





Research 29: Learned Database Systems

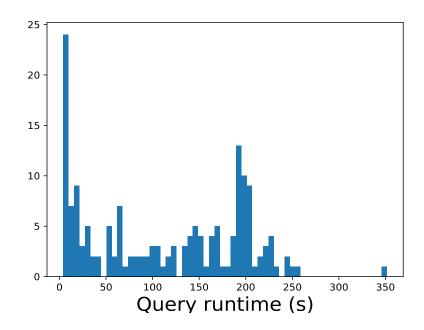
Improving DBMS Scheduling Decisions with Accurate Performance Prediction on Concurrent Queries

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Concurrency impacts latency heavily

- Deciding when to execute a query can be crucial
- Bad scheduling decisions can have a significant impact on query latency.
- Microexperiment:
 - 4 clients issuing closed-loop queries against IMDB dataset on Postgres.
 - Look at runtime of the same query under different concurrent settings.
- Scheduling can have a large impact.





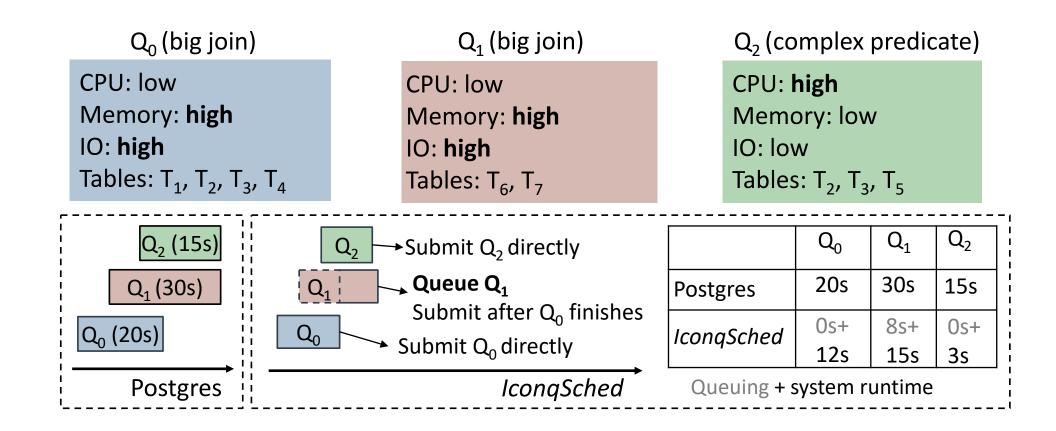
Can we build a reusable scheduler?

- We explore the design of a non-intrusive scheduler:
 - Coarser granularity (e.g. cannot schedule individual operators).
 - But can be applied to any underlying engine.

 Goal: improve query end-to-end time (queueing time + system runtime)



We need to capture resource contention





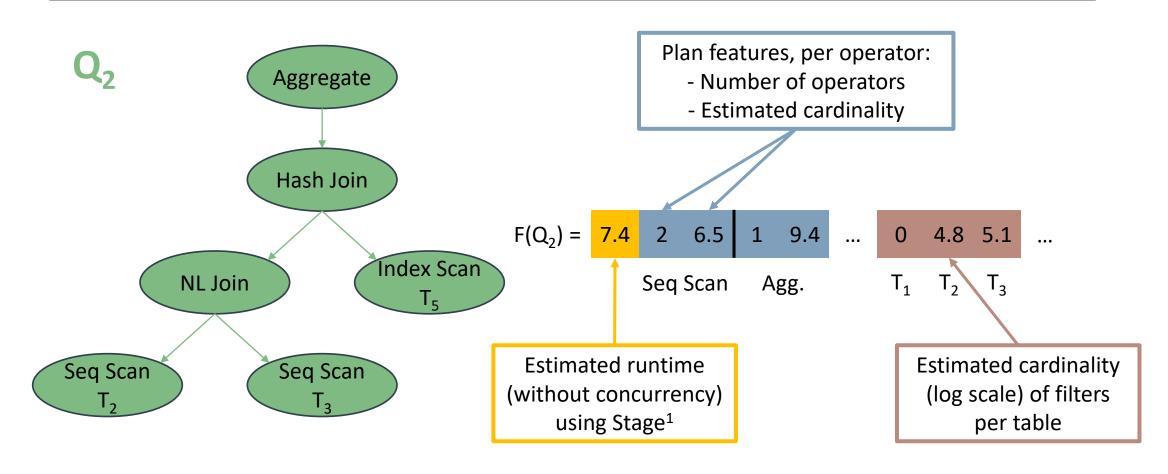
Key challenge: splitting past and future

- The latency of each query is affected by both:
 - Queries that were submitted before it and are still running.
 - Queries that are submitted while it is still executing.
- The latter are not available at scheduling time.
- How can we update estimates for running queries as new ones arrive?

