AutoFeat: Transitive Feature Discovery over Join Paths

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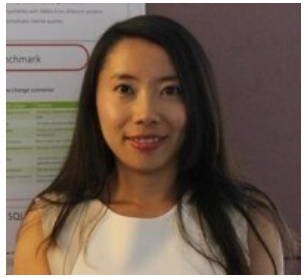

Rihan Hai

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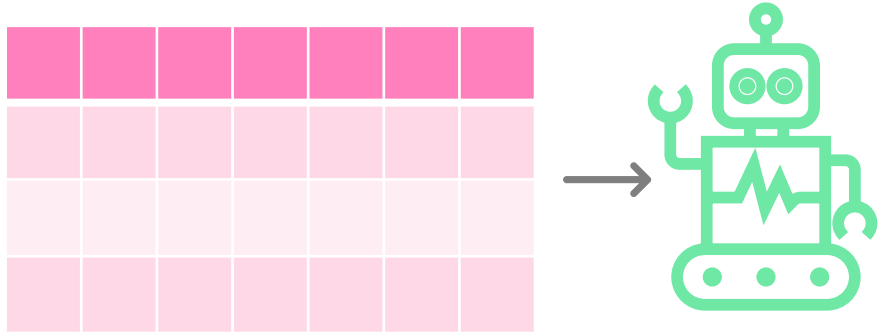
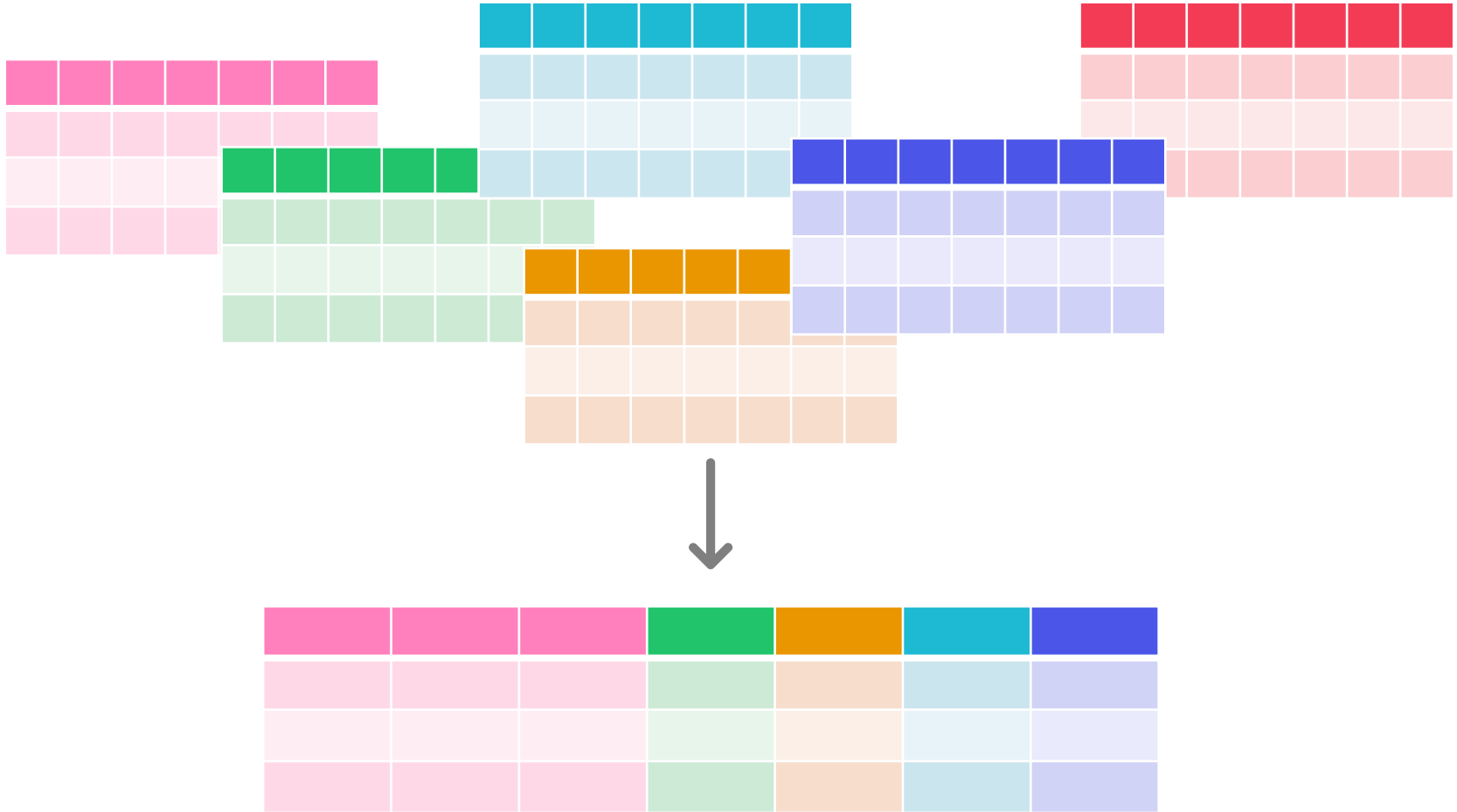
PROBLEM

