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CS 561: Data Systems Architectures

class 22

Machine Learning & Data Systems

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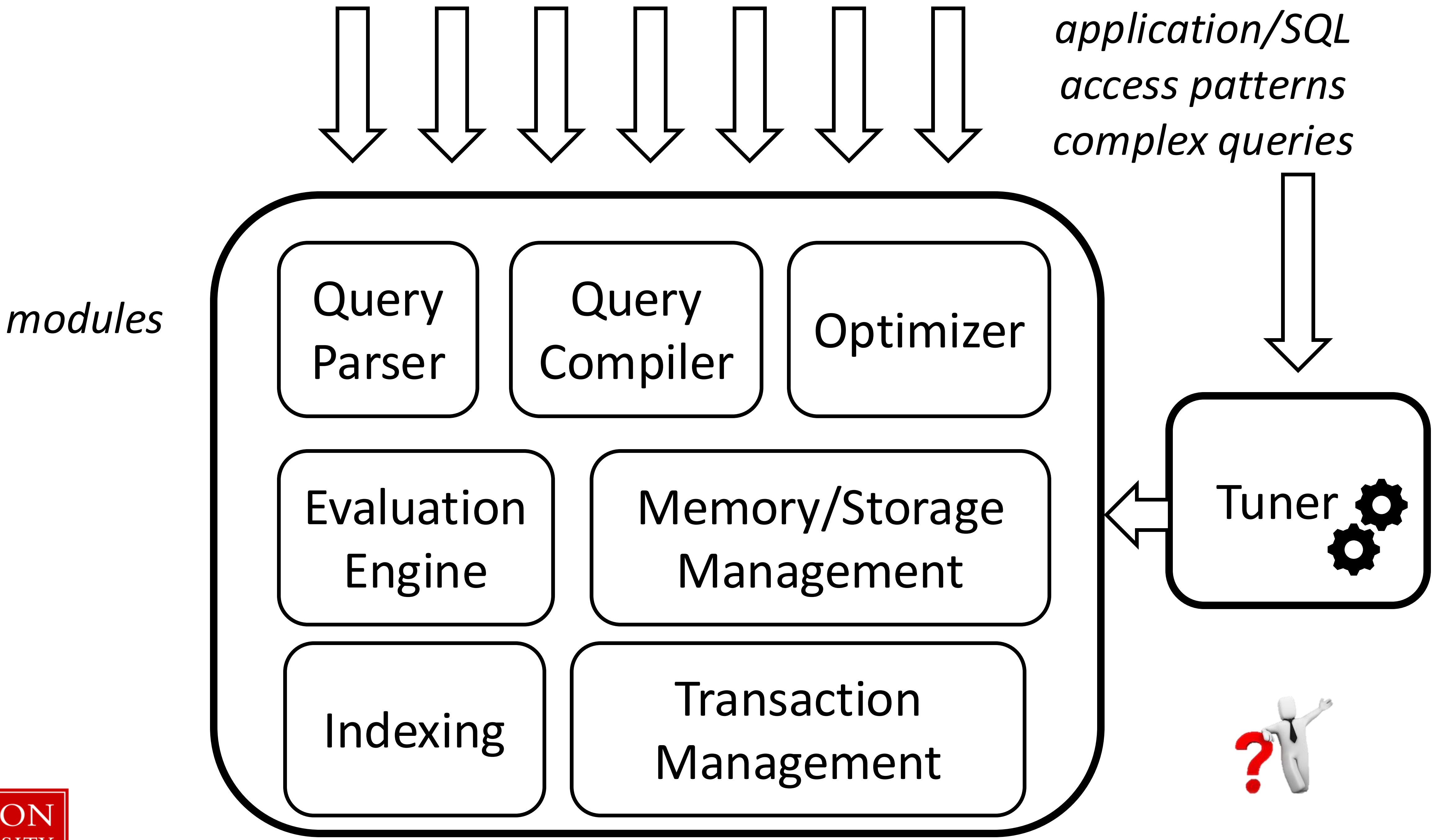
https://bu-disc.github.io/CS561/

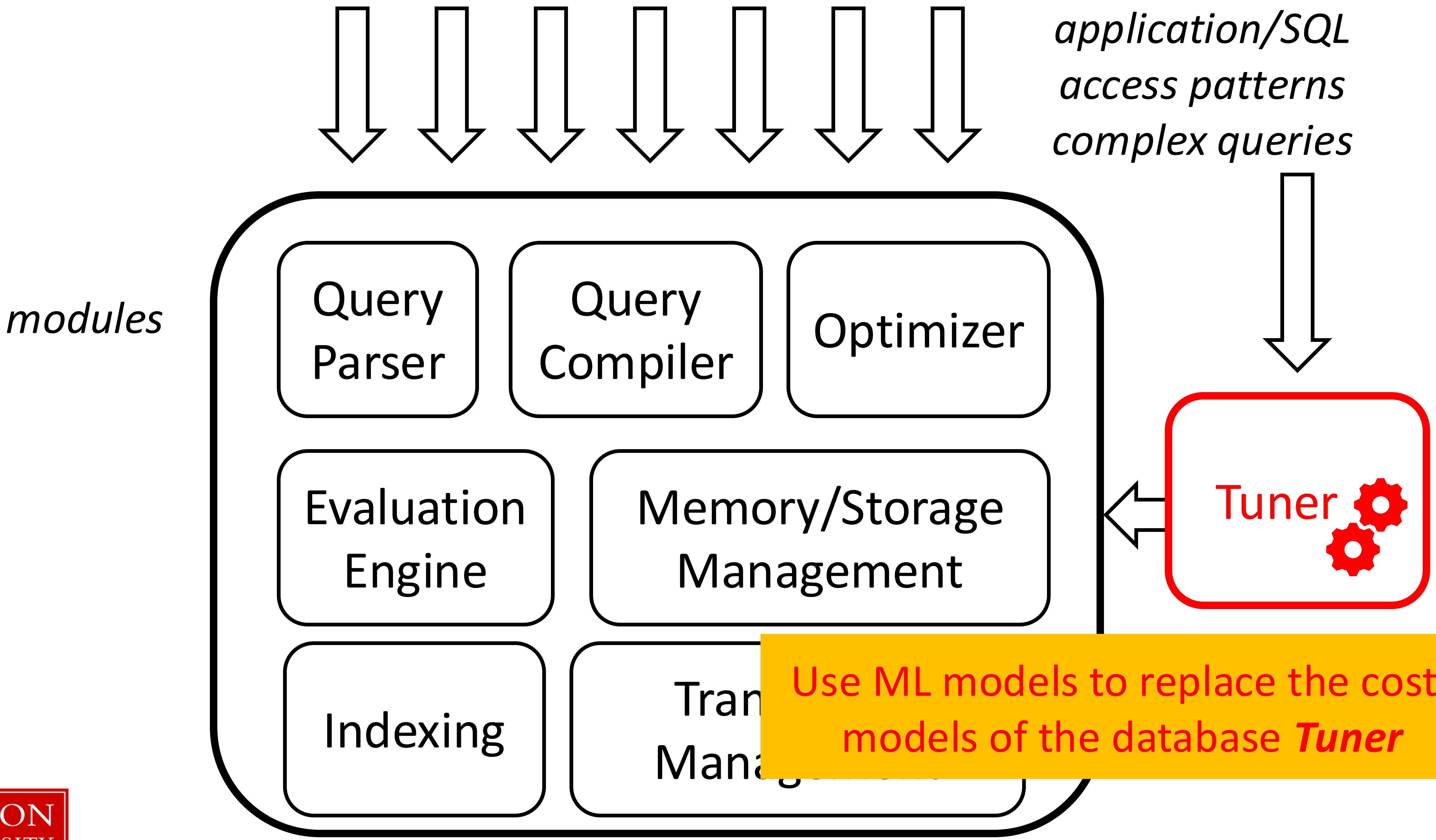
Machine learning algorithms improve *automatically* through *experience* and by the use of ***data***.

Machine learning algorithms build a model based on ***training data***, in order to make ***predictions*** or ***decisions*** without being explicitly programmed to do so.

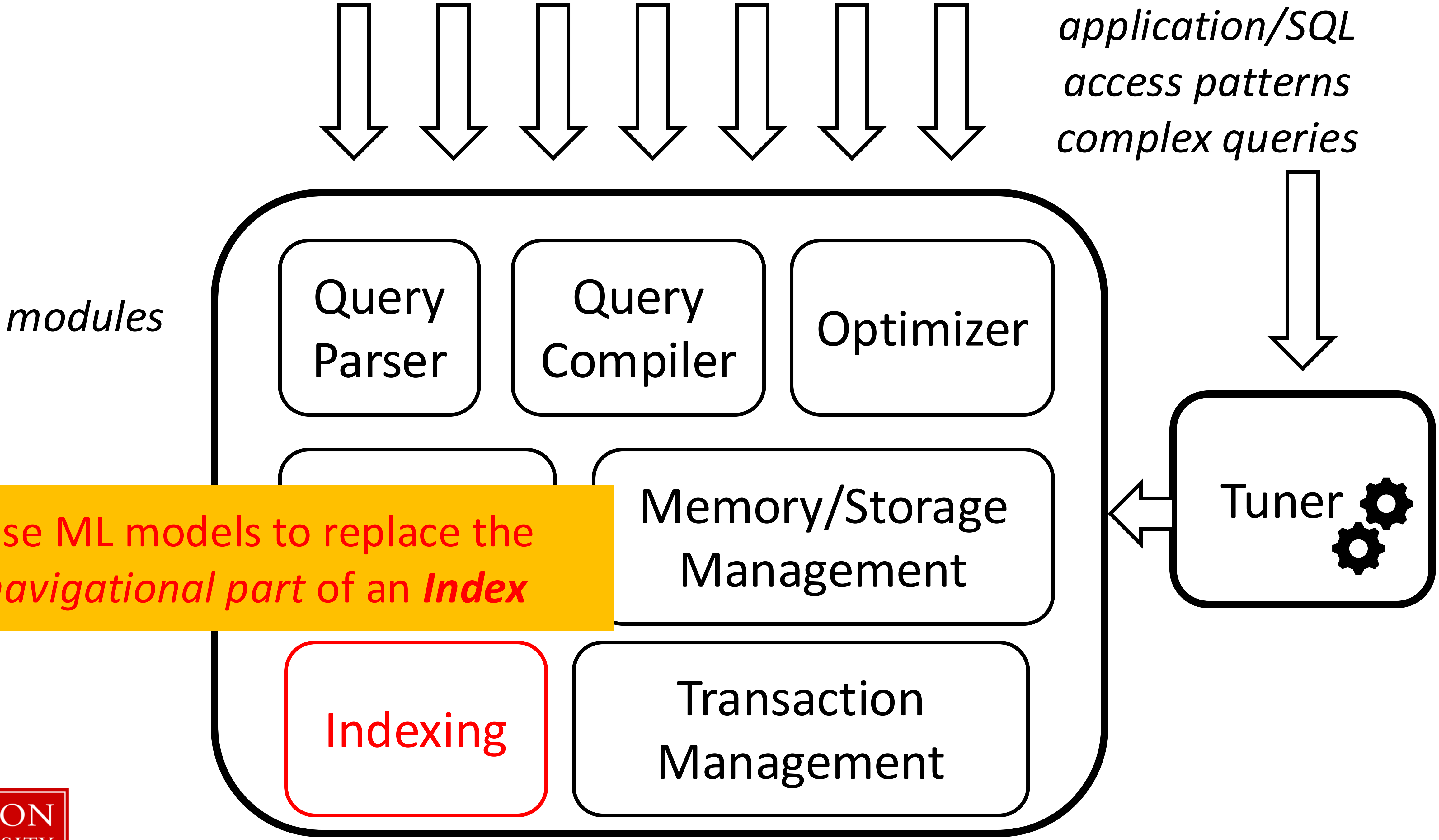
Which database systems components can benefit/be replaced by ML algorithms?



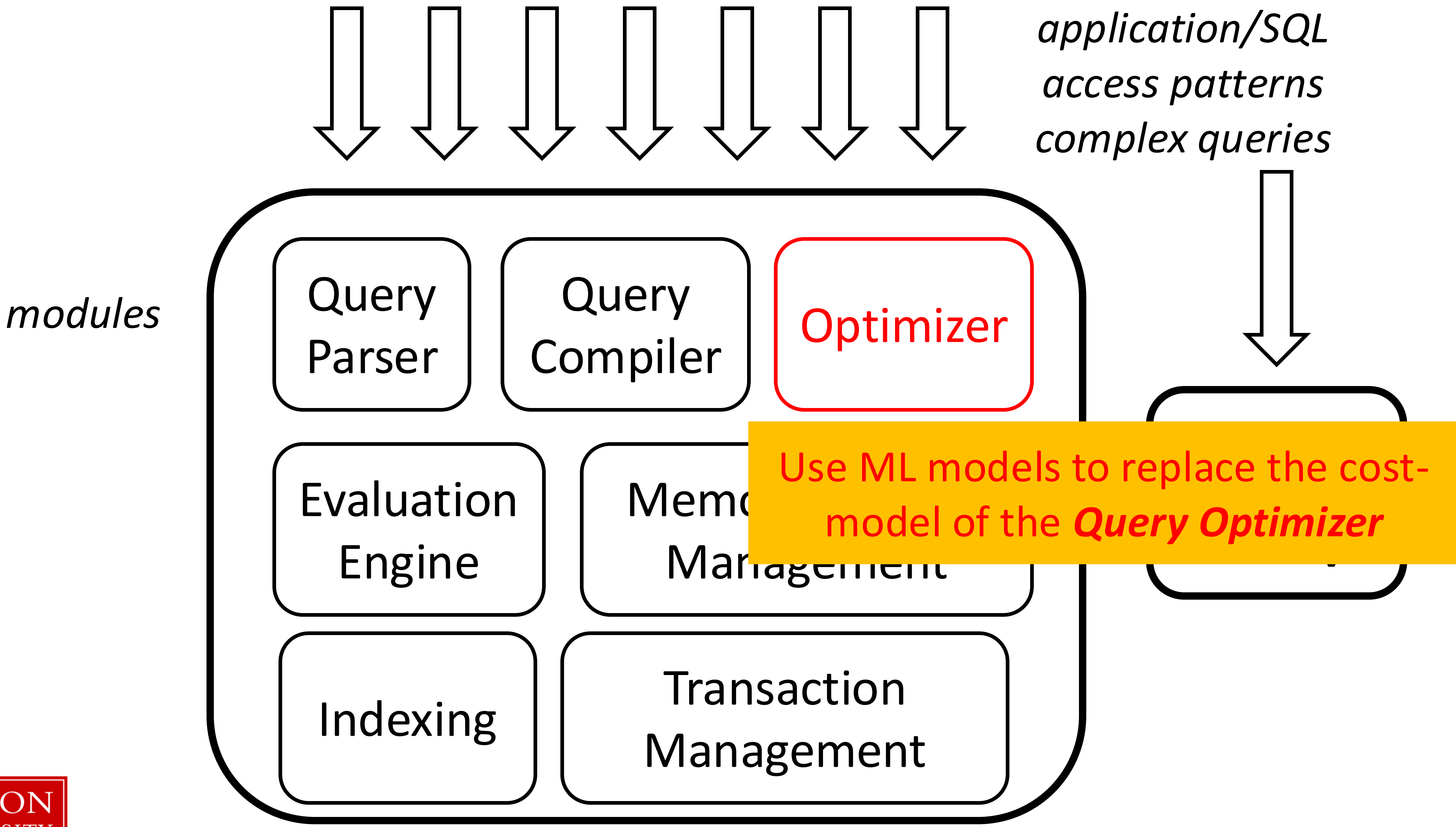
application/SQL
access patterns
complex queries
modules
Query Parser
Query Compiler
Optimizer
Evaluation Engine
Memory/Storage Management
Indexing
Transaction Management
Tuner