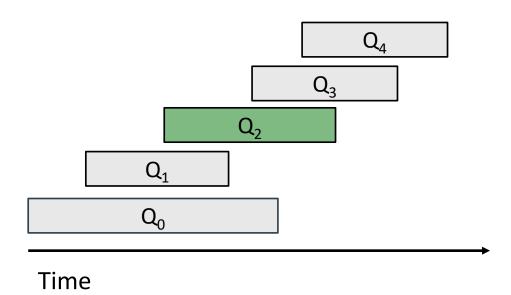
Solution preview: Bidirectional LSTM



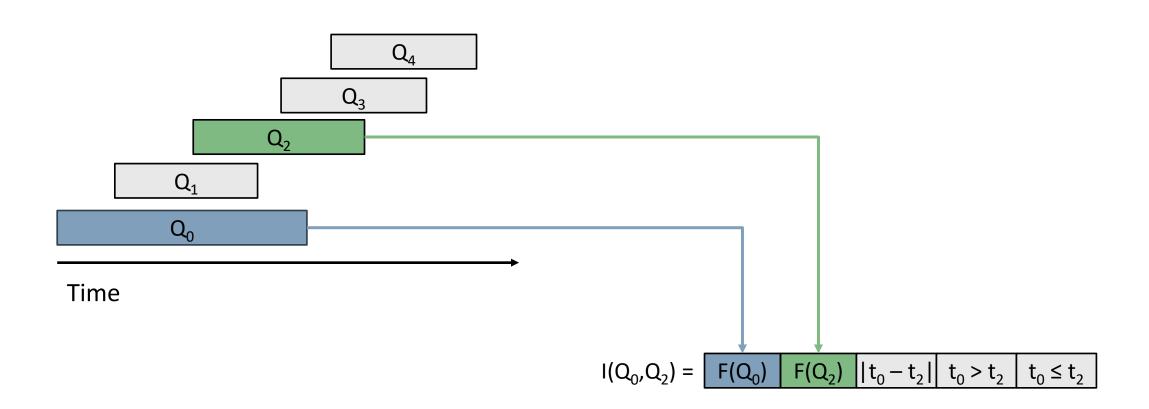
We first featurize a query using its plan



