Low Rank Approximation for Learned Query Optimization

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Checkout the paper for more detailed info:
zixy17.github.io/pdf/aiDM.pdf

Simple, low-overhead **Linear Methods** can perform nearly as effective as complex **deep learning approach** for **Offline Learned QO**.

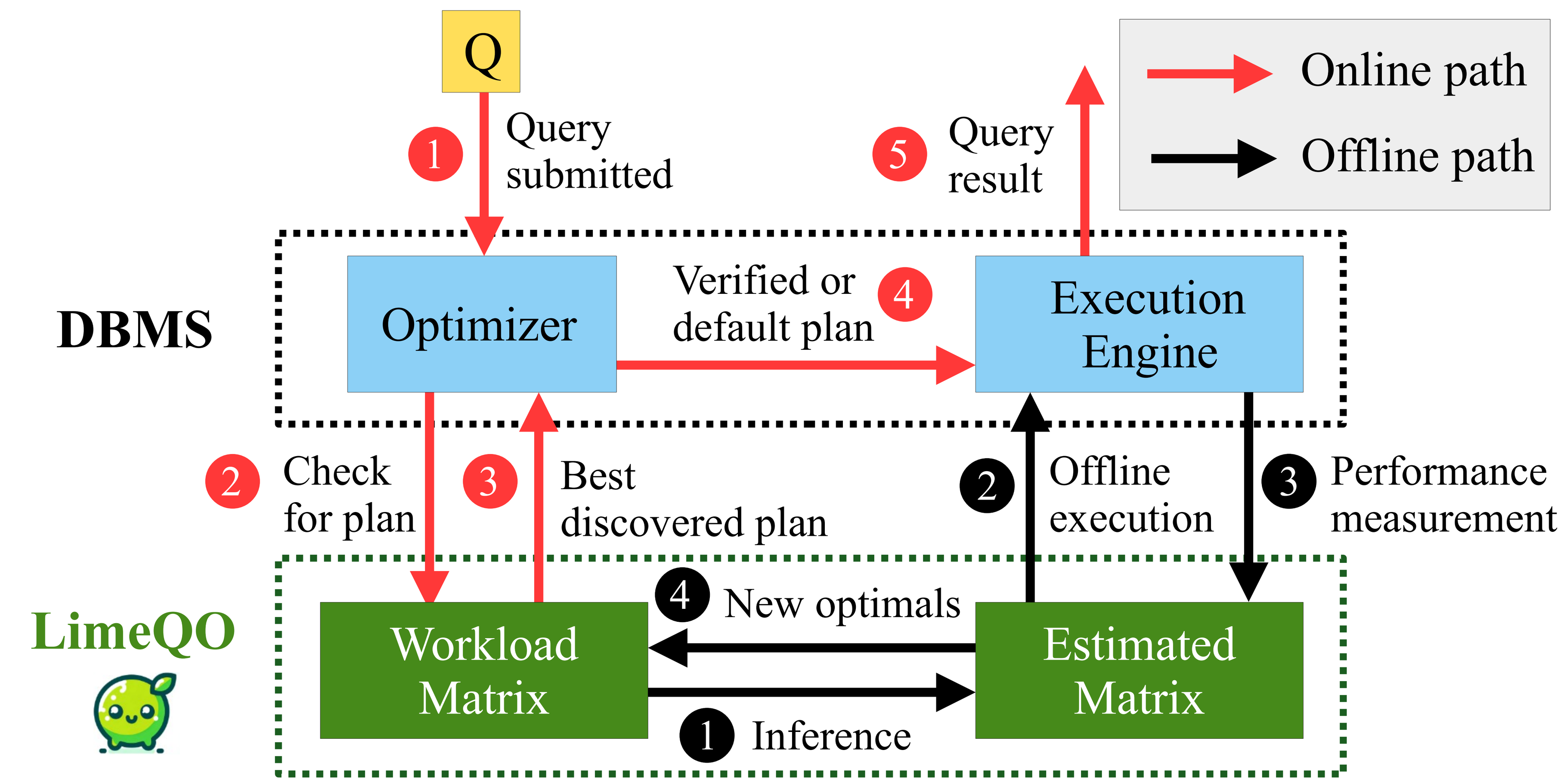
Offline Learned QO

Why? Current Learned QOs cause **unpredictable regressions**. ("my query was fast yesterday, why is it slow today?")

