Towards Query Optimizer as a Service (QOaaS) In a Unified Lakehouse Ecosystem:

Can One QO Rule Them All?

Presenter: Yuanyuan Tian

Gray Systems Lab (GSL), Microsoft

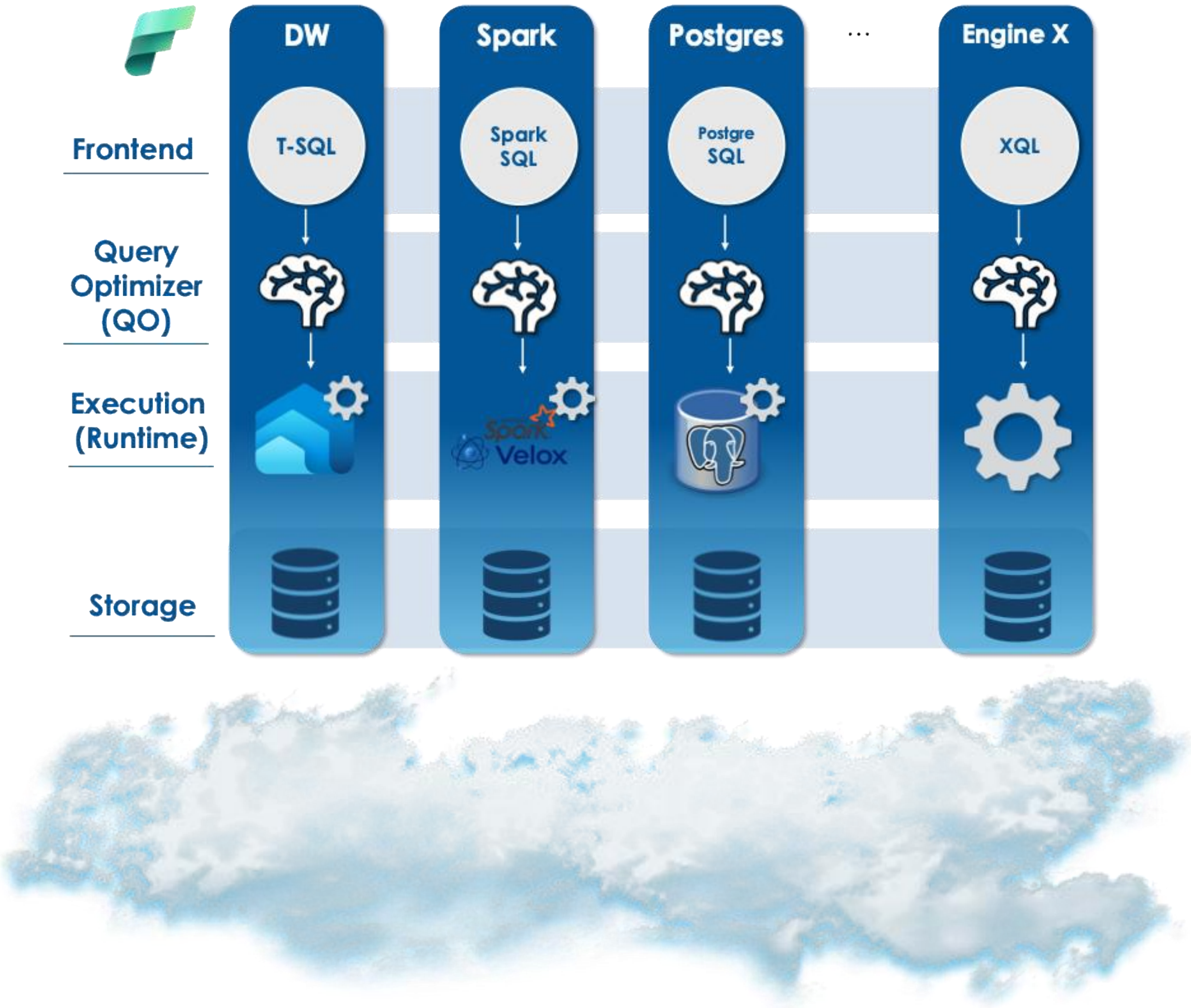
GSL: Rana Alotaibi*, Stefan Grafberger*, Nicolas Bruno, Brian Kroth, Sergiy Matusevych, Ashvin Agrawal, Carlo Curino
Fabric DW: Jesus Camacho-Rodríguez, Cesar Galindo-Legaria, Milind Joshi, Milan Potocnik, Beysim Sezgin, Xiaoyu Li
Fabric Spark: Mahesh Behera, Ashit Gosalia

