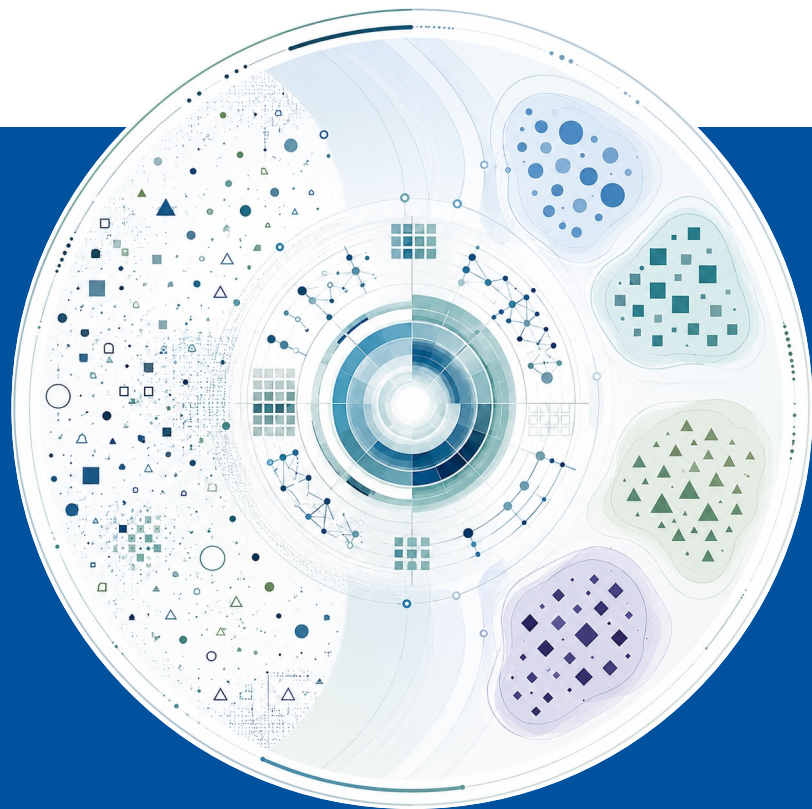


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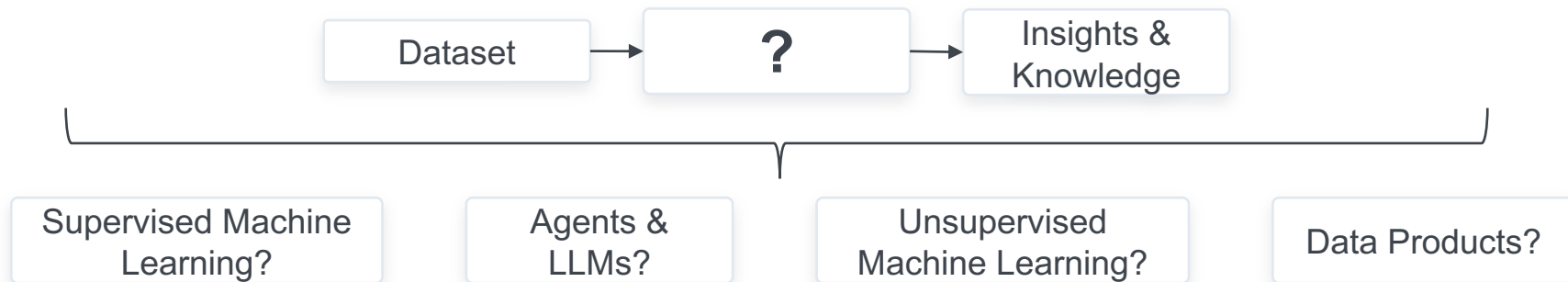
Institute for Parallel and Distributed Systems (IPVS)
Applications of Parallel and Distributed Systems

Unsupervised Automated Preprocessing: the Role of Meta-Features and Data Characteristics