Use ML models to replace the cost-models of the database ***Tuner***



Use ML models to replace the *navigational part* of an ***Index***



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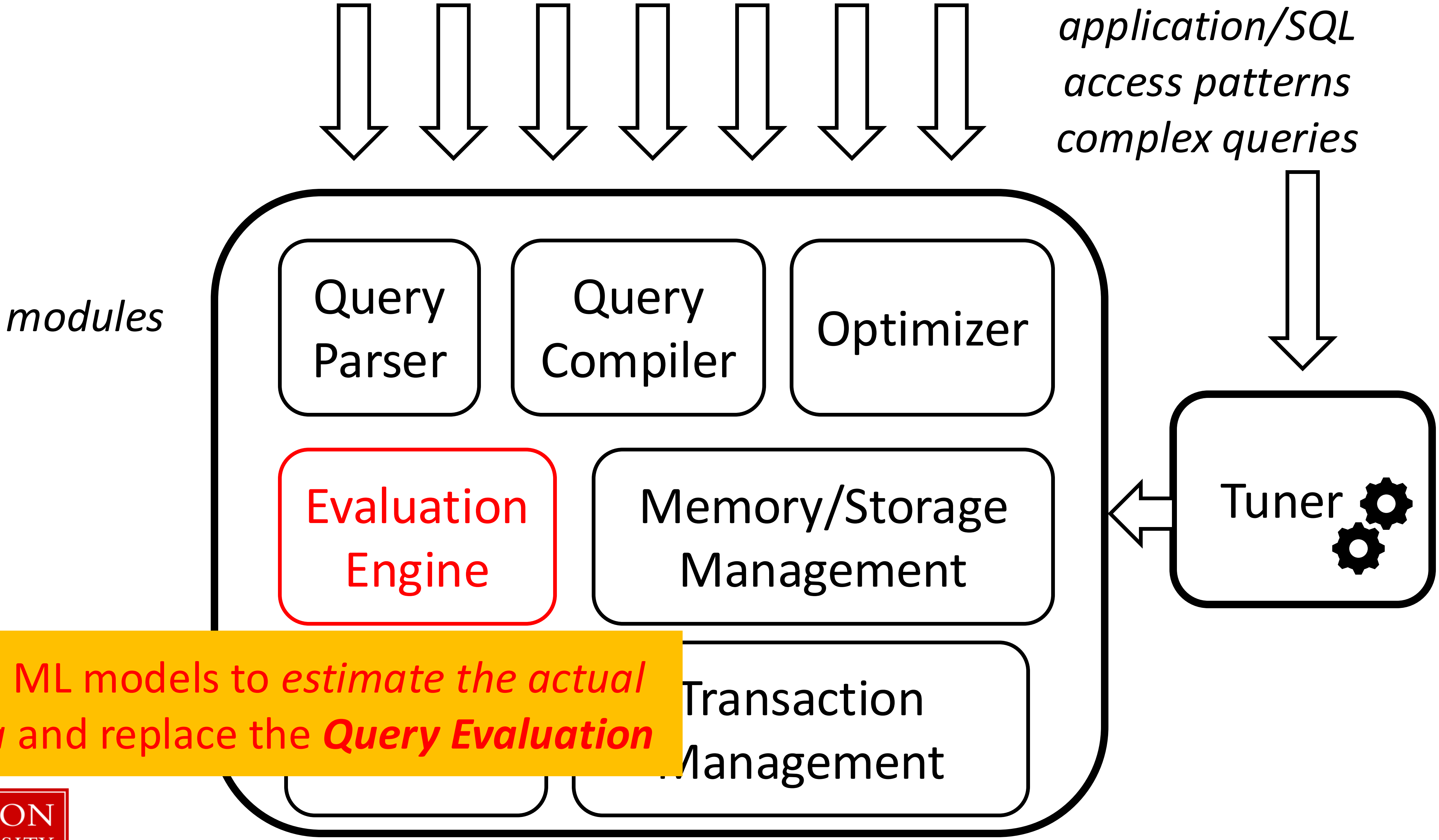
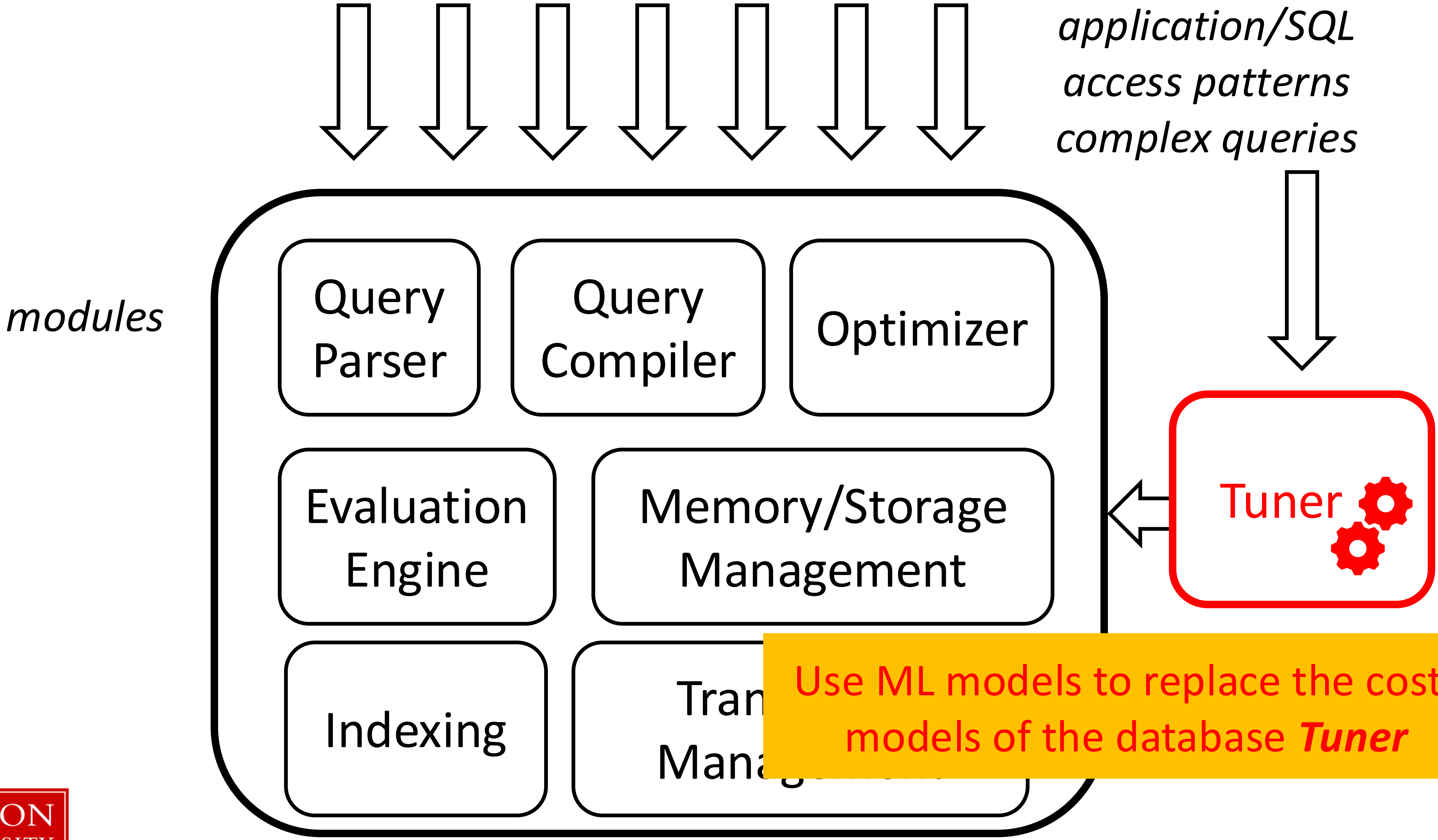


Use ML models to *estimate the actual data* and replace the ***Query Evaluation***



Use ML models to replace the cost-models of the database ***Tuner***

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Self-driving Data systems

Types of actions that a self-driving system needs to take ***automatically***

	Types	Actions
PHYSICAL	Indexes	AddIndex, DropIndex, Rebuild, Convert
	Materialized Views	AddMatView, DropMatView
	Storage Layout	Row→Columnar, Columnar→Row, Compress
DATA	Location	MoveUpTier, MoveDownTier, Migrate
	Partitioning	RepartitionTable, ReplicateTable
RUNTIME	Resources	AddNode, RemoveNode
	Configuration Tuning	IncrementKnob, DecrementKnob, SetKnob
	Query Optimizations	CostModelTune, Compilation, Prefetch

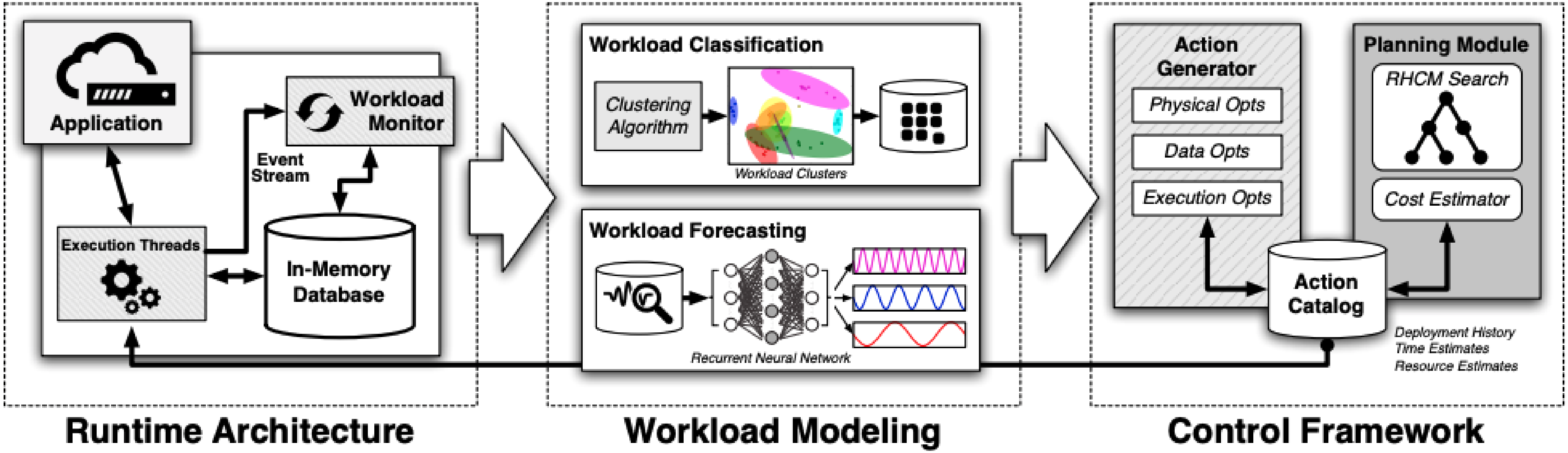
Use-case: Peloton Self-Driving Architecture

(A) Application

(B) Workload Monitoring

(C) Workload Classification
[unsupervised learning to group similar queries]

(E) Action Planning
[use tools like *receding-horizon control model* to select actions that might lead to better performance in the future]



(D) Workload Forecasting
[predict future workload to autoscale cloud instances]

(F) Action Generator
[select action and log them, reversals may also happen]

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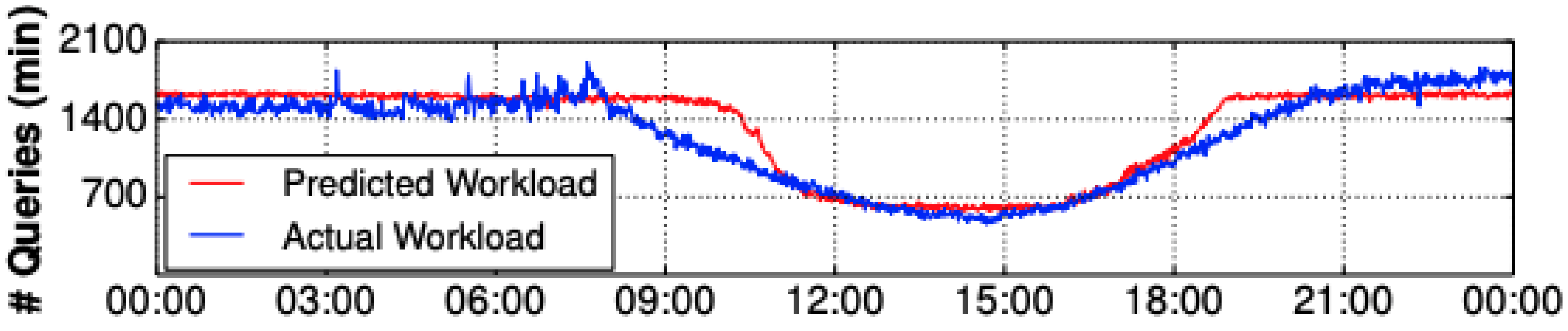
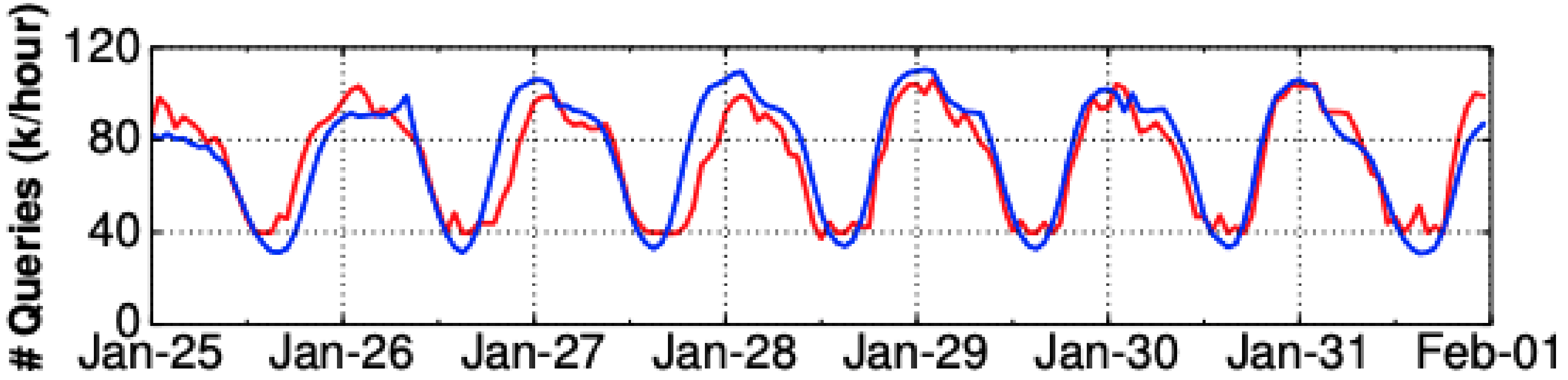
Workload forecasting

Using Recurrent Neural Networks (RNN) the model learns patterns and adapts to changes

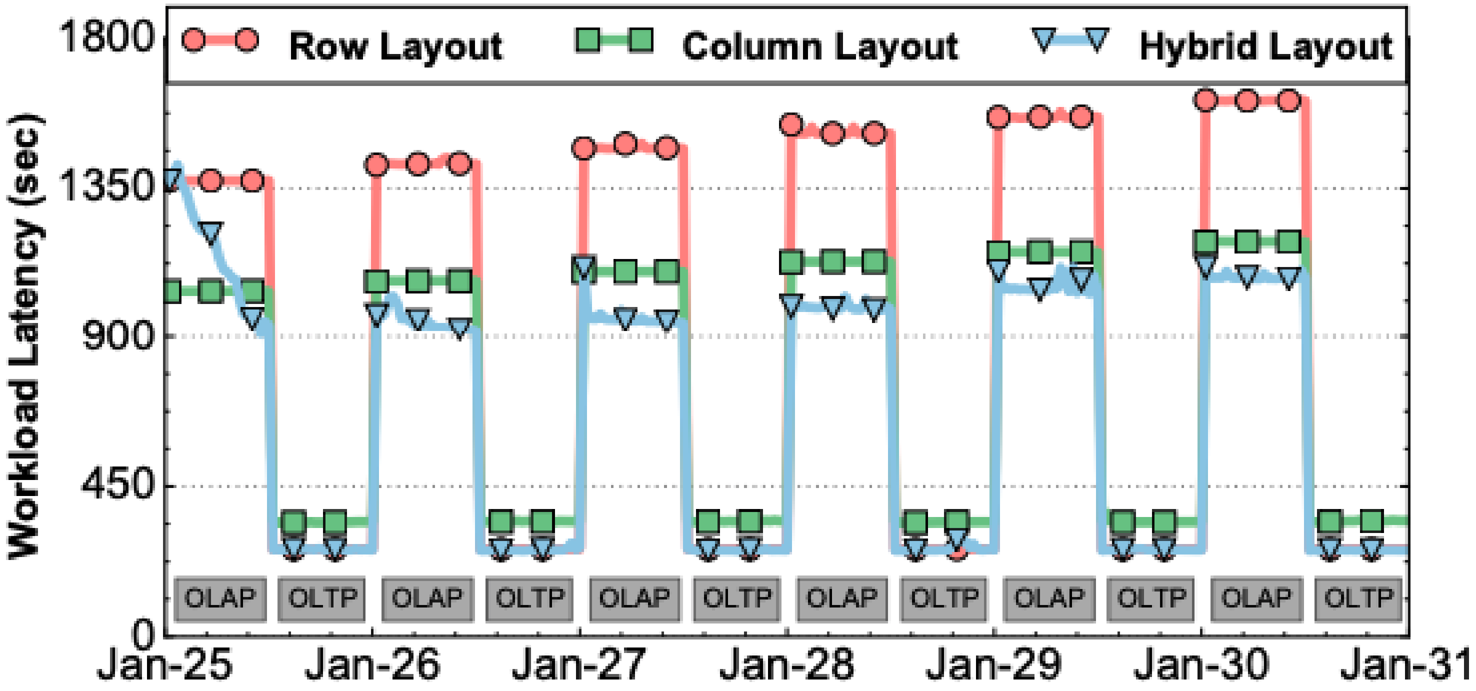


(a) RNN Forecast Model (24-Hour Horizon)



(b) RNN Forecast Model (7-Day Horizon)

Action example: adapting the storage layout

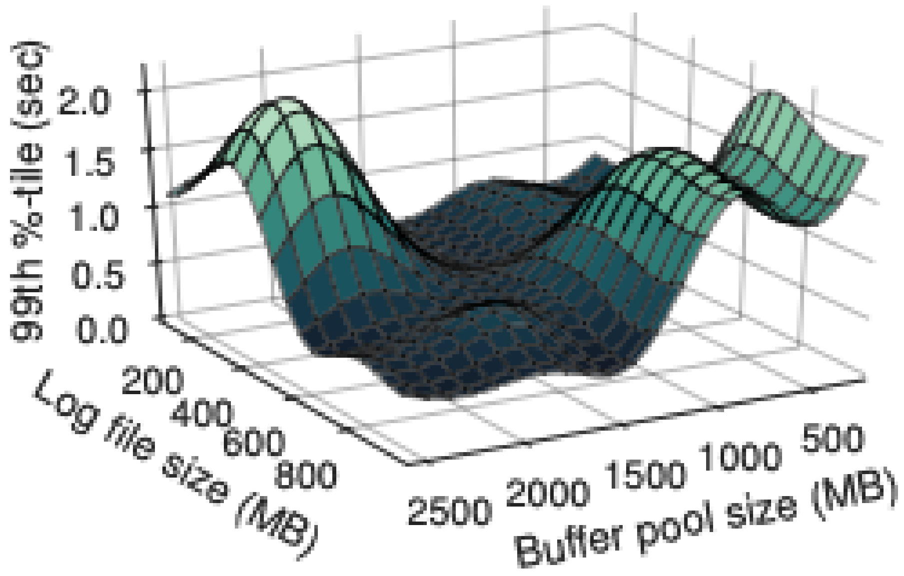


Columns are better for OLAP

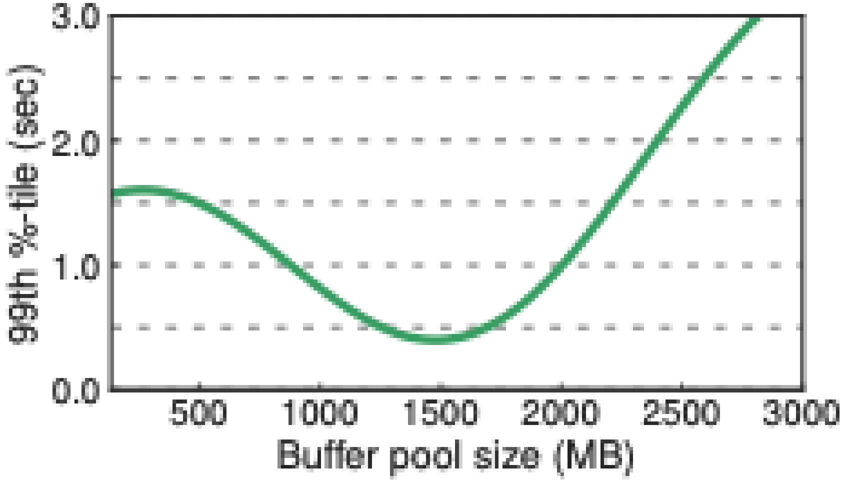
Rows are better for OLTP

Hybrid matches the best when workload alternates

Why automatic tuning is hard? (1/2)



(a) Dependencies



(b) Continuous Settings

Complex interdependencies between different tuning knobs!