Industry Trends

Demand: Fragmentation → Convergence

Microsoft Fabric

- Shared Data on Lake
- Shared Compute Resource
- Shared Governance Experience



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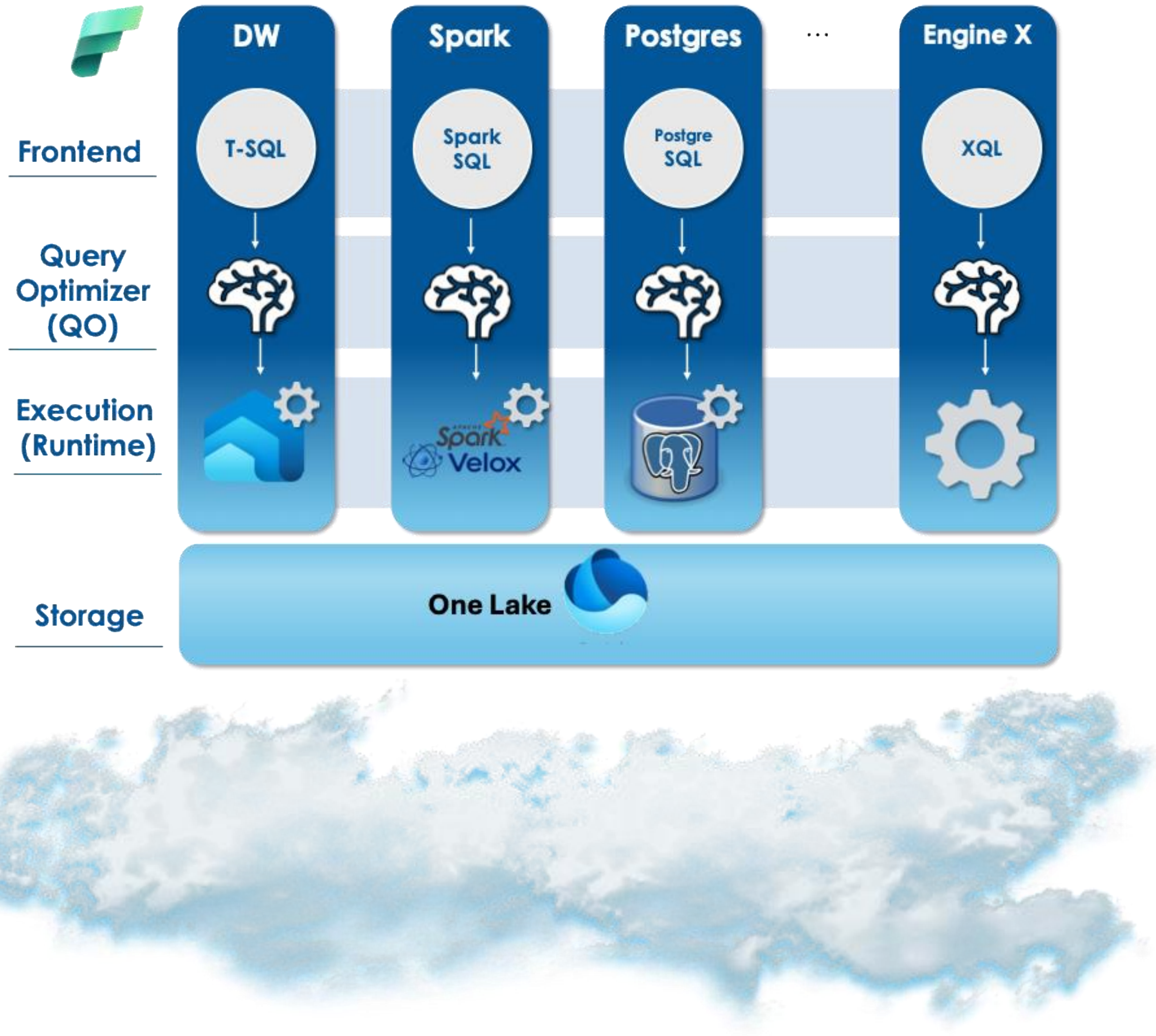

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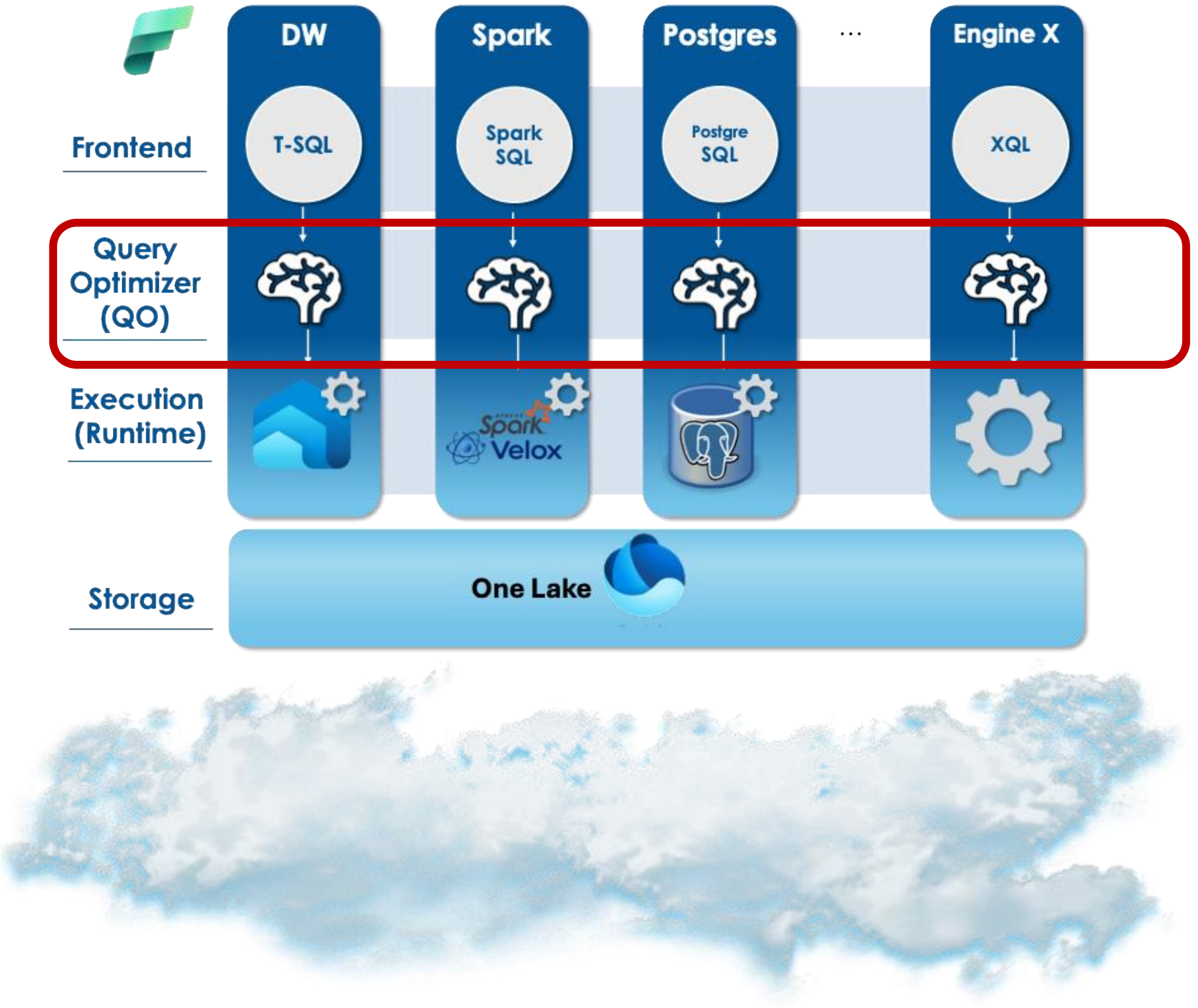
Architecture: Monolithic → Composable