Input data of an ML model is a single table

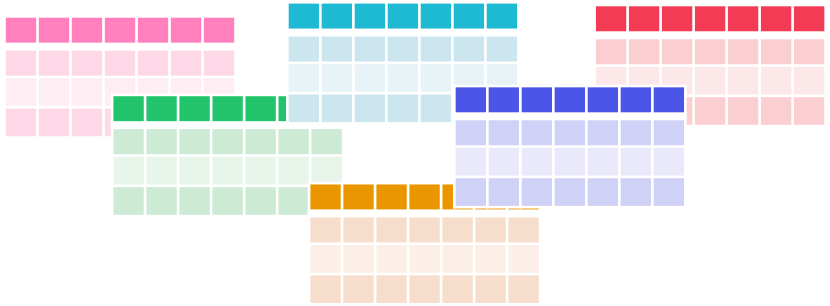


Input dataset is the result of data augmentation and feature selection

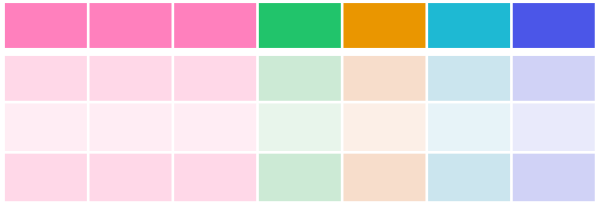


Dataset Augmentation

Collection of datasets

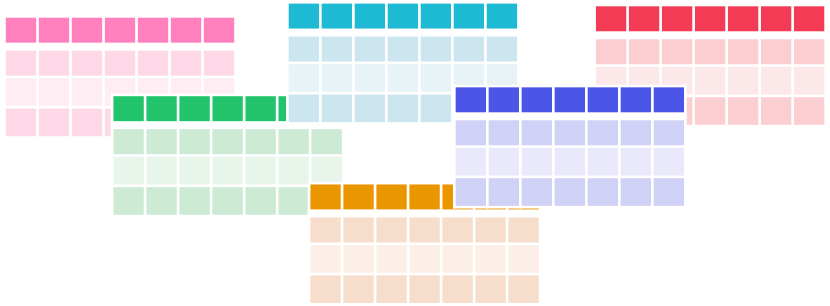


Training dataset

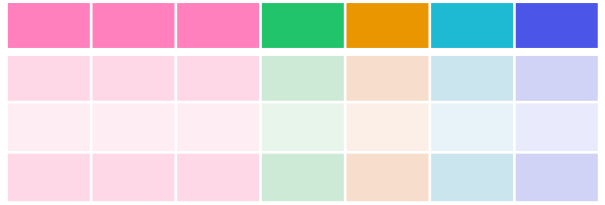


Dataset Augmentation

Collection of datasets



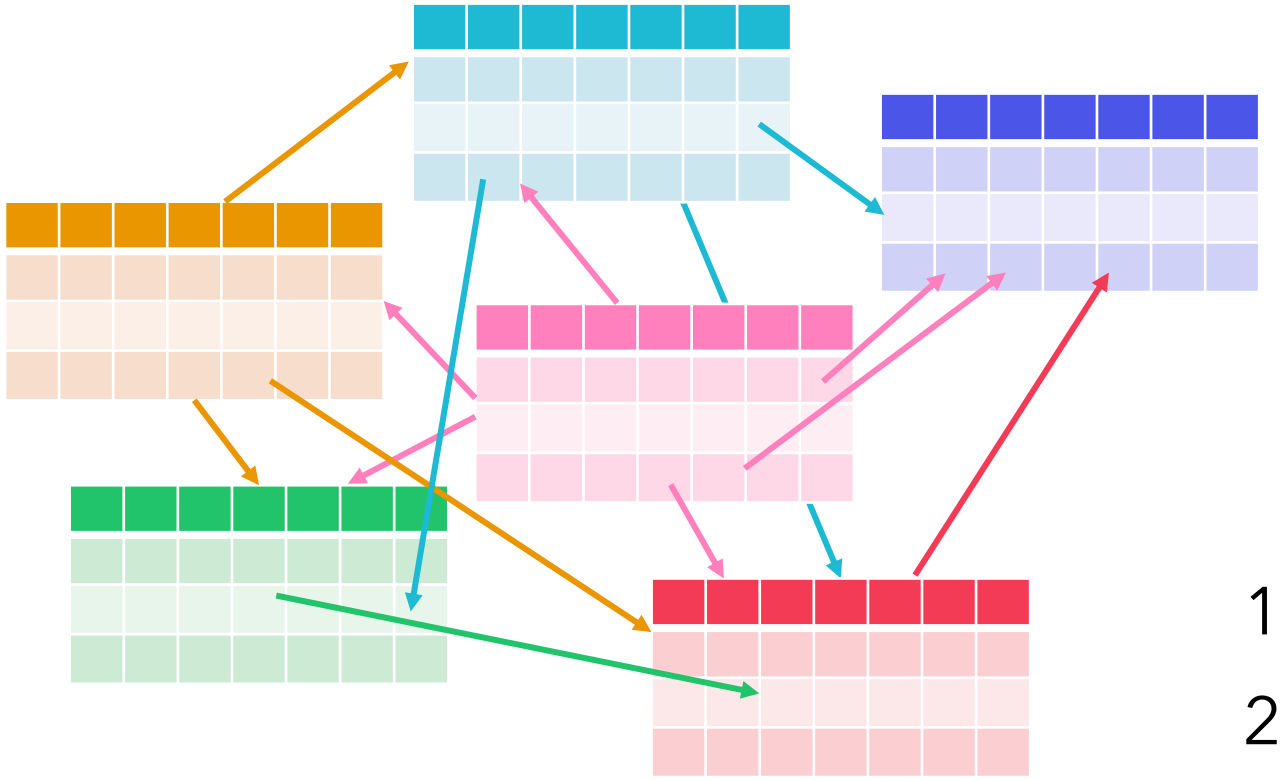
Training dataset



When PK-FK are known:

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

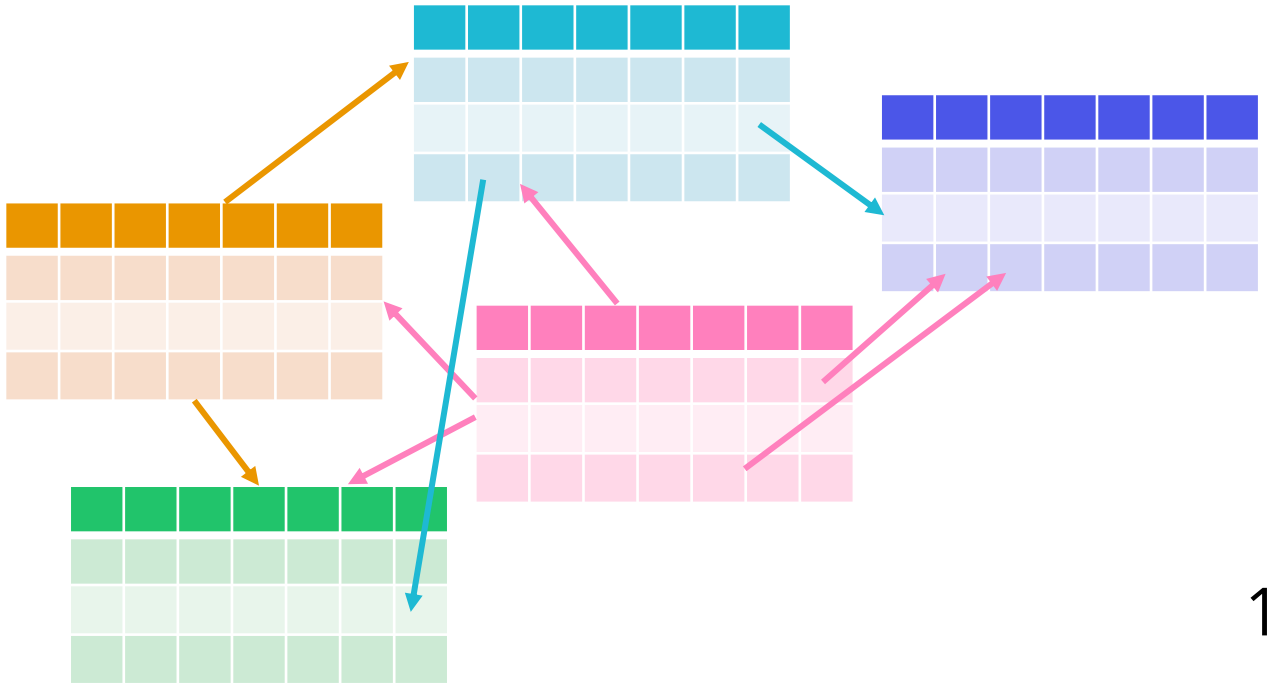
Dataset Augmentation



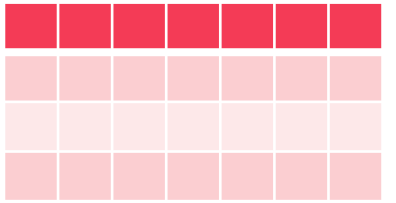
When PK-FK are missing:

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

Dataset Augmentation



- Spurious relations



When PK-FK are missing:

1. Dataset discovery
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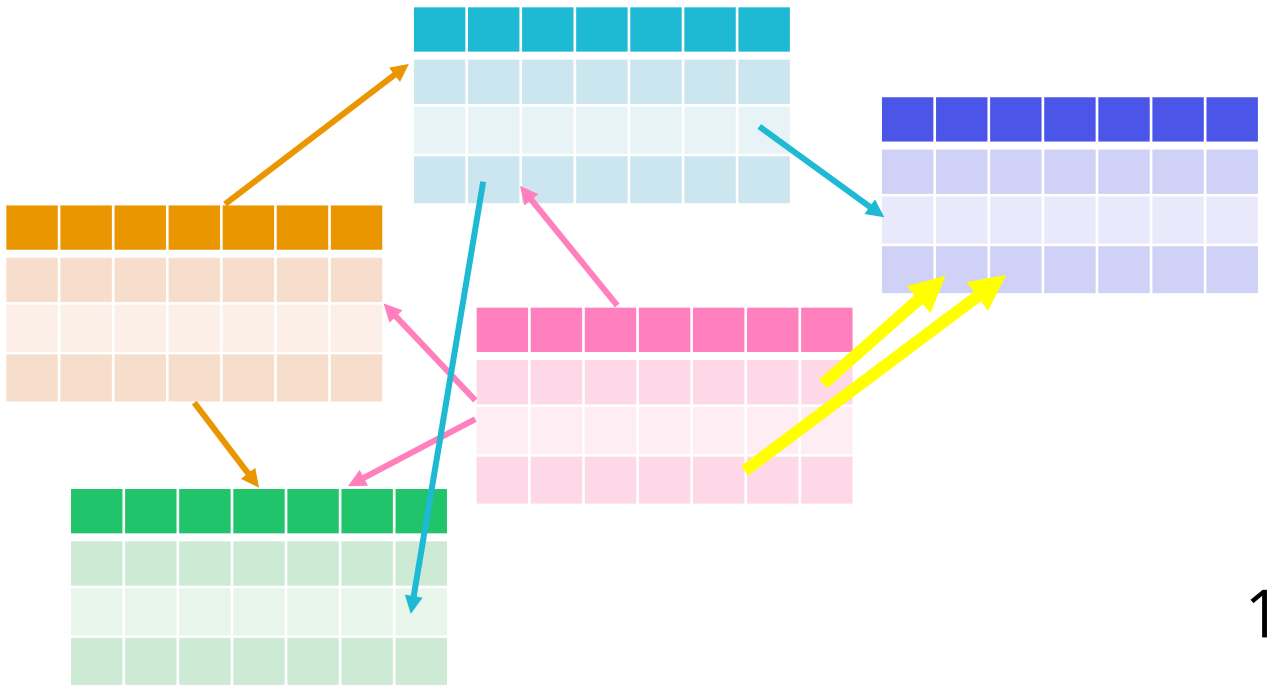
Dataset Augmentation



- Multiple join columns

When PK-FK are missing:

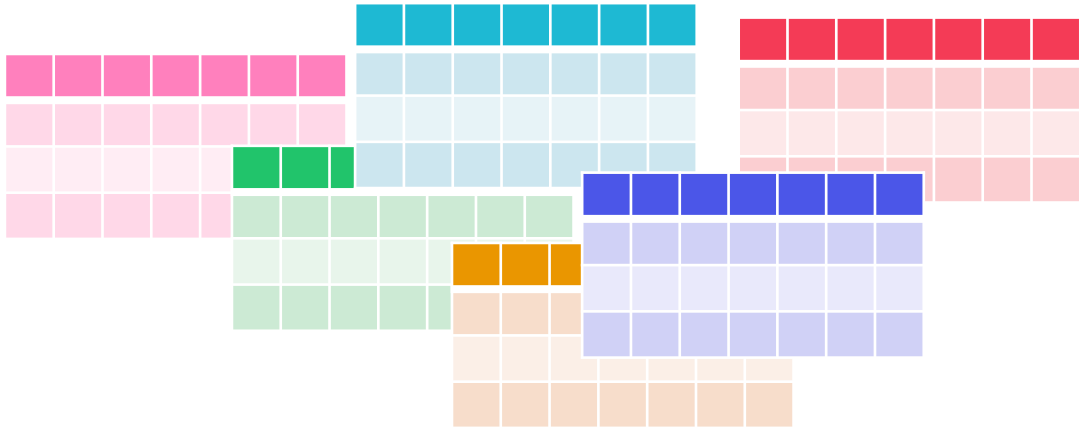
1. Dataset discovery
2. Join data
3. Apply feature selection

