The Unreasonable Effectiveness of LLMs for Query Optimization

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Database Group at The University of Pennsylvania

ML for Systems Workshop at NeurIPS 2024

Background: What is a query optimizer?

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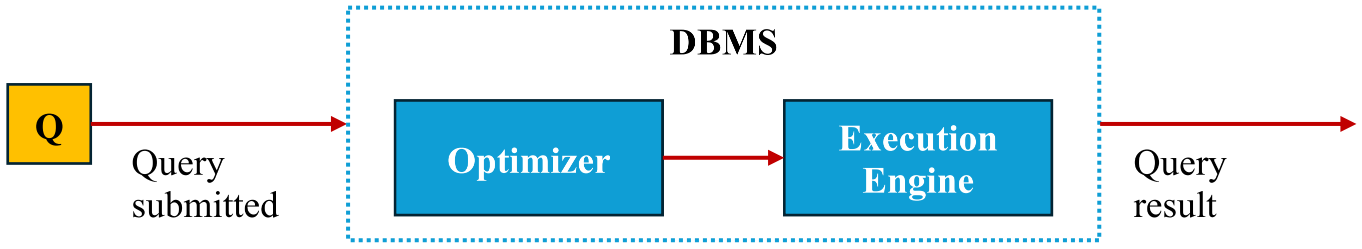

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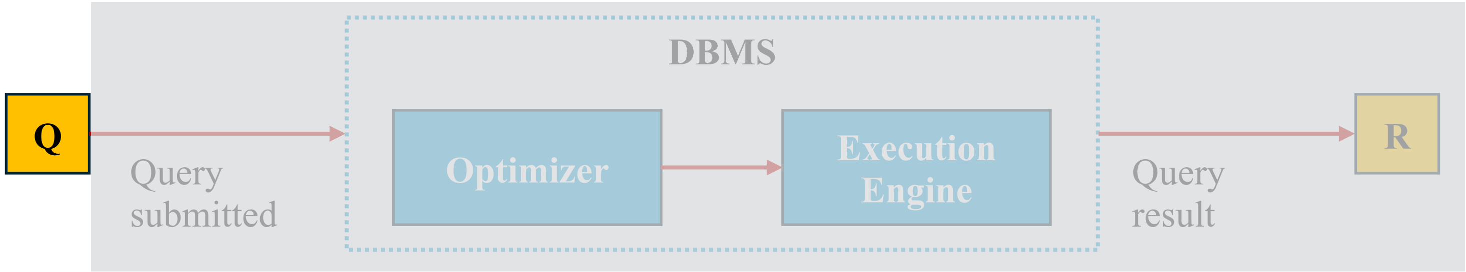


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SELECT t.title AS movie,
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FROM company_name AS cn,
     movie_companies AS mc,
     title AS t
WHERE t.production_year > 2005
      AND t.id = mc.movie_id
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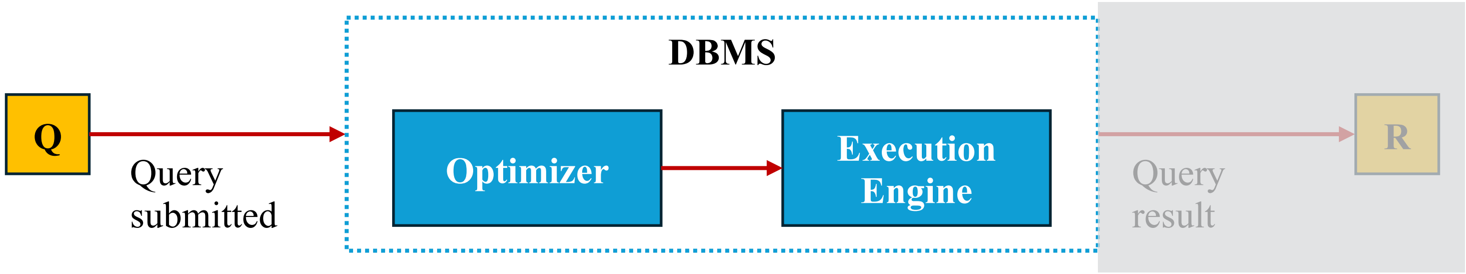


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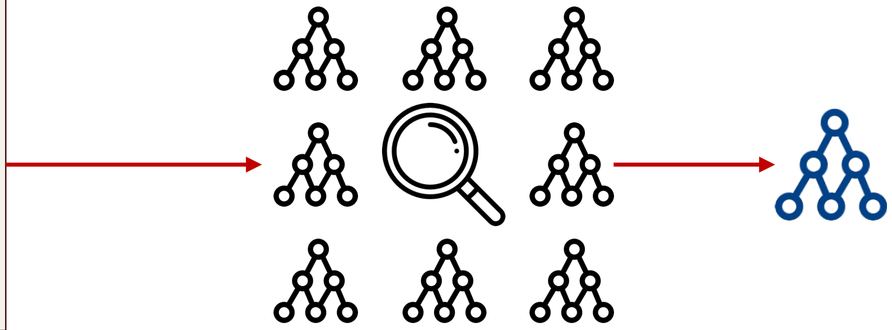

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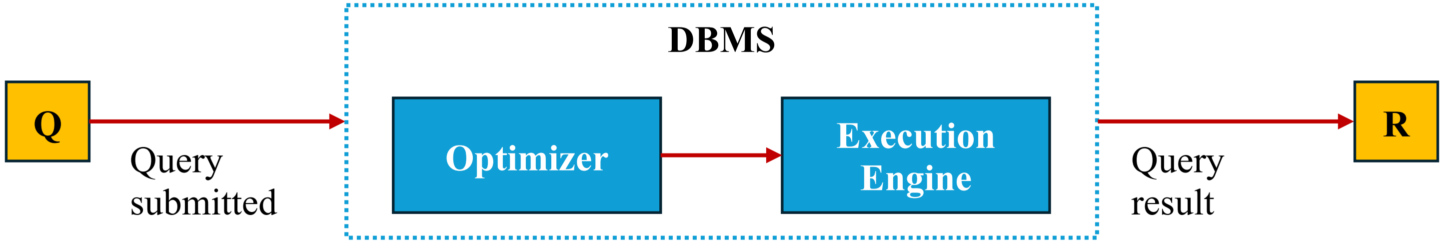


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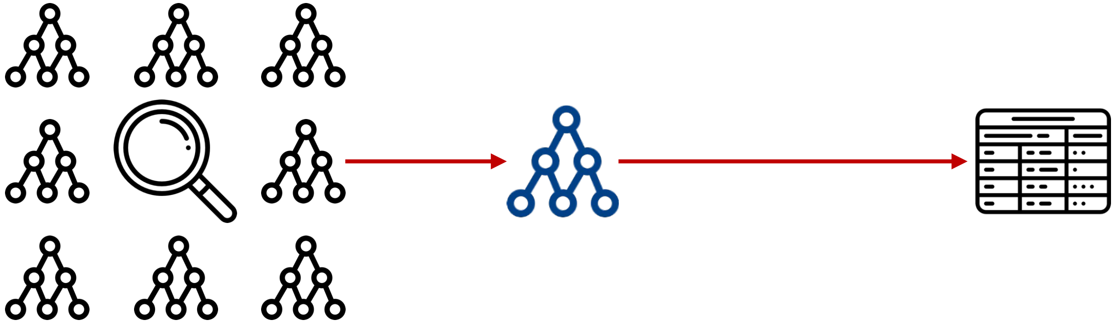