Continuous domain ("too many" knob options) with irregular benefits

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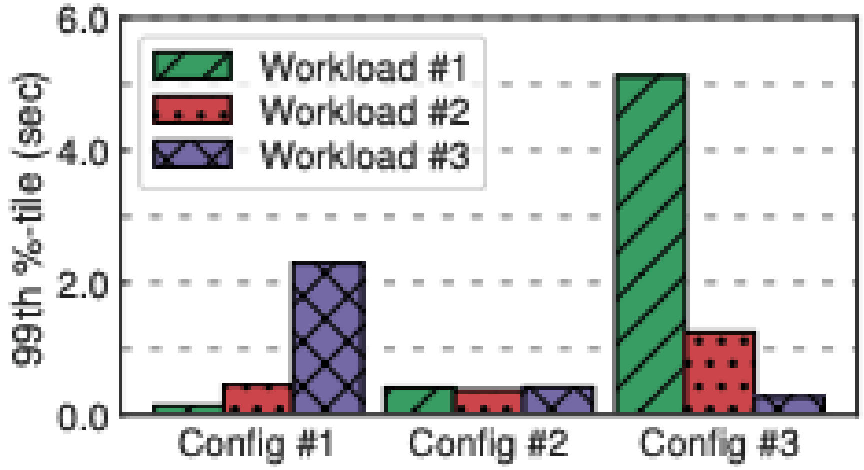
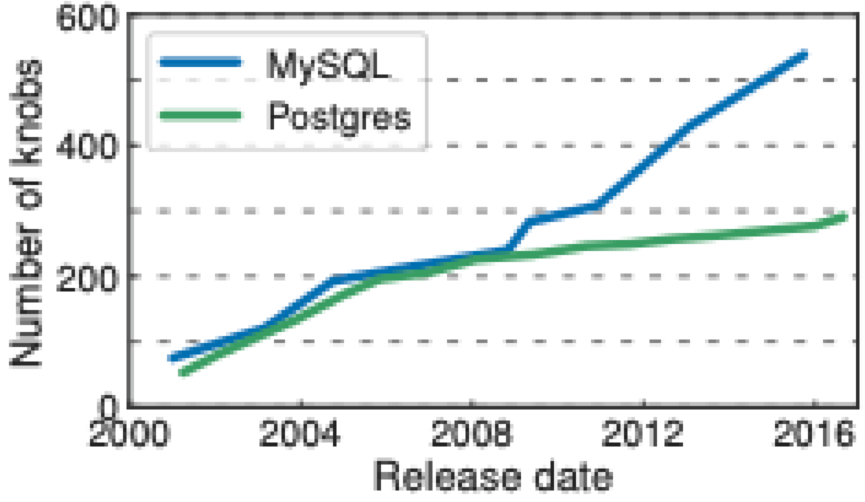
Why automatic tuning is hard? (2/2)



Non-reusable configurations!



Increasing tuning complexity

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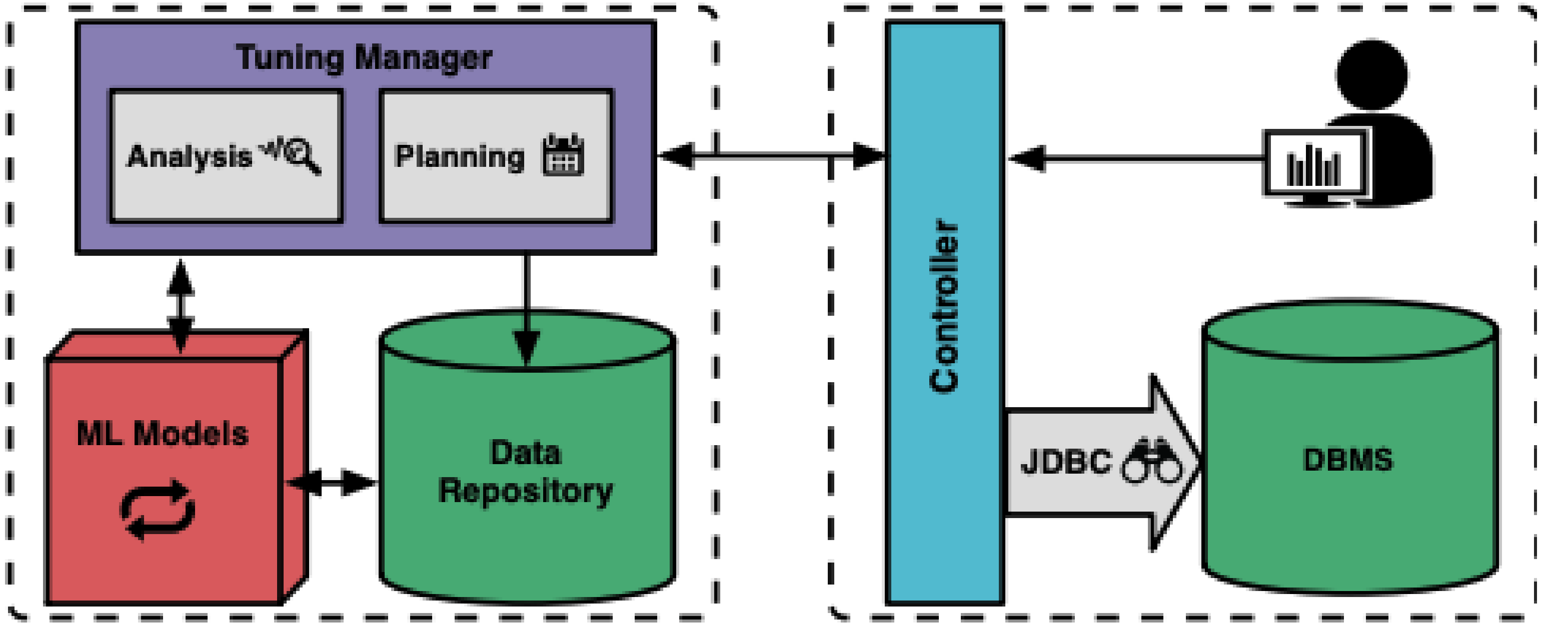
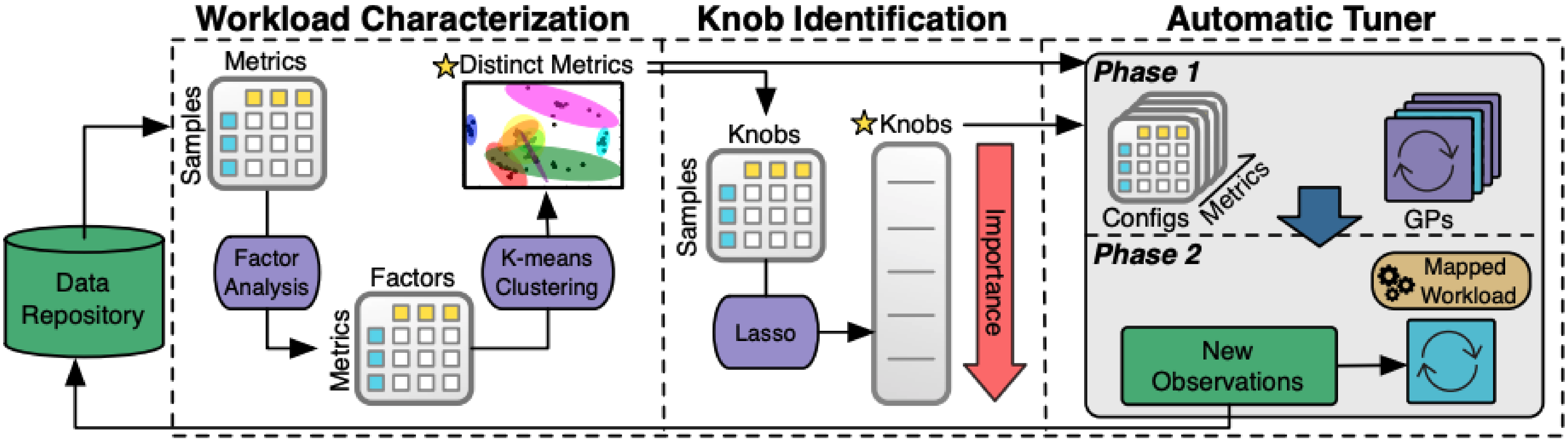
Use case: Ottertune



Two distinct components: the tuning manager **does not have access to data**, only to **performance metrics** and the values of the **tuning knobs**

All performance data are organized per system and per major version to ensure that no wrong, deprecated, or non-existing knobs are tuned.

OtterTune Machine Learning Pipeline



How to classify/characterize a workload?

What are possible challenges of this approach?

A workload is characterized based on the system metrics when it is executed (e.g., #pages reads/writes, cache utilization, locking overhead)

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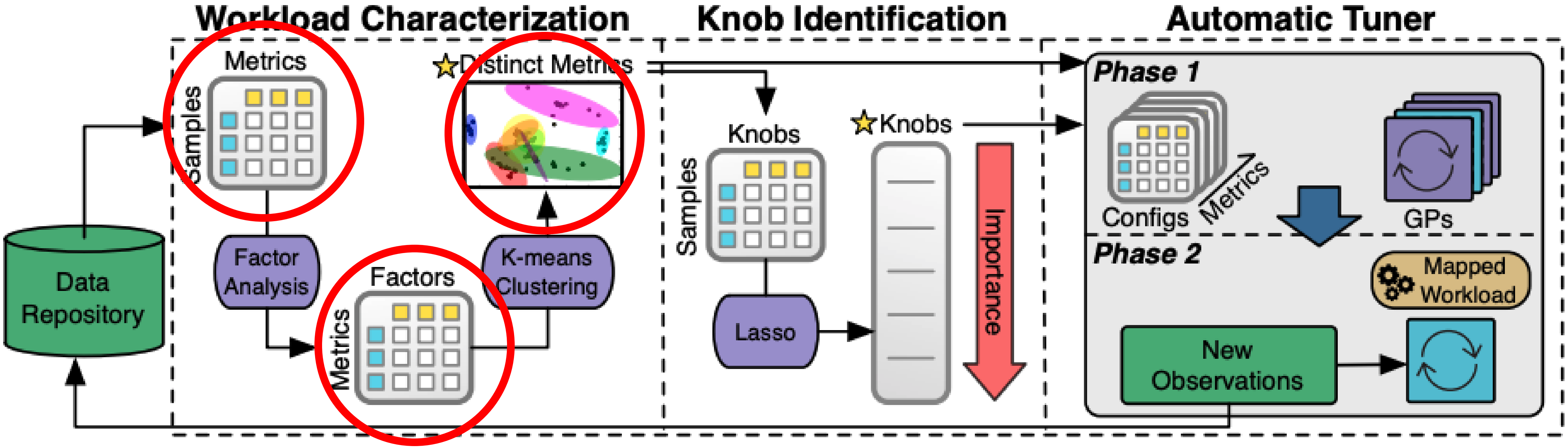
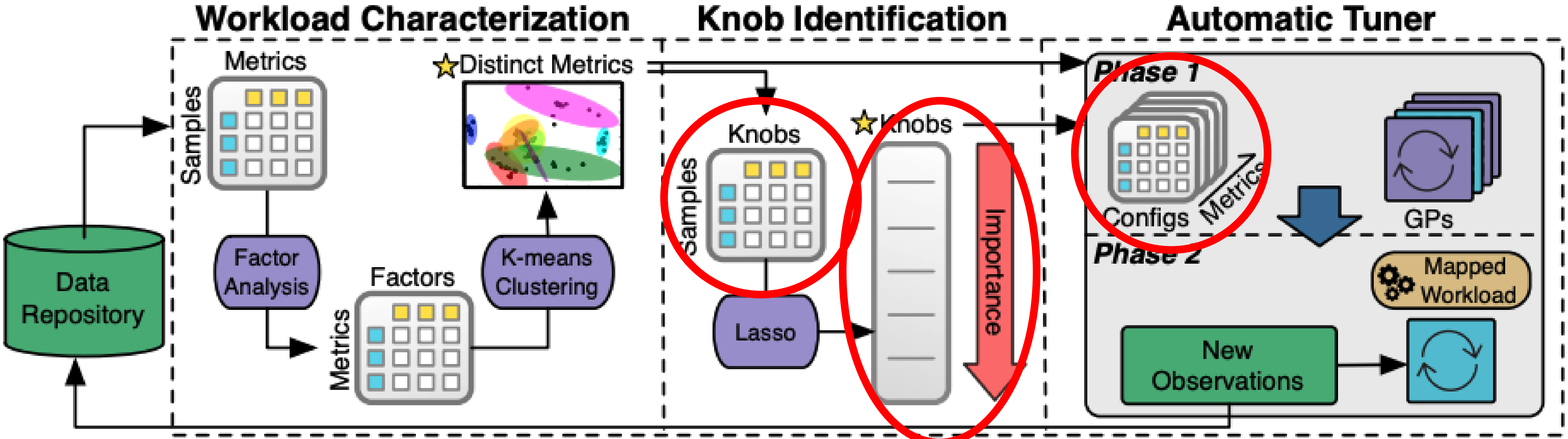
OtterTune Machine Learning Pipeline



Collect statistics at the global level (system-wide), per table proves to be challenging for various systems

Prune redundant metrics (e.g., data read and pages read are directly linked) via factor analysis and k-means clustering

OtterTune Machine Learning Pipeline



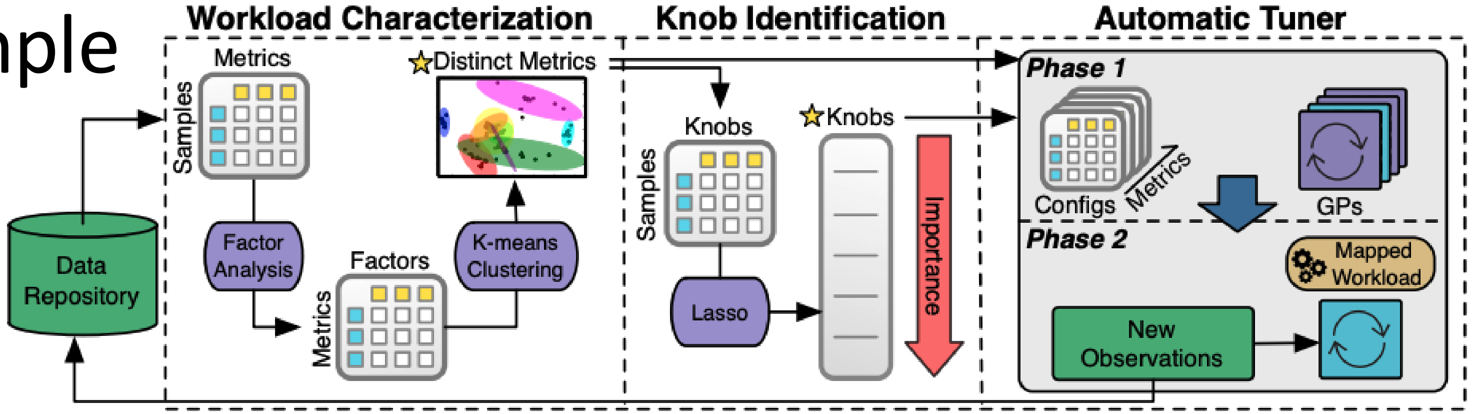
Identify important knobs

Order the knobs based on their significance on the system's performance (and identify knobs interdependencies)

Store in a repository observations

OtterTune Machine Learning Pipeline

Automated Tuning: an Example



Use the systems metrics to identify (classify) the workload

Iterative configuration recommendation balancing ***exploration*** vs. ***exploitation***

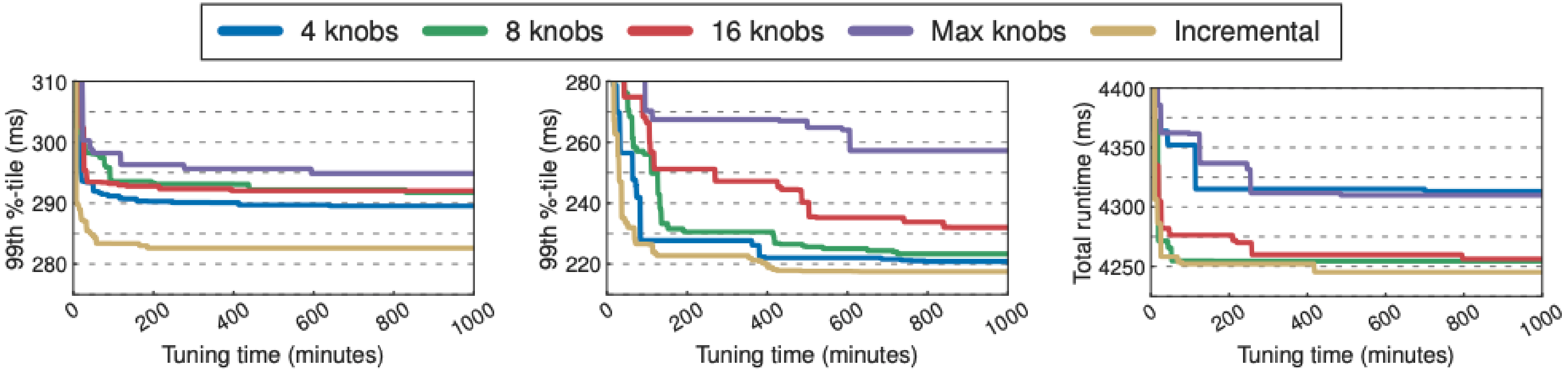
Exploration: try out a configuration for which there is not enough data in the repository

this is done when (i) there is not enough data for this workload (so more data are needed), or (ii) the system decides to try out new configurations that help collect more data in general

Exploitation: the systems uses small variations of a configuration that is close to optimal using the existing data

OtterTune in Action

Start by sweeping values of knobs to collect "training data"



(a) MySQL (TPC-C) (b) Postgres (TPC-C) (c) Vector (TPC-H)

The optimal number of knobs varies per *DBMS* **and** *workload*!

Increasing the number of knobs gradually is the best approach, because it balances complexity and performance.

OtterTune tunes MySQL and Postgres that have few impactful knobs, and Actian Vector that requires more knobs to be tuned in order to achieve good performance.