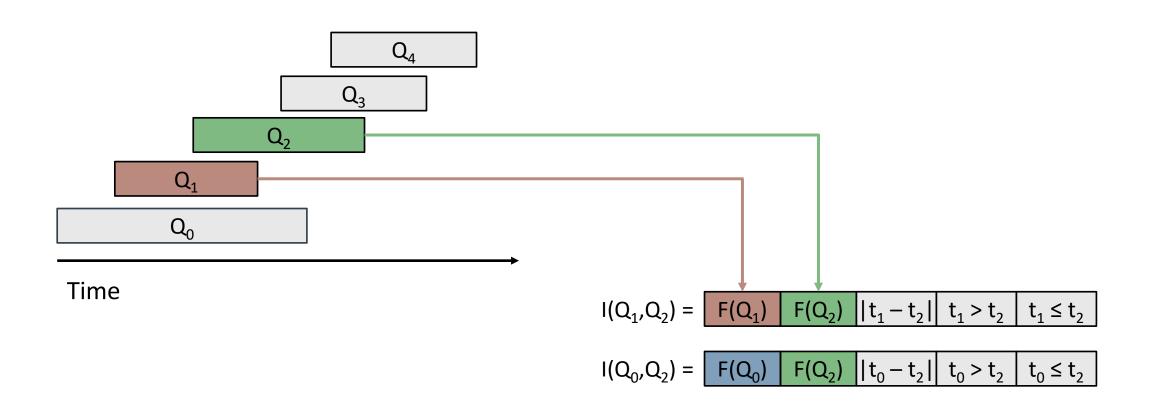




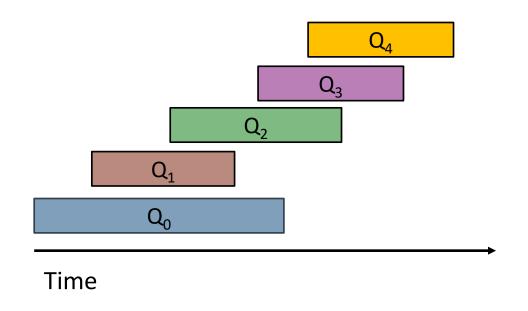












$$I(Q_1,Q_2) = F(Q_4) F(Q_2) |t_4 - t_2| t_4 > t_2 t_4 \le t_2$$

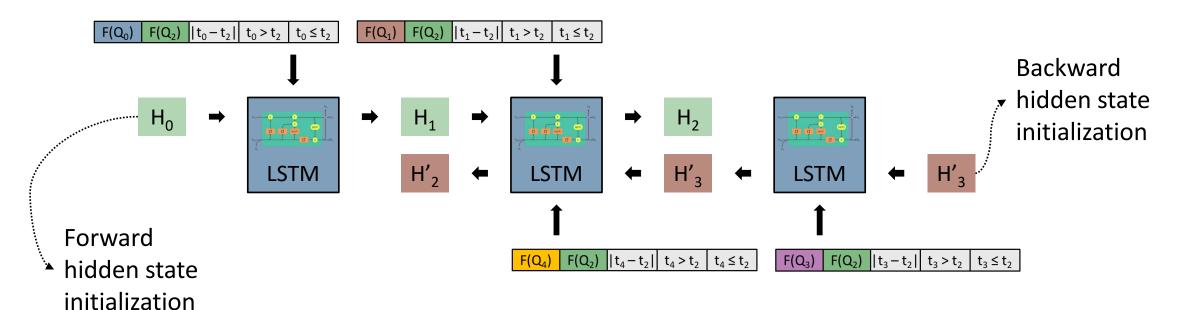
$$I(Q_3,Q_2) = F(Q_3) F(Q_2) |t_3 - t_2| t_3 > t_2 t_3 \le t_2$$

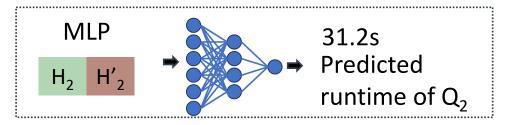
$$I(Q_1,Q_2) = F(Q_1) F(Q_2) |t_1 - t_2| t_1 > t_2 t_2$$

$$I(Q_0, Q_2) = F(Q_0) F(Q_2) |t_0 - t_2| t_0 > t_2 t_0 \le t_2$$



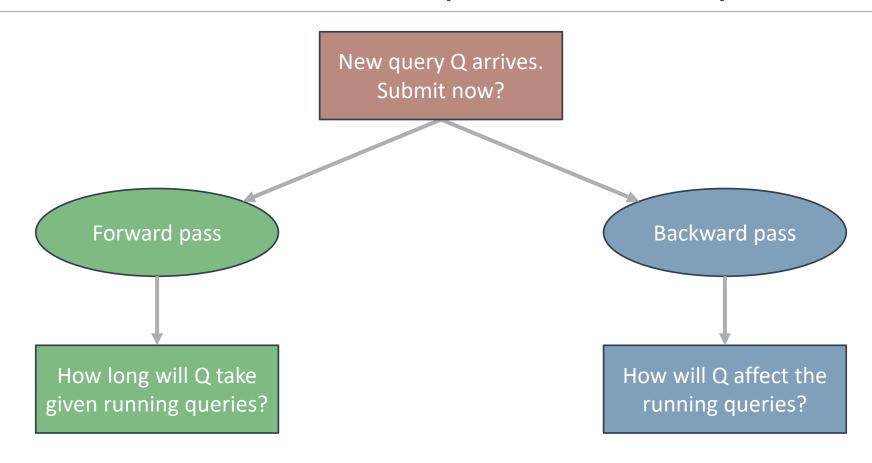
We then train Iconq: a bidirectional LSTM





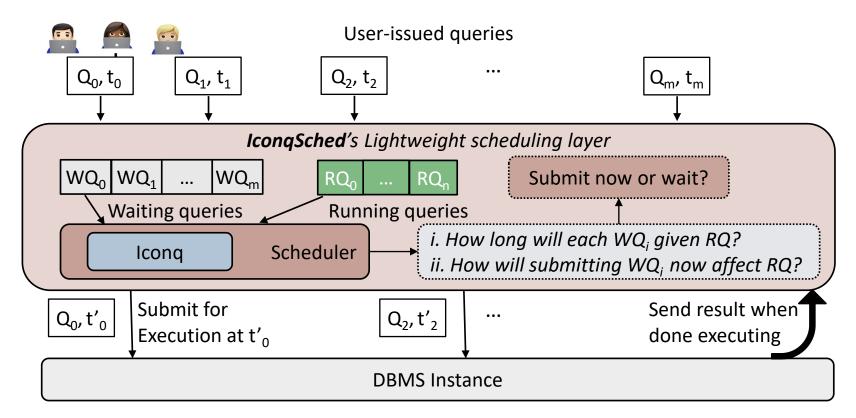


At inference time, separate the passes





Iconq is at the center of our scheduler



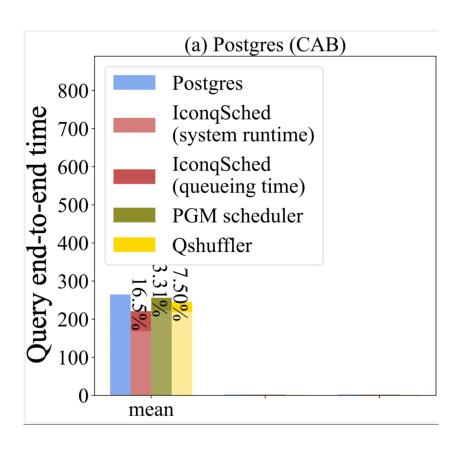
* For short queries
(Stage¹ estimate
< 5s), always submit,
since Iconq requires
around 100ms for
inference

