

Comparison of Low- vs. High-Dimensional Machine Learning Approaches for Sheet Metal Drawability Assessment

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Agenda

- Research question
- Mechanical application
- Dataset
- Machine Learning
- Conclusion and Outlook

Motivation

- How can one achieve maximal model accuracy?
- What is the data available for that task?

Research question

- What data-driven modeling approach (low- or high-dimensional) will return maximal model accuracy in a limited data environment?

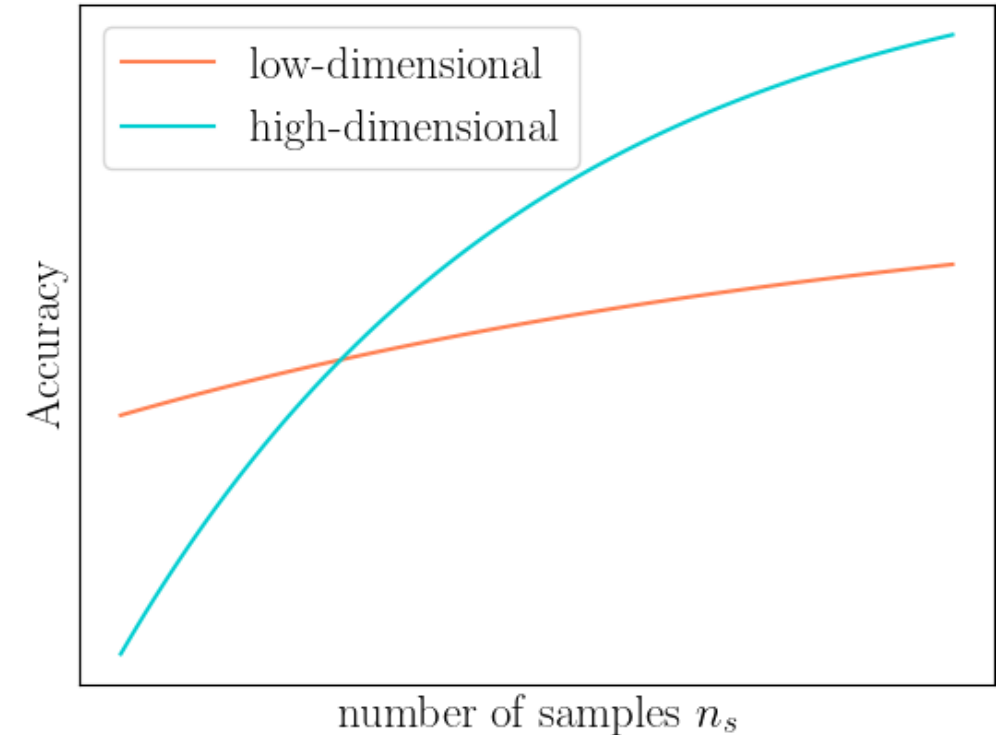


Fig. 1: Schematic trends of potential low- and high-dimensional model accuracies over an increasing number of training samples.

Deep drawing in car manufacturing

- Structural sheet metal parts of a car chassis
- High complexity and contrastive requirements
- Only a small fraction of topologically different structural deep drawn parts per chassis [1]

Data-driven drawability assessment

- Reduce iterations for manual geometry modifications
- Quantify assessment in the early-stage development phase

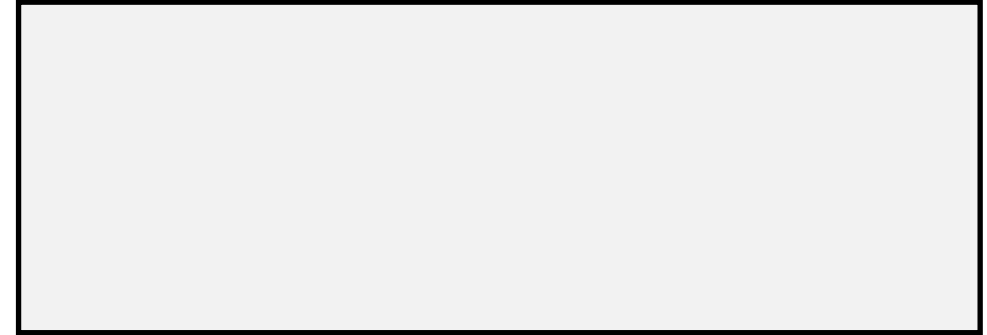


Fig. 2: Car chassis composed out of structural sheet metal parts. Adopted from [1].