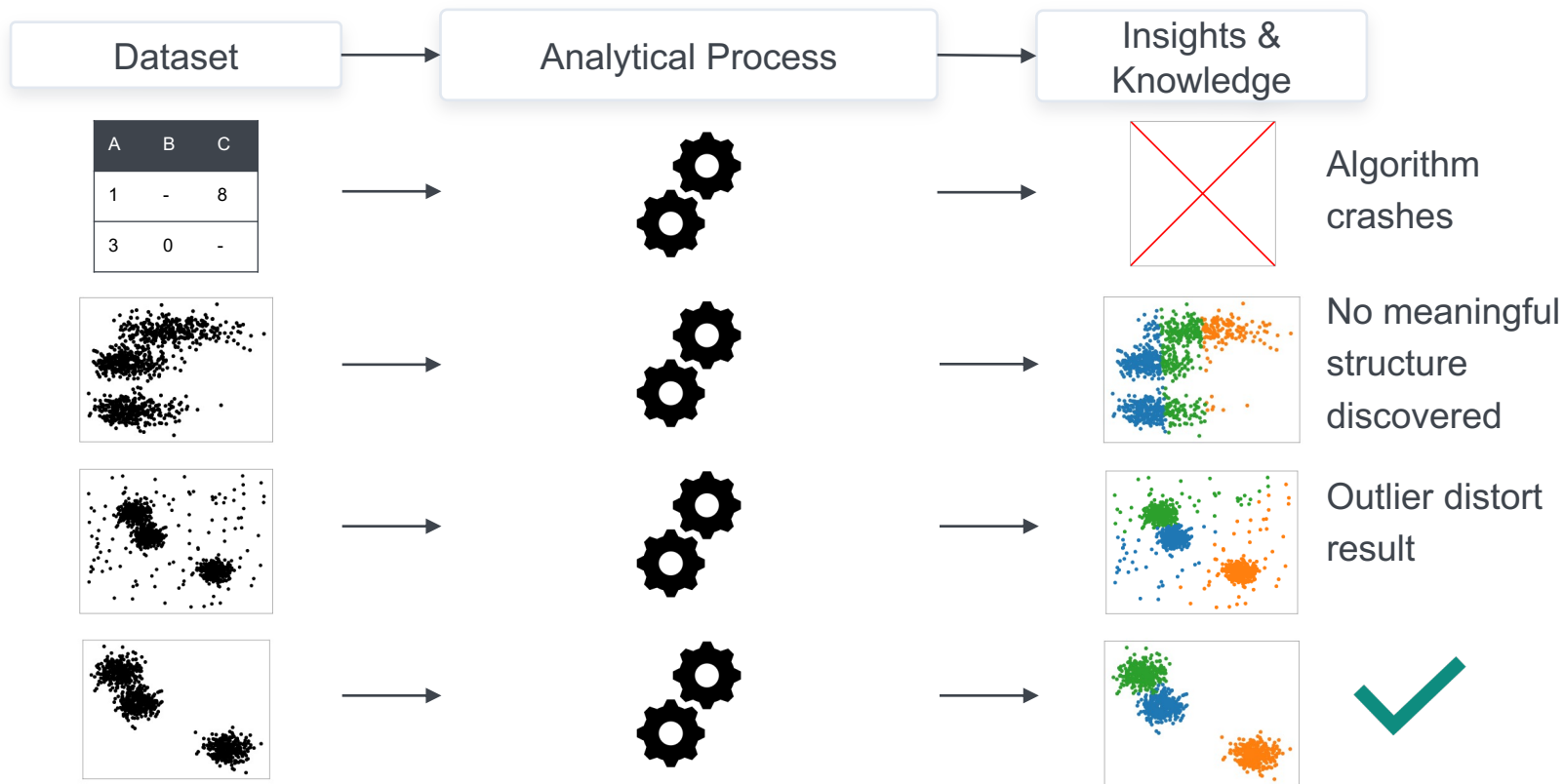
Leonard Labes, Dennis Treder-Tschechlov, Holger Schwarz