FEATURE DISCOVERY

Feature Discovery

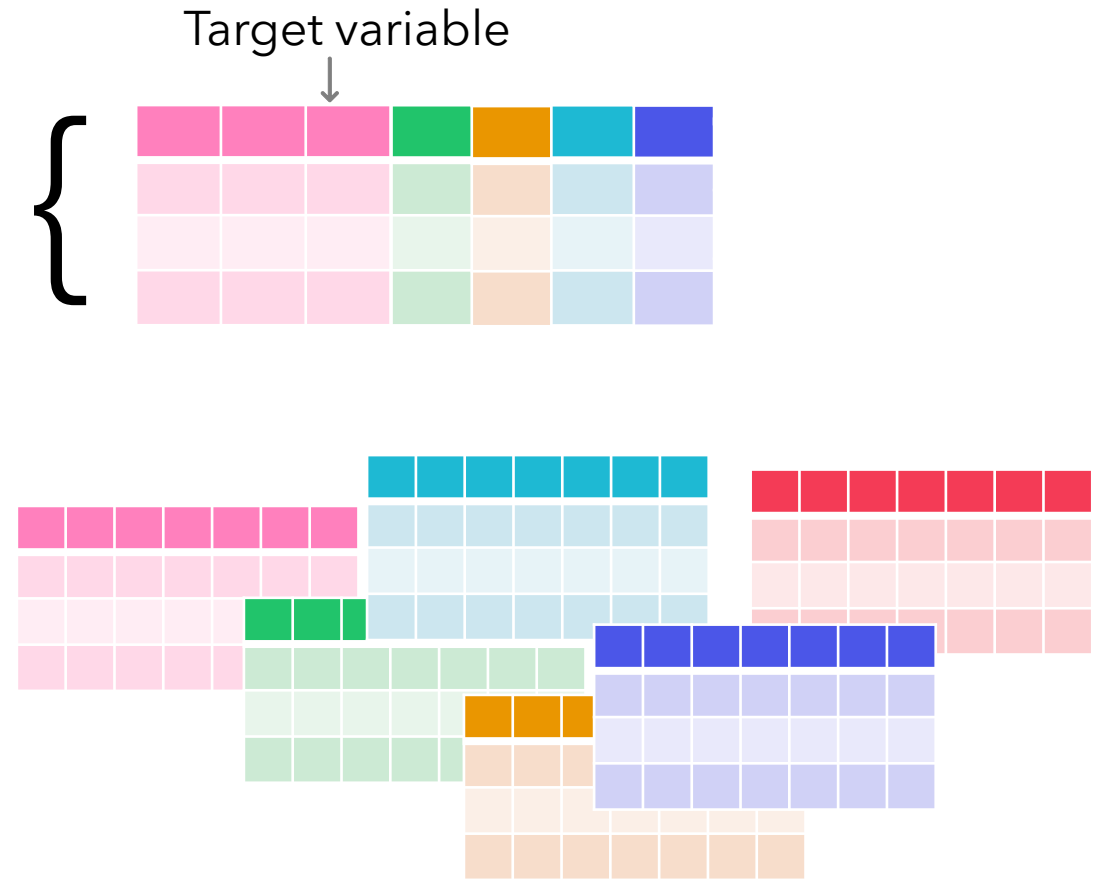
Target variable

Base table



Dataset collection

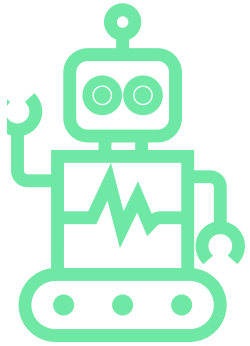
Feature Discovery



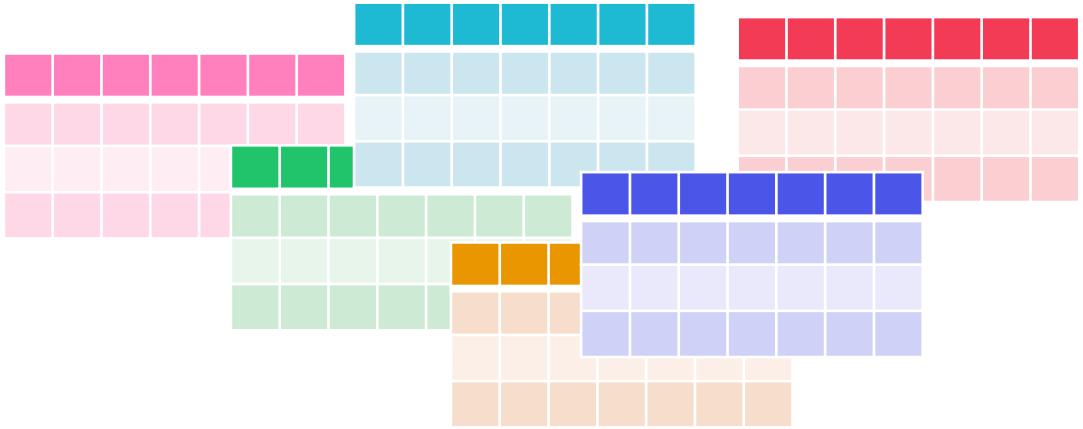
Feature Discovery

Target variable

Base table



ML model

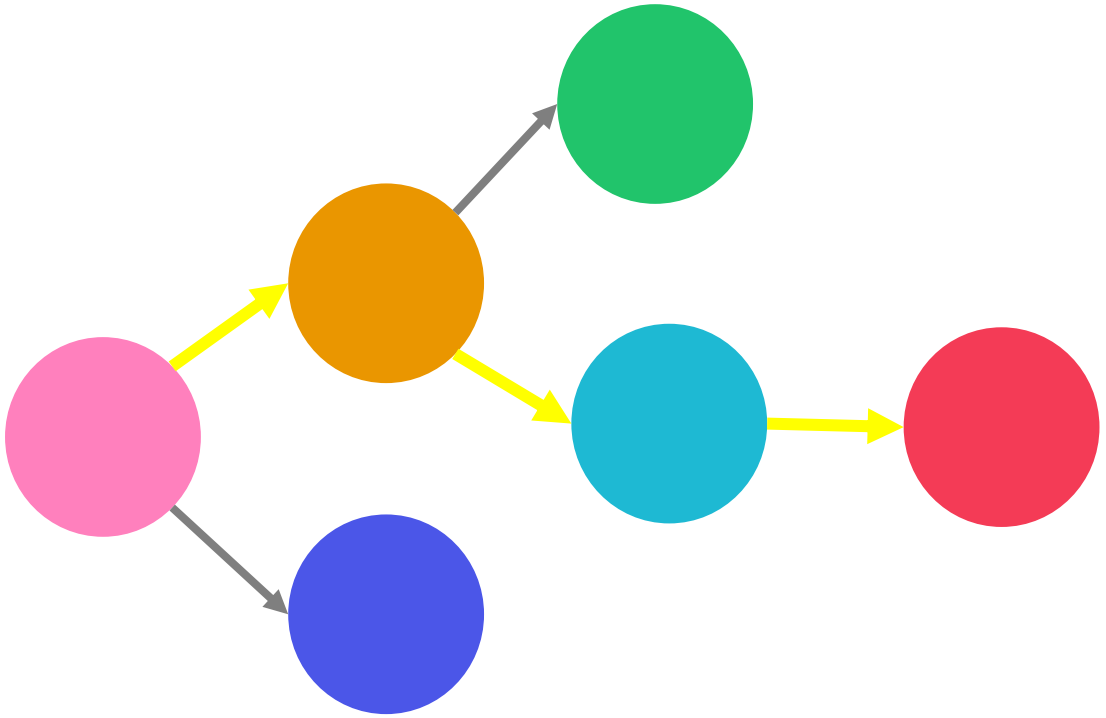


Dataset collection

AUTOFEAT

