AutoFeat: Transitive Feature Discovery over Join Paths

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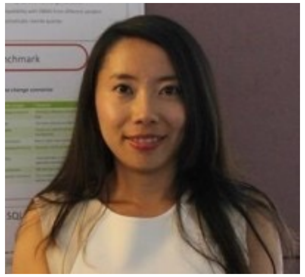


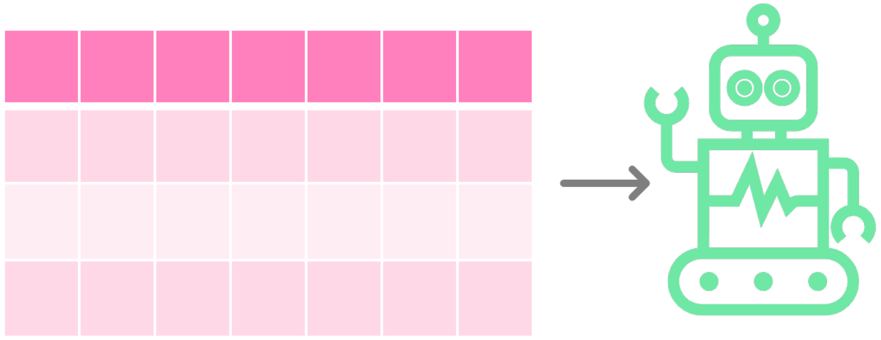
Rihan
Hai

Asterios
Katsifodimos

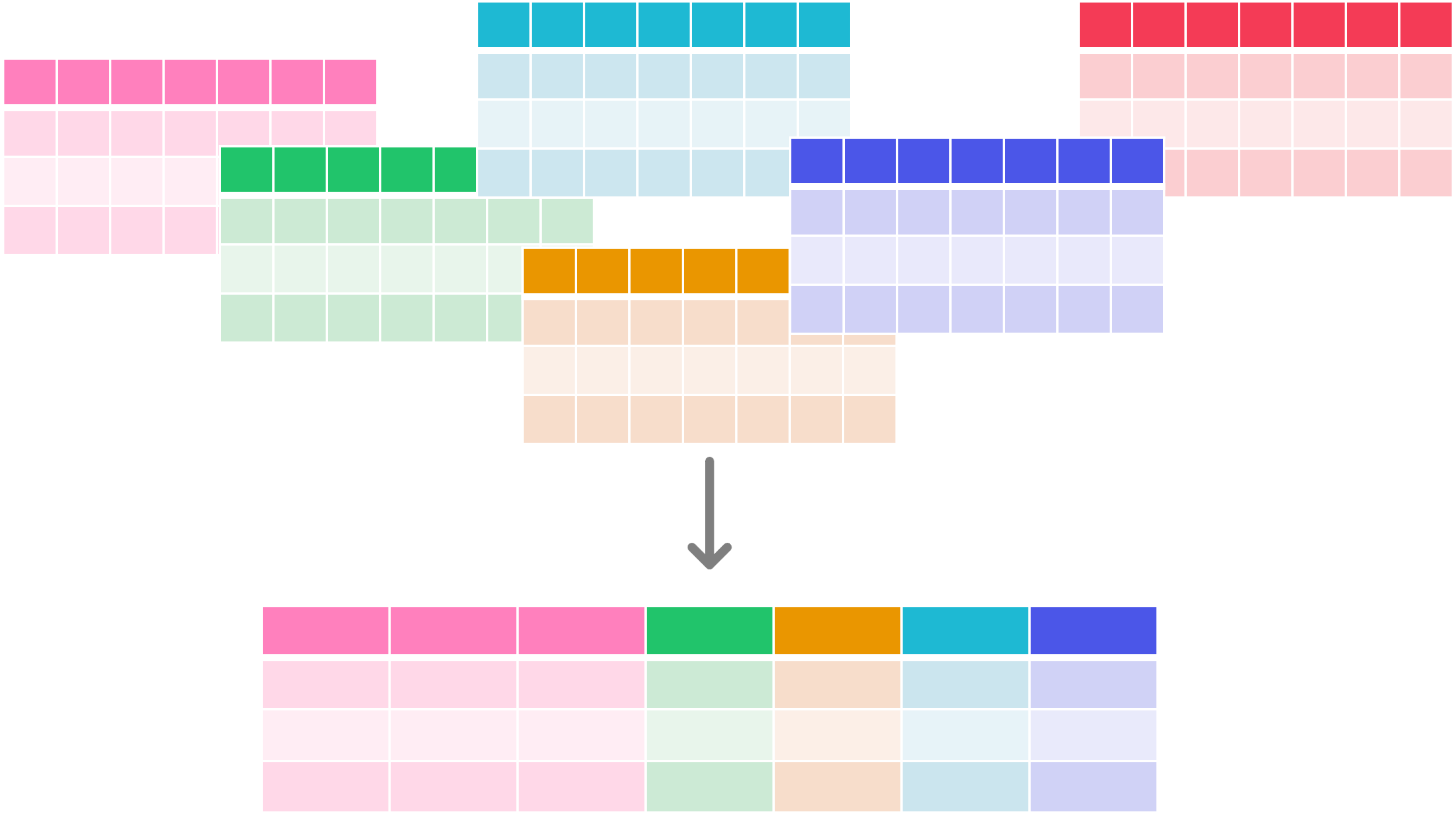
TUDelft

PROBLEM

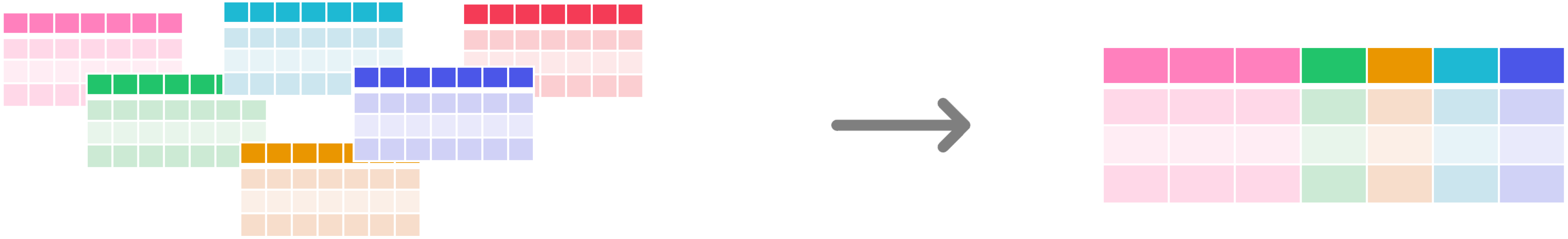
Input data of an ML model is a single table