How? verify that potential new query plans are actually better than the default plan.

Setting: **Repetitive** workload!

Goal: simultaneously minimize the workload latency and the total offline exploration time, while maintaining the "no-regressions" guarantee.



Low Rank Workload Matrix

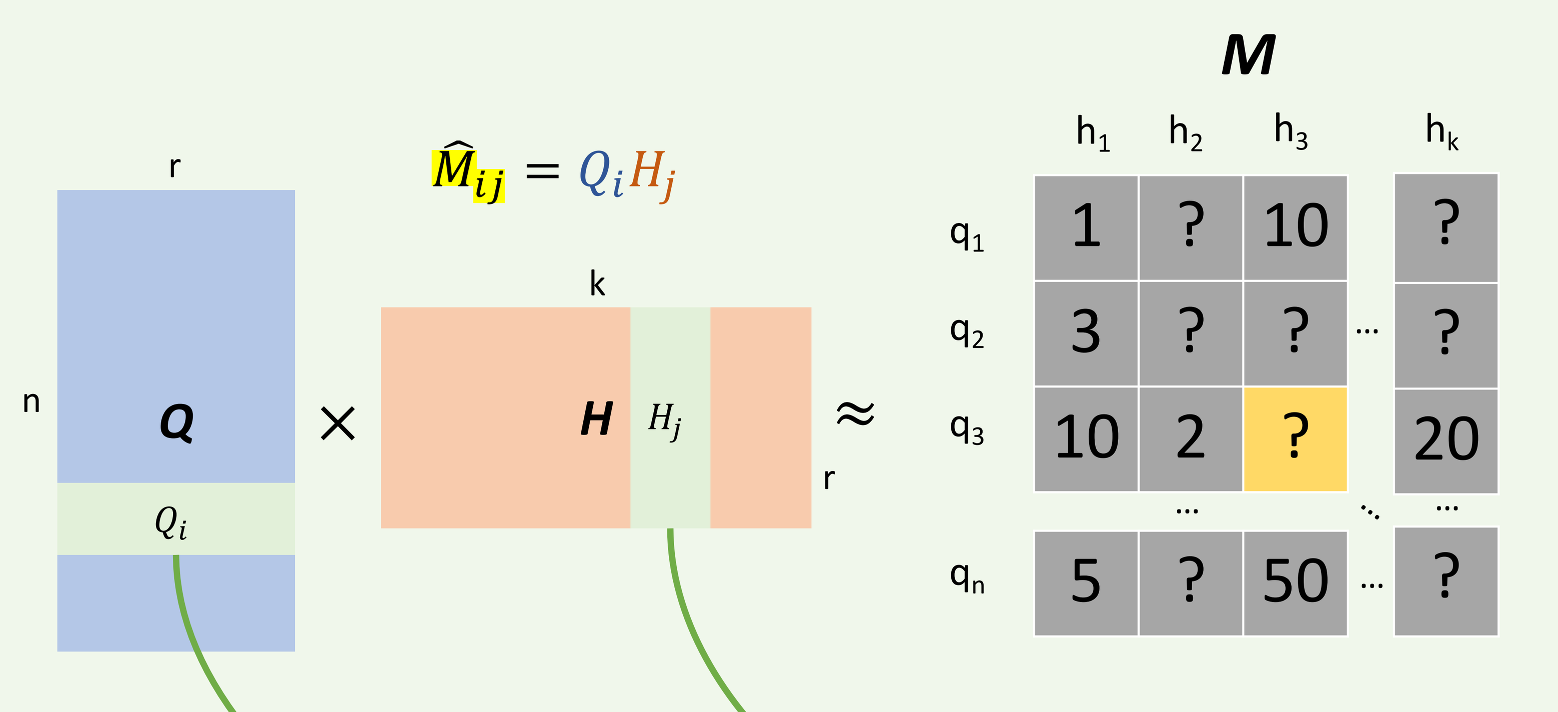
Workload Matrix *M*:
Each row represents a SQL query.
Each column represents a hint (parameterization of the QO).
One possible hint:
Disable Nested Loop Join
Enable Hash Join
Enable Merge Join
Enable Index Scan
Enable Seq Scan
Enable Index-only Scan

Each entry represents the latency time for DB to execute the query under the hint.

