potential viewer whether they are to be included in the target audience. In practice, such models can be very simple, often implicit, mental models ("If a potential viewer is female, she is part of the target audience"), as explored in [section 2.2](#). But for the sake of this analysis, we need to formalize such models in this section.

Targeting models can either be classification models or scoring models, i.e. they can either directly predict a label or compute a score for each individual case such that cases with higher scores should be targeted with higher priority. In our case, a respondent's score corresponds to that viewer's probability to consume a certain film. Therefore a targeting model effectively produces a ranking of all potential viewers from most likely to least likely. One may then define

4 Evidence-Based Target Audience Definitions and Revenue Prediction

an arbitrary threshold score (or maximum target audience size) to determine the target audience. The reasons to make the target audience smaller than the entire population is context-dependent: For example, a marketer may only have sufficient budget at hands to reach a certain share of the population, or – speaking from a producer’s perspective –, too broad a definition may be unhelpful to convince financiers.

So for the purpose of this analysis, we will understand targeting models as scoring models that can be used to define a target audience within a population of potential viewers. In addition to the scoring models, we will need an evaluation criterion by which to compare the quality of the target audiences defined by different targeting models, i.e. the efficiency of the targeting method. We will first discuss the different scoring approaches for gender-based targeting, age-based targeting, and genre-similarity based targeting, before we explain our evaluation approach.

When targeting by age or gender, we assume that a film has a stronger appeal among people that belong to a certain demographic sub-group. That means that the prevalence to watch the film among people of this group is higher. For example, 4.1 per cent of all male respondents in our dataset chose to watch THOR: TAG DER ENTSCHEIDUNG, but only 1.3 per cent of female respondents. A demographic targeting model exploits such differences to assign a score to each viewer depending on the subgroup they belong to. Because we do not have information about which demographic sub-group will be the most relevant for each film a priori, we will learn this from the data¹⁵. In order not to be misled by random fluctuations in the dataset, we divide the entire set of respondents randomly into a training set S_{train} ($|S_{train}| = 1283$), on which we learn the patterns, and an equally sized test set S_{test} ($|S_{test}| = 1272$), on which we will evaluate the effectiveness of the targeting model. We employ stratified sampling, i.e. the distribution of selected movies is identical between the two sets. We may compute an affinity score $s(m_0, r)$ for any given target movie m_0 and any respondent r who belongs to a demographically defined subset of all respondents D_r as the prevalence with which that film has been watched among respondents that belong both to the training sample S_{train} and the demographic sub-group D_r . If V_{m_0} denotes the set of all respondents that have viewed m_0 ,

¹⁵ Some sources on demographic audience composition for individual movies do exist, though. In Germany, the Federal Film Funding Board publishes an annual study breaking down the audiences of the top-grossing 75 films within each calendar year by age and gender. Yet not all of our movies are included in that study for 2017 (as they did not make the Top 75), thus we cannot rely on the FFA data to estimate movie-specific age and gender biases for this analysis.

we define

$$s(m_0, r) = \frac{|V_{m_0} \cap D_r \cap S_{train}|}{|D_r \cap S_{train}|}.$$

A gender-based targeting model for a specific target movie thus ranks all viewers in the test set by the prevalence of watching that target movie among viewers of the same gender in the training sample. To stick with our example from above, for THOR: TAG DER ENTSCHEIDUNG, all male respondents will be assigned the score 0.041 and thus be ranked higher than all female respondents who are assigned the score 0.013.

For demographic targeting, we use the subgroups from the German Federal Film Funding Board, i.e. binary genders (male/female) for gender-based targeting, and seven age groups (16-19 years, 20-24 years, 25-29 years, 30-39 years, 40-49 years, 50-59 years, and 60+ years) for age-based targeting. For age-and-gender-based targeting, respondents are grouped both by their gender and by their age group, which results in more and smaller subgroups.

For genre-similarity targeting, our main idea is to use past movie choices as an indicator of a viewer's movie preferences. We define the affinity score $s_{genre}(m, r, k)$ for any respondent r , any target movie m , and a number k of past movie choices as the mean of the genre similarity scores for all past movie choices reported by respondent r :

$$s_{genre}(m, r, k) = \frac{\sum_{i=1}^k sim(m, m_i)}{k},$$

where $sim(m_0, m_i)$ denotes the similarity score for the i^{th} past movie choice m_i and target movie m . Several movie similarity measures have been developed in the literature based on expert judgement, collaborative filtering, and content traits (Leng, Paulino, Haider, Lu, Zhou, Mengshoel, Brodin, Forgeat & Jude 2018). For the purpose of this analysis, we will employ a very basic content-based similarity score to measure similarity between two movies: On TMDb, usually several different genres are assigned to each film. We assume that two films are the more similar the more their assigned genres align. With g_{m_1} as the number of genres assigned to movie m_1 , g_{m_2} as the number of genres assigned to movie m_2 , and g_{m_1, m_2} as the number of genres assigned to both movie m_1 and movie m_2 , we define the genre similarity score $sim(m_1, m_2)$ for any given pair of two movies m_1 and m_2 as:

$$sim(m_1, m_2) = \frac{g_{m_1, m_2}}{g_{m_1} + g_{m_2}}.$$

4 Evidence-Based Target Audience Definitions and Revenue Prediction

Now that we have defined our targeting models, the procedure to define a target audience for any given target movie m containing a share p of all respondents based on genre similarity scores is depicted as pseudo-code in [algorithm 1](#), the targeting methods based on age and gender can be seen in [algorithm 2](#), [algorithm 3](#), and [algorithm 4](#), respectively¹⁶.

Data: Target movie m , Target percentage p , Number of past movie choices k

Result: Target audience A for m at target percentage p

define *targetable respondents* as all respondents who have not watched m in the past and at least reported k past movies;

for each targetable respondent r **do**

 randomly sample k of r 's past movies;

 compute genre similarity score for each of the k movies and m ;

 compute mean genre similarity score of the k movies, save as affinity score $s(r, m, k)$;

end

rank targetable respondents by affinity score $s(r, m, k)$;

define top $p * 100$ percentiles of ranked targetable respondents as target audience $A(m, p, k)$;

Algorithm 1: Target audience definition method for genre similarity-based targeting using k past movies per respondent

Data: Target movie m , Target percentage p

Result: Target audience A for m at target percentage p

define as targetable respondents all respondents who have not watched m in the past;

compute gender affinity score $s(m, r)$ for each targetable respondent r ;

rank targetable respondents by affinity score $s(m, r)$;

define top $p * 100$ percentiles of ranked targetable respondents as target audience $A(m, p, k)$ (if there are ties, select randomly);

Algorithm 2: Target audience definition method for gender-based targeting

Data: Target movie m , Target percentage p

Result: Target audience A for m at target percentage p

define as targetable respondents all respondents who have not watched m in the past;

compute age group affinity score $s(m, r)$ for each targetable respondent r ;

rank targetable respondents by affinity score $s(m, r)$;

define top $p * 100$ percentiles of ranked targetable respondents as target audience $A(m, p, k)$ (if there are ties, select randomly);

Algorithm 3: Target audience definition method for age-based targeting

There are several ways to determine the effectiveness and efficiency of such

¹⁶ Our actual implementation in R does not use for-loops, but the *apply*-function for the sake of computational efficiency, yet the general procedure is the same and this version can be easier understood by human readers because the code mimics the logical temporal order of operations more closely.

4 Evidence-Based Target Audience Definitions and Revenue Prediction

Data: Target movie m , Target percentage p

Result: Target audience A for m at target percentage p

define as targetable respondents all respondents who have not watched m in the past;

compute age and gender group affinity score $s(m, r)$ for each targetable respondent r ;

rank targetable respondents by affinity score $s(m, r)$;

define top $p * 100$ percentiles of ranked targetable respondents as target audience $A(m, p, k)$ (if there are ties, select randomly);

Algorithm 4: Target audience definition method for age-and-gender-based targeting

targeting methods. We can either assess the quality of the targeting model or of the resulting target audiences directly.

To start with the targeting model, we can perform an exploratory logistic regression and test if the scores produced by the different targeting models do indeed predict consumption among the test sample. To do so, we first identify all possible pairings of our 17 target films and the respondents in the test set, excluding for each film those respondents who have already mentioned the respective film as one of their recently watched films (because they are unlikely to watch it again). Then we compute the affinity scores according to gender-based targeting, age-based targeting, and genre-based targeting for each pairing. Respondents with missing values are excluded. We then perform a logistic regression with a binary response variable (1 if the viewer actually watched the respective film, 0 otherwise) and one independent variable (gender score, age group score, genre similarity score, respectively). We also compute two blended models: One that includes both age group and gender score, and one that includes all three variables. As can be seen from the regression results in [Table 4.4](#), all three scores are significant predictors of movie consumption. That is a very good indicator that the targeting models are indeed useful in finding relevant viewers.

A dominance analysis (Budescu 1993, Azen & Traxel 2009, Soares 2020) using McFadden's Pseudo- R^2 to determine the scores' relative importance in the blended model shows age-group prevalence to completely dominate gender prevalence and both demographic targeting scores to generally dominate the genre-based targeting score, i.e. their contribution to the results of the regression model is stronger. Yet we are not so much interested in the general ability to explain variance in the consumption behavior per se, but in the targeting models' ability to define suitable target audiences, which we will evaluate next.

	<i>Dependent variable:</i>				
	watched				
	(1)	(2)	(3)	(4)	(5)
gender_prevalence	9.993*** (0.493)			2.384* (1.202)	2.834* (1.227)
age_group_prevalence		9.488*** (0.446)		7.524*** (1.088)	7.314*** (1.110)
mean_genre_overlap			1.798*** (0.175)		1.881*** (0.191)
(Intercept)	-3.558*** (0.066)	-3.561*** (0.066)	-3.336*** (0.073)	-3.580*** (0.066)	-4.160*** (0.098)
Observations	9,739	9,739	9,722	9,739	9,722
$R^2_{McFadden}$	0.081	0.091	0.026	0.092	0.116

Note:

*p<0.05; **p<0.01; ***p<0.001

Table 4.4: Logistic regression results for movie consumption predicted by the scores of different targeting models

4 Evidence-Based Target Audience Definitions and Revenue Prediction

A widely adopted measure to gauge targeting methods' efficiency is called 'lift' (Piatetsky-Shapiro & Steingold 2000)¹⁷: For any targeting method M , let $TargetShare(M, p)$ be the share of relevant viewers captured by the first $p\%$ of the list as sorted by decreasing score of model M . Then we define

$$Lift(M, p) = \frac{TargetShare(M, p)}{p}.$$

For any target audience, a lift value can be computed using this formula. As can be seen from the genre-based targeting algorithm in [algorithm 1](#), for $k < 3$ there is a random element to the procedure, because a different subsample of past movie choices may be selected. As this can lead to slightly different lift values, we will repeat the target audience definition procedure 1,000 times over and take the mean lift value as our targeting efficiency indicator. There is also a random element to age-based and gender-based targeting, as there may be ties in the scored ranking produced by the model. So we will also repeat demographic targeting 1,000 times over again for each movie (randomly selecting some of the tied respondents each time) and take the mean lift value as our targeting efficiency indicator.

Lift as a performance indicator is specifically designed to compare a model's performance to the random model (which is equivalent to no model at all, i.e. random selection of targets). For example, if there are 37 viewers of THOR: TAG DER ENTSCHEIDUNG in the entire dataset and a given model M ranks all potential viewers such that among the highest-ranked 10 per cent, there are 7 relevant viewers, whereas a random model would be expected to identify 10 per cent of the relevant targets (= 3.7 viewers) among the highest-ranked 10 per cent of potential targets, the lift would be $7/3.7 = 1.89$. The lift of the random model is always 1 by definition (Michel et al. 2020). For illustrative purposes, [Figure 4.9](#) shows the lift values of the age-based targeting method (as described above) for THOR: TAG DER ENTSCHEIDUNG compared to a random model (dotted line) and a perfect model, i.e. a model which ranks all relevant targets higher than all non-relevant targets, thus capturing the entire relevant subset of the population among the first five percentiles.

Such lift charts can be used to visually compare the performance of different models. In [Figure 4.10](#), we see the lift curves of age-based and gender-based targeting (as described in detail below) for THOR: TAG DER ENTSCHEIDUNG. Again, the dotted line indicates a lift value of 1, i.e. random targeting. We

¹⁷ Sometimes, it is also referred to as 'cumulative lift', cf. Michel, Schnakenburg & Martens (2020)

4 Evidence-Based Target Audience Definitions and Revenue Prediction

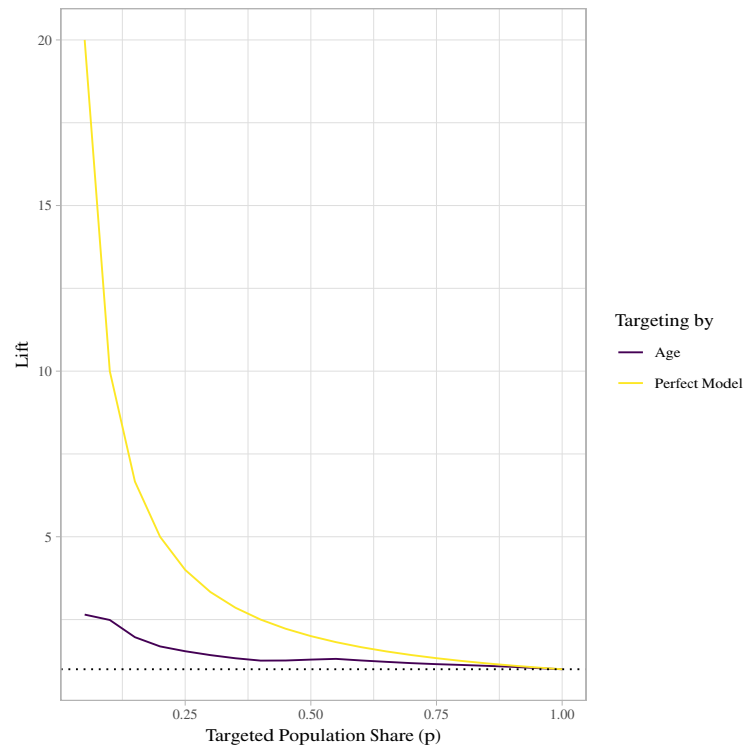


Figure 4.9: Lift chart of age-based targeting vs. random and perfect model for THOR: TAG DER ENTSCHEIDUNG

can now see that, for different targeted shares of the population, different models yield optimal results: For a target audience comprising 10 per cent of all viewers, age-based targeting captures more relevant viewers, whereas for a target audience containing 25 per cent of the population, gender-based targeting is superior.

The lift curves of all targeting methods for THOR: TAG DER ENTSCHEIDUNG can be seen in [Figure 4.11](#): In this case, all genre-based targeting (based on either 1, 2 or 3 past movie choices) is superior to all demographic targeting, regardless of the targeted audience share.

Note that for a population share of 100%, all models are equal, as the resulting selected target audience is always equivalent to the entire population. Typically, marketers use the lift in the top 5%, 10%, or 20% to select a model, dependent on the context (Piatetsky-Shapiro & Steingold 2000). For our purposes, we will look at the lift in the highest-ranked 10% throughout this work to compare different targeting methods, sometimes also referred to as the top-decile lift in marketing literature (Neslin, Gupta, Kamakura, Lu & Mason 2006). As even the highest grossing movies only reach a small fraction of the population (FFA 2020c), it is hardly relevant how well a model is able to differentiate

4 Evidence-Based Target Audience Definitions and Revenue Prediction

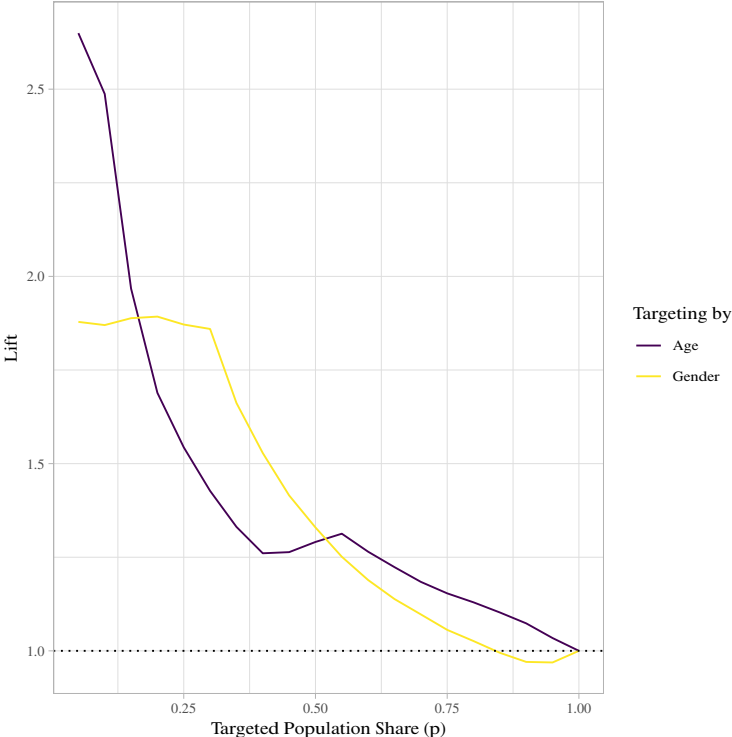


Figure 4.10: Lift chart of age-based targeting vs. gender-based targeting for THOR: TAG DER ENTSCHEIDUNG

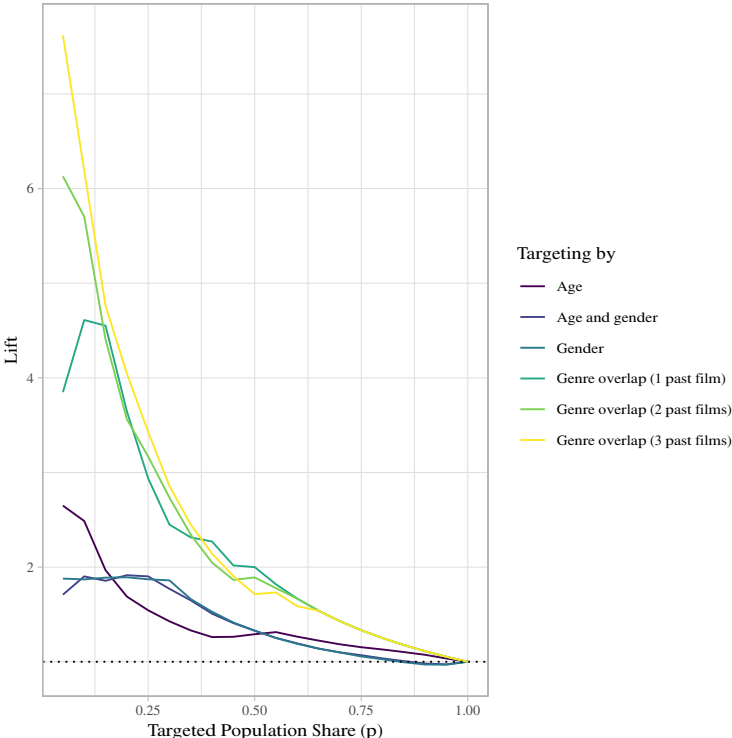


Figure 4.11: Lift chart of all targeting methods for THOR: TAG DER ENTSCHEIDUNG

4 Evidence-Based Target Audience Definitions and Revenue Prediction

between the affinities of the bottom 90% of potential viewers, as long as it is able to successfully capture relevant viewers within the first ten per cent. [Table 4.6](#) shows the lift values for all different targeting methods (targeting 10% of respondents in the test set each).

We can see that different targeting methods seem to produce the best results for different movies. The median lift values of the six targeting methods across all 17 movies can be seen in [Table 4.5](#).

Targeting Method	Median lift
gender-based targeting	1.12
age-based targeting	1.45
age and gender-based targeting	1.09
genre-based targeting (1 past film)	1.50
genre-based targeting (2 past films)	1.76
genre-based targeting (3 past films)	2.28

Table 4.5: Median lift values for different targeting methods across all 17 films

The median lift values are in line with our hypotheses: All targeting methods perform better than random targeting (their median lift value is higher than 1), genre-based targeting based on two past movie choices is better than genre-based targeting using one past movie choice and genre-based targeting based on three past movie choices is better than genre-based targeting based on two past movie choices. Also, genre-based targeting performs better than age-based, gender-based, or age-and-gender-based targeting.

Yet as this general trend does not hold true for every single movie, we can compare two targeting methods by running simple binomial signed-tests to see whether the probability to attain a superior targeting for each movie is higher than 0.5 when using the presumably superior targeting method. To start with [H1a](#), we see that the lift value for genre-based targeting based on three past movie choices is higher than 1 for 14 out of 17 movies. The probability to achieve such a result by random is < 0.01 , thus we can reject the null hypothesis and confirm [H1a](#). Targeting by similarity of past movie choices is indeed more efficient than random targeting. Targeting by genre-similarity of two past movie choices led to superior target audiences than targeting by genre-similarity of one past movie choice in 11 out of 17 cases. While the probability for such a result to occur randomly is only about 16%, this is not significant enough to reject the null hypothesis and confirm [H2a](#). The same holds true for [H2b](#), as targeting by genre-similarity of three past movie choices was better than targeting by genre-similarity of one past movie choice for 11 out of 17 movies as well. In

Movie Title	gender_lift	age_group_lift	age_and_gender_lift	genre_1_lift	genre_2_lift	genre_3_lift
THE SQUARE	0.94	1.93	0.94	0.86	1.51	1.88
AUS DEM NICHTS	1.41	0.78	1.25	1.50	1.76	2.28
BAD MOMS 2	0.41	1.45	1.06	3.62	2.08	2.33
BLADE RUNNER 2049	1.43	2.44	1.17	0.62	1.29	0.91
DIE UNSICHTBAREN	0.99	3.72	1.01	2.57	2.26	1.67
FACK JU GÖHTE 3	1.12	2.58	0.73	2.27	2.59	2.61
FIKKEFUCHS	0.88	0.87	1.04	1.05	1.10	0.65
GAUGUIN	0.97	2.74	0.76	2.07	3.03	3.75
JUSTICE LEAGUE	2.51	3.31	1.99	5.76	5.65	4.78
MORD IM ORIENT-EXPRESS	1.07	1.34	1.01	0.47	0.42	0.27
MANIFESTO	1.23	1.75	1.18	0.00	1.71	2.31
MAUDIE	1.37	0.62	1.09	2.40	3.07	3.60
SIMPEL	1.08	1.27	1.31	1.42	1.20	1.48
SUBURBICON	1.27	0.65	1.18	1.97	1.69	2.73
THE BIG SICK	1.13	0.96	1.16	1.18	1.74	1.92
THOR: TAG DER ENTSCHEIDUNG	1.87	2.50	1.90	4.61	5.70	6.19
WEIT	0.90	0.88	0.74	0.88	2.22	2.00

Table 4.6: Lift values for different targeting methods (targeting 10% of respondents in the test set)

4 Evidence-Based Target Audience Definitions and Revenue Prediction

general, the small sample size of only 17 target movies makes it very hard to confirm our hypotheses with statistical certainty.

When it comes to comparing genre-based targeting to demographic targeting, targeting by genre-similarity of three past movie choices yielded better results than gender-based targeting for 14 out of 17 films, which is significant at the $p < 0.01$ level. Thus we can reject the null hypothesis and confirm H3a. On a side note, while targeting by genre-similarity of two past movie choices is also significantly better than gender-based targeting (in 15 of 17 cases even), targeting by genre-similarity of one past movie choice is not, further supporting our (yet unproven) assumption that targeting efficiency increases with profile depth. Age-based targeting yielded quite good results overall and targeting by genre-similarity of three past movie choices resulted in higher lift values for only 10 out of 17 movies, a result that is only slightly better than what would be expected if the targeting methods were equally good. Thus we cannot confirm H4a. Targeting by age and gender combined, which we did not hypothesize about beforehand, seems to be inferior to targeting by age alone. This might be due to overfitting: The subgroups in the training sample as divided by age and gender become very small, thus the prevalence values are more subject to random effects and might generalize less well to the test sample.

To conclude our analysis, we have been able to confirm that movie preferences, as measured by past film choices, provide an efficient targeting method. Two past films someone saw in the theater tell us already more about their likelihood to watch another film in the future than their gender, and while we could not confirm this with sufficient certainty, we have reason to believe that targeting by such preferential information is also superior to age-based targeting.

We hypothesized that targeting efficiency would increase with profile depth, i.e. with the number of past movie choices available for each respondent, yet while our data point in that direction, we have not been able to confirm this hypothesis yet and will examine this now more closely in [section 4.3](#).

4.3 Profile Depth and Targeting Efficiency

4.3.1 Hypotheses

In [subsection 4.2.4](#) we have shown that we can indeed predict audiences for movies based on individual spectators' movie preferences, as revealed by their past consumption history. Yet as the maximum profile depth was limited to three past movies and we had only 17 cases to test our model on, we were not able to determine with any statistical significance whether targeting efficiency indeed increases with profile depth. In this section we will try to do exactly that and examine the following hypothesis:

Hypothesis 5a *The efficiency of targeting by similarity of past movie choices increases with profile depth, measured as the period of time over which the moviegoers' past choices are known.*

We will test this on a user dataset from a German cinema loyalty app.

4.3.2 Survey Design

The data are provided by German software and analytics company Cinuru Research¹⁸ and were collected using the cinema loyalty app Cinuru between March 1, 2018 and February 29, 2020.

The loyalty app is marketed by Cinuru Research to cinemas as a service. The cinemas promote the app to their clients as a tool for their customer relationship management. For end users, the app is free of charge and can be used to book tickets, look up showtimes, read about and rate movies, watch trailers, as well as collect and redeem bonus points in the cinemas' loyalty schemes. The app also offers a watchlist function and reminds users when a film that they put on that list is released in their local cinema. At the beginning of the observation period in March 2018, nine cinemas participated in the program, and at the end of the observation period, users could choose between 23 different cinemas in the app.

¹⁸ The company was spawned by the research transfer project "Greenlight Analytics" at Film University Babelsberg and co-founded by the author.

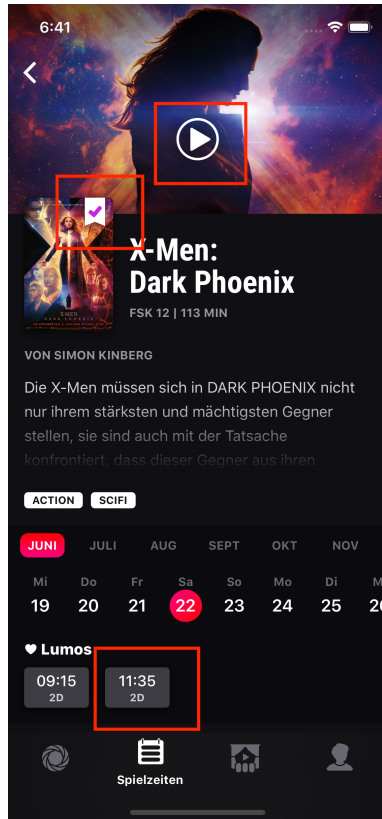


Figure 4.12: Cinuru: Screenshot of movie detail page

In the dataset, certain interactions between users and movies have been logged, namely watchlistings, bonus point collections, clicks on a showtime (presumably to buy a ticket), watched trailers, and positive ratings. [Figure 4.13](#), [Figure 4.14](#), [Figure 4.12](#), [Figure 4.15](#) show the respective functions of the app in more detail.

For each movie there is a movie detail page in the app, containing synopsis, poster, and cast and crew information (see [Figure 4.12](#)). If the user clicks on the play button at the top, the trailer starts playing and this is recorded as a trailer watching interaction. If the user clicks on the little plus/checkmark icon next to the poster, the movie is put on their watchlist (recorded as watchlisting interaction), and if they click on the showtime below to buy a ticket, this is recorded as a showtime click (i.e. ticket purchase) interaction. The red rectangles in [Figure 4.12](#) indicate where the respective functions can be triggered on the screen.

After a user has watched a trailer, they are asked whether they want to put that movie on their watchlist in a post-trailer dialog (see [Figure 4.13](#)). If yes, this is recorded as a watchlisting.

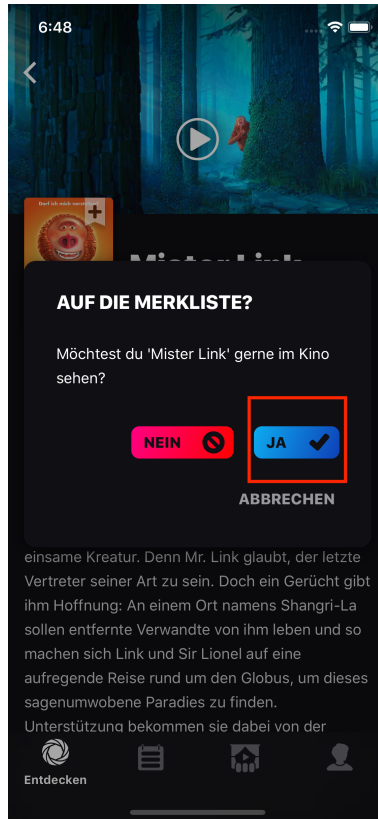


Figure 4.13: Cinuru: Screenshot of post-trailer dialog

If the user participates in the loyalty scheme of their local cinema, they have a digital loyalty card (see [Figure 4.14](#)), which they can show at the point of sale. A QR code will be scanned by the cinema staff, the user gets bonus points for their visit, and a bonus point collection interaction is being recorded in the database.

Finally, after a user has bought a ticket through the app or collected bonus points at the point of sale, they will be asked once the showtime ended how they liked the movie in question (so-called exit poll, see [Figure 4.15](#)). Any rating of four or five stars is counted as a positive rating interaction. At the same time, they will be prompted to watchlist movies that were trailed in the movie's pre-show. When they click on one of the plus/checkmark icons, this is again recorded as a watchlisting interaction. It is also possible to provide star ratings for movies outside exit polls (i.e. without purchasing a ticket through the app), in the bottom part of the movie's detail view, which will then also be recorded as a positive rating event for all ratings greater than or equal to four stars.

For each of the interactions as defined above, the user, the movie, the interaction type, and the date and time are recorded in the database.

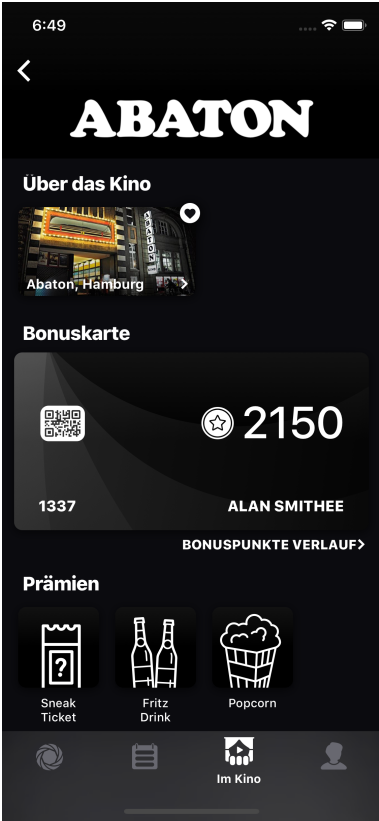


Figure 4.14: Cinuru: Screenshot of digital bonus card

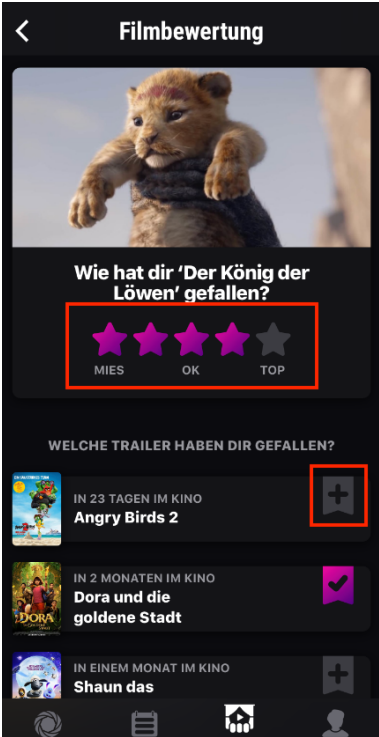


Figure 4.15: Cinuru: Screenshot of movie-rating dialog (exit poll)

4.3.3 Data

Overall, 75,224 interactions by 6,564 users were recorded. The most common interaction type was 'Showtime Link Clicked' (24,640), the least common 'Rated Positively'. The entire distribution can be seen in [Table 4.7](#).

Interaction Type	Number of interactions
Showtime Link Clicked	24640
Watchlisted	22618
Trailer Watched	11492
Bonus Points Collected	8742
Rated Positively	7732

Table 4.7: Distribution of interaction types among recorded interactions

Interactions were distributed across 4,960 different movies (a lot more than are released over a period of two years, because all repertoire movies that are screened in at least one of the participating cinemas can also be interacted with in the app).

Title	Number of interactions
SWING TANZEN VERBOTEN	1969
DAS PERFEKTE GEHEIMNIS	912
SNEAK PREVIEW	734
DIE EISKÖNIGIN 2	660
DER KÖNIG DER LÖWEN	625
JOKER	622
BOHEMIAN RHAPSODY	613
STAR WARS: DER AUFSTIEG SKYWALKERS	600
PHANTASTISCHE TIERWESEN: GRINDELWALDS VERBRECHEN	449
AVENGERS: ENDGAME	433
DER JUNGE MUSS AN DIE FRISCHE LUFT	430
PETS 2	388
JUMANJI: THE NEXT LEVEL	385
ONCE UPON A TIME IN HOLLYWOOD	383
MISSION: IMPOSSIBLE - FALLOUT	376
LLORONAS FLUCH	356
KNIVES OUT	347
GREEN BOOK - EINE BESONDERE FREUNDSCHAFT	346
PARASITE	318
SPIDER-MAN: FAR FROM HOME	310

Table 4.8: List of the movies that were interacted with most often

As expected, popular movies are also often interacted with in the cinema loyalty app. 15 of the top 20 movies are also either among the 20 most popular movies of 2018 or the 20 most popular movies of 2019 according to the German Federal Film Funding Board (FFA 2019a, FFA 2020a). The Sneak Preview is not a specific movie, but a surprise screening which many of the participating cinemas hold

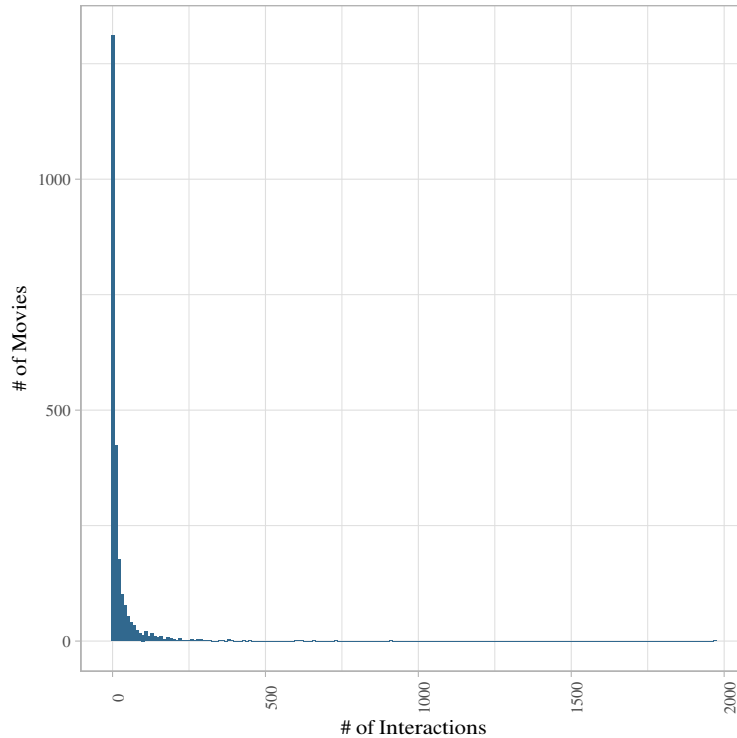


Figure 4.16: Distribution of interactions per movie

regularly. As this is a recurring event, the high number of interactions the Sneak Preview has garnered over the course of two years is unsurprising. KNIVES OUT was released in 2020 and thus has not made the annual top lists by the FFA, but was still a major hit. PARASITE was released in 2019, but received a lot of attention in 2020, when it was awarded with the "Best Picture" Academy Award. The two remaining outliers are LLORONAS FLUCH and SWING TANZEN VERBOTEN, the latter of which seems particularly odd, as there was only one single showtime for that movie in all participating cinemas during the observation period. A closer inspection of the recorded interactions reveals that a large part of the interactions are by a small number of users, who interacted with the movie over and over again, up to as many as 90 times. This might indicate a temporary malfunction of the app or the movie's online ticketing system which made several clicks on the purchase button necessary or some actual strange behavior by said users. One may argue that it would be warranted to exclude these data, but as they are limited to a small number of users and only one movie, we will keep them in the dataset and trust that the targeting method we are going to apply is robust enough to handle such oddities. At the other end of the spectrum, 1,552 movies have been interacted with less than 10 times, 595 movies only once. Figure 4.16 shows the distribution.

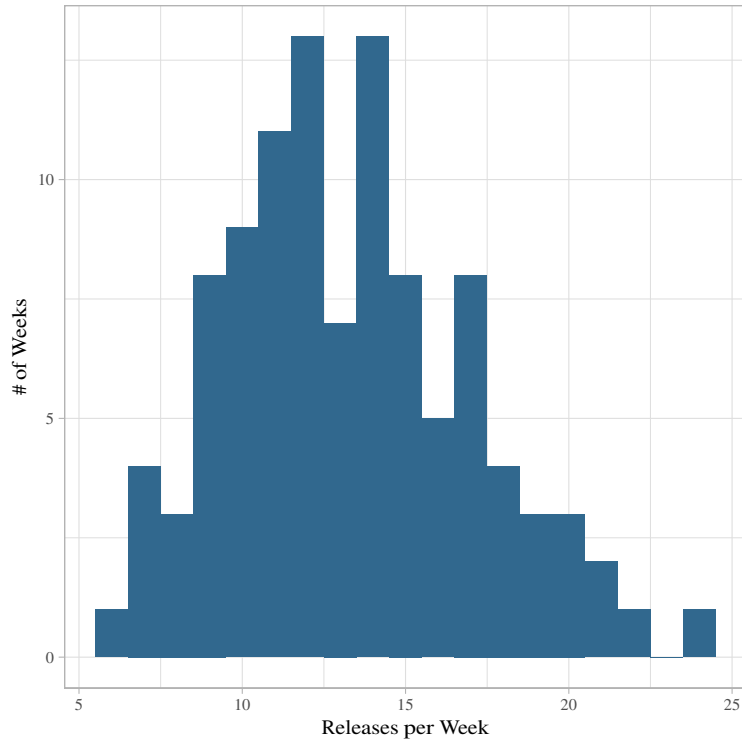


Figure 4.17: Distribution of releases per week during the observation period

Overall, 1383 different movies that had their nationwide release date during the observation period were featured in the app. On average, 13.3 movies were released per week (median: 13). [Figure 4.17](#) displays the distribution. The smallest number of movies (6) was released during the first week of the observation period, the most movies (24) during the last week. This is consistent with a constant increase in the number of participating cinemas during that time.