- Cloud DB: separation of storage from compute
- Open standards
  - Parquet, Arrow, Substrait
- OSS system-building libraries
  - Calcite, Orca, Velox, Datafusion



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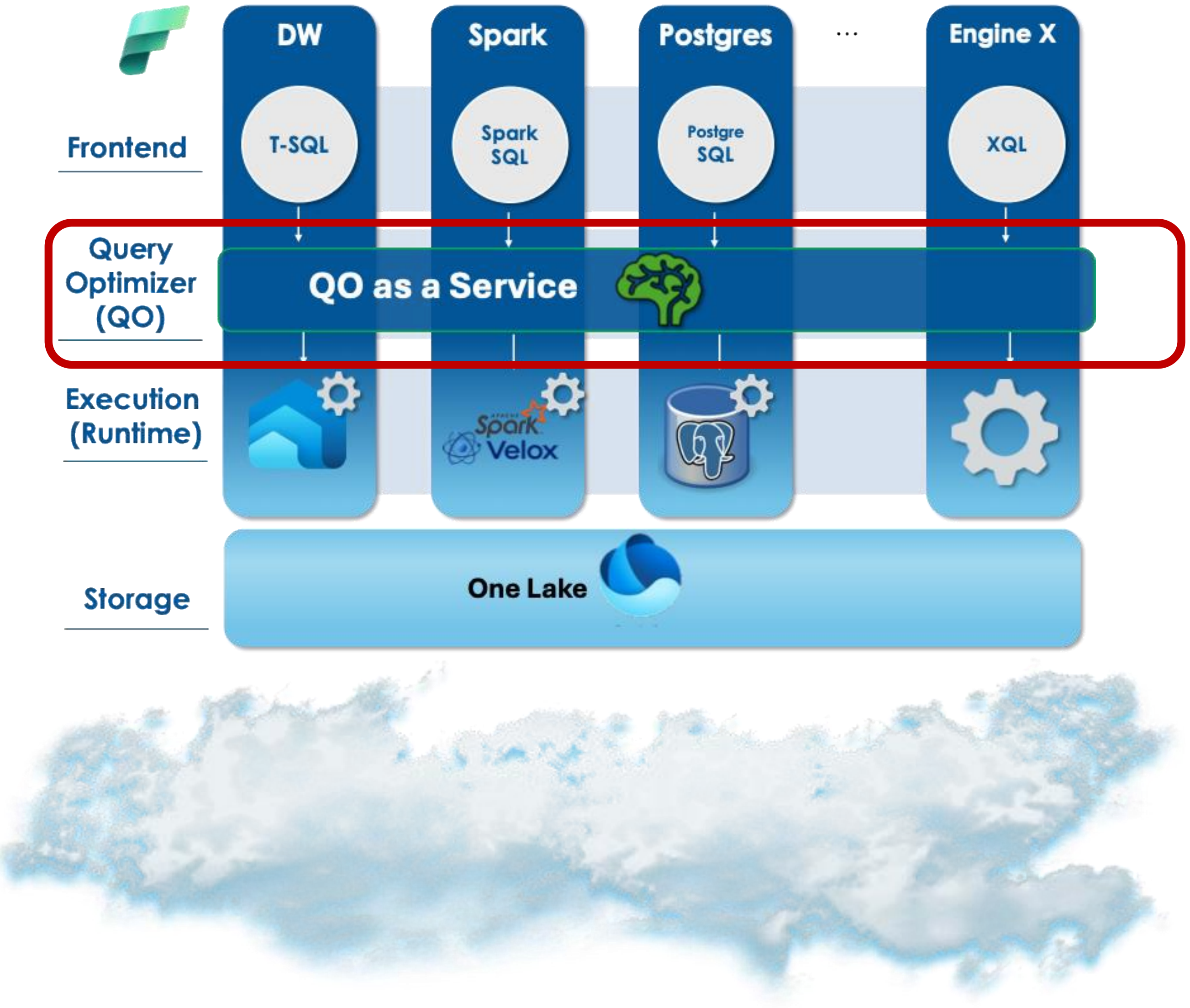
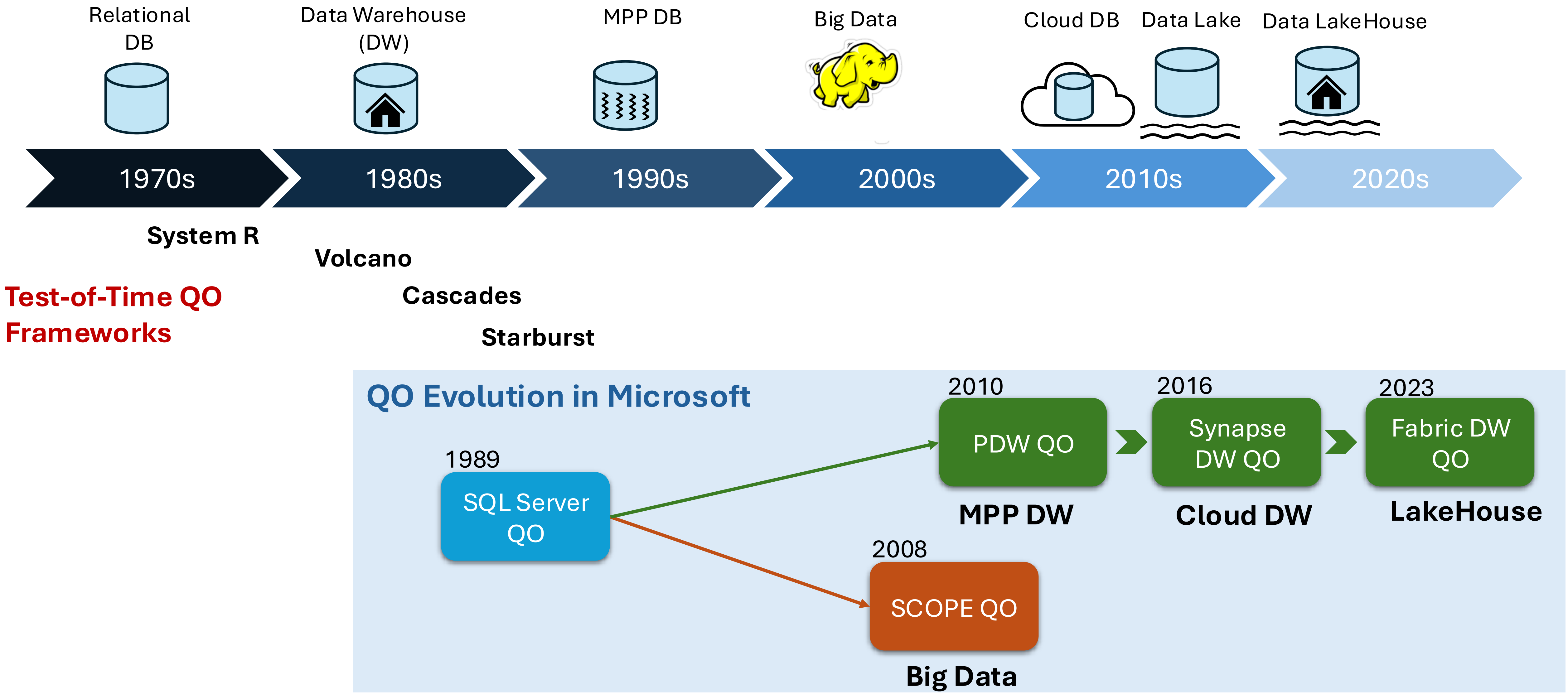