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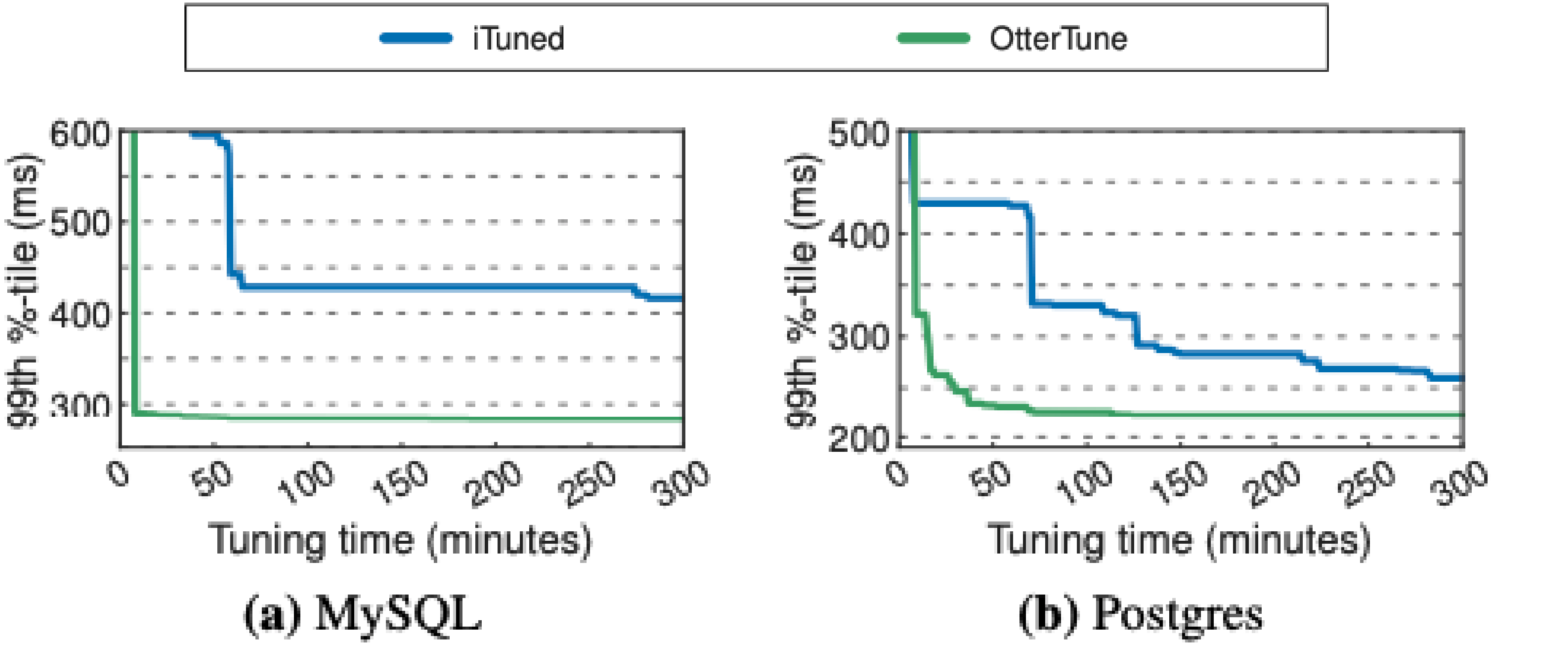
OtterTune vs iTunes on TPCC

iTuned uses an initial set of 10 DBMS configurations at the beginning of the tuning session.



OtterTune is trained with more data, so it can achieve a better end result!

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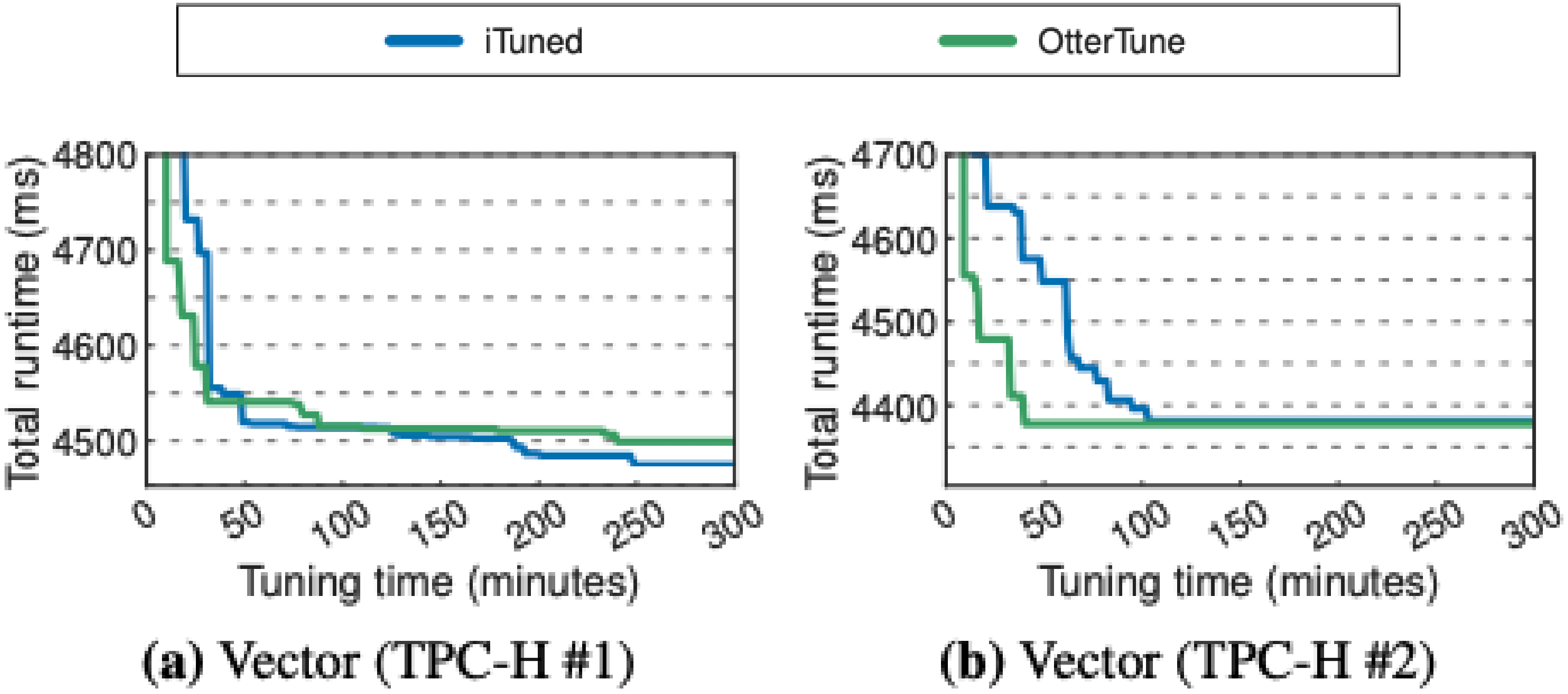
OtterTune vs iTunes on TPCH



Actian Vector allows fewer "bad" options, so the training is easier.

“A tuning knob is a database engineer not knowing what do”

take this with a grain of salt!

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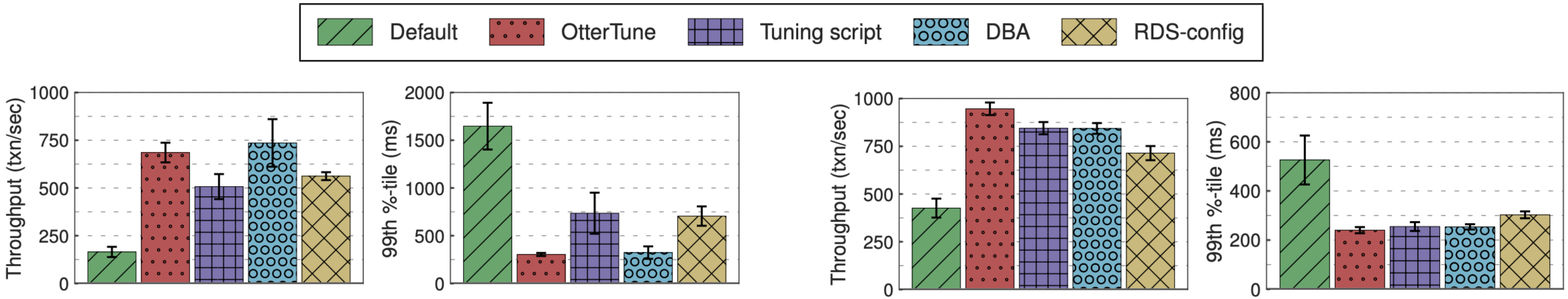
OtterTune Efficacy Comparison



(a) TPC-C (Throughput) **(b)** TPC-C (99%-tile Latency)

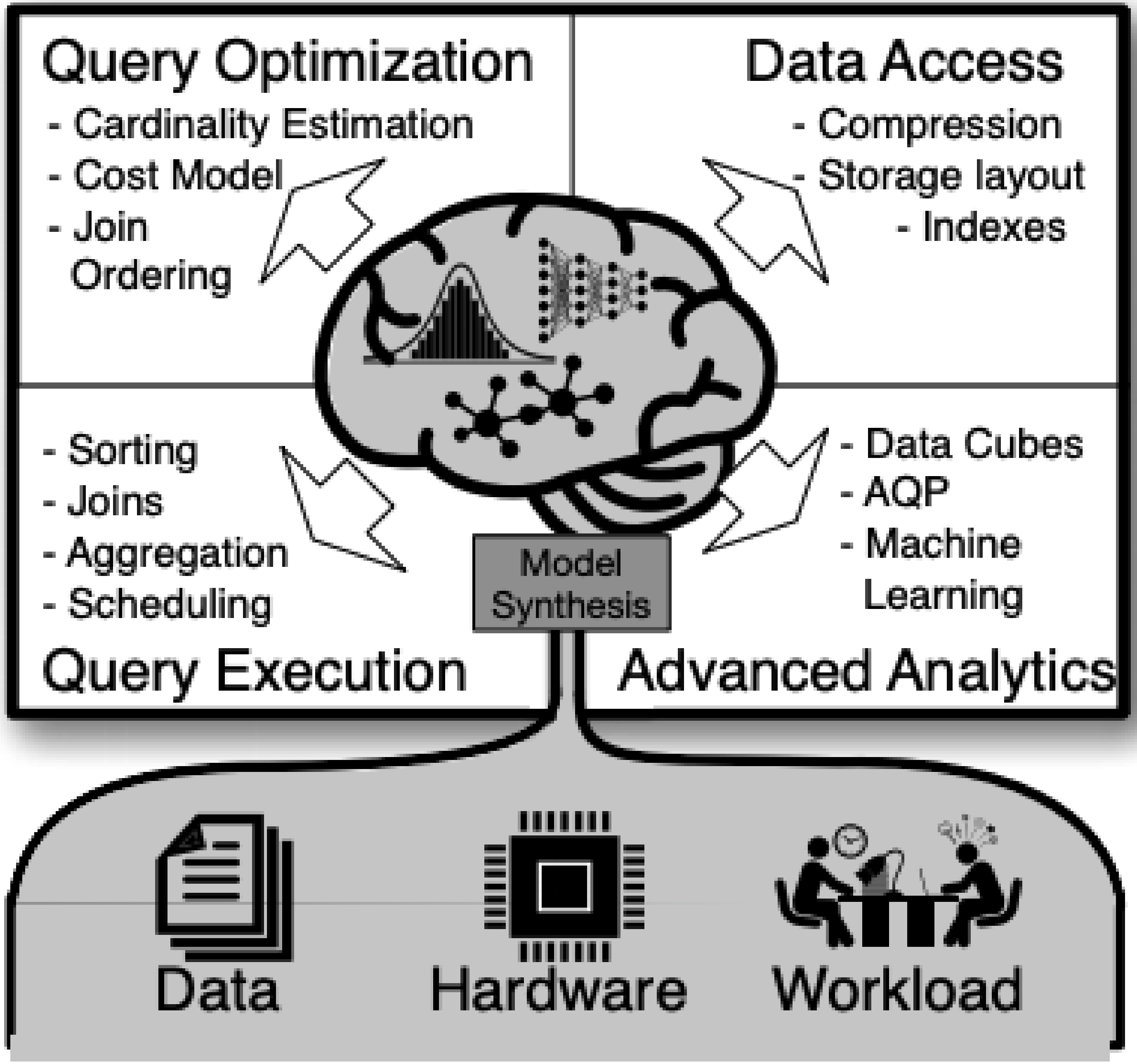
MySQL

(a) TPC-C (Throughput) **(b)** TPC-C (99%-tile Latency)

PostgreSQL

It is hard (but not impossible) to beat an expert DBA!

A Learned Database System



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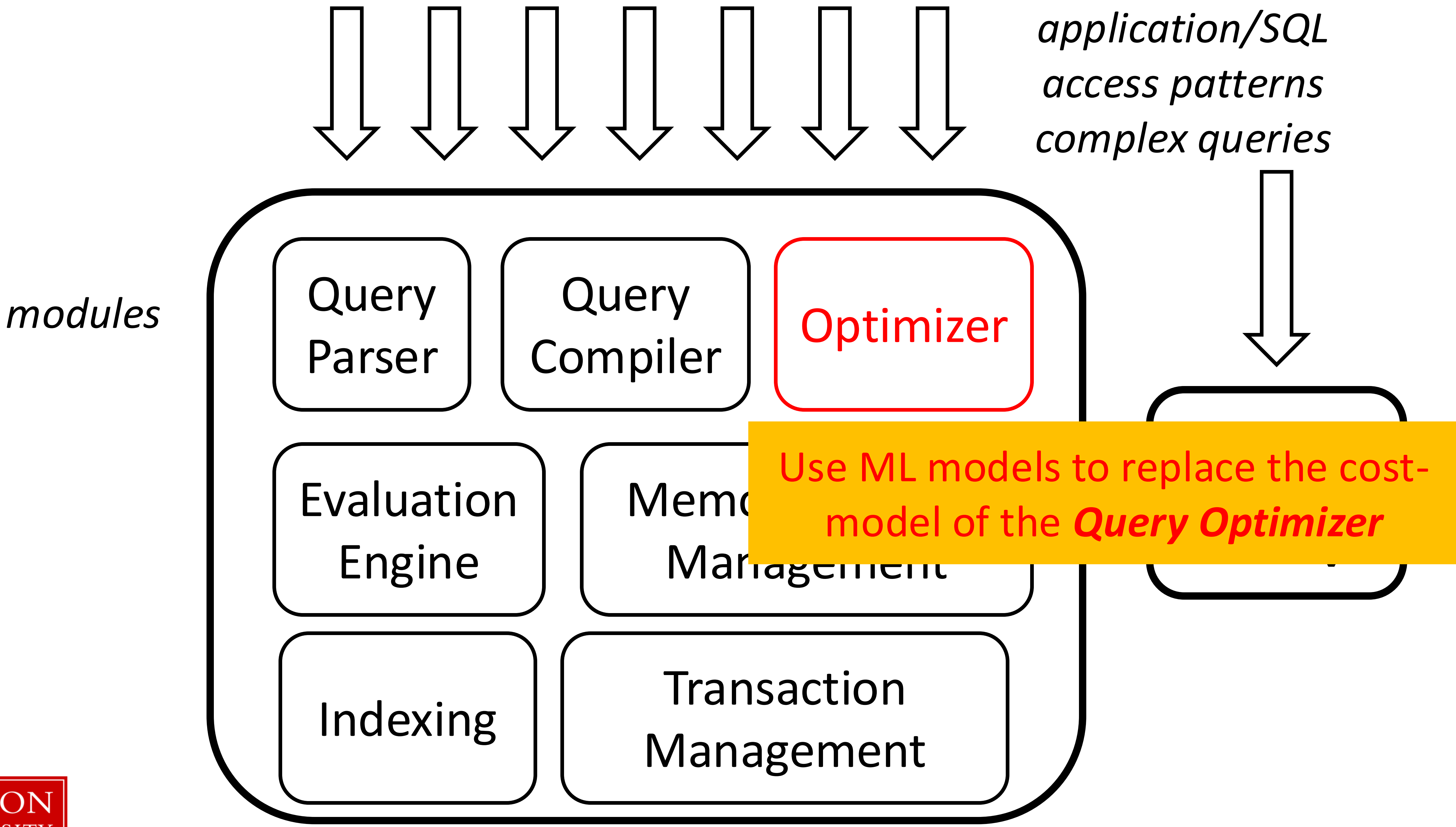
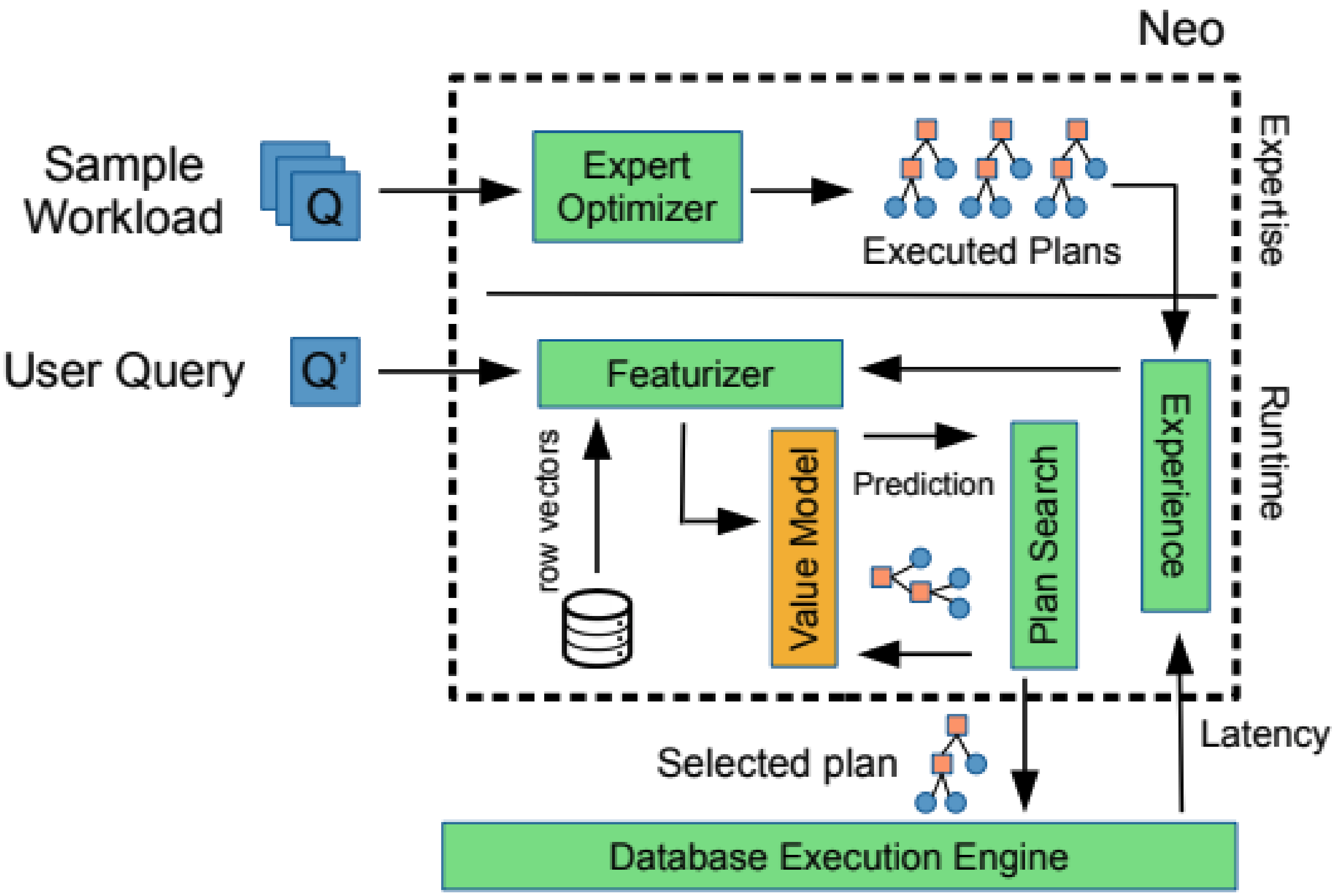