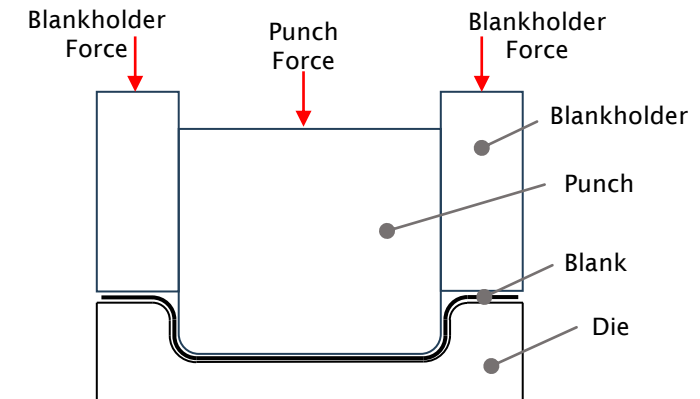


Fig. 3: Schematic deep drawing setup. Modified from [2].

[1] Birkert, Arndt; Haage, Stefan; Straub, Markus (2013): Umformtechnische Herstellung komplexer Karosserieteile. Berlin, Heidelberg: Springer.

[2] Siegert, Klaus (2015): Blechumformung. Berlin, Heidelberg: Springer Berlin Heidelberg.

Interpretation

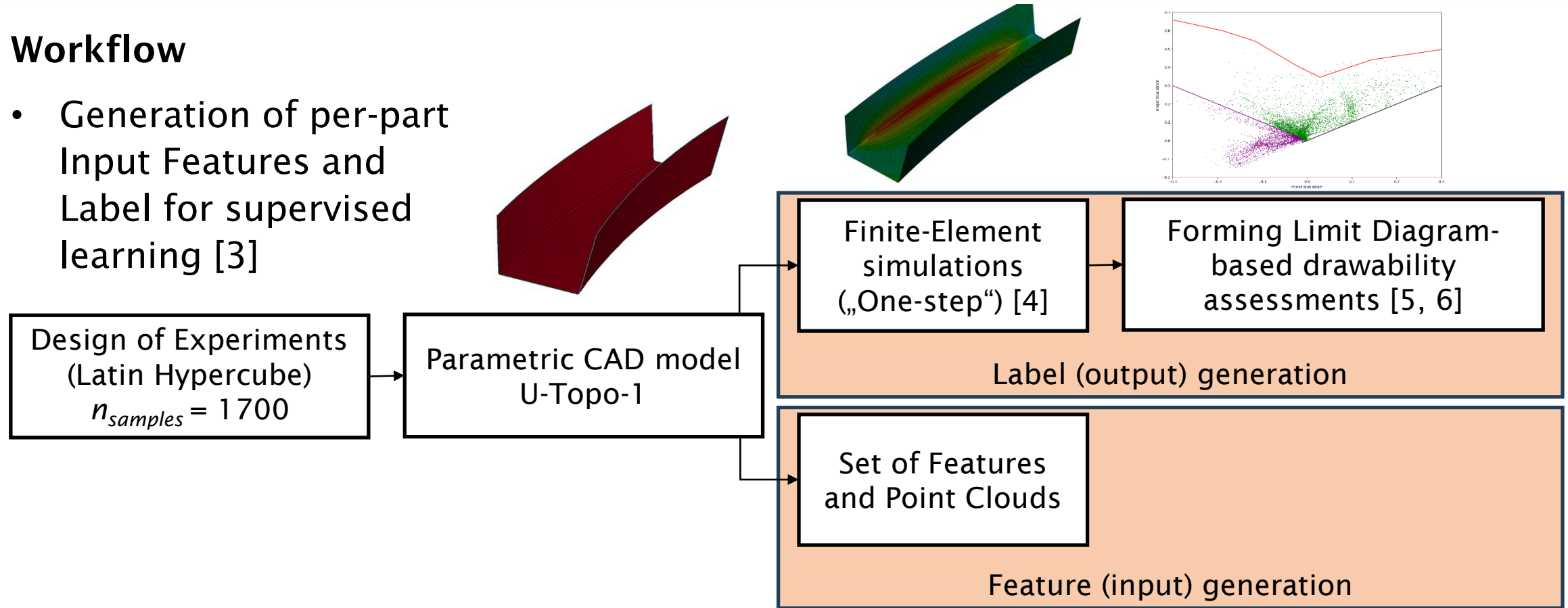
- Drawability assessment as binary classification between drawable or non-drawable

Definitions and assumptions

- Constant material properties for all parts (cold-rolled steel: CR1)
- Drawability assessment solely based on simulation
- purely mechanical manufacturability prediction (crack formation, wrinkling) for structural sheet metal parts
- One drawing operation per part

Workflow

- Generation of per-part Input Features and Label for supervised learning [3]



[3] Lehrer, Tobias; Kaps, Arne; Lepenies, Ingolf; Duddeck, Fabian; Wagner, Marcus (2023): 2S-ML: A simulation-based classification and regression approach for drawability assessment in deep drawing. In: Int J Mater Form 16 (5). DOI: 10.1007/s12289-023-01770-3.