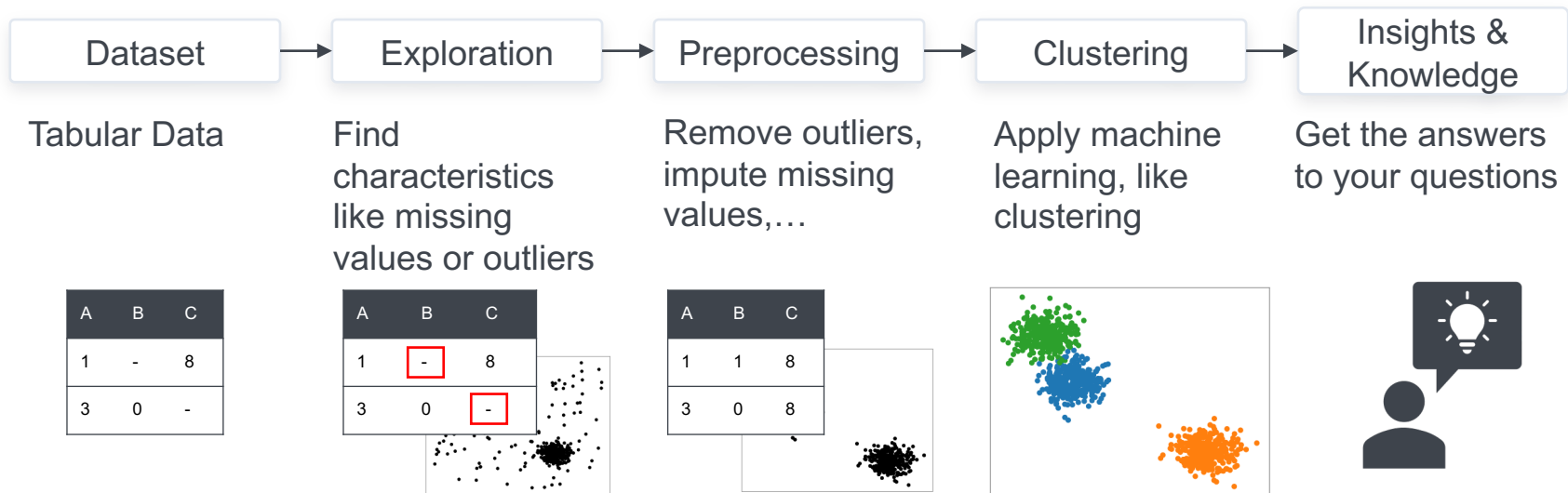
Motivation



Motivation



Motivation



Motivation

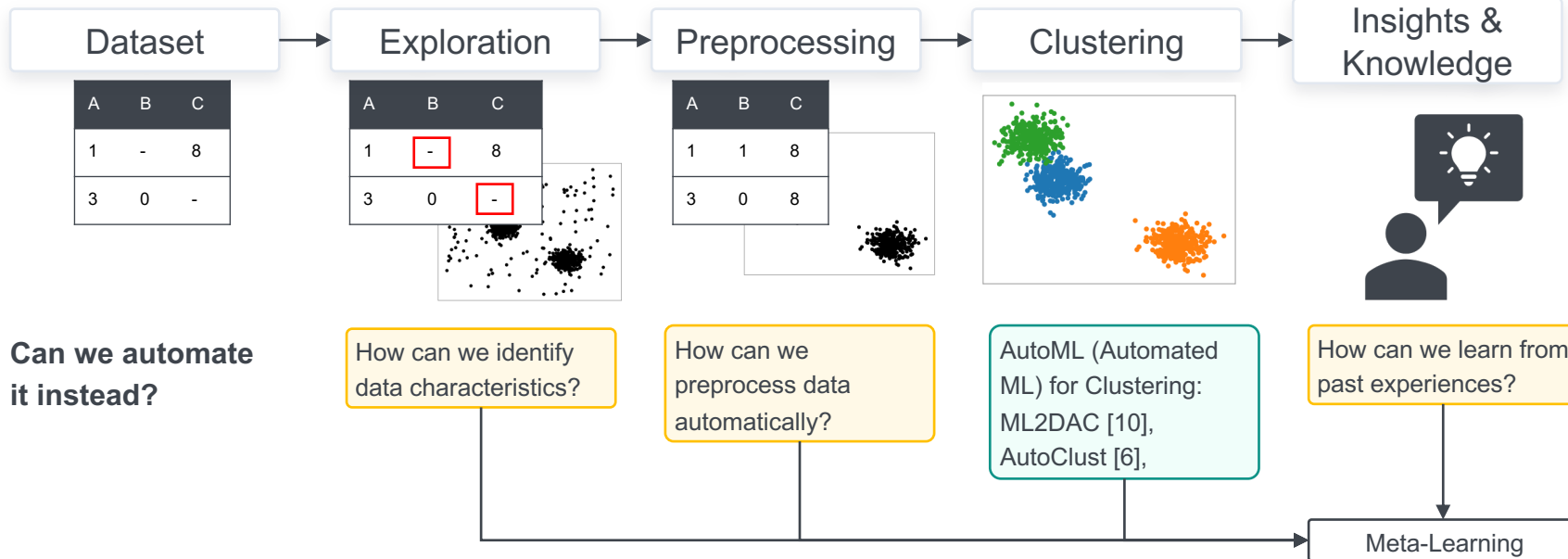
Decided by hand today:

What characteristics do I have?

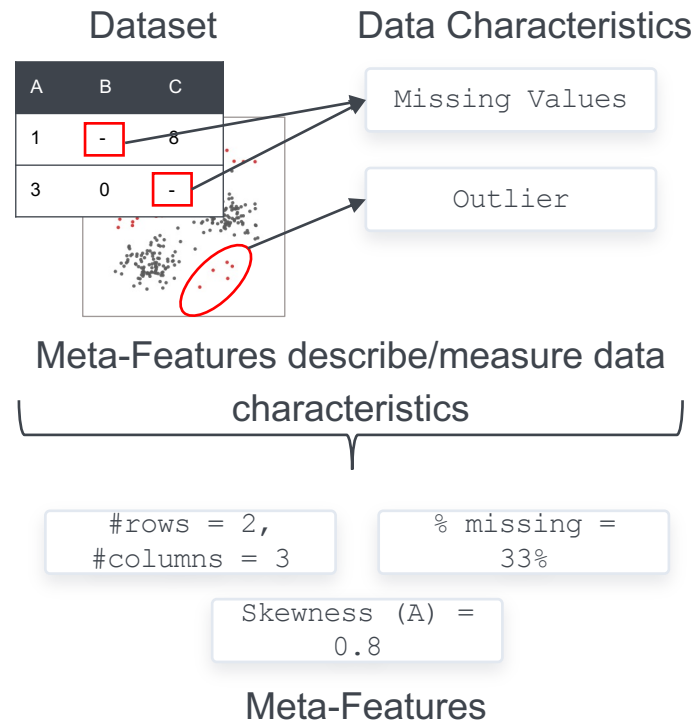
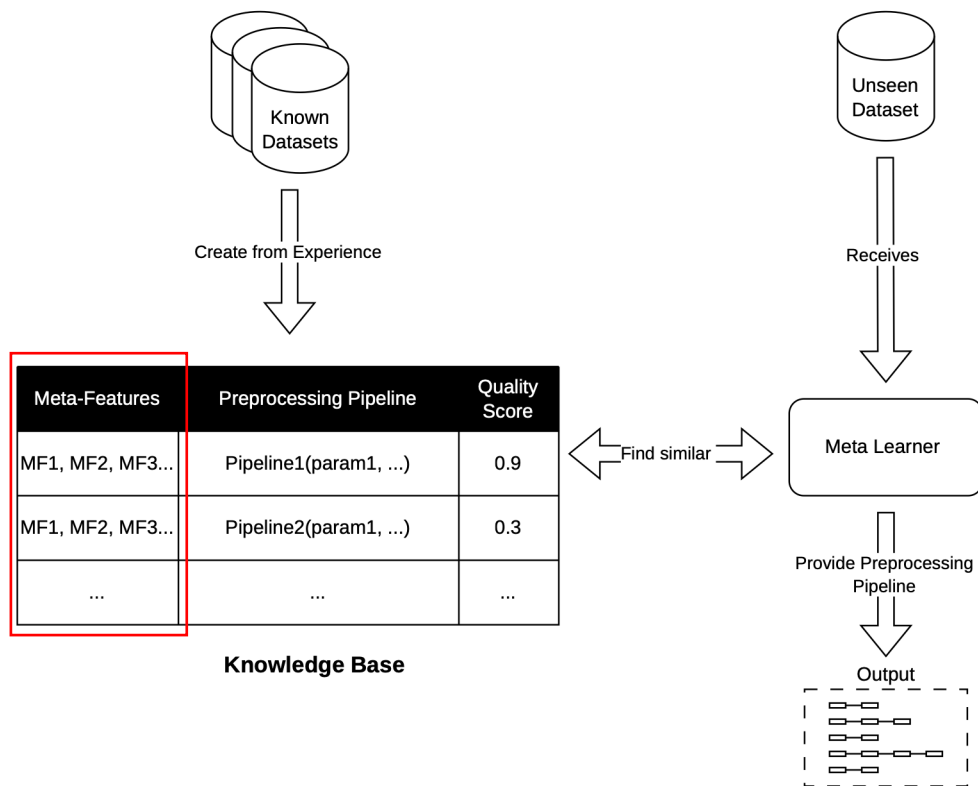
Which methods, parameters, and in which order?