As we will again use genre overlap as a similarity measure in [subsection 4.3.4](#), it makes sense to take a brief look at the genre data as well. There are 29 different genres in the Cinuru database which films can be potentially assigned. Genre information are either taken from TMDb, provided by the movie’s distributor, provided by the participating cinema, provided by movie metadata provider Comscore, or added manually by Cinuru Research’s editorial team. [Table 4.9](#) shows how often each genre occurs among the 4,960 movies for which interactions were recorded¹⁹

Of the 4,960 movies, 1,904 were assigned at least one genre. 831 movies have been assigned exactly one genre, 91 movies have five or more genres assigned. The movie with most genres is POKÉMON: MEISTERDETEKTIV PIKACHU, which

¹⁹ English translation by the author

4 Evidence-Based Target Audience Definitions and Revenue Prediction

Genre	Occurrences
Drama	824
Documentary	487
Comedy	485
Adventure	219
Family	218
Thriller	216
Music	178
Romance	175
Action	171
Fantasy	151
Animation	131
Crime	114
Horror	112
Science fiction	106
History	102
Mystery	86
Biography	48
War	32
Special event	26
Literature	25
Dance	15
Musical	12
Western	10
Concert	6
Sports	5
TV movie	5
Ballet	3
Classical concert	1
Theater	1

Table 4.9: Genre occurrences among movies in observation period

is listed as a fantasy, mystery, science-fiction, action, crime, family, comedy, adventure, and animation movie (9 genres overall). [Figure 4.18](#) shows the distribution.

As users do not necessarily use a cinema app on a daily basis and in many cases also cease to use the app at all at some point, it makes sense to look at the number of different weeks during which they interacted with movies in the app during the observation period to get a sense of their activity level. [Figure 4.19](#) displays the distribution. 3,319 users were only ever active during one week, the most frequent user interacted with movies in 83 out of 104 possible weeks.

In the following analysis, we will look at viewing opportunities: What users

4 Evidence-Based Target Audience Definitions and Revenue Prediction

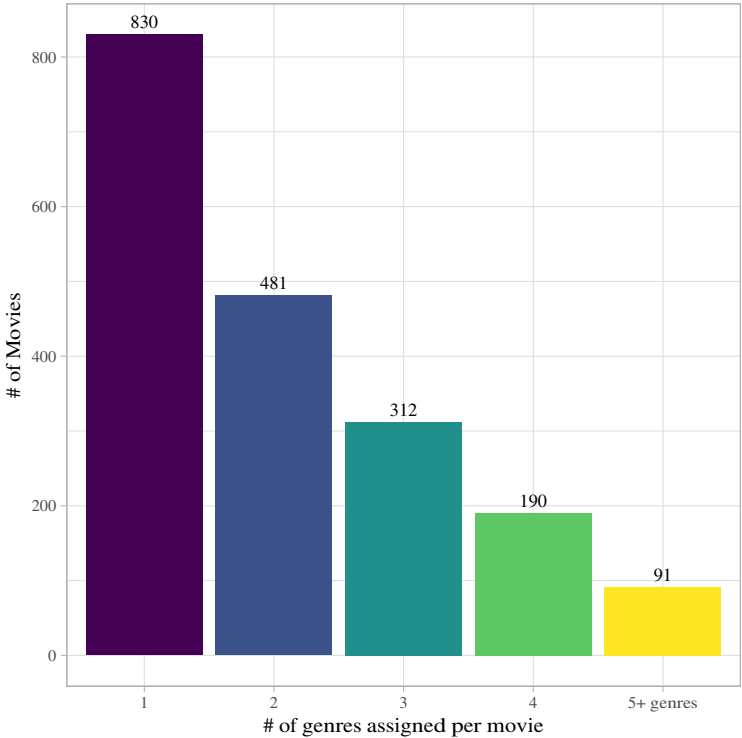


Figure 4.18: Distribution of number of genres among movies in dataset

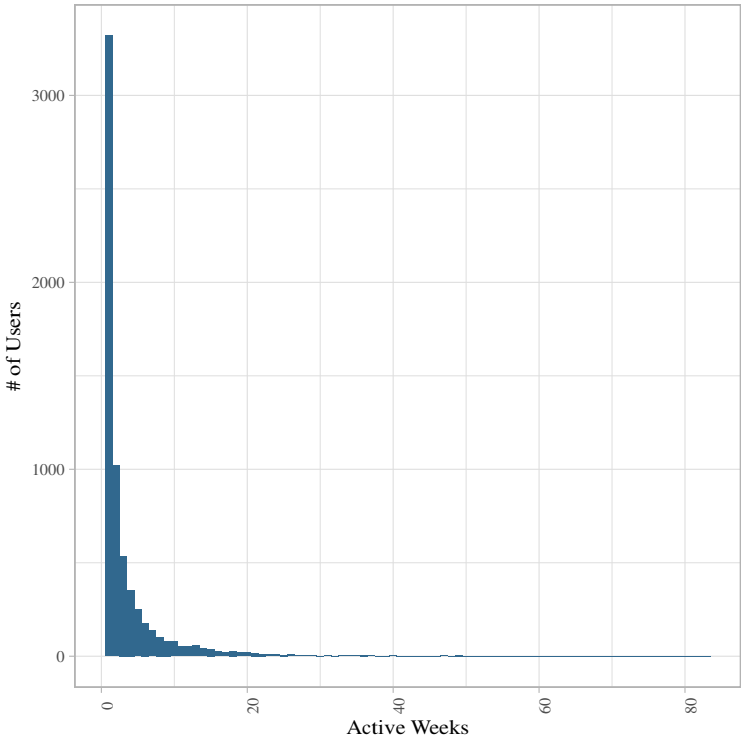


Figure 4.19: Distribution of active weeks per user

4 Evidence-Based Target Audience Definitions and Revenue Prediction

had access to what movies and did they in fact go watch it? We defined any movie as accessible to a user if there was at least one showtime in at least one cinema which the user had selected in the app during the period after the first and before the last interaction that was recorded for the respective user. We did include the last interaction as a criterion to exclude users who ceased to use the app when the film came out from the analysis to avoid too many false negatives. We also excluded users who were either employees of one of the cinemas or worked with Cinuru Research. After applying all these criteria, we identified 540,382 viewing opportunities.

We assume that such an opportunity has been seized, i.e. the movie has been watched by a user if we record one of three interactions: a click on the ticket purchase button, a collection of bonus points, or a positive star rating. Thus we identified 24,507 watched movies, i.e. user-movie-combinations where we have reason to believe that this user actually watched the movie. 3,721 users saw at least one movie, 3,163 of which (85%) watched 10 movies or less. 17 users watched more than 100 movies. While this is not impossible over the course of two years, it is highly dubious if the in-app behavior mirrors real-time consumption in these extreme cases. When we look exclusively at users who collect bonus points, i.e. users who are thus incentivized to record all their ticket purchases in the app, we find that the distribution of annual admission frequencies among app users is very similar to the general population (see [Figure 4.20](#)). We would have expected to find a bias for heavy users to be more likely to enroll in a loyalty scheme, but it seems like any such effect is offset by the non-observation of cinema visits as users cease to use the app during the observation period.

If we take a look at most-watched movies, we find the list to be very consistent with the movies that were interacted with most in general (cf. [Table 4.10](#)). With the exception of the Sneak Preview and again the strange data on SWING TANZEN VERBOTEN, it looks much like a list of the most successful movies in Germany during the observation period.

In [subsection 4.3.4](#), we will now see which of these consumption events we would have been able to predict with our targeting algorithm.

4.3.4 Analysis

Just as in [section 4.2](#), we will engage in a kind of response modeling, i.e. we will try for each movie to select a subset of the population ("target audience")

4 Evidence-Based Target Audience Definitions and Revenue Prediction

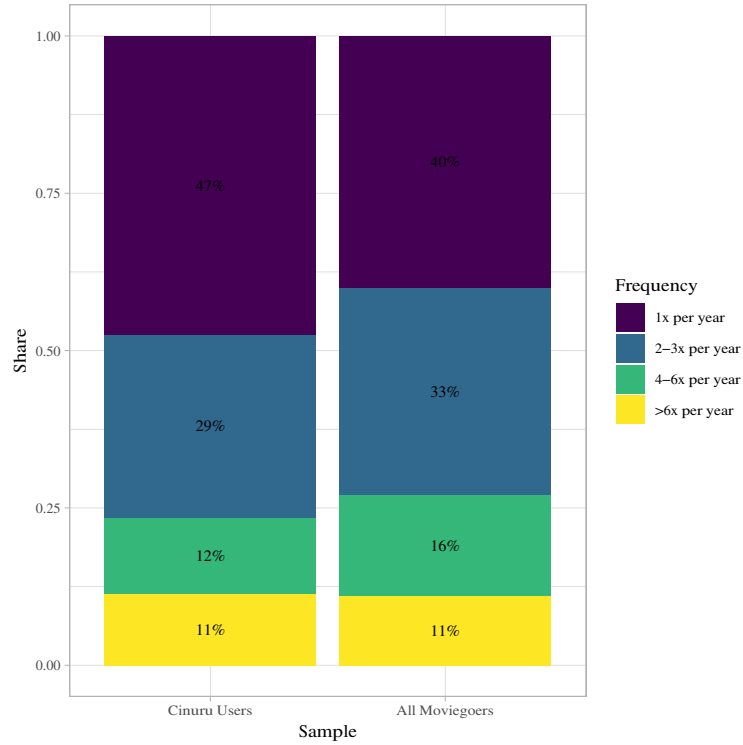


Figure 4.20: Distribution of moviegoing frequencies among app users compared to the entire population as per FFA (2018)

that has a higher probability to react positively to the message, i.e. to watch the movie (Lo 2009).

Again, we will base the selection of each target audience on the mean similarity of users' past movie choices up to that point, in this case defined as the mean similarity of all movies with which each user has interacted in the app up to that point in time. We will rely on genre overlap as defined in [subsection 4.2.4](#), i.e. we hold that two films are the more similar the more the assigned genres conform. With g_{m_1} as the number of genres assigned to movie m_1 , g_{m_2} as the number of genres assigned to movie m_2 , and g_{m_1, m_2} as the number of genres assigned to both movie m_1 and movie m_2 , we may then define the genre similarity score $sim(m_1, m_2)$ for any given pair of two movies m_1 and m_2 as:

$$sim(m_1, m_2) = \frac{g_{m_1, m_2}}{g_{m_1} + g_{m_2}}.$$

According to the results from [subsection 4.2.4](#), we assume that the mean similarity $s_{i,j}$ of all movie interactions in the interaction history of user u_i and movie m_j prior to the release date of m_j should be a good predictor of whether u_i will actually consume m_j . To test this assumption, we first compute $s_{i,j}$ for all user and movie pairings that occur in our dataset of viewing opportunities as identi-

Title	Users
DAS PERFEKTE GEHEIMNIS	290
SWING TANZEN VERBOTEN	237
BOHEMIAN RHAPSODY	222
DIE EISKÖNIGIN 2	214
AVENGERS: ENDGAME	209
STAR WARS: DER AUFSTIEG SKYWALKERS	202
DER KÖNIG DER LÖWEN	200
JOKER	196
PHANTASTISCHE TIERWESEN: GRINDELWALDS VERBRECHEN	183
DER JUNGE MUSS AN DIE FRISCHE LUFT	164
JUMANJI: THE NEXT LEVEL	144
AVENGERS: INFINITY WAR	133
CAPTAIN MARVEL	127
SNEAK PREVIEW	118
GREEN BOOK - EINE BESONDERE FREUNDSCHAFT	118
JURASSIC WORLD: FALLEN KINGDOM	113
DEADPOOL 2	106
SPIDER-MAN: FAR FROM HOME	105
NIGHTLIFE	99
AQUAMAN	95

Table 4.10: Most watched movies in dataset

fied in [subsection 4.3.3](#). Since $s_{i,j}$ is undefined whenever either m_j has no genre assigned or none of the movies in the past interaction history of u_i have at least one genre assigned, we only arrive at a definite mean similarity value for 432,059 of the 540,382 theoretical viewing opportunities. The mean similarity values range from 0 to 1. The mean (median) among all movie-user-combinations is about 0.24 (0.22). For the following analysis, we will focus only on movies that have been watched at least 10 times, because for smaller movies random effects are likely to overshadow any statistical patterns. This leaves us with a final set of 182,296 viewing opportunities. 6,783 of these combinations are positives, i.e. these users have actually watched these films.

To test if the mean similarity of past movie interactions is indeed a good predictor of moviegoing behavior, we perform a logistic regression with a dummy variable (1 = "did watch the movie", 0 = "did not watch the movie") as the dependent variable and *mean_genre_overlap* as the only predictor. Results can be seen in [Table 4.11](#). In fact, there seems to be a highly significant positive impact of the *mean_genre_overlap* $s_{i,j}$ for the interaction history of user u_i as compared with movie m_j on the consumption probability $p(i, j)$.

As we were able to confirm our basic assumption, we will now turn to lift modeling as in [subsection 4.2.4](#) again to see whether this statistical relationship

4 Evidence-Based Target Audience Definitions and Revenue Prediction

	Coefficient
(Intercept)	-3.99***
mean_genre_overlap	2.40***
Num. obs.	182296

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 4.11: Logistic regression results for watching behavior explained by mean similarity of past movie interactions

also translates into efficient target audience definitions and how that efficiency changes with increasing profile depth. First, we will run targeting experiments on the entire dataset, regardless of profile depth, i.e. how much we know about users. For each movie, we will again define the highest scored 10 per cent of all eligible users as that movie’s target audience.

For each movie, all users who were active in the app before and after the movie’s release date are eligible. We then choose the 10 per cent by highest *mean_genre_overlap*, as we have just established this value to be a significant predictor of actual consumption behavior. If the share of users in the predicted target audience which actually watched the film (*target_share*) is higher than the share of users who watched the movie among all eligible users (*expected_share*), i.e. the lift value is >1 , the targeting is deemed efficient. We define the targeting method’s *genre_lift* for a particular movie as the ratio between the movie’s *target_share* and its *expected_share*. The lift value is the factor by which the targeting method is more efficient than random targeting.

If we perform such targeting simulations for all 198 movies that were watched at least 10 times, we get lift values ranging from 0 to 5.45. 142 of the 198 values are larger than 1.0. A simple binomial signed test tells us this is highly significant ($p < 0.01$). The mean (median) lift is 1.57 (1.43).

In [subsection 4.3.1](#) we have theorized that the targeting efficiency, measured here as the mean lift value across movies, should increase with the amount of information we have on each user. We will thus now repeat the procedure described above and vary the set of eligible users from which we select ten per cent as the target audience for each movie based on users’ profile depth.

As a measure of profile depth $d_{i,j}$ for user u_i at the time of release of movie m_j , we will use the number of active weeks of u_i in the app before the release of m_j . Another possible choice would be the number of past interactions, but this would be likely conflated by users who are only shortly active in the app and

4 Evidence-Based Target Audience Definitions and Revenue Prediction

interact with a large number of movies to explore app functions. Such data contain very little information about those users' actual movie preferences and thus we assume that the data are the better the longer we have been able to monitor a user's behavior in the app. For each of the relevant 182,296 viewing opportunities for which we have similarity scores, a value for the profile depth d (measured in active weeks before the respective movie's release date) can be computed. Obviously, not for every movie there were users with every number of active weeks before that movie's release date (for example, for a movie that was released four weeks after the beginning of the observation period, the maximum number of active weeks was 3). In general, we have the less data to base our targeting experiment on the more profile depth we require. In the following simulation, we will go from $d = 1$ to $d = 30$. For each movie and each value of d , we define the eligible users, i.e. those users who had a viewing opportunity for that movie and had been active in the app during d different weeks before the release of that movie. Then we select ten per cent of these eligible users based on highest *mean_genre_overlap* as the movie's target audience and compare the incidence of users who actually watched the movie among that target audience (*target_share*) to the incidence among all eligible users (*expected_share*). The ratio of *target_share* and *expected_share* is defined as the *genre_lift* for this movie and this value of d . Algorithm 5 outlines the procedure.

The results for *mean_genre_lift* by profile depth d are plotted in Figure 4.21. While values are consistently higher than 1.0, mean lift seems to increase with profile depth, reaching a high point of 5.28 at $d = 30$ (which corresponds to a 5-fold increase in efficiency as compared to random targeting).

To test whether this trend is statistically significant, we perform a standard linear regression with *mean_genre_lift* as the dependent variable and the number of active weeks d as the only predictor. The results can be seen in Table 4.12. We may thus confirm H5a: The efficiency of targeting by similarity of past movie choices does indeed increase with profile depth, i.e. the period of time over which the moviegoers' past choices are known.

On an interesting side note, the mean lift values for different profile depths in Figure 4.21 even for small values of d are well above the mean lift value at which we arrived for the entire sample before (1.57). A reasonable explanation for this is that the *mean_genre_lift* is not stable over different profile depths: If for example the genre overlap values are typically higher for users after only a few active weeks, because it is more likely to randomly get a high value with

Data: Profile depth d

Result: Mean targeting performance (mean genre lift) across all movies for profile depth d

for each value of d **do**

for each target movie m **do**

 define as eligible users all users who had a viewing opportunity for m and have been active for exactly d weeks before the release of m ;

 determine share of eligible users that have watched m ;

 save as *expected_share* for m and d ;

for each eligible user u **do**

 compute *mean_genre_overlap* for m and the interaction history of u up to the release of m ;

 save as *mean_genre_overlap* for u , m , and d ;

end

 rank eligible users by *mean_genre_overlap* for m and d ;

 select top 10 per cent of users as target audience $A(m, d)$ for m and d ;

 compute share of users in *target_audience* that have watched m and

 save as *target_share* for m and d ;

 divide *target_share* by *expected_share* for m and d ;

 save as *genre_lift* for m and d ;

end

 Compute mean of *genre_lift* among all target movies;

 Return as *mean_genre_lift* for d ;

end

Algorithm 5: Algorithm to compute *mean_genre_lift* by profile depth d

just a few interactions, and that value decreases over time, any targeting effort would naturally gravitate toward users with low profile depth and miss more suitable, deeper profiles. In contrast, when only profiles with identical depth are being compared, this is more of an apples-to-apples comparison in terms of *mean_genre_overlap*. To test whether this is a plausible explanation, we can look at the median threshold value for *mean_genre_overlap* that users needed to pass in order to be included in the target audience for any profile depth d . The results are plotted in [Figure 4.22](#).

We can see that indeed the threshold falls over time. So while we were able to show that the *mean_genre_overlap* provides an efficient targeting criterion, this goes to show that our measure for interaction history similarity toward a newly released movie may require some further engineering to mirror actual movie-user-affinity more accurately. In [section 4.4](#) we will look at a more sophisticated way to model such affinities based on explicitly stated preferential information by moviegoers.

4 Evidence-Based Target Audience Definitions and Revenue Prediction

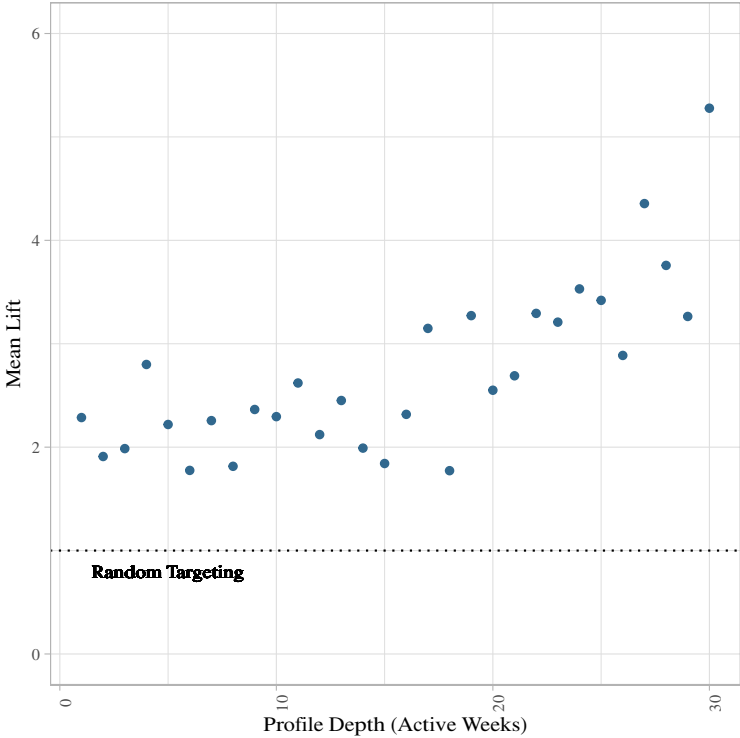


Figure 4.21: Mean lift for genre-based targeting across all target movies by profile depth of eligible users

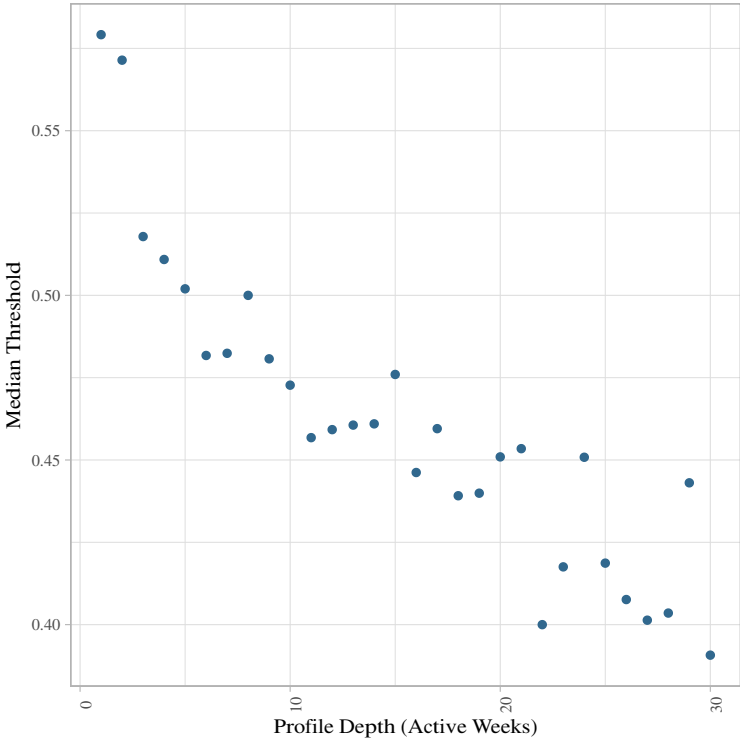


Figure 4.22: Median threshold value across all movies for the *mean_genre_overlap* similarity measure required from a user to be included in a movie's target audience

	Coefficient
(Intercept)	1.63***
d	0.07***
R^2	0.57
Num. obs.	30

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 4.12: Linear regression results for mean lift across all movies explained by the number of active weeks per user before release (profile depth d)

4.4 Targeting by Preferences Learned from Movie Ratings

4.4.1 Hypotheses

In [section 4.2](#) we have been able to show that past movie choices – interpreted as an indicator of movie preferences – may provide the basis for a targeting model to more efficiently define target audiences for upcoming movie releases. In [subsection 4.3.4](#) we have established that in general such targeting gets more efficient if moviegoers’ behavior is observed over a longer period of time beforehand, leading to a more precise estimation of their affinity score for any given new release.

Such data are inherently observational, i.e. moviegoers are monitored in order to gather these information. In this chapter, we will look at the potential value of expressly stated preferential information to determine future film choices. If it is possible to ask moviegoers directly how much they liked different films and derive valuable targeting information from their responses for future films, such data may serve as a foundation for quick targeting and maybe even general clustering of similar audience members into targetable market segments (see [section 4.5](#)).

Modern recommender algorithms provide a tool to predict a likely movie-user-affinity score $s(u, m)$ of a given moviegoer (user) u toward a given target movie m from past movie ratings (cf. [section 4.1](#)). We will use a well-established recommender algorithm in this experiment to test the following hypotheses:

Hypothesis 6a *Targeting by predicted movie-user-affinity based on past movie ratings is an efficient targeting method, i.e. more efficient than random targeting.*

Hypothesis 6b *Targeting by predicted movie-user-affinity based on past movie ratings gets more efficient with the number of available movie ratings for each user from the past.*

We will test this on a dataset from an online survey conducted with self-reported moviegoers in Germany.

4.4.2 Survey Design

The online survey from which the data for the analysis in this chapter were gained served several different purposes. Originally it was mainly intended to test the possibility of concept testing for entertainment products as part of a master thesis at the University of Münster (Schumacher 2017). As the study was prepared collaboratively by the Marketing Center Muenster at the University of Muenster and the project team Greenlight Analytics at Film University Babelsberg, it was possible to add additional items to the survey beyond the scope of the concept testing study, which were intended and subsequently used to conduct the analysis presented henceforth.

A web-based questionnaire was used to collect the data, which was easy to implement in terms of time and cost²⁰ and allowed us to reach a large number of people within a short period of time (Hudson, Seah, Hite & Haab 2004).

The core of the questionnaire was a fictitious cinema offering, from which participants were allowed to select up to three movies (in a ranked choice) which they were most interested in watching. This movie program always consisted of ten movies, eight of which were the same for all participants. These eight movies, which were all released in Germany between March and April 2017 (a few weeks after the survey was conducted), were chosen by the project team to realistically reflect a cinema program at the time. The movie titles and their German release dates can be seen in [Table 4.13](#).

The other two movies, which were different for each respondent, were selected from a set of comedy movies released in Germany between 2011 and 2013 and pertain to the concept testing part of the study (Schumacher 2017), which is of no further interest here. The movies were presented with their poster, synopsis, along with genre, country of origin, as well as cast and crew information,

²⁰ The technical implementation of the survey was done by the Greenlight Analytics programming team.

4 Evidence-Based Target Audience Definitions and Revenue Prediction

Title	Release Date (Germany)
GHOST IN THE SHELL	2017-03-30
SMURFS: THE LOST VILLAGE	2017-04-06
POWER RANGERS	2017-03-23
FREE FIRE	2017-04-06
THE FOUNDER	2017-04-20
LOMMBOCK	2017-03-23
HEAVEN WILL WAIT	2017-03-23
TIGER GIRL	2017-04-06

Table 4.13: Movies to be selected from in fictitious cinema program

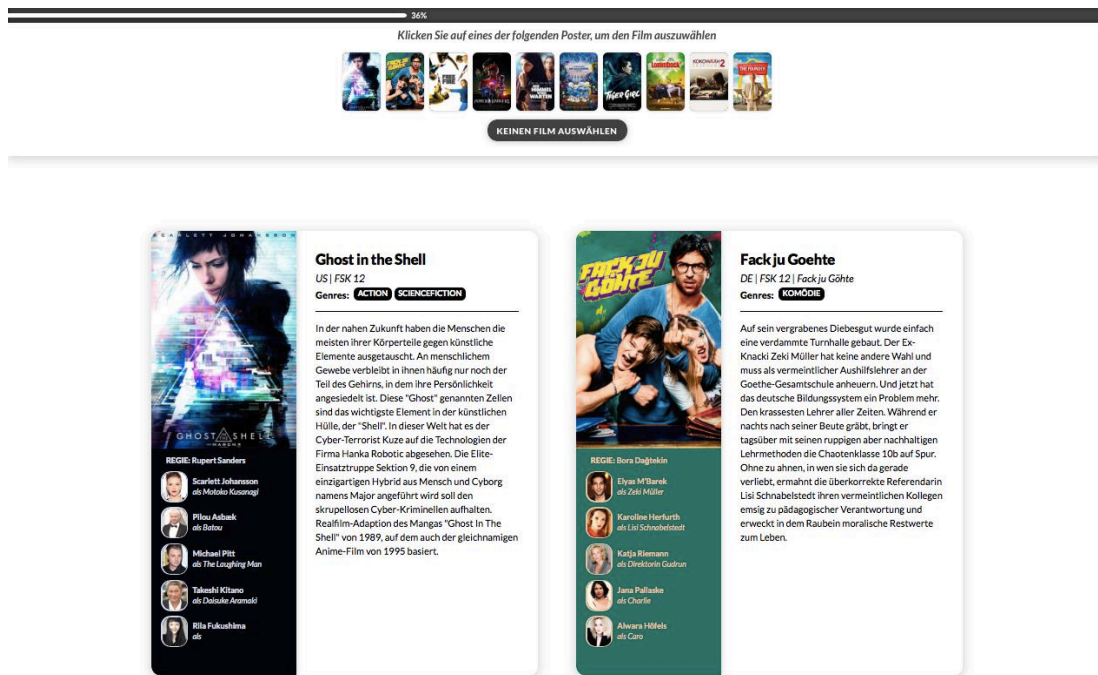


Figure 4.23: Screenshot of fictitious cinema program in online survey

to most closely mimic the decision-making situation moviegoers may find themselves confronted with when they plan an actual visit to the cinema and look at the theater’s website (see a screenshot of the respective page of the survey in [Figure 4.23](#)). Posters were taken from TMDb. For synopses, it was aimed for a unified, promotional tone. Thus, the texts were obtained from iTunes and manually shortened to similar lengths (i.e., a maximum number of 110 words) by the master student (Schumacher 2017).

In order to encourage truthful movie choices, respondents were told in the beginning that the cinema vouchers they could win might be film-specific for the movie they selected from the fictitious cinema offering.

At the beginning of the survey, respondents were presented with at least six

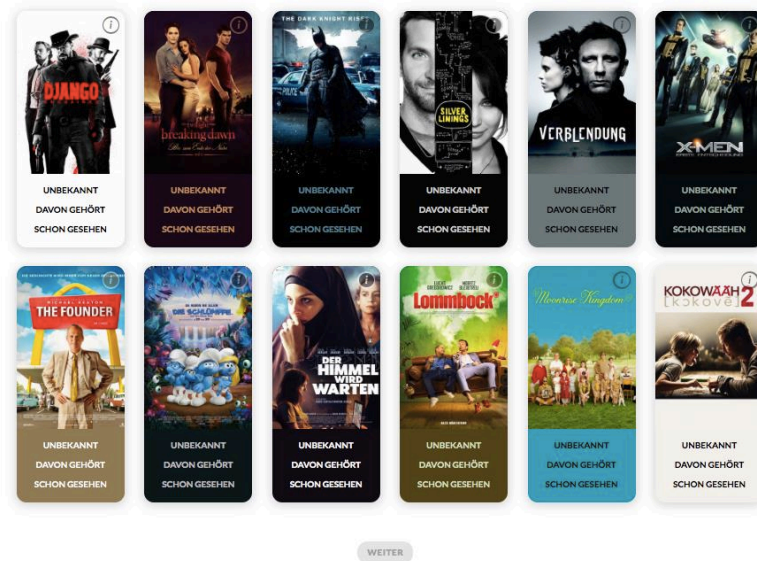


Figure 4.24: Awareness screening at the beginning of the online questionnaire

pages of eight movies each (titles and posters) for which they were asked to indicate whether they were familiar with the movie (had heard of it or already seen it). This was done in order to select unfamiliar comedy movies to stand in as "movie concepts" of new movies which were subsequently included in the cinema program for the aforementioned concept testing study (see [Figure 4.24](#)).

For the purposes of the analysis presented here, it was important to have respondents explicitly rate a number of movies. This was done at the end of the survey and respondents were asked for a number of films each: a) whether they had seen it, b) where they had seen it ("in a theater", "not in a theater", "can't remember"), c) if the film had met their expectations, and finally d) how much they liked the film on a scale of 1-5 stars (see [Figure 4.25](#)). Rating films on a five- or ten-star scale to express affinity is well-established online, as similar scales are used at the Internet Movie Database IMDb, as well as large German movie platforms Filmstarts.de and moviepilot.de.

Respondents were asked to rate at least 30 different movies by their synopses in order to get a good impression of their preferences. Afterwards, they had the chance to rate additional movies. When they rated at least 20 more, their chances to win a cinema voucher were doubled.

Respondents were asked how often they go to the movies in general (on a scale ranging from 1 = "never" to 6 = "at least once a week") and to what extent they are

The screenshot shows a survey interface for the movie "Ghost in the Shell". On the left is a movie poster. On the right, the movie title "Ghost in the Shell" is displayed with its US rating "FSK 12" and genres "ACTION" and "SCIENCEFICTION". A short synopsis follows. Below the synopsis is a list of cast members with their roles: Rupert Sanders (Regie), Scarlett Johansson (Motoko Kusanagi), Pilou Asbæk (Batou), Michael Pitt (The Laughing Man), Takashi Kiyano (Detektiv Aramaki), and Kika Fukuhashima (Batou). The survey questions are as follows:

Würden Sie diesen Film sehen?
 Ja, im Kino Nur zu Hause Gar nicht

Mit wem würden Sie diesen Film sehen? Eine Mehrfachauswahl ist möglich.
 Mit Freunden / Bekannten Mit meinem Partner / Date Mit Mitgliedern meiner Familie Alleine

Sind Sie ein Fan von einem der Darsteller?
 Ja Nein

Kennen Sie eine Vorlage, eine andere Version oder einen Vorgänger von dem Film?
 Ja Nein

Wie ansprechend finden Sie dieses Film Konzept?
 ☆☆☆☆ keine Meinung

Buttons for "WEITER" and "ZURÜCK" are at the bottom.

Figure 4.25: Rating page in online survey

accompanied by friends, family, their partner, or no one, respectively. Also they were presented with a list of "sources of awareness", as in the annual moviegoer studies by the German Federal Film Board (Filmförderungsanstalt, FFA), to indicate where they are usually made aware of upcoming movie releases in the first place (see [Figure 4.26](#)).

In addition, we asked each respondent to estimate how often they went to see films of nine different popular movie genres (Action, Animation, Comedy, Drama, Fantasy, Horror, Romance, Science Fiction, Thriller) on a five-step scale from "never" to "very often" (see [Figure 4.27](#)).

In addition, all respondents were requested to provide general demographic information, specifically age, gender, household income, postal code, and formal education (see [Figure 4.28](#)). They were also asked to identify a cultural heritage to which they felt a particular proximity, as e.g. because of a history of migration in their family or a prolonged stay abroad. They could name one or several countries, here.

For the purposes of the concept study, a number of additional indicators were recorded. Users were asked questions regarding their innovativeness and expertise – data which will not be used in the analysis below. The entire questionnaire is reproduced in [Appendix B](#).

4 Evidence-Based Target Audience Definitions and Revenue Prediction

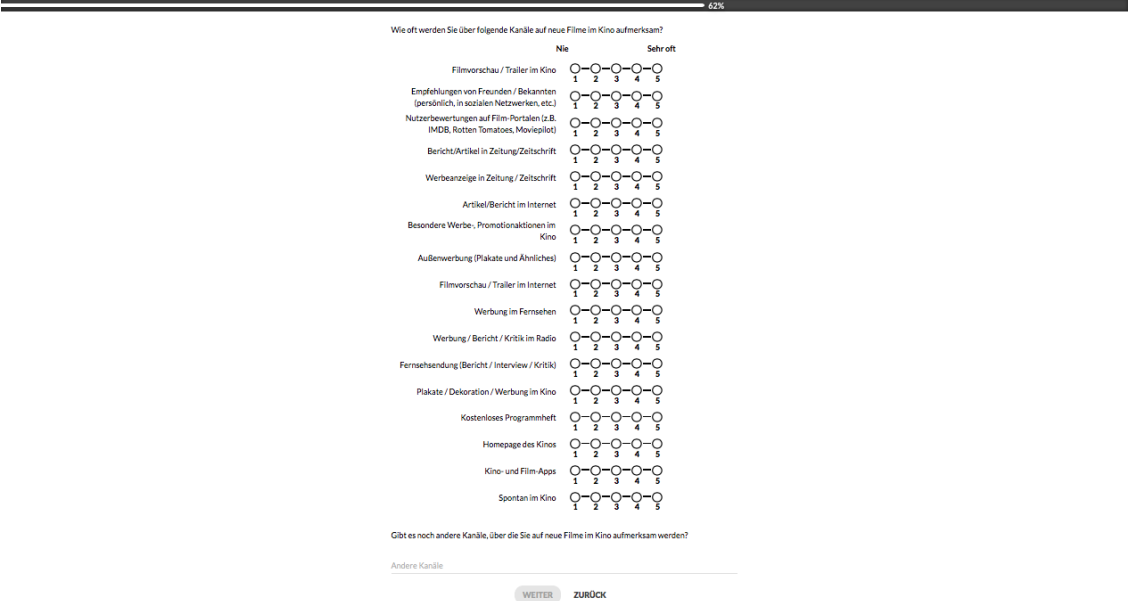


Figure 4.26: Sources of awareness rating in online questionnaire

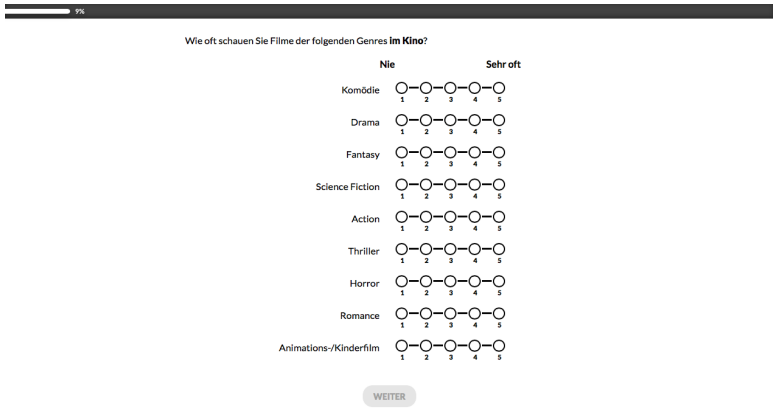


Figure 4.27: Genre Frequency Page in Online Survey

67%

Wie alt sind Sie?

Alter

Welches Geschlecht haben Sie?

Männlich Weiblich keine Angabe

Wie hoch ist Ihr monatliches Haushaltsnettoeinkommen?

weniger als 1000€ 1000€ bis 2000€ 2000€ bis 3000€
 3000€ bis 4000€ 4000€ bis 5000€ 5000€ oder mehr
 Keine Angabe

Um die Repräsentativität der Umfrage sicherzustellen, benötige ich auch Ihre **Postleitzahl**.

Postleitzahl:

Der **Kultur** welcher Länder fühlen Sie sich (zum Beispiel auf Grund ihrer Herkunft oder der Herkunft ihrer Eltern) besonders verbunden.

Kulturelles Erbe aus folgenden Ländern:

Figure 4.28: Demographics page in online questionnaire

The questionnaire was published on 20 February 2017 for a period of two weeks and promoted across online forums, social media, and among friends and family of the students and project team members. Such convenience sampling obviously has repercussions for generalizability concerns, which is why we will not use these data to test hypotheses on demographic traits, as will be addressed in more detail below.

4.4.3 Data

Overall, 6,425 users interacted with the online questionnaire. 2,186 provided responses that included at least one movie rating and exactly 700 respondents completed the entire questionnaire and rated at least 30 movies.

These 700 respondents will be referred to as "target users" hereinafter, as they provide the basis upon which all subsequent targeting experiments will be conducted in [subsection 4.4.4](#). Yet movie ratings by all 2,186 respondents will be used as input data for the recommender algorithm.