Use ML models to replace the cost-model of the ***Query Optimizer***

Learned Query Optimization



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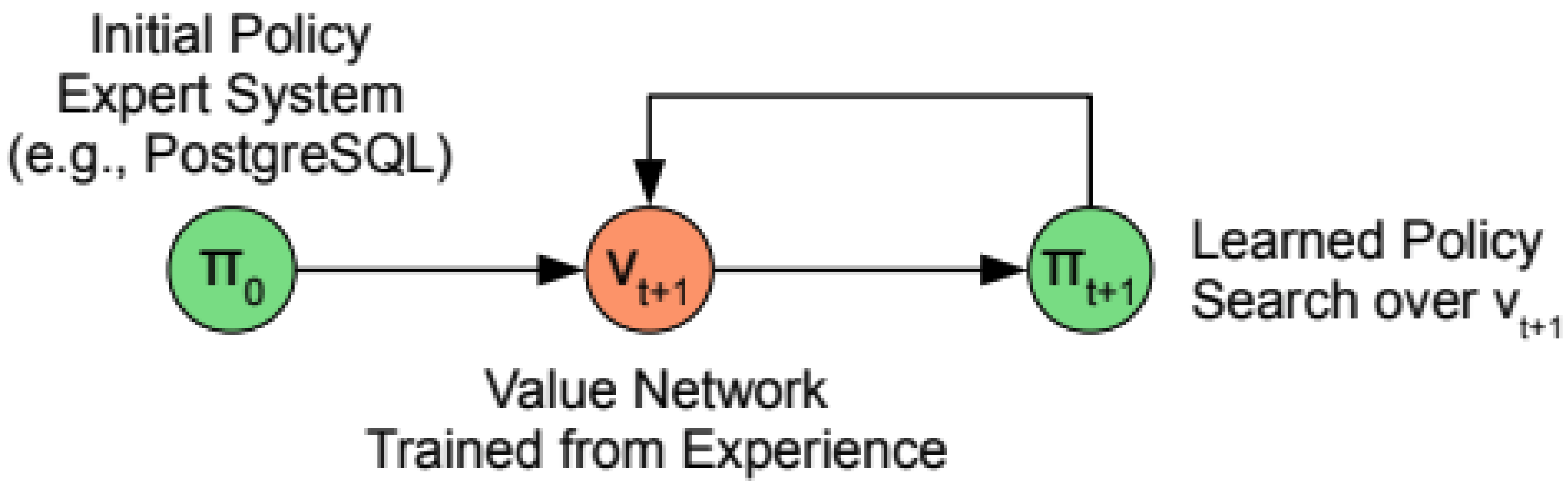
Learned Query Optimization



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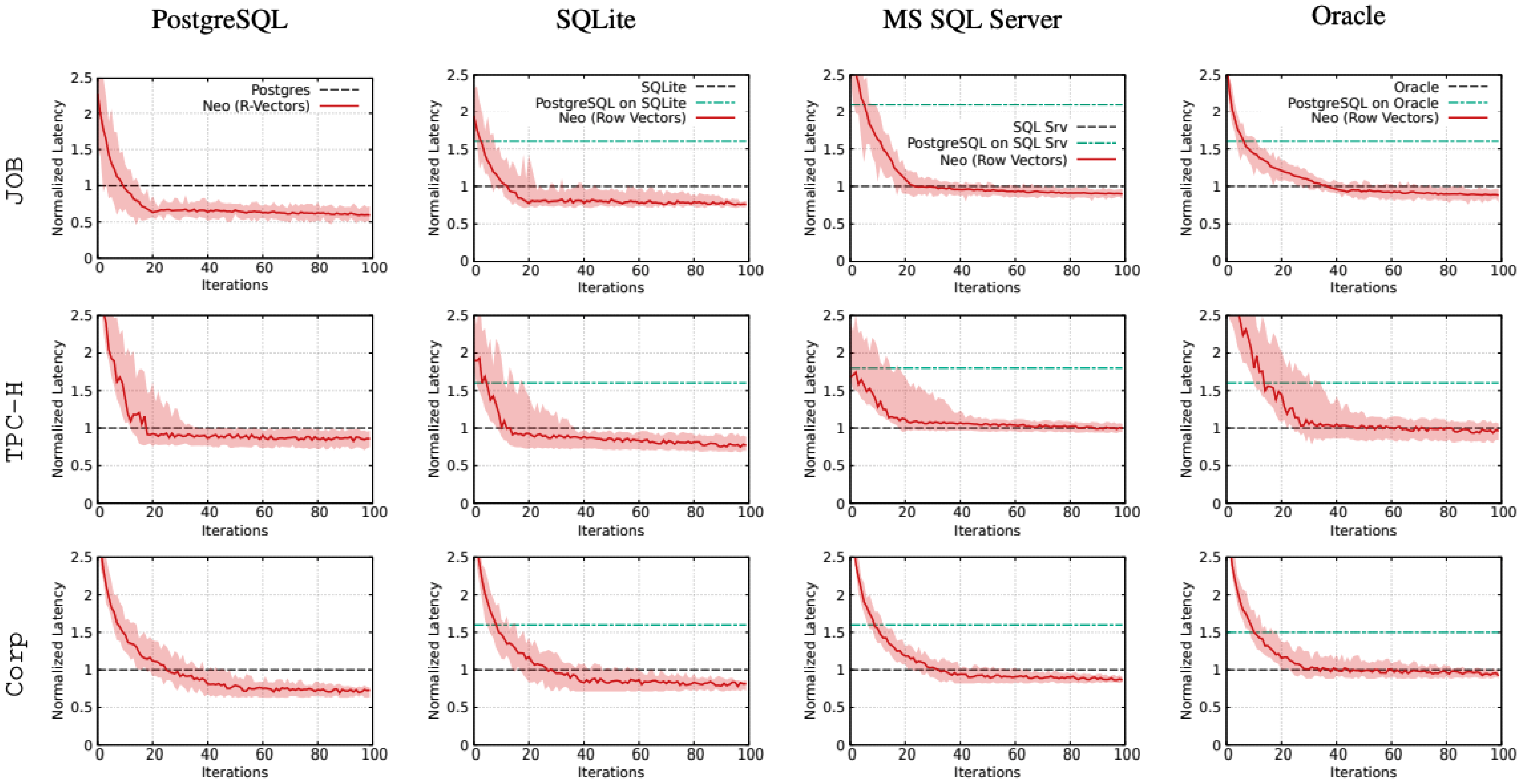
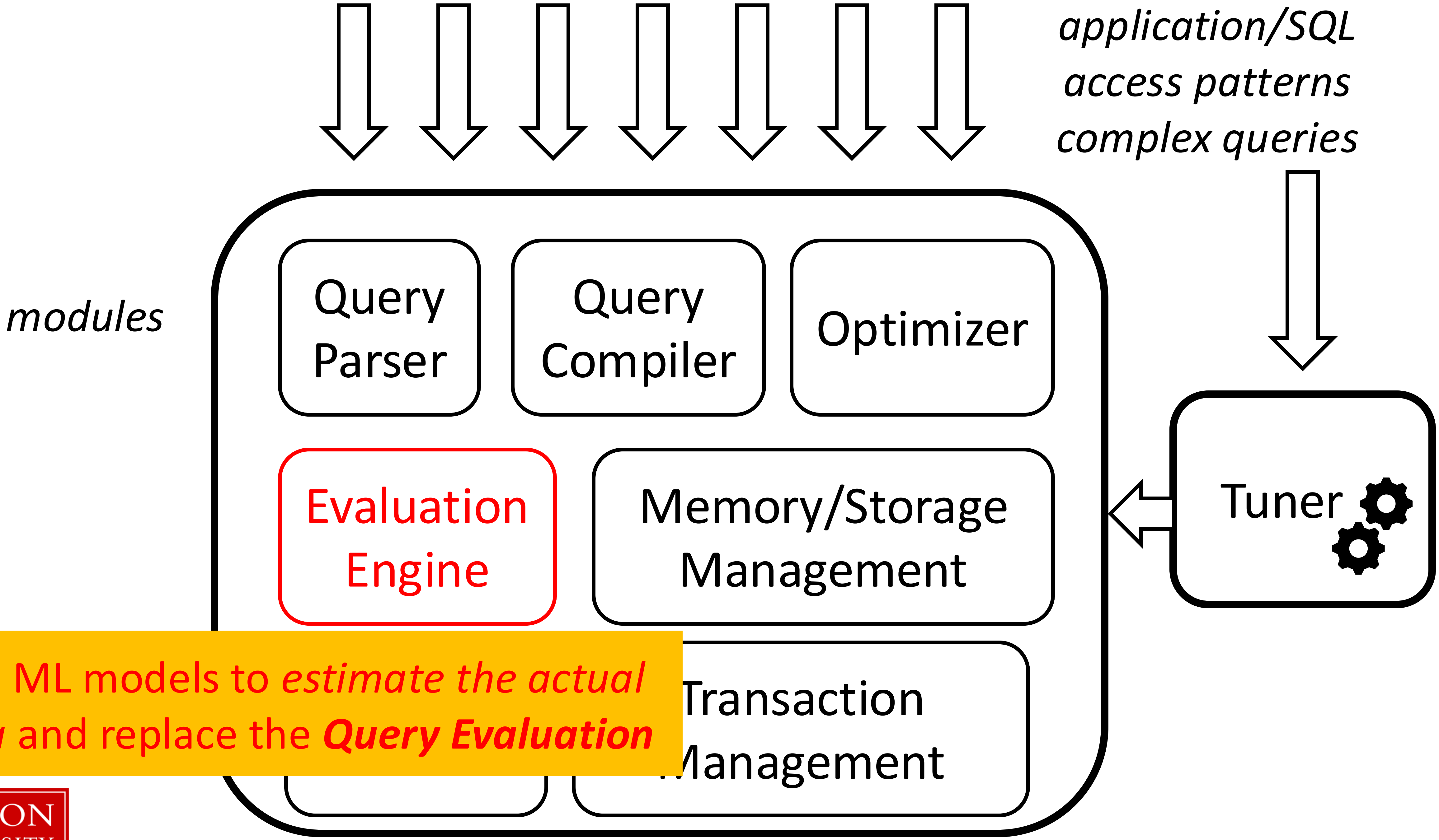


PostgreSQL
SQLite
MS SQL Server
Oracle
JOB
TPC-H
Corp
Postgres
Neo (R-Vectors)
SQLite
PostgreSQL on SQLite
Neo (Row Vectors)
SQL Srv
PostgreSQL on SQL Srv
Neo (Row Vectors)
Oracle
PostgreSQL on Oracle
Neo (Row Vectors)
Normalized Latency
Iterations



Use ML models to *estimate the actual data* and replace the ***Query Evaluation***

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Motivation

In the era of big data, exact analytical query processing is too "expensive".

Agarwal, Sameer, et al. "BlinkDB: queries with bounded errors and bounded response times on very large data." *Proceedings of the 8th ACM European Conference on Computer Systems*. ACM, 2013.

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Motivation

In the era of big data, exact analytical query processing is too "expensive".

A large class of analytical queries takes the form:

SELECT AF(**y**) FROM table

WHERE **x** BETWEEN lb AND ub

[GROUP BY **z**]

Such queries are very popular on emerging datasets/workloads: IoT, sensors, scientific, etc.

Approximate Query Processing

Targeting ***Analytical*** Queries **– why?**

Goal: fast data analytics over large volumes of data

Tradeoff: accuracy vs. latency **– why?**

Is an accurate response always necessary?

exploratory analytics, business intelligence, analytics for ML

Basic tool: sampling

Current Solutions

- Online Aggregations
- Data Sketches
- Sample-based Approaches (the dominating approach)

Uniform Sampling

Stratified Sampling

Hash Sampling

- Limited supported aggregate functions
- Still, very time-consuming
- Space Overhead – samples can be very large
- Support for join (multi-way)
- Support for nesting

Query-time sampling

Queries ***explicitly specify*** sample operations

Sample then execute query

Uniform sampling: may miss small groups
Distinct sampler: online sampling of distinct values

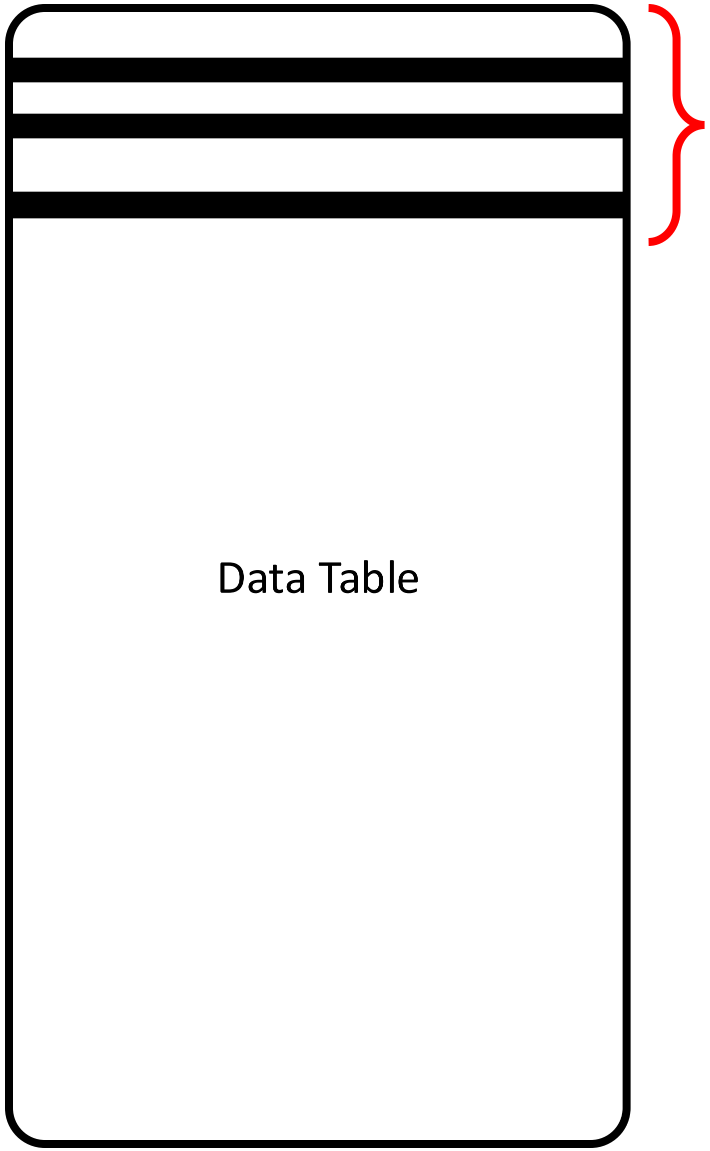
With joins: want to sample ***before*** joins not after **– why?**

Online aggregation

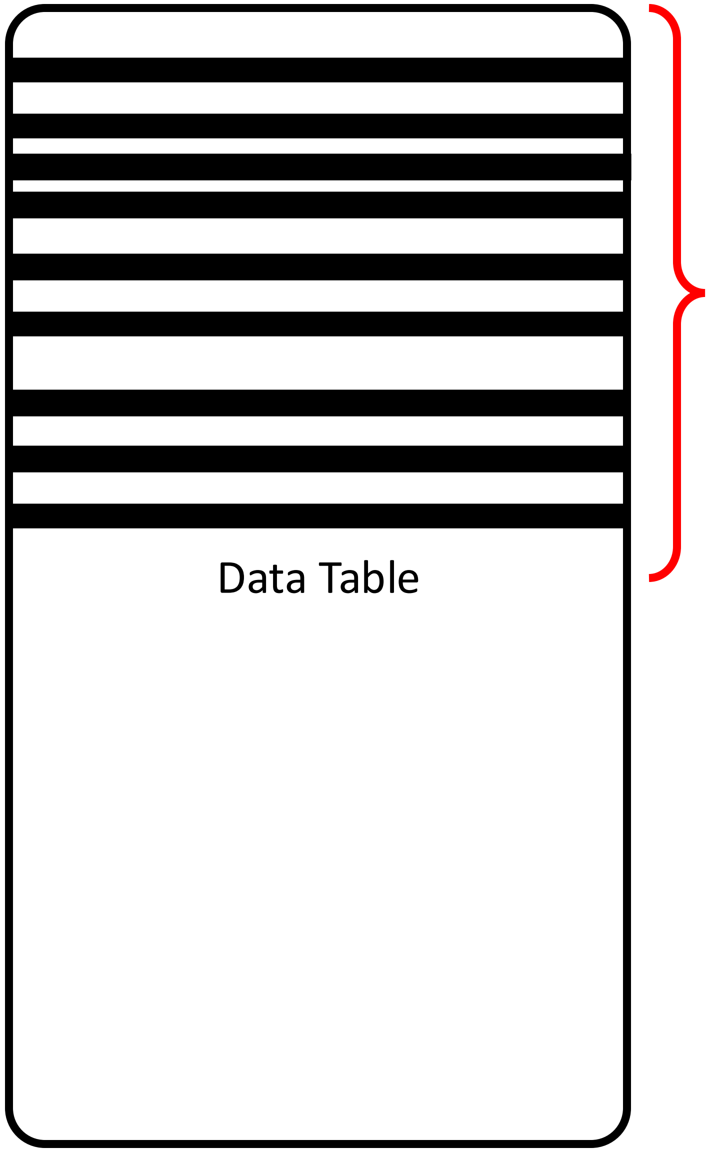
Execute query on growing random samples

Preliminary outputs are constantly updated **– which?**

- Query result
- Estimated error



expected mean: 1003
[990, 1020] with confidence 95%



expected mean: 1002
[995, 1007] with confidence 96%

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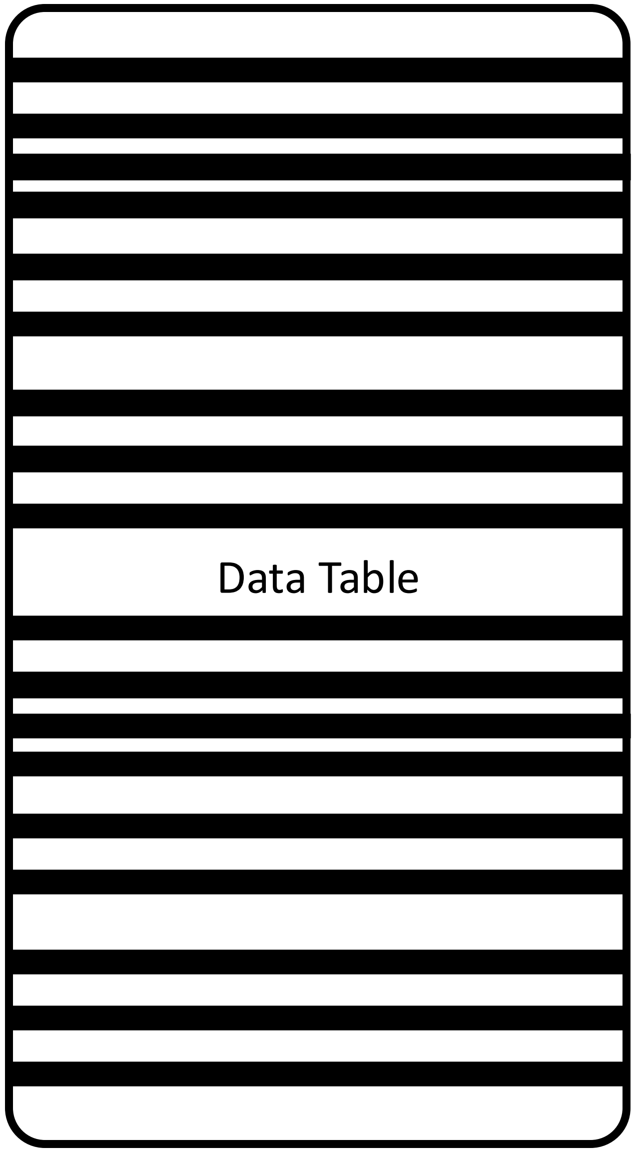

expected mean: 1001
[1001, 1001] with confidence 100%

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Online aggregation

Execute query on growing random samples

Preliminary outputs are constantly updated **– which?**

- Query result
- Estimated error

Hard to execute efficiently **– why?**

- Random sample → Random access
- Random samples might contain few rows that join
- Can be improved using join indices