What clustering algorithm, parameters, and evaluation score do I use?

Did I face similar problems in the past?



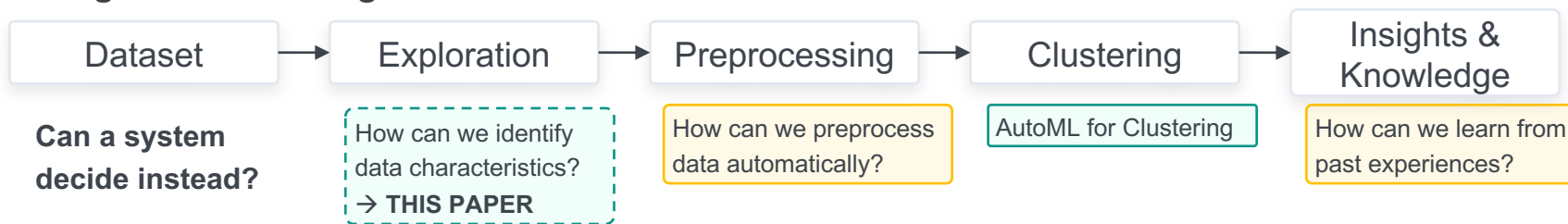
Meta-Learning and Meta-Features



Our Contribution

Data Characteristics, preprocessing [4], meta-features [1,11], and meta-learning [7,11] all exist.

Sorting and connecting them does not.



1 **Collect and define** preprocessing-relevant data characteristics for clustering.

2 **Map** these characteristics to meta-features.

3 **Assess** how useful these meta-features are for unsupervised preprocessing decisions.

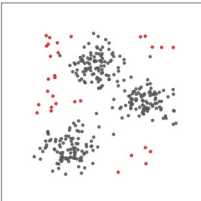
Data Characteristics

- Preprocessing problems occur at different levels of the data.
 - We identify 15 data characteristics

Dataset-level 6 characteristics

Outlier

distort distances & summary statistics



High #dimensions

High #features

Sparsity

Noise

Feature & dimension ratio

Feature-level 6 characteristics

Missing Values

reduce information, bias estimates

A	B	C
1	-	8
3	0	-

Irrelevant features

Different scales

Skewed
distributions

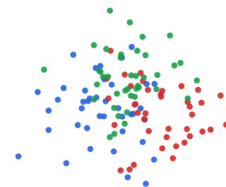
Duplicate and
redundant
features

Categorical values

Cluster-level 3 characteristics

Overlapping Clusters

poor separation, unstable partition



Convex and non-convex shapes

Imbalanced Clusters

Our Contribution

1

Collect and define preprocessing-relevant data characteristics for clustering.