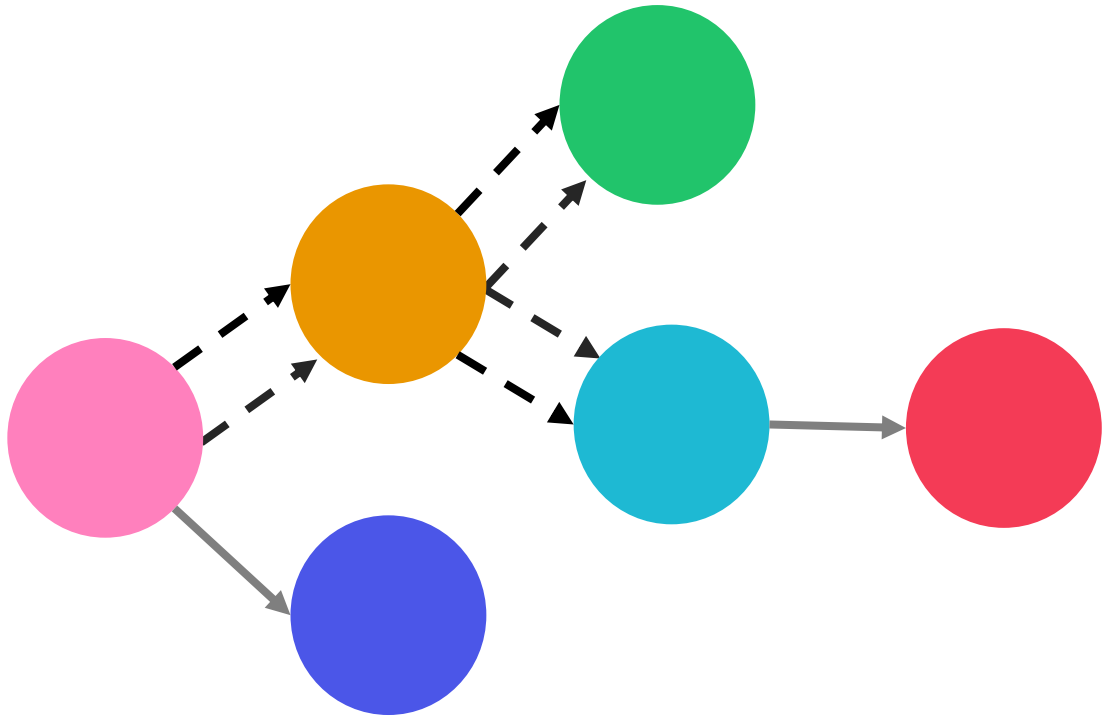
AutoFeat

- Join-path length:
  - ✓ single-hop
  - ✓ multi-hop



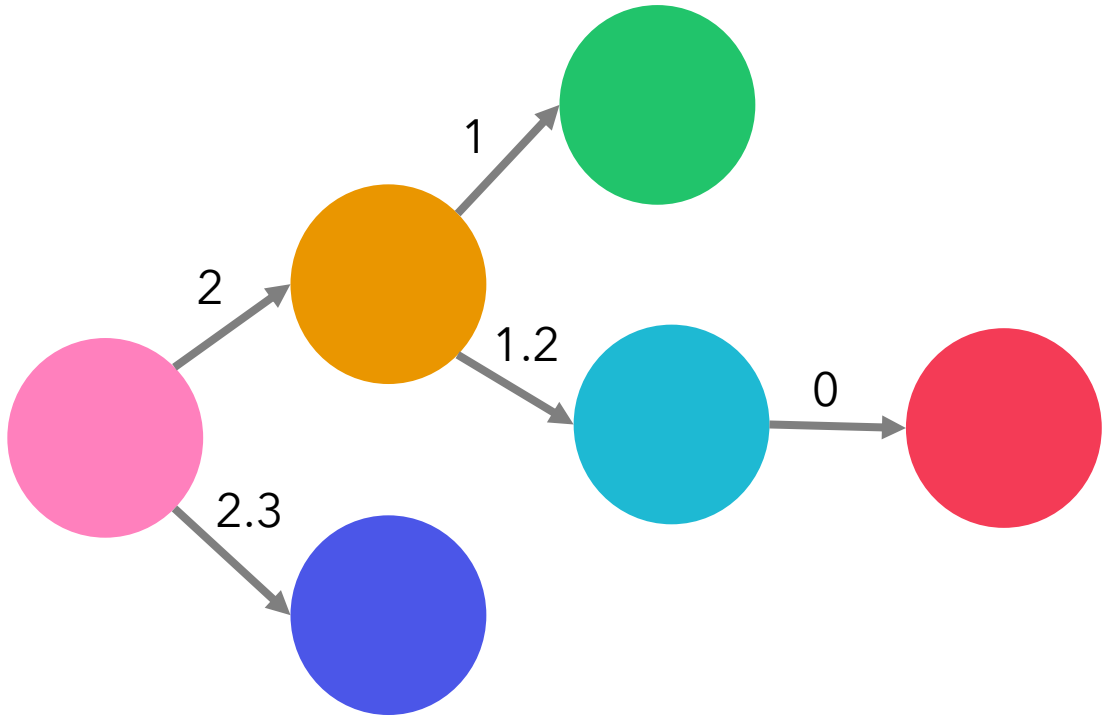
AutoFeat

- Joinability graph
  - ✓ simple graph
  - ✓ multi-graph



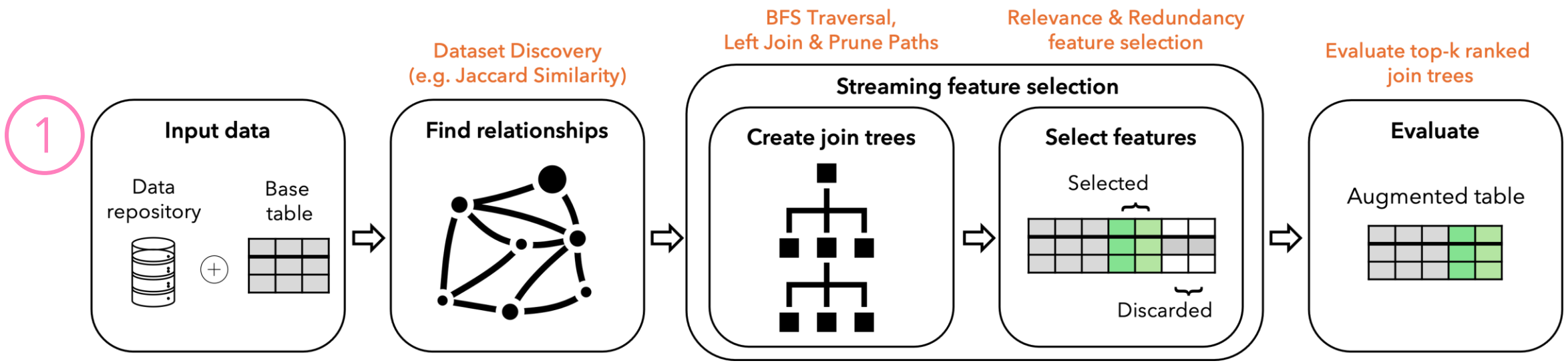
AutoFeat

- Path / Feature selection:
  - ✓ ranking-based
  - ✗ model-execution based

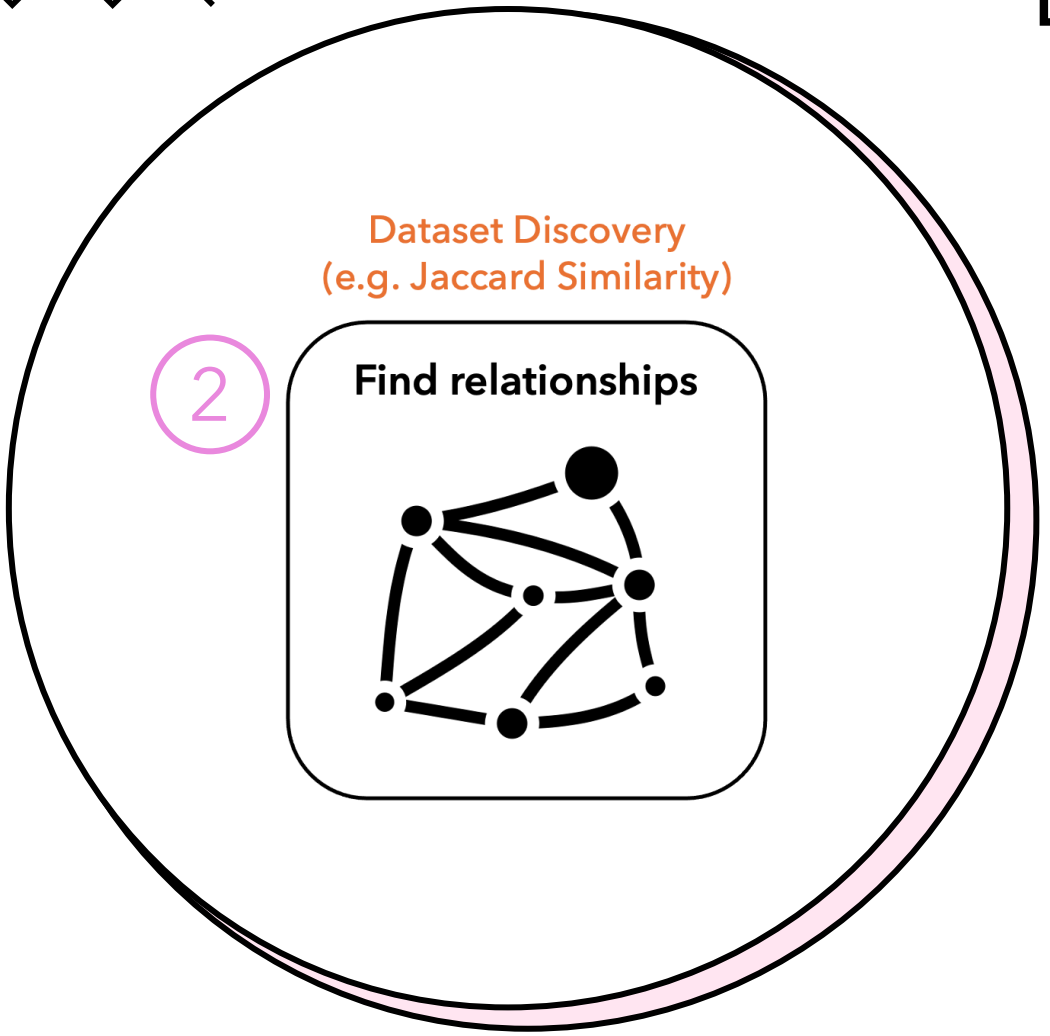


PIPELINE