Input dataset is the result of data augmentation and feature selection



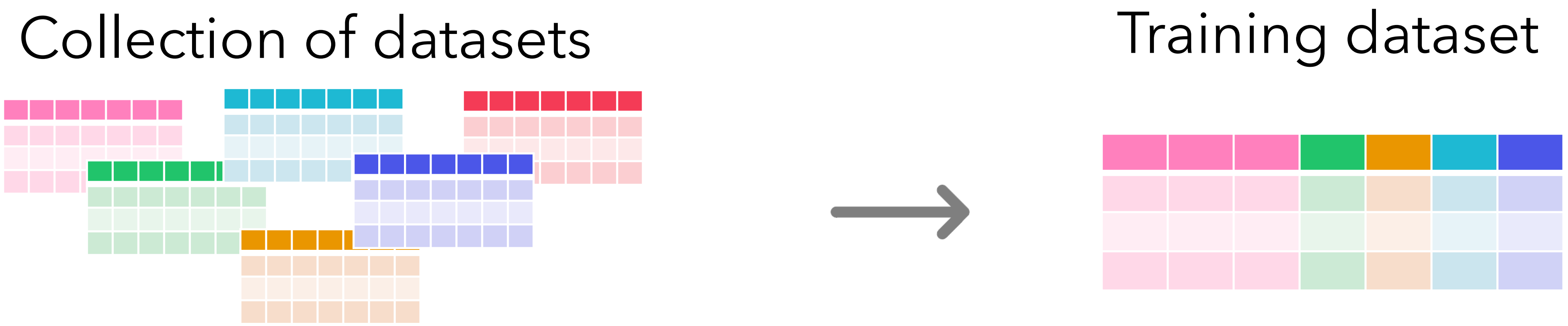
Dataset Augmentation



Collection of datasets

Training dataset

Dataset Augmentation



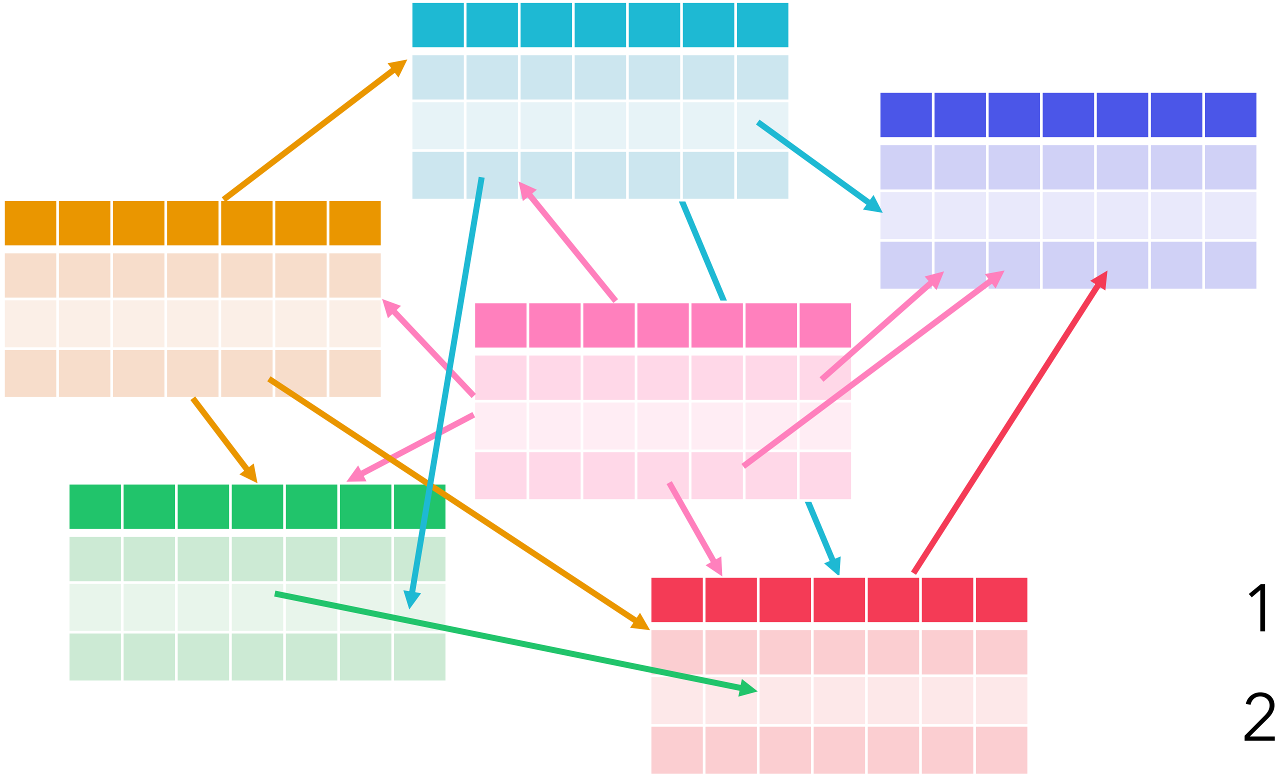
Collection of datasets

Training dataset

When PK-FK are known:

1. Search for datasets
2. Join datasets
3. Apply feature selection

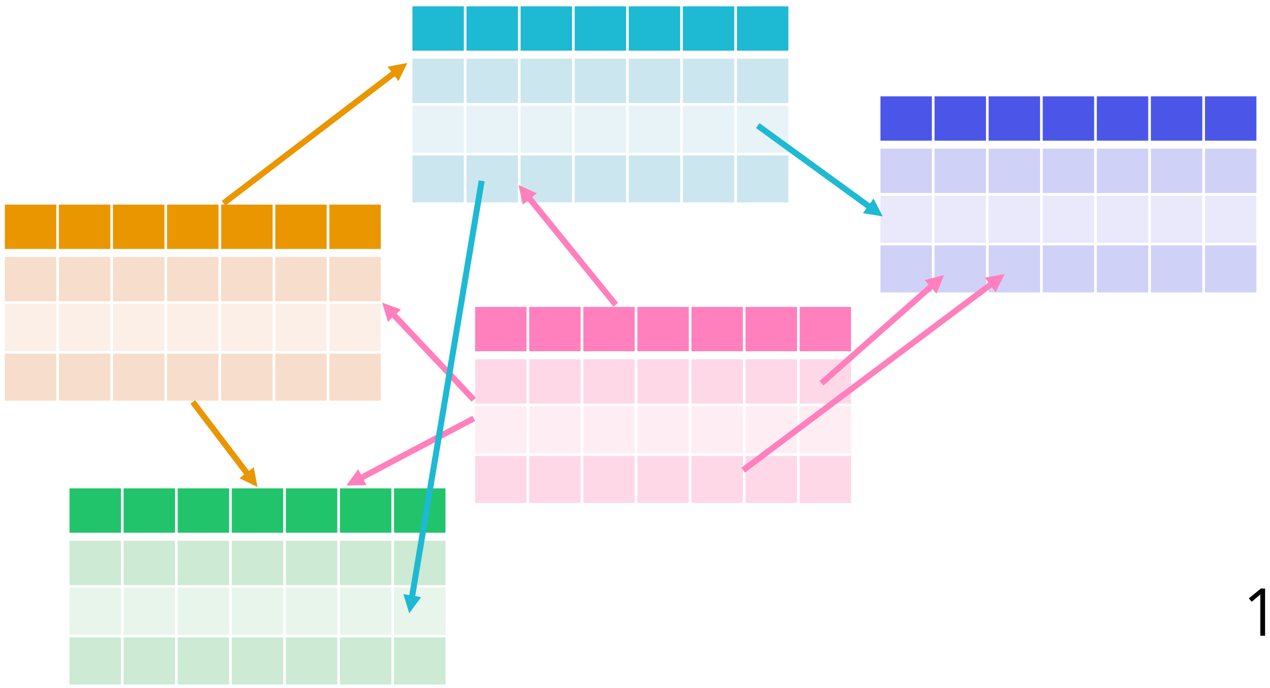
Dataset Augmentation



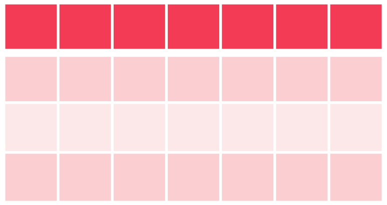
When PK-FK are missing:

1. Dataset discovery
2. Join data
3. Apply feature selection

Dataset Augmentation



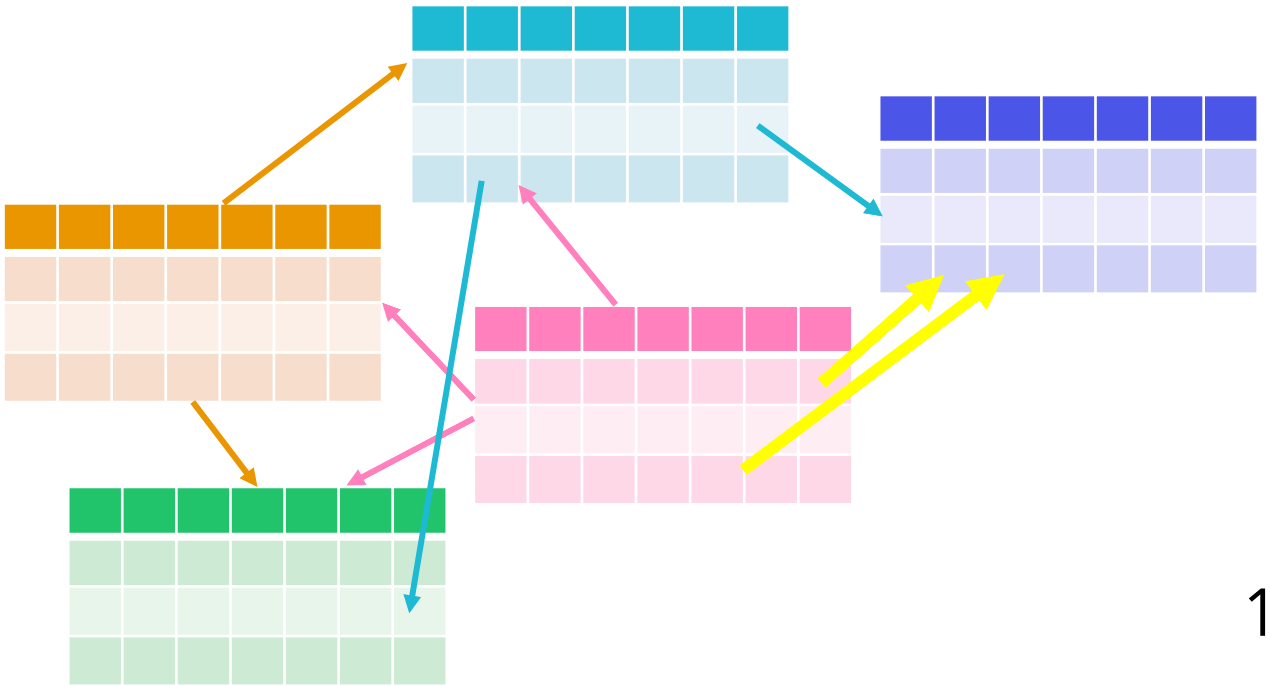
- Spurious relations



When PK-FK are missing:

1. Dataset discovery
2. Join data
3. Apply feature selection

Dataset Augmentation



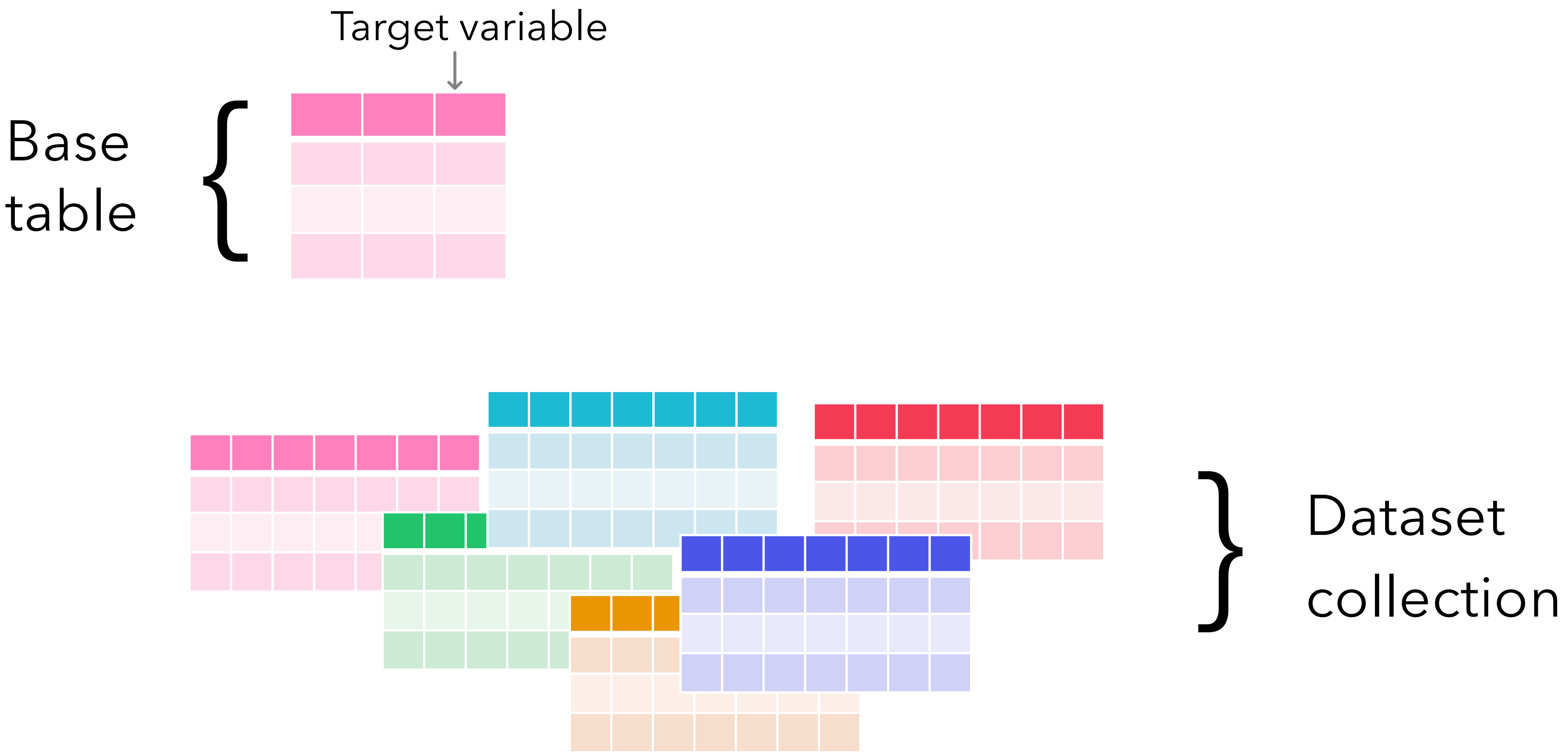
- Multiple join columns

When PK-FK are missing:

1. Dataset discovery
2. Join data
3. Apply feature selection

FEATURE DISCOVERY

Feature Discovery

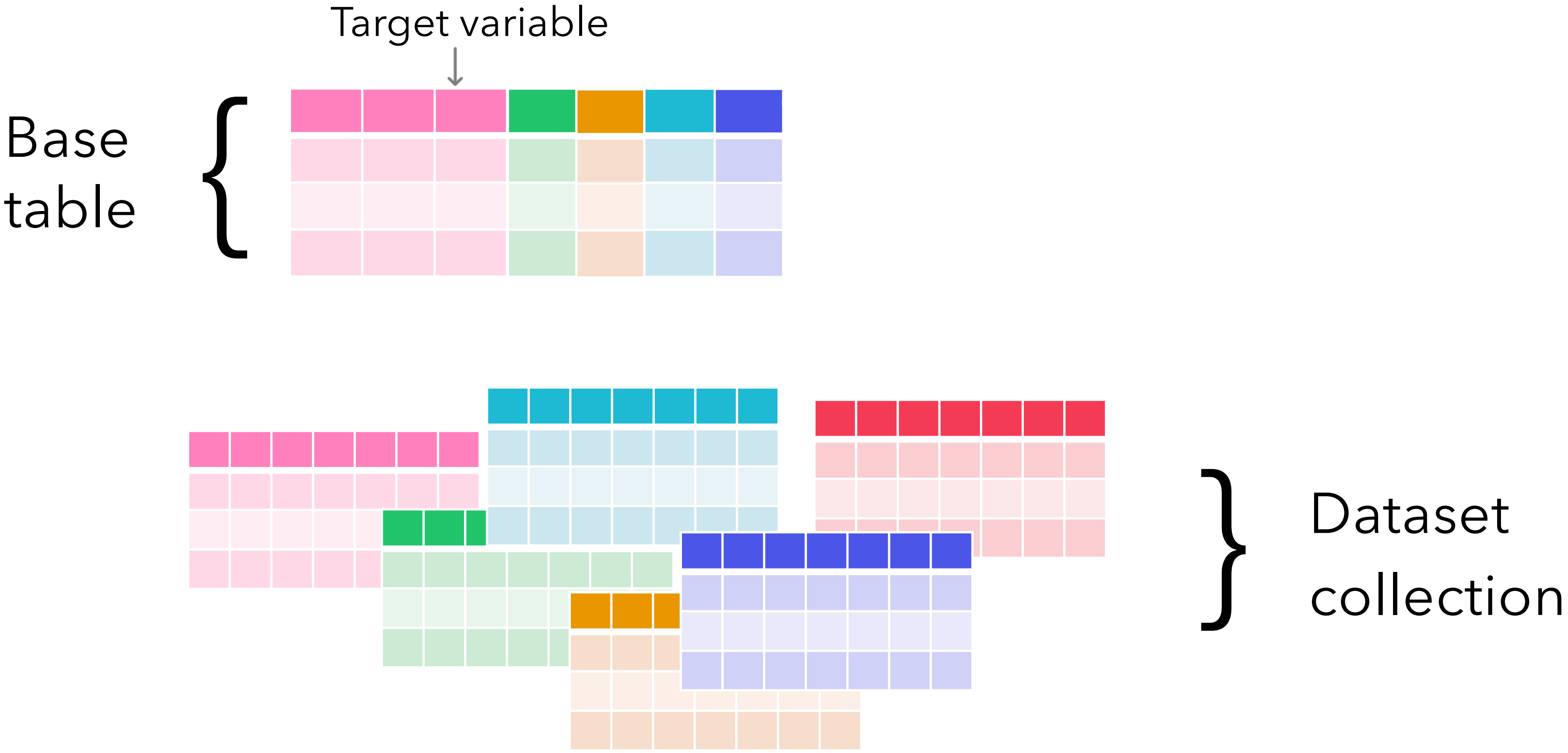


Target variable

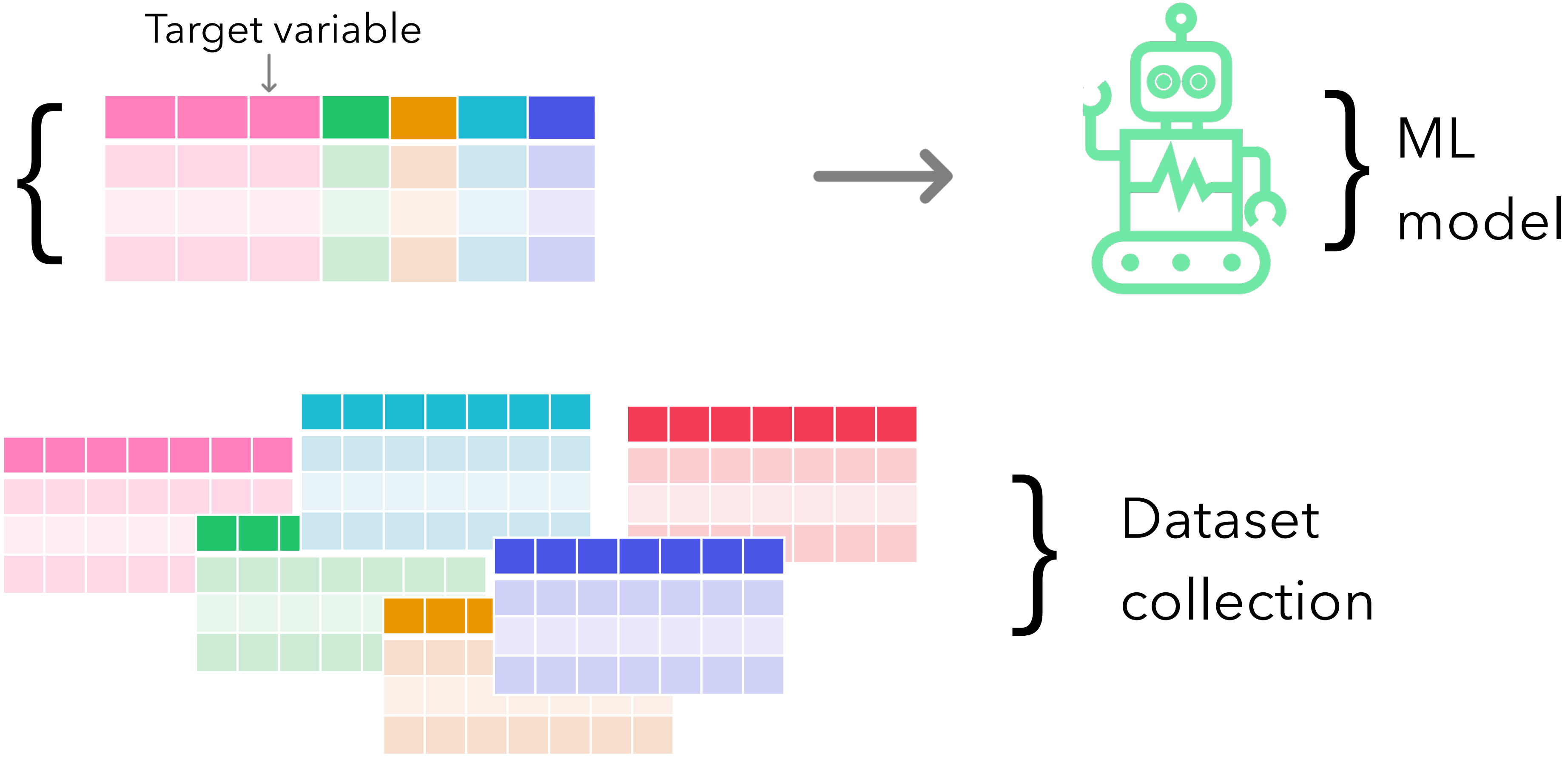
Base table

Dataset collection

Feature Discovery



Feature Discovery



Base table

Target variable

ML model

Dataset collection

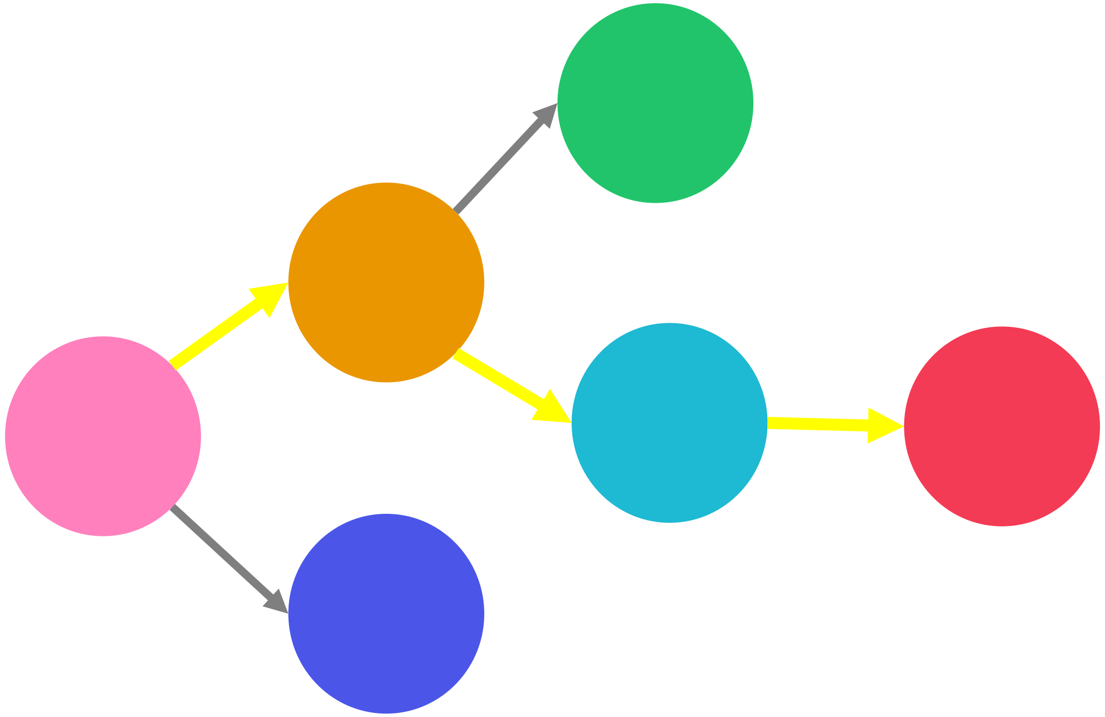
AUTOFEAT

AutoFeat

- Join-path length:

✓ multi-hop

✗ single-hop

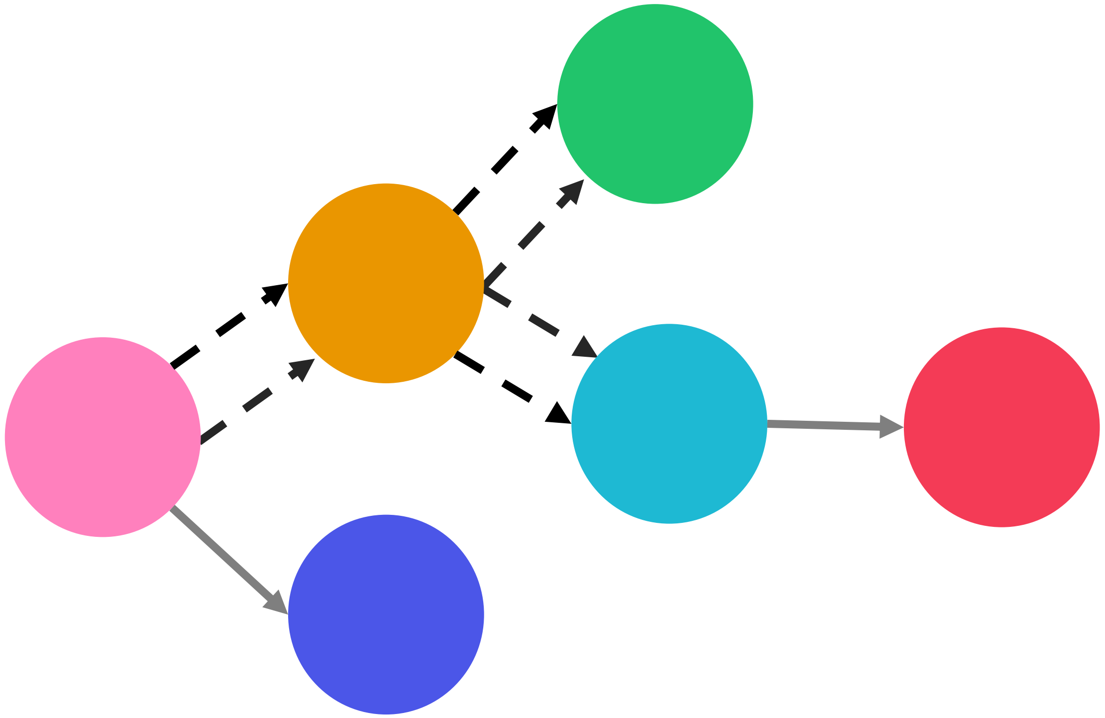


AutoFeat

- Joinability graph

✓ multi-graph

✗ simple graph

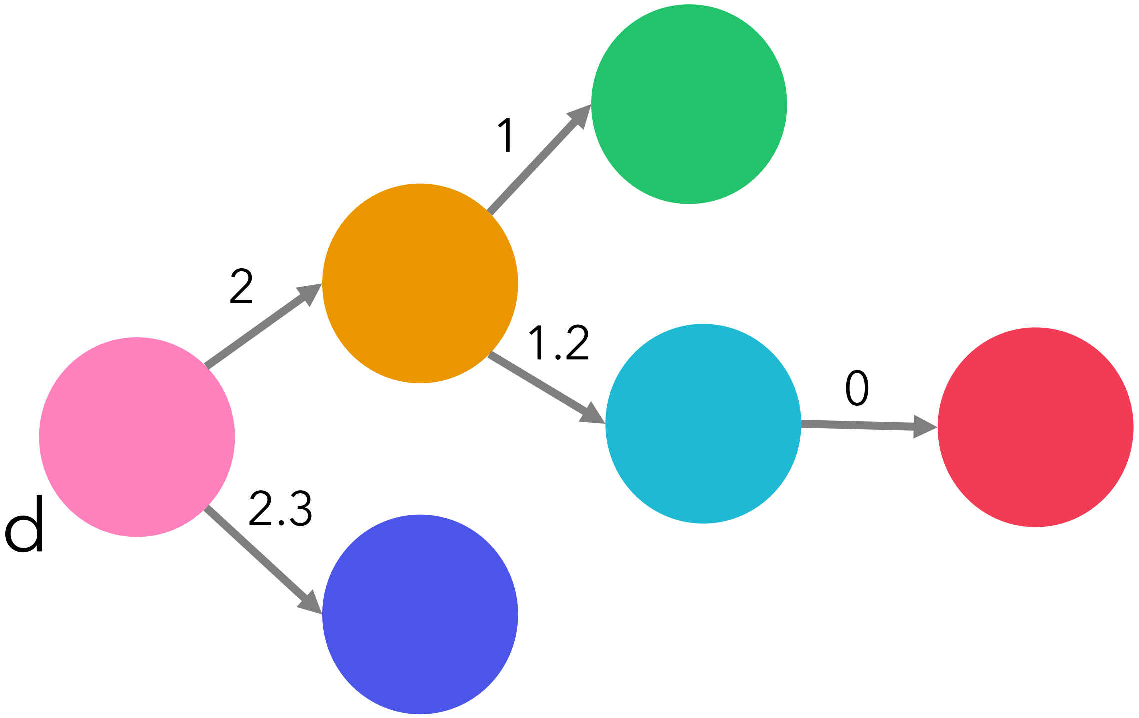


AutoFeat

- Path / Feature selection:

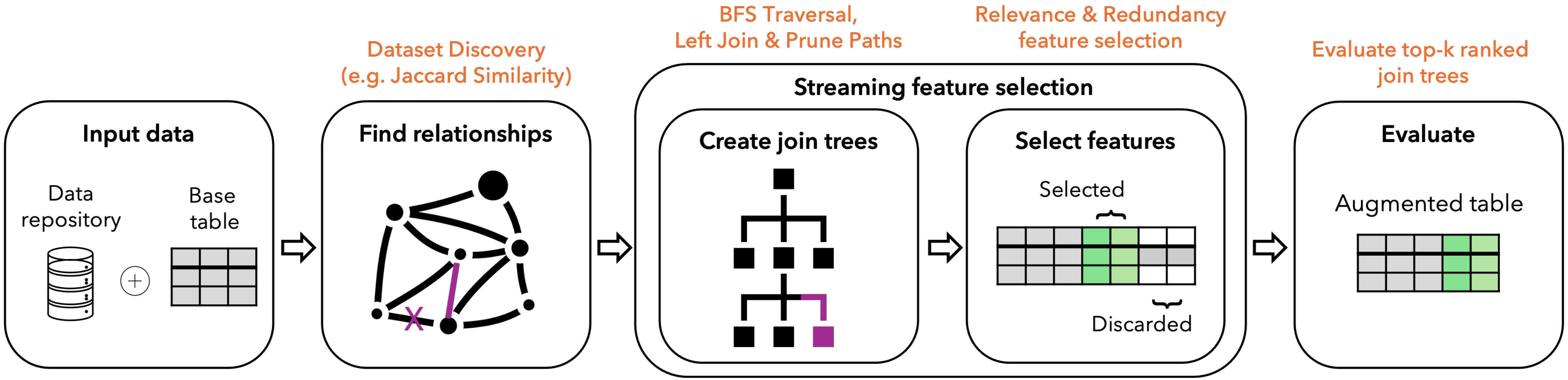
✓ ranking-based

✗ model-execution based



PIPELINE

AutoFeat Pipeline



Input data

Data repository

Base table

Dataset Discovery (e.g. Jaccard Similarity)

Find relationships

Streaming feature selection

BFS Traversal, Left Join & Prune Paths

Create join trees

Relevance & Redundancy feature selection

Select features

Selected

Discarded

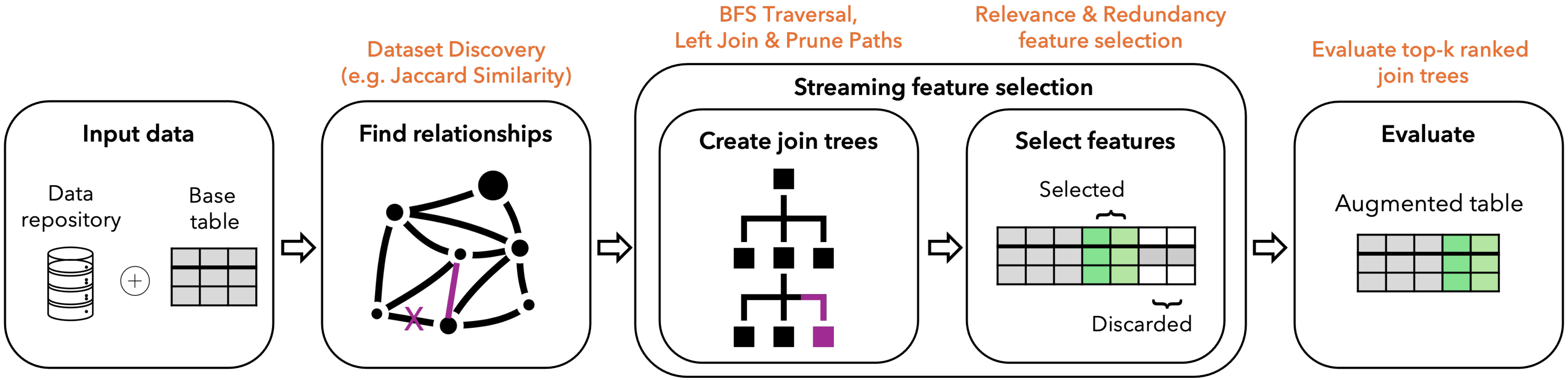
Evaluate top-k ranked join trees

Evaluate

Augmented table

1

AutoFeat Pipeline



Dataset Discovery (e.g. Jaccard Similarity)