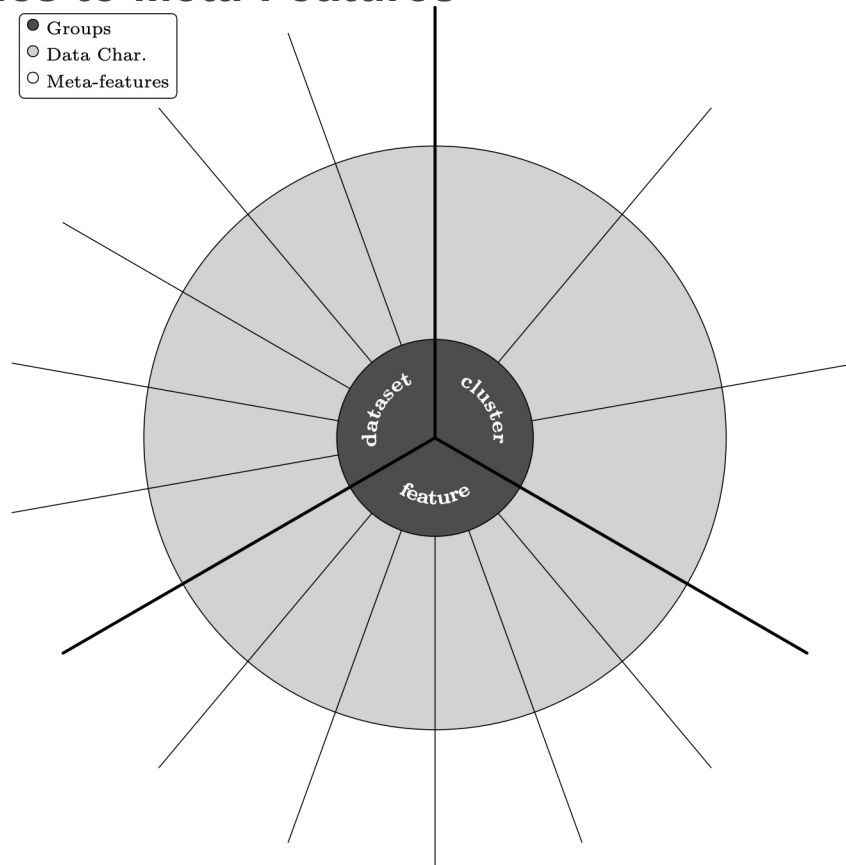
2

Map these characteristics to meta-features.

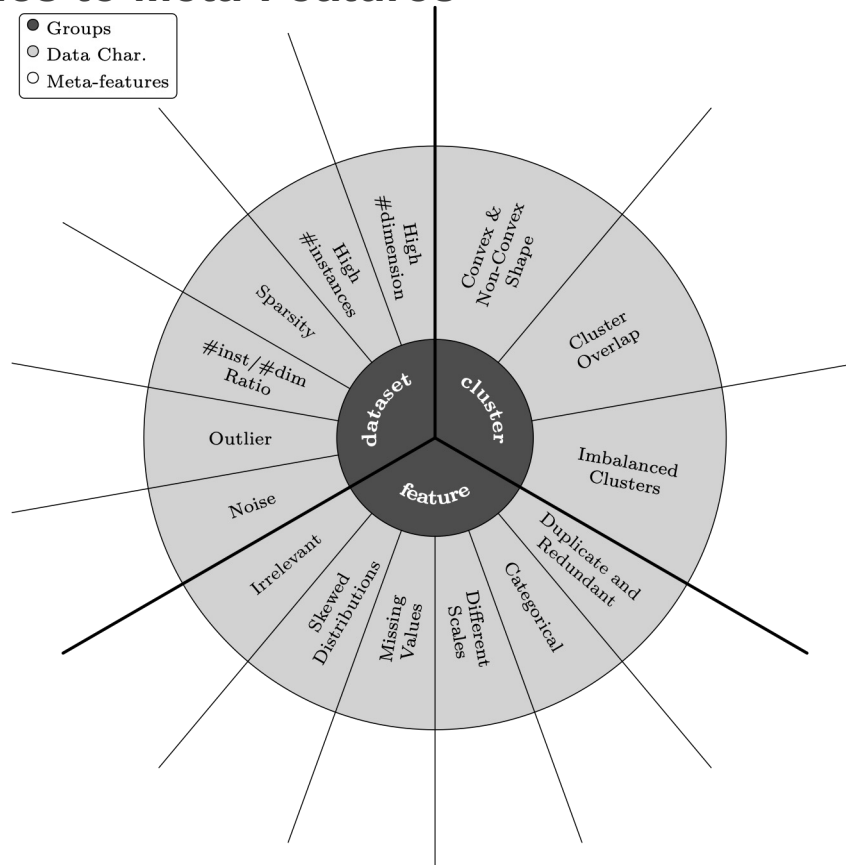
3

Assess how useful these meta-features are for unsupervised preprocessing decisions.