[4] Guo, Y. Q.; Batoz, J. L.; Detraux, J. M.; Duroux, P. (1990): Finite element procedures for strain estimations of sheet metal forming parts. In: Int J Numer Methods Eng 30 (8), S. 1385-1401. DOI: 10.1002/nme.1620300804.

[5] Kaps, Arne; Lehrer, Tobias; Lepenies, Ingolf; Wagner, Marcus; Duddeck, Fabian (2023): Multi-fidelity optimization of metal sheets concerning manufacturability in deep-drawing processes. In: Struct Multidiscip Optim 66 (8). DOI: 10.1007/s00158-023-03631-8.

[6] Jakumeit, J.; Herdy, M.; Nitsche, M. (2005): Parameter optimization of the sheet metal forming process using an iterative parallel Kriging algorithm. In: Struct Multidiscip Optim 29 (6), S. 498-507. DOI: 10.1007/s00158-004-0455-3.

Low-dimensional Linear Support Vector Classification

- Fits hyper-surface which separates the classes (manufacturable, non-manufacturable)
- Separation surface is fitted with the maximum possible distance to data points (components)

Feature Engineering

- Features inspired by the drawing process and differential geometry [3]
- Principal Component Analysis (PCA) to reduce colinearity between features
- Normalization (min-max) of the features

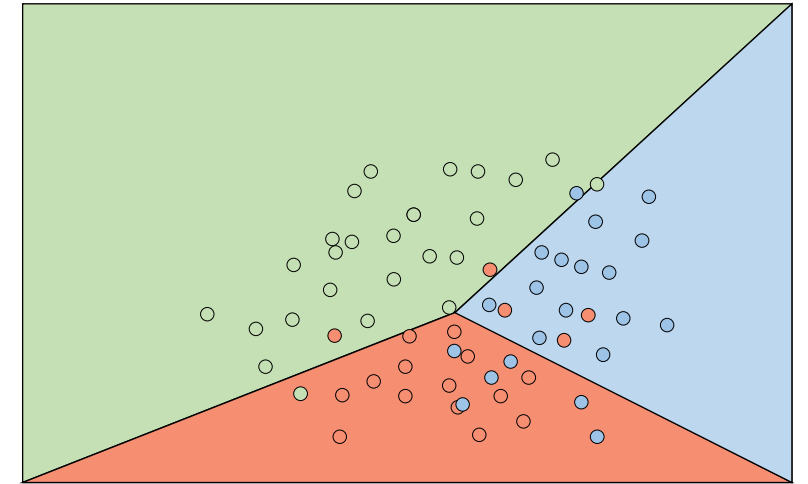


Fig. 4: Schematic Multiclass Classification using Linear Support Vector. Modified from [7].

[3] Lehrer, Tobias; Kaps, Arne; Lepenies, Ingolf; Duddeck, Fabian; Wagner, Marcus (2023): 2S-ML: A simulation-based classification and regression approach for drawability assessment in deep drawing. In: *Int J Mater Form* 16 (5). DOI: 10.1007/s12289-023-01770-3.

[7] Pedregosa, Fabian; Varoquaux, Gaël; Gramfort, Alexandre; Michel, Vincent; Thirion, Bertrand; Grisel, Olivier et al. (2011): Scikit-learn: Machine Learning in Python. In: *JMLR* 12 (85), S. 2825-2830. <http://jmlr.org/papers/v12/pedregosa11a.html>, Accessed 16.11.2022.

High-dimensional model

- Invariance regarding translations and rotations (T-Net) [8]
- Modification concerning binary classification (sigmoid instead of softmax layer)