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Queries on Pre-Computed Samples

Low latency because ***sampling cost*** is assumed ***offline***

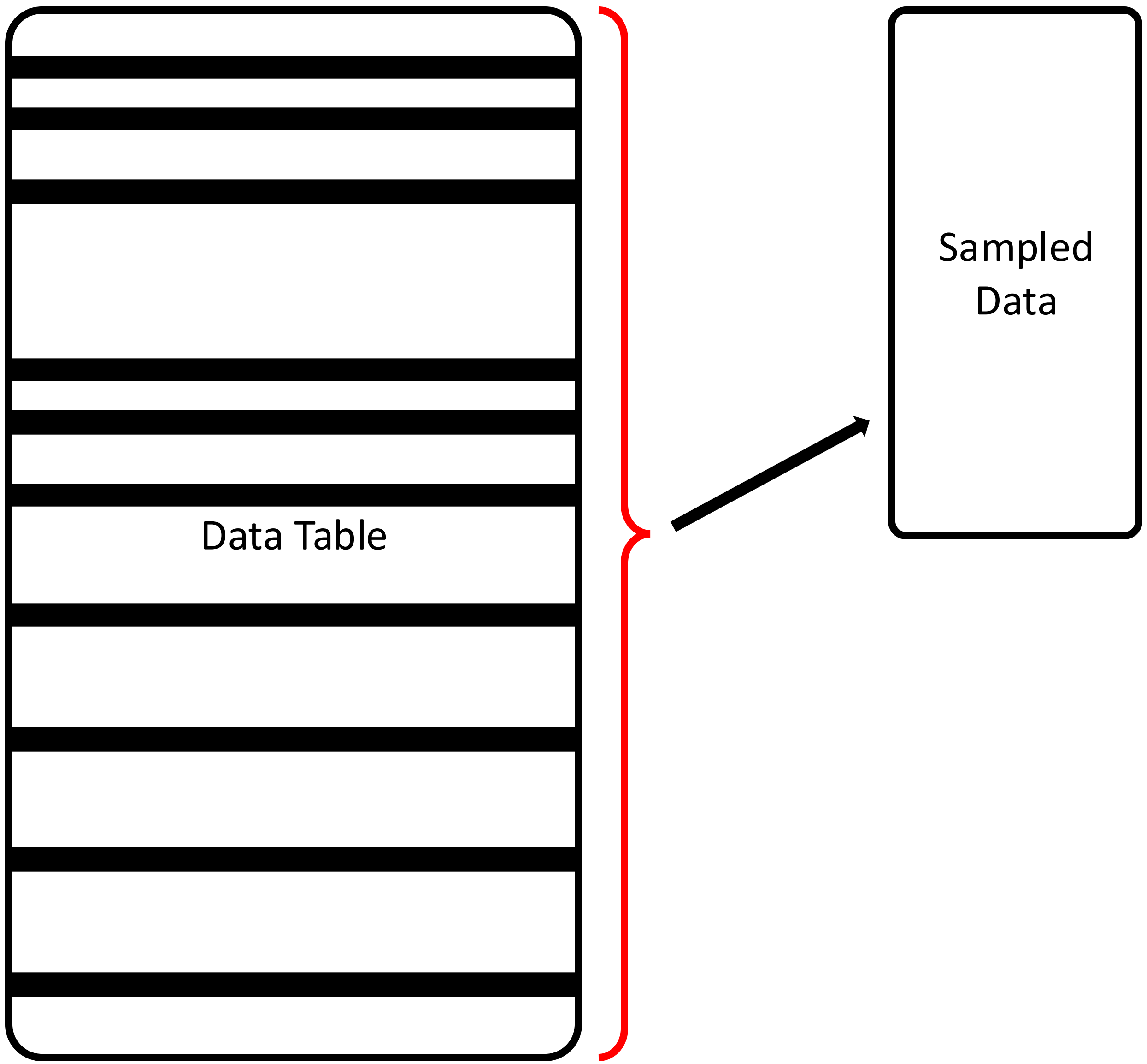
operate ***only on the sample***

Additional space (to keep sample)

Cannot provide fixed error bounds

Error bounds are data dependent (high variance = large error)

They can be arbitrarily large


Data Table
Sampled
Data

SQL additions

Aggregate is computed on a group

Group is defined based on certain columns

Extend specification with bounds

Error-bound query

```
SELECT count(*)
FROM Sessions
WHERE Genre=`western`
GROUP BY OS
ERROR WITHIN 10% AT CONFIDENCE 95%
```

Time-bound query

```
SELECT count(*)
FROM Sessions
WHERE Genre=`western`
GROUP BY OS
WITHIN 5 SECONDS
```

Offline vs online sampling

	Offline	Online
Assumption:	(partially) known workload	No assumption
Speedup:	High	Low

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Offline vs online sampling

	Offline	Online
Assumption:	(partially) known workload	No assumption
Speedup:	High	Low

Offline vs online sampling

	Offline	Online
Assumption:	(partially) known workload	No assumption
Speedup:	High	Low

Both are helpful:

- offline sampling is used for (partially) predictable workloads,
- online sampling is for the rest.

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DBEst: transparent AQP

Very small query execution times (e.g., ms),

With **small state** (memory/storage footprint) (e.g., KBs), and

High accuracy (e.g., a few % relative error)

***Regardless** of data **size**?*

YES! (for a large class of analytical queries)

- rests on simple SML models
- Built over samples of tables

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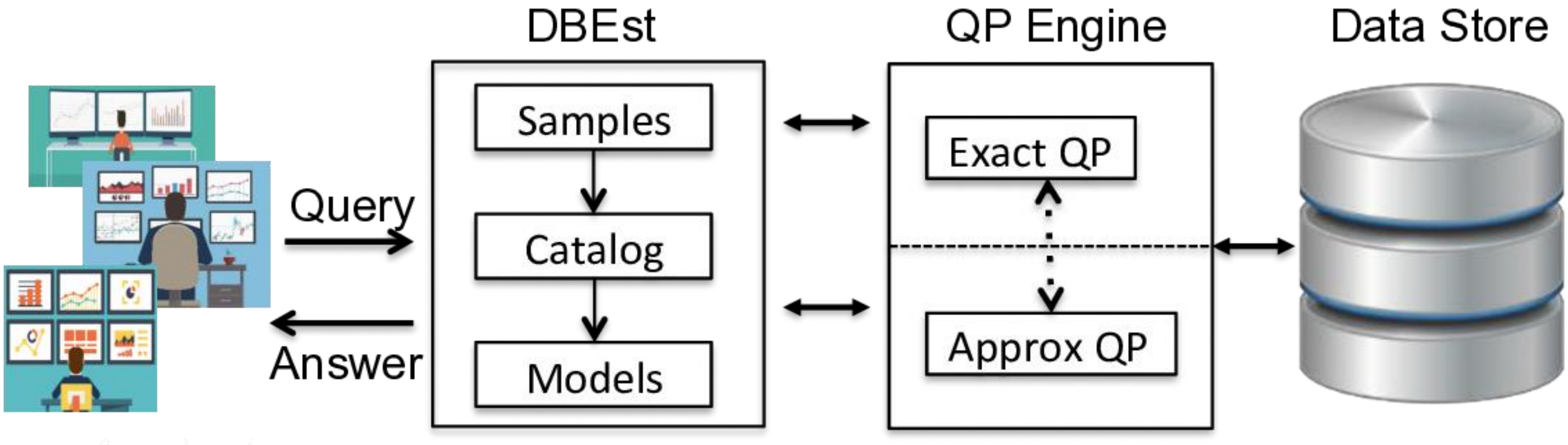
DBEst Contributions

DBEst shows that

- Models can be built over small samples
- Can generalize nicely, ensuring accuracy
- Model state is small (KBs)
- ***AQP over models is much faster than over samples***
- Model training overhead is acceptable – inline with sample generation.

DBEst Architecture



DBEst and ML models

*which **aggregate functions** are very **hard to answer** via **approximate** query processing?*

which are easy?

- Problem SQL query

  SELECT AF(**y**) from table

  WHERE **x** between *low* and *high*

  [GROUP BY **z**]

- What models?

Regression y=R(x)

- LR, PR...
- **XGBoost**, GBoost...

Density Estimator D(x)

- **Kernel Density**
- Nearest neighbor method
- Orthogonal series estimator

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Density Estimator

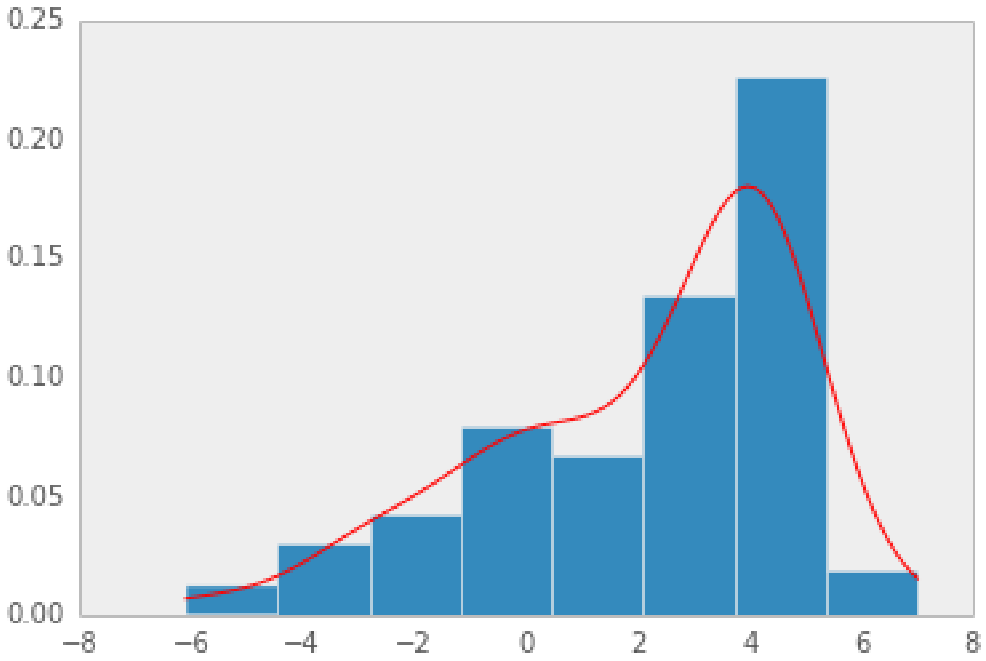

*image from wikipedia

Histograms is the simplest form of **density estimator**

DBEst is **gradually learning** a function
that **approximates** the **actual density** function of the data

e.g., “how many values exist between *low* and *hi*?”

Regression Model

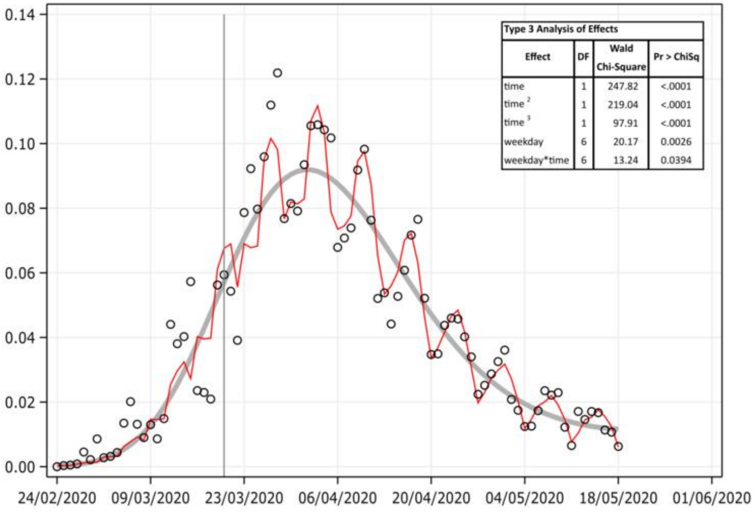

*image from wikipedia

A **regression model** describes the **relationship between two variables**
$y = F(x)$

DBEst uses a regression model to capture "matches" from selection

e.g., "which values of y exist for x between low and hi?"

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How to use regression and density estimation to answer queries?

```
SELECT count(*)
FROM Table
WHERE x between lb and ub
```

$$COUNT(y) \approx N \cdot \int_{lb}^{ub} D(x)dx$$

fraction of values in [lb,ub]

```
SELECT avg(y)
FROM Table
WHERE x between lb and ub
```

$$\begin{aligned} AVG(y) &= \mathbb{E}[y] \\ &\approx \mathbb{E}[R(x)] \\ &= \frac{\int_{lb}^{ub} D(x)R(x)dx}{\int_{lb}^{ub} D(x)dx} \end{aligned}$$

relationship of x values with y values

fraction of values in [lb,ub]

```
SELECT sum(y)
FROM Table
WHERE x between lb and ub
```

$$\begin{aligned} SUM(y) &= COUNT(y) \cdot AVG(y) \\ &\approx COUNT(y) \cdot \mathbb{E}[R(x)] \\ &= N \cdot \int_{lb}^{ub} D(x)dx \cdot \frac{\int_{lb}^{ub} D(x)R(x)dx}{\int_{lb}^{ub} D(x)dx} \\ &= N \cdot \int_{lb}^{ub} D(x)R(x)dx \end{aligned}$$

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How to use regression and density estimation to answer queries?

```
SELECT variance(y)
FROM Table
WHERE x between lb and ub
```

$$\begin{aligned} VARIANCE\_y(y) &= \mathbb{E}\left[y^2\right] - \left[\mathbb{E}\left[y\right]\right]^2 \\ &\approx \mathbb{E}\left[R^2(x)\right] - \left[\mathbb{E}\left[R(x)\right]\right]^2 \\ &= \frac{\int_{lb}^{ub} R^2(x)D(x)dx}{\int_{lb}^{ub} D(x)dx} - \left[\frac{\int_{lb}^{ub} R(x)D(x)dx}{\int_{lb}^{ub} D(x)dx}\right]^2 \end{aligned}$$

```
SELECT percentile(x,p)
FROM Table
```

PERCENTILE.

If the reverse of the CDF, $F^{-1}(p)$, could be obtained, then the p^{th} percentile for Column x is

$$\alpha = F^{-1}(p) \tag{5}$$

Note that $F^{-1}(p)$ is derived using $\mathrm{F(p)} = \int_{-inf}^{p} D(x)dx$

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More support on SQL

```
SELECT avg(y)
FROM Table
WHERE x1 between lb1 and ub1
  AND x2 between lb2 and ub2
```

$$
\begin{aligned}
AVG(y) &= \mathbb{E}[y] \\
&\approx \mathbb{E}[R(x_1, x_2)] \\
&= \frac{\int_{lb_1}^{ub_1} \int_{lb2}^{ub2} D(x_1, x_2) R(x_1, x_2) dx_2 dx_1}{\int_{lb_1}^{ub_1} \int_{lb_2}^{ub_2} D(x_1, x_2) dx_2 dx_1}
\end{aligned}
$$

Supporting GROUP BY

- build models for each group by value,
- create **model bundles**:
  - E.g., each bundle stores ~500 groups
  - Store bundles in, say, an SSD (~100 ms to deserialize and compute AF on bundle).

Supporting join

- Join table is flattened -> make samples -> build models.

Limitations

- Group By Support ->too many groups
  - Model Training time ↑, Query Response time ↑, space overhead ↑.
- No error guarantee

DBEst Summary

- DBEst: a model-based AQP engine, using simple SML models:
  - Much smaller query response times
  - High(er) accuracy
  - Much smaller space-time overheads
  - Scalability
- Ensuring high accuracy, efficiency, scalability with low money investments -- resource (cpu, memory/storage/ network) usage.
- Future work: more efficient support for
  - Joins
  - Categorical attributes
  - Improved parallel/distributed DBEst

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A perspective on ML in Database Systems

from: ML-In-Databases: Assessment and Prognosis, IEEE Data Engineering Bulletin

New *Forces*

(1) End-user want to

democratize data (all business units to have access to all data)

make data-driven decisions (often in real time)

(2) New applications

structured query processing (SQL) + natural language processing (NLP) + Complex Analytics (exploratory + predictive ML)

New *Forces*

(3) Data integration

diverse and inconsistent datasets are combined in common data repositories (data lakes)

(2) New hardware + the move to the cloud

moving from full ownership to pay-as-you-go

self-tuning systems *en masse* in the cloud (as we discussed today)

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Consequences and New Directions

Storage ***hierarchy*** is still relevant, but the layers are elastic (in the cloud)

ML models can be deployed at-will as "functions"

New push for ***serverless computing***

use only services and not rent an entire server

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CS 561: Data Systems Architectures

class 22

Machine Learning & Data Systems

Prof. Manos Athanassoulis

https://bu-disc.github.io/CS561/

DBEst experiments

Evaluation

systematically showing sensitivities on

- range predicate selectivity + sample sizes + AFs

Performance under Group By and Joins

Comparisons against

- State of the art AQP (VerdictDB and BlinkDB)
- State of the art columnar DB (MonetDB)

Using data from TPC-DS and 3 different UCI-ML repo datasets.