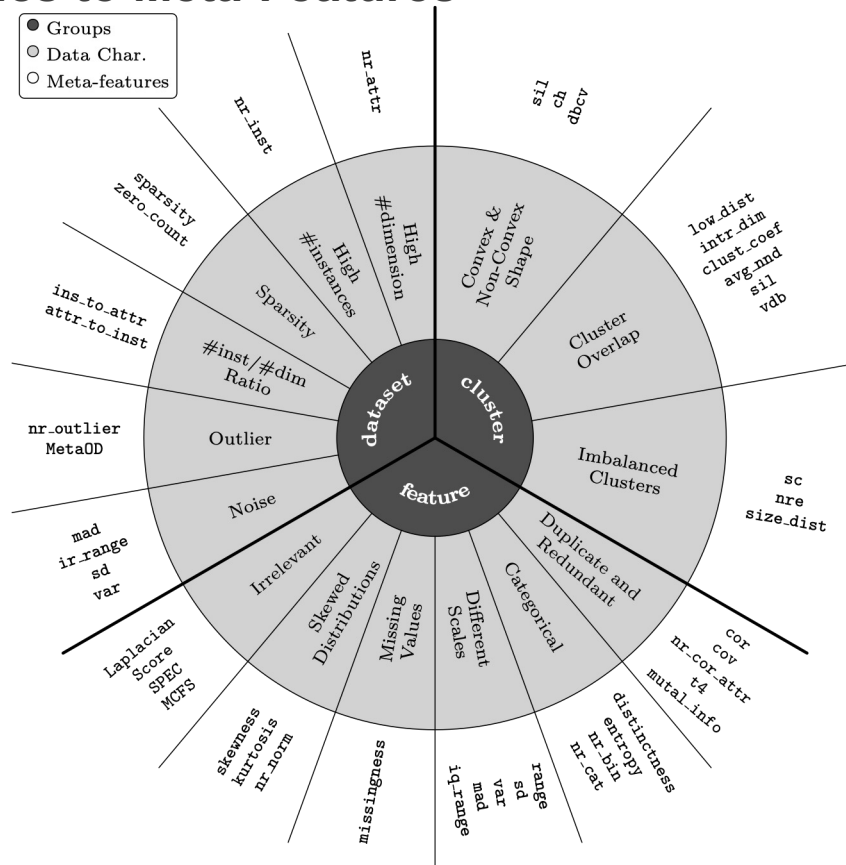
From Characteristics to Meta-Features



From Characteristics to Meta-Features



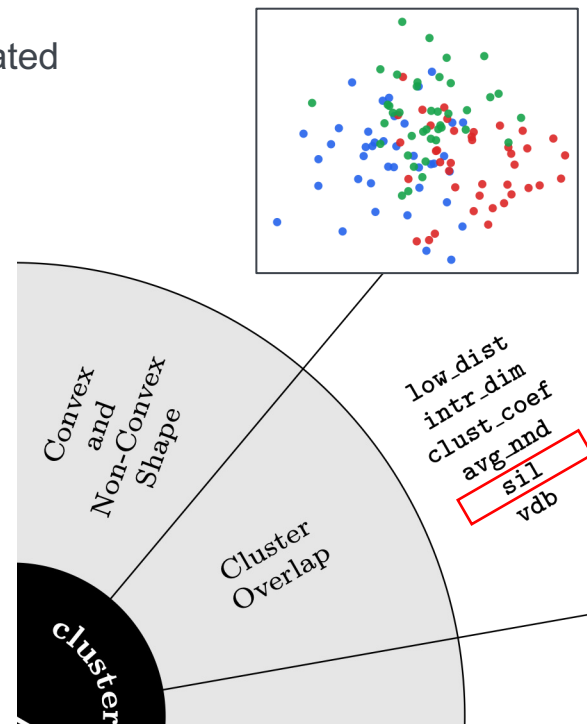
From Characteristics to Meta-Features



From Characteristics to Meta-Features

Cluster Level: Cluster Overlap: How strongly clusters are separated

- `sil[9]`: Silhouette-based proxy for cluster separation after provisional clustering
 - Compares the distance of points in their own cluster with the distance of points from other clusters
 - Low or near-zero values indicate weak separation



Our Contribution

1

Collect and define preprocessing-relevant data characteristics for clustering.