The sampling method led to a very skewed age distribution in the sample, as may be easily seen when compared to the official data which is annually

4 Evidence-Based Target Audience Definitions and Revenue Prediction

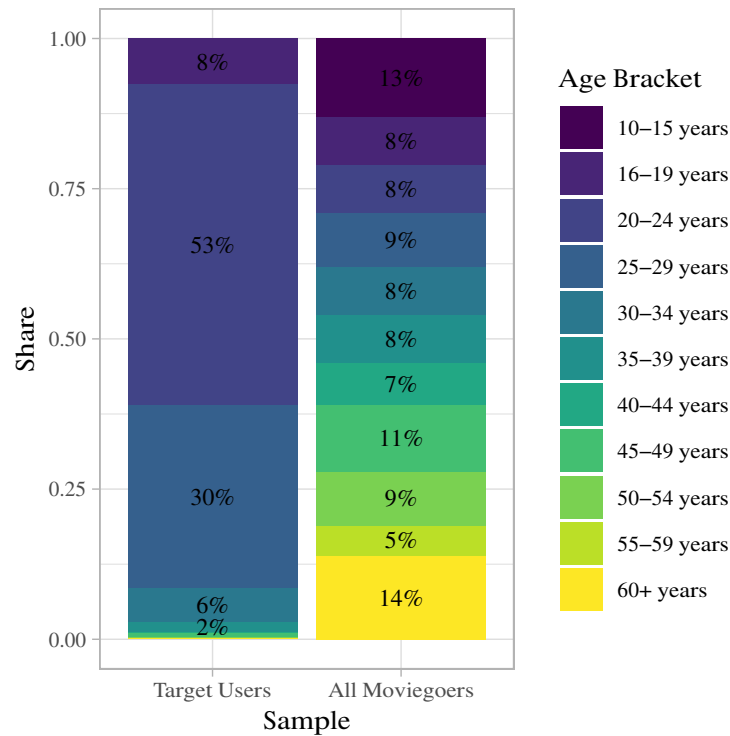


Figure 4.29: Age distribution of target users compared to age distribution among all moviegoers in Germany in 2017 as per FFA (2018)

published by the German Federal Film Funding Board FFA (2018) (see [Figure 4.29](#)). Since the questionnaire was distributed mainly on social media and amongst friends and acquaintances of the predominantly young project teams, the median age was 23. As respondents were (expectedly) so different from the overall moviegoing population in terms of age, we will not be able to fairly assess the efficiency of age-based targeting on this sample and compare it to other targeting methods. Thus no such claims will be made in [subsection 4.4.4](#).

The gender distribution was also slightly skewed, but much closer aligned with overall numbers (see [Figure 4.30](#)). The survey conducted by the FFA does not offer a third gender option for respondents to choose.

Consistent with the aforementioned assumption that students are largely over-represented in the sample, roughly 75% of respondents reported a household income < 1,000 EUR (see also [Figure 4.31](#)). Income data for moviegoers in general are no longer regularly surveyed by the FFA, but it is generally assumed that higher income correlates with more cinema visits (Reuband 2011).

Participants were asked to provide their postal code and this was used to iden-

4 Evidence-Based Target Audience Definitions and Revenue Prediction

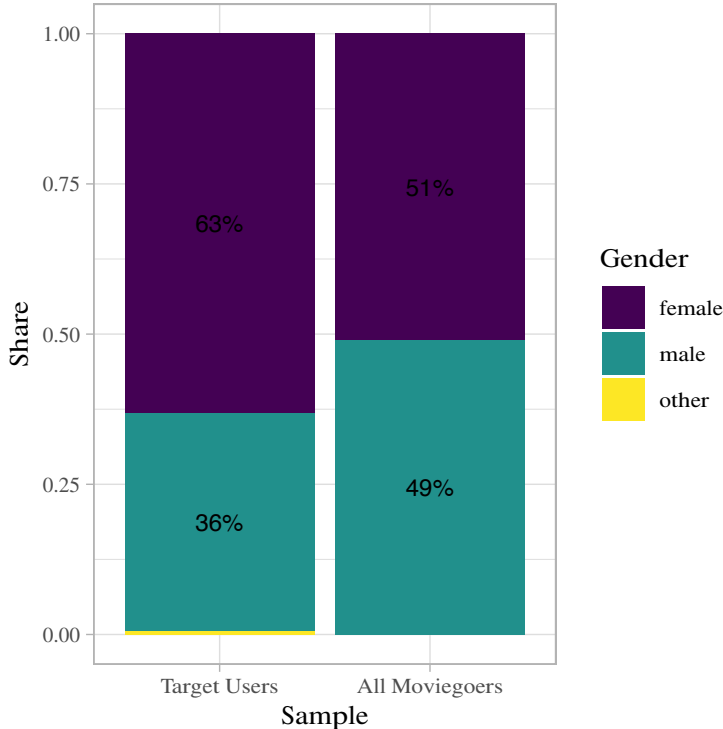


Figure 4.30: Gender distribution of target users compared to age distribution among all moviegoers in Germany in 2017 as per FFA (2018)

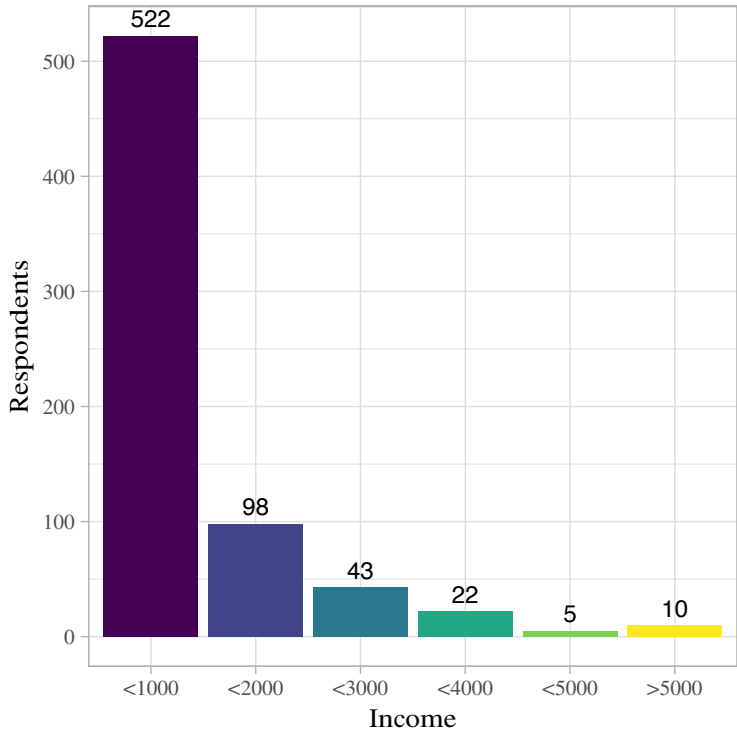


Figure 4.31: Income distribution of target users

4 Evidence-Based Target Audience Definitions and Revenue Prediction

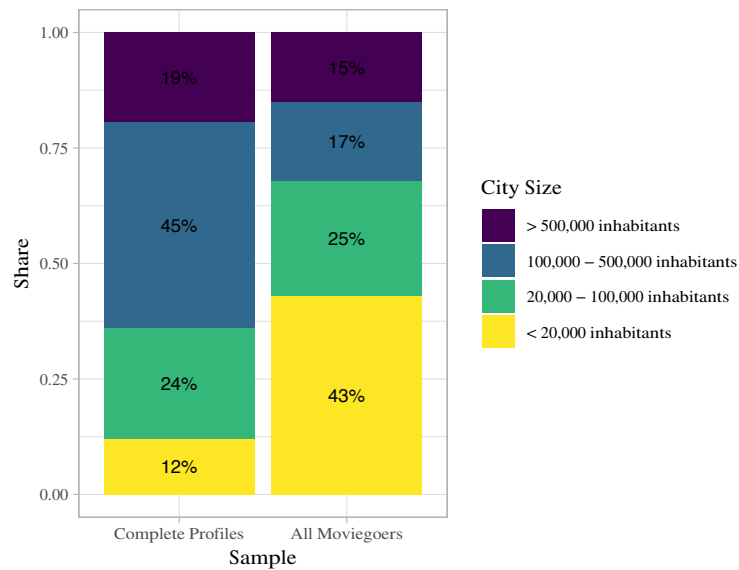


Figure 4.32: Home city size distribution of target users, compared to overall moviegoer population in 2001, according to historic data from Neckermann (2002)

tify the city size of their respective home cities. Home city sizes are no longer included in the FFA’s annual report, so the latest publicly available data on home city size distribution among moviegoers date back to 2001. One can infer from [Figure 4.32](#) that medium-sized cities (100,000 - 500,000 inhabitants) are vastly overrepresented in the sample, which again is likely due to convenience sampling, with Münster being the most frequent residential location as per the provided postal codes²¹

Since we used a very different scale, our data on moviegoing frequency (see [Figure 4.33](#)) are hardly comparable to publicly available data on the entire population. Yet the much smaller share of people who reported going to the cinema only once every year (16% in our sample vs. 51% of all moviegoers according to FFA (2019b)) suggests that their might be a selection bias at work, wherein frequent moviegoers are simply more interested in taking part in a cinema-related survey or potentially winning movie theater vouchers. That would mean that our sample over-represents heavy users that attend cinemas more frequently. As a methodical caveat we should note that using the data from [section 4.2](#), we found that respondents tend to overestimate how often they go to the movies (we used the release dates of their three reported cinema visits to estimate an average in-between time period and compared this to their self-reported frequency). A diary approach, wherein respondents record each

²¹ population data per postal code obtained from <https://www.suche-postleitzahl.org/downloads>

4 Evidence-Based Target Audience Definitions and Revenue Prediction

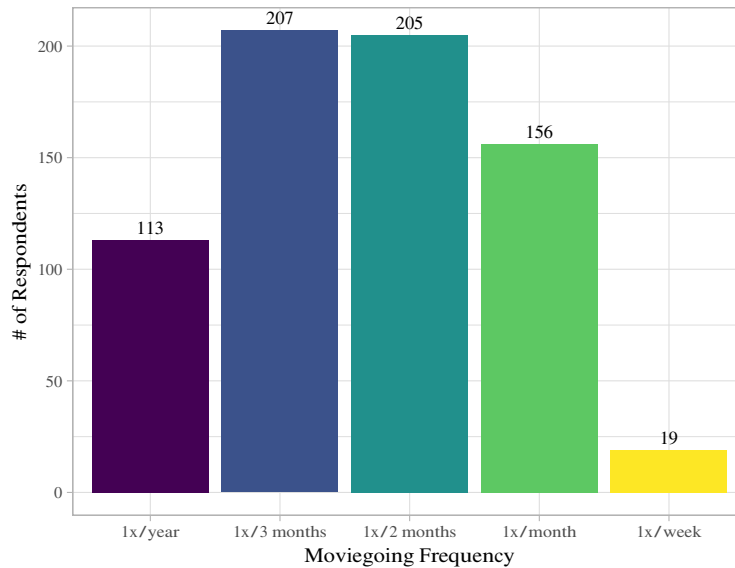


Figure 4.33: Moviegoing frequencies of target users, compared to overall moviegoer population as per FFA (2018)

visit swiftly thereafter, as pursued by the FFA, seems much better suited to realistically assess someone's moviegoing frequency.

From the relative frequencies of genres, we computed which genre was the most-frequented (i.e. "favorite" genre) for each user. The distribution can be seen in [Figure 4.34](#).

78,321 movie ratings were recorded overall, 28,789 of which were provided by the 700 target users, i.e. on average each target user rated about 41 films. The median was 44. As may be inferred from [Figure 4.35](#), a large share of respondents (243 or roughly 35%) rated 50 movies or more, almost all of which (240) stopped at exactly 50 movies, the threshold at which their chances in the lottery were doubled. Of the three users who voluntarily continued to rate more, one went as far as to rate 82 different movies.

The mean overall rating across all target users was 3.56. Users show very different levels of generosity in their ratings, with respective means ranging from 2.32 to 4.64 (median value: 3.56). [Figure 4.36](#) displays the distribution.

On average, respondents reported for 77.6% of movies that the movie fulfilled their expectations (median value: 78.4%). The most generous user saw their expectations fulfilled by 100%, the most critical user by only 37% of movies. The distribution of the share of movies which each user found satisfactory can be seen in the histogram in [Figure 4.37](#).

4 Evidence-Based Target Audience Definitions and Revenue Prediction

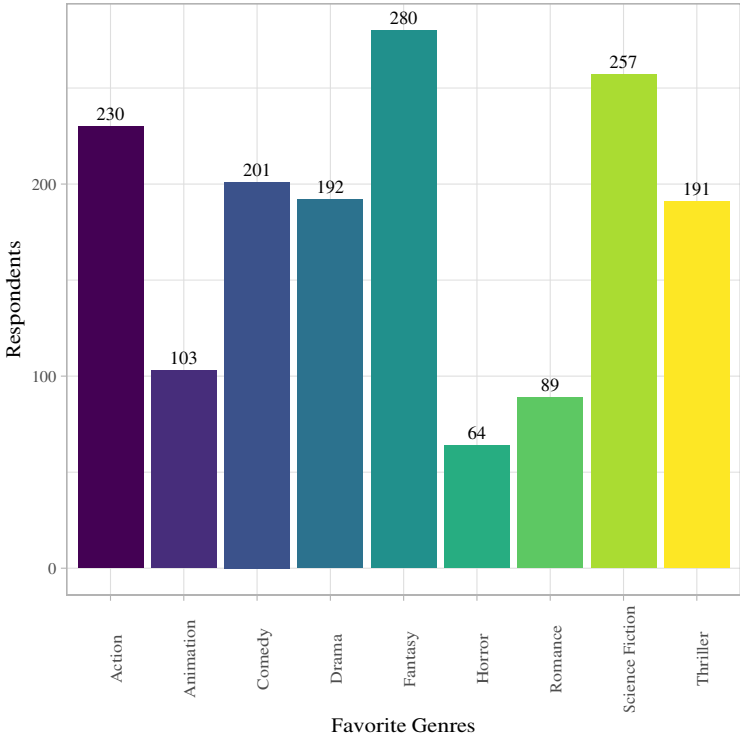


Figure 4.34: Favorite, i.e. most-often frequented, genres of target users

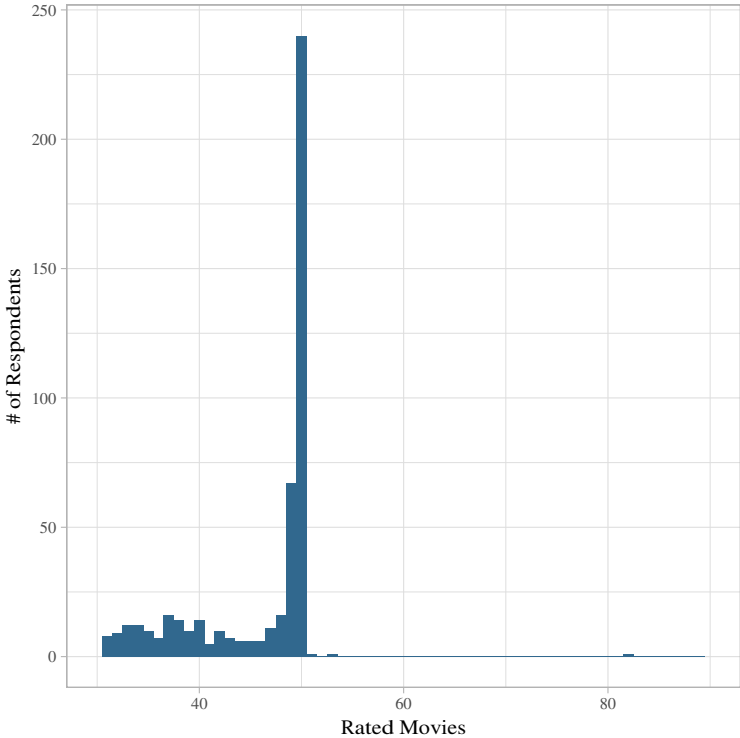


Figure 4.35: Histogram of ratings per target user

4 Evidence-Based Target Audience Definitions and Revenue Prediction

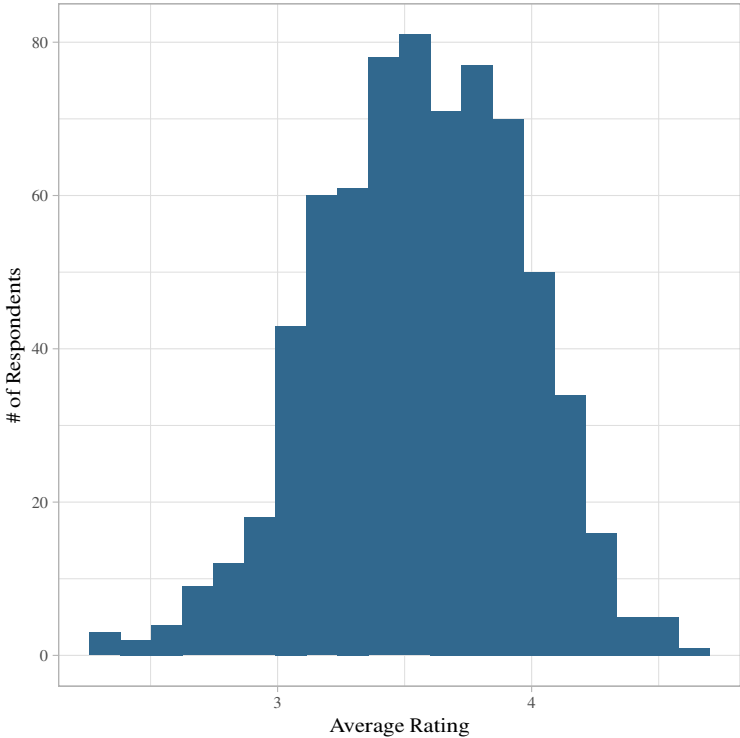


Figure 4.36: Histogram of mean ratings per target user

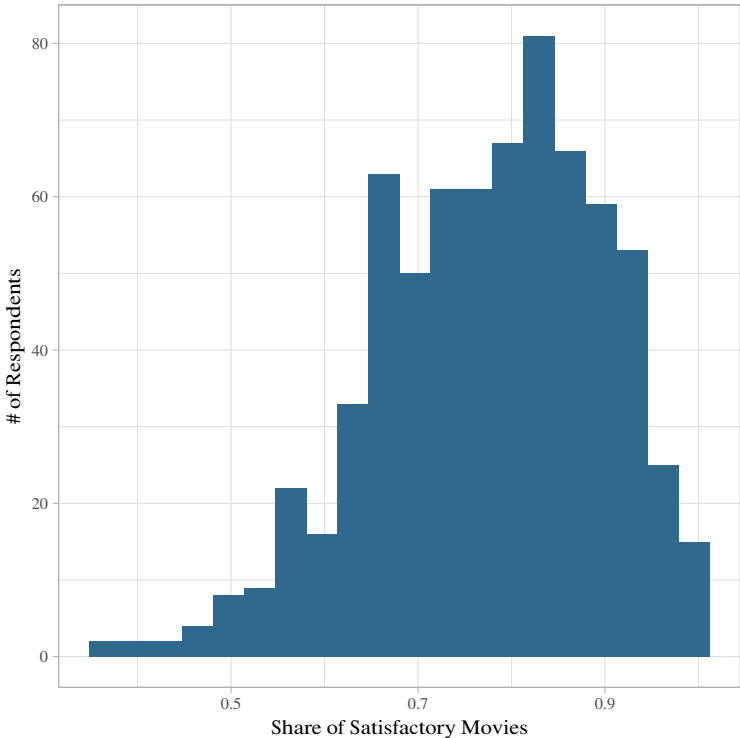


Figure 4.37: Histogram for share of satisfactory movies among target users

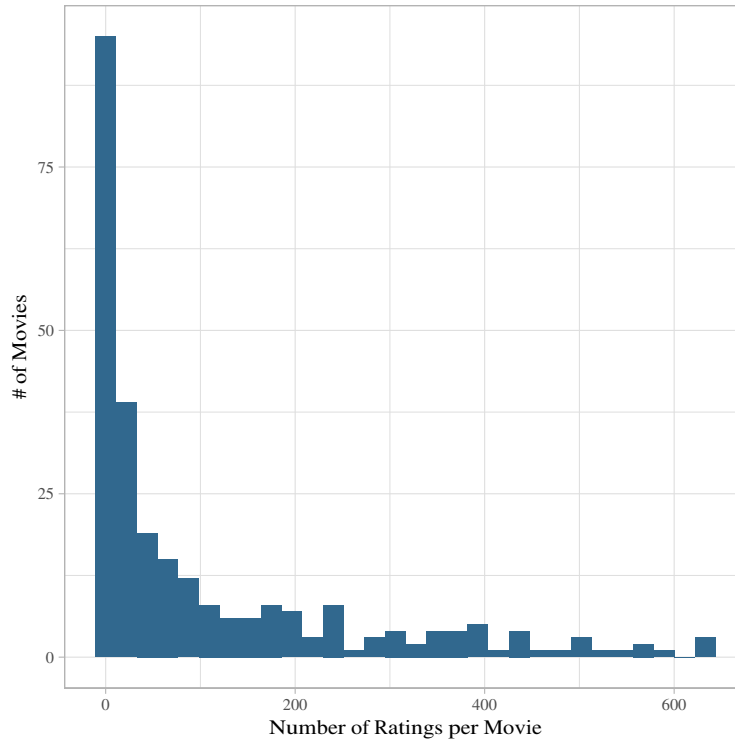


Figure 4.38: Histogram for ratings per movie

267 different films were rated by target users. 38 movies were rated just once, whereas the most-rated film, *THE HUNGER GAMES*, was rated 634 times. The median number of ratings per film was 31, whereas the mean was 107.8, which goes to show that the ratings are dominated by a small number of heavily rated films. [Figure 4.38](#) displays the distribution.

Movies are not only rated by very different numbers of respondents, the mean values of each movie's ratings also differ vastly. Of all movies that were rated at least 10 times, the worst mean score is 2.06 for *SCARY MOVIE 5*, the best mean score is 4.48 for *THE INTOUCHABLES*.

Of 28,789 movies rated by target users, 8,904 (~31%) have been watched theatrically, 18,595 (~65%) have been consumed at home, and for 1,290 movies (~4%) respondents were unable to recall where they had seen them. The mean rating of movies which were watched in a cinema was 3.93, whereas the mean rating of movies watched at home or where people could not recall the context of consumption was 3.39. A Chi-Square Two Sample Test to compare the distribution of ratings among movies watched in cinemas with those of movies watched elsewhere (see [Table 4.14](#)) reveals a significant difference ($p < 0.001$) between the two distributions, which is a strong indicator that this is no coincidence, but in fact, people tend to like movies more for which they buy cinema

tickets.

rating	cinema	home
1	273	996
2	703	2804
3	1703	5872
4	2911	5640
5	3314	3283

Table 4.14: Distribution of ratings for films watched in cinemas and at home

The obvious explanation would be that people most likely chose films more carefully when they buy a cinema ticket as compared to streaming them or simply turning on the TV (cf. [subsection 3.2.3](#)). Other reasons such as the entirety of the theatrical experience, which might endow the consumption with a more event-like character, could also factor into this. Yet a strong correlation between watching movies in theaters and explicitly rating them positively is encouraging for all subsequent attempts to infer future moviegoing behavior from past ratings as will be undertaken in [subsection 4.4.4](#).

As expected, participants' movie selections in the fictitious cinema programs section of the online questionnaire were very unevenly distributed among the eight target movies, with the largest movie GHOST IN THE SHELL being selected by 317 respondents, and as few as 25 and 26 participants in favor of SMURFS and FREE FIRE, respectively. [Figure 4.39](#) shows the distribution.

This class imbalance needs to be taken into account when splitting the data in a training and a test sample for the analysis in [subsection 4.4.4](#).

4.4.4 Analysis

To evaluate the efficiency of targeting based on preferential data, we will again simulate a target audience definition as in [section 4.2](#), i.e. for each of our eight target movies we will try to algorithmically select a population subset which will then be the "target" of a marketing message, wherein targeting should aim for the selected subset to have a higher probability of reacting positively to the message (response modeling).

First we will split our dataset into a train and a test set so we can use the train set to learn rules whose application to the test set we can then study (James, Witten, Hastie & Tibshirani 2013). To keep the test set large enough for the smaller

4 Evidence-Based Target Audience Definitions and Revenue Prediction

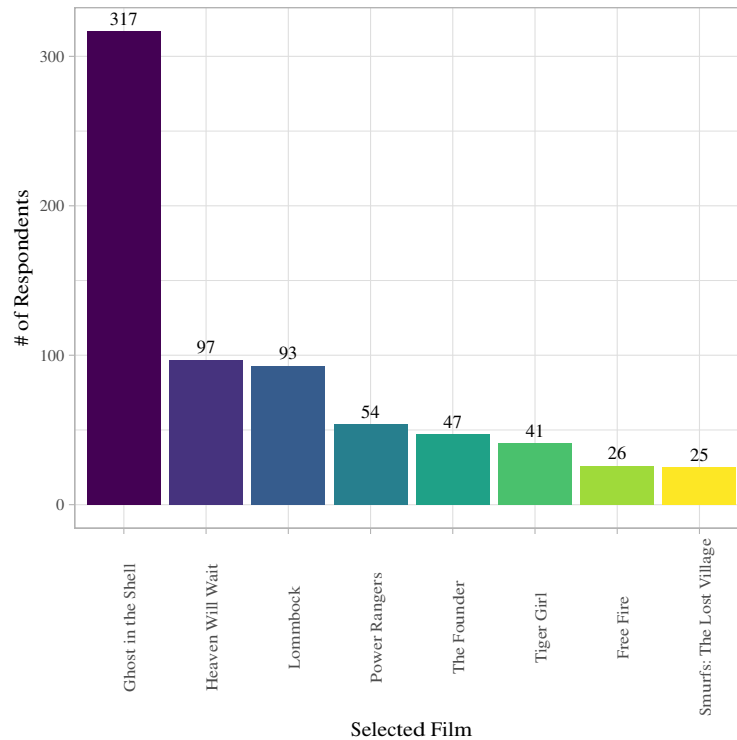


Figure 4.39: Movie selections of target users

target movies to still have a measurable appeal among respondents, we will use a 50/50 split and employ stratified sampling, i.e. the random sampling is done independently for all eight selected movies, in order to make sure the target and test set each have the same distribution of selected movies. [Figure 4.40](#) and [Figure 4.41](#) show the respective distributions.

As in previous sections, we will try to define a suitable subgroup (target audience) for each film that consists of 10 per cent of our respondent population of 347 in the test sample. A "targeting method" is any algorithm that allows us to choose which ten per cent to target. A targeting method's "yield" is the number of people within the target audience which actually select the movie in the fictitious cinema program for which they are being targeted, and the targeting method's "lift" is the factor by which its yield is higher than the yield that would be expected to occur randomly (as defined before). For example, a target audience of 35 respondents (ten percent of the test sample) for GHOST IN THE SHELL would be statistically expected to contain 15.94 people who actually choose GHOST IN THE SHELL. If the target audience selected by a specific targeting method yields 20 respondents who choose the film, its lift would be roughly 1.25, and if it only contains 10 moviegoers that choose GHOST IN THE SHELL, its lift would be roughly 0.63. The higher this lift, the higher the targeting

4 Evidence-Based Target Audience Definitions and Revenue Prediction

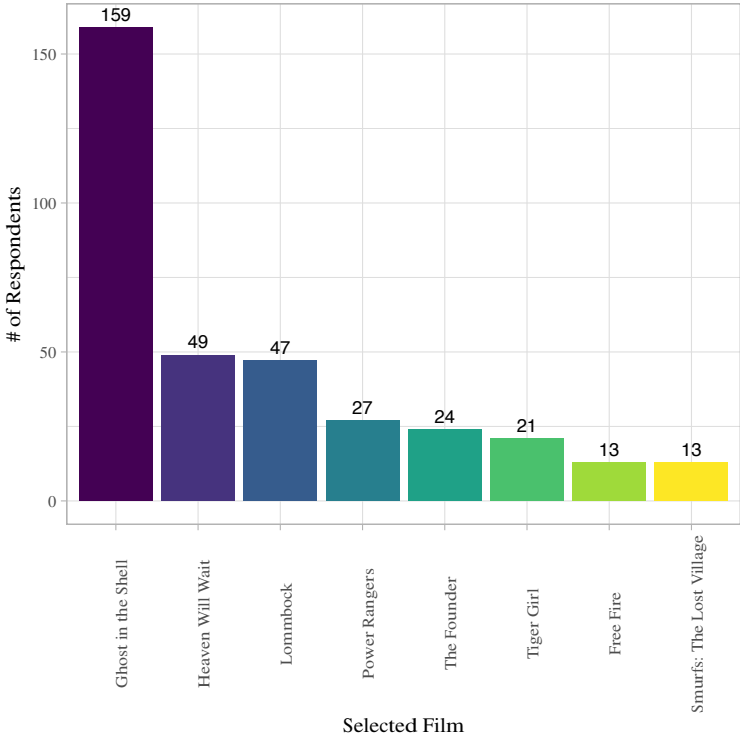


Figure 4.40: Movie selections of target users in training sample ($n = 353$)

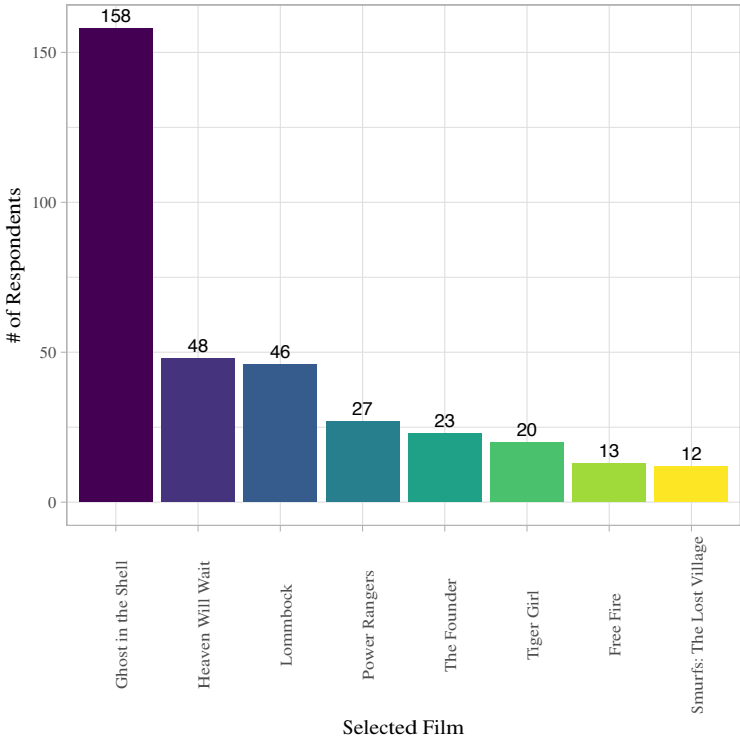


Figure 4.41: Movie selections of target users in test sample ($n = 347$)

4 Evidence-Based Target Audience Definitions and Revenue Prediction

method’s efficiency. Thus any targeting method with a lift greater than 1 can be considered more efficient than random targeting.

While we are not going to test hypotheses on age and gender targeting on this sample (due to its imbalanced composition), we will nonetheless try targeting methods similar to the ones established in [section 4.2](#) on the sample to provide a benchmark for subsequent targeting attempts to beat. Just like in [subsection 4.2.4](#), the score for each respondent u in demographic subgroup D_u and target movie m is equal to the prevalence of watching m among all respondents in the intersection of D_u and S_{train} ²². The targeting method follows exactly the procedures outlined in [subsection 4.2.4](#): All users are scored, ranked, and the highest-ranked 10 per cent of users are defined as the target audience. The resulting lift values for each targeting method and each target movie can be seen in [Table 4.15](#).

It becomes immediately obvious that age-based targeting does not work particularly well on this dataset, in fact even slightly worse than random targeting, which is unsurprising given the dataset’s relative homogeneity in terms of respondent age. Across all eight movies, the mean (median) lift values are 1.26 (1.28) for gender-based targeting, 0.96 (0.95) for age-based targeting, and 1.23 (1.29) for age-and-gender-based targeting. By the standards applied in [subsection 4.2.4](#), only gender targeting is significantly better than random targeting ($p < 0.05$). For the aforementioned reasons, it would be questionable to generalize any age-related results from the given dataset to the entire moviegoing population, so the values here will just serve as a plausibility benchmark for subsequent targeting attempts.

Title	gender	age	age_and_gender
GHOST IN THE SHELL	1.16	1.17	1.32
SMURFS: THE LOST VILLAGE	1.75	0.75	1.25
POWER RANGERS	0.59	0.70	0.56
FREE FIRE	1.46	1.15	1.46
THE FOUNDER	1.48	1.00	0.87
LOMMBOCK	1.37	0.89	1.35
HEAVEN WILL WAIT	1.19	0.90	1.25
TIGER GIRL	1.10	1.10	1.80

Table 4.15: Lift values for different demographic targeting methods

Next we will try to use the self-expressed genre affinity data to target moviegoers. Therefore we need to define a genre-based targeting model. Every target

²² This is technically very similar to classification by association approaches (Liu, Hsu & Ma 1998), where the prevalence would be called the ‘confidence’ of an association rule, just without putting a threshold on minimal support.

4 Evidence-Based Target Audience Definitions and Revenue Prediction

movie has been assigned one or several genres on TMDb (cf. [Table 4.16](#)). For each movie-user-combination, we compute an affinity score $s(u, m)$ for user u and movie m as the mean rating of all genre ratings $r(u, g_1), \dots, r(u, g_n)$ for genres g_1, \dots, g_n assigned to m as rated by u :

$$s(u, m) = \frac{\sum_{i=1}^n r(u, g_i)}{n}.$$

Then we use these scores again to rank users and select the highest-ranked 10 per cent as our target audience to determine top-decile lift.

Title	Genres
GHOST IN THE SHELL	Drama, Action, Thriller, Science Fiction
SMURFS: THE LOST VILLAGE	Animation, Comedy
POWER RANGERS	Action, Science Fiction
FREE FIRE	Action
THE FOUNDER	Drama
LOMMBOCK	Comedy
HEAVEN WILL WAIT	Drama
TIGER GIRL	Action

Table 4.16: Genres assigned to target movies on TMDb

The resulting lift values can be seen in [Table 4.17](#). Across all eight movies, the mean (median) lift value is 1.40 (1.54) for genre-based targeting, and the lift value is greater than 1.0 for 6 out of 8 movies. Of the two movies with a lift value < 1.0 , one is "Tiger Girl", for which the genre assignment of "Action" on TMDb seems questionable. Thus the genre targeting method appears to be superior to demographic targeting.

Title	genre_lift
GHOST IN THE SHELL	1.30
SMURFS: THE LOST VILLAGE	1.92
POWER RANGERS	1.89
FREE FIRE	1.54
THE FOUNDER	0.52
LOMMBOCK	1.76
HEAVEN WILL WAIT	1.54
TIGER GIRL	0.70

Table 4.17: Lift values for genre targeting method

We will now employ a more sophisticated recommender algorithm, namely matrix factorization, to use the preferential data on past movies in order to define a target audience.

4 Evidence-Based Target Audience Definitions and Revenue Prediction

As explained in [section 4.1](#), matrix factorization techniques aim to compute user and item embedding matrices U and V such that the product UV^T is a good approximation of the original ratings matrix R .

In a 700×267 rating matrix of all ratings by all target users for all movies, 28,789 or 15.4% of all possible ratings are known. Compared with the popular MovieLens 100K dataset (Harper & Konstan 2015), which contains 100,000 movie ratings for 1,700 different movies by 1,000 different users, our dataset is almost three times as dense and should allow for meaningful matrix factorization. To further improve the prediction accuracy, we can also leverage the movie rating information from users who did not complete the entire questionnaire, but rated movies nonetheless (incomplete profiles).

To test whether the lift of a targeting method based on matrix factorization will indeed improve with the depth of past movie preference information ([H6b](#)), we will do several iterations in which we vary the number k of ratings by the target users in the test sample which we include in the rating matrix from which the item (movie) and user embeddings are computed. For example, if $k = 5$, only five ratings of each test sample user will be included in the rating matrix. We assume that the higher k , the more accurate the user embedding, which may be interpreted as a mathematical description of that user's movie preferences. The affinity prediction quality and thus the targeting lift should increase with k . The k ratings to include for each user will be selected randomly and we will cycle through a number of iterations to account for random effects on targeting efficiency.

Because we aim to predict a binary variable (each respondent will either select the target movie or not), we will binarize the matrix and use so-called implicit-feedback matrix factorization (Koren et al. 2009). To transform the matrix to binary notation, each rating ≥ 4 is interpreted as 1, all other ratings as 0. When a user in the training sample has selected one of the target movies in the fictitious cinema program, this is also represented as 1, else 0. For the respondents in the test sample, their selections in the fictitious cinema program are disregarded: These are exactly the interactions which we want to predict, thus they cannot be included in the rating matrix upon which the predictions will be based.

So for each targeting iteration, the ratings matrix R consists of: 1) all 49,416 explicit movie ratings by respondents with incomplete profiles, 2) 14,813 explicit movie ratings by respondents in the training sample, 3) 353 "artificial" movie ratings by respondents in the training sample, each a "1", denoting which movie

4 Evidence-Based Target Audience Definitions and Revenue Prediction

they selected in the fictitious cinema program, and finally 4) $347 \times k$ explicit movie ratings by respondents in the test sample (k ratings selected randomly for each respondent in the test sample). In the following description of the algorithm (algorithm 6), rating sets 1) through 3) will be referred to collectively as the base ratings matrix.

Implicit-feedback matrix factorization owes its name to the fact that such binary matrices can be easily generated from implicit feedback, e.g. a user clicking on a certain movie on a website (1) or not (0). Yet in our case, we employ the technique to analyze explicit feedback, as the respondents explicitly rate the movies, which we have just binarized to conform to the nature of the underlying targeting problem more closely.

We will use the implementation of alternating least squares (ALS) matrix factorization in the Recommenderlab R package (Hahsler 2020). ALS matrix factorization has been consistently shown to produce very good movie recommendations (Koren et al. 2009). As detailed in section 4.1, one can manually set a rank d , i.e. a number of dimensions for the embeddings. Values between 10 and 250 have yielded useful results in the past (Rackaitis 2019). The standard procedure to determine a number of dimensions is cross-validation, but as this would be too computationally expensive here and matrix factorizations of movie ratings have worked well with as few as ten dimensions in the past (Ruhrländer, Boissier & Uflacker 2018), we will settle for $d = 15$ dimensions here.

The matrix factorization results in the two embedding matrices U and V . We can then compute the predicted ratings for each respondent j in the test sample and each target movie i as the dot product $U_j \cdot V_i$ of the respective user and movie embedding vectors. To select a target audience for movie m , we will compute this product for m and all respondents in the test set, and then select the 10 per cent of respondents with the highest value. Algorithm 6 shows the step-by-step procedure in pseudo-code. Obviously, there is a random element to the algorithm when it comes to sampling k past ratings, so we will repeat the procedure several (10) times over and take the mean of the obtained top-decile lift scores as our final lift value.

As we asked all respondents to rate at least 30 movies, we will first look at targeting results for $k = 30$ and then repeat the procedure with different values for k .

As we can see from the targeting results for $k = 30$ in Table 4.18, this targeting

4 Evidence-Based Target Audience Definitions and Revenue Prediction

Data: target movie m , number of past movie ratings k

Result: target audience for target movie m and number of past movie ratings k

randomly select k ratings from each user in test sample;

combine these ratings with base ratings matrix to ratings matrix R ;

compute embeddings matrices U and V from R using ALS algorithm;

for each user u in test set **do**

 compute dot product of target movie m 's embedding vector V_m and user embedding vector U_u ;

 save as predicted rating $s(m, u)$ for movie m and respondent u ;

end

rank all respondents in test sample by $s(m)$;

select the highest ranked 10 per cent of respondents as target audience

$A(m, k)$;

Algorithm 6: Matrix-factorization targeting method using k past ratings from online survey data

method yields lift values greater than 1 for 8 out of 8 target movies. The likelihood of such a result to occur randomly is $p < 0.003906$, which is highly significant, so we can confirm [H6a](#) and conclude that targeting by predicted movie-user-affinity based on past movie ratings is indeed more efficient than random targeting. In addition, the mean (median) lift is 1.98 (1.50), which is higher than both the lift values of the demographic targeting methods and the genre-based targeting discussed above.

