🌰 Instance-Optimized String Fingerprints

Mihail Stoian*, Johannes Thürauf*, Andreas Zimmerer,
Alexander van Renen, Andreas Kipf

Data Systems Lab x Discrete Optimization Lab @UTN

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UTN Technische Universität Nürnberg

Data Pruning

	salary	location
min:	100K	Barcelona
max:	200K	Paris
min:	200K	Madrid
max:	300K	Redmond

Data Pruning

WHERE salary = 250K

	salary	location	
min:	100K	Barcelona	❌ (skip)
max:	200K	Paris	
min:	200K	Madrid	🔍 (maybe)
max:	300K	Redmond	

Data Pruning

❄️ WHERE location LIKE ‘B%’

		salary	location	
	min:	100K	Barcelona	✅ (match)
	max:	200K	Paris	
	min:	200K	Madrid	❌ (skip)
	max:	300K	Redmond	

Data Pruning

WHERE location LIKE '%ch%'

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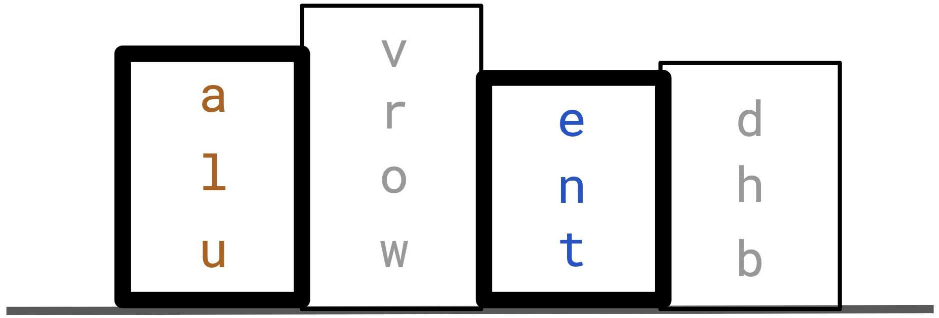

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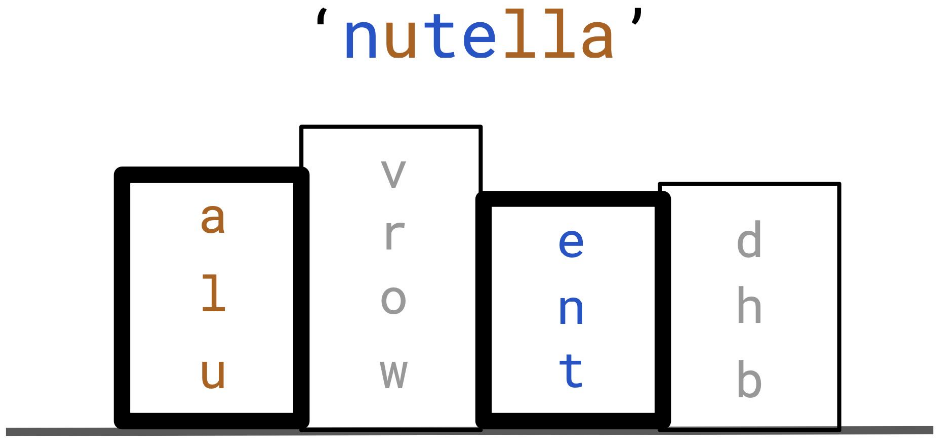

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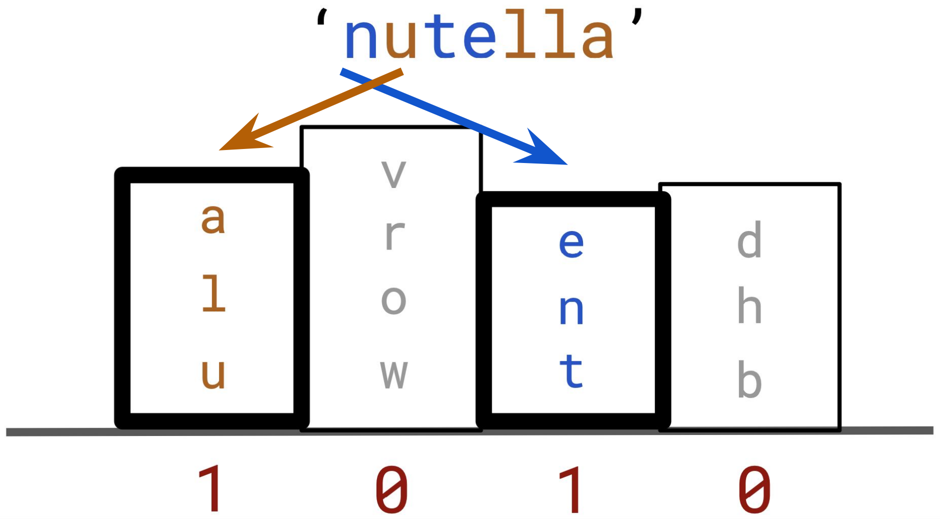

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- Intuition: Minimize the number of wasted LIKE evaluations.
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⇒ Objective: *Minimize the number of false positives.*

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- Words **W**: The string column.
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- Objective: $\max \Sigma_{q \in Q} \Sigma_{w \in W \setminus f(q)} \eta_{w,q}$.
- Constraints: Details in the paper.

Evaluation

- Setup: Column `title.title` in IMDb dataset (2.37M tuples; no UTF-8).
- *Workload*:
  - 300 queries ⇒ 10 high-, mid-, low-frequency {1, …, 10}-grams from the column.
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- Baseline: Round-robin placement of letters into bins.