2

Map these characteristics to meta-features.



3

Assess how useful these meta-features are for unsupervised preprocessing decisions.

Assesing the Connection

Four Dimensions

1

Directness

To what extent does the meta-feature measure the characteristic

2

Grounding

Computable from raw data, does it need clustering first, or even more assumptions?

3

Actionability

Which preprocessing methods should I use?

4

Context robustness

How much does the value depend on thresholds and choices?

Levels of fulfilment
per dimension



Overview of Assessment

Class	Meta-features of Data Characteristic	Directness			Grounding			Actionability			Context robustness		
A	High number of instances												
	High dimensionality												
	Sample-to-dimension ratio												
	Missing values												
B	Sparsity												
	Outliers												
	Skewed distributions												
	Different feature scales												
	Categorical-valued features												
	Duplicate / redundant feat.												
C	Noise												
	Imbalanced clusters												
	Cluster overlap												
	Convex / non-convex shapes												
	Irrelevant features												

Reading: **Directness:** *direct* → *near-direct* → *proxy*

Grounding: *raw-data* → *partition-dependent* / *assumption-heavy*

Actionability: *clear* → *partial* → *weak*

Context robustness: *moderate* → *high* → *extreme*

Conclusion & Outlook

1

Collect and define preprocessing-relevant data characteristics for clustering.



2

Map these characteristics to meta-features.



3

Assess how useful these meta-features are for unsupervised preprocessing decisions.



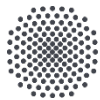
Outlook:

- Empirical evaluation of this assessment
- Embed it in a preprocessing-aware meta-learning system that recommends preprocessing pipelines

For more **details** about this **work** and the overall topic of **automated preprocessing**, feel free to check out my posters.

References

1. Alcobaça, E., et al.: Mfe: Towards reproducible meta-feature extraction. *Journal of Machine Learning Research* 21(111), 1–5 (2020)
2. Alcobaça, E., Siqueira, F.: PyMFE Documentation: Meta-feature Description Table (2021), <https://pymfe.readthedocs.io/>, version 0.4.2, accessed 2026-03-30
3. Fernandes, L.H.d.S., et al.: Towards understanding clustering problems and algorithms: an instance space analysis. *Algorithms* 14(3), 95 (2021)
4. Han, J., et al.: *Data Mining: Concepts and Techniques*. Morgan Kaufmann (2022)
5. Pargent, F., et al.: Regularized target encoding outperforms traditional methods in supervised machine learning with high cardinality features. *arXiv preprint arXiv:2104.00629* (2021)
6. Poulakis, Y., et al.: Autoclust: A framework for automated clustering based on cluster validity indices. In: *2020 IEEE Int. Conf. on Data Mining (ICDM)*, pp. 1220–1225. IEEE (2020)
7. Rice, J.R.: The algorithm selection problem. In: *Advances in Computers*, vol. 15, pp. 65–118. Elsevier (1976)
8. Rivolli, A., et al.: Meta-features for meta-learning. *Knowledge-Based Systems* 240, 108101 (2022)
9. Rousseeuw, P.J.: Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics* 20, 53–65 (1987)
10. Treder-Tschechlov, D., et al.: MI2dac: Meta-learning to democratize automl for clustering analysis. *Proc. of the ACM on Management of Data* 1(2), 1–26 (2023)
11. Vanschoren, J.: Meta-learning: A survey. *arXiv preprint arXiv:1810.03548* (2018)
12. Zhao, Y., et al.: Automatic unsupervised outlier model selection. *Advances in Neural Information Processing Systems* 34, 4489–4502 (2021)



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Thank you!



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