

SCHEMA INFERENCE FOR TABULAR DATA WITH EXPLAINABLE ARTIFICIAL INTELLIGENCE

SYSTEMATIC REVIEW PROTOCOL - THIRD VERSION

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1. INTRODUCTION

Data engineering is an integral part of the data science process [1] [2]. In CRISP-DM the equivalent process stage is called “data preparation” [3, pp. 23-26]. It comprises tasks such as data ingestion, data transformation, and data quality assurance. In order to fulfill these tasks, schema inference is an important capability [4]. Its goal is to detect the structure of a dataset and to derive metadata on hierarchies, data types, etc. [5] Artificial intelligence (AI) has the potential to automate schema inference and thus increase the efficiency of the data science process. However, as government institutions are subject to special regulations, explainability of AI models can be a mandatory requirement. Transparency of AI models is particularly relevant for high-risk systems in domains such as employment services, law enforcement and critical infrastructure.* Goal of this research protocol is to plan a systematic review of literature on schema inference for tabular data with explainable AI (XAI). The document is the first part of a series of publications in the quest for AI models that a.) increase the efficiency of schema inference for tabular data and b.) are explainable to both end users and regulators in government organizations. This third version was derived from two earlier review protocols [7] [8].

2. REVIEW QUESTION

Purpose of the planned review is to systematically collect and analyze relevant literature on the following question: *What explainable AI models can government institutions use for schema inference for tabular data?* Key focus of the review lies on schema inference for tabular data and explainability. It is assumed that AI models meeting these

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*This document follows the concept of high-risk systems as defined in the draft of the Artificial Intelligence Act of the European Union [6].

requirements are in principle qualified for the use in government institutions—even in high-risk environments.

3. INCLUSION CRITERIA

In accordance with the search strategy described below, the review will include all studies that address the use of XAI for schema inference for tabular data. For the term "artificial intelligence", we rely on Tegmark's definition. Here, AI is the ability of a machine to "accomplish complex goals" [9, p. 39]. Thus, we implicitly identify schema inference as such a complex task. Since "machine learning" (ML) is an important technique in AI development, we include this expression in the list of search terms.

As pointed out by Vilone and Longo [10], there is no universally accepted notion of "explainability" in the context of XAI. In our review, we build on a human-centred definition, formulated by the Defense Advanced Research Projects Agency (DARPA). Accordingly, XAI techniques "enable end users to better understand, trust, and effectively manage artificially intelligent systems" [11, p. 1] [12]. This definition does not necessarily demand interpretability, where users are expected to understand the inner workings of an AI model. Instead, the definition allows for black-box algorithms that generate results in a way that is trustworthy to end users.

For the notion "schema", we refer to Mlynková [13, p. 16], who interprets an XML schema as a formal, context-free grammar, following Berstel and Boasson [14]. Since our focus lies on data engineering, we define schema inference as the process of describing the structure of a dataset using a formal language. Our analysis does not target particular schema types, like XML or database schemas, but considers all variants. Under "tabular data" we understand all datasets consisting of rows and columns. This includes various possible formats such as CSV, JSON or XLS.

Although the target group of our review are government entities, publications from other sectors, such as banking or manufacturing, will be considered as well. We include all English literature; publications in other languages will be excluded from the study. Our main interest is in peer-reviewed articles. However, if the search strategy does not yield a sufficient number of documents, we will also consider other publication types.

4. SEARCH STRATEGY

Adapting the example of Pearson et al. [15], the search strategy comprises the following three stages:

- (1) Limited search to identify relevant keywords contained in title and abstract of the results.
- (2) Terms identified in this way, and the synonyms will be used in an extensive search of literature.

- (3) Reference lists and bibliographies of the articles collected from those identified in stage two will be searched.

Our search will be performed using the subsequent search engines/digital libraries:

- Google Scholar
- ACM Digital Library
- IEEE Xplore

For the initial search, we used the following terms:

- ("artificial intelligence" OR "machine learning") AND ("explainable" OR "explainability") AND "schema inference" AND "data"

As a result of the first review iterations, we use this extended list in the next steps:

- ("artificial intelligence" OR "machine learning") AND ("explainable" OR "explainability") AND ("schema inference" OR "schema detection" OR "schema discovery" OR "schema extraction" OR "schema induction") AND ("tabular" OR "table") AND "data"

Compared to the initial search, we have narrowed our scope from all datasets to "tabular data". The reason for this is that we consider tabular data to be important for data science/data engineering and hope to obtain more specific information on this topic. To not overly limit the search results, we omit the term "government" from the list. In earlier iterations, we identified several synonyms for "schema inference" and added them as search terms. In addition to the classical search described above, we will also address our review question to the following large language models (LLMs):

- ChatGPT
- Llama

Responses from LLMs are discussed in a dedicated section of the resulting paper, separate from regular search results.

5. DATA COLLECTION

Following the example of Pearson et al. [15], full copies of the articles identified in the search meeting the inclusion criteria based on their title and abstract are collected for data analysis. Publications identified through reference lists and bibliographies will be considered based on their title. Two reviewers will independently search for articles. Discrepancies in reviewer selection will be resolved in a meeting before finalizing the data collection.

6. DATA ANALYSIS

In the analysis stage, we will systematically arrange and analyze collected literature. In a first step, literature is divided into categories. These categories are defined by reviewers in an iterative process. In the second step, literature will be evaluated both quantitatively and qualitatively. The quantitative analysis focuses primarily on document metadata such as number of items collected, year of publication, category, etc. Qualitative analyses will focus on the text of the selected literature. Here we utilize the general inductive approach proposed by Thomas [16]. In addition, our qualitative analysis will apply methods of natural language processing. Examples are n-grams and their pointwise mutual information (PMI), as suggested by Curch and Hanks [17].

7. IMPLEMENTATION AND OUTLOOK

In order to ensure the quality of this protocol before implementation, its content was validated using the checklist of Moher et al. [18]. Stages planned in this protocol may be performed in several iterations. Each iteration comprises one or more review stages. Newly identified or changed requirements may lead to an update of this protocol and an adaptation of the review procedure.

APPENDIX A. GLOSSARY

Term	Definition
AI	See Artificial Intelligence
Artificial Intelligence	Ability of a machine to accomplish complex goals.
Explainable Artificial Intelligence	Machine learning techniques enabling end users to better understand, trust, and effectively manage artificially intelligent systems.
ML	Machine Learning
Schema Detection	See Schema Inference
Schema Discovery	See Schema Inference
Schema Extraction	See Schema Inference
Schema Induction	See Schema Inference
Schema Inference	Process of describing the structure of a dataset using a formal language.
Tabular Data	Dataset consisting of rows and columns. This definition includes various possible formats such as CSV, JSON or XLS.
XAI	See Explainable Artificial Intelligence

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