AutoFeat Pipeline



Dataset Relation Graph



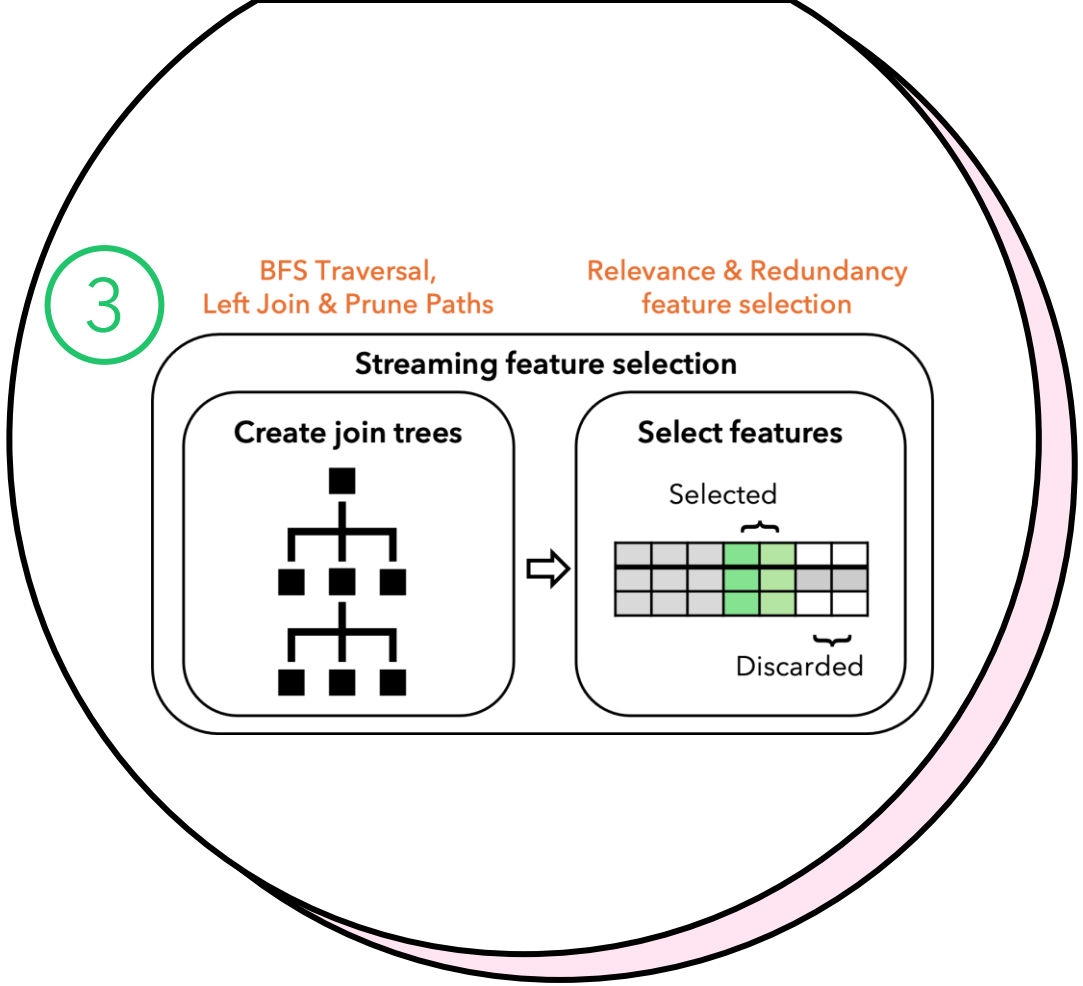
Dataset Discovery

- Valentine – schema matching tool suite [1]

DRG - weighted graph

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

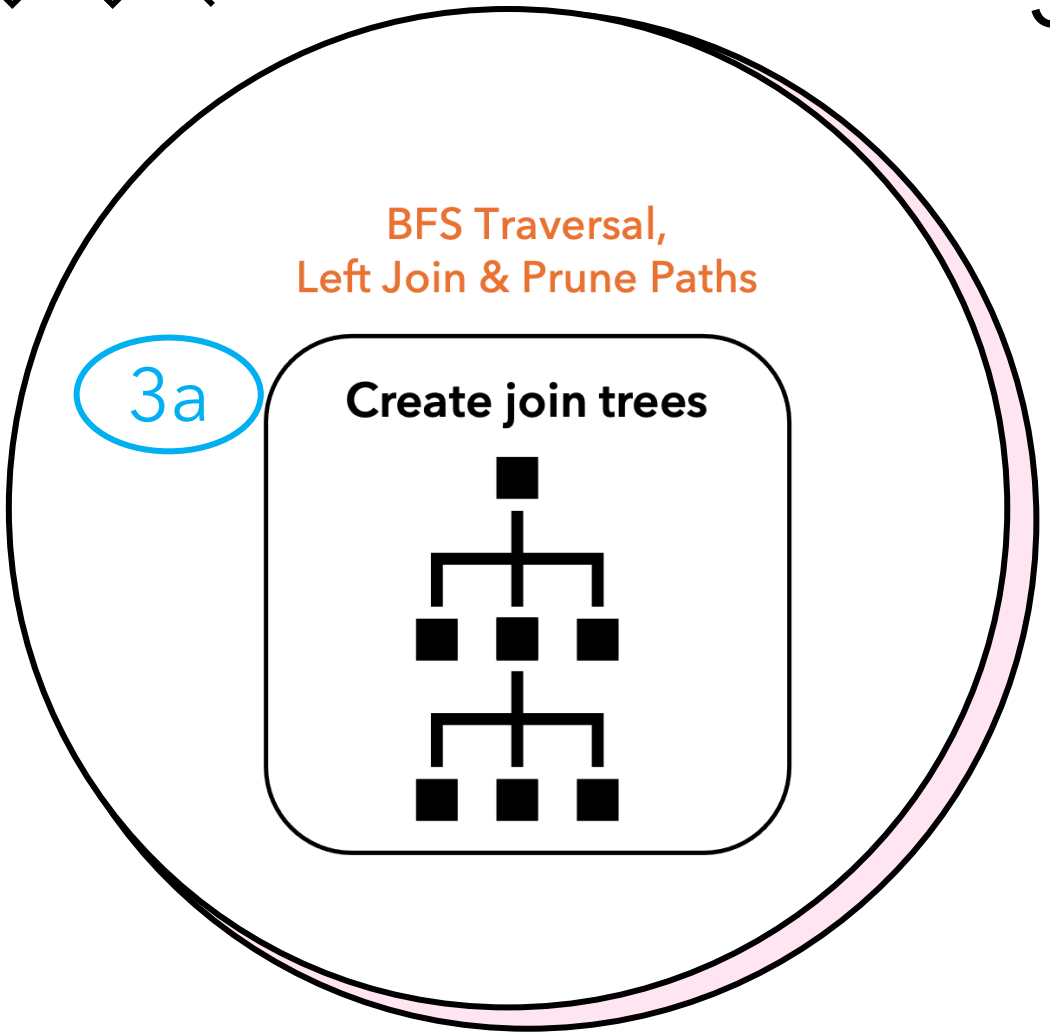
[1] Christos Koutras, et al. "Valentine: Evaluating matching techniques for dataset discovery." 2021 ICDE