Title	matrix_factorization_lift
GHOST IN THE SHELL	1.44
SMURFS: THE LOST VILLAGE	4.46
POWER RANGERS	1.54
FREE FIRE	1.83
THE FOUNDER	1.47
LOMMBOCK	1.25
HEAVEN WILL WAIT	1.45
TIGER GIRL	2.38

Table 4.18: Lift values for matrix factorization targeting, using $k = 30$ past movie ratings

Next we will look at how results change for different values of k , ranging from $k = 2$ to $k = 50$ (if a respondent has rated less than k movies, all that user's ratings will be included in all iterations of the matrix factorization). [Figure 4.42](#) shows the results for all eight target movies in one graph, with a linear fit line for each movie to indicate the trend.

We can immediately see that the general trend is in line with our reasoning: the more past movie preferences we know from our target users, the more efficiently

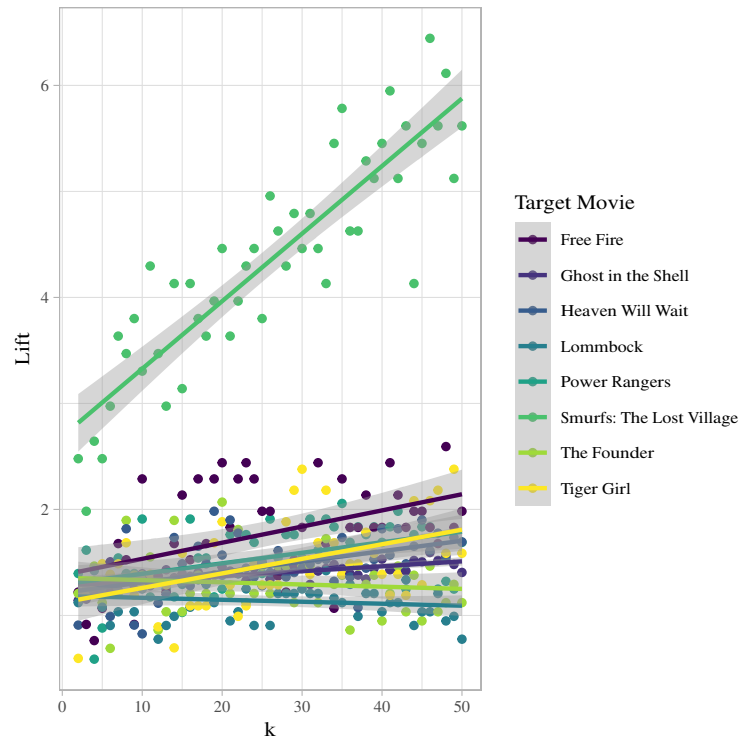


Figure 4.42: Lift of matrix factorization targeting for different numbers of past rated movies k

we can identify those who will actually choose the movie in question. Yet the effect does not seem to be equally strong for all movies. To check whether it is significant, we perform a standard OLS regression, taking the target movie into account as a categorical variable.

As displayed in [Table 4.19](#), the model explains 85% of the variance in lift, and the number of past rated movies k has a highly significant positive impact ($p < 0.001$) on targeting lift. Thus we may also confirm [H6b](#) and conclude that targeting by predicted movie-user-affinity based on past movie ratings gets in fact more efficient with an increasing number of available movie ratings for each user from the past, although we should qualify that finding with the caveat that the predicted effect could not be observed for all target movies alike.

When we compare targeting based on matrix factorization to demographics- and genre-based targeting, as in [Figure 4.43](#) through [Figure 4.50](#), matrix factorization targeting becomes the most efficient targeting method for 5 out of 8 movies when a certain number of past movie ratings are available. For POWER RANGERS, genre-based targeting is more efficient, for THE FOUNDER, gender-based targeting works best, and for LOMMBOCK, both methods prove superior

4 Evidence-Based Target Audience Definitions and Revenue Prediction

	Coefficient
(Intercept)	1.41*** (0.07)
k	0.01*** (0.00)
GHOST IN THE SHELL	-0.38*** (0.08)
HEAVEN WILL WAIT	-0.31*** (0.08)
LOMMBOCK	-0.64*** (0.08)
POWER RANGERS	-0.23** (0.08)
SMURFS: THE LOST VILLAGE	2.57*** (0.08)
THE FOUNDER	-0.48*** (0.08)
TIGER GIRL	-0.30*** (0.08)
R ²	0.85
Adj. R ²	0.85
Num. obs.	392

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 4.19: Linear regression results for lift explained by number of past rated movies k

to matrix-factorization-based targeting, which even seems to get worse with an increasing number of past rated movies, in this case. A possible reason could be that the "taste profile" of movies for which matrix factorization-based targeting underperforms, i.e. the logic of who they likely appeal to, might have been captured poorly by the ratings in the first place. Compared to large online platforms such as MovieLens or Moviepilot, let alone Netflix, we operate on a much smaller scale of rating numbers here, and a few outlier ratings may already lead the algorithm to a false conclusion about a movie's appeal.

To assess whether this explanation is reasonable, we can try to better understand how well the algorithm has categorized each movie in terms of what users it appeals to. The 15-dimensional movie embedding can be thought of as a positioning of the movie in a 15-dimensional space (similar to the 2-dimensional space depicted in [Figure 4.3](#)), wherein each dimension represents a latent movie trait, which need not necessarily be human-understandable. But in absence of clear natural language terms to describe the area of this "taste space" in which the movie has been situated by the algorithm, we can look at the nearest neighbors, i.e. other movies that are deemed similar by the algorithm. "Similar"

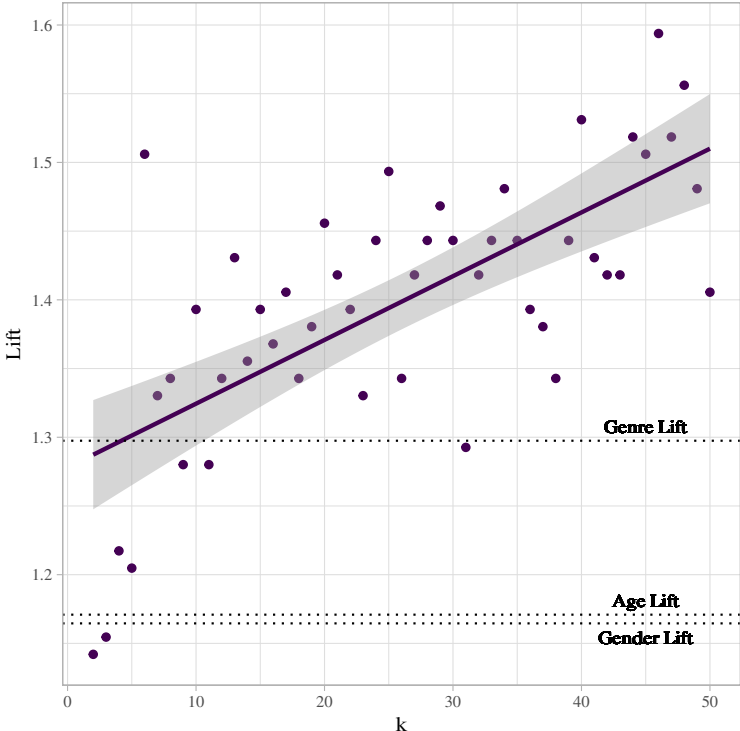


Figure 4.43: Lift of matrix factorization targeting for GHOST IN THE SHELL, using different numbers of past rated movies k , compared to other targeting methods

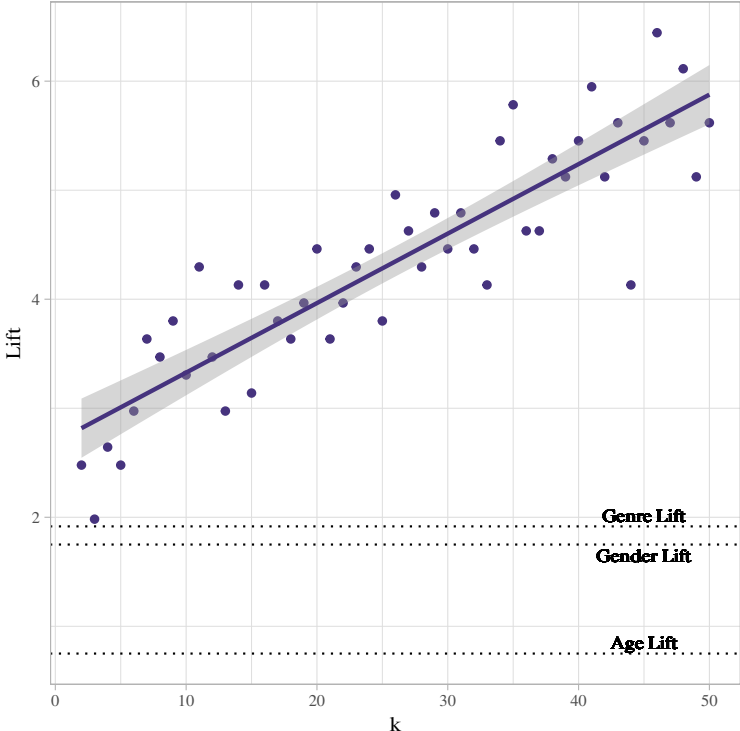


Figure 4.44: Lift of matrix factorization targeting for SMURFS: THE LOST VILLAGE, using different numbers of past rated movies k , compared to other targeting methods

4 Evidence-Based Target Audience Definitions and Revenue Prediction

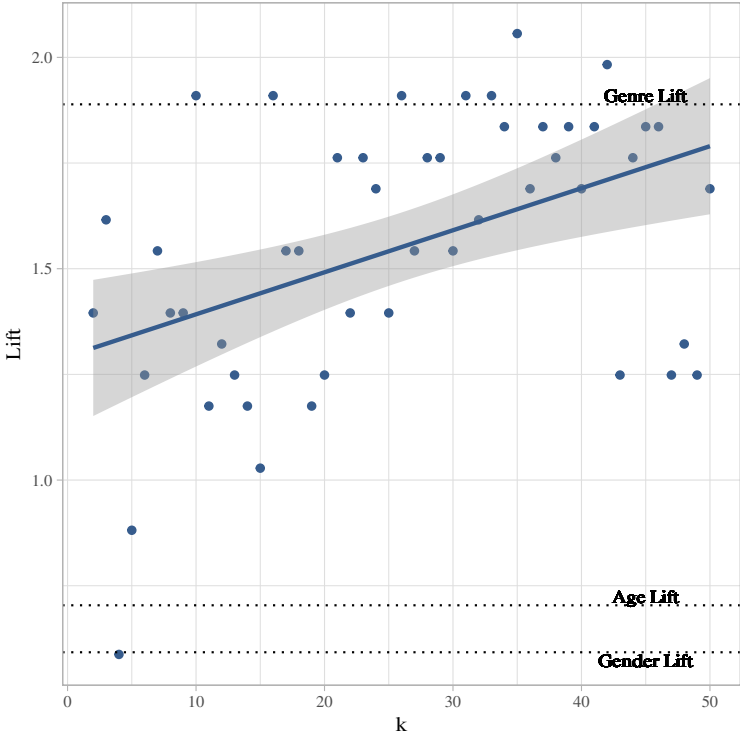


Figure 4.45: Lift of matrix factorization targeting for POWER RANGERS, using different numbers of past rated movies k , compared to other targeting methods

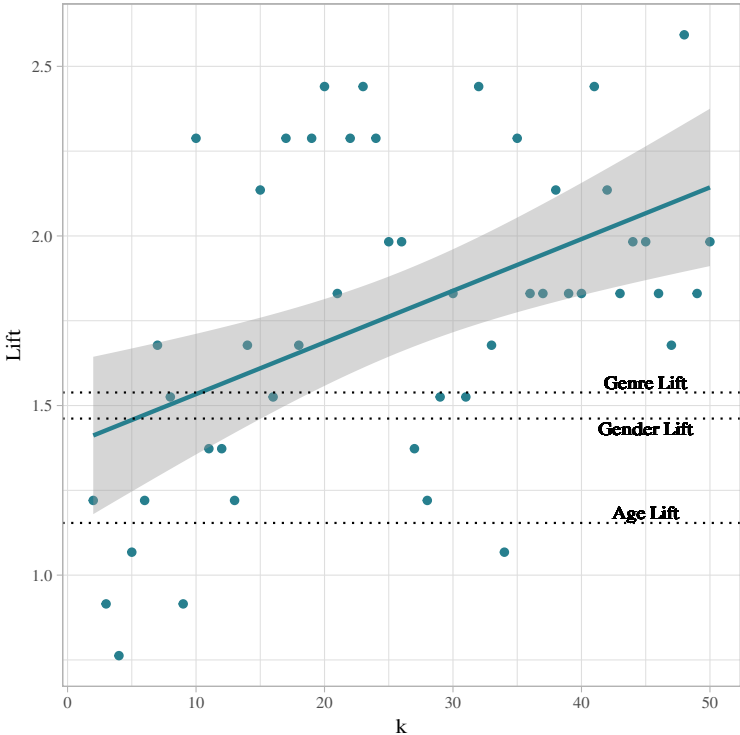


Figure 4.46: Lift of matrix factorization targeting for FREE FIRE, using different numbers of past rated movies k , compared to other targeting methods

4 Evidence-Based Target Audience Definitions and Revenue Prediction

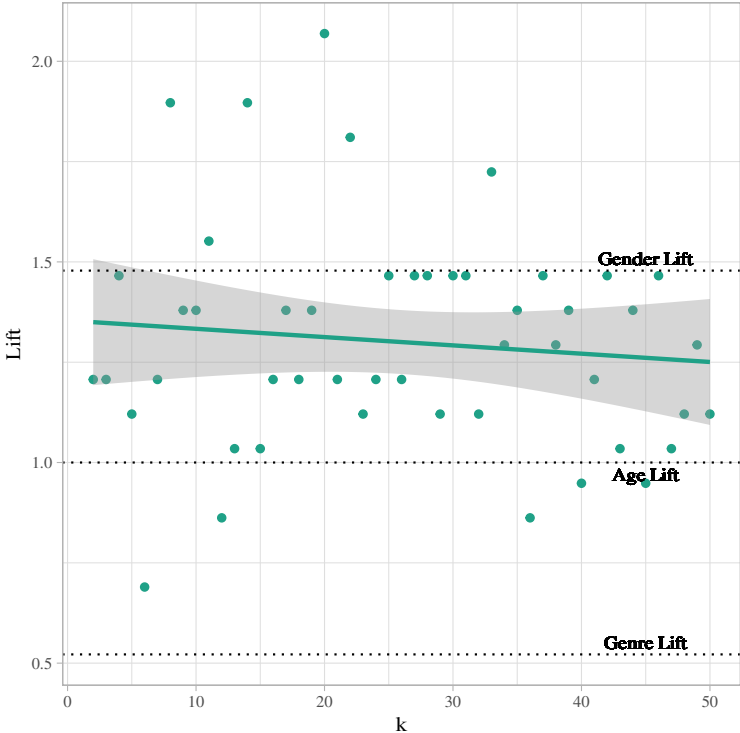


Figure 4.47: Lift of matrix factorization targeting for THE FOUNDER, using different numbers of past rated movies k , compared to other targeting methods

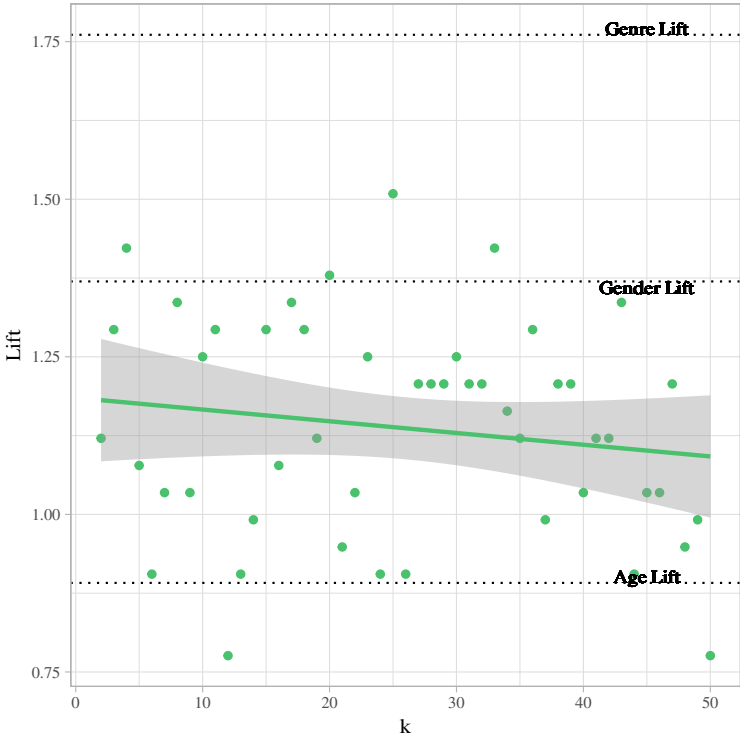


Figure 4.48: Lift of matrix factorization targeting for LOMMBOCK, using different numbers of past rated movies k , compared to other targeting methods

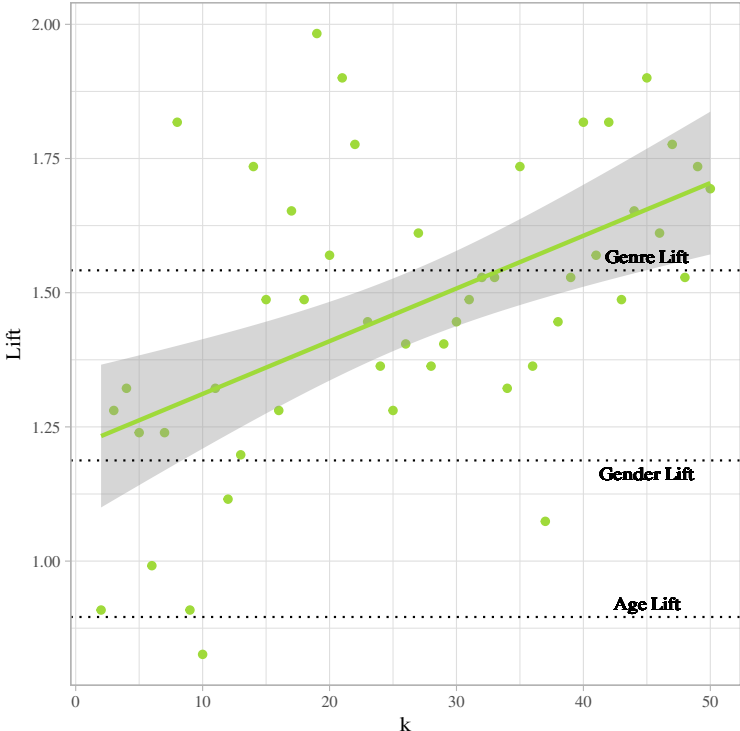


Figure 4.49: Lift of matrix factorization targeting for HEAVEN WILL WAIT, using different numbers of past rated movies k , compared to other targeting methods

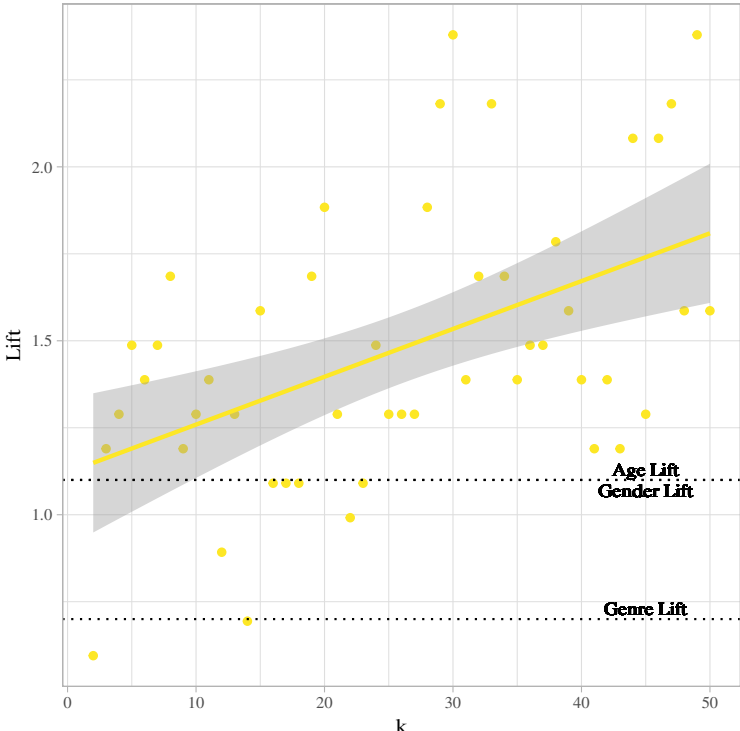


Figure 4.50: Lift of matrix factorization targeting for TIGER GIRL, using different numbers of past rated movies k , compared to other targeting methods

4 Evidence-Based Target Audience Definitions and Revenue Prediction

movies in this sense mean movies that appeal to the same moviegoers. The nearest neighbors for each movie are those movies for which the dot product of the respective embedding vectors is highest. [Table 4.20](#) shows the five most similar movies according to the matrix factorization algorithm for each of the eight targeting movies.

We can now compare this to human intuition about movie similarity. Of course, this is not an exact scientific method, but as we take advantage of the vast implicit contextual knowledge we all have as lifelong movie consumers, some basic reasoning can at least help to uncover weaknesses in the mathematical models. Looking at [Table 4.20](#), it seems like the embedding quality is indeed different for different movies: GHOST IN THE SHELL has been understandably clustered with other slightly cerebral, yet action-heavy science fiction films such as ELYSIUM and SOURCE CODE. Among the most similar movies to SMURFS: THE LOST VILLAGE are two more animation films (RIO, PUSS IN BOOTS), and TIGER GIRL has been deemed similar to female-led arthouse fare such as BLACK SWAN and MELANCHOLIA. Yet on the other hand, German comedy LOMMBOCK finds itself situated next to movies as different as fantasy blockbuster THE HOBBIT: AN UNEXPECTED JOURNEY and science fiction thought experiment LIMITLESS, which renders the comparably poor performance of the targeting algorithm in this case rather unsurprising.

We will further explore the clustering potential of these embeddings in [section 4.5](#). At this point, we are able to confirm both our hypotheses as proposed in [subsection 4.4.1](#) and to state that targeting by predicted movie-user-affinity based on past preferential movie ratings is an efficient targeting method, which is not only more efficient than random targeting, but also increasingly efficient with a rising number of available movie ratings for each user from the past.

4 Evidence-Based Target Audience Definitions and Revenue Prediction

Target Movie	Similar Movies
GHOST IN THE SHELL	CLOUD ATLAS
	PROMETHEUS
	SOURCE CODE
	ELYSIUM
	127 HOURS
SMURFS: THE LOST VILLAGE	THE TWILIGHT SAGA: BREAKING DAWN - PART 2
	PUSS IN BOOTS
	RIO
	THE TWILIGHT SAGA: BREAKING DAWN - PART 1
POWER RANGERS	SNOW WHITE AND THE HUNTSMAN
	THE AVENGERS
	CAPTAIN AMERICA: THE FIRST AVENGER
	IRON MAN 3
	MISSION: IMPOSSIBLE - GHOST PROTOCOL
FREE FIRE	FROZEN
	DRIVE
	MONEYBALL
	ARGO
	PRISONERS
THE FOUNDER	THE DARK KNIGHT RISES
	TRUE GRIT
	THE KING'S SPEECH
	LIFE OF PI
	DRIVE
LOMMBOCK	MONEYBALL
	THE HOBBIT: AN UNEXPECTED JOURNEY
	LIMITLESS
	CARNAGE
	SHERLOCK HOLMES: A GAME OF SHADOWS
HEAVEN WILL WAIT	DRIVE
	THE PERKS OF BEING A WALLFLOWER
	THE GIRL WITH THE DRAGON TATTOO
	BLACK SWAN
	CARNAGE
TIGER GIRL	THE GREAT GATSBY
	MOONRISE KINGDOM
	DRIVE
	BLACK SWAN
	MELANCHOLIA
	WRECK-IT RALPH

Table 4.20: Five most similar movies in movie sample for each target movie, according to matrix factorization algorithm

4.5 Building Movie Preference Clusters

4.5.1 Hypotheses

We have shown in [section 4.2](#), [section 4.3](#), and [section 4.4](#) that it is well possible to predict individual moviegoing behavior based on past movie interactions, may they be implicit and transactional or explicit and preferential in type. We have also shown that our prediction capability and thus targeting efficiency improves with the amount of information we have on individual moviegoers.

To move from the individual to the aggregate level, we will now look whether it is possible to use such data on individual consumers' movie preferences to build meaningful clusters. Ideally, such clusters retain most of the preference information and allow us to target moviegoers based on their cluster affiliation, and at the same time provide producers with a structure to talk about target audiences as well – in a manner that is both evidence-based and understandable in human language.

In this section, we will thus examine the following hypotheses:

Hypothesis 7a *Based on past movie ratings, moviegoers can be assigned to clusters in a way that targeting by cluster affiliation is an efficient (i.e. better than random) targeting method.*

Hypothesis 7b *Targeting based on such clusters will be more efficient than targeting based on traditional genres.*

We will test these on the same dataset from the online survey that we used in [section 4.4](#).

4.5.2 Data and Analysis

For a detailed exploration of the dataset, see [subsection 4.4.3](#). For targeting purposes, we will again use the same training and test sample split as before, in order to apply any emerging pattern to a different set of data as we learned it from. Recycling the random split from [subsection 4.4.4](#) allows us to compare results directly.

4 Evidence-Based Target Audience Definitions and Revenue Prediction

At the end of [subsection 4.4.4](#), we looked at the most similar movies for each of our target movies according to the dot product of their latent space embeddings as learned by the ALS matrix factorization algorithm. In the same way we computed the similarities between those eight and all other movies, it is possible to compute similarities between all possible pairings of movies or pairings of users.

There is no easy way to manually assess the quality of user clusterings, because we do not know the respondents and their movie preferences personally and therefore cannot judge whether users that are clustered together indeed have a similar taste. Yet as movie consumers, we do have an intuitive idea of whether movies are similar to each other. Thus we will first try the clustering algorithm on movies for illustrative purposes and then move to users subsequently.

We start again with a binarized sparse ratings matrix A that consists of 1) all 49,416 explicit movie ratings by respondents with incomplete profiles, 2) 14,813 explicit movie ratings by respondents in the training sample, 3) 353 "artificial" movie ratings of the eight target movies by respondents in the training sample, denoting that the respective user chose the respective target movie, and 4) 14,092 explicit movie ratings by users in the test sample that do not pertain to target movies. This results in 78,674 ratings overall.

This matrix is then factorized by the ALS algorithm again into two embedding matrices U and V :

$$A = U \cdot V,$$

wherein U denotes the user embeddings and V the item (movie) embeddings in a latent feature space.

To obtain similarity values for all pairings of movies, we now simply compute the dot product:

$$S_{movies} = V \cdot V^T$$

The resulting 305×305 matrix S_{movies} contains a similarity value $sim_{i,j}$ for each pairing of movies i and j .

In order to use these similarity values for clustering, we have to scale them linearly so that all values are between 0 and 1. We do so by dividing the difference between each similarity value $sim_{i,j}$ and the smallest value in the

4 Evidence-Based Target Audience Definitions and Revenue Prediction

matrix $\min(sim)$ by the difference between the largest and the smallest similarity value in the matrix:

$$s_{i,j} = \frac{sim_{i,j} - \min(sim)}{\max(sim) - \min(sim)}$$

Subsequently we convert the values from similarities to distances, maintaining the scale:

$$d_{i,j} = 1 - s_{i,j}$$

On the resulting distance matrix D_{movies} we can then perform the clustering. We employ the hierarchical clustering technique, which accepts a distance matrix as its input data.

Hierarchical clustering does not come up with a fixed number of clusters by itself, but computes an entire dendrogram which can then be cut at any height to obtain n clusters which are optimized for maximum inter-cluster distance and minimum intra-cluster distance. To settle on an "ideal" number of clusters n is not a mathematically solvable task, but very much context-dependent challenge (Giordani, Ferraro & Martella 2020). We tried several goodness criteria from the literature such as Frey index (Frey & van Groenewoud 1972), C-Index (Hubert & Levin 1976), and McClain index (McClain & Rao 1975), using the comprehensive NBClust package in R (Charrad, Ghazzali, Boiteau & Niknafs 2014), but no clear trend was evident. Thus we take a strictly context-based approach to settle on a number of clusters: As we seek to find a fine-grained, data-based alternative to movie genres, it might make sense to aim for a similar number of clusters as there are popular movie genres. On TMDb, movies are labeled with 19 different genres, so we will go with 20 clusters here for illustrative purposes²³. When clustering users below, we will also examine what different choices for the number of clusters entail in terms of targeting efficiency.

We end up with 20 clusters of movies that differ in size, ranging from 4 movies in the smallest cluster and 37 in the largest. [Figure 4.51](#), [Figure 4.52](#), and [Figure 4.53](#) display the cluster affiliations for all 305 movies. Not all clusters seem to "make sense" at first sight, but the clustering is also evidently not random. Clusters such as cluster 2 and cluster 7 for example clearly appear to capture similarities of movies that are also understandable to humans.

²³ As genres can almost arbitrarily be re-combined, an actually implementable clustering of different movie segments would likely contain more clusters.

Cluster 1	Cluster 2	Cluster 3	Cluster 5	Cluster 7
Sherlock Holmes: A Game of Shadows	Moonrise Kingdom	50/50	Life of Pi	Brave
Frozen	Midnight in Paris	Drive	Gravity	Despicable Me 2
Black Swan	The King's Speech	The Girl with the Dragon Tattoo	127 Hours	Rio
The Hobbit: An Unexpected Journey	The Best Exotic Marigold Hotel	The Skin I Live In	J. Edgar	Wreck-It Ralph
The Avengers	Before Midnight	True Grit	The Fighter	Monsters University
Thor	Frances Ha	Rise of the Planet of the Apes	The Lincoln Lawyer	The Croods
Django Unchained	Inside Llewyn Davis	Another Earth	Captain Phillips	Hotel Transylvania
Silver Linings Playbook	The Hobbit: The Desolation of Smaug	Prometheus	Moneyball	Rise of the Guardians
Harry Potter and the Deathly Hallows: Part 2	Blue Jasmine	The Cabin in the Woods	The Founder	Puss in Boots
X-Men: First Class	A Dangerous Method	Let Me In	21 & Over	Cars 2
Skyfall	Carnage	Young Adult	Don Jon	Ice Age: Continental Drift
The Amazing Spider-Man	The Artist	Whip It	The Guard	Hall Pass
The Hunger Games: Catching Fire	Melancholia	Ghost in the Shell	Free Fire	
The Hunger Games	Cloud Atlas	Movie 43		
The Intouchables	Beginners			
The Twilight Saga: Breaking Dawn - Part 2	The Iron Lady	Cluster 4	Cluster 6	Cluster 8
The Twilight Saga: Breaking Dawn - Part 1	Only Lovers Left Alive	Hugo	Bridesmaids	Argo
The Dark Knight Rises	Heaven Will Wait	The Help	Magic Mike	Source Code
Crazy, Stupid, Love.	The Tree of Life	About Time	Friends with Benefits	Limitless
Dark Shadows		The Perks of Being a Wallflower	Pitch Perfect	The Adjustment Bureau
Star Trek Into Darkness		Oz the Great and Powerful	We're the Millers	Mission: Impossible - Ghost Protocol
Captain America: The First Avenger		Ruby Sparks	The Five-Year Engagement	The Debt
Thor: The Dark World		Wer's glaubt wird selig	Hysteria	Haywire
Snow White and the Huntsman		To Rome with Love	RED 2	
Iron Man 3			This Means War	
Man of Steel			Fly Me to the Moon	
Project X			This Means War	
Power Rangers				
Here Comes the Boom				

Figure 4.51: Movie clusters based on preferential data (1/3)

Cluster 9 21 Jump Street Ted 00 Schneider - Im Wendekreis der Eidechse Lommbock American Reunion Die Superbullen Das Hochzeitsvideo Johnny English Reborn Zettl Something Borrowed	Cluster 11 Frau Ella Turkish for Beginners Men in the City 2 Scary Movie 5 Break Up Man Kokowääh Suck Me Shakespeer Russendisko Grown Ups 2 Woman in Love What a Man	Cluster 12 Trophy Wife Frisch gepresst Salmon Fishing in the Yemen Asterix & Obelix: God Save Britannia Love Is All You Need A Thousand Words Morning Glory	Cluster 14 Eine ganz heiße Nummer Buddy Offroad When Inge Is Dancing Resturlaub Agent Ranjid rettet die Welt Red Riding Hood Pigeons on the Roof Vatertage - Opa über Nacht Jonas Kein Sex ist auch keine Lösung Bachelorette Last Vegas Welcome to the South
Cluster 10 On the Other Side of the Tracks In Time Pirates of the Caribbean: On Stranger Tides Eine Insel namens Udo Elysium Oblivion Super 8 The Hangover Part II Now You See Me Horrible Bosses Men in Black 3 World War Z TRON: Legacy Pacific Rim Arschkalt We Bought a Zoo The Internship	Hope Springs Kokowääh 2 Almania: Welcome to Germany Men Do what Men Can How Do You Know Sushi in Suhl I Give It a Year Paulette Chalet Girl LOL Heartbreaker One for the Money Nothing to Declare Big Mommas: Like Father, Like Son Wanderlust Le Chef Jesus liebt mich Quality Time Partly Sunny	Cluster 13 The Bourne Legacy The Dictator Unknown The Next Three Days Fast Five Taken 2 The Expendables 2 Jack Reacher The Place Beyond the Pines The Green Hornet Kick-Ass 2 End of Watch Side Effects Rango Seven Psychopaths Paul The Adventures of Tintin This Is the End The World's End Kung Fu Panda 2 My Life in Orange Larry Crowne The Pursuit of Unhappiness	Beautiful Lies The Infidel A Few Best Men Playing for Keeps Hyde Park on Hudson The Woman in Black Shark Alarm at Müggel Lake Tiger Girl Was weg is, is weg The Bling Ring Parental Guidance Omamamia

Figure 4.52: Movie clusters based on preferential data (2/3)

<p>Cluster 15 The Great Gatsby Flight The Ides of March The Descendants Contagion Tinker Tailor Soldier Spy Zero Dark Thirty Lincoln Winter's Bone Prisoners The Grey The Way Back The Raid</p>	<p>Cluster 17 John Carter Rush War Horse Fast & Furious 6</p>	<p>Cluster 19 This Is 40 Bad Teacher Our Idiot Brother King Ordinary Jeff, Who Lives at Home The Hangover Part III Cedar Rapids Zookeeper Jackass Presents: Bad Grandpa The Dilemma Jack and Jill I Don't Know How She Does It Gulliver's Travels Arthur</p>	<p>Cluster 20 The Change-Up New Year's Eve Love & Other Drugs Mr. Popper's Penguins Delivery Man Monte Carlo What's Your Number? Gambit Happiness Never Comes Alone What's in a Name Starbuck New Kids Turbo New Kids Nitro The Family The Watch A Haunted House Quartet The Big Wedding That's My Boy</p>
<p>Cluster 16 Chronicle Sucker Punch Transformers: Dark of the Moon Green Lantern Total Recall Ender's Game Real Steel The Wolverine Hanna Dredd Cowboys & Aliens Riddick</p>	<p>Cluster 18 Les Misérables Smurfs: The Lost Village The Muppets I Am Number Four Warm Bodies No Strings Attached The Conjuring Identity Thief Tucker and Dale vs. Evil The Heat Insidious Margin Call Battle: Los Angeles</p>	<p>Just Go with It 30 Minutes or Less The Incredible Burt Wonderstone The Guilt Trip What to Expect When You're Expecting</p>	

Figure 4.53: MMovie clusters based on preferential data (3/3)

4 Evidence-Based Target Audience Definitions and Revenue Prediction

As mentioned before, we will now proceed to cluster respondents using the same technique. Clustering movies only served illustrative purposes to shine some light on how this procedure may find meaningful groupings of items on the available data without requiring any input on movie content or respondent traits, simply inferring similarities from underlying patterns in the respondents' movie rating behavior.

To obtain user clusters, we first compute a user similarity matrix S_{users} as the dot product of the user embeddings matrix and the transformed user embeddings matrix:

$$S_{users} = U \cdot U^T$$

Then we scale the similarity values and convert them to distances as before, ending up with a $2,186 \times 2,186$ matrix D_{users} of user-to-user-distances.

Hierarchical clustering yields 20 clusters of the sizes depicted in [Table 4.21](#). We can now affiliate each respondent in both training and test sample with one of these 20 clusters. Thus we can use the cluster affiliation as a targeting criterion similar to a demographic grouping such as an age or gender group in [subsection 4.4.4](#) and learn from the training sample in which clusters the prevalence for each target movie is highest. The resulting targeting model assigns each pairing of target movie m and respondent r from cluster C_r the affinity score $s(m, r)$:

$$s(m, r) = \frac{|W_m \cap C_r \cap S_{train}|}{|C_r \cap S_{train}|},$$

where W_m denotes the set of all respondents that have viewed m and S_{train} is the set of all respondents in the training sample. The corresponding target audience definition procedure is detailed in [algorithm 7](#)

Data: Target movie m , target percentage p

Result: Target audience A for m at target percentage p

compute cluster affinity score $s(m, r)$ for each targetable respondent r ;

rank targetable respondents by affinity score $s(m, r)$;

define top $p * 100$ percentiles of ranked targetable respondents as target audience $A(m, p)$ (if there are ties, select randomly);

Algorithm 7: Target audience definition method for cluster-based targeting

For evaluation, we will again select ten per cent of respondents in the test set as our target audience each and compare the relative frequency of watching the target movie among that target audience with the prevalence in the entire test sample (top-decile lift).

4 Evidence-Based Target Audience Definitions and Revenue Prediction

Cluster	# of Respondents
1	84
2	292
3	72
4	75
5	145
6	186
7	163
8	70
9	142
10	142
11	67
12	39
13	112
14	73
15	111
16	68
17	139
18	83
19	60
20	63

Table 4.21: Number of respondents per cluster

The mean (median) lift across all eight target movies is 1.65 (1.51). [Table 4.22](#) shows the detailed results. The lift is higher than 1.0 in 7 out of 8 cases, which is statistically significant ($p < 0.05$). Thus we can confirm [H7a](#): Based on past movie ratings, moviegoers can indeed be assigned to clusters in a way that targeting by cluster affiliation is an efficient (i.e. better than random) targeting method.