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Experimental Setup

Ubuntu 18.04 with Xenon X5650 12-core CPU, 64 GB RAM And 4TB SSD

Datasets: TPC-DS, Combined Cycle Power Plant (CCPP), Beijing PM2.5

Query types:

- Synthetic queries: 0.1%, 1%, to 10% query range
- Number of queries: vary between 30 to1000 queries.
- Complex TPC-DS queries: Query 5, 7, and 77.

Compared against VerdictDB, BlinkDB and MonetDB, for error

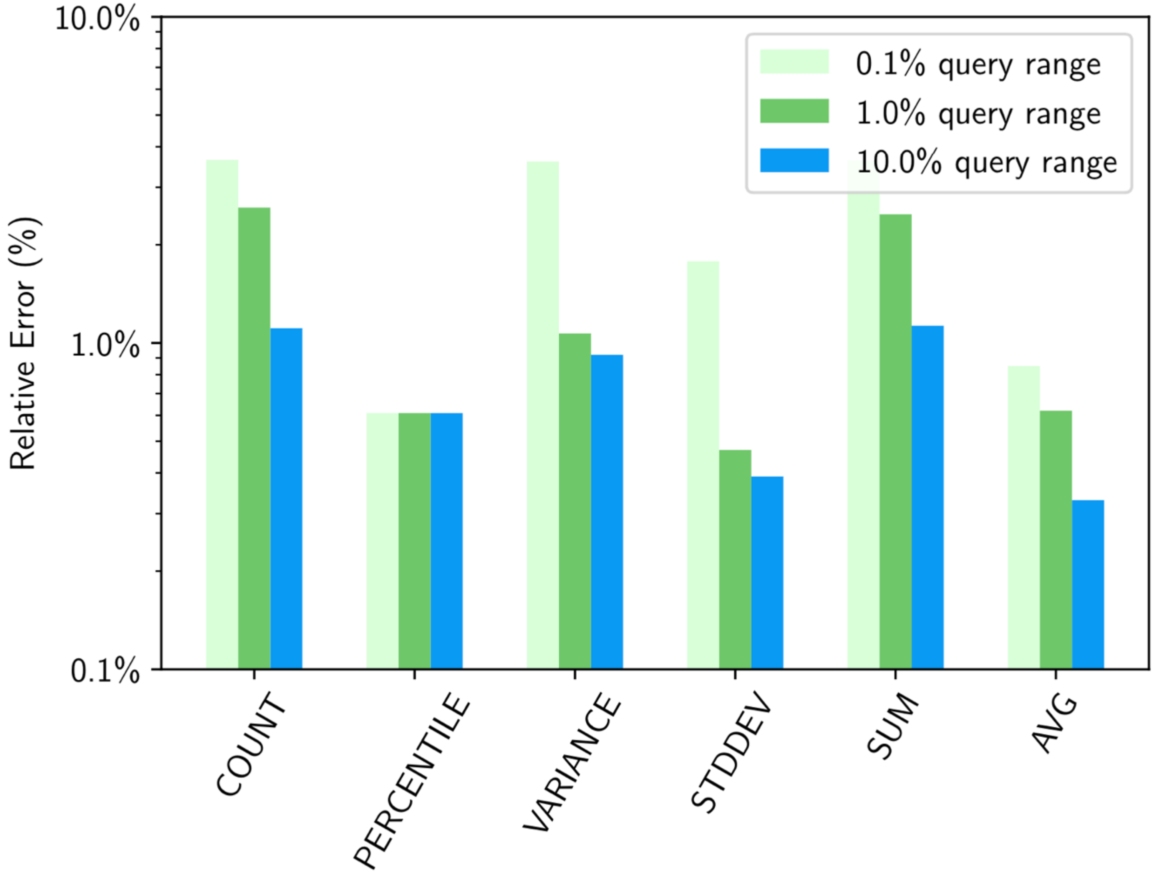
- VerdictDB uses 12 cores while DBEst runs on 1 core. (Multi-threaded DBEst is also evaluated)

Report execution times + system throughput for the parallel version

Report performance of joins and group by

Performance – Sensitivity Analysis
Query range effect

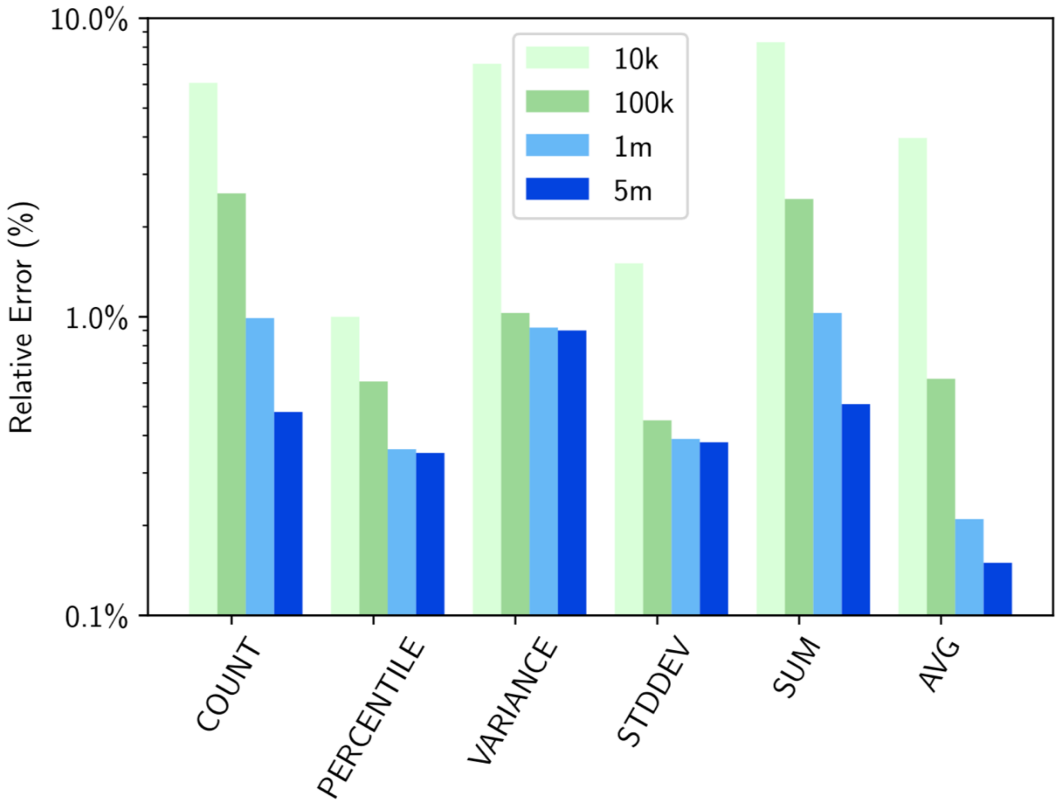
Dataset: TPC-DS
Sample size: 100k
540 synthetic queries
Column pair:
[ss_list_price, ss_wholesale_cost]



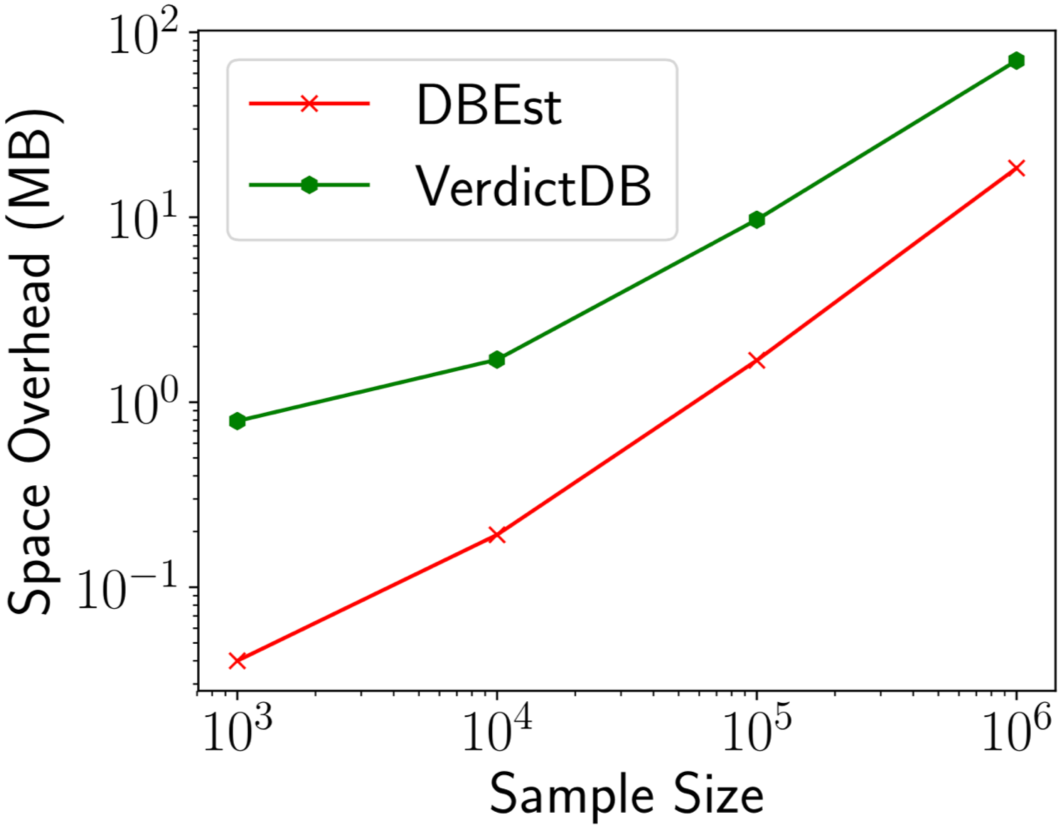
Influence of query range on relative error

Performance – Sensitivity Analysis
Sample size effect

Dataset: TPC-DS
Query range: 1%
1200 synthetic queries
Column pair:
[ss_list_price, ss_wholesale_cost]



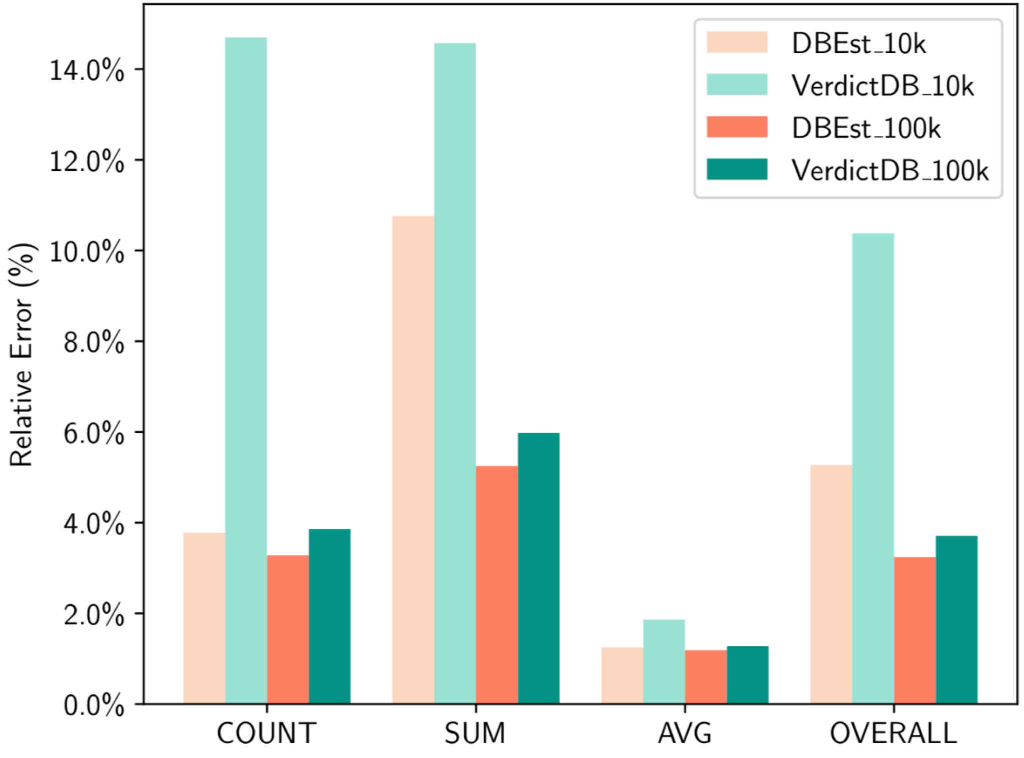
Influence of sample size on relative error



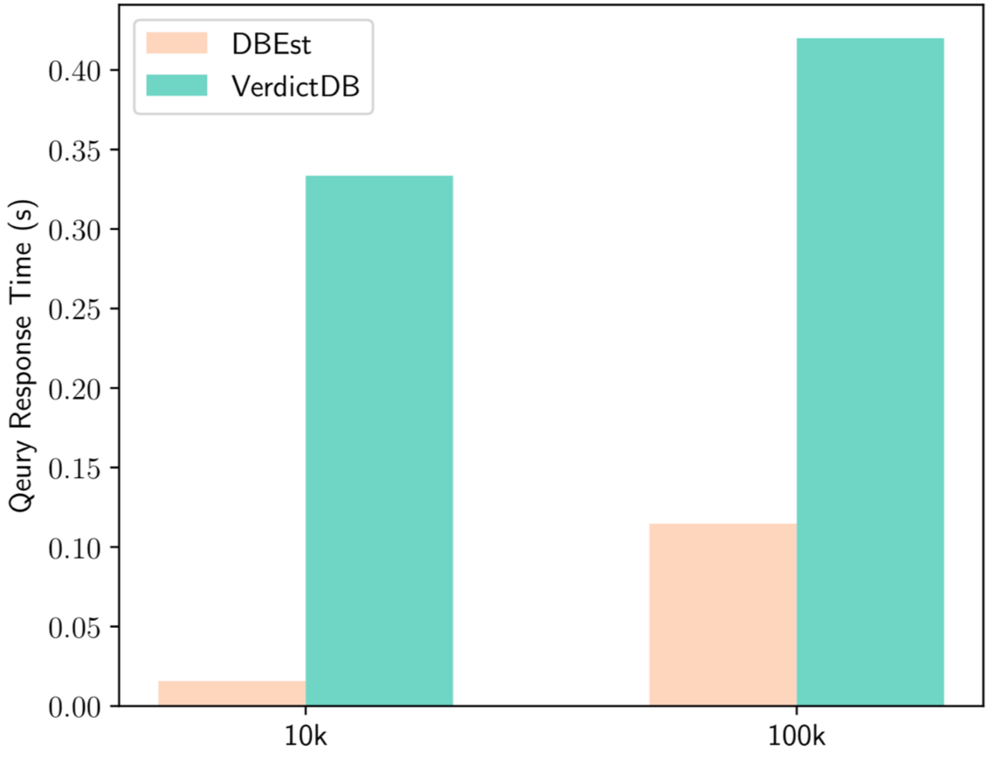
Influence of sample size on space overhead

Performance Comparison
TPC-DS dataset

Query range: 0.1%, 1%, 10%
~100 queries, involving 16 column pairs.
Sample size: 10k, 100k



Relative Error: DBEst vs VerdictDB



Query Response Time: DBEst vs VerdictDB

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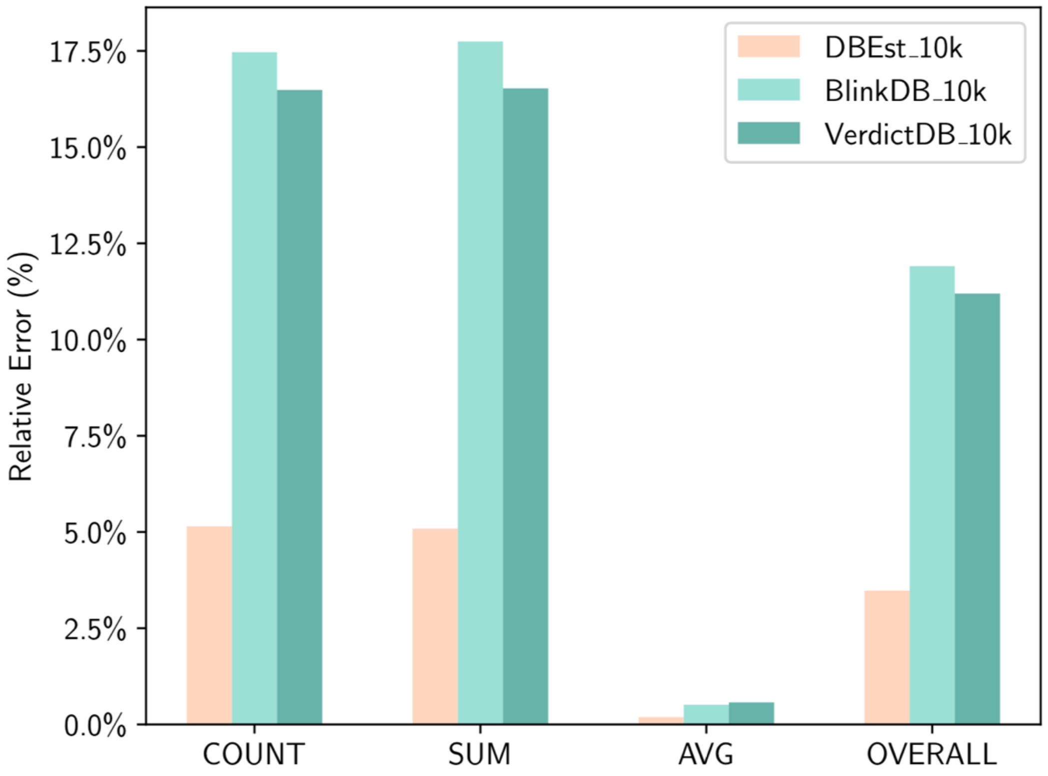
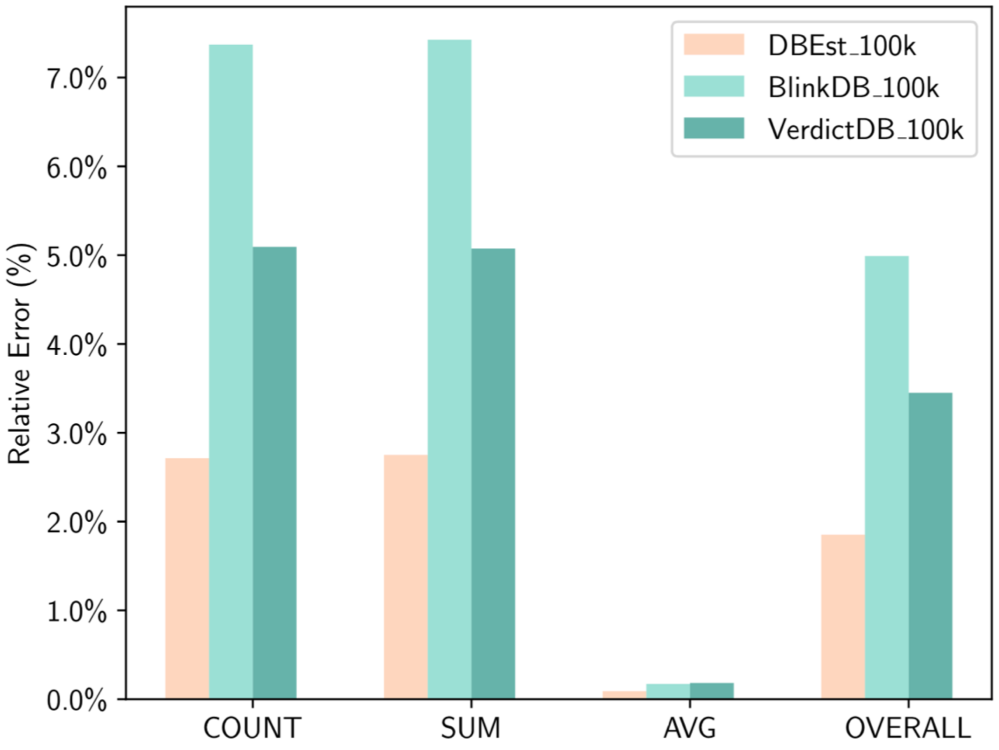
Performance Comparison
CCPP dataset