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There are many ways we can execute a query – "Find all flights by Air Canada that originate in Vancouver, CA with a destination of Tokyo, JP"

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2	YVR	HND	1
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AIRPORT

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HND	Tok	JAP
…	…	…

PLANE

p_id	airline	model
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ar_id	name
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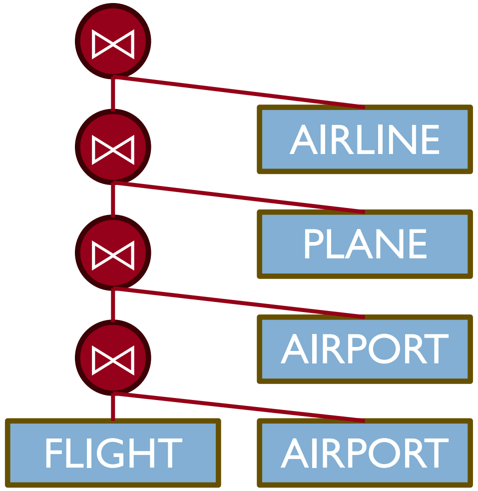

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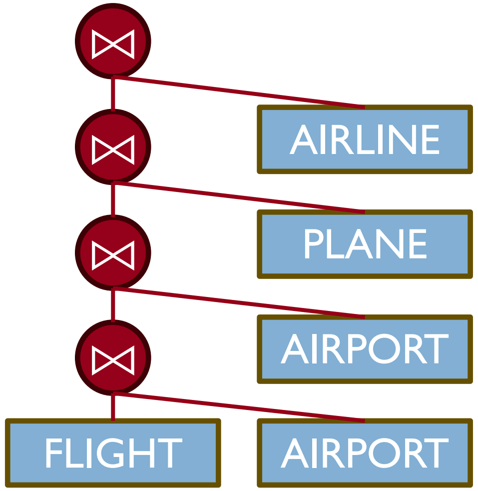

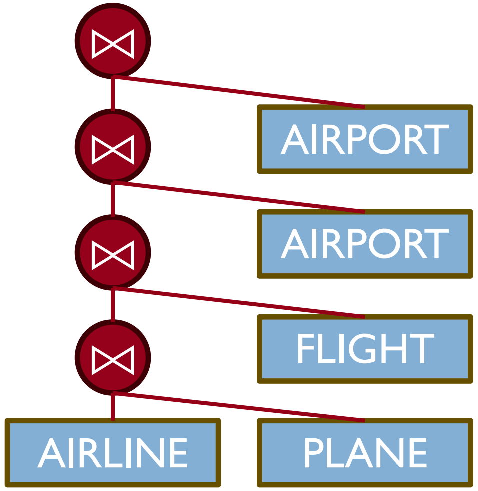

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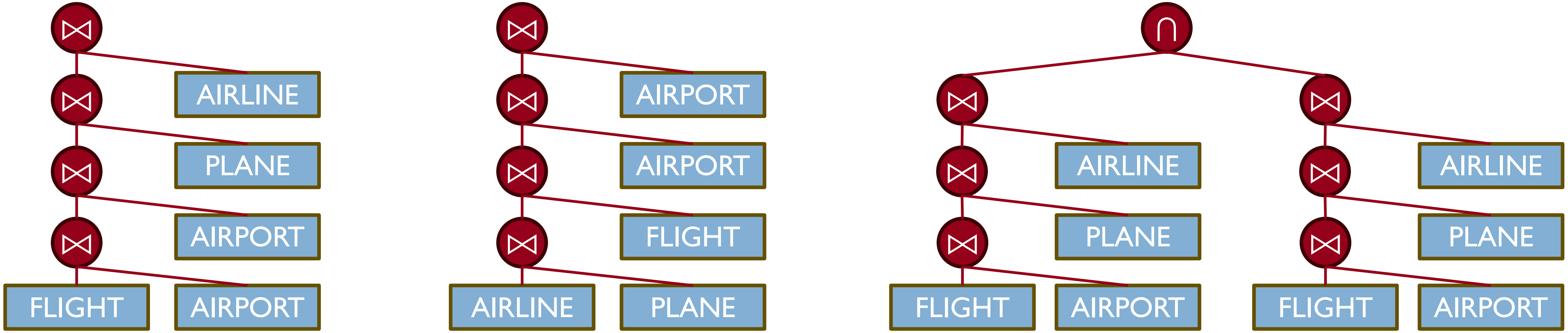

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Additionally, the query optimizer must still choose the physical operators for each join, that is, *how* to perform each join – hash join, nested for loop, sort then merge

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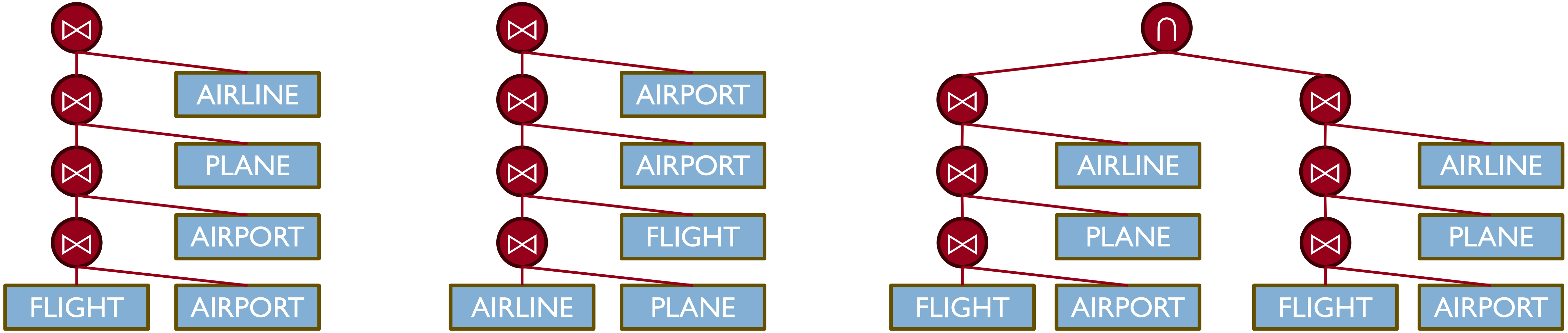