Title	cluster_lift
GHOST IN THE SHELL	1.32
SMURFS: THE LOST VILLAGE	2.75
POWER RANGERS	1.00
FREE FIRE	1.31
THE FOUNDER	1.26
LOMMBOCK	2.04
HEAVEN WILL WAIT	1.85
TIGER GIRL	1.70

Table 4.22: Lift values for cluster targeting method, $n = 20$

Now we will look into how a different number of clusters would have impacted results. Therefore we repeat the exact same procedure several times, only varying the number of clusters n . [Figure 4.54](#) displays the mean lift values for different numbers of clusters. While they are > 1.0 across the board, the targeting

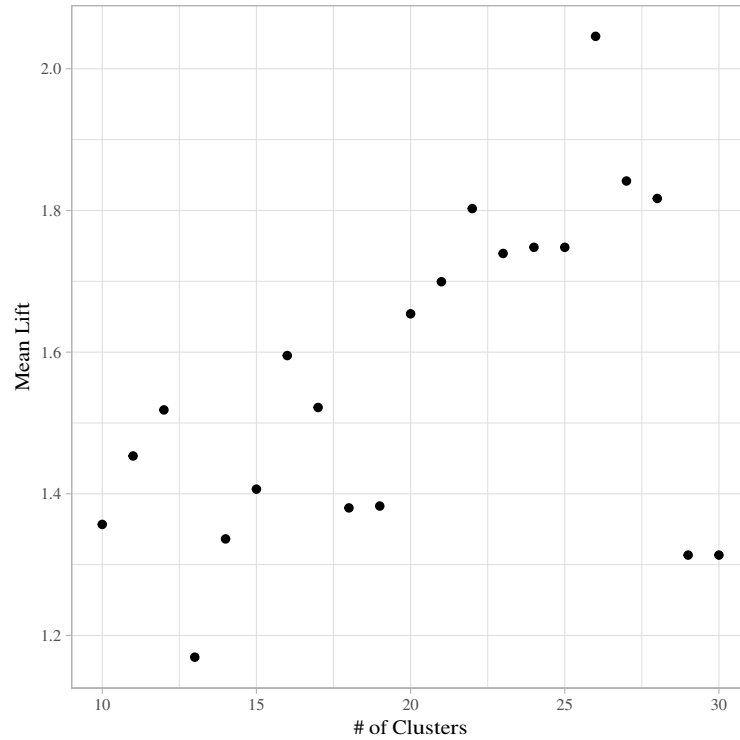


Figure 4.54: Lift for cluster targeting using different numbers of clusters n

quality evidently depends on the choice of n . There would have been no way for us to infer that $n = 26$ would yield the best results predicting the audience for our target movies, yet it is well conceivable that such a system could be devised on a sample that is representative for the entire moviegoing population, and then be tuned with hundreds of target movies to determine clusters which consistently yield efficient targeting results.

To test H7b, we compare the results to those of our genre-based targeting algorithm from subsection 4.4.4. Table 4.23 shows the lift values for all eight target movies side-by-side.

Title	genre_lift	cluster_lift
GHOST IN THE SHELL	1.30	1.32
SMURFS: THE LOST VILLAGE	1.92	2.75
POWER RANGERS	1.89	1.00
FREE FIRE	1.54	1.31
THE FOUNDER	0.52	1.26
LOMMBOCK	1.76	2.04
HEAVEN WILL WAIT	1.54	1.85
TIGER GIRL	0.70	1.70

Table 4.23: Lift values for cluster-based targeting and genre-based targeting on a per-film basis

4 Evidence-Based Target Audience Definitions and Revenue Prediction

The mean lift of cluster-based targeting is higher than the mean lift value of the genre-based targeting method (1.65 vs. 1.40). As discussed above, this gets even more pronounced if we take another, more optimized number of clusters. Yet the results for the individual target movies are only better in 6 out of 8 cases, which is not significant in a simple binomial signed test. Although we still have a strong indication to believe that targeting based on data-derived clusters can yield superior results to target audience definition based on traditional genre affinities, we cannot reject the null hypothesis with sufficient statistical confidence. Thus H_7b remains unconfirmed.

As we wrap up our discussion of the online survey dataset, we may take a look at a comparison of all tested targeting algorithms as depicted in [Table 4.24](#).

Targeting Method	Mean Lift	Median Lift
Age-Based	0.96	0.95
Gender-Based	1.26	1.28
Age and Gender-Based	1.23	1.29
Genre-Based	1.40	1.54
Matrix Factorization-Based	1.98	1.50
Cluster-Based ($n = 20$)	1.65	1.51

Table 4.24: Mean and median lift values for all different targeting methods on online survey data

Predicting the affinity towards target movies for each individual respondent based on their past movie ratings with matrix factorization seems like the best approach overall, but using clusters derived from these past movie rating data yields only slightly inferior results (and, as we saw, is in most cases superior to genre-based targeting).

Such segmentation could provide the basis for a generic target audience definition framework. While it does not make sense to examine the specific 20 clusters we have found here on the online survey data in too great detail, as the data are far too unrepresentative for the clusters to extend to the general moviegoing public, we can well imagine descriptions of such clusters that make it possible for producers to judge which cluster their upcoming movie may appeal to, which would provide them with an evidence-based descriptor for their intended audiences. To do so, we may look at differences in behavior between clusters. Which movies have been consumed theatrically by which cluster? Which movies are rated higher/lower than in the general population by which cluster? How often do respondents from each cluster go to the movies? In our example clustering, we would find for example that users from cluster

14 are 4.7 times more likely to have seen MOONRISE KINGDOM in a theater than the dataset average. The next four movies in terms of over-attendance for this cluster would be MELANCHOLIA (4.57), THE WORLD'S END (4.28), INSIDE LLEWYN DAVIS (4.08), and MIDNIGHT IN PARIS (3.54). Users in this cluster go to the movies 9.72 times per year on average (by their own account, cf. caveats mentioned in [section 4.4](#)) and estimate to go alone in 12.7 per cent of cases (the average value across the entire dataset is 3.98 per cent). By contrast, the two most over-attended movies in cluster 20 are German comedies BREAK UP MAN (12.2 times more likely than in the entire dataset) and KOKOWÄÄH (11.6). Users in this cluster estimate the number of their annual cinema attendances to be 5.67, and go alone in less than 1 per cent of cases. Among our dataset, there are 73 users in cluster 14 and 63 users in cluster 20.

Such data can help producers to intuit both who is their audience and how many audience members there are to target their film to (target audience definition and revenue prediction). In contrast to segmentation methods discussed in [subsection 3.2.4](#), clusters are built on actual movie preferences directly, clustering together users who preferred similar films in the past and are likely to also make similar consumption choices in the future. Building such a segmentation on a representative dataset, preferably one that captures data in a longitudinal study, is definitely a promising research objective moving forward (cf. [chapter 5](#)).

4.6 Revenue Prediction

4.6.1 Research Objective

In sections [4.2-4.5](#) we have demonstrated different ways to model film preferences in order to answer the question of *who* will be interested in a certain movie, i.e. we have focused on target audience definition. Now we will turn to predicting *how many* viewers can be reached by a certain movie.

As discussed in [section 3.4](#), the questions of *who* and *how many*, i.e. target audience definition and revenue prediction, have been largely treated independently of one another in heretofore published literature, with the respective branches of research often referred to as the "psychological" and the "economic" approach. Building on what we have found out about movie preferences and how movie attendance behavior is (partly) determined by these underlying

4 Evidence-Based Target Audience Definitions and Revenue Prediction

preferences, several paths of reconciling these two approaches are conceivable.

One possibility would be modeling the individual moviegoing behavior either on the census level or on a representative sample. This approach was pioneered by Ruhrländer et al. (2018) who – lacking a representative sample – used the MovieLens dataset to predict individual moviegoing decisions of thousands of users and then estimated a weighing function to combine individual predicted decisions into a revenue forecast. Results were very promising and outperformed prediction models from the classic economic approach that work purely on the aggregate level.

Another approach builds on the cluster targeting idea examined in [section 4.5](#). Provided qualitative descriptions of well-defined moviegoer segments along with personas (Cooper 1999) and typical past moviegoing histories, producers could estimate likely affinities of these segments relative to other films and then, given the relative box office importance of these clusters, derive an estimated guess of their own movie's audience potential, which would be evidence-based and could be used convincingly during fundraising (cf. [subsection 2.2.2](#)). We deem this approach very promising, as it does not demand high levels of data literacy from individual producers, and the more demanding analytical tasks of determining and describing the clusters must only be performed once, which could be done on an institutional level (cf. [chapter 5](#)). Yet this approach cannot be pursued within the scope of this dissertation due to the lack of representative data.

Yet another, simpler method of incorporating the idea of different movie preferences into the process of box office prediction is niche-specific modeling: In [section 3.4](#), we have identified a common misconception in econometric box office forecasting literature: All movies are mostly being treated equally, notwithstanding the fact that past research has shown genre-specific models to yield superior results (Hennig-Thurau & Wruck 2000, Antipov & Pokryshevkaya 2011). Estimating regression models on a sample of very different movies implicitly assumes that there are common rules for box office success that hold true across a variety of different movies. From such models, we can only expect very generic statements, such as "higher budgets lead to higher revenues", whereas more niche-specific patterns will go undetected. Lovallo et al. (2012) have shown similarity-based forecasting to yield superior results compared to regression models, using manually assigned similarity scores. The measures of movie similarity explored in sections [4.2](#)[4.5](#) can provide a novel way to define niches

of similar movies for which niche-specific rules may then be inferred. In the following sections, we will try to do this and examine whether such niche-specific models lead to superior results compared to a generic regression model that applies to all movies.

4.6.2 Data

For the prediction task, we are going to employ a very simple linear regression model using the most common predictors for financial movie success as discussed in [section 3.3](#): budget, cast popularity, director popularity, and genre.

Because of superior data availability, we focus exclusively on movies that were released in the United States of America. Most of the data collection (except for MovieLens data) was done in fall 2015. Because the Google Trends data, as discussed below, start in 2004, we limited our scope to films released between January 2004 and June 2015.

Budget and revenue data were obtained from Box Office Mojo²⁴. For revenues, we focused on cumulative domestic revenues, i.e. earnings in cinemas across the North American market (US/Canada) during the entirety of the movie's theatrical run.

Director and cast for each movie as well as genres and MPAA ratings were obtained from the The Open Movie Database (OMDb) via the OMDb API, using 18 genres (Action, Adventure, Animation, Comedy, Crime, Documentary, Drama, Family, Fantasy, History, Horror, Music, Mystery, Romance, Science Fiction, Thriller, War, Western).

We use online search volume as a measure for cast and director popularity at the point of a movie's initial release. To do so, we crawled weekly historical interest data from Google and Wikipedia for the director and the first four cast members of each film. Usually the first four actors provided by the OMDb API are also the first four actors in the film's credits, which generally encompasses the most popular actors as long as they play a major role.

Google provides the "Google Trends" tool to assess a specific search term's popularity (as measured by search volume) over time. For each search term (in our case the full name of the respective actor or director) and time frame,

²⁴ <https://boxofficemojo.com>

4 Evidence-Based Target Audience Definitions and Revenue Prediction

it provides a sequence of weekly measurements on a scale between 0 and 100. A value of 100 always denotes the week during the respective time frame in which the popular interest was greatest. A value of 50 means there were half as many search queries during that week as in the week with the largest volume, and a value of 0 means there were too few queries to assign a value on the scale altogether. Given these historical values, one can well assess how public interest in each cast or crew member varied over time, but not how their appeal compared to other stars or directors.

To make different actors and directors comparable with one another, we need to calibrate the relative scale with an absolute value, which we obtain from Wikipedia usage statistics: For each actor and director, we take the number of cumulative page hits on that person's Wikipedia entry during October 2015 and, for each past week, multiply said number with that respective week's Google Trends value divided by the Google Trends value for the last week of October 2015. This way, we get a popularity value for each actor and director for each week between January 2004 and October 2015. If an actor or director has a Google Trends value of 0 during the last week of the observation period, we replace that 0 by 1 to avoid division by 0.

For each movie, we then take the highest out of the values for the first four actors during the week exactly 6 months prior to the movie's release date as a measurement of cast popularity and that same week's value for the director's popularity. The lag between popularity measurement and movie release is meant to get a more accurate assessment of the actor's or director's popularity independent of the particular movie in question, therefore we take the value at a point in time before the marketing campaign of the upcoming release really hits the public and may start to affect online search interest. For films released in the first half of 2004, we just take the earliest value we have.

Since we plan to build niche-specific models based on the movies' target audiences, we also need data to define who that target audience is for each movie. Similarly as in [subsection 4.4.4](#) and [subsection 4.5.2](#), we will look at target audiences based on individual preferential data. Therefore, we use the MovieLens 25M Dataset provided by the GroupLens Research Group at the University of Minnesota. This dataset contains 25,000,095 movie ratings on a five-star scale from the online movie recommendation service MovieLens. All data were created by 162,541 users between January 09, 1995 and November 21, 2019. For more information on the MovieLens datasets, please see Harper & Konstan (2015).

4 Evidence-Based Target Audience Definitions and Revenue Prediction

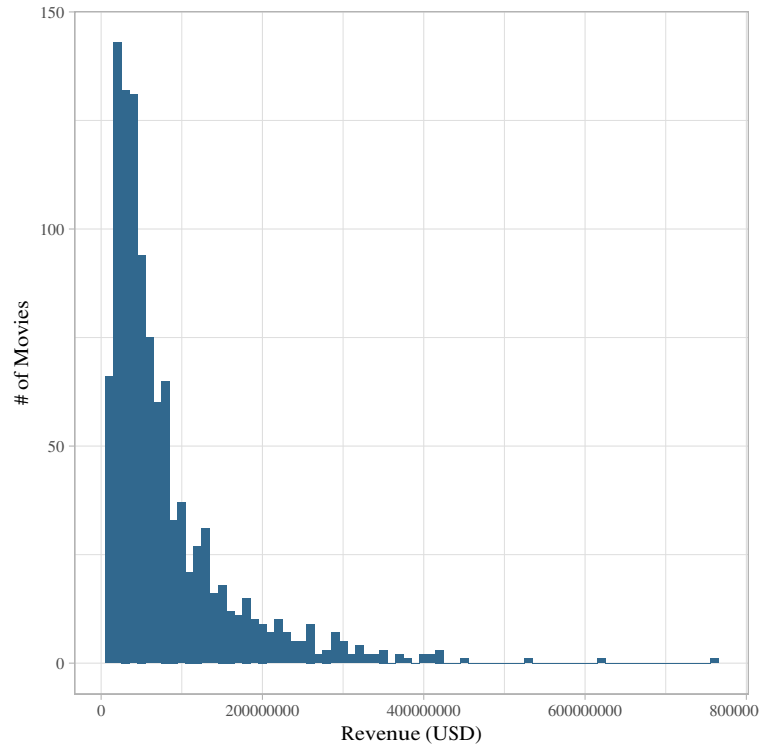


Figure 4.55: Distribution of revenues across movies in sample ($n = 1093$)

Because many smaller movies have incomplete data and also random effects may hide possible patterns for smaller movies, we will limit our analysis to movies with at least \$10 million in revenues and \$10 million in budget as well as at least 100 ratings on MovieLens.

With these restrictions applied, we were able to obtain complete data for 1,093 movies. Regarding revenues, the highest-grossing movie in the dataset is AVATAR with \$760,507,625, the lowest-grossing is THE FOUNTAIN which earned \$10,144,010. [Figure 4.55](#) displays the entire distribution, which shows the typical power law shape.

The same can be said about budgets as shown in [Figure 4.56](#). The film with the highest budget in the dataset is again AVATAR with an estimated cost of \$425,000,000. The cheapest film in the dataset is IN THE LAND OF WOMEN, which cost \$10,500,000.

The value of the popularity score as described above has no real-world unit, but is just a relative measurement. [Figure 4.57](#) shows the distribution of cast popularity among movies. The movie with the highest score overall is THE DARK KNIGHT, which is probably due to the untimely death of lead actor Heath Ledger seven months before the movie's release leading to a spike in

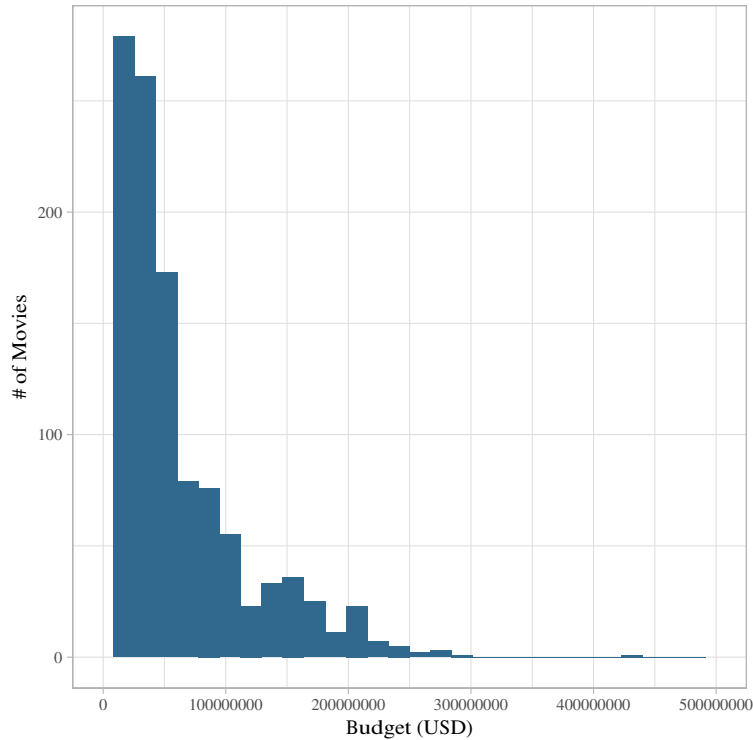


Figure 4.56: Distribution of budgets across movies in sample ($n = 1093$)

interest.

The highest director popularity score was recorded for *THE VILLAGE*, directed by M. Night Shyamalan. The distribution follows the typical power law shape as well, as can be seen in [Figure 4.58](#).

Movies in the dataset were assigned 2.79 genres on average (median: 3). 143 movies had only one genre apiece, whereas *YU-GI-OH!* was assigned as many as eight different genres. The most common genre among the movies in the dataset is "Drama" (assigned to 446 movies), the least common being "Western" (9 movies). The numbers of occurrences for all 18 genres in the dataset can be seen in [Figure 4.59](#).

Regarding age ratings, the most common rating was "PG-13", the least common one was "R". [Figure 4.60](#) displays the full distribution.

4.6.3 Analysis

As noted in [subsection 4.6.2](#), we now intend to use collaborative filtering on the individual users' rating data in the MovieLens dataset to uncover latent film similarities and thus identify a subset of similar movies for every film, on

4 Evidence-Based Target Audience Definitions and Revenue Prediction

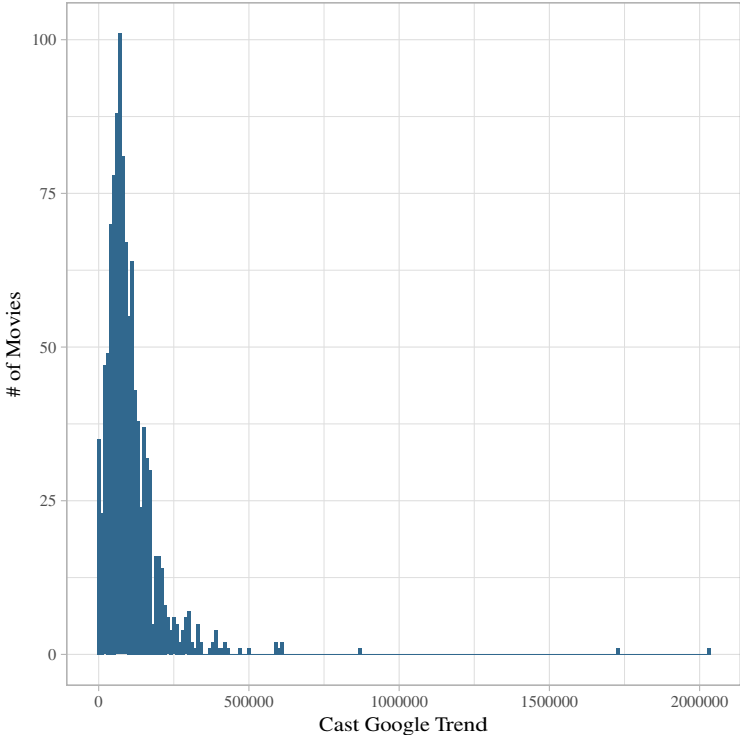


Figure 4.57: Distribution of Google Trends popularity values of the most popular cast member across movies in sample

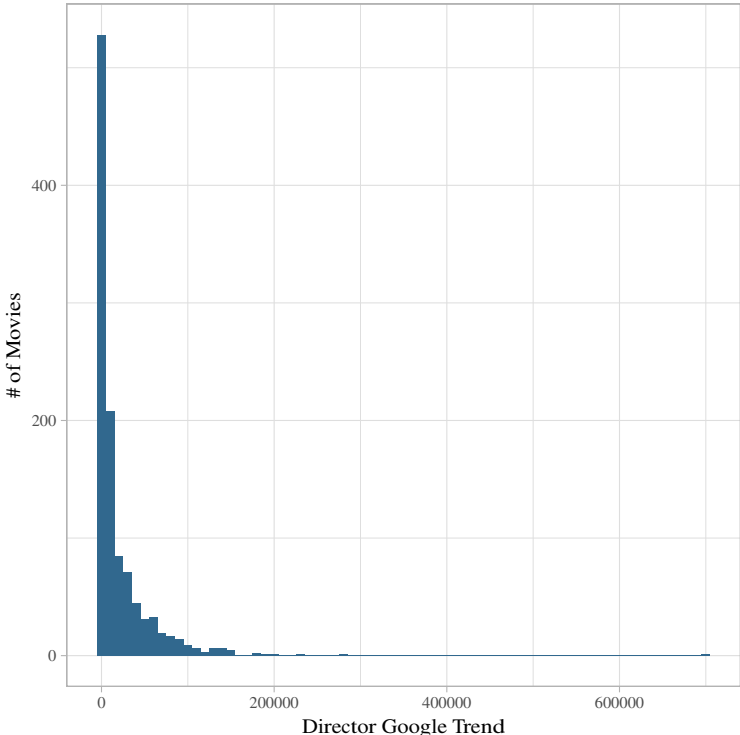


Figure 4.58: Distribution of Google Trends popularity values of the director across movies in sample

4 Evidence-Based Target Audience Definitions and Revenue Prediction

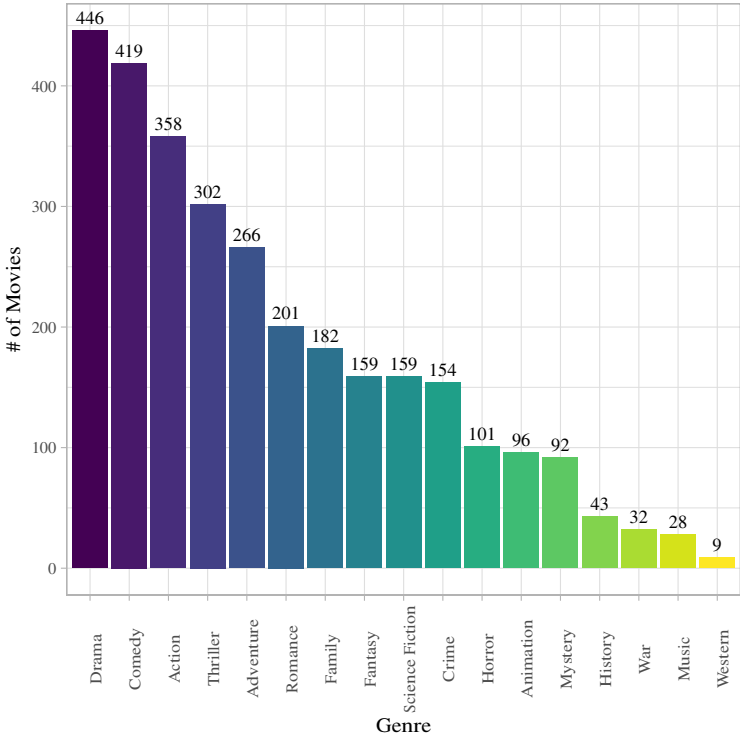


Figure 4.59: Occurences of genres across movies in sample

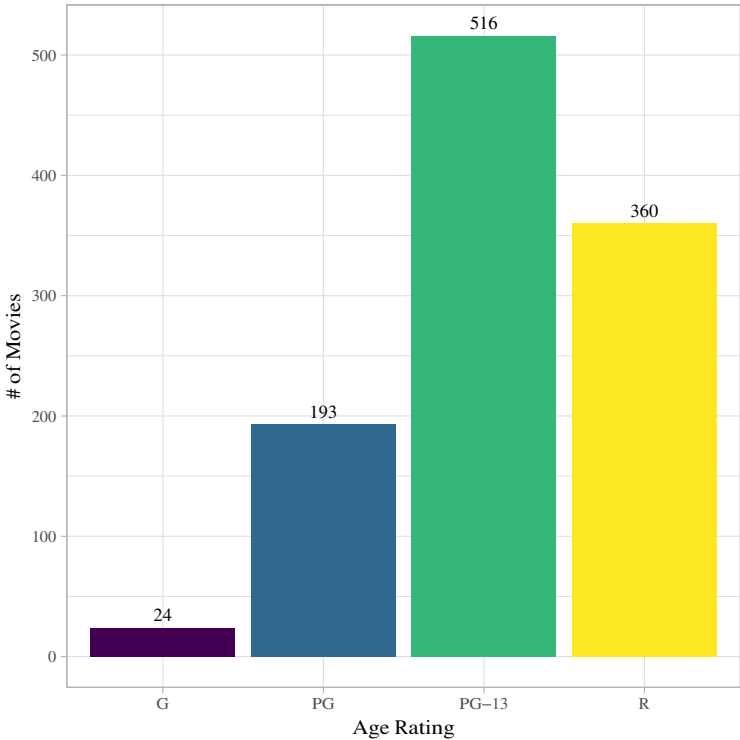


Figure 4.60: Distribution of age ratings across movies in sample

4 Evidence-Based Target Audience Definitions and Revenue Prediction

which we will subsequently learn a regression model for box office revenues specific to this respective "niche" of films.

By doing so, we implement the industry standard of "comparables" into the forecasting process, providing a well-defined similarity measure that deems two movies the more similar the more their audiences overlap.

To gauge the effectiveness of this approach, we will first estimate a benchmark model on the entire 1,093 movies in the dataset. Because of the power law distribution of the revenues variable, we will instead use the log of revenues as our dependent variable²⁵. The independent variables are *log_budget*, *log_cast_popularity*, *log_director_popularity*, a dummy variable for each genre (1 if the genre was assigned to a certain movie, 0 otherwise), a dummy variable for all but one MPAA age ratings (1 if the age rating was assigned to a certain movie, 0 otherwise, taking "R" as the baseline), and a dummy variable denoting whether the movie's original language is English (0) or any other language (1). On these data, we perform an ordinary least squares regression, the results of which are displayed in [Table 4.25](#).

The model is able to account for roughly 40 per cent of the variance among the dataset. There seems to be a large and significant influence of budget on revenues, small yet significant positive impact of director popularity, a quite strong and significant negative impact of the Action and History genres, a significant positive impact of the "PG-13" age rating, and a very strong and highly significant negative impact of any other original language but English.

The strong positive impact of budget is in line with what we expect from previous research. All age ratings but "R" having a positive impact on revenues is probably mostly indicative of the fact that R-rated movies have a smaller potential audience overall. The same logic applies to the original language considering that we look at North American box office numbers here. The influences of individual genres are not backed particularly well by previous research. We would expect these trends – just like age ratings or the impact of director popularity – to vary across different niches. While action films among these particular 1,093 movies are faring a little worse than movies with the same traits except the action would be expected to, there are certainly niches in which action clearly figures as a positive.

25 As usually done in box office modeling literature, cf. [subsection 3.3.1](#)

4 Evidence-Based Target Audience Definitions and Revenue Prediction

	<i>Dependent variable:</i>
	log_revenue
log_budget	0.667*** (0.035)
log_cast_popularity	0.010 (0.014)
log_director_popularity	0.011* (0.005)
Action	-0.194*** (0.057)
Adventure	-0.0004 (0.060)
Animation	0.050 (0.100)
Comedy	-0.014 (0.056)
Crime	-0.075 (0.068)
Drama	-0.100 (0.052)
Family	0.061 (0.112)
Fantasy	-0.100 (0.064)
History	-0.355** (0.113)
Horror	-0.014 (0.080)
Music	0.104 (0.131)
Mystery	-0.142 (0.078)
Romance	-0.106 (0.060)
Science Fiction	-0.070 (0.066)
Thriller	-0.109 (0.058)
War	0.030 (0.130)
Western	-0.209 (0.225)
G	0.080 (0.182)
PG	0.017 (0.104)
PG-13	0.109* (0.051)
non_english	-0.598* (0.277)
(Intercept)	6.007*** (0.601)
Observations	1,093
R ²	0.417
Adjusted R ²	0.404
Residual Std. Error	0.665 (df = 1068)
F Statistic	31.836*** (df = 24; 1068)

Note: *p<0.05; **p<0.01; ***p<0.001

Table 4.25: Regression results for the entire dataset of 1,093 films

4 Evidence-Based Target Audience Definitions and Revenue Prediction

We will now turn to building niche-specific models. To do so, we have to first establish a measure of movie similarity again. We will use a combination of a simple content-based similarity (minimum genre-overlap) and collaborative filtering: For each movie m , all other movies that do share at least one genre with m are deemed more similar to m than those that do not. Within both groups, movies are ranked by their similarity to m defined as the dot product of each respective movie's latent space embedding vector with the latent space embedding vector of m after performing ALS matrix factorization on the MovieLens 25M dataset to obtain a movie embeddings matrix. For the matrix factorization, we use the BiasedMF class from the Python implementation provided by LensKit (Ekstrand 2020) with explicit feedback data and 15 dimensions. The computation of the collaborative filtering similarity measure is identical to the procedure in [subsection 4.4.4](#) and [subsection 4.5.2](#), we just add the additional criterion of a minimum genre overlap to the ranking. Tables [4.26](#) and [4.27](#) show the 20 most similar movies for Wes Anderson's auteur animation feature FANTASTIC MR. FOX and young adult blockbuster THE TWILIGHT SAGA: BREAKING DAWN - PART 1, respectively, ranked by similarity as defined above.

Top 20 Similar Movies for FANTASTIC MR. FOX	
1	WHERE THE WILD THINGS ARE (2009)
2	I HEART HUCKABEES (2004)
3	BIRDMAN (2014)
4	THE LIFE AQUATIC WITH STEVE ZISSOU (2004)
5	THE GRAND BUDAPEST HOTEL (2014)
6	MOONRISE KINGDOM (2012)
7	THE FOUNTAIN (2006)
8	BURN AFTER READING (2008)
9	FRANKENWEENIE (2012)
10	THE MEN WHO STARE AT GOATS (2009)
11	YOUNG ADULT (2011)
12	CORALINE (2009)
13	THE SPONGEBOB SQUAREPANTS MOVIE (2004)
14	PARANORMAN (2012)
15	SIDEWAYS (2004)
16	THE BOXTROLLS (2014)
17	THE INFORMANT (2009)
18	WINNIE THE POOH (2011)
19	OBSERVE AND REPORT (2009)
20	WEATHER MAN, THE (2005)

Table 4.26: Similar Movies for FANTASTIC MR. FOX

Using this ranking, we can define a niche of k similar films for each movie m , which can be arbitrarily narrow, ranging from a niche of $k = 1$, only containing

Top 20 Similar Movies for THE TWILIGHT SAGA: BREAKING DAWN - PART 1	
1	THE TWILIGHT SAGA: BREAKING DAWN - PART 1 (2011)
2	THE TWILIGHT SAGA: ECLIPSE (2010)
3	THE TWILIGHT SAGA: NEW MOON (2009)
4	TWILIGHT (2008)
5	FIFTY SHADES OF GREY (2015)
6	HIGH SCHOOL MUSICAL 3: SENIOR YEAR (2008)
7	SEX AND THE CITY 2 (2010)
8	SEX AND THE CITY (2008)
9	HANNAH MONTANA: THE MOVIE (2009)
10	THE HUNGER GAMES: MOCKINGJAY - PART 1 (2014)
11	STEP UP 3D (2010)
12	INSURGENT (2015)
13	THE HUNGER GAMES: CATCHING FIRE (2013)
14	DIVERGENT (2014)
15	STEP UP REVOLUTION (2012)
16	BEVERLY HILLS CHIHUAHUA (2008)
17	THE HUNGER GAMES (2012)
18	HARRY POTTER AND THE HALF-BLOOD PRINCE (2009)
19	HARRY POTTER AND THE ORDER OF THE PHOENIX (2007)
20	STEP UP 2 THE STREETS (2008)

Table 4.27: Similar Movies for THE TWILIGHT SAGA: BREAKING DAWN - PART 1"

the movie most similar to m , to a niche of $k = 1,092$, encompassing all movies in the dataset (except for m itself). Regression models can then be trained solely on the movies within that niche and the resulting model used to predict revenues for the film in question. We hypothesize that the optimal niche size k will be a lot smaller than 1,092, suggesting that meaningful patterns in the data get obscured by pooling together different films, for which different rules of box office success apply, into one overly simplified model. To test this assumption, we will follow the procedure described in [algorithm 8](#) to get predicted venue values for all movies and all values for k ranging from 50 to 1,075 (by steps of 25).

Data: Movie m , number of similar movies k , set of predictor variables V

Result: Predicted (log) revenues

Rank all other movies by if they share at least one genre with m ;

within those two groups, rank movies by the dot product of their latent space embedding vector and the latent space embedding vector of m ;

Define k highest-ranked (=most similar) movies as the *niche sample* of m ;

exclude dummy variables with 2 or less occurrences in the *niche sample* from V ; define as V' ;

specify a regression model R predicting $\log_revenues$ by the remaining predictor variables V' on *niche sample*;

use regression model R to predict $\log_revenues$ of m ;

Algorithm 8: Niche-specific regression box office prediction algorithm

4 Evidence-Based Target Audience Definitions and Revenue Prediction

When building the niche-specific regression models, we use the same predictor variables as in the overall regression model. Yet for small values of k , i.e. small niche sizes, some of the genres may only appear once or twice in the sample and the estimation of their importance might therefore be based on just one observation. Thus we exclude all genre and age rating dummy variables for which there are two or less observations in the niche sample.

To assess the performance of this estimation procedure, we look at four well-established error measures: root-mean-square error (RMSE), root-median-square error (RMdSE), mean absolute percentage error (MAPE), and median absolute percentage error (MdAPE). They are all calculated by comparing the predicted values for *log_revenues* with the actual observations. Figures 4.61, 4.62, 4.63 and 4.64 display how the error measures change for different values of k . The general shape of the curve suggests that error values are smaller, i.e. predictions are better, for small values of k , then get worse for larger niche sizes, and better again for yet larger samples. Table 4.28 shows for all four error measures which k minimizes them. They are all much lower than the maximum niche size of 1,075, suggesting that indeed smaller samples of similar movies are more useful to make revenue predictions. The fact that the two median-based error measures RMdSE and MdAPE get minimized for an even smaller niche size than the mean-based error measures suggests that for many films, the smaller samples produce superior results, but the small sample-based predictions are way off for some outlier movies which boost mean error values.

Error Metric	Optimal k	Lowest Value
RMSE	250	0.64
MAPE	250	2.90
RMdSE	100	0.42
MdAPE	100	2.40

Table 4.28: Optimal values for k according to different error measures

In Figure 4.65, we see for each niche size (value of k), for how many movies in the dataset the forecast based on that niche size produces the optimal forecast. Indeed a small niche size seems preferable for most movies. Selecting the optimal model for each movie, the median value for k among those optimal models is 100, i.e. for half of all movies the best revenue prediction can be obtained by building a model on 100 or fewer similar movies. This is a strong indicator that not only the industry standard of basing revenue prediction on comparables is reasonable, but that also the rules for what makes a movie commercially successful vary across different types of movies in such a way

4 Evidence-Based Target Audience Definitions and Revenue Prediction

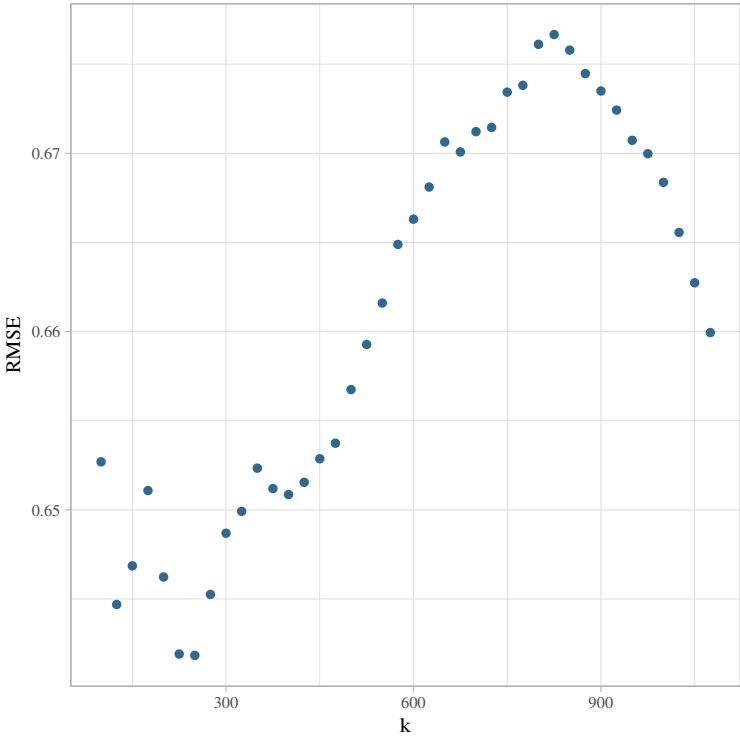


Figure 4.61: RMSE for different number of similar movies k to base model on

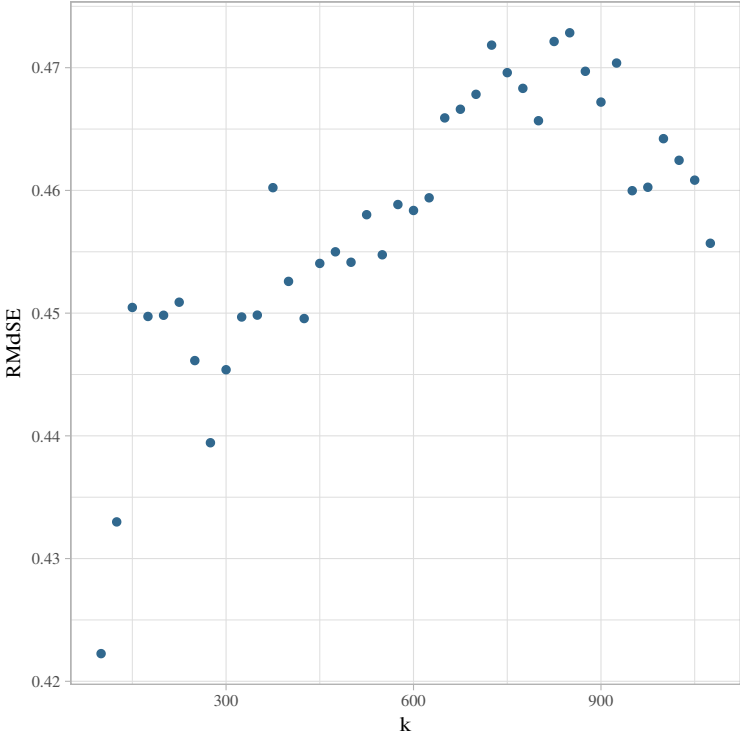


Figure 4.62: RMdSE for different number of similar movies k to base model on

4 Evidence-Based Target Audience Definitions and Revenue Prediction

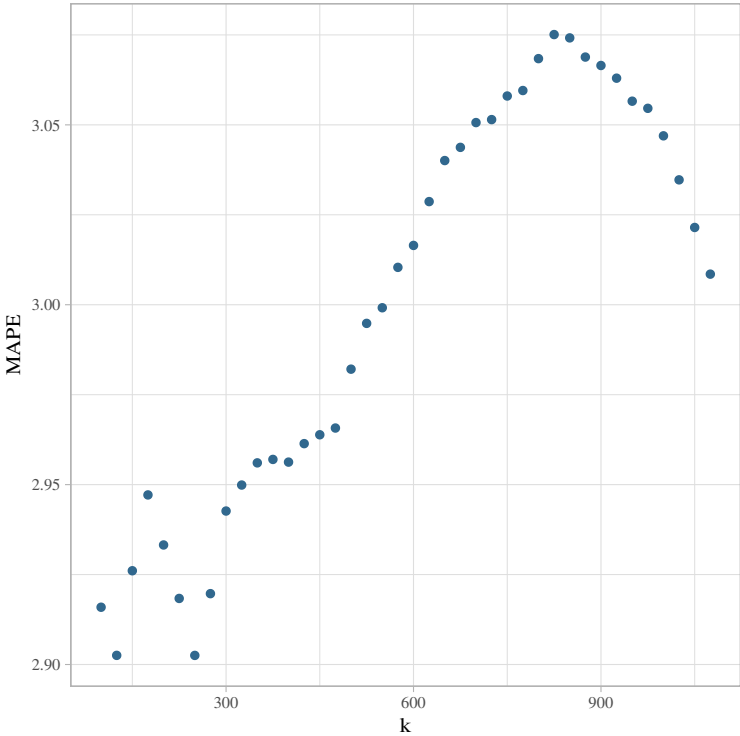


Figure 4.63: MAPE for different number of similar movies k to base model on

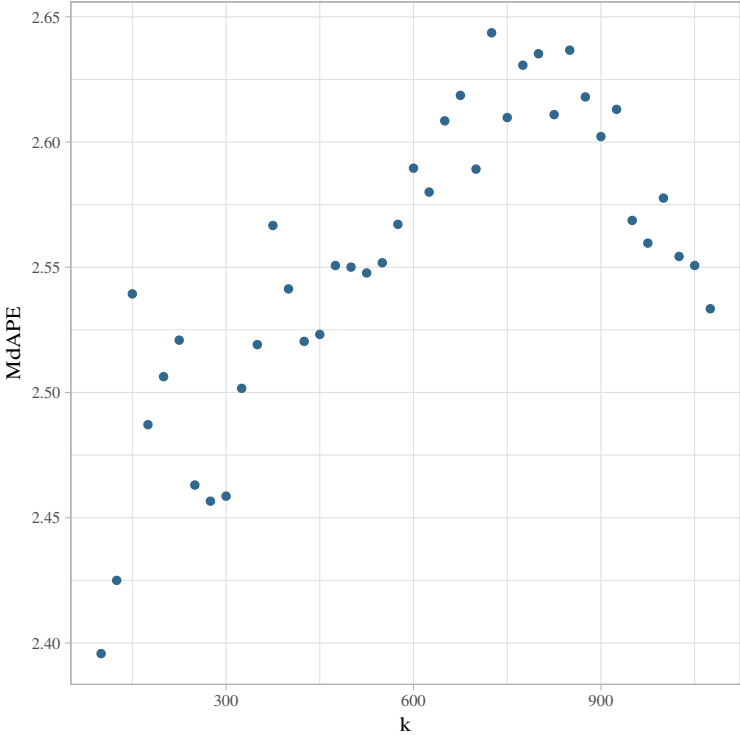


Figure 4.64: MdAPE for different number of similar movies k to base model on

4 Evidence-Based Target Audience Definitions and Revenue Prediction

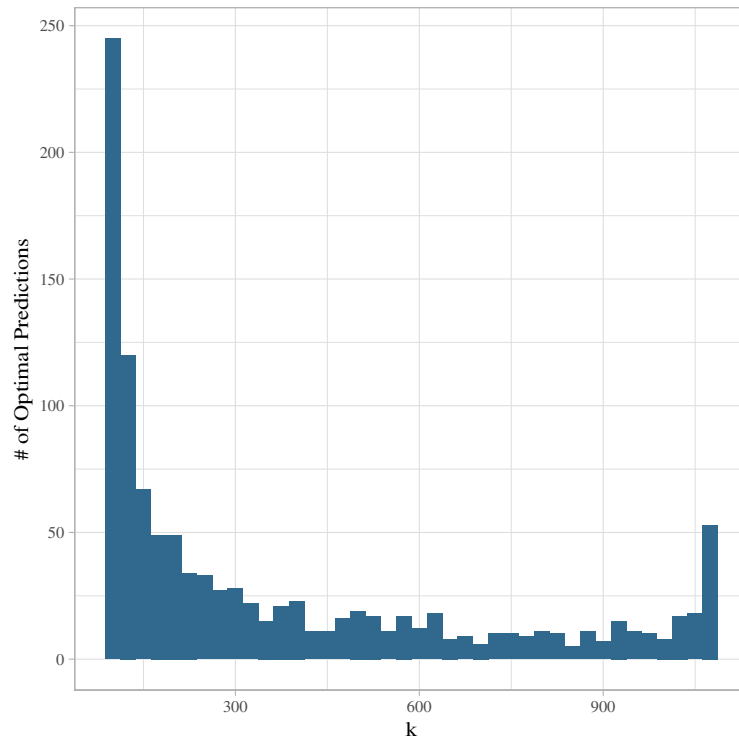


Figure 4.65: Distribution of movies by value of k for which prediction becomes optimal

that pooling too many movies together for a regression analysis can actually obscure patterns.