2.6 billion records, 1.4TB
Query range: 0.1%, 0.5%, 1.0%
108 queries, involving 3 column pairs.
Sample size: 10k, 100k



Relative error (10k sample)

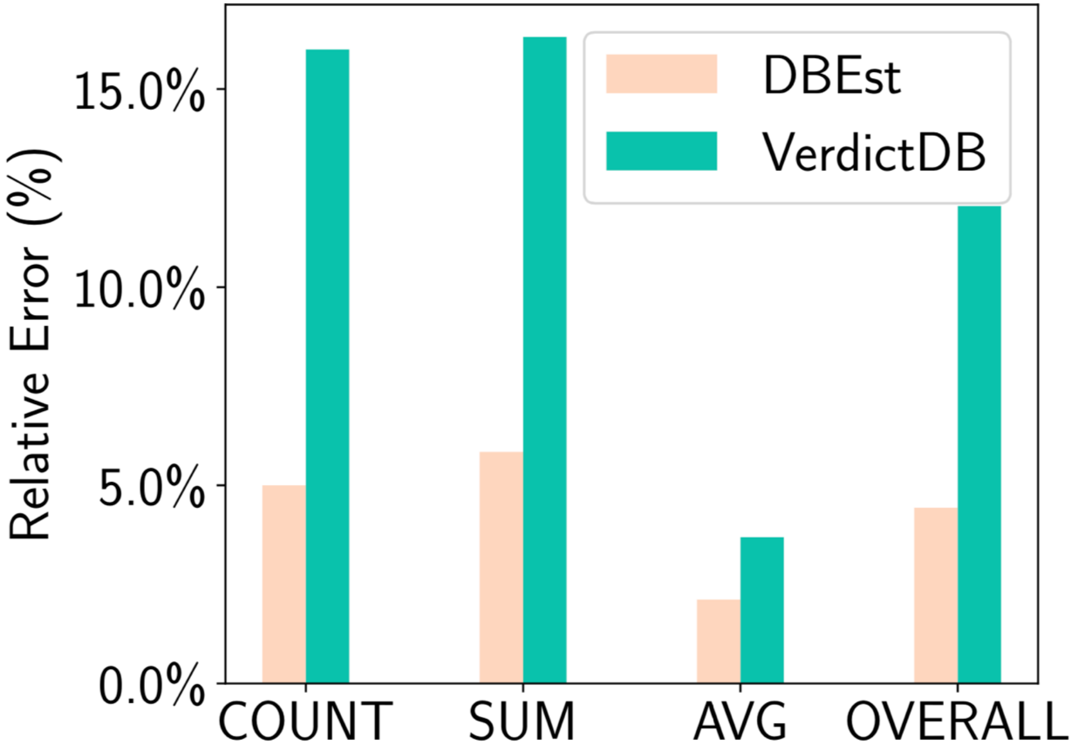


Relative error (100k sample)

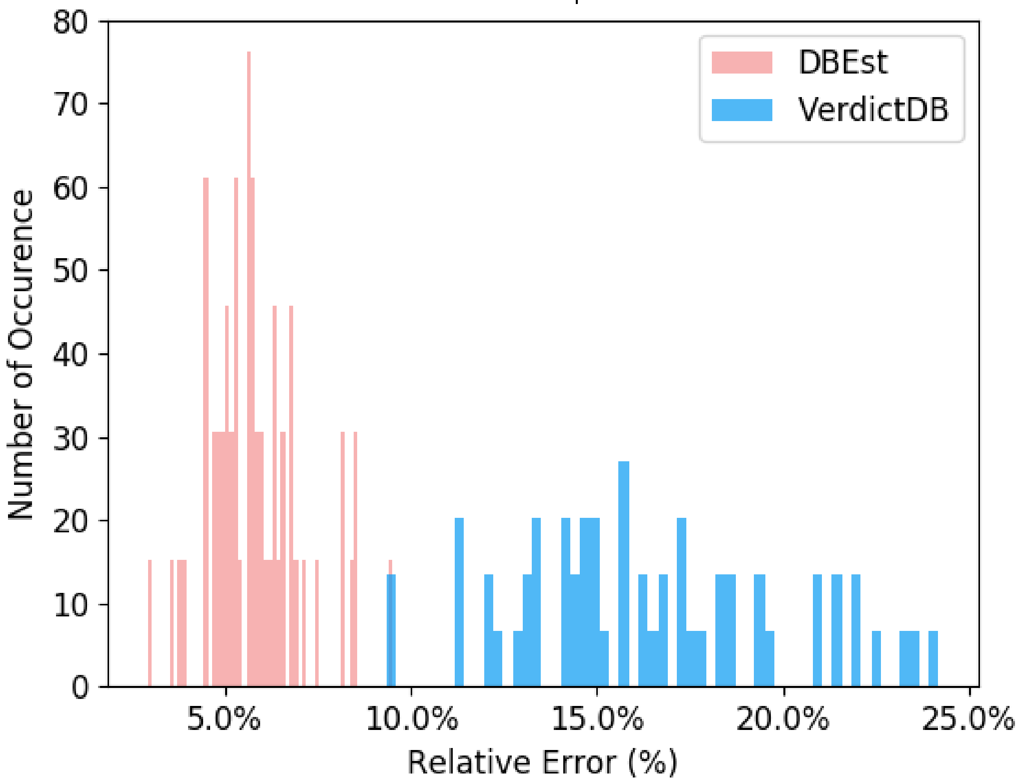
Performance Comparison Group By

SELECT AF(ss_list_price)
FROM store_sales
WHERE ss_wholesale_cost_sk …
GROUP BY ss_store_sk

- 90 queries, 57 groups
- Sample size: 10k



Relative error for group by queries



Accuracy histogram for SUM

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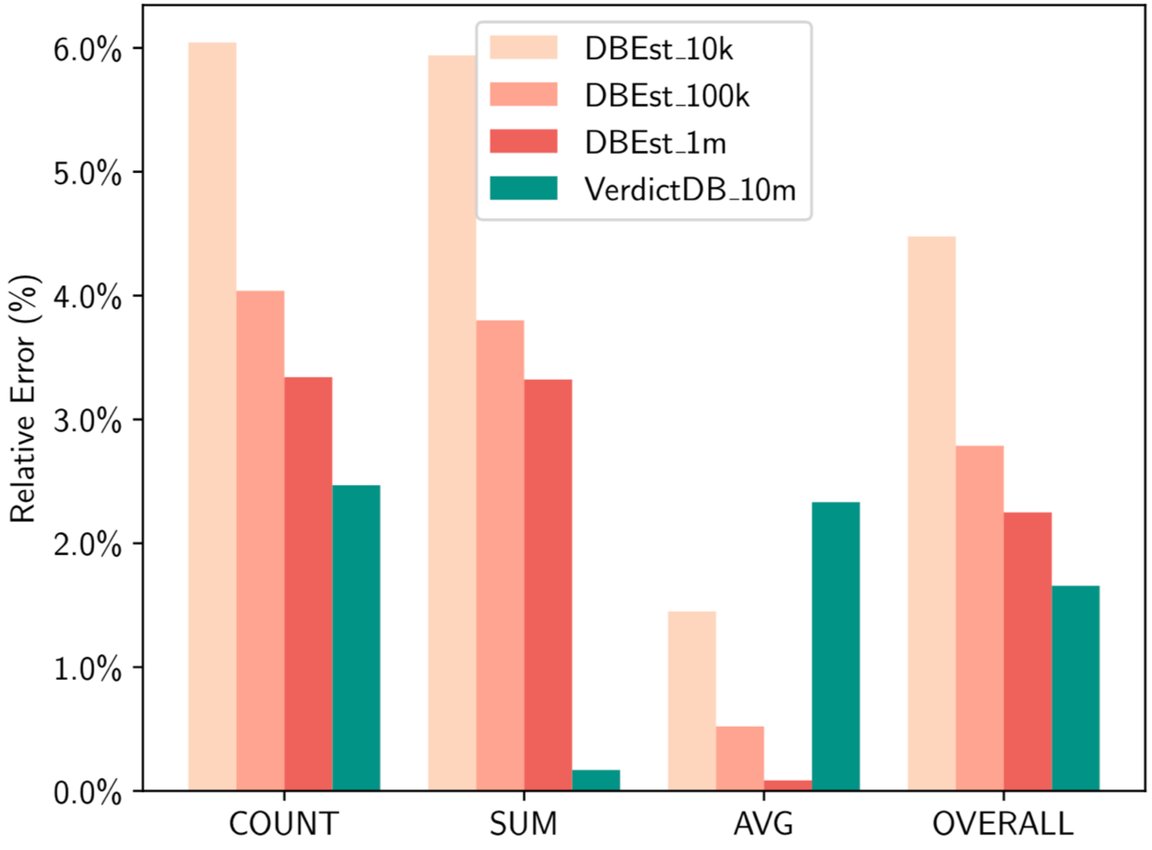
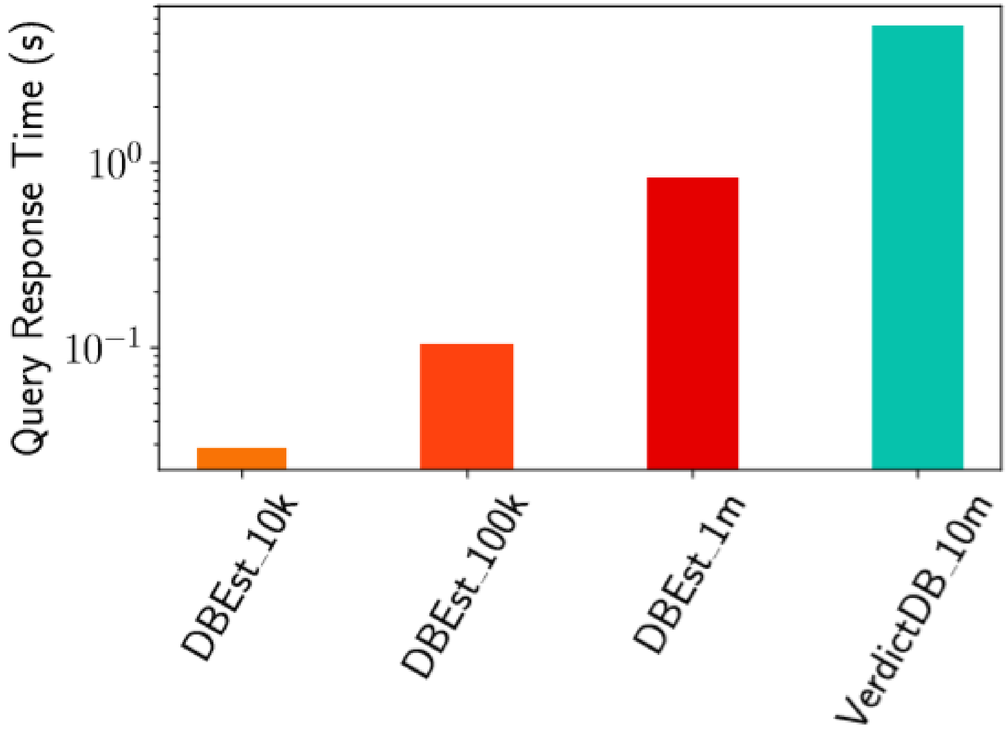
Performance Comparison Join

SELECT AF(ss_wholesale_cost), AF(ss_net_profit)
FROM store_sales, store
WHERE ss_store_sk=s_store_sk
AND s_number_of_employees BETWEEN ...

- 42 queries.



Join accuracy comparison for the TPC-DS dataset



Query response time (s) for the TPC-DS dataset

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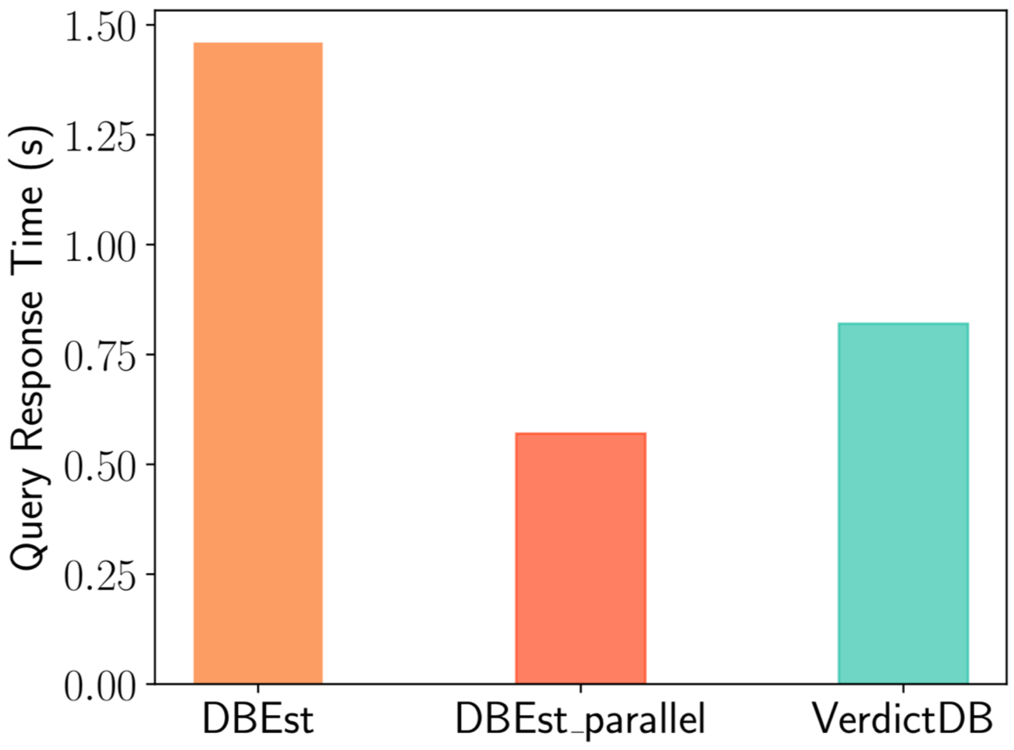
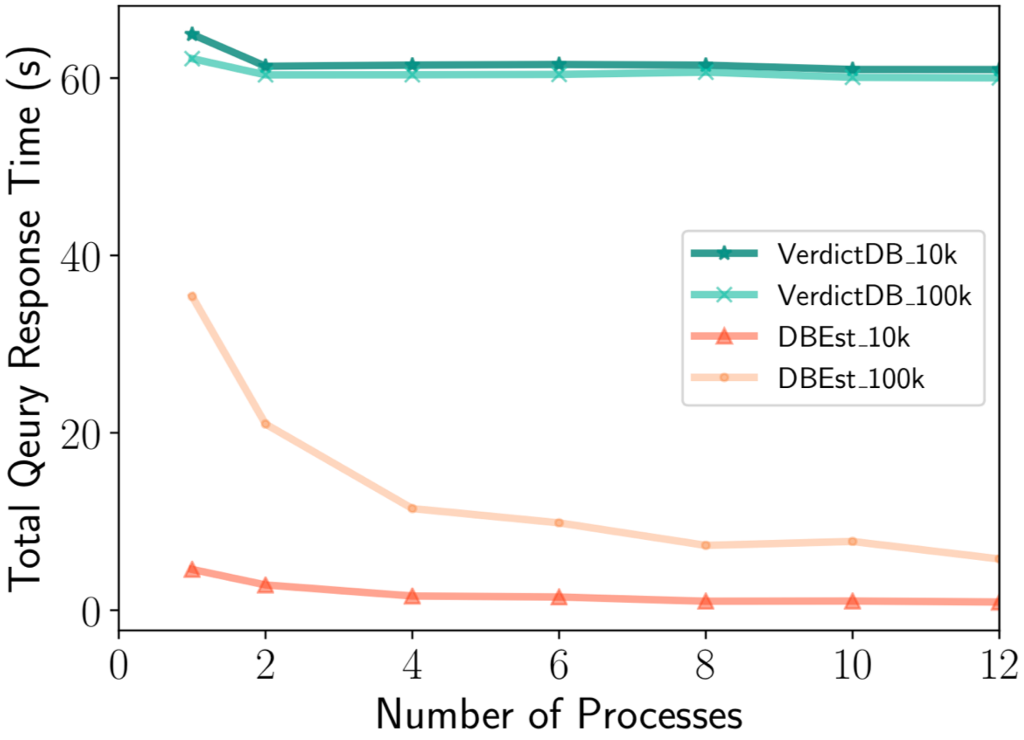
Parallel Query Execution

1 core versus 12 cores



Group by query response time reduction (TPC-DS)



Throughput of parallel execution (CCPP)

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