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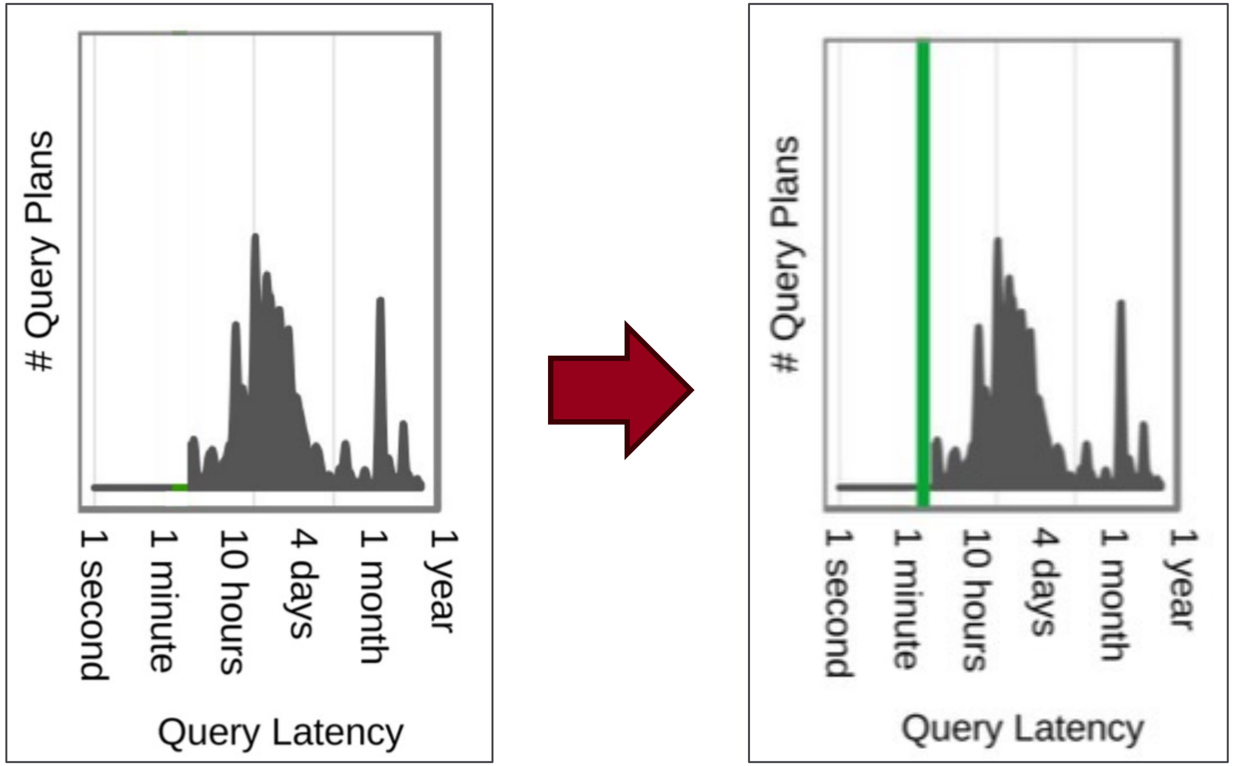

- The number of possible query plans follows Catalan numbers
- At $n = 19$ there are more than 2^{32} query plans
    - Traditional QOs use complex heuristics to eliminate very bad plans
    - But often select suboptimal plans, leaving performance on the table

Note: Figures from *Machine Learning for Query Optimization* by Ryan Marcus (https://rm.cab/brown22)

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- Hints are optional clauses that can be inserted into a query to guide the optimizer into generating plans with specific characteristics

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- SQL hints provide a coarse-grained way to influence a query's execution plan, often chosen based on *a priori* knowledge of the data

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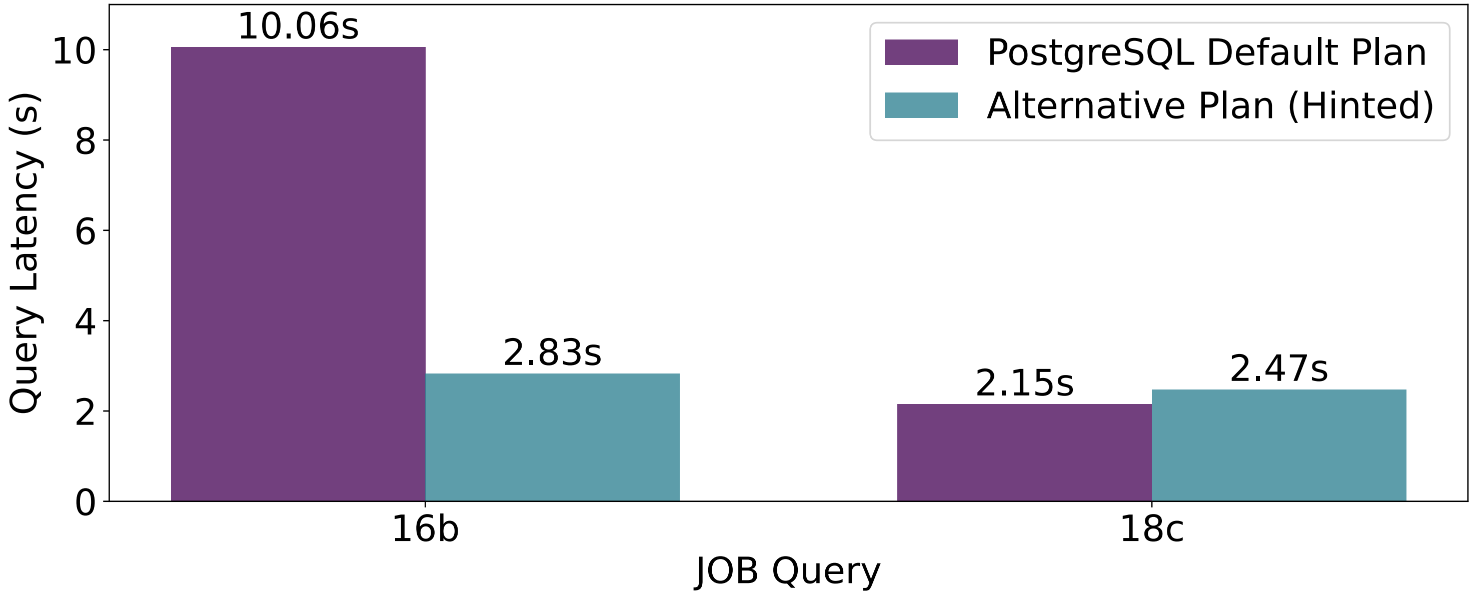

- Selecting hints can be extremely complicated for users, and providing the optimizer with incorrect hints can severely degrade query latency
- Different hints improve performance of some queries and degrade performance of others – this difference is often asymmetric

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FROM flight AS fl,
        plane AS pl, airline AS al
        airport AS ap_1, airport AS ap_2,
WHERE al.name = "Air Canada"
        AND ap_1.city = "Vancouver"
        AND ap_1.cntry = "CAN"
        AND ap_2.city = "Tokyo"
        AND ap_2.cntry = "JAP"
        AND pl.airline = al.ar_id
        AND fl.orig = ap_1.ap_id
        AND fl.dest = ap_2.ap_id
        AND fl.plane = pl.p_id;
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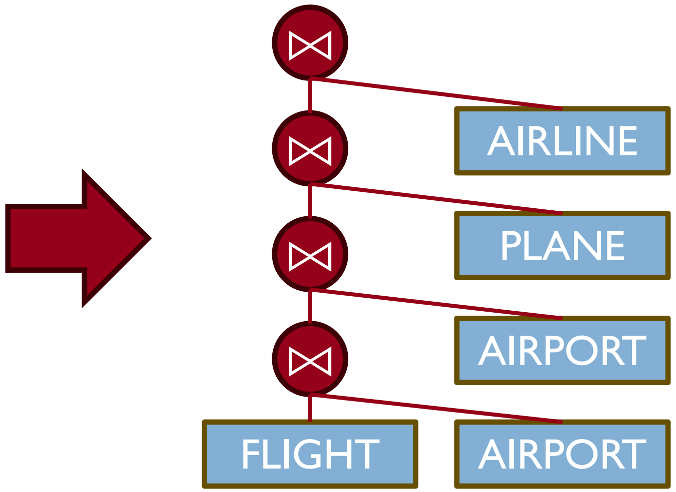