To exemplify how these niche-specific models uncover hidden patterns within the data, we show two such models side-by-side in [Table 4.29](#) that were based on the 100 most similar films for FANTASTIC MR. FOX and THE TWILIGHT SAGA: BREAKING DAWN - PART 1, respectively. While the influence of the budget on revenues seems to be strong and highly significant across niches, many of the other observations in the benchmark model (cf. [Table 4.25](#)) do not hold across niches. For example, while we observed a strong negative impact of the "Action" genre in the benchmark mode, the same effect is almost non-existent for films similar to FANTASTIC MR. FOX, yet even more pronounced for films similar to THE TWILIGHT SAGA: BREAKING DAWN - PART 1. Such niche-specific models exist for all possible niche sizes and all movies in the prediction movies dataset. Due to the relatively large number of variables and the comparably small sample size, we expect fewer statistically significant relationships in these models, yet a higher predictive power, as some information about the audience potential for this kind of movies is already contained simply in the mean of revenues across the niche sample.

4 Evidence-Based Target Audience Definitions and Revenue Prediction

	<i>Dependent variable:</i>	
	log_revenue	
	FANTASTIC MR. FOX	BREAKING DAWN 2
log_budget	0.662*** (0.148)	0.502*** (0.141)
log_cast_popularity	0.041 (0.079)	0.166** (0.062)
log_director_popularity	0.013 (0.024)	0.038 (0.020)
Action	-0.023 (0.212)	-0.623** (0.210)
Adventure	-0.187 (0.184)	0.096 (0.245)
Animation	-0.089 (0.230)	0.413 (0.346)
Comedy	0.206 (0.204)	-0.329 (0.212)
Crime	-0.415 (0.330)	0.259 (0.380)
Drama	-0.197 (0.192)	-0.146 (0.202)
Family	0.221 (0.311)	0.070 (0.241)
Fantasy	0.090 (0.195)	-0.051 (0.186)
Music	-0.346 (0.363)	0.253 (0.264)
Romance	0.033 (0.225)	0.036 (0.224)
Science Fiction	-0.203 (0.273)	0.417 (0.231)
Thriller	-0.098 (0.357)	-0.531* (0.222)
G	0.018 (0.495)	-0.279 (0.489)
PG	-0.193 (0.315)	-0.204 (0.377)
PG-13	-0.292 (0.249)	-0.175 (0.323)
(Intercept)	5.691* (2.499)	7.695** (2.576)
Observations	100	100
R ²	0.489	0.562
Adjusted R ²	0.375	0.464
Residual Std. Error (df = 81)	0.675	0.624
F Statistic (df = 18; 81)	4.303***	5.766***

Note:

*p<0.05; **p<0.01; ***p<0.001

Table 4.29: Two models based on niches of 100 similar films each for FANTASTIC MR. FOX and THE TWILIGHT SAGA: BREAKING DAWN - PART 1, side-by-side

4 Evidence-Based Target Audience Definitions and Revenue Prediction

As discussed in [subsection 4.6.1](#), predicting box office revenues by regression models on high-level predictor variables such as budget and genres is probably not the most efficient way of forecasting, especially compared to the possibility of aggregating individual moviegoer behavior based on past data. Yet we have been able to not only show that niche-specific regression modeling produces superior revenue prediction results to regression modeling across all movies, but it can also help to understand rules of success pertinent to a specific niche of comparable films and could thus provide evidence for a movie's potential that producers can cite when pitching projects to possible financiers (cf. [chapter 2](#)).

5 Conclusion and Outlook

5.1 Summary of Findings

Over the course of this work, we assumed an independent producer's perspective and examined how the way feature film producers define their target audience and forecast box office revenues might be improved upon by the use of large-scale individual user data and digital methods of modeling movie preferences.

First, we clarified what a producer's role is in the production process. Drawing from the productions studies approach, we performed a qualitative study to complement findings from literature research, and concluded that German feature film producers, whose main responsibilities may be described as development and fundraising, entertain mostly anecdotal audience conceptions based on chance encounters with individual audience members and their own intuitions. While they use criteria such as demographics, lifestyle & interests, behavior, and (vaguely defined) film taste to describe their audiences, there seems to be no common language or structured way to define target audiences among producers. We also found that, given the financial structure of German feature film productions, producers are to a large degree financially disenfranchised from their movies' box office success, as the numbers in most cases do not affect their bottom line. If producers perform any revenue forecasting at all, they usually come up with estimates based on comparable films and gut feeling. The main purpose of these forecasts is promotional: to convince possible financiers at the fundraising stage that there is indeed a viable target audience for this film and it is thus worth investing (or buying rights, or granting subsidies, respectively).

We went on to look at findings from academia on movies' target audiences and box office success patterns, to see whether such insights provide a basis for more evidence-based audience conceptions. We identified two main streams

5 Conclusion and Outlook

of research, which have been characterized as the "psychological" and the "economic" approach.

The psychological approach is concerned with individual viewers' motivations to watch movies and how these decisions are being made. A variety of different motives for movie attendance have been proposed and (in parts) empirically tested. Literature suggests that there are large differences both between moviegoers and between specific movies as to what drives attendance. Each individual spectator may seek a unique combination of different gratifications under any given circumstances. Yet there seems to be a rather stable part underlying each individual's choices as well, which we have dubbed "movie preferences". As these are hard to measure, the few practical implementations of audience segmentation for the theatrical context do not include movie preferences directly so far, but either use proxy variables such as age, gender, education, and income to cluster audiences into different sub-groups, or revert to more abstract "lifestyle" milieus. While segmentation in general appears to be a good tool from a producer's perspective to assist target audience definition, the retreat to demographics seems like an inappropriate simplification, and the reliance on the lifestyle concept appears overly abstract.

The economic approach on the other hand takes a more structural perspective and tries to uncover the rules that govern box office receipts and profits on a macro-level. Using regression models, diffusion patterns, and advanced machine learning methodology, researchers have examined the influence of movie traits (budget, genre, director, cast, etc.), third-party information (e.g. critical reviews, awards, user ratings), and market environment factors (e.g. seasonality, competition) on movie earnings. Most of these studies are explanatory, not predictive in nature, and while they do help deepen our understanding of the industry's economic mechanisms, for a producer working on an individual project, the results are not applicable to box office forecasting: The variables used are generally too broad to capture the specifics of a certain project, and a common misconception of these models is to treat all films equally and try to find a model that fits them all, whereas industry wisdom suggests that there are distinct success patterns in different niches: Rules that apply to American horror films need not be relevant for European arthouse dramas. Consequently, there is much less practical implementation of such models across the industry than the implied risk mitigation potential would suggest.

Subsequently we proposed a different route: Defining a target audience first, in an empirically rigorous manner, and then estimating earnings based on that

5 Conclusion and Outlook

specific target audience and similar films' performance. For target audience definition, we suggest modeling the movie preferences of individuals from past movie choices (or movie ratings), as has been pioneered in computer science for what is known as recommender systems.

We then set out to test whether this technological approach can indeed help predict who will attend a certain movie in the cinema, employing three different datasets of German moviegoers. Using the concept of lift from response modeling, we were able to show with offline survey data ($n = 2,374$) that past choices on the individual level do provide reliable guidance for who will be the target audience of a future film release. We found that a target audience definition based on as few as three past movie is not only significantly more efficient, as measured by lift, than random targeting, but outperformed targeting by demographic proxies (age, gender) in terms of median lift across films. Also, the precision of the target audience definition seemed to increase with the amount of information available per moviegoer. The latter finding was backed up with another dataset using implicit feedback from a cinema app ($n = 6,564$), which confirmed that indeed target audience definitions become more precise with increasing profile depth of the viewers among the audience. To test whether explicit statements of preference may be used instead of transactional data, we analyzed a dataset from an online survey ($n = 700$) and found that target audiences could be defined efficiently (i.e. better than random) by using explicit preferential information provided by the viewers themselves, using recommender algorithms based on the matrix factorization approach. The precision of such target audience definitions again increased with profile depth and they generally outperformed targeting by favorite genres alone. Subsequently, we used the underlying abstract preference information (as captured in a user embeddings matrix) to develop clusters of similar moviegoers and found these clusters to be an efficient way to come up with target audience definitions as well, suggesting that they provide a useful way to implement our findings for practical applications by producers, given a more representative dataset from the outset. Thus we came up with a clear blueprint for how to develop more evidence-based audience conceptions.

Finally, we attempted to leverage the same technology to provide more accurate revenue forecasts. While it was out of scope to model individual preferences for a representative set of moviegoers, recommender algorithms provided us with a way to assess movie similarity based on individual user ratings and thus come up with sets of similar movies for any given film, allowing us to run standard OLS regression models not on the entirety of all (very different) movies, but

just inside a certain, well-defined niche. Using the 25 million user ratings from the MovieLens dataset and a sample of 1,093 movies released in the United States between 2004 and 2015, we were able to show that such niche-specific models indeed provide superior predictions as compared to models estimated on the entire sample, making the case for a hybrid approach of data mining and similarity-based forecasting.

5.2 Managerial Implications

While we tried to adhere as closely as possible to a producer's perspective, it was (expectedly) beyond the scope of this work to come up with "a generic intervention to solve a generic field problem", which Van Aken & Romme (2012, 4) defined as the ultimate objective of design science research. Yet we certainly were able to provide a blueprint of how such a generic intervention may be crafted. Expressed in the terminology of the CIMO logic (Denyer et al. 2008), we examined the context (C) of target audience definition and revenue forecasting in practice, suggested clustering as a meaningful intervention technique (I), and discussed a combination of data-mining, recommender algorithms, and response modeling as a possible mechanism by which to obtain a favorable outcome (O) of said practices. Building on our findings, future research should be able to test our ideas and provide tools for practical application by producers.

Our findings show that relatively small datasets can already be leveraged to derive meaningful results, thus it is definitely reasonable for producers to increase direct (digital) exposure to members of their audiences and build up evidence on their preferences. Yet it will certainly require many independent companies to band together and share their data to cover the moviegoing population across different taste cultures. In Europe, funding bodies might take on a facilitator role in such a process. It is also well conceivable that third parties will come up with commercial applications similar to the segmentation approach proposed here¹.

It would be a stretch to suggest that producers should or will ever become data-driven, as that would be most likely inconsistent with their self-conception (Caldwell 2008). Yet in order to develop more evidence-based audience conceptions, producers need to be exposed to more scientific findings (Rynes,

1 Recent EU funding for Gruvi's audience project could point into that direction (Gruvi 2020).

5 Conclusion and Outlook

Giluk & Brown 2007) such as discussed in this work and enter into a dialog with academia. While being a producer does not require any specific educational background, film schools play an important role in providing the industry with emerging talent, and thus they make for a good starting point to develop more data literacy and awareness of scientific findings among practitioners. In addition to that, there is a number of professional education workshops and events in the industry (e.g. teaching producers about marketing or "audience design"²), which could provide another promising starting point for developing more evidence-based audience conceptions. Over the next years it will also become evident how the influx of a new generation into the industry might change the way producers view their audiences, given that up-and-coming filmmakers grew up with user-generated content platforms and the corresponding extensive data analytics capabilities (Johnson & Nicola 2017).

Even if there are limited possibilities to apply evidence-based methods in their own target audience definitions and revenue forecasting practices, producers should at least consider individual-level user data as a factor when it comes to anticipating the overall development of the industry and their own strategic positioning within that context. Knowledge about audiences on an individual level has become an important competitive advantage for the large, vertically integrated media corporations (Ball 2019). As such in-depth knowledge is difficult if not impossible for producers to obtain (and if it is shared, the disclosure is typically confined to a crude, aggregate level), "producers will have a tough time second-guessing their counter-parties motives in detail" (Franklin 2016); a trend which exacerbates existing imbalances of power. Producers may want to partner up with companies who are willing to share data and actively demand such disclosure during the negotiation of deals.

For decades, there has been a bifurcation process in the film industry "into makers of high-concept blockbuster films on the one side, and more modest independent filmmakers on the other" (Scott 2005, 35), a process which may be viewed through a lens of industrial specialization strategy. Just as early computer-assisted analysis of survey data helped US publishers reshape an increasingly specialized magazine market in the 1960s (Barnes & Thomson 1994), the ability to identify, reach, and measure (Napoli 2011, Napoli 2012) more narrowly defined audiences by means of electronic media and direct-to-consumer business models may well further a "trend toward segmentation and fragmentation" (McQuail 1997, 132) that has existed for more than twenty years

2 The Torino Film Lab e.g. used to host a regular audience design workshop.

now. Actively embracing such specialization could provide a viable path for producers today: It is much easier to know a small fraction of the audience better than anyone than it is to compete with the media conglomerations at large when it comes to knowing the entirety of viewers.

5.3 Directions for Further Research

As pointed out in [section 5.2](#), more work needs to be done to turn the insights gained by this dissertation into an actually implementable tool for producers. An obvious extension of the work at hand would thus be to conduct a survey similar to the one described in [section 4.4](#), using a more representative sample of moviegoers in order to come up with segments (as tested in [section 4.5](#)) that are generalizable to the entire population and may theretofore function as a target audience definition tool for producers. As a design science research result, such a segmentation should then be tested with practitioners under real conditions to examine whether such evidence-based audience definitions can indeed assist producers in performing their fundraising tasks.

Besides just continuing on the path laid out by the present work, there is also plenty of room to improve upon its methodology. While we were able to sketch a potential method by combining basic approaches from recommender systems, response modeling, and clustering, more advanced techniques have been proposed in any one of those fields. For example, the logistic matrix factorization approach developed at Spotify (Johnson 2014) tries to predict probabilities of consumption in a more direct way than the implicit matrix factorization technique we used. In modern response-modeling, the results of different algorithms are often blended together by meta-models (Tröscher et al. 2009). Such model optimization may prove critical if one aims to actually build a practically implementable segmentation.

Another area that could be improved upon is the intelligibility of clusters³. In today's industry-led, data-driven consumer research practice, research results are not necessarily required to be explicable or comprehensible to humans. As Boyd & Crawford (2012, 665) note, "Big Data reframes key questions about the constitution of knowledge, the processes of research, how we should engage with information, and the nature and the categorization of reality." Yet, while it

³ Some progress has been made in recent years to provide explanations for algorithmic movie recommendations, e.g. by Marchand & Marx (2020). Such approaches might be built upon to improve segmentation intelligibility.

5 Conclusion and Outlook

has been argued that "with enough data, the numbers speak for themselves" (Anderson 2008) and theory is no longer needed, we observed in [section 2.1](#) that producers' main objective when it comes to defining audiences and forecasting revenues is to convince financiers that there is a viable audience for their movie project during the fundraising stage. The more intelligible such predictions are, e.g. the more they hark back to the psychological theories discussed in [section 3.2](#), the more well-founded they will seem to their addressees, and the more convincing they are likely to be. Thus it seems like a rewarding endeavour to decode the hidden patterns behind movie preferences.

The present work has also made a case for taking a close look at practitioners' role in the wider context of their industry as suggested by the production studies approach and using these insights to frame practically relevant research questions. As Cascio (2007, 1012) notes, "it is certainly reasonable to assume that practitioners will dismiss research findings that are not relevant to the business issues that they face. One way to enhance relevance is to design research with implementation in mind." We certainly hope that further studies on the motion picture industry will continue along that path.

In any way, it will be interesting to see whether such research will be carried out by academia or behind the closed doors of large media corporations. Limited access to data poses a challenge not only to independent producers, but increasingly also to the scientific community. Boyd & Crawford (2012, 673) observe that this development "produces considerable unevenness in the system: those with money – or those inside the company – can produce a different type of research than those outside. Those without access can neither reproduce nor evaluate the methodological claims of those who have privileged access." With Netflix only selectively publishing their own viewership data (Jenke 2018) we already see such problems in film industry research as well and it will be a major challenge in the decades to come to ensure a level of data access that allows for the democratized production of knowledge (Napoli 2016).

This leads us to the final part of our work: We must think critically about the ethical, societal, and political implications of the technologies discussed in this work.

5.4 Critical Considerations

Up to this point, we have discussed target audience definition and revenue forecasting techniques based on individual-level user data from a purely instrumentalist perspective of how such approaches may help producers to perform their (economic) functions within the film-making process. As Murschetz & Schlütz (2018, 25) argue, "research into big data requires much closer attention to critical studies in the social and cultural sciences". Indeed there are at least three angles from which the methodology outlined in this dissertation may be critically challenged:

First, there are reasonable reservations against the phenomenon described as "big data" as a whole and its epistemological and societal impact. Secondly, it can be alleged that successful application of more empirical approaches to target audience definition and revenue forecasting might instill some form of cultural conservatism in practitioners: Basing future works on what has worked in the past would, as per such reasoning, lead to an increased reproduction of the same old content. Thirdly, one may argue that the market research approach taken in this study reduces producer-audience relations to a mere economic exchange and ignores other lenses through which those relationships may be viewed.

While covering these criticisms in full depth is beyond the scope of the present work, we deem it important to at least acknowledge them briefly (without trying to dismiss them) in the context of this conclusion, as neither practical applications of our findings nor further research will (or should) be able to circumnavigate these issues indefinitely.

We have alluded to some of the issues with technology depending on the availability of large-scale individual user data in sections [5.2](#) and [5.3](#): Boyd & Crawford (2012, 663) astutely define "big data" as a "cultural, technological, and scholarly phenomenon" resting on an interplay of "technology", "analysis", and "mythology", the latter describing "the widespread belief that large data sets offer a higher form of intelligence and knowledge that can generate insights that were previously impossible, with the aura of truth, objectivity, and accuracy." Such mythology has led to the development of grandiose utopian and dystopian narratives (Boyd & Crawford 2012), and it is important for serious research to stay clear of overblown claims as to what technology can and cannot achieve. Therein lies also an important caveat for the work at hand: While we have made the case for an "evidence-based" audience conception in previous chapters, one

5 Conclusion and Outlook

must be aware at all times that algorithms are human-made, their results are subject to interpretation, and they need to be confounded with theory. Not always is a quantitative measurement indeed more accurate than a qualitative description. Such claims of objectivity are particularly problematic if they rest on privileged access to proprietary datasets. Data access and computational skills constitute new hierarchies of power, as discussed in [section 5.2](#). Another criticism of big data concerns how technological feasibility often trumps ethical considerations: While movie preference data may seem like comparably harmless information on consumers, when it comes to personal data, privacy is always an issue as well. Using the Netflix Prize dataset⁴, Narayanan & Shmatikov (2008) have shown that such anonymous data can be de-anonymized – a research finding which led to a class-action lawsuit in the US against Netflix, led amongst others by a closeted homosexual woman who feared she might be outed against her will by de-anonymization of her movie ratings history (Singel 2009). Any responsible utilization of moviegoers' digitally represented preferences will necessarily require informed consent.

The inherent conservatism argument is frequently voiced by practitioners when confronted with the ideas in this study or similar works. In recent years, the idea of "filter bubbles" (Pariser 2011) has been widely discussed, suggesting that the wide-spread use of recommender algorithms on the Internet leads to a reinforcement of the users' already held beliefs as they are only being confronted with conforming information. Similarly, the use of such algorithmic audience analysis at the production stage might lead to endless repetition of what has worked in the past. While this is not necessarily wrong, reducing the issue to the role of technology ignores the powerful forces leading to such reproductive creation that are already in place today, even without a digital grasp on consumers' preferences: Lamenting standardization and the perceived uniformity of all content produced by the cultural industry has been a staple of critical theory for decades (Marcuse 1991, Horkheimer & Adorno 1988). It seems like such standardization is the effect of risk mitigation behavior at the corporate level. As Ryan (1992, 154) observes: "In essence, corporations orient their production towards commercialism, where audience taste preferences, as indexed by existing patterns of commodity sales, dictate the direction of creation. This creates a logic of repetition which surfaces as formatting, as a management control applied to the project team and which has the effect of rationalising the creative stage of production." Such formatting can manifest as a reliance on genres, on sequels, on screenplay rules, on stars, and on adaptations of pre-

⁴ The dataset contained 100 million movie ratings from 480,000 users back in the time when Netflix was still a DVD rental company.

5 Conclusion and Outlook

existing intellectual property. The underlying corporate strategy is "designed to guide producers and directors in managing the project team by incorporating the impersonal laws of the marketplace as necessity into its constitution, it limits the play of artistic imagination to predictable arenas" (Ryan 1992, 167). Viewed through a critical theory lens, data-assisted target audience definition certainly constitutes another form of such formatting. And certainly even the best algorithm cannot capture the full complexity of individual formation of preferences as discussed in [section 3.2](#) (Alexander 2016). Yet it would be naïve to suppose that algorithmically supported audience research had the power to impose a regime of strict rationalization onto an industry previously free from economic constraints. Business considerations – powered by gut feelings as much as audience research – have dominated film investment decisions in the past as well (Vogel 2004). In a personal conversation with the author, a former Hollywood studio development executive attested to the supremacy of the marketing team's evaluation on the greenlighting decisions committee at the major studio level. Yet the conservative bias in marketing toward things that can be recognized by audiences and thus readily marketed is by no means absolute: innovation remains possible, as there is a counteracting mechanism: "Despite a cautious desire for their stars to immediately repeat their previous best seller, the corporations of culture have a contradictory longer-term reliance on them to create innovative works which initiate the new styles they can exploit through form-based production" (Ryan 1992, 225). Any criticism of evidence-based strategies in target audience definition and revenue forecasting should thus start with a deep analysis of how economic incentives are construed and followed in today's industry. We argue that while algorithmic prediction of commercial success can certainly lead to new forms of formatting, this problem is not unique to the application of more data-based modes of target audience definition and revenue forecasting, but there is a tension between (audiences' and creators' desire for) originality and (financiers' demand for) predictability inherent to any cultural production organized in the form of a "culture industry" under the conditions of market capitalism. And as Peukert (2018, 201) concludes, it remains yet to be determined whether "data-driven supply [...] lead[s] to a convergence of cultural content, or the deepening of certain niches, and under which circumstances [...] each outcome [is] more likely".

Finally, the market approach of audience analysis which has been adopted throughout this work may be questioned in general: As McQuail (1997, 9) points out, such thinking "links sender and receiver in a 'calculative' rather than

5 Conclusion and Outlook

a normative or a social relationship, as a cash transaction between producer and consumer rather than a communication relationship. [...] It privileges socioeconomic criteria and focuses on media *consumption* rather than reception." While it is an undoubtedly useful point of view for producers (in their role as cultural managers), it is also "implicitly manipulative" (McQuail 1997, 9). There has always been a tension between commercial and artistic values for creators in the culture industry. In her anthropological examination of the movie industry, Powdermaker (1950, 286) observes that the "human properties of the artist, his [sic!] sensitivity, his imagination, his ability to create" suffer from subjection to the values of commerce. While the business role is an important part of the producer's function within the production process, it cannot be their only role: Considerations of effective communication, social discourse, and artistic integrity are equally important.

Discussing these critical considerations more deeply would go beyond the scope of this work, so we will leave it at that. It was not our goal to outright dismiss any of the criticisms that could be mounted against the approach presented in this work. Rather we hope to show how such arguments fit into a wider discourse and are mostly not confined to the specific technological methods as presented herein, but rather touch upon the underlying "art/capital contradiction" (Ryan 1992, 260). Yet it is certainly important to take these critical stances into account when trying to foresee technology's potential impact. As Boyd & Crawford (2012, 662) remark: "Technology is neither good nor bad; nor is it neutral", but it is engaged in a complex interplay with environmental, social, and economic factors that often transcends its original purpose. The ideal of the reflective practitioner, as laid out in the introduction, must thus not only encompass utilitarian reasoning about technology and commercial application of research findings, but also critical reflection of one's own role within the wider context of culture.

A Offline Questionnaire

Umfrage

Casino

Hilf uns mit deinen Antworten das Angebot des Casino zu verbessern und die **Kinoapp Cinuru** zu entwickeln. Mit der Teilnahme an der Umfrage kannst du 2 Freikarten gewinnen.

- a) Welche Filmvorstellung besuchst du gerade? _____
- b) Wie viele Begleitpersonen hast du dabei? _____
- c) Wie oft besuchst du durchschnittlich ein Kino im Jahr? _____ Mal
- d) Welche 3 Filme hast du zuletzt im Kino gesehen?
1. _____ 2. _____ 3. _____
- e) Welche davon hast du im Casino geguckt? 1. () 2. () 3. ()
- f) Welche anderen Kinos besuchst du regelmäßig?
1. _____ 2. _____ 3. _____
- g) Benutzt du ein Smartphone und Apps? Ja () Keine Apps () Nein ()
- h) Benutzt du Kino- oder Filmapps? Wenn ja, welche? _____
- i) Wie könnte das Casino dein Kinoerlebnis noch besser gestalten?
-

Alter: _____ Jahre Postleitzahl: _____

Geschlecht: weiblich () männlich () keine Angabe ()

() Ich möchte am **Gewinnspiel** um 2x2 Freikarten teilnehmen*

() Ich möchte gerne den **Casino Newsletter** abonnieren*

* Bitte gib dafür Deine Emailadresse an: _____@_____

Vielen Dank für Deine Teilnahme!

www.cinuru.com/umfrage



Figure A.1: Questionnaire as handed out to moviegoers in participating cinemas

B Online Questionnaire

0%

Willkommen

Liebe Teilnehmerin, lieber Teilnehmer,

im Rahmen meiner Masterarbeit am Lehrstuhl für Marketing und Medien an der Westfälischen Wilhelms-Universität Münster in Kooperation mit dem Projekt Greenlight Analytics an der Filmuniversität Babelsberg führe ich eine Studie zum **Thema Filmkonsum** durch.

Die Beantwortung der Umfrage wird etwa **20 Minuten** in Anspruch nehmen. Ihre Angaben stehen ausschließlich den oben genannten Institutionen zur Verfügung und werden selbstverständlich **anonym und vertraulich** behandelt. Die erhobenen Daten werden **ausschließlich für wissenschaftliche Zwecke** verwendet.

Wenn Sie am Ende der Befragung Ihre E-Mail-Adresse hinterlassen, können Sie an der **Verlosung von einem von 30 Kinogutscheinen** teilnehmen.

Bitte lesen Sie die Fragen aufmerksam durch und beantworten Sie sie möglichst **wahrheitsgemäß entsprechend Ihrer persönlichen Meinung und Einschätzung** - es gibt keine richtigen oder falschen Antworten.

Bei Fragen oder Anmerkungen können Sie sich per **E-Mail** an mich wenden.

Herzlichen Dank für Ihre Unterstützung und viel Spaß!

Joel Schumacher

LOS GEHTS!

Figure B.1: Online Survey, page 1

4%

Zu Beginn würde ich Ihnen gerne ein paar Fragen zu Ihrem Kinobesuchsverhalten stellen.

Wie oft gehen Sie **ungefähr** ins Kino?

- Seltener als 1x im Jahr
- 1x bis 2x im Jahr
- 1x jedes Vierteljahr (4x im Jahr)
- 1x alle zwei Monate (6x im Jahr)
- 1x pro Monat (12x im Jahr)
- Mindestens 1x pro Woche

Bitte stellen Sie sich vor, dass Sie 10 Mal ins Kino gehen. Wer ist Ihre Begleitung? Bitte verteilen Sie **genau 10 Punkte** auf folgende Kategorien. Wenn Sie zum Beispiel 3 von 10 Kinobesuchen mit Freunden unternehmen, tragen Sie eine 3 in das erste Feld ein. **Sollten Sie mit einer der Kategorien nie ins Kino gehen, tragen sie eine 0 ein.**

von 10 Kinobesuchen unternehme ich mit Freunden/Bekanntem

von 10 Kinobesuchen unternehme ich mit meinem Partner/Date

von 10 Kinobesuchen unternehme ich mit Mitgliedern meiner Familie

von 10 Kinobesuchen unternehme ich alleine

WEITER

Figure B.2: Online Survey, page 2

B Online Questionnaire

7%

Wenn Sie mit **Freunden/Bekanntem** ins Kino gehen, wer schlägt überwiegend den Film vor?

Ich Einer meiner Freunde/Bekanntem Mal so, mal so

Wenn Sie mit **Ihrem Partner/Date** ins Kino gehen, wer schlägt überwiegend den Film vor?

Ich Mein Partner/Date Mal so, mal so

Wenn Sie mit **Mitgliedern Ihrer Familie** ins Kino gehen, wer schlägt überwiegend den Film vor?

Ich Ein anderes Familienmitglied Mal so, mal so

WEITER

Figure B.3: Online Survey, page 3

9%

Wie oft schauen Sie Filme der folgenden Genres **im Kino**?

Nie Sehr oft

Komödie	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Drama	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Fantasy	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Science Fiction	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Action	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Thriller	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Horror	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Romance	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Animations-/Kinderfilm	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

WEITER


75

Figure B.4: Online Survey, page 4


B Online Questionnaire

24%

Klicken Sie auf eines der folgenden Poster, um den Film auszuwählen



KEINEN FILM AUSWÄHLEN




Ghost in the Shell
US | FSK 12
Genres: **ACTION** **SCIENCEFICTION**

In der nahen Zukunft haben die Menschen die meisten ihrer Körperteile gegen künstliche Elemente ausgetauscht. An menschlichem Gewebe verbleibt in ihnen häufig nur noch der Teil des Gehirns, in dem ihre Persönlichkeit angesiedelt ist. Diese "Ghost" genannten Zellen sind das wichtigste Element in der künstlichen Hülle, der "Shell". In dieser Welt hat es der Cyber-Terrorist Kuze auf die Technologien der Firma Hanka Robotic abgesehen. Die Elite-Einsatztruppe Sektion 9, die von einem einzigartigen Hybrid aus Mensch und Cyborg namens Major angeführt wird, soll den skrupellosen Cyber-Kriminellen aufhalten. Realfilm-Adaption des Mangas "Ghost In The Shell" von 1989, auf dem auch der gleichnamigen Anime-Film von 1995 basiert.

REGIE: Rupert Sanders

- Scarlett Johansson als Motoko Kusanagi
- Pilou Asbæk als Batou
- Michael Pitt als The Laughing Man
- Takeshi Kitano als Daisuke Aramaki
- Rila Fukushima als



Fack ju Göhste
DE | FSK 12 | Fack ju Göhste
Genres: **KOMÖDIE**

Auf sein vergrabenes Diebesgut wurde einfach eine verdammte Turnhalle gebaut. Der Ex-Knacki Zeki Müller hat keine andere Wahl und muss als vermeintlicher Aushilfslehrer an der Goethe-Gesamtschule anheuern. Und jetzt hat das deutsche Bildungssystem ein Problem mehr. Den krassesten Lehrer aller Zeiten. Während er nachts nach seiner Beute gräbt, bringt er tagsüber mit seinen ruppigen aber nachhaltigen Lehrmethoden die Chaotikklasse 10b auf Spur. Ohne zu ahnen, in wen sie sich da gerade verliebt, ermahnt die überkorrekte Referendarin Lisi Schnabelstedt ihren vermeintlichen Kollegen emsig zu pädagogischer Verantwortung und erweckt in dem Raubein moralische Restwerte zum Leben.

REGIE: Bora Dagtekin

- Elyas M'Barek als Zeki Müller
- Karin Herfurth als Lisi Schnabelstedt
- Katja Riemann als Direktorin Guadron
- Jana Palluafe als Chorlie
- Alexandra Höfels als Caro

Figure B.8: Online Survey, page 8

39%

Bitte stellen Sie sich nun vor, dass Sie noch einen **weiteren Film** aus demselben Kinoprogramm auswählen können. Bitte wählen Sie wieder einen Film aus, in den Sie gehen würden, oder entscheiden Sie sich dafür, in keinen weiteren Film zu gehen.

Ihre Entscheidung hat nun **keinen Einfluss mehr auf das Gewinnspiel**.


OK ZURÜCK

Figure B.9: Online Survey, page 9


B Online Questionnaire

39%

Klicken Sie auf eines der folgenden Poster, um den Film auszuwählen



KEINEN WEITEREN FILM AUSWÄHLEN



Ghost in the Shell
US | FSK 12
Genres: **ACTION** **SCIENCEFICTION**

In der nahen Zukunft haben die Menschen die meisten ihrer Körperteile gegen künstliche Elemente ausgetauscht. An menschlichem Gewebe verbleibt in ihnen häufig nur noch der Teil des Gehirns, in dem ihre Persönlichkeit angesiedelt ist. Diese "Ghost" genannten Zellen sind das wichtigste Element in der künstlichen Hülle, der "Shell". In dieser Welt hat es der Cyber-Terrorist Kuze auf die Technologien der Firma Hanka Robotic abgesehen. Die Elite-Einsatztruppe Sektion 9, die von einem einzigartigen Hybrid aus Mensch und Cyborg namens Major angeführt wird, soll den skrupellosen Cyber-Kriminellen aufhalten. Realfilm-Adaption des Mangas "Ghost In The Shell" von 1989, auf dem auch der gleichnamigen Anime-Film von 1995 basiert.

REGIE: Rupert Sanders

- Scarlett Johansson als Motoko Kusanagi
- Piloa Anbak als Batou
- Michael Pitt als The Laughing Man
- Takeshi Kitano als Daisuke Aramaki
- Rita Fuchuzhima als



Fack ju Göhte
DE | FSK 12 | Fack ju Göhte
Genres: **KOMÖDIE**

Auf sein vergebenes Diebesgut wurde einfach eine verdammte Turnhalle gebaut. Der Ex-Knacki Zeki Müller hat keine andere Wahl und muss als vermeintlicher Aushilfslehrer an der Goethe-Gesamtschule anheuern. Und jetzt hat das deutsche Bildungssystem ein Problem mehr. Den krassesten Lehrer aller Zeiten. Während er nachts nach seiner Beute gräbt, bringt er tagsüber mit seinen ruppigen aber nachhaltigen Lehrmethoden die Chaotenklasse 10b auf Spur. Ohne zu ahnen, in wen sie sich da gerade verliebt, ermahnt die überkorrekte Referendarin Lisi Schnabelstedt ihren vermeintlichen Kollegen emsig zu pädagogischer Verantwortung und erweckt in dem Raubein moralische Restwerte zum Leben.

REGIE: Bora Dagtekin

- Elyas M'Barek als Zeki Müller
- Katharina Herfurth als Lisi Schnabelstedt
- Katja Riemann als Direktorin Gudrun
- Jana Pallaska als Charlie
- Ahnera Höfels als Caro

Figure B.10: Online Survey, page 10

44%

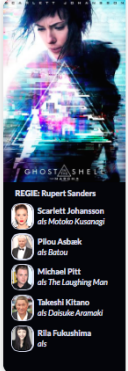
Filmbeschreibungen

Im Folgenden sehen Sie noch einmal eine Reihe von Filmen in Form von **Filmbeschreibungen**. Bitte beantworten Sie die Fragen dazu **möglichst wahrheitsgemäß entsprechend Ihrer persönlichen Meinung und Einschätzung**.