Setting up the evaluation

- Two different DBMS engines:
 - PostgreSQL
 - Amazon Redshift
- Two different open-source benchmarks:
 - CAB¹: Cloud Analytics Benchmark
 - BRAD²: IMDB data + Snowset query arrival timestamps
- Two different state-of-the-art baselines:
 - PGM Scheduler³: Estimate memory and keep total bounded.
 - Qshuffler⁴: Represent system state as counts per query cluster.

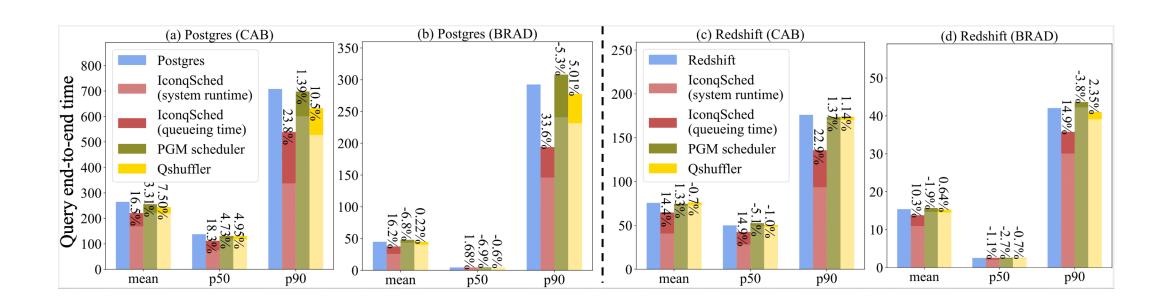


We improve query end-to-end time



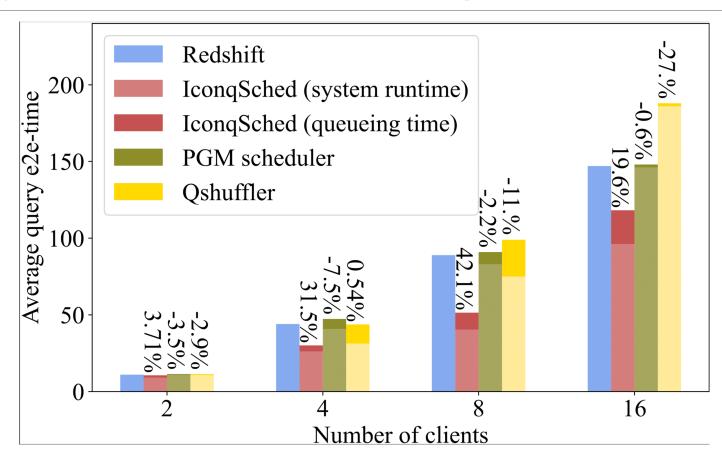


We outperform baselines across settings





Iconq performs under high concurrency







Key Takeaway

IconqSched reduces
query end-to-end time
without accessing DBMS internals



Thank you!















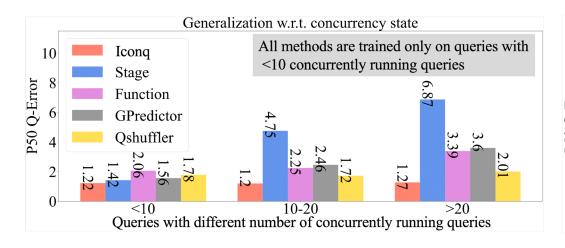


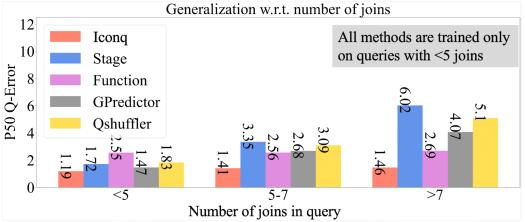
Paper: https://www.vldb.org/pvldb/vol18/p4185-wu.pdf

Questions? Reach out at ziniuw@mit.edu



Iconq generalizes well to harder contexts





$$Q_{\text{error}} = max\left(\frac{true}{pred}, \frac{pred}{true}\right)$$