M is LOW RANK
Intuition: two queries that behave similarly on some hints are likely to behave similarly on other hints as well.

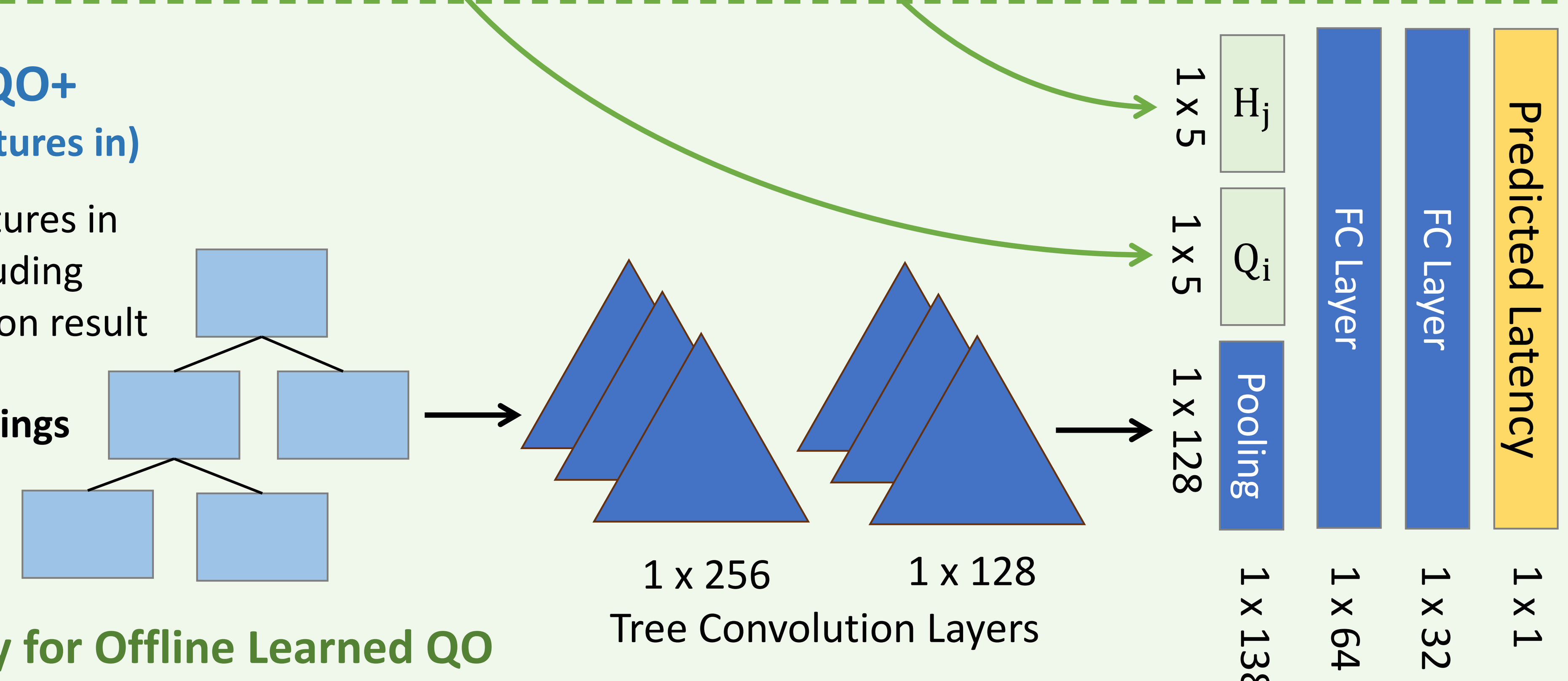
Option1: LimeQO
(Linear Method Only)

Use **Alternating Least Squares** Algorithm to recover the unobserved entries from the observed ones.