LOS GEHT'S! ZURÜCK

Figure B.11: Online Survey, page 11

45%



Ghost in the Shell
US | FSK 12
Genres: ACTION SCIENCEFICTION

In der nahen Zukunft haben die Menschen die meisten ihrer Körperteile gegen künstliche Elemente ausgetauscht. An menschlichem Gewebe verbleibt in ihnen häufig nur noch der Teil des Gehirns, in dem ihre Persönlichkeit angesiedelt ist. Diese "Ghost" genannten Zellen sind das wichtigste Element in der künstlichen Hülle, der "Shell". In dieser Welt hat es der Cyber-Terrorist Kuze auf die Technologien der Firma Hanka Robotic abgesehen. Die Elite-Einsatztruppe Section 9, die von einem einzigartigen Hybrid aus Mensch und Cyborg namens Major angeführt wird, soll den skrupellosen Cyber-Kriminellen aufhalten. Realfilm-Adaption des Mangas "Ghost In The Shell" von 1989, auf dem auch der gleichnamigen Anime-Film von 1995 basiert.

REGIE: Rupert Sanders

Scarlett Johansson
als Motoko Kusanagi

Piloa Adbak
als Batou

Michael Pitt
als The Laughing Man

Takeshi Kitano
als Daisuke Aramaki

Rila Fukushima
als

Würden Sie diesen Film sehen?

Ja, im Kino Nur zu Hause Gar nicht

Mit wem würden Sie diesen Film sehen? Eine Mehrfachauswahl ist möglich.

Mit Freunden / Bekannten Mit meinem Partner / Date Mit Mitgliedern meiner Familie Alleine

Sind Sie ein Fan von einem der Darsteller?

Ja Nein

Kennen Sie eine Vorlage, eine andere Version oder einen Vorgänger von dem Film?

Ja Nein

Wie ansprechend finden Sie dieses Film Konzept?

☆☆☆☆☆ keine Meinung

WEITER ZURÜCK

Figure B.12: Online Survey, page 12 (repeated multiple times)

55%

Kinobesuchsverhalten

Danke, dass Sie noch dabei sind! Ich möchte nun gerne mehr über Ihr **Kinobesuchsverhalten** erfahren. Es gibt wie gesagt **keine richtigen oder falschen Antworten**.

OK ZURÜCK

Figure B.13: Online Survey, page 13

B Online Questionnaire

56%

Inwiefern stimmen Sie den folgenden Aussagen zu?

	Stimme überhaupt nicht zu	Stimme voll und ganz zu
Allgemein gehöre ich zu den ersten, die einen neuen Film im Kino sehen.	<input type="radio"/> 1	<input type="radio"/> 5
Ich gehe selten in Filme, bei denen ich mir unsicher bin, wie sie mir gefallen werden.	<input type="radio"/> 1	<input type="radio"/> 5
Ich gehe bei der Auswahl von Filmen, die ich im Kino sehe, gerne ein Risiko ein.	<input type="radio"/> 1	<input type="radio"/> 5
Ich mag es nicht, in einen neuen Film zu gehen, bevor andere Leute dies getan haben.	<input type="radio"/> 1	<input type="radio"/> 5
Ich gehe häufig in Sneak Previews (zufällige Filmvorschau vor dem offiziellen Release)	<input type="radio"/> 1	<input type="radio"/> 5

[WEITER](#) [ZURÜCK](#)

Figure B.14: Online Survey, page 14

60%

Inwiefern stimmen Sie den folgenden Aussagen zu?

	Stimme überhaupt nicht zu	Stimme voll und ganz zu
Unter meinen Freunden bin ich einer der „Experten“ für Filme.	<input type="radio"/> 1	<input type="radio"/> 5
Ich weiß ziemlich viel über Filme.	<input type="radio"/> 1	<input type="radio"/> 5
Ich fühle mich nicht sehr gut über Filme informiert.	<input type="radio"/> 1	<input type="radio"/> 5
Im Vergleich zu den meisten anderen Menschen weiß ich weniger über Filme.	<input type="radio"/> 1	<input type="radio"/> 5
Wenn es um Filme geht, weiß ich wirklich nicht viel.	<input type="radio"/> 1	<input type="radio"/> 5
Ich benutze sehr oft Film-Informationsportale wie IMDb, Rotten Tomatoes, Moviepilot, etc.	<input type="radio"/> 1	<input type="radio"/> 5

[WEITER](#) [ZURÜCK](#)

Figure B.15: Online Survey, page 15

B Online Questionnaire

62%

Wie oft werden Sie über folgende Kanäle auf neue Filme im Kino aufmerksam?

Nie Sehr oft

1 2 3 4 5

Filmvorschau / Trailer im Kino 1 2 3 4 5

Empfehlungen von Freunden / Bekannten (persönlich, in sozialen Netzwerken, etc.) 1 2 3 4 5

Nutzerbewertungen auf Film-Portalen (z.B. IMDb, Rotten Tomatoes, Moviepilot) 1 2 3 4 5

Bericht/Artikel in Zeitung/Zeitschrift 1 2 3 4 5

Werbeanzeige in Zeitung / Zeitschrift 1 2 3 4 5

Artikel/Bericht im Internet 1 2 3 4 5

Besondere Werbe-, Promotionalaktionen im Kino 1 2 3 4 5

Außenwerbung (Plakate und Ähnliches) 1 2 3 4 5

Filmvorschau / Trailer im Internet 1 2 3 4 5

Werbung im Fernsehen 1 2 3 4 5

Werbung / Bericht / Kritik im Radio 1 2 3 4 5

Fernsehsendung (Bericht / Interview / Kritik) 1 2 3 4 5

Plakate / Dekoration / Werbung im Kino 1 2 3 4 5

Kostenloses Programmheft 1 2 3 4 5

Homepage des Kinos 1 2 3 4 5

Kino- und Film-Apps 1 2 3 4 5

Spontan im Kino 1 2 3 4 5

Gibt es noch andere Kanäle, über die Sie auf neue Filme im Kino aufmerksam werden?

Andere Kanäle

[WEITER](#) [ZURÜCK](#)

Figure B.16: Online Survey, page 16

66%

Inwiefern stimmen Sie den folgenden Aussagen zu?

Stimme überhaupt nicht zu Stimme voll und ganz zu

1 2 3 4 5

Es ist teuer, aktuelle Filme zu schauen. 1 2 3 4 5

Es ist schwierig, sich mit Freunden auf einen Film zu einigen. 1 2 3 4 5

Es ist schwierig, herauszufinden, in welchem Kino ein Film verfügbar ist. 1 2 3 4 5

Es ist schwierig, die Filme zu finden, von denen ich glaube, dass sie mir gefallen werden. 1 2 3 4 5

Es ist schwierig, Menschen zu finden, mit denen ich einen bestimmten Film gemeinsam schauen kann, den ich sehen möchte. 1 2 3 4 5

[WEITER](#) [ZURÜCK](#)

Figure B.17: Online Survey, page 17

B Online Questionnaire

67%

Wie alt sind Sie?

Alter

Welches Geschlecht haben Sie?

Männlich Weiblich keine Angabe

Wie hoch ist Ihr monatliches Haushaltsnettoeinkommen?

weniger als 1000€ 1000€ bis 2000€ 2000€ bis 3000€
 3000€ bis 4000€ 4000€ bis 5000€ 5000€ oder mehr
 Keine Angabe

Um die Repräsentativität der Umfrage sicherzustellen, benötige ich auch Ihre **Postleitzahl**.

Postleitzahl:

Der **Kultur** welcher Länder fühlen Sie sich (zum Beispiel auf Grund ihrer Herkunft oder der Herkunft ihrer Eltern) besonders verbunden.

Kulturelles Erbe aus folgenden Ländern:

Figure B.18: Online Survey, page 18

70%

Welches ist ihr **höchster bisher erreichter Bildungsabschluss**?

Kein Abschluss
 Hauptschul- / Volkshochschulabschluss
 Abschluss an einer polytechnischen Oberschule
 Realschulabschluss
 Fachhochschulreife
 Abitur
 Bachelor
 Master
 Diplom
 Magister
 Staatsexamen
 Promotion

Befinden Sie sich zurzeit noch **in der Ausbildung** für einen (weiteren) Bildungsabschluss?

Ich befinde mich nicht in einer Ausbildung
 Hauptschul- / Volkshochschulabschluss
 Abschluss an einer polytechnischen Oberschule
 Realschulabschluss
 Fachhochschulreife
 Abitur
 Bachelor
 Master
 Diplom
 Magister
 Staatsexamen
 Promotion

Bitte ordnen Sie **Ihren Beruf** einer der **folgenden Kategorien** zu (bei Arbeitslosigkeit, Arbeitsunfähigkeit oder Pensionierung: Bitte letzter ausgeübter Beruf). Falls der Beruf nicht in der folgenden Liste enthalten ist, wählen Sie bitte die **ähnlichste Berufsgruppe** aus. Wenn Sie sich noch in der Ausbildung befinden, wählen Sie bitte den mit Ihrer Ausbildung **angestrebten Beruf** aus.

Hausfrau/Hausmann
 Körperliche Tätigkeit / Arbeit (z.B. Handwerker/in)
 Arbeit im Servicebereich (z.B. Kundenservice)
 Tätigkeit mit geringem Anteil an Führungsaufgaben
 Lehrer/in, Unternehmer/in oder Tätigkeit in leitender Position
 Kulturschaffender, Kreativ- oder Wissenschaftler/in

Figure B.19: Online Survey, page 19

74%

Filmgeschmack

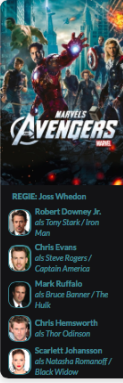
Zum Abschluss möchte ich Sie noch bitten, **30 bereits erschienene Filme zu bewerten**, damit ich Ihren Filmgeschmack besser einschätzen kann. Dazu lege ich Ihnen wieder **Filmbeschreibungen** vor.

Bitte geben Sie an, wie Ihnen der jeweilige Film gefallen hat und wo sowie mit wem Sie den Film gesehen haben.

OK

Figure B.20: Online Survey, page 20

74%



Marvel's The Avengers

US | FSK 12 | The Avengers

Genres: **ACTION** **SCIENCEFICTION**

Marvel präsentiert MARVELS THE AVENGERS, das ultimative Team. Die legendären Superhelden Iron Man, der unglaubliche Hulk, Thor und Captain America versammeln sich zum ersten Mal in einer neuen actiongeladenen Story mit den Schauspielern Robert Downey Jr., Scarlett Johansson und Samuel L. Jackson in den Hauptrollen und unter der Regie von Joss Whedon. Als ein unerwarteter Feind den Weltfrieden und die globale Sicherheit bedroht, sieht sich Nick Fury, führender Kopf der mächtigen internationalen Friedensorganisation S.H.I.E.L.D., gezwungen ein Team zusammenzustellen, das die Welt vor dem Absturz in die Katastrophe bewahrt. MARVELS THE AVENGERS ist voller Action, Abenteuer und mit spektakulären Spezialeffekten bepackt.

REGIE: Joss Whedon

Robert Downey Jr. als Tony Stark / Iron Man

Chris Evans als Steve Rogers / Captain America

Mark Ruffalo als Bruce Banner / The Hulk

Chris Hemsworth als Thor Odinson

Scarlett Johansson als Natasha Romanoff / Black Widow

Haben Sie diesen Film gesehen?

Ja Nein

Wo haben Sie diesen Film gesehen?

Im Kino Nicht im Kino Ich weiß es nicht mehr

Hat der Film Ihre Erwartungen erfüllt?

Ja Nein

Wie bewerten Sie diesen Film?

☆☆☆☆☆

WEITER ZURÜCK

Figure B.21: Online Survey, page 21 (repeated multiple times)

98%

Verlosung

Wenn Sie an der **Verlosung von einem der 30 Gutscheine** teilnehmen möchten, tragen Sie bitte unten in das Textfeld Ihre E-Mail-Adresse ein.

E-Mail

Ich stimme zu, dass:

der Lehrstuhl für Marketing und Medien der Universität Münster sowie die Filmuniversität Babelsberg/Greenlight Analytics mich für den zweiten Teil dieser Umfrage in einigen Monaten wieder kontaktieren dürfen. Meine E-Mail-Adresse darf ausschließlich zu diesem Zweck mit meinen übrigen Angaben gespeichert werden. Die E-Mail-Adresse wird in diesem Kontext lediglich dafür verwendet, die Daten aus beiden Umfragen miteinander zu verknüpfen. Die Auswertung der Daten bleibt dabei vollständig anonym.

Sie können ihre **Gewinnchancen verdoppeln** und uns helfen unsere Modelle zu verbessern, indem Sie jetzt noch schnell **20 weitere Filme bewerten**.

20 WEITERE FILME BEWERTEN

UMFRAGE BEENDEN

Figure B.22: Online Survey, page 22

Vielen Dank!

Sie haben es geschafft! Vielen Dank, dass Sie sich die Zeit genommen haben bei der Umfrage für meine Masterarbeit teilzunehmen.

Sollten Sie weitere Fragen haben oder an den Ergebnissen interessiert sein, stehe ich Ihnen unter folgender E-Mail-Adresse gerne zur Verfügung: joel.schumacher@uni-muenster.de.



Figure B.23: Online Survey, page 23

Bibliography

- Adamowicz, W., Hanemann, M., Swait, J., Johnson, F., Layton, D., Regenwetter, M., Reimer, T. & Sorkin, R. (2005), 'Decision Strategy and Structure in Households: A "Groups" Perspective', *Marketing Letters* **16**, 387–399.
- Adler, M. (1985), 'Stardom and Talent', *American Economic Review* **75**, 208–212.
- Ainslie, A., Drèze, X. & Zufryden, F. (2005), 'Modeling Movie Life Cycles And Market Share', *Marketing Science* **24**, 508–517.
- Alba, J. W. & Williams, E. F. (2013), 'Pleasure Principles: A Review of Research on Hedonic Consumption', *Journal of Consumer Psychology* **23**(1), 2–18.
- Albert, S. (1998), 'Movie stars and the distribution of financially successful films in the motion picture industry', *Journal of Cultural Economics* **22**, 249–270.
- Alexander, N. (2016), Catered to Your Future Self: Netflix's "Predictive Personalization" and the Mathematization of Taste, in K. McDonald & D. Smith-Rowsey, eds, 'The Netflix Effect', Bloomsbury Academic.
- Allen, A. S. (2012), 'Has Hollywood Lost its Way?', <https://www.shortoftheweek.com/news/has-hollywood-lost-its-way/>.
- Altman, R. (1999), *Film/Genre*, BFI.
- Amatriain, X. & Basilico, J. (2015), Recommender Systems in Industry: A Netflix Case Study, in F. Ricci, L. Rokach & B. Shapira, eds, 'Recommender Systems Handbook', Springer, New York, pp. 385–420.
- An der Gassen, F. (2019), *Der Deutsche Erfolgsfilm: Determinanten Erfolgreicher Kinofilme und Typisierung Eines «Deutschen Geschmacks» Im Kontext Zuschauerrelevanter Kriterien der Filmauswahl, Medienästhetik und Mediennutzung.*, Peter Lang GmbH, Internationaler Verlag der Wissenschaften.
- Anderson, C. (2006), *The Long Tail - Why the Future of Business is Selling Less of More*, Hyperion.

Bibliography

- Anderson, C. (2008), 'The End of Theory: The Data Deluge Makes the Scientific Method Obsolete', <https://www.wired.com/2008/06/pb-theory/>.
- Anderson, D. R., Collins, P. A., Schmitt, K. L. & Jacobvitz, R. S. (1996), 'Stressful life events and television viewing.', *Communication Research* **23**(3), 243–260.
- Ang, I. (1991), *Desperately Seeking the Audience*, Routledge.
- Antipov, E. & Pokryshevkaya, E. (2011), 'Accounting for latent classes in movie box office modeling', *Journal of Targeting, Measurement and Analysis for Marketing* **19**(1), 3–10.
- Aribarg, A., Arora, N. & Kang, M. Y. (2010), 'Predicting joint choice using individual data', *Marketing Science* **29**(1), 139–157.
- Arora, N. & Allenby, G. M. (1999), 'Measuring the influence of individual preference structures in group decision making', *Journal Of Marketing Research* **36**, 476–487.
- Asur, S. & Huberman, B. A. (2010), Predicting the future with social media, in 'Proceedings of the 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology', pp. 492–499.
- Austin, B. A. (1983), *The film audience. An international bibliography of research; with annotations and an essay.*, Scarecrow Press.
- Austin, B. A. (1986), 'Motivations for movie attendance', *Communication Quarterly* **34**(2), 115–126.
- Azen, R. & Traxel, N. (2009), 'Using dominance analysis to determine predictor importance in logistic regression', *Journal of Educational and Behavioral Statistics* **34**(3), 319–347.
- Backen, I. (2009), *Theorie und Praxis des Kinofilmmarketing*, PhD thesis, Freie Universität Berlin.
- Bagella, M. & Becchetti, L. (1999), 'The determinants of motion picture box office performance: Evidence from movies produced in Italy', *Journal of Cultural Economics* **23**(4), 237–256.
- Ball, M. (2016a), 'Letting it go: The end of windowing (and what comes next)', *REDEF Originals* .
- Ball, M. (2016b), 'Why Disney is Closer than Ever to Walt's 60 Year Old Vision', <https://www.matthewball.vc/all/dass>.

Bibliography

- Ball, M. (2019), 'The Mining of Media (or The "Streaming Wars" are Just a Battle)', <https://www.matthewball.vc/all/minedmedia>.
- Barnes, B. E. & Thomson, L. M. (1994), Power to the people (meter): Audience measurement technology and media specialization, in J. S. Ettema & D. C. Whitney, eds, 'Audience-making: How the media create the audience', Sage, Thousand Oaks, pp. 75–94.
- Barrett, B. (2016), 'Netflix's Grand, Daring, Maybe Crazy Plan to Conquer the World', <https://www.wired.com/2016/03/netflixs-grand-maybe-crazy-plan-conquer-world/>.
- Bass, F. M. (1969), 'A new product growth model for consumer durables', *Management Science* **15**(5), 215–227.
- Bassett, M. E. (2015), 'Data science and the future of the movie business (Ringvorlesung 'Entrepreneurship at Goethe-Universität Frankfurt)', <https://electure-ms.studiumdigitale.uni-frankfurt.de/vod/clips/CR0ks0DPgS/quicktime.mp4>.
- Bastian, R. (2017), Better film business through data-driven decision support tools, in J. Funk, ed., 'Big Data, Big Movies – How Algorithms Transform The Film TV Industry (Conference Proceedings)', Erich Pommer Institut, Potsdam, pp. 49–54.
- Basuroy, S., Chatterjee, S. & Ravid, S. A. (2003), 'How critical are critical reviews? the box office influence of film critics, star-power and budgets', *Journal of Marketing* **67**, 103–117.
- Basuroy, S., Desai, K. K. & Talukdar, D. (2006), 'An empirical investigation of signaling in the motion picture industry', *Journal of Marketing Research* **43**, 287–295.
- Baum, H. (2003), Entscheidungsparameter bei der Filmauswahl von Kinogängern in Deutschland, PhD thesis, Freie Universität Berlin.
- Behrens, R., Foutz, N. Z., Franklin, M., Funk, J., Gutierrez-Navratil, F., Hofmann, J. & Leibfried, U. (2020), 'Leveraging analytics to produce compelling and profitable film content.', *Journal of Cultural Economics Online Special Issue*, 1–41.
- Beier, L.-O. & Evers, M. (2005), 'Jeder hat seine Mission', *Der Spiegel* **25.04.2005**.

Bibliography

- Bell, R. M., Koren, Y. & Volinsky, C. (2007), 'The BellKor Solution to the Netflix Prize', http://www.netflixprize.com/assets/ProgressPrize2007_KorBell.pdf.
- Benesch, A. (2004), *Kinofilmrezeption: Nutzungsmotive und Entscheidungskriterien bei der Filmauswahl*, GRIN.
- Bennett, J. & Lanning, S. (2007), The Netflix Prize, in 'Proceedings of KDD Cup and Workshop 2007'.
- Berauer, W. (2007), 'Quellenanalyse deutscher Filme 1997-2006. Woher kommt der Stoff der deutschen Traumfabrik?', <https://www.spio-fsk.de/?seitid=394&tid=3>.
- Blothner, D. (1999), *Erlebniswelt Kino: über die unbewusste Wirkung des Films*, Bastei Lübbe, Bastei-Verlag Lübbe.
- Blothner, D. (2000), *Filminhalte und Zielgruppen*, FFA, Berlin.
- Blothner, D. (2001), *Filminhalte und Zielgruppen 2*, FFA, Berlin.
- Blothner, D. (2003), *Filminhalte und Zielgruppen und die Wege der Filmauswahl*, FFA, Berlin.
- Blothner, D. (2004), *Filminhalte und Zielgruppen 4*, FFA, Berlin.
- Boatwright, P., Basuroy, S. & Kamakura, W. (2007), 'Reviewing the reviewers: The impact of individual film critics on box office performance', *Quantitative Marketing and Economics* .
- Bourdieu, P. (1984), *Distinction: A Social Critique of the Judgement of Taste*, Polity Short Introductions, Harvard University Press.
- Boyd, D. & Crawford, K. (2012), 'Critical questions for big data', *Information, Communication & Society* **15**(5), 662–679.
- Bracken, C. & Lombard, M. (2001), 'Uses and gratifications: A classic methodology revisited', *New Jersey Journal of Communication* **9**(1), 103–116.
- Brewer, S., Kelley, J. & Jozefowicz, J. (2009), 'A Blueprint For Success In the US Motion Picture Industry', *Applied Economics* **41**(5), 589–606.
- Brown, C. (2015), 'Key considerations in film finance', <https://filmonomics.slated.com/key-considerations-in-film-finance-white-paper-3-of-4-67e91846d070>.

Bibliography

- Bruneel, C., Guy, J. L., Haughton, D., Lemerrier, N., McLaughlin, M., Mentzer, K. & Zhang, C. (2018), *Movie analytics and the future of film finance. Are Oscars and box office revenue predictable?*, in P. Murschetz, R. Teichmann & M. Karmasin, eds, 'Handbook of state aid for film', Springer, Cham.
- Bryant, J. & Zillmann, D. (1984), 'Using television to alleviate boredom and stress', *Journal of Broadcasting* **28**(19), 1–20.
- Buder, E. (2017), 'Can AI Predict a Movie's Success? Algorithmic Screenplay Service 'Scriptbook' Causes Major Backlash', <https://nofilmschool.com/2017/04/scriptbook-black-list-screenwriting-ai-algorithm>.
- Budescu, D. V. (1993), 'Dominance analysis: A new approach to the problem of relative importance of predictors in multiple regression', *Psychological Bulletin* **114**(3), 542–551.
- Burkert, Z. & Kelly, M. (n.d.), 'The Diversity Demand: Securing the Future of Moviegoing (Movio Whitepaper)', <https://movio.co/diversity-demand-securing-future-moviegoing/>.
- Burzynski, M. & Baker, D. (1977), 'The effect of positive and negative prior information on motion picture appreciation.', *Journal of Social Psychology* **101**, 215–218.
- Buß, M. & Neuwöhner, U. (1999), 'Die MedienNutzerTypologie in der Fernsehprogrammplanung - Anwendungsmöglichkeiten der Publikumstypologie von ARD und ZDF', *Media Perspektiven* **10**, pp. 548.
- Calantone, R. J., Yeniyurt, S., Townsend, J. D. & Schmidt, J. B. (2010), 'The effects of competition in short product life-cycle markets: The case of motion pictures', *Journal of Product Innovation Management* **27**, 349–361.
- Caldwell, J. (2008), *Production Culture: Industrial Reflexivity and Critical Practice in Film/Television*, Duke University Press.
- Calvario, L. (2016), 'Impossible Things' Trailer: Kickstarter-Backed Horror Film Co-Written by Artificial Intelligence'. <https://www.indiewire.com/2016/08/impossible-things-trailer-kickstarter-horror-film-co-written-artificial-intelligence-1201714007/>.
- Cameron, S. (1988), 'The impact of video recorders on cinema attendance', *Journal of Cultural Economics* **12**(1), 35–47.

Bibliography

- Cameron, S. (1995), 'On the role of critics in the culture industry.', *Journal of Cultural Economics* **19**(4), 321–331.
- Campo, M., Hsieh, C., Nickens, M., Espinoza, J. J., Taliyan, A., Rieger, J., Ho, J. & Sherick, B. (2018), Collaborative metric learning recommendation system: Application to theatrical movie releases. (preprint, arXiv:1803.00202).
- Capozio, A. (2020), 'TMDb: Access to TMDb API', <https://CRAN.R-project.org/package=TMDb>. R package version 1.1.
- Carr, D. (2013), 'Giving Viewers What They Want', <https://www.nytimes.com/2013/02/25/business/media/for-house-of-cards-using-big-data-to-guarantee-its-popularity.html>.
- Cascio, W. F. (2007), 'Evidence-based management and the marketplace for ideas', *Academy of Management Journal* **50**(5), 1009–1012.
- Cassidy, J. (1997), 'Chaos in Hollywood', *The New Yorker* **73**(6), 36–44.
- Castendyk, O. & Goldhammer, K. (2012), *PRODUZENTENSTUDIE 2012 - Daten zur Film- und Fernsehwirtschaft in Deutschland 2011/2012 - Zusammenfassung*, Vistas.
- Castle, J. J. & Stepp, K. (2018), 'Silver screen sorting: Social identity and selective exposure in popular film viewing', *The Social Science Journal* **55**(4), 487–499.
- Caves, R. (2000), *Creative Industries: Contracts Between Art and Commerce*, Harvard University Press, Cambridge, MA.
- Chang, B.-H. & Ki, E.-J. (2005), 'Devising a practical model for predicting theatrical movie success: Focusing on the experience good property', *Journal of Media Economics* **18**(4), 247–269.
- Charrad, M., Ghazzali, N., Boiteau, V. & Niknafs, A. (2014), 'NbClust: An R package for determining the relevant number of clusters in a data set', *Journal of Statistical Software* **61**(6), 1–36.
- Chen, X., Chen, Y. & Weinberg, C. (2013), 'Learning about movies: the impact of movie release types on the nationwide box office', *Journal of Cultural Economics* **37**(3), 359–286.
- Chintagunta, P. & Lee, J. (2012), 'A pre-diffusion growth model of intentions and purchase', *Journal of the Academy of Marketing Science* **40**(1), 137–154.

Bibliography

- Chisholm, D. (2004), 'Two-part share contracts, risk, and the life cycle of stars: Some empirical results from motion picture contracts', *Journal of Cultural Economics* **28**(1), 37–56.
- Clement, M. (2004), 'Erfolgsfaktoren von Spielfilmen im Kino', *M&K* **52**(2), pp. 250.
- Clement, M., Fabel, S. & Schmidt-Stolting, C. (2006), 'Diffusion of hedonic goods: A literature review', *International Journal on Media Management* **8**(4), 155–163.
- Clement, M., Fischer, M. & Görke, B. (2007), 'Neuprodukteinführungen in der Filmindustrie: Wie reagieren Kapitalmarktinvestoren auf den Umsatzerfolg neuer Kinofilme?', *Die Betriebswirtschaft* **67**(4), 418–444.
- Clement, M., Wu, S. & Fischer, M. (2014), 'Empirical generalizations of demand and supply dynamics for movies', *International Journal of Research in Marketing* **31**(2), 207 – 223.
- Collins, A. & Hand, C. (2005), 'Analyzing moviegoing demand: an individual level cross-sectional approach', *Managerial and Decision Economics* **26**, 319–330.
- Collins, A., Hand, C. & Snell, M. C. (2002), 'What makes a blockbuster? economic analysis of film success in the united kingdom.', *Managerial and Decision Economics* **23**(6), 343–354.
- Connor, J. (2015), 'The Sony Hack: Data and Decision in the Contemporary Studio', *Media Industries Journal* **2**(2), 42–58.
- Conor, B. (2014), 'Gurus and Oscar Winners: How-To Screenwriting Manuals in the New Cultural Economy', *Television & New Media* **15**(2), 121–138.
- Cooper, A. (1999), *The Inmates are Running the Asylum*, Sams.
- Craig, C. S., Greene, W. H. & Douglas, S. P. (2005), 'Culture Matters: Consumer Acceptance of U.S. Films in Foreign Markets', *Journal of International Marketing* **13**(4), 80–103.
- Croyé, D. (2017), 'Building JustWatch, Part 2: Audience as a Service', <https://www.justwatch.com/blog/post/justwatch-audience-as-a-service/>.
- Csikszentmihalyi, M. (1975), 'Play and intrinsic rewards', *Journal of Humanistic Psychology* **15**(3).

Bibliography

- Csikszentmihalyi, M. & Csikszentmihalyi, I. (2000), *Beyond Boredom and Anxiety: Experiencing Flow in Work and Play*, Wiley.
- Cuadrado, M. & Frassetto, M. (1999), 'Segmentation of cinema audiences: An exploratory study applied to young consumers', *Journal of Cultural Economics* **23**(4), 257–267.
- De Vany, A. (2006), The movies, in V. A. Ginsburgh & C. D. Throsby, eds, 'Handbook of the Economics of Art and Culture Vol. 1', Elsevier.
- De Vany, A. & Walls, W. D. (1996), 'Bose-Einstein dynamics and adaptive contracting in the motion picture industry.', *Economic Journal* **106**, 1493–1514.
- De Vany, A. & Walls, W. D. (1999), 'Uncertainty in the movie industry: Does star power reduce the terror of the box office?', *Journal of Cultural Economics* **23**(4), 285–318.
- De Vany, A. & Walls, W. D. (2002), 'Does Hollywood make too many R-rated movies? Risk, stochastic dominance, and the illusion of expectation.', *Journal of Business* **75**(3), 425–451.
- Deerwester, S., Dumais, S., Furnas, G., Landauer, T. & Harshman, R. (1990), 'Indexing by latent semantic analysis', *Journal of the American Society for Information Science* **41**(6), 391–407.
- Dellarocas, C., Zhang, X. M. & Awad, N. F. (2007), 'Exploring the values of online product reviews in forecasting sales: The case of motion pictures', *Journal of Interactive Marketing* **21**(4), 23–45.
- Denyer, D., Tranfield, D. & Van Aken, J. E. (2008), 'Developing design propositions through research synthesis', *Organization Studies* **29**(3), 393–413.
- Deuchert, E., Adjamah, K. & Pauly, F. (2005), 'For Oscar Glory Or Oscar Money?', *Journal of Cultural Economics* **29**(3), 159–176.
- Dietz, J. (2011), 'Are Original Movies Really Better than Derivative Works?', <http://www.metacritic.com/feature/movie-sequels-remakes-and-adaptations>.
- Duvvuri, S. (2007), *Öffentliche Filmförderung in Deutschland*, Fischer (Reinhard), München.
- Eco, U. (1984), *The Role of The Reader: Explorations in the Semiotics of Text*, Indiana University Press, Bloomington.

Bibliography

- Egger, A. & Windgasse, T. (2007), 'Radionutzung und MNT 2.0', *Media Perspektiven* **5**, 255–263.
- Eick, D. (2006), *Drehbuchtheorien - Eine vergleichende Analyse*, UVK.
- Einav, L. & Ravid, S. A. (2009), 'Stock market response to changes in movies' opening dates', *Journal of Cultural Economics* **33**(4), 311–319.
- Eisenstein, S. (1974), 'Montage of attractions: For "enough stupidity in every wiseman"', *The Drama Review: TDR* **18**(1), 77–85.
- Ekstrand, M. D. (2020), LensKit for Python: Next-Generation Software for Recommender Systems Experiments, in 'Proceedings of the 29th ACM International Conference on Information and Knowledge Management (CIKM '20)'.
- Elberse, A. (2007), 'The power of stars: Do star actors drive the success of movies?', *Journal of Marketing* **71**(4), 102–120.
- Elberse, A. (2013), *Blockbusters: Hit-making, Risk-taking, and the Big Business of Entertainment*, Henry Holt and Co.
- Elberse, A. & Anand, B. (2007), 'The effectiveness of pre-release advertising for motion pictures: An empirical investigation using a simulated market.', *Information Economics and Policy* **19**, 319–343.
- Elberse, A. & Eliashberg, J. (2003), 'Demand and supply dynamics for sequentially released products in international markets: The case of motion pictures', *Marketing Science* **22**(3), 329–354.
- Eliashberg, J., Elberse, A. & Leenders, M. A. (2006), 'The motion picture industry: Critical issues in practice, current research, and new research directions', *Marketing Science* **25**(6), 638–661.
- Eliashberg, J., Hui, S. K. & Zhang, Z. J. (2007), 'From storyline to box office: A new approach for green-lighting movie scripts', *Management Science* **53**(6), 881–893.
- Eliashberg, J., Hui, S. K. & Zhang, Z. J. (2014), 'Assessing box office performance using movie scripts: A kernel-based approach', *IEEE Transactions on Knowledge and Data Engineering* **26**(11), 2639–2648.
- Eliashberg, J. & Sawhney, M. S. (1994), 'Modeling goes to Hollywood: predicting individual differences in movie enjoyment.', *Management Science* **40**, 1151–1173.

Bibliography

- Eliashberg, J. & Shugan, S. M. (1999), 'Film critics: Influencers or predictors?', *Journal of Marketing* **61**(2), 68–78.
- Eliashberg, J., Swami, S., Weinberg, C. & Wierenga, B. (2001), 'Implementing and evaluating silverscreener: A marketing management support system for movie exhibitors.', *Interfaces* .
- Epstein, E. (2005), 'The Midas Formula: How to Create a Billion-Dollar Movie Franchise', http://www.slate.com/articles/arts/the_hollywood_economist/2005/05/the_midas_formula.html.
- Epstein, E. (2012), *The Hollywood Economist: The Hidden Financial Reality Behind the Movies*, Melville House Pub.
- Evangelista, C. (2020), 'The Pandemic Could Kill Mid-Budget Films at the Box Office For Good', <https://www.slashfilm.com/mid-budget-movies/>.
- Eyal, N. & Biddle, G. (2018), 'How Netflix's Customer Obsession Created a Customer Obsession'.
<https://medium.com/behavior-design/how-netflixs-customer-obsession-created-a-customer-obsession-726c09c2d52b>.
- Festinger, L. (1957), *A theory of cognitive dissonance*, Stanford University Press, Stanford.
- Fettweis, F. (2018), Datengetriebene Entscheidungsfindung in Chinas Filmbusiness und Lektionen für den deutschen Markt, Master's thesis, Filmuniversität "Konrad Wolf" Potsdam-Babelsberg.
- FFA (2006), *Motivations-Studie Kino*, FFA, Berlin.
- FFA (2012), *Entwicklung der Kinostandorte, Spielstätten und Kinosäle 2010 bis 2012*, FFA, Berlin.
- FFA (2018), *Strukturen und Entwicklungen auf Basis des GfK-Panels*, FFA, Berlin.
- FFA (2019a), *Filmhitliste Jahreshitliste (international) 2018*, FFA, Berlin.
- FFA (2019b), *Kinobesucher 2018: Strukturen und Entwicklungen auf Basis des GfK-Panels*, FFA, Berlin.
- FFA (2020a), *Filmhitliste Jahresliste (international) 2019*, FFA, Berlin.
- FFA (2020b), *Geschäftsbericht 2019*, FFA, Berlin.

Bibliography

- FFA (2020c), *Kinobesucher 2019: Strukturen und Entwicklungen auf Basis des GfK-Panels*, FFA, Berlin.
- Finney, A. (1996), *Developing Feature Films in Europe. A Practical Guide*, Routledge.
- Follows, S. (2016), 'Do Hollywood movies make a profit?', <https://stephenfollows.com/hollywood-movies-make-a-profit/>.
- Follows, S. (2017), 'How many films are released each year?', <https://stephenfollows.com/how-many-films-are-released-each-year/>.
- Follows, S. (2018), 'How important is the opening week to a movie's total box office?', <https://stephenfollows.com/how-important-is-the-opening-week-to-a-movies-total-box-office/>.
- Follows, S. (2019), 'What percentage of independent films are profitable?', <https://stephenfollows.com/what-percentage-of-independent-films-are-profitable/>.
- Foutz, N. Z. (2016), Pre-launch analysis of competitive dynamics, in J. Funk, ed., 'Big Data, Big Movies – How Algorithms Transform The Film TV Industry (Conference Proceedings)', Erich Pommer Institut, pp. 26–28.
- Frank, B. (1994), 'Optimal timing of movie releases in ancillary markets: The case of video releases', *Journal of Cultural Economics* **18**(2), 135–133.
- Franklin, M. (2016), 'How SVOD is changing film production', <http://meces.co.uk/how-svod-is-changing-film-production/>.
- Frey, T. & van Groenewoud, H. (1972), 'A cluster analysis of the d2 matrix of white spruce stands in saskatchewan based on the maximum-minimum principle', *Journal of Ecology* **60**(3), 873–886.
- Fuchs, S. (2010), *Spielfilme im Fernsehen: Zuschauerprognose und monetäre Bewertung von Senderechten*, Josef Eul Verlag.
- Gaitanides, M. (2001), *Ökonomie des Spielfilms*, Fischer (Reinhard), München.
- Galloway, J. J. & Meek, F. L. (1981), 'Audience uses and gratifications: An expectancy value model', *Communication Research* **8**(4), 435–449.
- Gans, H. (2010), *Popular Culture and High Culture: An Analysis and Evaluation of Taste Revised and Updated*, Basic Books, New York.
- Garlin, F. V. & McGuiggan, R. L. (2002), 'Sex, spies and celluloid: Movie content preference, choice, and involvement', *Psychology & Marketing* **19**, 427–445.

Bibliography

- Gates, R. (1999), *Production Management for Film and Video*, Focal Press.
- Gehrau, V. (2003), '(Film-) Genres und die Reduktion von Unsicherheit', *Medien Kommunikationswissenschaft* **51**(2), 213–231.
- Gemser, G., Van Oostrum, M. & Leenders, M. A. (2007), 'The impact of film reviews on the box office performance of art house versus mainstream motion pictures', *Journal of Cultural Economics* .
- GfK (2015), 'Big Questions, Big Answers. Will harnessing smart data for audience analytics save the broadcast industry?', <https://www.gfk.com/insights/big-questions-big-answers>.
- Ghiassi, M., Lio, D. & Moon, B. (2015), 'Pre-production forecasting of movie revenues with a dynamic artificial neural network', *Expert Systems with Applications* **42**(6), 3176–3193.
- Gilboa, I. & Schmeidler, D. (1995), 'Case-based decision theory', *Quarterly Journal of Economics* **110**(3), 605–639.
- Giordani, P., Ferraro, M. & Martella, F. (2020), *An Introduction to Clustering with R*, Behaviormetrics: Quantitative Approaches to Human Behavior, Springer Singapore.
- Gladwell, M. (2006), 'The formula', *The New Yorker* .
- Goetzmann, W. N., Ravid, S. A. & Sverdlove, R. (2013), 'The pricing of soft and hard information: economic lessons from screenplay sales', *Journal of Cultural Economics* **37**(2), 271–307.
- Goldman, W. (1983), *Adventures in the Screen Trade*, Grand Central Publishing.
- Goldmedia (2010), 'Filmforecasting: Kinoerfolg vorher testen', <https://www.goldmedia.com/aktuelles/info/article/filmforecasting-kinoerfolg-vorher-testen/>.
- Golub, G. H. & Kahan, W. (1965), 'Calculating the singular values and pseudo-inverse of a matrix', *SIAM Journal of Numerical Analysis B* **2**(2), 205–224.
- Gomez-Uribe, C. & Hunt, N. (2015), 'The Netflix recommender system: Algorithms, business value, and innovation', *ACM Transactions on Management Information Systems* **6**(4), Article 13.