Some Relevant Context

Relational DB & QO History



QO Status Quo: Reinventing Wheels

A proliferation of analytical engines with their own QOs following similar patterns

- Same relational algebra, similar search spaces, and same stages

Parsing/ Algebrization → **Simplification/ Normalization** → **Exploration (CBO)** → **Post-optimization**

Parsing/ Algebrization

- AST → algrebraic tree
- Name resolution
- Type inference

Simplification/ Normalization

- Iteratively apply transformation rules
- E.g. filter push-down, constant folding, decorrelation, etc

Exploration (CBO)

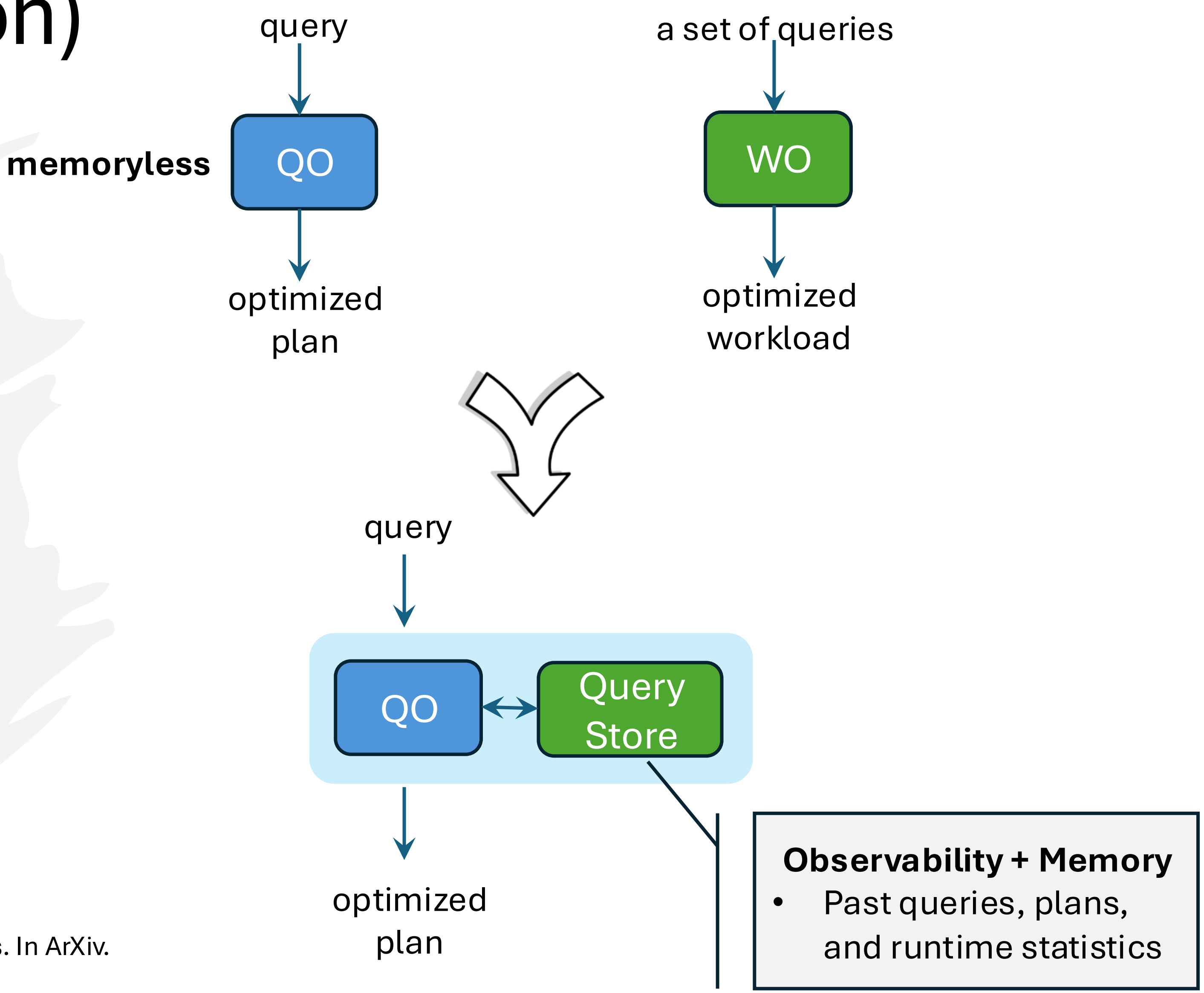
- Cost-based exploration
  - search space
  - enumeration strategy
    - DP or MEMO
  - cost model

Post-optimization

- Peephole transformations on the final plan

A Practical QO Trend: Convergence of QO with WO (Workload Optimization)

- Adding workload insight into QO
  - SQL Server
    - Query Store: monitors the performance of query to detect plan changes and regressions
  - Oracle:
    - SQL Plan Management: keep track of a set of valid plans for a query



[1] Yuanyuan Tian 2025. Query Optimization in the Wild: Realities and Trends. In ArXiv.