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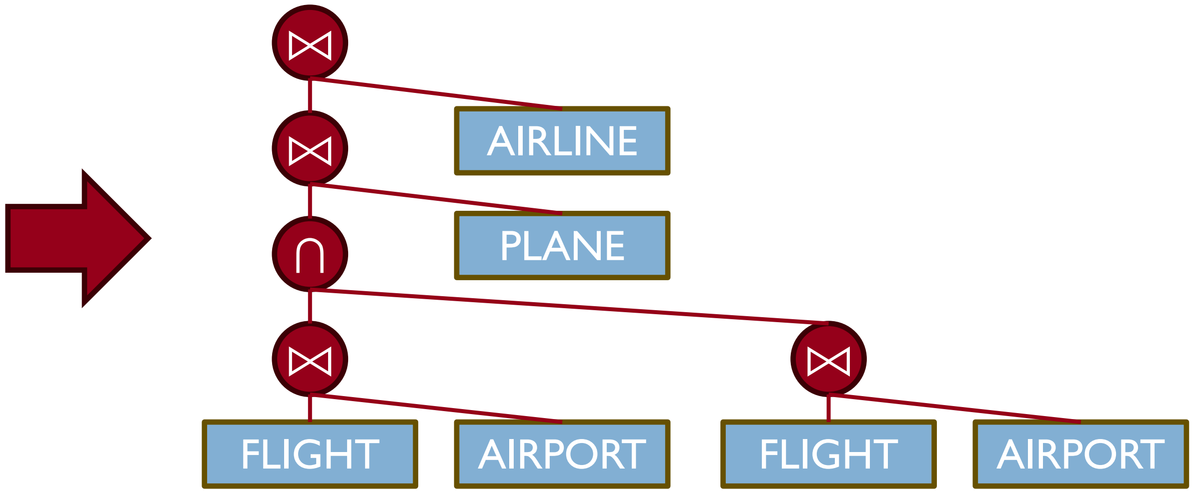

Motivation: Simplify query optimization through steering

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- Modern methods use supervised learning[1], RL[2], or hybrid approaches[3], but perform sophisticated feature engineering on internal database statistics

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Simplify feature engineering and learn to steer the query optimizer using hints!

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1. ~3000 SQL queries from the join order[1] and cardinality estimation[2] benchmarks
2. Gathered 48 well-known PostgreSQL hints used in prior work[3-4]
3. Executed queries 5 times per hint – mean latency was used for analysis
4. The hint with the best performance gains relative to the default PostgreSQL plan was selected *a priori* as the Alternative plan

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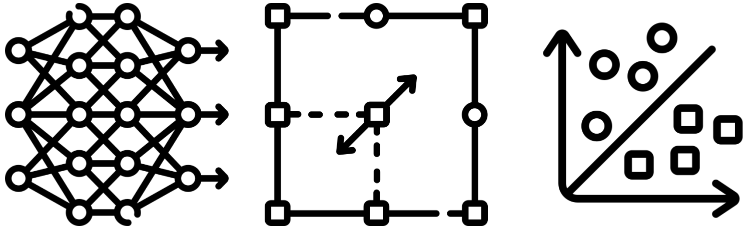

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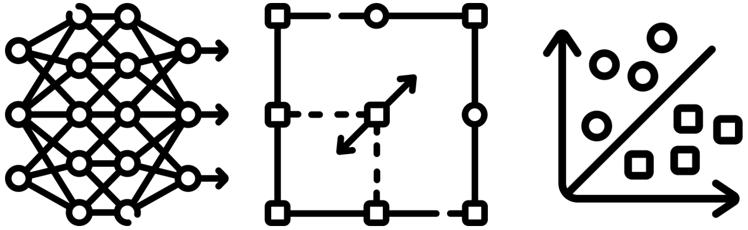

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LLMSteer: A simpler approach to query optimization using large language models

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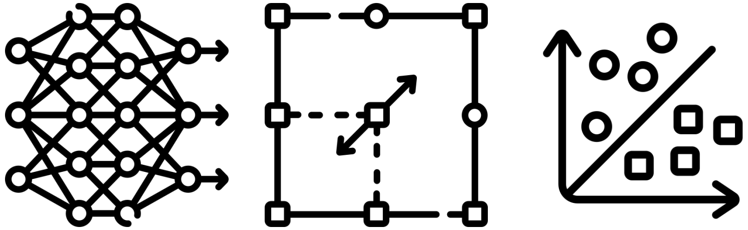

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LLMSteer

Evaluation

1. Stratified cross-validation
2. Query Optimization Metrics:
   I. Cumulative execution time of queries (*total latency*)
   II. 90th percentile latency of queries (*P90 latency*)
3. Classification Metrics:
   I. Recall
   II. AUROC
   III. Accuracy

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LLMSteer: A simpler approach to query optimization using large language models