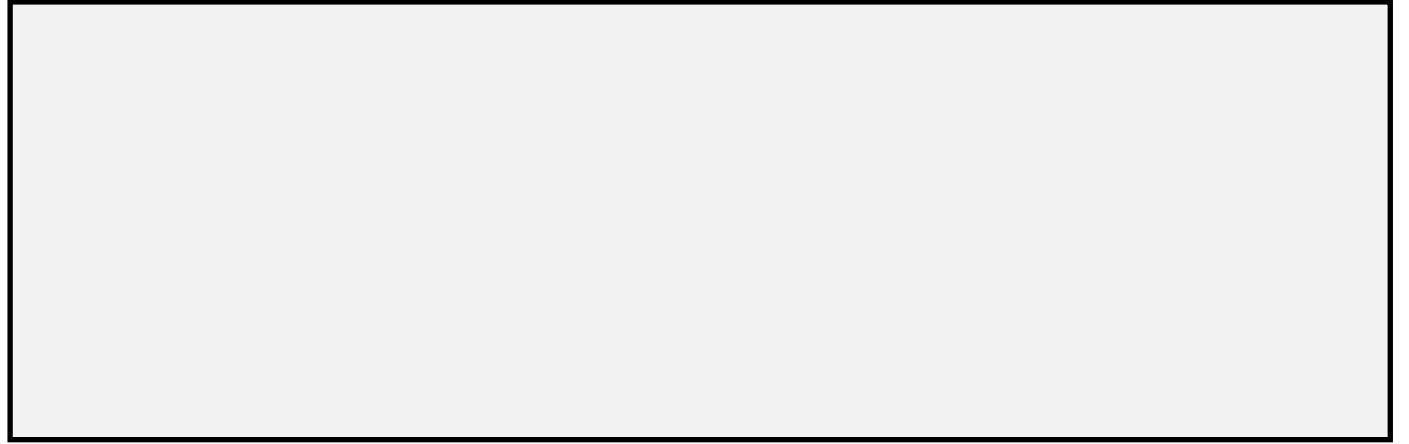


Fig. 5: Architecture of PointNet model. Adopted from [8].

Point Clouds

- Curvature-based meshing with subsequent random subsampling of FEM-nodes as points
- $n_{points} = 1024$

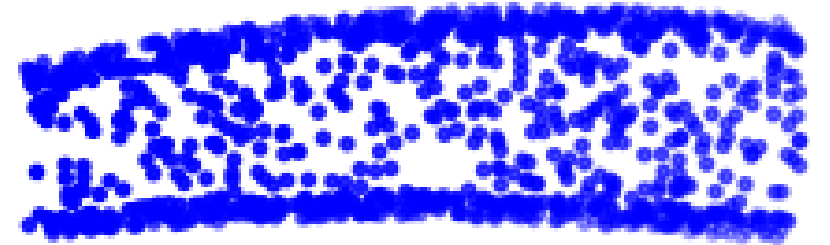


Fig. 6: Point Cloud sample of the generated dataset with 1024 points.

[8] Qi, Charles R.; Su, Hao; Mo, Kaichun; Guibas, Leonidas J. (2016): PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation. <https://arxiv.org/pdf/1612.00593>, Accessed 23.08.2023.

Training and Testing

- Consistent test set comprising 200 parts for all models
- Training sets are subsampled from the remaining 1500 parts in the total training set
- High- and Low-dimensional models utilize the same parts for training (per number of training samples)