STREAMING FEATURE SELECTION

FEATURES ARRIVE IN A STREAMING FASHION WITH EVERY JOIN

Join Trees



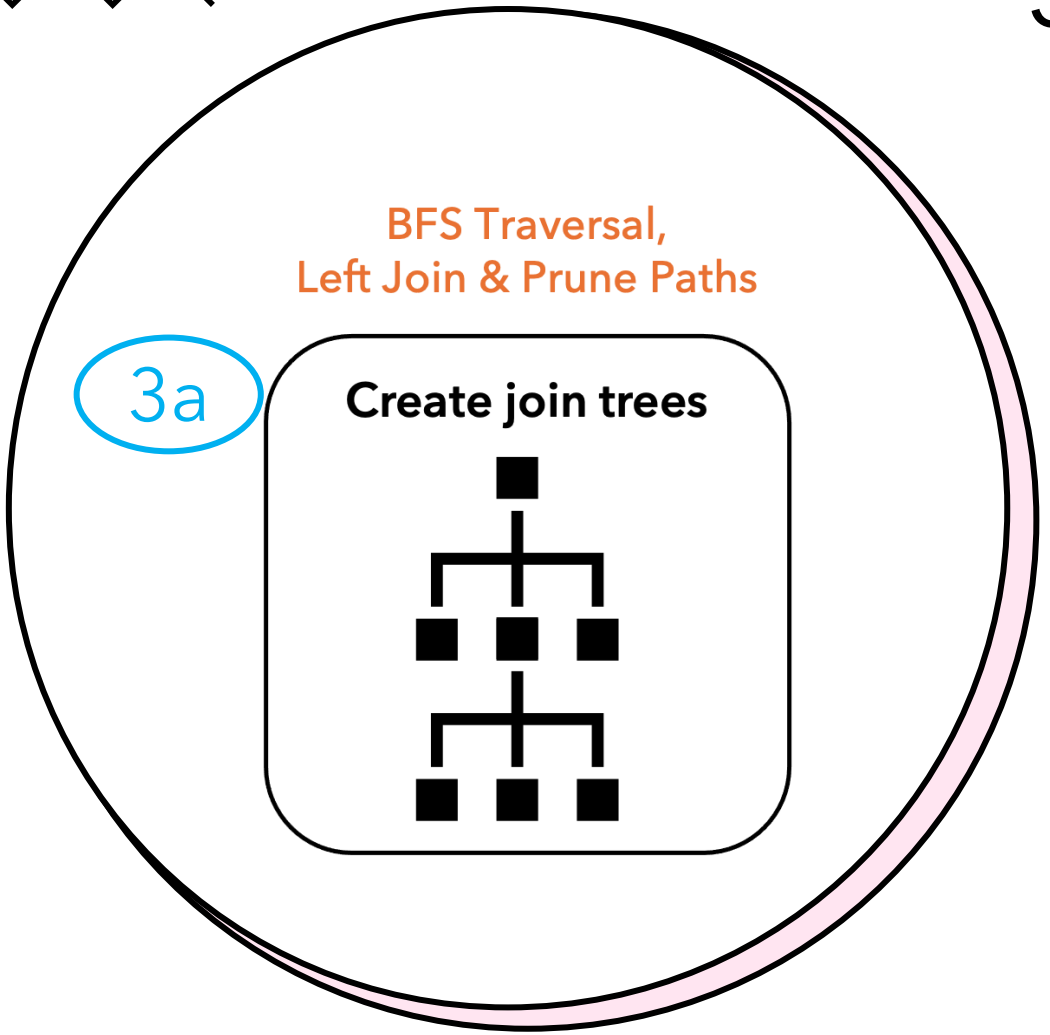
Graph traversal

- 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



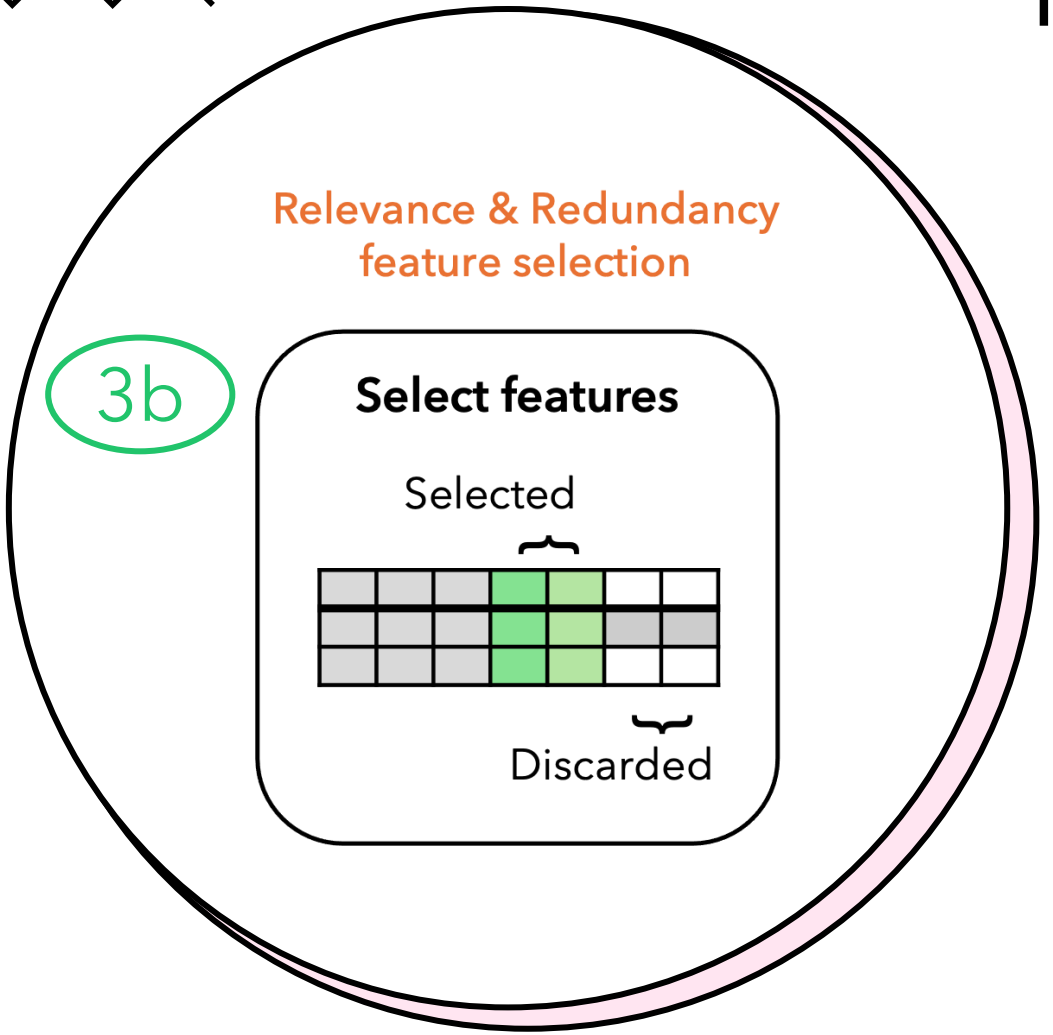
Join paths

- Sequence of edges
- Chain of joins

Prune paths

- Similarity score
- Data quality – null values ratio

Feature Selection



Relevance

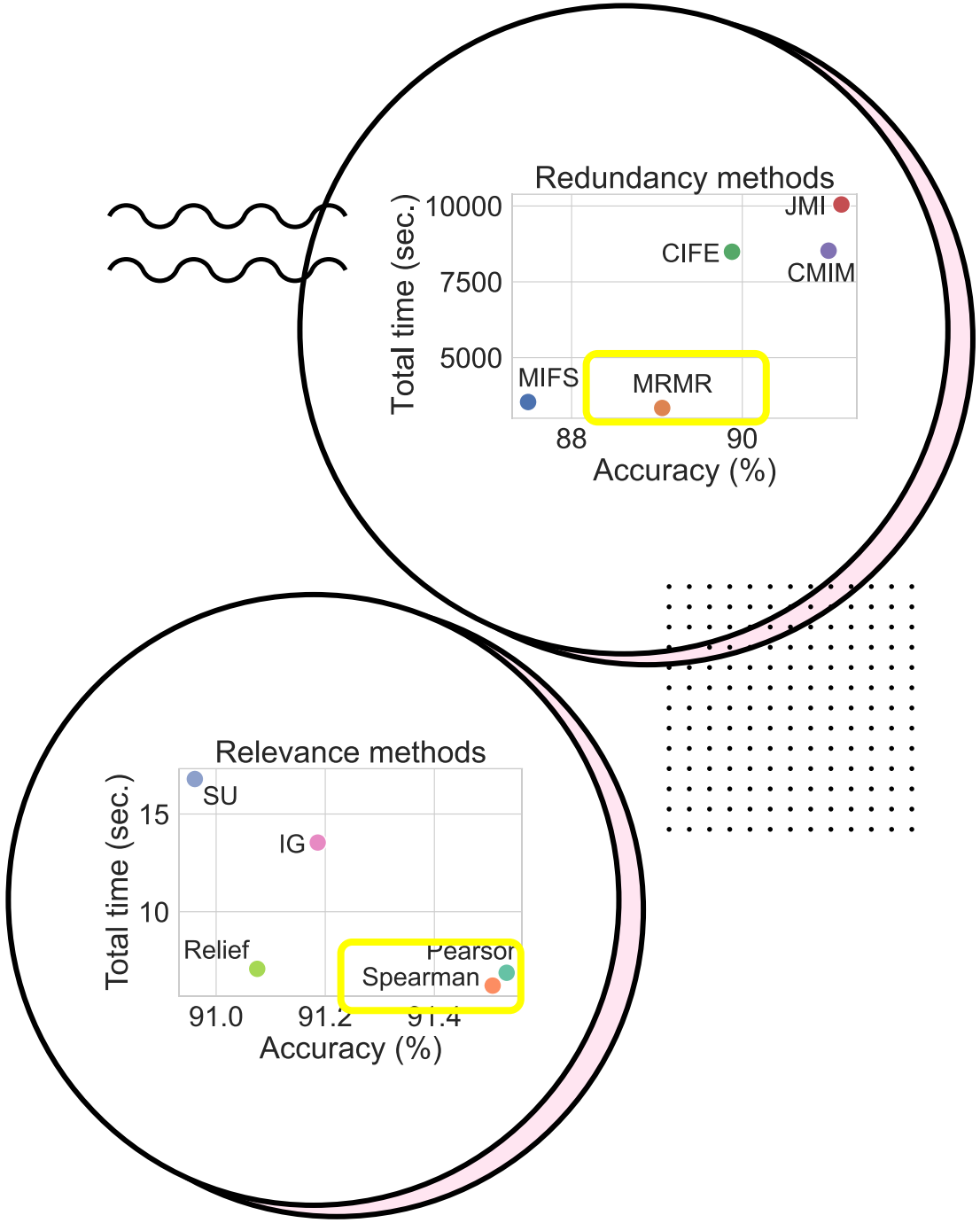
- Spearman correlation – rank correlation