About Learned QO

- All learned QO approaches are essentially WO
  - Rely on the fact: Queries are often recurrent and similar
  - Learning from the past to improve the future

“Pacemaker” is easier to adopt than a “heart transplant”!

- Complexity
- Explainability
- Debuggability
- Regression
- Training & inference Cost

Industry

Coming Back to QOaaS

QOaaS

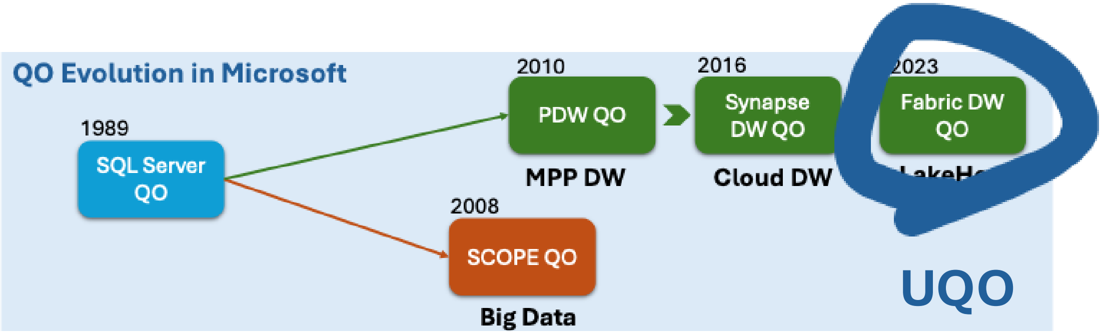
- Independent QO service interacting with multiple engines over RPC

Focus: for *analytical* engines in a *unified Lakehouse* ecosystem, e.g. Microsoft Fabric

Features	Custom QO	QO as a Library (Calcite, Orca)	QOaaS
Innovation speed	✗	✓	✓
Engineering efficiency	✗	✓	✓
New engine time-to-market	✗	✓	✓
QO scalability	✗	✗	✓
Workload Observability	✗	✗	✓
Workload Optimization	✗	✗	✓
Cross-engine optimization	✗	✗	✓

Steps Towards QOaaS

- Building on our own experience
  - Developing Calcite
  - Evolving Cascades framework within Microsoft
- Initial focus
  - Two engines: DW and Spark on Fabric Ecosystem
  - Adapting UQO (Fabric DW QO) to QOaaS
- Key Challenges:
  - **CH1: Exchanging plans in and out of QO**
  - **CH2: Adapting UQO for different engines**
  - **CH3: Adjusting the cost model**



CH1: Standardizing Plan Specification

- **Substrait**: open-source, *cross-language* plan specification for relational algebra
    - Various serialization formats
    - Extensibility for custom operations
    - Ecosystem for libraries and toolings

Substrait

- Making Substrait as the cross-engine plan specification on Fabric
    - Ongoing collaborative effort across GSL, DW, Spark, and Power BI
    - Current coverage: TPC-H, TPC-DS, internal workloads

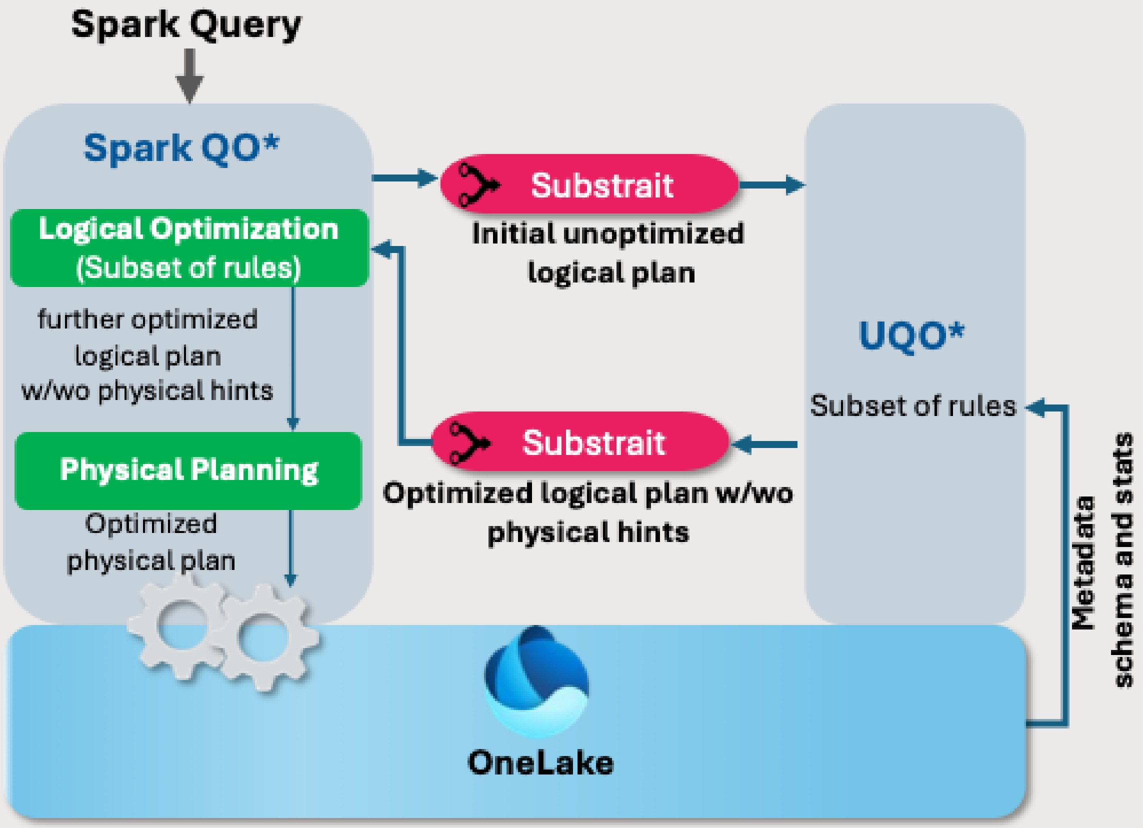
CH2: Can UQO optimize Spark Queries?