Comparison

- Model accuracies intersect at around 500 parts

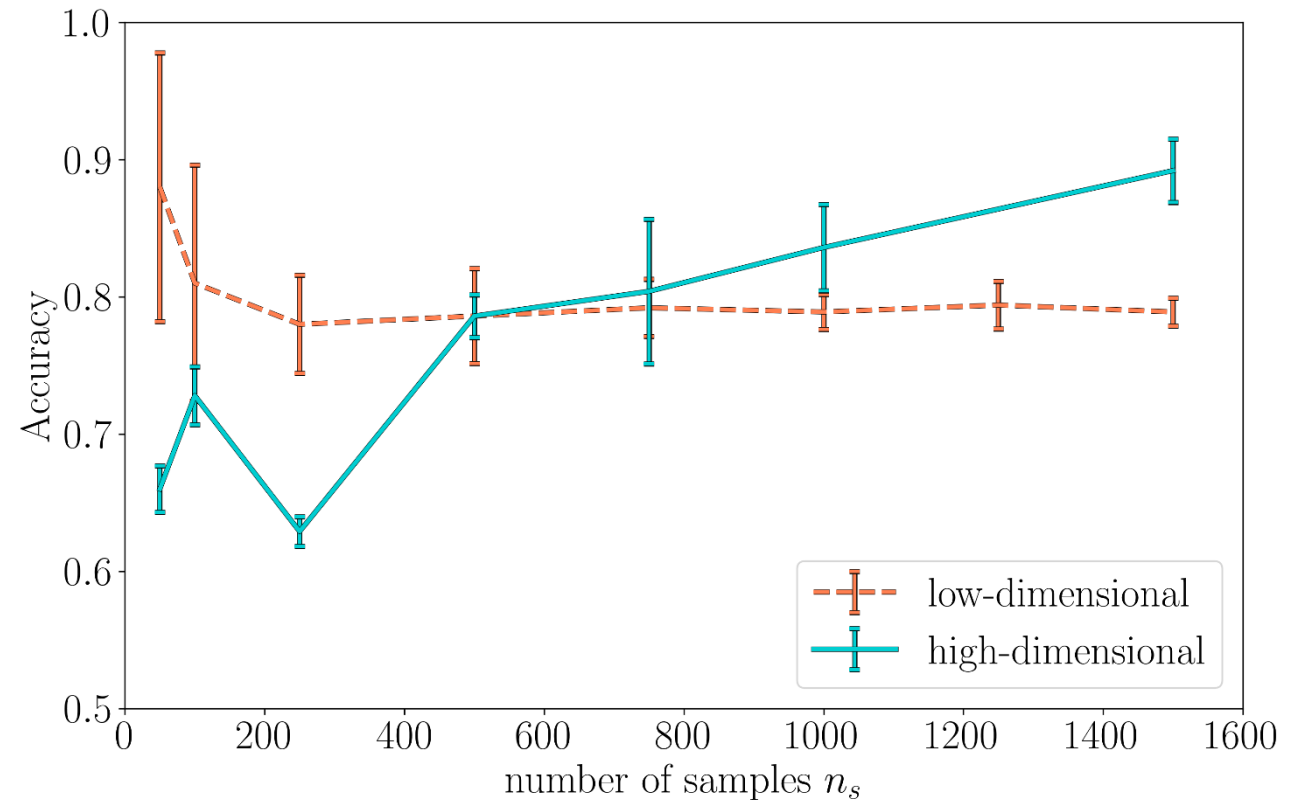


Fig. 7: Model accuracy over an increasing number of training samples.

Second U-Topology dataset

- Identical material properties and sheet thickness
- $N_{U-Topo-2} = 96$

Generalizability

- Training on U-Topo-1 and subsequent testing on U-Topo-2
 - No cross-validation
- No topology generalizability for both modeling approaches to similar, unseen geometries

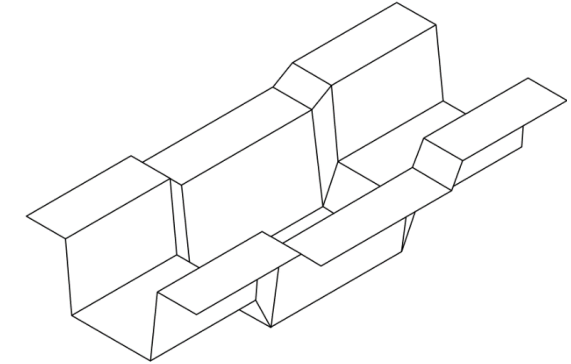


Fig. 8: Sample of the „U-Topo-2“ dataset. Compared to the hitherto geometry, there is an offset, deeper middle part and no curved feature lines.

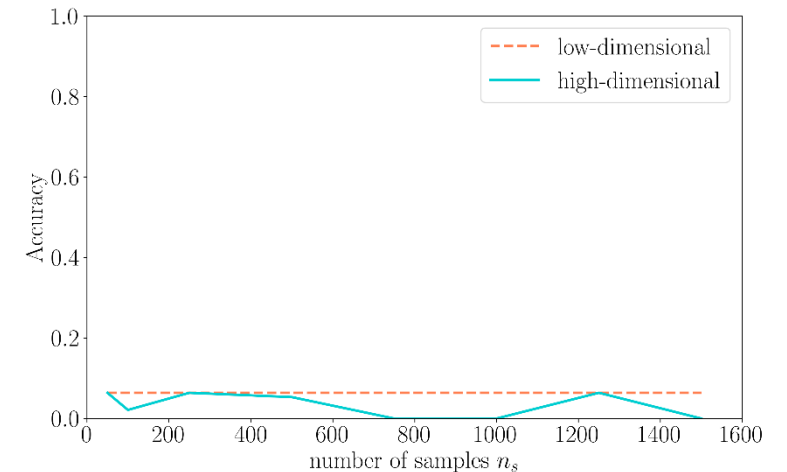


Fig. 9: Classification accuracies of both modeling approaches with U-Topo-2 test set.

Conclusion

- High-dimensional approach demonstrates enhanced performance in drawability assessment from 500 (geometrically similar) sheet metal parts onwards
- Both modeling approaches are infeasible to generalize on topologically similar parts

Outlook

- Incorporating material and process influences into the high-dimensional model
- Introducing Geometric Data Augmentation methods
- Exploring the synergistic potential of combining low- and high-dimensional models
- Broadening geometry generalizability with (dis)similarity measures and transfer learning techniques