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1 LLM embedding

$$[-0.04813609, -0.43741802, \ldots, -0.28336727, 0.98100264]$$

d-dimensional query embedding

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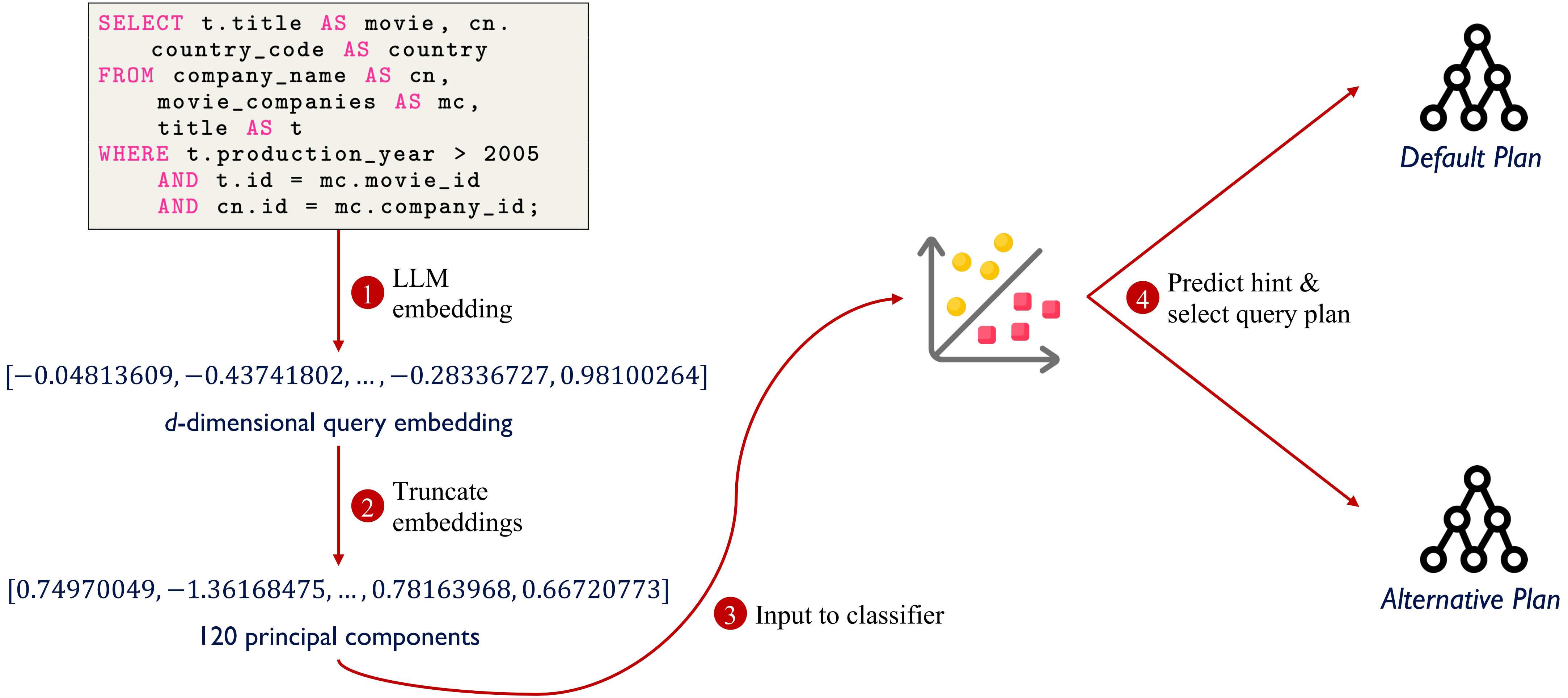
LLMSteer: A simpler approach to query optimization using large language models



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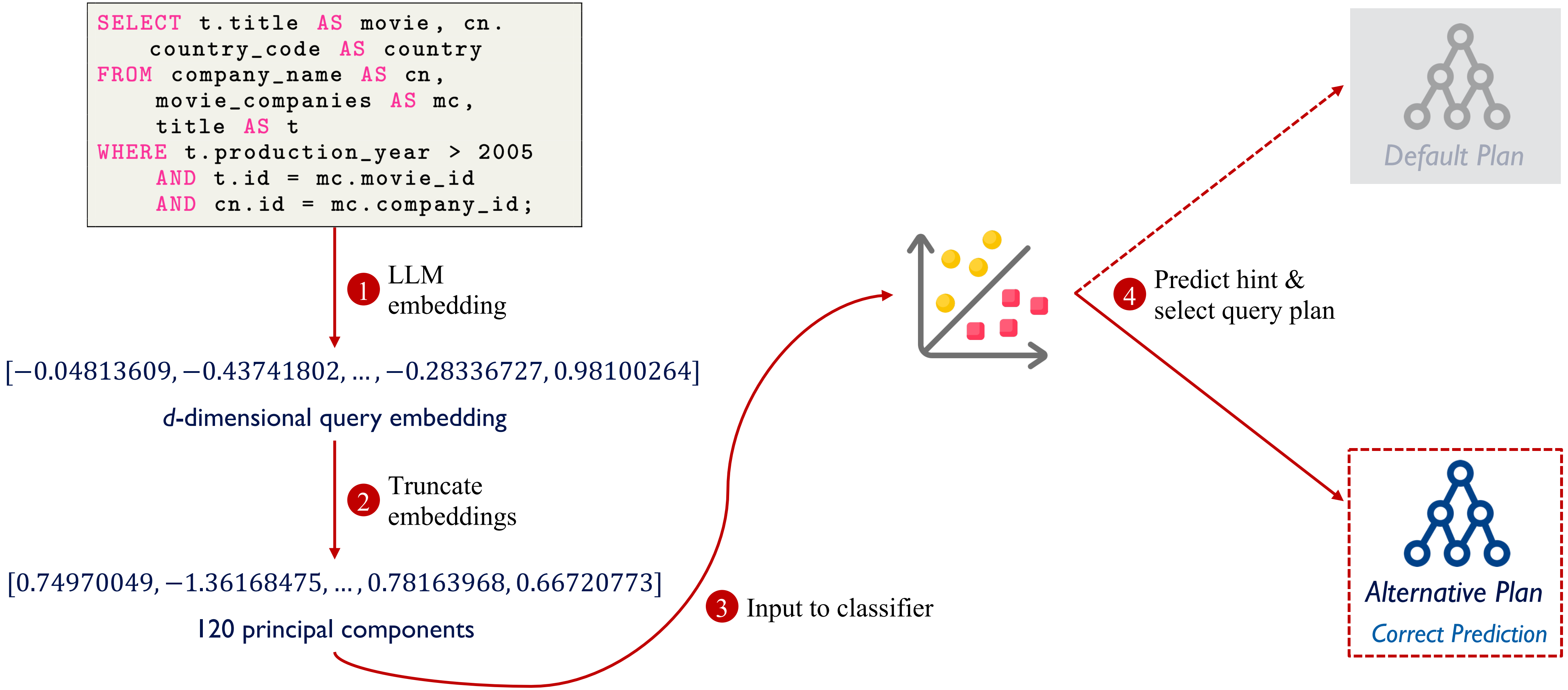

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Experiment 1: Comparative performance of LLMSteer

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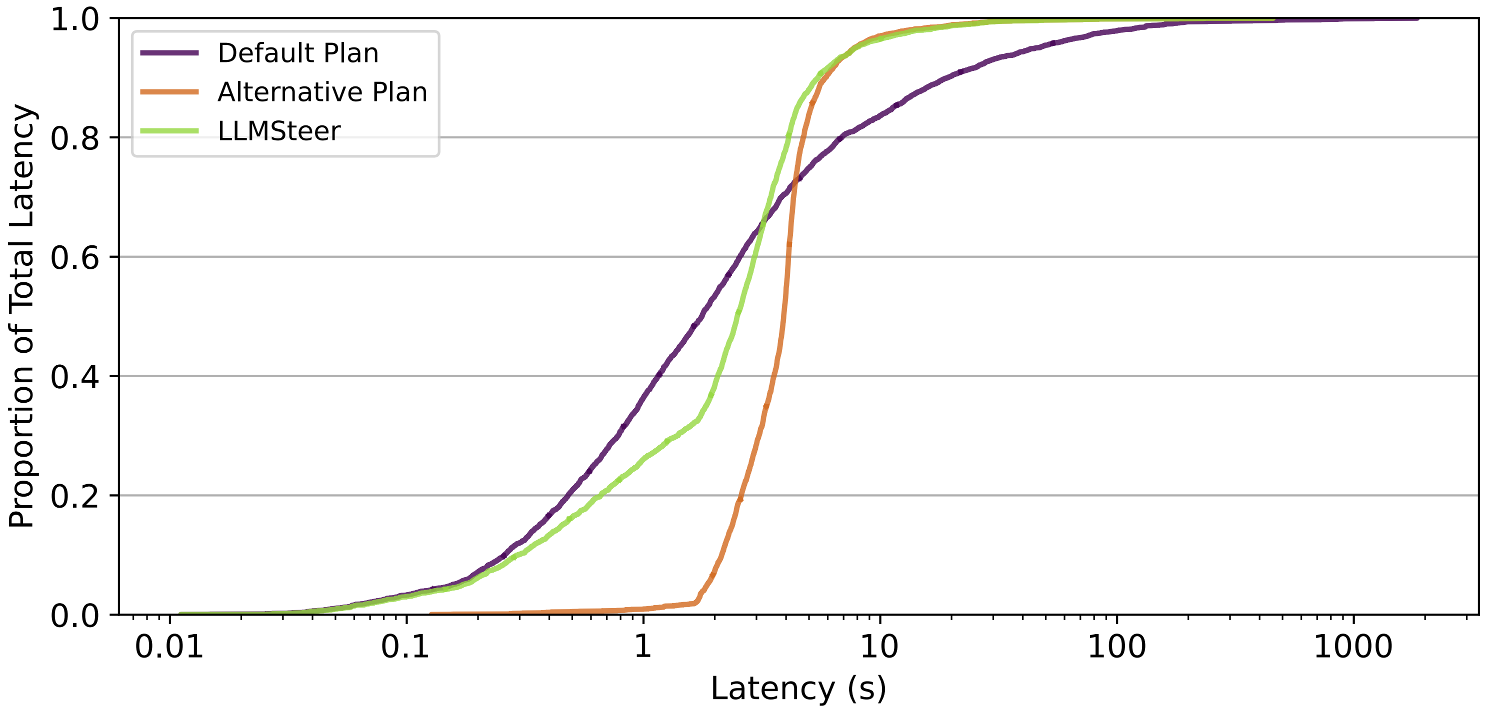