Option2: LimeQO+
(Adding Query Features in)

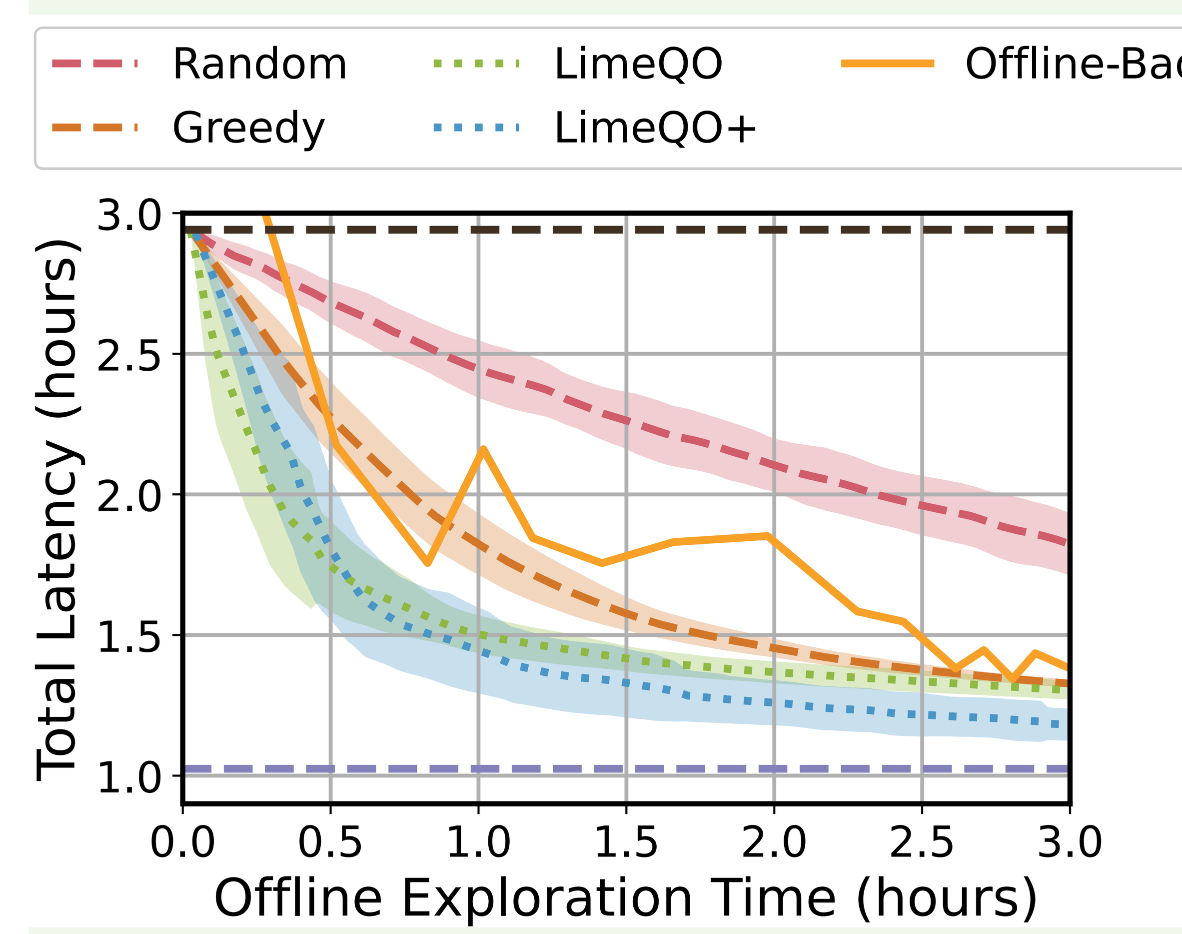
Use query plan features in tree structure (including cardinality estimation result and cost) and QH Matrix **embeddings** as input.



LimeQO strategy for Offline Learned QO
Generate the full matrix, then explore the queries with the **biggest potential gain ratio** (current min observed value – predicted row min) / predicted row min

Experiments

Dataset: CEB core workload
- 3133 queries in total
- takes ~3 hours for PostgreSQL default to finish
- ~1 hour if every query is chosen the optimal hint



Caption: Both LimeQO and LimeQO+ outperform Bao. Even without any features, pure linear method (LimeQO) can perform nearly as effective as the one using complex Neural Network (LimeQO+).

Random randomly explore unobserved entries.
Greedy explore the tail latency queries first.
LimeQO uses only Linear Method to predict.
LimeQO+ uses query features and matrix embeddings to train and predict.
Offline-Bao uses TCNN to select unobserved entries to explore. It does not verify plans before selecting them so regressions happens.

Total Latency Time is simply adding up the observed row minimum in the workload matrix.
Offline Exploration Time is the total time to execute the query plan + overhead time of the technique. We also applied timeout and censored techniques to reduce offline time.