Redundancy

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

Ranking

- Linear function of relevance and redundancy scores



Feature Selection

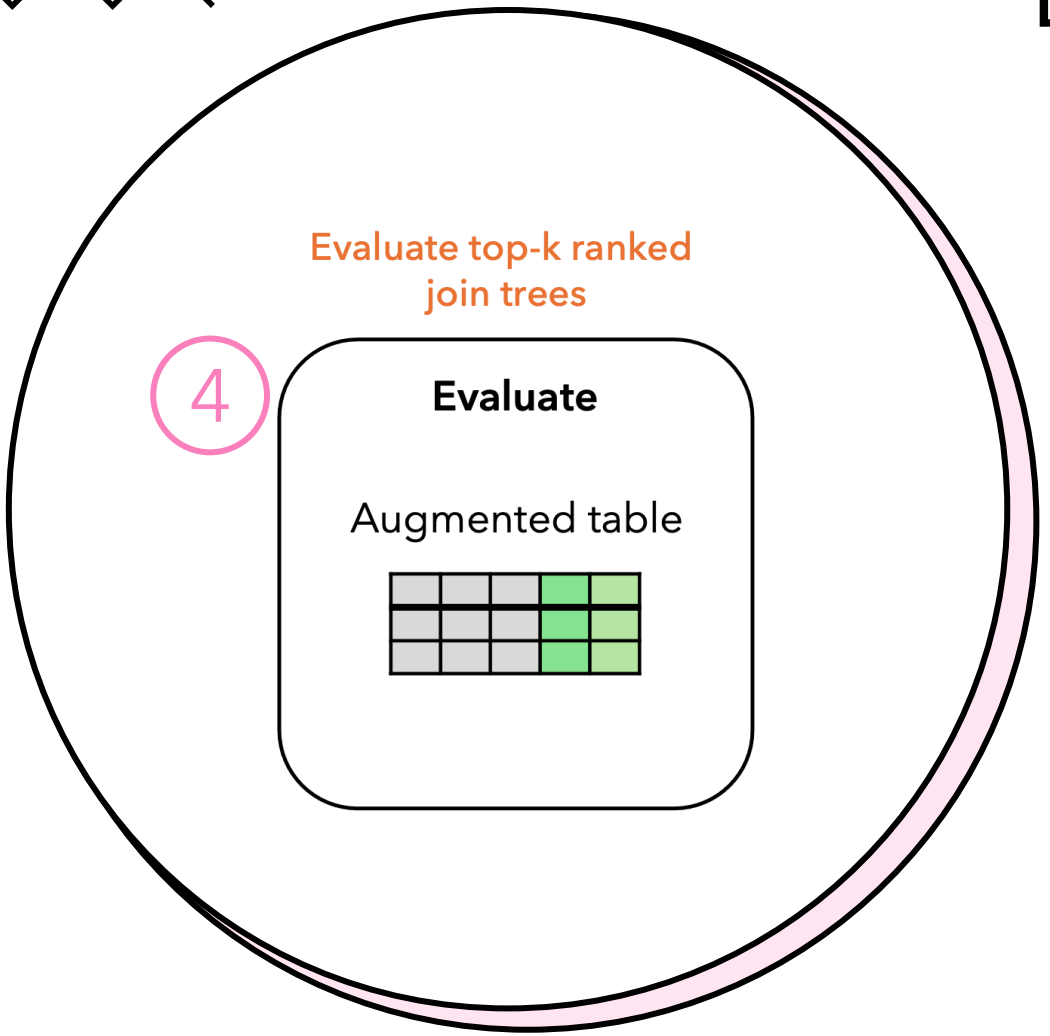
Relevance

- 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

Evaluate Join Trees



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

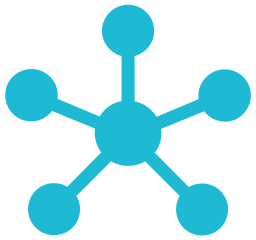
- Efficiency
- Effectiveness

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

Scenarios



Known Relations

Known PK-FK connections

Star/Snowflake schema

Reproduce the results from baselines

Discovered Relations

Unknown PK-FK connections

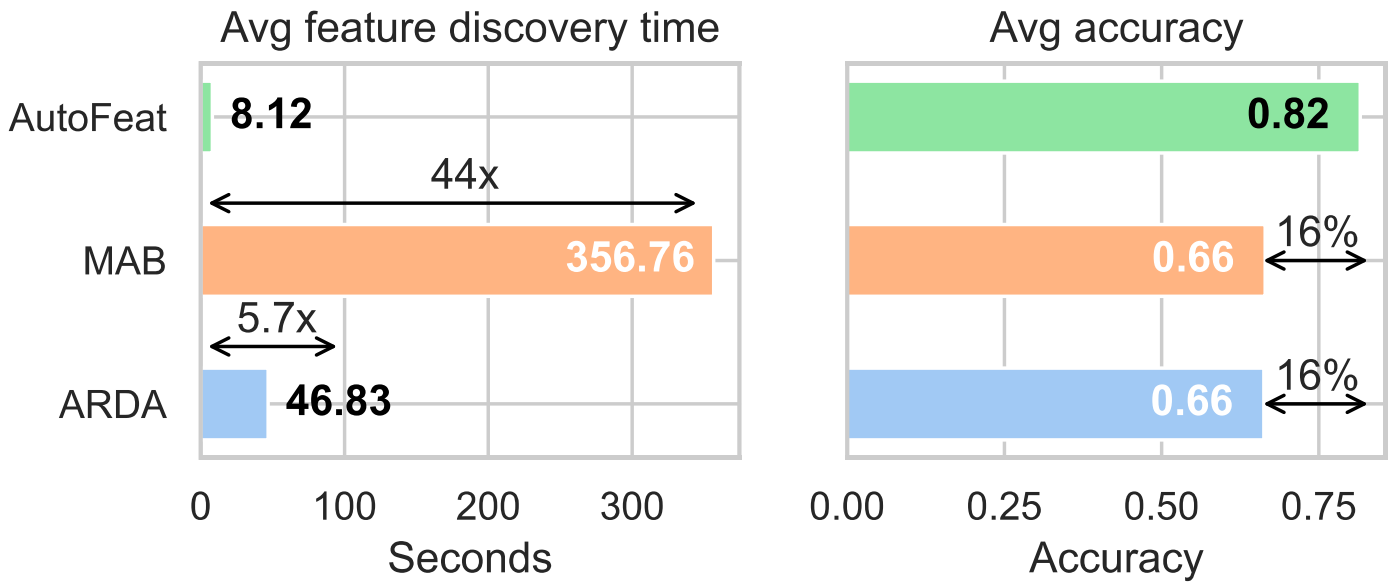
Dense multi-graph

Show the predictive power of AutoFeat

RESULTS

ON AVERAGE

16% AVERAGE INCREASE IN ACCURACY ACROSS ALL DATASETS AND MODELS



KNOWN RELATIONS

	# joins	Accuracy	Runtime
	Less joins	Higher	Lower
	More joins	Higher	Lower

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

DISCOVERED RELATIONS

Path analysis

AutoFeat explores the join space in depth

Prunes out irrelevant tables

Effectiveness

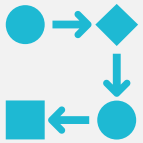
AutoFeat shows increased accuracy from the base table

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

AutoFeat relies on heuristics to prune out irrelevant tables and features.

Thank you!

Open for work

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TU Delft

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