Evaluation: False Positive Rate

MIP Optimization

Queries • Data: ○ seen • 1st block sample □ seen • 1st block ✚ seen • table △ *unseen* • 1st block ✖ *unseen* • table

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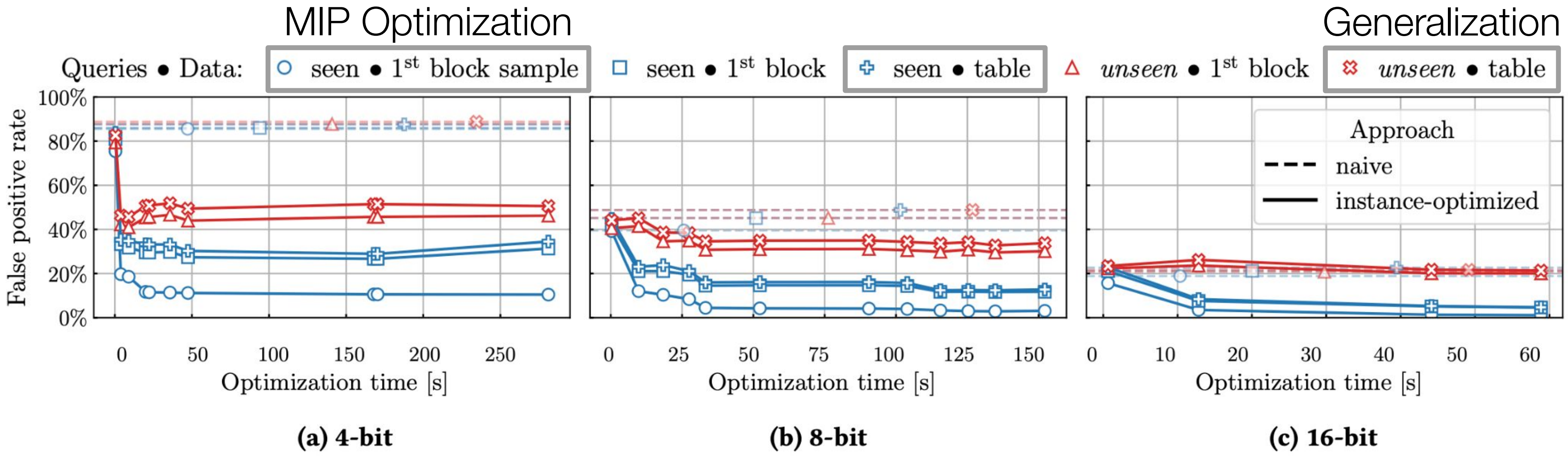


(a) 4-bit

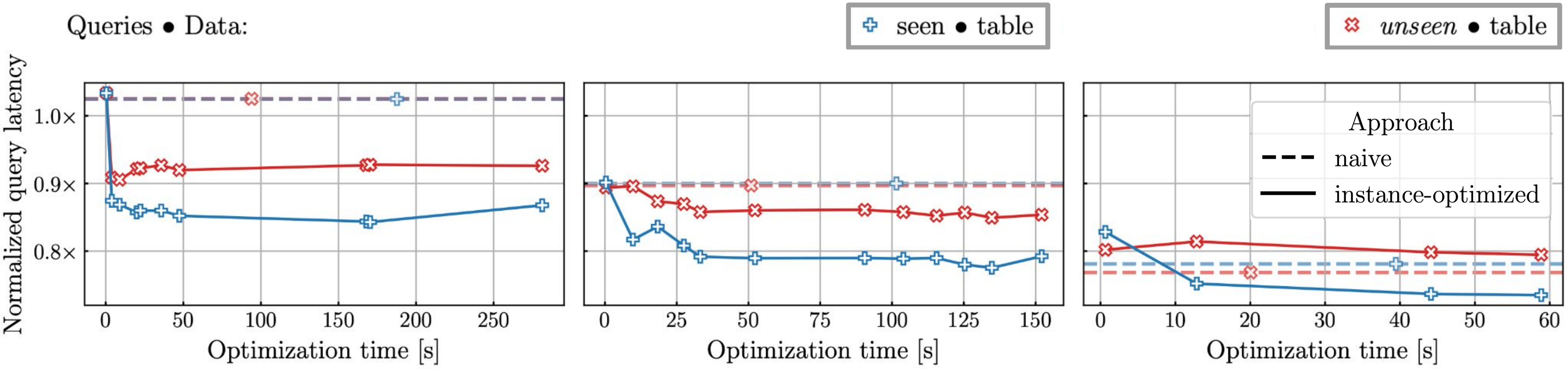
(b) 8-bit

(c) 16-bit

Evaluation: Normalized Query Latency

- Note: Run on the *full* table.

Generalization



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Evaluation: Takeaways

- <20% false positive rate on the full table.
- 🪄 Generalization to *unseen* queries (unlike predicate caching).
- 🚀 Up to 1.36x speedup for seen queries & 1.26x speedup for unseen queries.

(Many) Future Work Directions

- Instead of 1-grams, i.e., letters ⇒ Why not 2-/3-grams?
  - Intuition: We can capture the *order* of the letters.
- String zonemaps:
  - String fingerprints enable pruning for infix predicates 😲.
- String cardinality estimation.
  - Take the supersets and sum up their corresponding cardinality.
- Table clustering:
  - Sort by the fingerprint.

Wanna More Cool Research?

See you **tmrw** in *Research 8* (**Westminster 4F**), 1.45pm - 3.15pm!

“Parachute: Single-Pass Bi-Directional Information Passing”

🚀 **1.54x** speedup over `duckdb`