Empirical CDF of latency across cross-validation testing workloads

- Purple indicates selecting the default plan for all queries
- Orange indicates selecting the alternative plan for all queries

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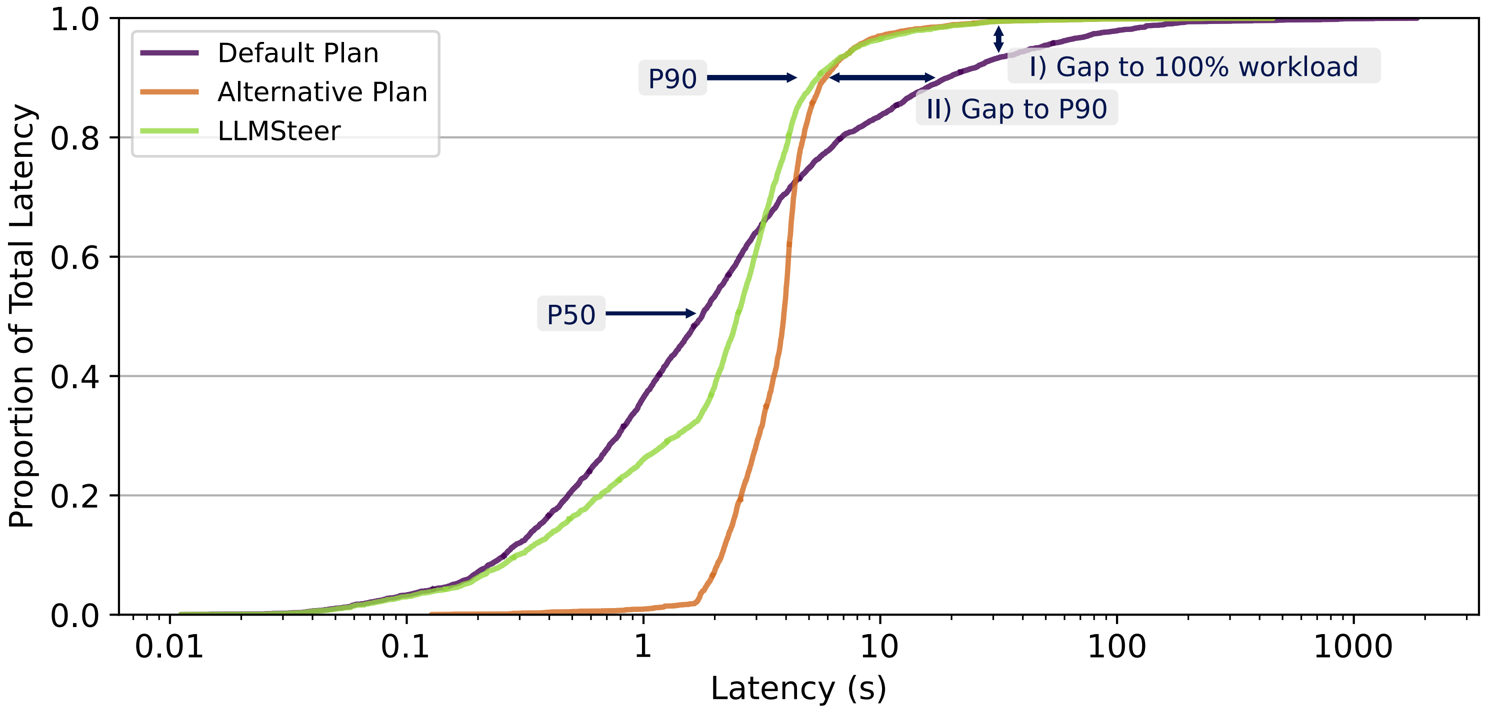

- LLMSteer outperforms both the default and alternative plans at the higher end of the distribution, achieving a lower P90 (II) and saturating just as fast the Alternative plan (I)

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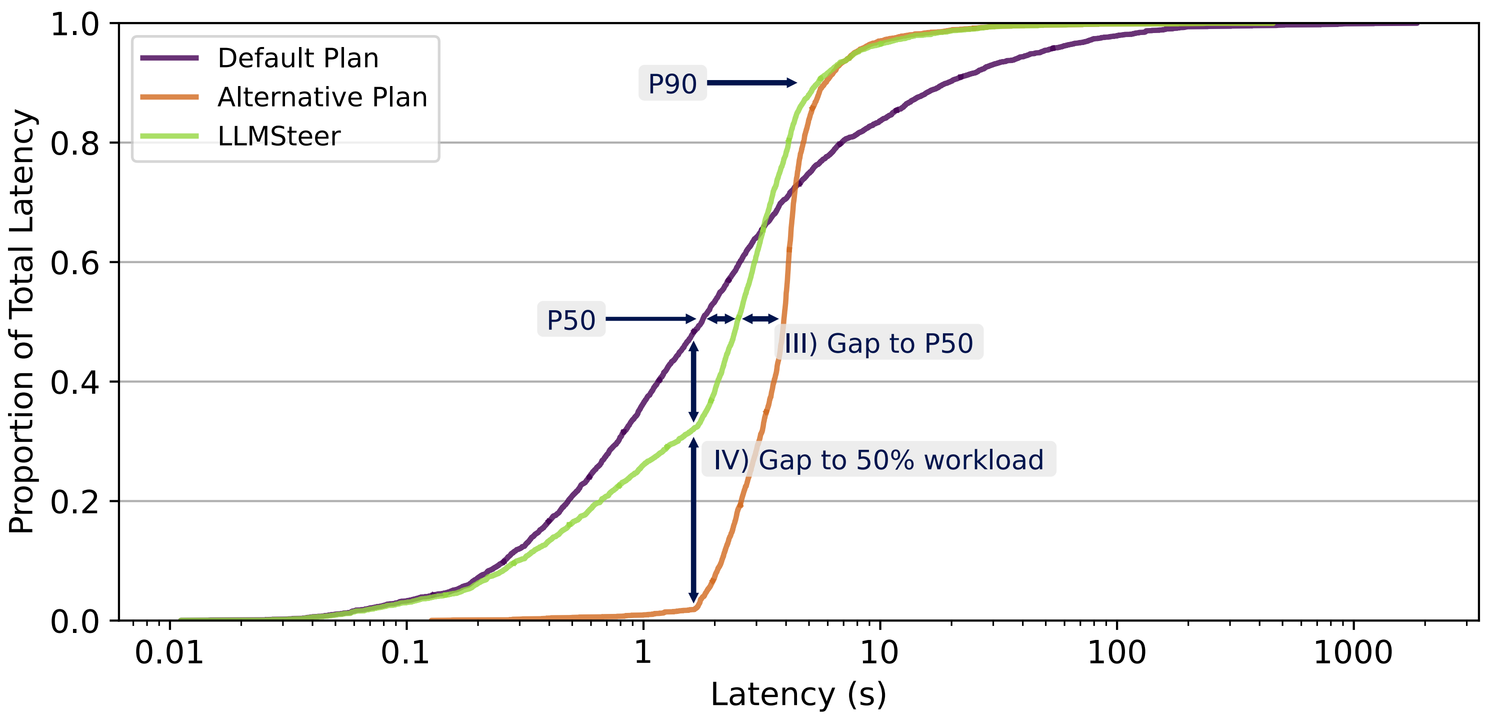