Spark QO	UQO
• Mostly non-CBO • CBO only applies to join ordering and broadcast-vs-shuffle join decision	• Full-stack Cascades framework with 255 CBO rules • Sophisticated cost model

Naïve replacement won't work!

- **Physical Operator Gaps**
  - Some Fabric DW physical operators are unsupported in Spark
    - Example: nested loop join
- **Feature Support Disparities**
  - UQO cannot fully exploit Spark-specific features
    - Example: Hive-style partitioning

A Simple QOaaS Prototype

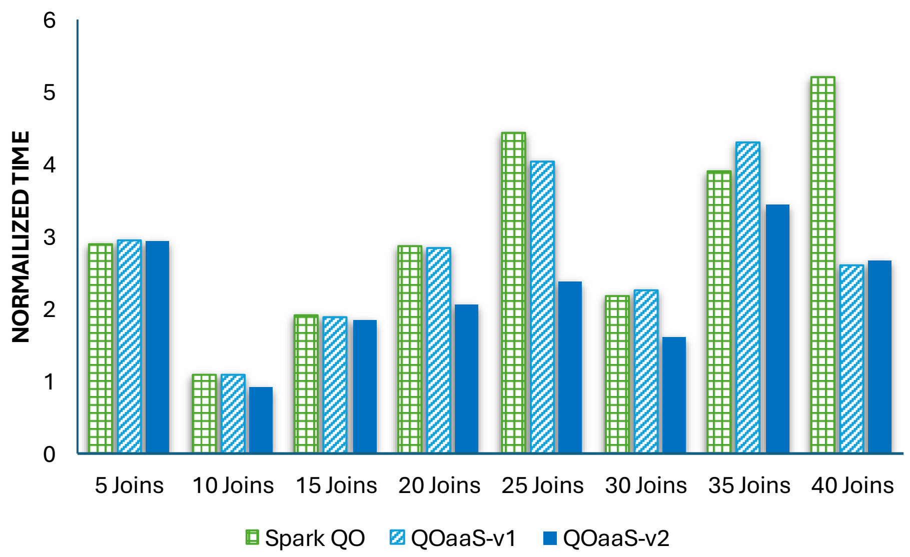


- **UQO***
  - Not generating unsupported operators in Spark
- **Spark QO***
  - Only include Spark specific optimization rules lacking in UQO

	UQO*	Spark QO*
QOaaS-v1	logical optimization	further optimization + physical implementation
QOaaS-v2	logical + physical optimization	further optimization + physical implementation based on hints from UQO*

Performance Study

MSSales Workload
- 627 tables on OneLake (5TB, delta parquet)
- Highly templatized queries, join heavy



Takeaway
- UQO-based QOaaS looks promising!
- QOaas-v2 performs better than QOaaS-v1

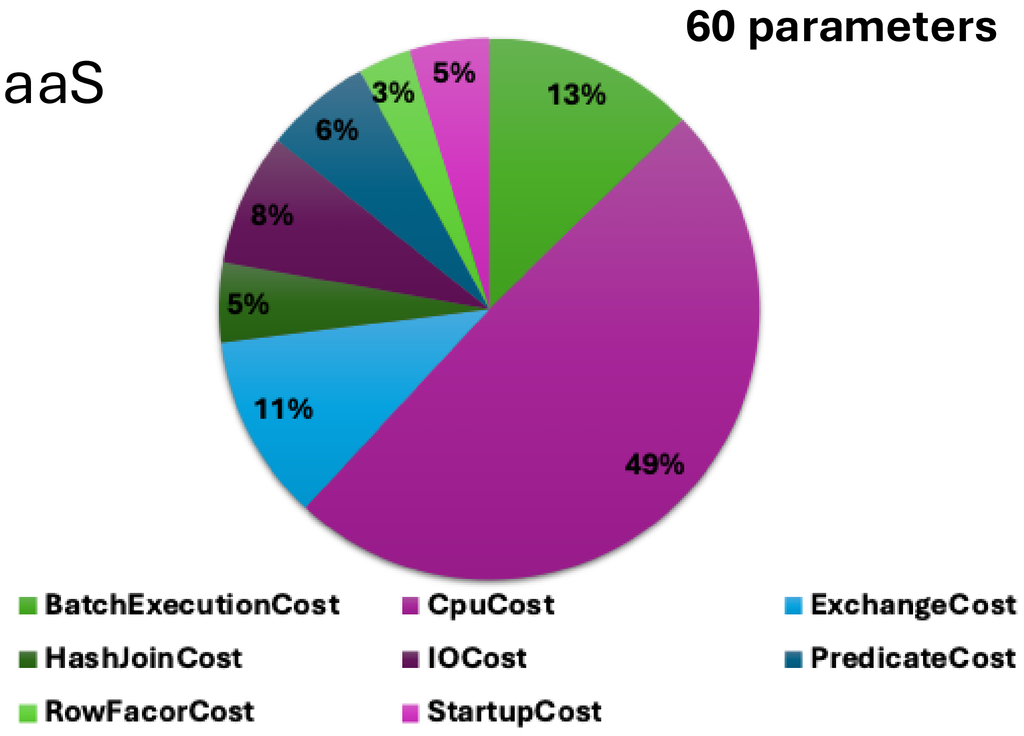
TPC-H SF1000 (1TB)

- QOaaS-v2 is comparable to SparkQO
  - Average diff <6%
- Q5 is 1.5x slow
  - Not fully utilizing Bloom filters

- Adding optimizations retroactively is suboptimal, all optimization opportunities should be explored!