BFS Traversal, Left Join & Prune Paths

Relevance & Redundancy feature selection

Evaluate top-k ranked join trees

Input data

Data repository

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Select features

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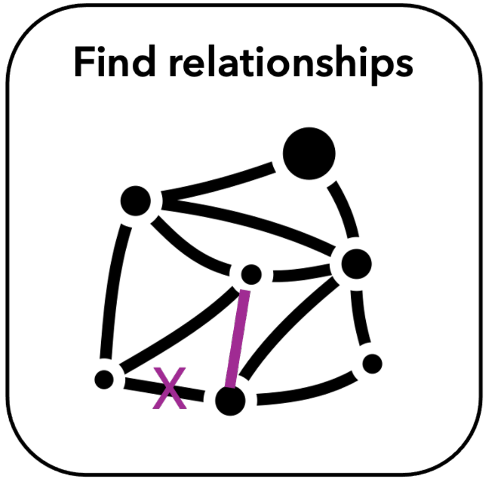
Evaluate

Augmented table

Dataset Relation Graph

Dataset Discovery
(e.g. Jaccard Similarity)



Find relationships

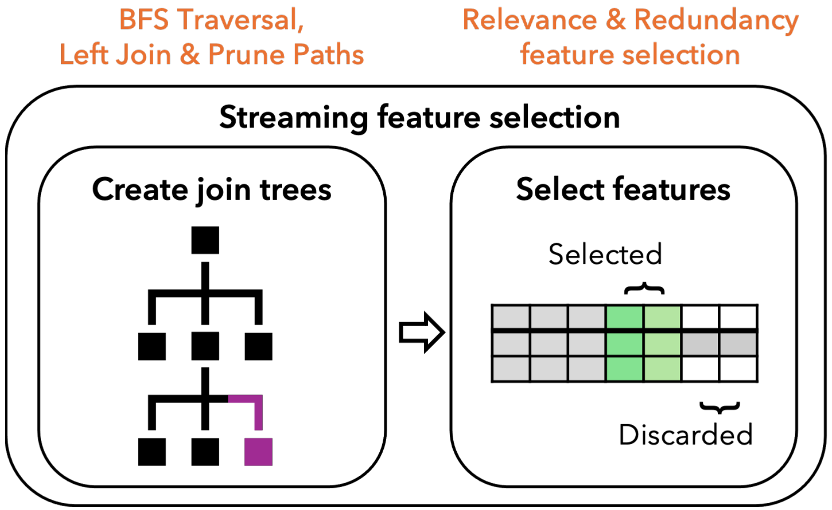
Dataset Discovery

- Valentine – schema matching tool suite [1]

DRG - weighted graph

- Nodes → Tables
- Edges → Relationships
  - Weight = 1 (PK-FK)
  - Weight = similarity score

[1] Christos Koutras, et al. "Valentine: Evaluating matching techniques for dataset discovery." 2021 ICDE



BFS Traversal,
Left Join & Prune Paths

Relevance & Redundancy
feature selection

Streaming feature selection

Create join trees

Select features

Selected

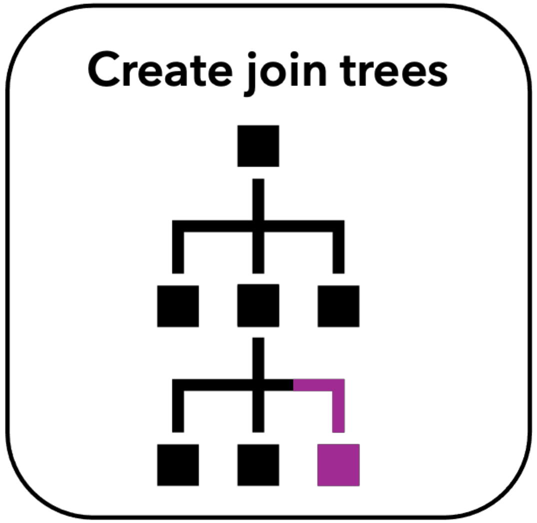
Discarded

STREAMING FEATURE SELECTION

FEATURES ARRIVE IN A STREAMING FASHION WITH EVERY JOIN

Join Trees

BFS Traversal,
Left Join & Prune Paths



Graph traversal

- Breadth First Search (BFS)
- Evaluate data quality after each level
- Easier error management

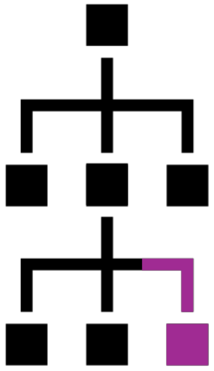
Join type

- Left join
- Preserve number of rows
- Avoid introducing class imbalance

Join Trees

BFS Traversal,
Left Join & Prune Paths

Create join trees



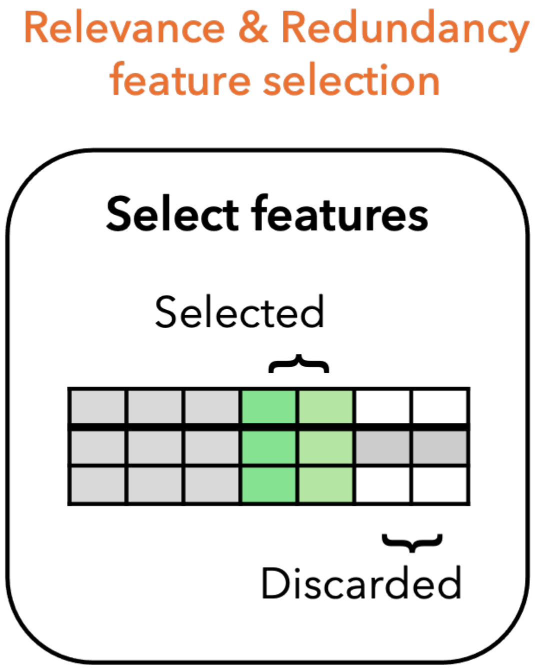
Join paths

- Sequence of edges
- Chain of joins

Prune paths

- Similarity score
- Data quality – completeness

Feature Selection



Relevance

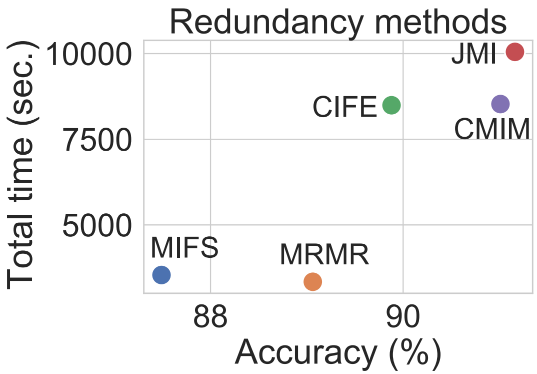
- Spearman correlation – rank correlation