- LLMSteer improves on the alternative plan, lowering the performance gap to the default plan, capturing more of the total latency earlier and improving the median latency

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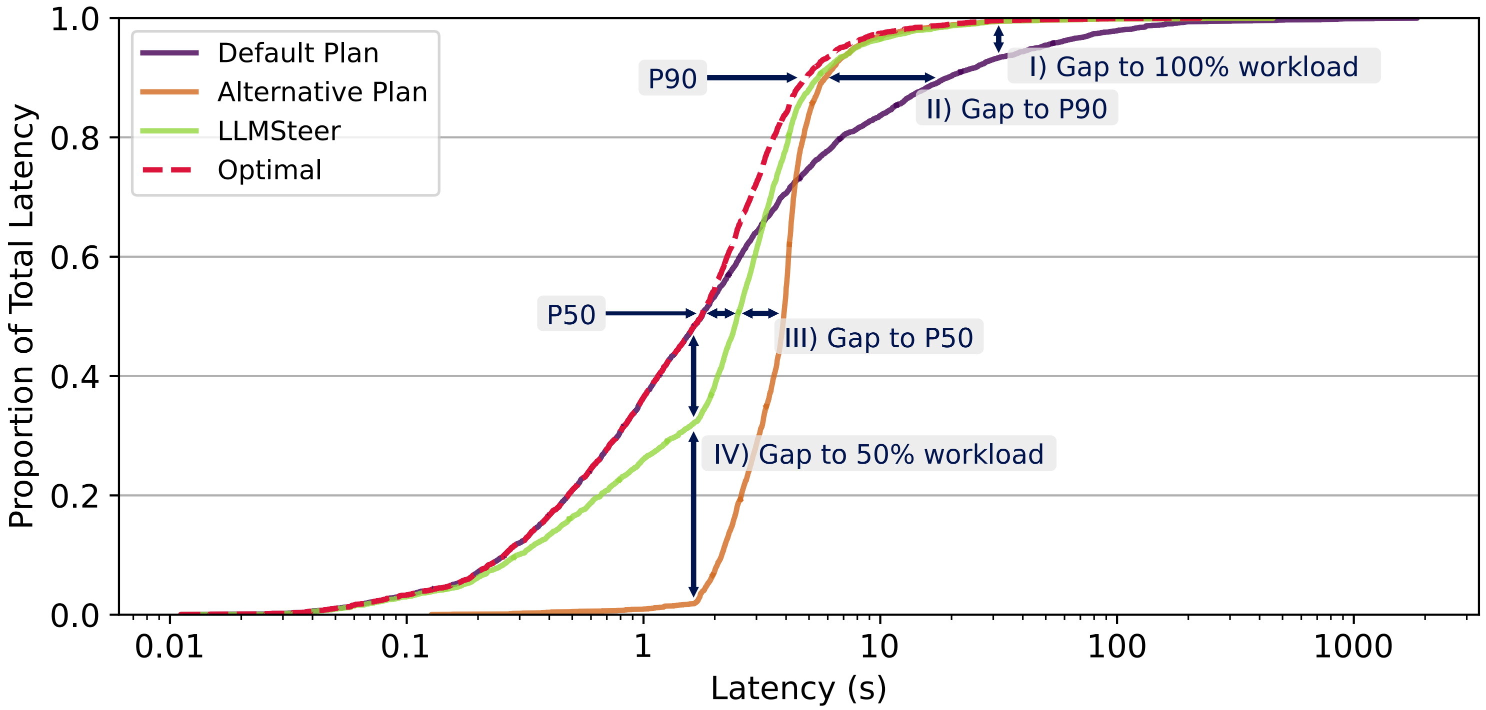

- LLMSteer falls short of the optimal steering strategy, but effectively combines the benefits of the default PostgreSQL plan and the alternative