CH3: Recalibrating and Tuning the Cost Model

- A fixed cost model is unlikely to work for QOaaS
- 1st attempt: changing cost model without rewrite
  - Recalibrating and tuning *constant parameters* in UQO's cost formula
  - MLOS [2] : OSS ML-powered tuner



[2] MLOS. https://github.com/microsoft/MLOS

Performance Study

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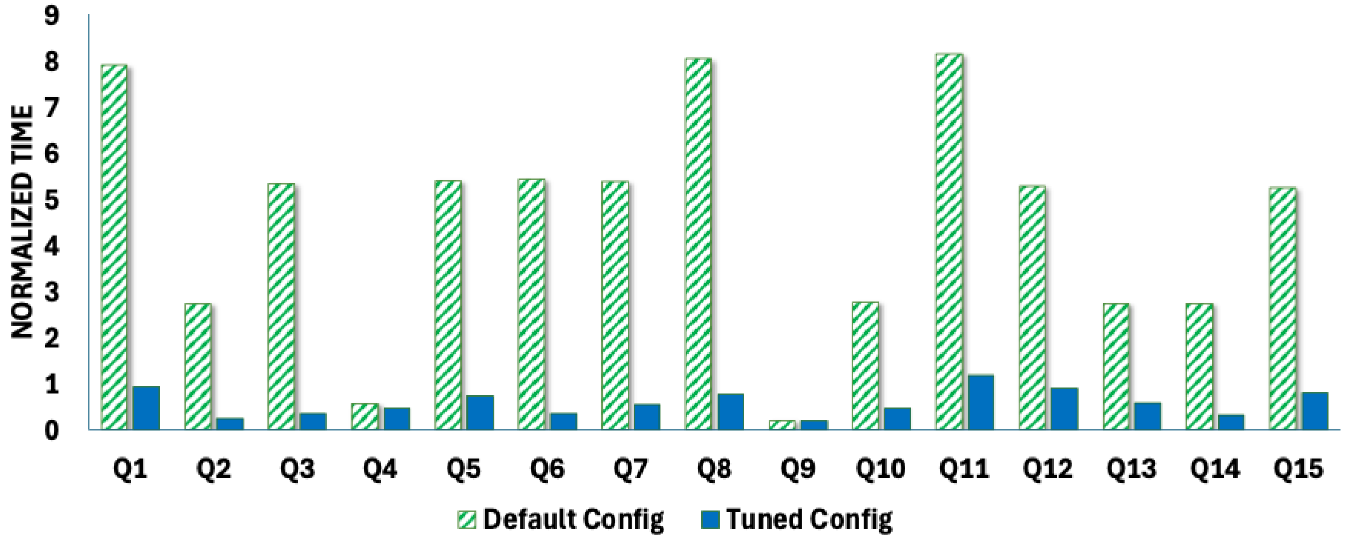
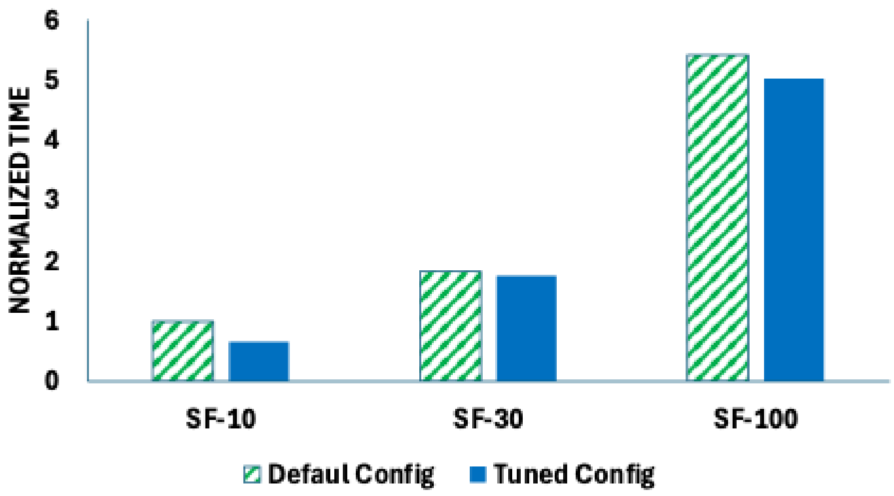


TPC-H



Observation

- Really encouraging results for cost model tuning!
- Tuned parameters are not transferrable!
  - Overfitting to a workload → a benchmark workload with coverage of all operators
  - Interplay with cardinality estimation errors → injecting true cardinality leveraging prior work [3]

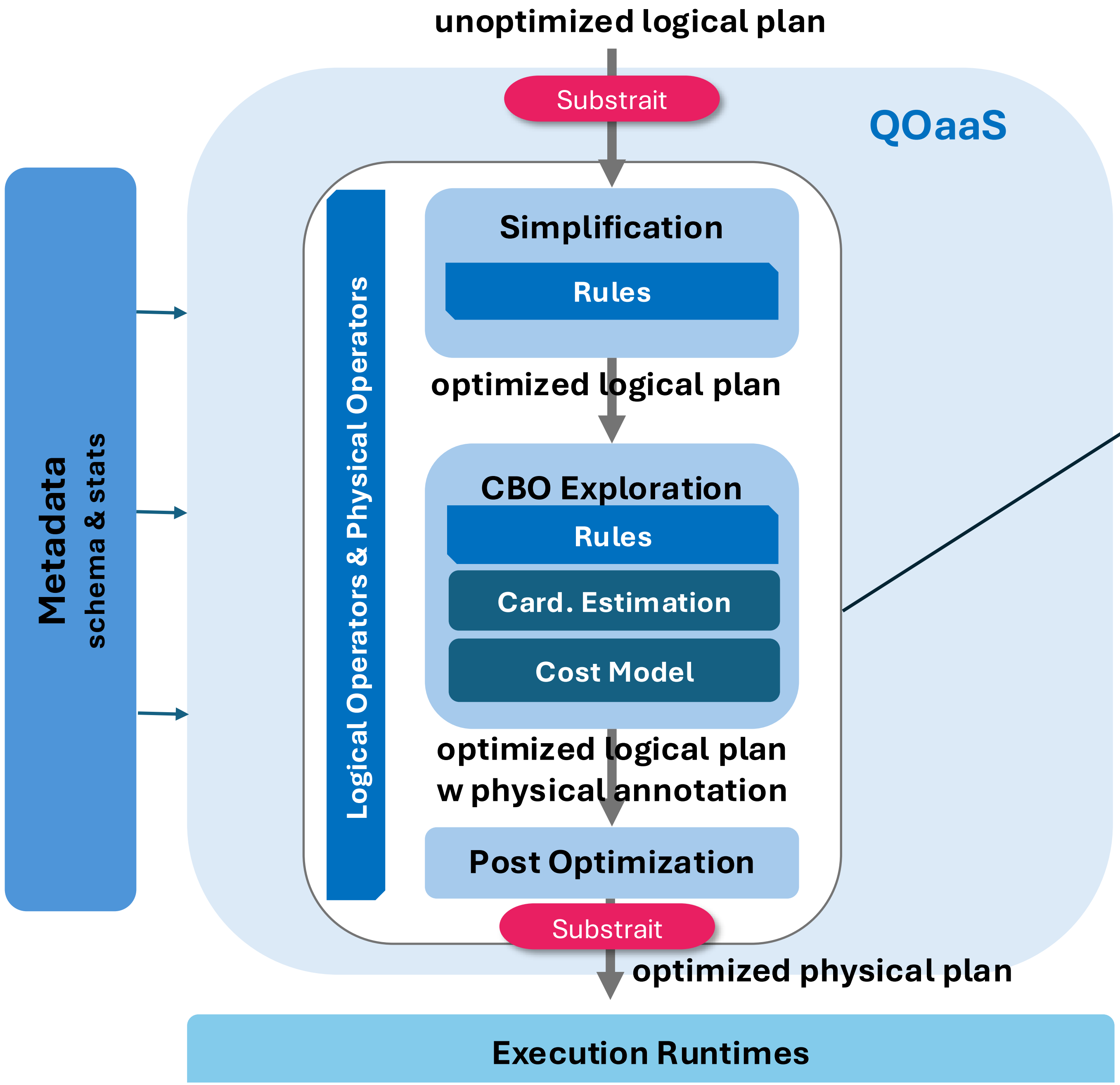
[3] Kukjin Lee, et al. 2023. Analyzing the Impact of Cardinality Estimation on Execution Plans in Microsoft SQL Server. In PVLDB.