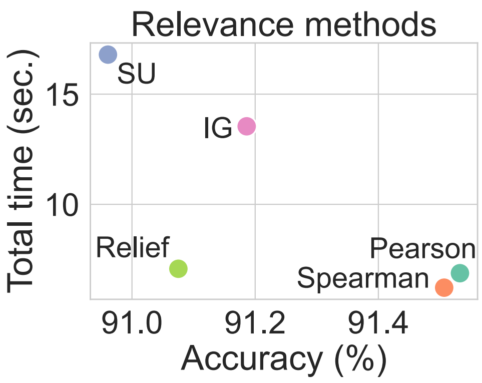
Redundancy

- MRMR – with more selected features, the effect of redundancy is reduced

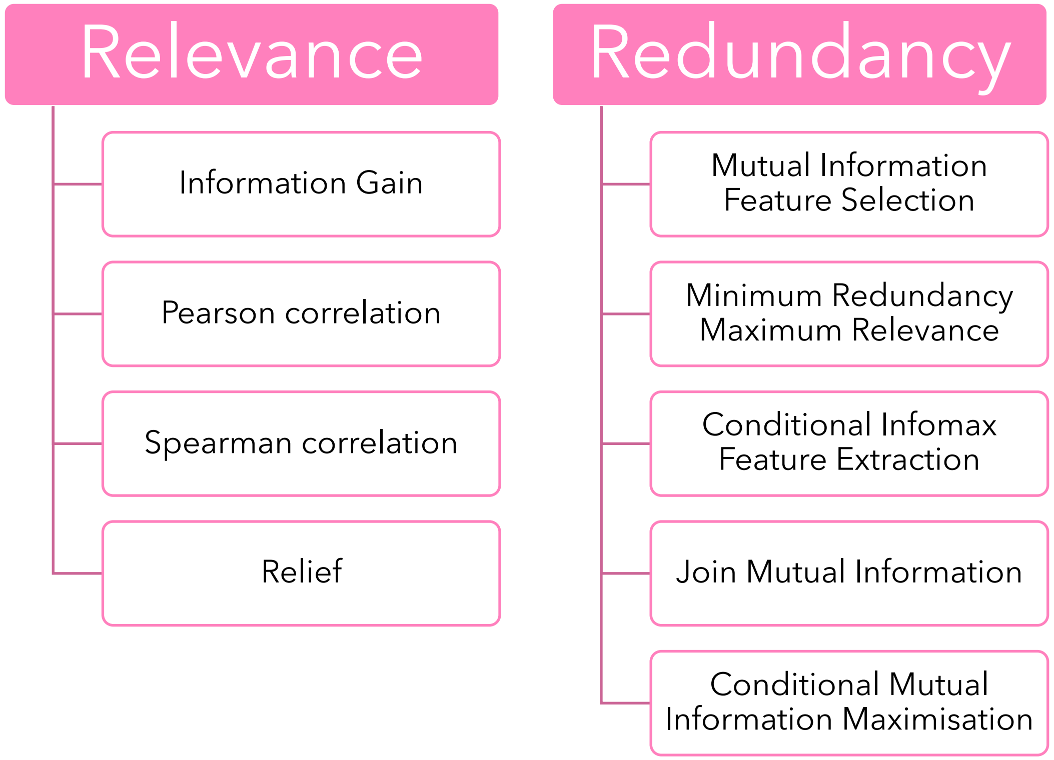
Ranking

- Linear function of relevance and redundancy scores





Feature Selection



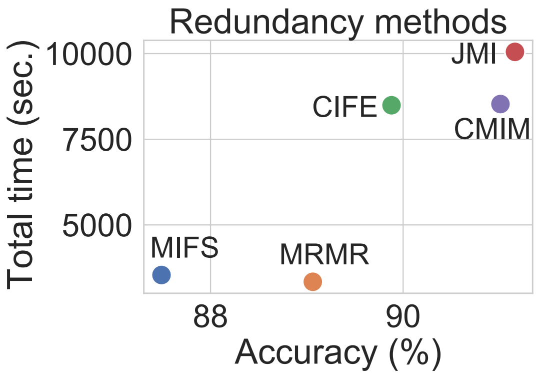
Relevance

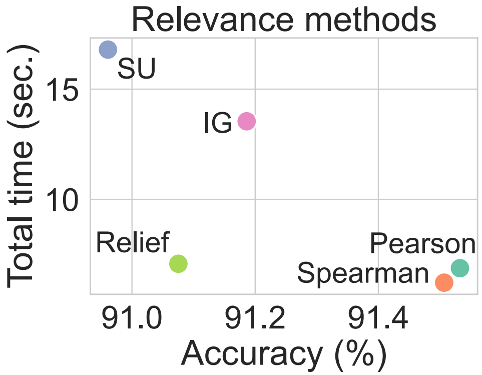
- Information Gain
- Pearson correlation
- Spearman correlation
- Relief

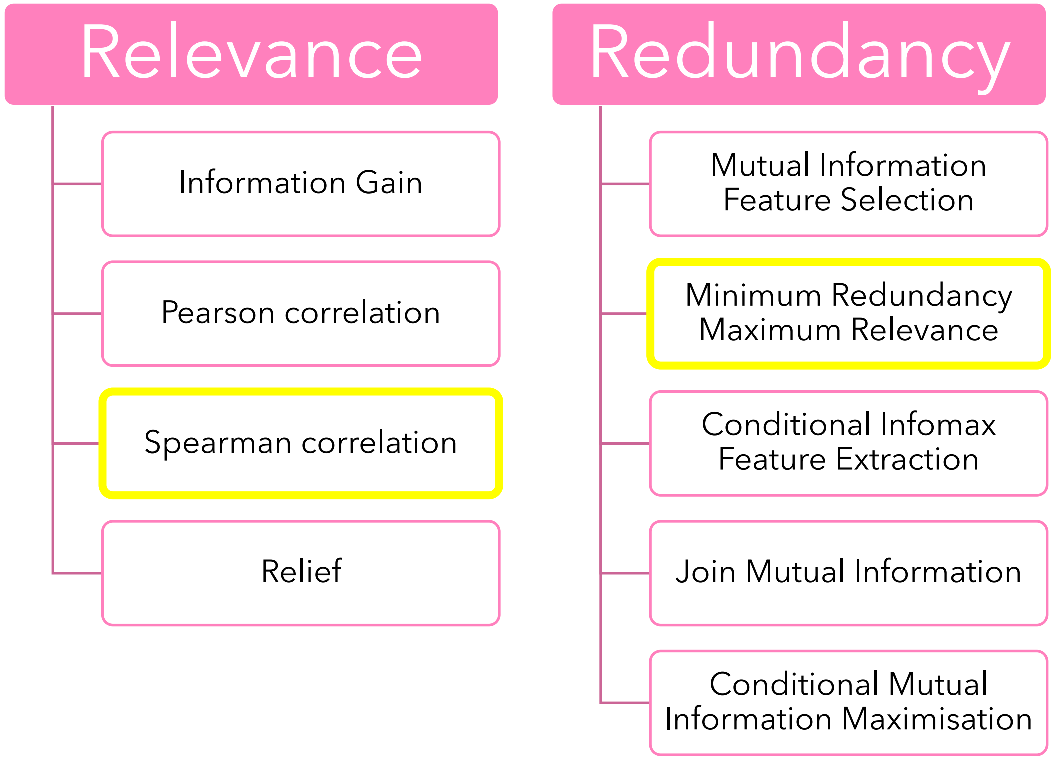
Redundancy

- Mutual Information Feature Selection
- Minimum Redundancy Maximum Relevance
- Conditional Infomax Feature Extraction
- Join Mutual Information
- Conditional Mutual Information Maximisation

Feature Selection







Relevance

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Redundancy

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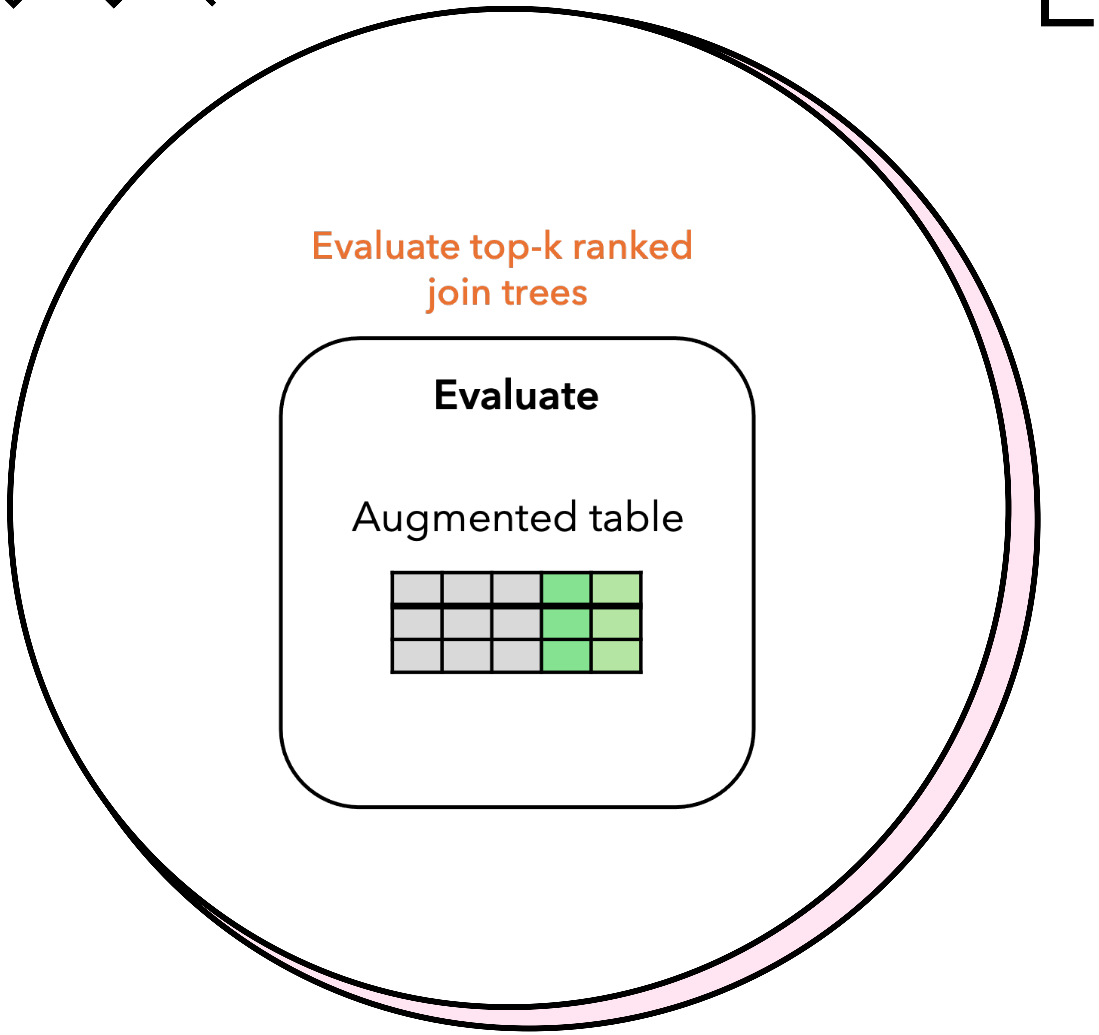
Evaluate Join Trees