Bibliography

- Goodfellow, M. (2020), '20 European producers sign up for AI trial with Switzerland's Largo'.
<https://www.screendaily.com/news/20-european-producers-sign-up-for-ai-trial-with-switzerlands-largo/5152821.article>.
- Google (2020), 'Recommendation Systems', <https://developers.google.com/machine-learning/recommendation>.
- Green, M. C. (2008), Transportation theory, in W. Donsbach, ed., 'International Encyclopedia of Communication', Wiley-Blackwell, Oxford, pp. 5170–5175.
- Green, M. C. & Brock, T. C. (200), 'The role of transportation in the persuasiveness of public narratives', *Journal of Personality and Social Psychology* 79(5), 701–721.
- Green, M. C., Brock, T. C. & Kaufman, G. F. (2004), 'Understanding media enjoyment: The role of transportation into narrative worlds', *Communication Theory* 14(4), 311–327.
- Groeben, N. & Vorderer, P. (1988), *Leserpsychologie: Lesemotivation—Lektuerewirkung*, Aschendorffsche Verlagsbuchhandlung., Münster.
- Grothaus, M. (2018), 'How I Got My Dream Job Of Getting Paid To Watch Netflix', <https://www.fastcompany.com/40547557/how-i-got-my-dream-job-of-getting-paid-to-watch-netflix>.
- Gruvi (2020), 'The Audience Project: using audience behaviour to improve admissions and predict success'.
<https://www.gruvi.tv/post/the-audience-project-using-audience-behaviour-to-improve-admissions-and-predict-success>.
- Gunning, T. (1997), The cinema of attractions. early films, its spectator and the avant-garde., in T. Elsaesser, ed., 'Early Cinema', British Film Institute, pp. 63–70.
- Gutierrez-Navratil, F., Fernandez-Blanco, V., Orea, L. & Prieto-Rodriguez, J. (2012), 'How do your rivals' releasing dates affect your box office?', *Journal of Cultural Economics* .
- Hadida, A. (2009), 'Motion picture performance: A review and research agenda', *International Journal of Management Reviews* 11(3), 297–335.
- Hadida, A. (2010), 'Commercial success and artistic recognition of motion picture projects', *Journal of Cultural Economics* 34(1), 45–80.

Bibliography

- Hahsler, M. (2020), 'recommenderlab: Lab for Developing and Testing Recommender Algorithms', <https://CRAN.R-project.org/package=recommenderlab>.
- Hall, A. E. (2019), 'Identification and parasocial relationships with characters from Star Wars: The Force Awakens', *Psychology of Popular Media Culture* 8(1), 88–98.
- Hand, C. (2002), 'The distribution and predictability of cinema admissions', *Journal of Cultural Economics* 26, 53–64.
- Harper, F. M. & Konstan, J. A. (2015), 'The MovieLens Datasets: History and Context', *ACM Transactions on Interactive Intelligent Systems (TiiS)* 5(4), 19:1–19:19.
- Hartmann, P. & Höhne, I. (2007), 'MNT 2.0 – Zur Weiterentwicklung der MedienNutzerTypologie', *Media Perspektiven* 5, pp.235.
- Hartmann, P. & Neuwöhner, U. (1999), 'Lebensstilforschung und Publikumssegmentierung - Eine Darstellung der MedienNutzerTypologie', *Media Perspektiven* 10, pp.531.
- Henkel, L., James, M. & Croce, N. (2016), 'Would You Like Popcorn with That Download? A Uses and Gratifications Study Into the Motivations of Legal and Illegal Film Consumption', *Publication Cover Quarterly Review of Film and Video* 33(1).
- Hennig-Thurau, T. (2004), 'Spielfilme als Anlageobjekte. Die Höhe des Filmbudgets als Grundlage der Investitionsentscheidung', *Schmalenbachs Zeitschrift für betriebswirtschaftliche Forschung* 56(3), 171–188.
- Hennig-Thurau, T. (2011), Die deutsche filmindustrie im 21. jahrhundert: Ökonomische betrachtungen aus wissenschaftlicher sicht, in 'Guru Talk - Die deutsche Filmindustrie im 21. Jahrhundert'.
- Hennig-Thurau, T., Fuchs, S. & Houston, M. B. (2013), 'What's a movie worth? determining the monetary value of motion pictures' tv rights', *International Journal of Arts Management* 15(3), 4–20.
- Hennig-Thurau, T. & Henning, V., eds (2009), *Guru Talk - Die deutsche Filmindustrie im 21. Jahrhundert*, Schüren, Marburg.

Bibliography

- Hennig-Thurau, T., Henning, V., Sattler, H., Eggers, F. & Houston, M. B. (2007), 'The Last Picture Show? Timing and Order of Movie Distribution Channels', *Journal of Marketing* **71**, 63–83.
- Hennig-Thurau, T. & Houston, M. (2018), *Entertainment Science: Data Analytics and Practical Theory for Movies, Games, Books, and Music*, Springer International Publishing.
- Hennig-Thurau, T., Houston, M. B. & Heitjans, T. (2009), 'Conceptualizing and measuring the monetary value of brand extensions: The case of motion pictures', *Journal of Marketing* **73**, 167–183.
- Hennig-Thurau, T., Houston, M. B. & Sridhar, S. (2006), 'Can good marketing carry a bad product? evidence from the motion picture industry', *Marketing Letters* **17**(3), 205–219.
- Hennig-Thurau, T., Houston, M. B. & Walsh, G. (2006), 'The differing roles of success drivers across sequential channels: An application to the motion picture industry.', *Journal of the Academy of Marketing Science* **34**(4), 559–575.
- Hennig-Thurau, T., Houston, M. B. & Walsh, G. (2007), 'Determinants of motion picture box office and profitability: An interrelationship approach', *Review of Managerial Science* pp. 65–92.
- Hennig-Thurau, T., Marchand, A. & Hiller, B. (2012), 'The relationship between reviewer judgments and motion picture success: re-analysis and extension', *Journal of Cultural Economics* **36**(3), 249–283.
- Hennig-Thurau, T., Marchand, A. & Marx, P. (2012), 'Can automated group recommender systems help consumers make better choices?', *Journal of Marketing* **76**(5), 89–109.
- Hennig-Thurau, T., Walsh, G. & Bode, M. (2004), Exporting Media Products: Understanding the Success and Failure of Hollywood Movies in Germany, in B. E. Kahn & M. F. Luce, eds, 'Advances in Consumer Research Volume 31', Association for Consumer Research, Valdosta.
- Hennig-Thurau, T., Walsh, G. & Wruck, O. (2001), 'An investigation into the factors determining the success of service innovations: The case of motion pictures', *Academy of Marketing Science Review* **1**(6).
- Hennig-Thurau, T. & Wruck, O. (2000), 'Warum wir ins Kino gehen - Erfolgsfaktoren von Kinofilmen', *Marketing ZFP* **22**(3), 241–258.

Bibliography

- Henning, B. & Vorderer, P. (2001), 'Psychological escapism: Predicting the amount of television viewing by need for cognition', *The Journal of Communication* **51**(1), 100–120.
- Hirschman, E. C. (1987), 'Consumer preferences in literature, motion pictures, and television programs', *Empirical Studies of the Arts* **5**(1), 31–46.
- Holbrook, M. (1999), 'Popular appeal versus expert judgments of motion pictures', *Journal of Consumer Research* **26**, 144–155.
- Horkheimer, M. & Adorno, T. (1988), *Dialektik der Aufklärung: philosophische Fragmente*, Fischer Wissenschaft, Fischer.
- Horton, D. & Wohl, R. R. (1956), 'Mass communication and para-social interaction; observations on intimacy at a distance.', *Psychiatry* **19**(3), 215–29.
- Hsu, G. (2006), 'Jacks of all trades and masters of none: audiences' reactions to spanning genres in feature film production.', *Administrative Science Quarterly* **51**, 420–450.
- Hubert, L. J. & Levin, J. R. (1976), 'A general statistical framework for assessing categorical clustering in free recall', *Psychological Bulletin* **83**(6), 1072–1080.
- Hudson, D., Seah, L., Hite, D. & Haab, T. (2004), 'Telephone presurveys, self-selection, and non-response bias to mail and internet surveys in economic research', *Applied Economics Letters* **11**(4), 237–240.
- Huff, A. S. (2000), 'Changes in organizational knowledge production', *Academy of Management Review* **25**(2), 288–293.
- Hunt, D., Ramón, A. & Tran, M. (2019), 'Hollywood Diversity Report 2019. Report by The Division of Social Sciences at UCLA.', <https://socialsciences.ucla.edu/wp-content/uploads/2019/02/UCLA-Hollywood-Diversity-Report-2019-2-21-2019.pdf>.
- Hunter, S., Smith, S. & Singh, S. (2016), 'Predicting box office from the screenplay: A text analytical approach', *Journal of Screenwriting* **7**(2), 135–154.
- James, G., Witten, D., Hastie, T. & Tibshirani, R. (2013), *An Introduction to Statistical Learning: with Applications in R*, Springer Texts in Statistics, Springer, New York.
- Jannach, D., Zanker, M., Felfernig, A. & Friedrich, G. (2011), *Recommender Systems: An Introduction*, Cambridge University Press.

Bibliography

- Jansen, C. (2005), 'The performance of German motion pictures, profits and subsidies: Some empirical evidence', *Journal of Cultural Economics* **29**(3), 191–212.
- Jedidi, K., Krider, R. & Weinberg, C. (1998), 'Clustering at the movies', *Marketing Letters* **9**(4), 393–405.
- Jenke, M. (2018), 'Austausch dringend gesucht! - Contentproduzierende, Zuschauer*innen und Medienwissenschaft', *Navigationen: Medienindustrien – Aktuelle Perspektiven aus der deutschsprachigen Medienwissenschaft* **18**(2), 67–82.
- Johnson, B. & Nicola, M. (2017), *Winning your audiences: Marketing movies in the connected world*, Gruvi.
- Johnson, C. (2014), Logistic matrix factorization for implicit feedback data, in 'Advances in Neural Information Processing Systems'.
- Jolliffe, I. & Cadima, J. (2016), 'Principal component analysis: a review and recent developments', *Phil. Transactions R. Soc. A* **374**(20150202.).
- Joshi, A. & Mao, H. (2012), 'Adapting to Succeed? Leveraging the Brand Equity of Best Sellers to Succeed at the Box Office', *Journal of the Academy of Marketing Science* **40**, 558–571.
- Kahneman, D. & Tversky, A. (1979), 'Intuitive predictions: biases and corrective procedures', *Management Science* **12**, 313–327.
- Kanzler, M. (2019), *Fiction film financing in Europe: A sample analysis of films released in 2017*, European Audiovisual Observatory, Strasbourg.
- Karniouchina, E. V. (2011a), 'Are Virtual Stock Markets Efficient Predictors of New Product Success? The Case of the Hollywood Stock Exchange', *Journal of Product Innovation Management* **28**, 470–484.
- Karniouchina, E. V. (2011b), 'Impact of star and movie buzz on motion picture distribution and box office revenue', *International Journal of Research in Marketing* **28**(62-74).
- Katz, E., Blumler, J. G. & Gurevitch, M. (1973), 'Uses and gratifications research', *Public Opinion Quarterly* **37**, 509–523.
- Kim, S., Namkee, P. & Park, S. H. (2013), 'Exploring the effects of online word of mouth and expert reviews on theatrical movies' box office success', *International Journal on Media Management* **26**(2), 98–114.

Bibliography

- Kim, T. (2018), 'Netflix briefly tops Disney as the biggest pure media company in the world by market value', <https://www.cnbc.com/2018/05/24/netflix-passes-disney-and-is-now-biggest-pure-media-company.html>.
- Knapp, A.-K., Hennig-Thurau, T. & Mathys, J. (2013), 'The importance of reciprocal spillover effects for the valuation of bestseller brands: introducing and testing a contingency model', *Journal of the Academy of Marketing Science* **42**, 205–221.
- Knobloch, S. & Zillmann, D. (2002), 'Mood management via the digital jukebox', *Journal of Communication* **52**(2), 351–366.
- Knobloch-Westerwick, S. (2015), *Choice and Preference in Media Use: Advances in Selective Exposure Theory and Research*, Routledge Communication, Routledge.
- Knobloch-Westerwick, S., Gong, Y., Hagner, H. & Kerbeykian, L. (2012), 'Tragedy viewers count their blessings: Feeling low on fiction leads to feeling high on life', *Communication Research* **40**(6), 747–766.
- Knobloch-Westerwick, S., Sharma, N., Hansen, D. L. & Alter, S. (2005), 'Impact of popularity indications on readers' selective exposure to online news', *Journal of Broadcasting & Electronic Media* **49**(3), 296–313.
- Konstan, J. & Riedl, J. (2012), 'Deconstructing Recommender Systems: How Amazon and Netflix predict your preferences and prod you to purchase', *IEEE Spectrum* **49**.
- Koren, Y., Bell, R. M. & Volinsky, C. (2009), 'Matrix factorization techniques for recommender systems', *Computer* **42**(8), 30–37.
- Koschat, M. A. (2012), 'The impact of movie reviews on box office: Media portfolios and the intermediation of genre', *Journal of Media Economics* **25**(1), 35–53.
- Kosterich, A. & Napoli, P. (2015), 'Reconfiguring the audience commodity: The institutionalization of social tv analytics as market information regimentation of social tv analytics as market information regime.', *Television & New Media* **17**(3), 254–271.
- Krauß, F. & Loist, S. (2018), 'Medienindustrieforschung im deutschsprachigen Raum', *Navigationen: Medienindustrien – Aktuelle Perspektiven aus der deutschsprachigen Medienwissenschaft* **18**(2), 7–26.

Bibliography

- Kumb, F. (2017), *Local Movie Supply in the German Motion Picture Industry: An Industrial Organization Perspective*, Springer.
- Lang, B. (2017), 'Fox's Stacey Snider Gets Candid About Netflix, Diversity and the Future of Wolverine', <https://variety.com/2017/film/features/stacey-snider-21st-century-fox-first-year-1202563799/>.
- Lang, D. M., Switzer, D. M. & Swartz, B. J. (2011), 'DVD sales and the R-rating puzzle', *Journal of Cultural Economics* **35**(4), 267–286.
- Lange, C. (1999), *Erfolgspotenziale für Spielfilme*, Verlag für Wissenschaft und Forschung.
- Lash, M. & Zhao, K. (2016), 'Early predictions of movie success: the who, what, and when of profitability', *Journal of Management Information Systems* **33**(3), 874–903.
- Lazarsfeld, P. F., Berelson, B. & Gaudet, H. (1948), *The people's choice: How the voter makes up his mind in a presidential campaign*, Duell, Sloan, and Pearce.
- Leenders, M. A. & Eliashberg, J. (2011), 'The antecedents and consequences of restrictive age-based ratings in the global motion picture industry', *International Journal of Research in Marketing* **28**(4).
- Lehmann, D. R. & Weinberg, C. (2000), 'Sales through sequential distribution channels', *Journal of Marketing* **64**, 18–33.
- Leng, H., Paulino, C., Haider, M., Lu, R., Zhou, Z., Mengshoel, O., Brodin, P., Forgeat, J. & Jude, A. (2018), Finding similar movies: Dataset, tools, and methods, in 'Proceedings of the 8th International Conference on Semantic Systems (WSCG'2018)', Plzen.
- Leuven, J. (1981), 'Expectancy theory in media and message selection', *Communication Research* **8**(4), 425–434.
- Lins, G. (2000), *Strategien der Filmstoffauswahl bei deutschen Film und Fernsehproduktionen*, Nomos.
- Litman, B. (1983), 'Predicting success of theatrical movies: An empirical study', *Journal of Popular Culture* **16**, 159–175.
- Litman, B. & Kohl, L. S. (1989), 'Predicting financial success of motion pictures: The '80s experience', *Journal of Media Economics* **2**(2), 35–50.

Bibliography

- Liu, B., Hsu, W. & Ma, Y. (1998), Integrating classification and association rule mining, in 'Proceedings of the 1998 SIGKDD'.
- Liu, Y. (2006), 'Word of mouth for movies: Its dynamics and impact on box office revenue', *Journal of Marketing* 70(3), 74–89.
- Lo, V. S. (2009), *New opportunities in marketing data mining*, IGI Global, pp. 1409–1415.
- Lovullo, D., Clarke, C. & Camerer, C. (2012), 'Robust analogizing and the outside view: Two empirical tests of case-based decision making', *Strategic Management Journal* 33, 496–512.
- Macdonald, I. (2003), 'Finding the needle. How readers see screen ideas', *Journal of Media Practice* 4(1), 27–40.
- Madrigal, A. (2014), 'How Netflix Reverse-Engineered Hollywood', <https://www.theatlantic.com/technology/archive/2014/01/how-netflix-reverse-engineered-hollywood/282679/>.
- Maltby, R. (2004), *Hollywood Cinema*, Malden.
- Marchand, A. & Marx, P. (2020), 'Automated product recommendations with preference-based explanations', *Journal of Retailing* 96(3), 328–343.
- Marcuse, H. (1991), *One-dimensional Man: Studies in the Ideology of Advanced Industrial Society*, Routledge Classics, Beacon Press.
- Marolda, M. & Krigsman, M. (2018), 'Moneyball' for Movies: Data and Analytics at Legendary Entertainment.', <https://www.cxotalk.com/episode/moneyball-movies-data-analytics-legendary-entertainment>.
- Marx, P. (2011), *Providing Actionable Recommendation*, Josef Eul Verlag.
- Mayer, J. & Gaschke, Y. (1988), 'The experience and meta-experience of mood.', *Journal of Personality and Social Psychology* 55, 102–111.
- Mayring, P. (2014), *Qualitative Content Analysis: Theoretical Foundation, Basic Procedures and Software Solution*, SSOAR, Klagenfurt.
- McClain, J. O. & Rao, V. R. (1975), 'Clustisz: A program to test for the quality of clustering of a set of objects', *Journal of Marketing Research* 12(4), 456–460.
- McKee, R. (2010), *Story: Style, Structure, Substance, and the Principles of Screenwriting*, HarperCollins.

Bibliography

- McKenzie, J. (2013), 'Australian films at the Australian box office: performance, distribution, and subsidies', *Journal of Cultural Economics* **37**(2), 247–269.
- McQuail, D. (1997), *Audience Analysis*, SAGE Publications.
- Meiseberg, B., Ehrmann, T. & Dormann, J. (2008), 'We don't need another hero – implications from network structure and resource commitment for movie performance', *Schmalenbachs Business review* **60**, 74–98.
- Mestyan, M., Yasseri, T. & Kertész, J. (2013), 'Early Prediction of Movie Box Office Success Based on Wikipedia Activity Big Data', *PLOS ONE* **8**(8).
- Michel, R., Schnakenburg, I. & Martens, T. (2020), *Targeting Uplift: An Introduction to Net Scores*, Springer International Publishing.
- Miller, D. & Shamsie, J. (2001), 'Learning across the life cycle: experimentation and performance among the Hollywood studio heads', *Strategic Management Journal* **22**(8), 725–745.
- Möller, K. E. K. & Karppinen, P. (1983), 'Role of motives and attributes in consumer motion picture choice', *Journal of Economic Psychology* **4**(3), 239–262.
- Moon, S., Bergey, P. K. & Iacobucci, D. (2010), 'Dynamic Effects Among Movie Ratings, Movie Revenues, and Viewer Satisfaction', *Journal of Marketing* **74**, 108–121.
- Moore, S. (2007), *The Biz: The Basic Business, Legal and Financial Aspects of the Film Industry*, Silman-James Press.
- MPA (2020), *MPA Theme Report 2019*, MPA.
- Murschetz, P. C. & Schlütz, D. (2018), 'Big data and television broadcasting: A critical reflection on big data's surge to become a new techno-economic paradigm and its impacts on the concept of the «addressable audience».', *Fonseca, Journal of Communication, Salamanca* **17**, 23–38.
- Napoli, P. (2011), *Audience Evolution: New Technologies and the Transformation of Media Audiences*, Columbia University Press, New York.
- Napoli, P. (2012), 'Audience evolution and the future of audience research', *International Journal on Media Management* **14**(2), 79–97.
- Napoli, P. (2016), 'Special issue introduction: Big data and media management', *International Journal on Media Management* **18**(1), 1–7.

Bibliography

- Narayanan, A. & Shmatikov, V. (2008), Robust de-anonymization of large sparse datasets, in '2008 IEEE Symposium on Security and Privacy (sp 2008)', pp. 111–125.
- Nardone, J. M. (1982), 'Is the movie industry contracyclical?', *Cycles* **33**(3).
- Neckermann, G. (2001a), 'Das Kinopublikum 1993 bis 2000', *Media Perspektiven* **10**, 514–523.
- Neckermann, G. (2001b), *Das Programmkinopublikum*, FFA.
- Neckermann, G. (2002), *Die Kinobesucher 2001: Strukturen und Entwicklungen auf Basis des GfK Panels*, FFA, Berlin.
- Neckermann, G. & Blothner, D. (2001), *Das Kinobesucherpotential 2010 nach sozio-demographischen und psychologischen Merkmalen*, FFA, Berlin.
- Neemaligham, R. & Chintagunta, P. (1999), 'A Bayesian model to forecast new product performance in domestic and international markets', *Marketing Science* **18**(2), 115–136.
- Neemaligham, R. & Jain, D. (1999), 'Consumer choice process for experience goods: An econometric model and analysis', *Journal of Marketing Research* **36**(3), 373–386.
- Nelson, J. (2016), 'Audience currencies in the age of big data', *International Journal on Media Management* **18**(1), 9–24.
- Nelson, R. A. & Glotfelty, R. (2012), 'Movie stars and box office revenues: an empirical analysis', *Journal of Cultural Economics* **36**(2), 141–166.
- Neslin, S., Gupta, S., Kamakura, W., Lu, J. & Mason, C. (2006), 'Defection detection: Measuring and understanding the predictive accuracy of customer churn models', *Journal of Marketing Research* **43**(2), 204–211.
- Oatley, K. (1994), 'A taxonomy of the emotions of literary response and a theory of identification in fictional narrative', *Poetics* **23**, 53–74.
- Oehmichen, E. (2007), 'Die Mediennutzertypologie MNT 2.0', *Media Perspektiven* **5**, pp. 226.
- Oliver, M. (1993), 'Exploring the paradox of the enjoyment of sad films', *Human Communication Research* **19**(3), 315–342.
- Oliver, M. B. (2008), 'Tender affective states as predictors of entertainment preference', *Journal of Communication* **58**(1), 40–61.

Bibliography

- Orme, T. & Vogel, H. L. (2020), 'Is the motion-pictures industry recession proof?', *International Advances in Economic Research* **26**, 363–375.
- Ortner, S. B. (2009), *Studying Sideways – Ethnographic Access in Hollywood*, in V. Mayer, M. J. Banks & J. Caldwell, eds, 'Production Studies: Cultural Studies of Media Industries'.
- Palmer, W. (2018), 'Dynamic Content: Why It Matters To The Movie Industry', <https://movio.co/blog/dynamic-content-why-it-matters-to-the-movie-industry/>.
- Palmgreen, P., Cook, P. L., Harvill, J. G. & Helm, D. M. (1988), The motivational framework of moviegoing: uses and avoidances of theatrical films., in B. A. Austin, ed., 'Current Research in Film', Vol. 4, Ablex, Norwood.
- Palmgreen, P. & Rayburn, J. D. (1982), 'Gratifications sought and media exposure: An expectancy value model', *Communication Research* **9**(4), 561–580.
- Panaligan, R. & Chen, A. (2013), 'Quantifying Movie Magic with Google Search', <http://de.scribd.com/doc/146029829/Quantifying-Movie-Magic-with-Google-Search>.
- Pardoe, I. (2005), 'Just How Predictable Are the Oscars?', *Chance* **18**(4), 32–39.
- Pariser, E. (2011), *The Filter Bubble: What The Internet Is Hiding From You*, Penguin Books Limited.
- Pasick, A. (2015), 'The Magic that Makes Spotify's Discover Weekly Playlists So Damn Good', <https://qz.com/571007/the-magic-that-makes-spotifys-discover-weekly-playlists-so-damn-good/>.
- Pearlin, L. I. (1959), 'Social and personal stress and escape television viewing', *Public Opinion Quarterly* **23**(2), 255–259.
- Pennock, Lawrence, Giles & Nielsen (2001), The power of play: Efficiency and forecast accuracy in web market games. NEC Research Institute Technical Report 2000-168. A brief version appears in *Science* **291**: 987-988, February 9 2001.
- Perse, E. M. & Rubin, A. M. (1988), 'Audience activity and satisfaction with favorite television soap opera', *Journalism Quarterly* **68**, 368–375.
- Peukert, C. (2018), 'The next wave of digital technological change and the cultural industries', *Journal of Cultural Economics* **43**(2), 189–210.

Bibliography

- Pfeffer, J. & Sutton, R. I. (2006), 'Evidence-based management', *Harvard Business Review* **84**(1), 62–74.
- Piatetsky-Shapiro, G. & Steingold, S. (2000), 'Measuring lift quality in database marketing', *SIGKDD Explorations* **2**(2), 76–80.
- Powdermaker, H. (1950), *Hollywood, the Dream Factory: An Anthropologist Looks At the Movie-Makers*, Little and Brown.
- Prag, J. & Casavant, J. (1994), 'An empirical study of determinants of revenues and marketing expenditures in the motion picture industry', *Journal of Cultural Economics* **18**, 217–235.
- Prommer, E. (1997), Kinopublikumsforschung in Deutschland, in H. Amend & M. Bütow, eds, 'Der bewegte Film - Aufbruch zu neuen deutschen Erfolgen', Vistas.
- Prommer, E. (2010), Das Kinopublikum im Wandel: Forschungsstand, historischer Rückblick und Ausblick, in P. Glögner & P. Föhl, eds, 'Das Kulturpublikum', pp. 195–237.
- R Core Team (2020), 'R: A language and environment for statistical computing', <http://www.R-project.org/>.
- Rackaitis, T. (2019), 'Introduction to Latent Matrix Factorization Recommender Systems'.
<https://towardsdatascience.com/introduction-to-latent-matrix-factorization-recommender-systems-8dfc63b94875>.
- Radas, S. & Shugan, S. M. (1998), 'Seasonal marketing and timing new product introductions', *Journal of Marketing Research* **35**, 296.
- Rao, V. R. & Steckel, J. H. (1991), 'A polarization model for describing group preferences', *Journal of Consumer Research* **18**(1), 108–118.
- Ravid, S. A. (1999), 'Information, blockbusters, and stars: A study of the film industry', *Journal of Business* **72**(4).
- Ravid, S. A. (2002), Are They All Crazy Or Just Risk Averse? Some Movie Puzzles and Possible Solutions. Working Paper, Rutgers University, Newark, June 2002.
- Ravid, S. A. & Basuroy, S. (2004), 'Managerial objectives, the R-rating puzzle, and the production of violent films', *Journal of Business* **77**, 155–192.

Bibliography

- Rayburn, J. D. & Palmgreen, P. (1984), 'Merging uses and gratifications and expectancy value theory', *Communication Research* **11**(4), 537–562.
- Redondo, I. & Holbrook, M. (2010), 'Modeling the appeal of movie features to demographic segments of theatrical demand', *Journal of Cultural Economics* **34**(4), 299–315.
- Reeves, B., Lang, A., Kim, E. Y. & Tatar, D. (1999), 'The effects of screen size and message content on attention and arousal', *Media Psychology* **1**(1), 49–67.
- Reinstein, D. & Snyder, D. (2005), 'The influence of expert reviews on consumer demand for experience goods: A case study of movie critics', *Journal of Industrial Economic* **53**(1), 27–51.
- Reiss, J. (2010), *Think Outside the Box Office: The Ultimate Guide to Film Distribution and Marketing for the Digital Era*, Hybrid Cinema.
- Reuband, K.-H. (2011), 'Kinobesuch im großstädtischen Kontext', *KM. Das Monatsmagazin von Kulturmanagement Network* **53 (Schwerpunkt „Film & Kino“)**(9-33).
- Ricci, F., Rokach, L. & Shapira, B. (2015), *Recommender Systems Handbook*, Springer, New York.
- Rimscha, B. v. (2010), *Risikomanagement in der Entwicklung und Produktion von Spielfilmen: Wie Produzenten vor Drehbeginn Projektrisiken steuern*, VS Verlag für Sozialwissenschaften.
- Rimscha, B. v. (2013), 'It's not the economy, stupid! External effects on the supply and demand of cinema entertainment', *Journal of Cultural Economics* **37**(4), 433–455.
- Rosen, S. (1981), 'The economics of superstars', *American Economic Review* **71**, 845–858.
- Rousseau, D. M. (2012), Envisioning evidence-based management, in D. M. Rousseau, ed., 'Handbook of Evidence-Based Management (Digital Edition)', Oxford University Press.
- Rubin, A. M. & Perse, E. M. (1987), 'Audience activity and soap opera involvement: A uses and effects investigation', *Human Communication Research* **14**(2), 246–268.

Bibliography

- Ruhrländer, R. P., Boissier, M. & Uflacker, M. (2018), Improving box office result predictions for movies using consumer-centric models., in 'Proceedings of the 24th ACM SIGKDD', ACM, pp. 655–664.
- Ryan, B. (1992), *Making Capital From Culture - The Corporate Form Of Capitalist Cultural Production*, de Gruyter.
- Ryan, R. M. & Deci, E. L. (2000), 'Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being', *American Psychologist* **55**(1), 68–78.
- Rynes, S., Giluk, T. & Brown, K. G. (2007), 'The very separate worlds of academic and practitioner periodicals in human resource management', *Academy of Management Journal* **50**(5), 987–1008.
- Sawhney, M. S. (1996), 'A parsimonious model for forecasting gross box-office revenues of motion pictures', *Marketing Science* **15**(2), 113–131.
- Schön, D. (1983), *Reflective Practitioner*, Basic Books.
- Schulz, T. (2005), 'Es wird Geld regnen', <http://www.spiegel.de/spiegel/print/d-42983369.html>.
- Schulze, G. (1992), *Die Erlebnisgesellschaft - Kultursoziologie der Gegenwart*, Campus, Frankfurt.
- Schumacher, J. (2017), Concept test for entertainment products, Master's thesis, University of Muenster.
- Schweitzer, D. (1996), *Film als Marktleistung: Absatzpolitik filmwirtschaftlicher Produktionsunternehmen*, DUV: Wirtschaftswissenschaft, Dt. Univ.-Verlag.
- Scott, A. (2005), *On Hollywood: The Place, the Industry*, Princeton University Press.
- Sears, D. O. & Freedman, J. L. (1967), 'Selective exposure to information: A critical review', *Public Opinion Quarterly* **31**(2), 194–213.
- Silver, N. (2012), *The Signal and the Noise: Why So Many Predictions Fail-but Some Don't*, Penguin Press HC.
- Simens, D. (2000), *From Reel to Deal: Everything You Need to Create a Successful Independent Film*, Grand Central Publishing.
- Simon, H. A. (1996), *The Sciences of the Artificial (eBook)*, MIT Press, Cambridge, MA.

Bibliography

- Simonton, D. K. (2011), *Great Flicks: Scientific Studies of Cinematic Creativity and Aesthetics*, Oxford University Press.
- Singel, R. (2009), 'Netflix Spilled Your Brokeback Mountain Secret, Lawsuit Claims', <https://www.wired.com/2009/12/netflix-privacy-lawsuit/>.
- Skinner, B. F. (1969), *Contingencies of reinforcement: A theoretical analysis*, Appleton, New York.
- Slated (2016), 'Using science to pick hit movies', <https://filmonomics.slated.com/using-science-to-pick-hit-movies-ad0e2d6cf678>.
- Smith, M. & Telang, R. (2016), *Streaming, Sharing, Stealing: Big Data and the Future of Entertainment*, The MIT Press, MIT Press.
- Snyder, C. (2001), *Coping with Stress: Effective People and Processes*, OUP E-Books, Oxford University Press.
- Soares, F. (2020), 'Exploring Predictors' Importance in Binomial Logistic Regressions', <https://cran.r-project.org/web/packages/dominanceanalysis/vignettes/da-logistic-regression.html>.
- Sochay, S. (1994), 'Predicting the performance of motion pictures', *Journal of Media Economic* 7(4), 1–20.
- Sood, S. & Drèze, X. (2006), 'Brand extensions of experiential goods: Movie sequel evaluations', *Journal of Consumer Research* 33(3), 352–360.
- Stempel, T. (2001), *American Audiences on Movies and Moviegoing*, University Press of Kentucky.
- Stiff, D. (2019), 'The True Concept Drivers for Aquaman's Global Box Office Dominance', <https://www.vault-ai.com/posts/aquamans-global-box-office-dominance.html>.
- Storm, S. (2000), *Strukturen der Filmfinanzierung in Deutschland*, Schriftenreihe zur Film-, Fernseh- und Multimediaproduktion, Verlag für Berlin-Brandenburg.
- Stradella Road, I. (2010), 'Moviegoers 2010', Company report, no longer available online.
- Stroud, N. J. (2007), 'Media Effects, Selective Exposure, and Fahrenheit 9/11', *Political Communication* 24(4), 415–432.

Bibliography

- Suarez-Vásquez, A. (2011), 'Critic power or star power? The influence of hallmarks of quality of motionpictures: an experimental approach', *Journal of Cultural Economics* **35**(2), 119–135.
- Tajfel, H. (1978), *Differentiation Between Social Groups: Studies in the Social Psychology of Intergroup Relations*, Economic Theory, Econometrics, and Mathematical Economics, European Association of Experimental Social Psychology by Academic Press.
- Tan, E. S.-H. (2008), 'Entertainment is emotion: The functional architecture of the entertainment experience', *Media Psychology* **11**(1), 28–51.
- Tefertille, A. (2017), 'Moviegoing in the Netflix Age: Gratifications, Planned Behavior, and Theatrical Attendance', *Communication & Society* **30**(4), 27–44.
- Tesser, A., Millar, K. U. & Wu, C. (1988), 'On the perceived functions of movies', *The Journal of Psychology: Interdisciplinary and Applied* **122**(5), 441–449.
- Thorndike, E. L. (1932), *The Fundamentals of Learning*, Columbia University, Teachers College, Bureau of Publications, New York.
- Tooby, J. & Cosmides, L. (2001), 'Does beauty build adapted minds? toward an evolutionary theory of aesthetics, fiction and the arts.', *SubStance* **94-95**, 6–27.
- Tröscher, A., Jahrer, M. & Bell, R. M. (2009), 'The BigChaos Solution to the Netflix Grand Prize', http://www.stat.osu.edu/~dmsl/GrandPrize2009_BPC_BigChaos.pdf.
- Troy Research (2008), *Tracking Accuracy Concerns II (Internal Discussion Notes)*, Troy Research (via Wikileaks).
- Troy Research (n.d.), *Troy Tracking Box Office Prediction Model*, Troy Research (via Wikileaks).
- Turitz, N. (2016), 'Is There Still Hope For The Mid-Budget Movie?', <https://www.tracking-board.com/is-there-still-hope-for-the-mid-budget-movie/>.
- Valenzuela, S. (2015), 'Historical dramas, current political choices: Analyzing partisan selective exposure with a docudrama', *Mass Communication and Society* **18**(4), 449–470.

Bibliography

- Van Aken, J. E. (2005), 'Management research as a design science: Articulating the research products of mode 2 knowledge production in management', *British Journal of Management* **16**(1), 19–36.
- Van Aken, J. E. & Romme, A. G. L. (2012), A design science approach to evidence-based management, in D. M. Rousseau, ed., 'The Oxford Handbook of Evidence-Based Management (Digital Edition)', Oxford University Press.
- Van de Ven, A. H. (2007), *Engaged scholarship: A guide for organizational and social research*, OUP Oxford.
- Vogel, H. L. (2004), *Entertainment Industry Economics*, Cambridge University Press.
- Vorderer, P. (1996), 'Rezeptionsmotivation: Warum nutzen Rezipienten mediale Unterhaltungsangebote?', *Publizistik* **41**(3), 310–326.
- Vorderer, P., Steen, F. F. & Chan, E. (2006), Motivation, in J. Bryant & P. Vorderer, eds, 'Psychology of Entertainment', Vol. E-Book, Routledge.
- Wallace, W. T., Seigerman, A. & Holbrook, M. (1993), 'The Role of Actors and Actresses in the Success of Films: How Much Is a Movie Star Worth', *Journal of Cultural Economics* **17**(1), 1–27.
- Wei, L. (2006), 'Invited commentary: making sense of these million-dollar babies – rationale behind superstar profit participation contracts', *Marketing Science* **25**, 678–680.
- Weinstein, A. (2004), *Handbook of Market Segmentation: Strategic Targeting for Business and Technology Firms*, Haworth Press.
- Weiyang, L. (2015), 'A historical overview of uses and gratifications theory', *Cross-Cultural Communication* **11**(9), 71–78.
- Wendling, E. (2008), *Filmproduktion: Eine Einführung in die Produktionsleitung*, Praxis Film, Uvk Verlags GmbH.
- Wright, D. (2014), *Understanding Cultural Taste: Sensation, Skill and Sensibility*, Palgrave Macmillan UK.
- Wu, T. (2015), 'Netflix's Secret Special Algorithm Is a Human', <http://www.newyorker.com/business/currency/hollywoods-big-data-big-deal>.
- Wyatt, R. O. & Badger, D. P. (1990), 'Effects of information and evaluation in film criticism', *Journalism Quarterly* **67**, 359–368.

Bibliography

- Zafirau, S. (2009), Audience Knowledge and the Everyday Lives of Cultural Producers in Hollywood, in V. Mayer, M. J. Banks & J. Caldwell, eds, 'Production Studies: Cultural Studies of Media Industries', Routledge.
- Zag, R. (2005), *Der Publikumsvertrag*, TR Verlag Union.
- Zillmann, D. (1988), 'Mood management through communication choices', *American Behavioral Scientist* **31**(3), 327–340.
- Zillmann, D. (1991), Empathy: Affect from bearing witness to the emotions of others., in J. Bryant & D. Zillmann, eds, 'Responding to the screen: Reception and reaction processes', Erlbaum, Hillsdale, NJ, pp. 135–167.
- Zillmann, D. (1994), 'Mechanisms of emotional involvement with drama', *Poetics* **23**(1-2), 33–51.
- Zillmann, D. & Bryant, J. (1985), *Selective Exposure To Communication*, Routledge Communication Series, Taylor & Francis.
- Zillmann, D., Hezel, R. T. & Medoff, N. J. (1980), 'The effect of affective states on selective exposure to televised entertainment fare', *Journal of Applied Social Psychology* **10**(4), 323–339.
- Zuckerman, E. & Kim, T.-Y. (1999), 'The highbrow trade-off: Market mediation and success in the film industry', <https://www.gsb.stanford.edu/faculty-research/working-papers/highbrow-trade-market-mediation-success-film-industry>. Working Paper.
- Zuckerman, M. & Litle, P. (1986), 'Personality and curiosity about morbid and sexual events.', *Personality and Individual Differences* **7**(1), 49–56.
- Zufryden, F. (1996), 'Linking advertising to box office performance of new film releases', *Journal of Advertising Research* **36**(4), 29–41.
- Zuta, P. (2007), *Publikumspräferenzen für Kinofilme - Die publikumsinduzierte Kreation im Filmproduktionsprozess. Konsequenzen einer ressourcenorientierten Sicht auf die Filmherstellung*, Vistas.
- Zwirner, A. (2011), *Finanzierung und Förderung Von Kinospielefilmen in Deutschland*, Film, Fernsehen, Medienkultur, VS Verlag für Sozialwissenschaften.