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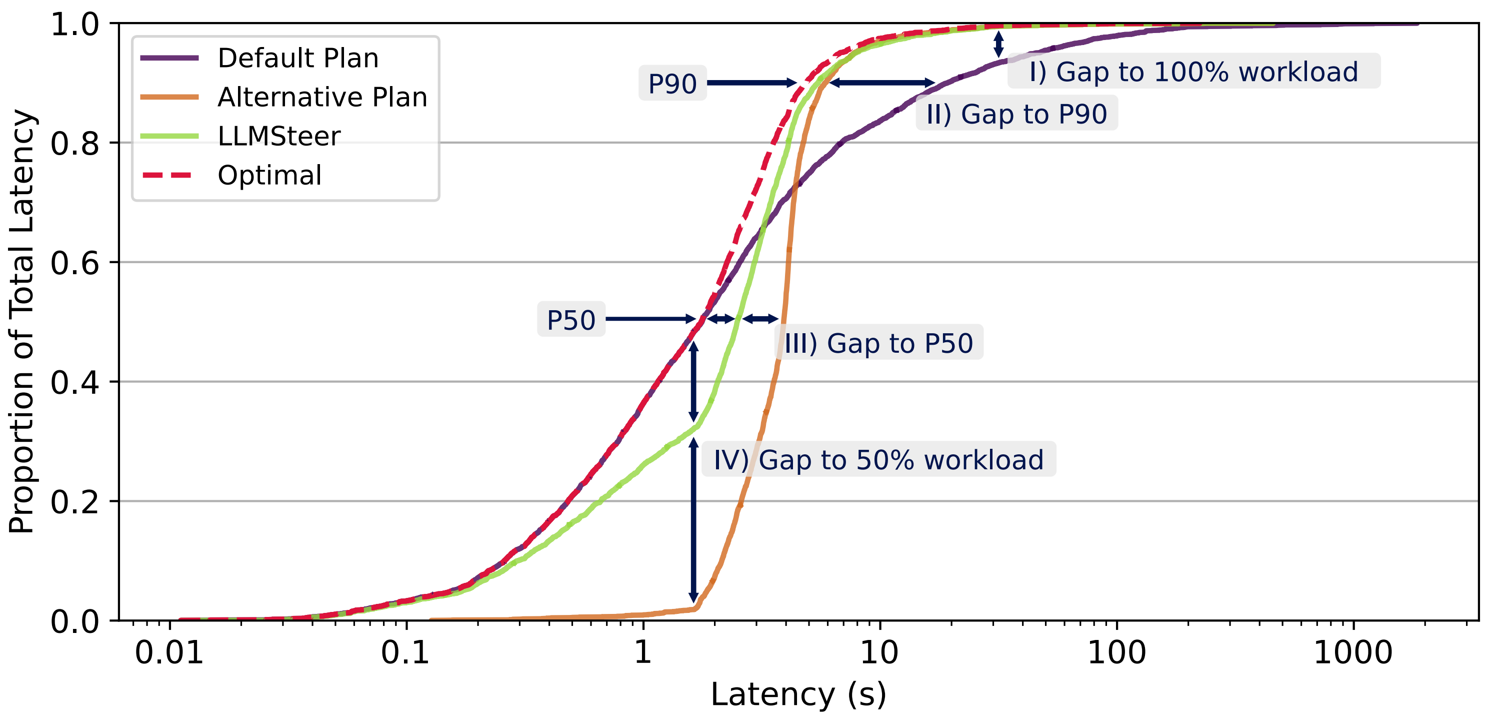

- The system can be seen as trading a small increase in median latency for a large reduction in P90 and total latency, a trade-off that is worthwhile in most practical applications

Cautious Optimism and Next Steps

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- Internet-scale language models
  - Were LLMs trained on the JOB and CEB benchmark data?
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- Quantization may play an essential role in improving latency and developing LLM-powered QOs

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There are still far more open questions than answers!

Thank you! Questions?

Our group: https://db.cis.upenn.edu

Our code: https://github.com/peter-ai/LLMSteer

Reach me at: peterai@seas.upenn.edu

ArXiv **Code** **Me**

Appendix

Experiment II: Robustness to non-semantic syntactic changes in SQL query formatting

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Experiment 11: Robustness to non-semantic syntactic changes in SQL query formatting

The original SQL queries were single line statements – we evaluate LLMSteer on query formats that align more closely with how queries are written in production systems

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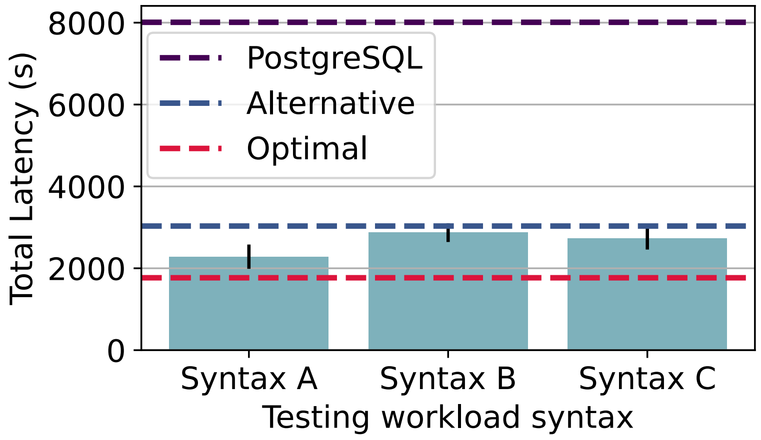

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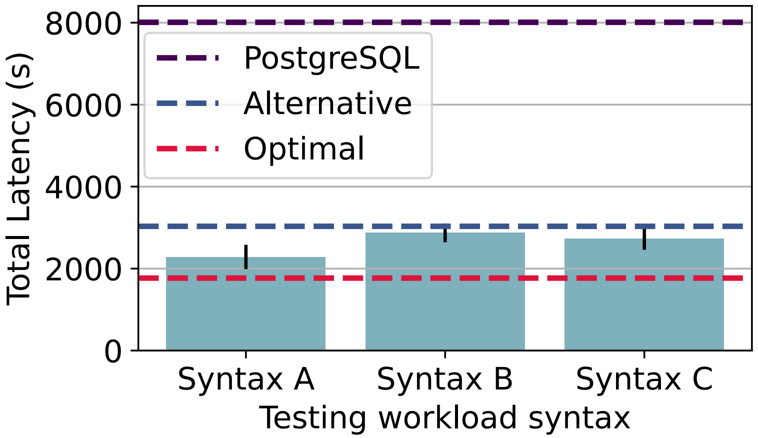

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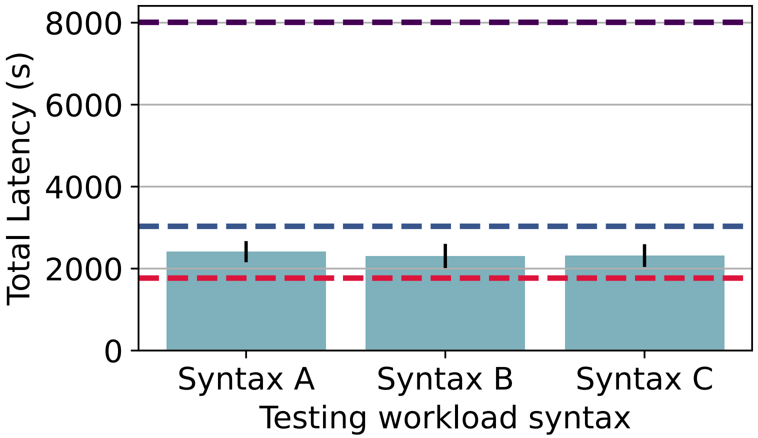
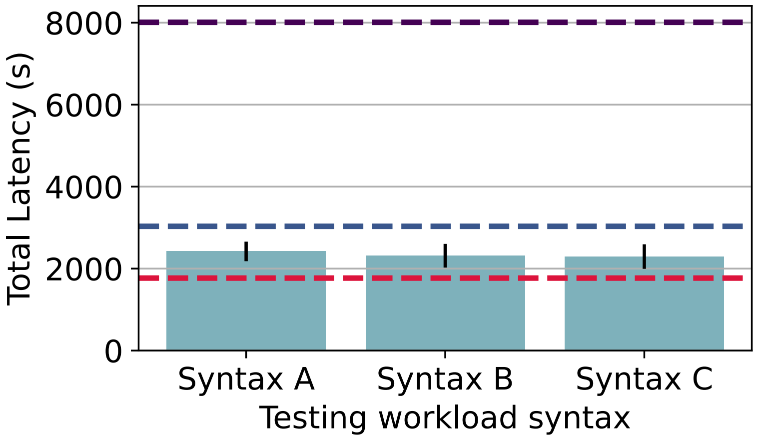


b) Trained on Syntax B



c) Trained on Syntax C