Evaluate top-k ranked join trees

Evaluate

Augmented table

Top-k join trees

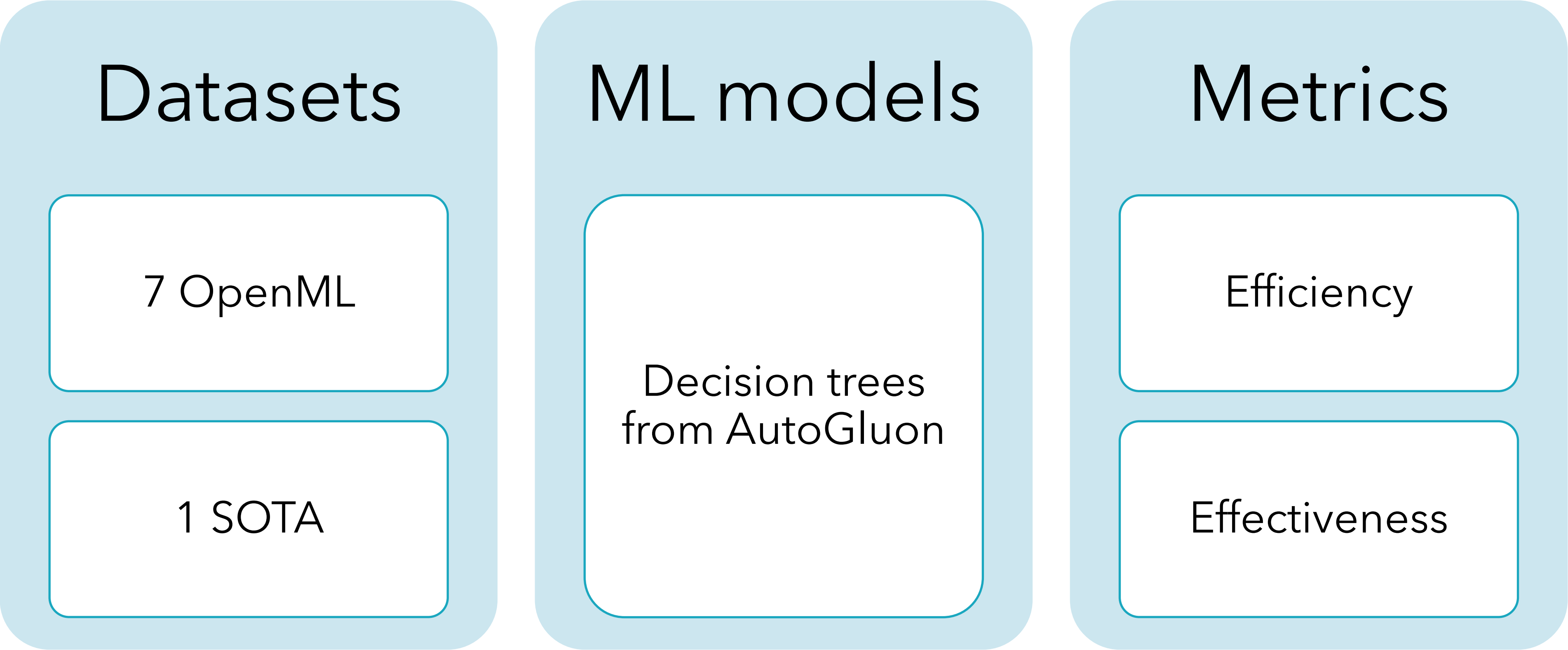
- Based on the ranking

Augment Base Table

- Train ML model

EVALUATION

Setup



Datasets

7 OpenML

1 SOTA

ML models

Decision trees from AutoGluon

Metrics

Efficiency

Effectiveness

Baselines

Base	• Non-augmented base table
Join All	• Join all tables
Join All + FS	• Join all, then apply feature selection
ARDA [2]	• Random Injection of noise
Multi-Armed Bandit [3]	• Exploration - Exploitation strategy

[2] Chepurko, Nadiia, et al. "ARDA: Automatic Relational Data Augmentation for Machine Learning." 2020 VLDB
[3] Liu, Jiabin, et al. "Feature augmentation with reinforcement learning." 2022 ICDE

Scenarios

Benchmark

Known PK-FK connections

Snowflake schema

Reproduce the results from baselines

Data Lake

Unknown PK-FK connections

Dense multi-graph

Show the predictive power of AutoFeat

RESULTS

BENCHMARK SCENARIO

16% INCREASE IN ACCURACY ACROSS ALL DATASETS AND MODELS

	# joins	Accuracy	Runtime
★	AutoFeat prunes out all the irrelevant tables		
	AutoFeat < ARDA/MAB	AutoFeat > ARDA/MAB	AutoFeat < ARDA/MAB
❄	ARDA and MAB only join the directly connected tables		
	AutoFeat > ARDA/MAB	AutoFeat > ARDA/MAB	AutoFeat < ARDA/MAB

AUTOFEAT HAS SAME ACCURACY AS JOIN ALL(+FS) AT A FRACTION OF TIME

DATA LAKE SCENARIO

Path analysis

AutoFeat explores the join space in depth

Prunes out irrelevant tables

Effectiveness:

AutoFeat shows increased accuracy from the base table

ARDA/MAB show marginal increase, or none compared to base

Efficiency:

10x faster than MAB

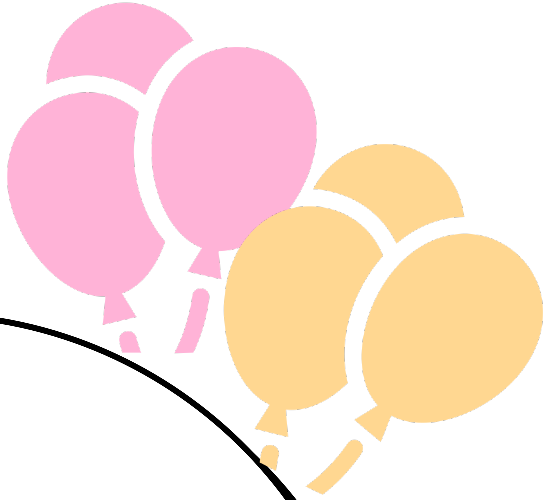
3x faster than ARDA

Conclusion

AutoFeat is a more efficient and effective method for automatic feature discovery over long join paths.

AutoFeat works with both star and snowflake schema.

AutoFeat decouples the model training step from feature discovery process and relies on heuristics to prune out irrelevant tables and features.



Thank you!

AutoFeat: Transitive Feature Discovery Over Join Paths

https://github.com/delftdata/autofeat

andradenisio