Key Lessons Learned

Time for a new design?

- A standard plan specification is essential for QOaaS
- QOaaS should explore all possible optimization opportunities
- QOaaS needs to generate engine-specific costs
- QOaaS should allow workload-based optimization (e.g. ML-based QO enhancement)
- Fiddling with a production-level customized QO for QOaaS requires significant engineering effort

A QOaaS Proposal



Core Component

- Standard plan specification
- Modular, extensible components
- Adding ***engines-property*** to operators and rules
- New cross-engine data exchange operator
- Engines-property is enforced during optimization
- Cost model takes target engine as an additional input

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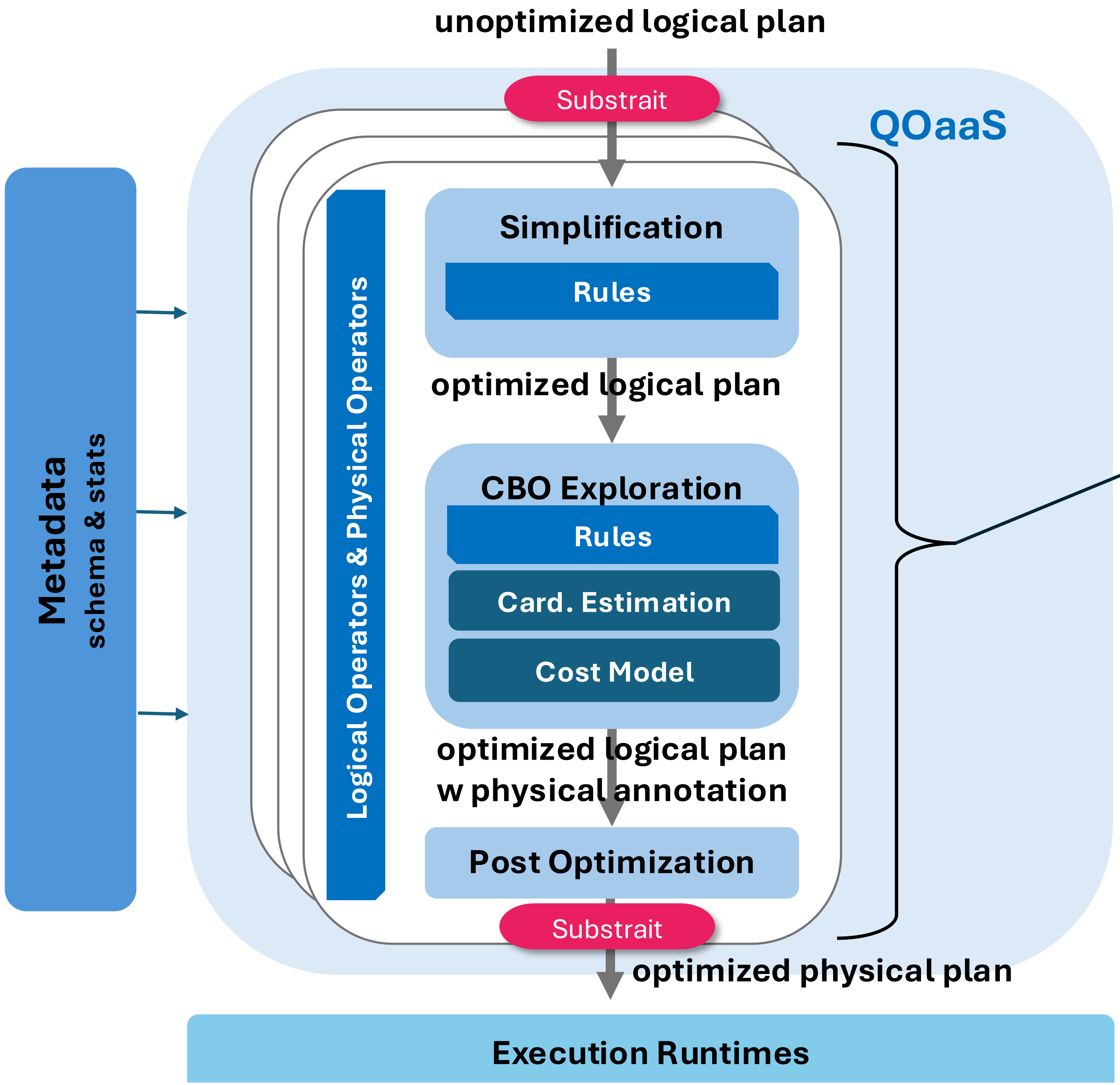

Servification

- Dedicated resources for QOaaS
- Elastic scale up and out independently
- Can run different versions of QO simultaneously
- Easy deployment and testing

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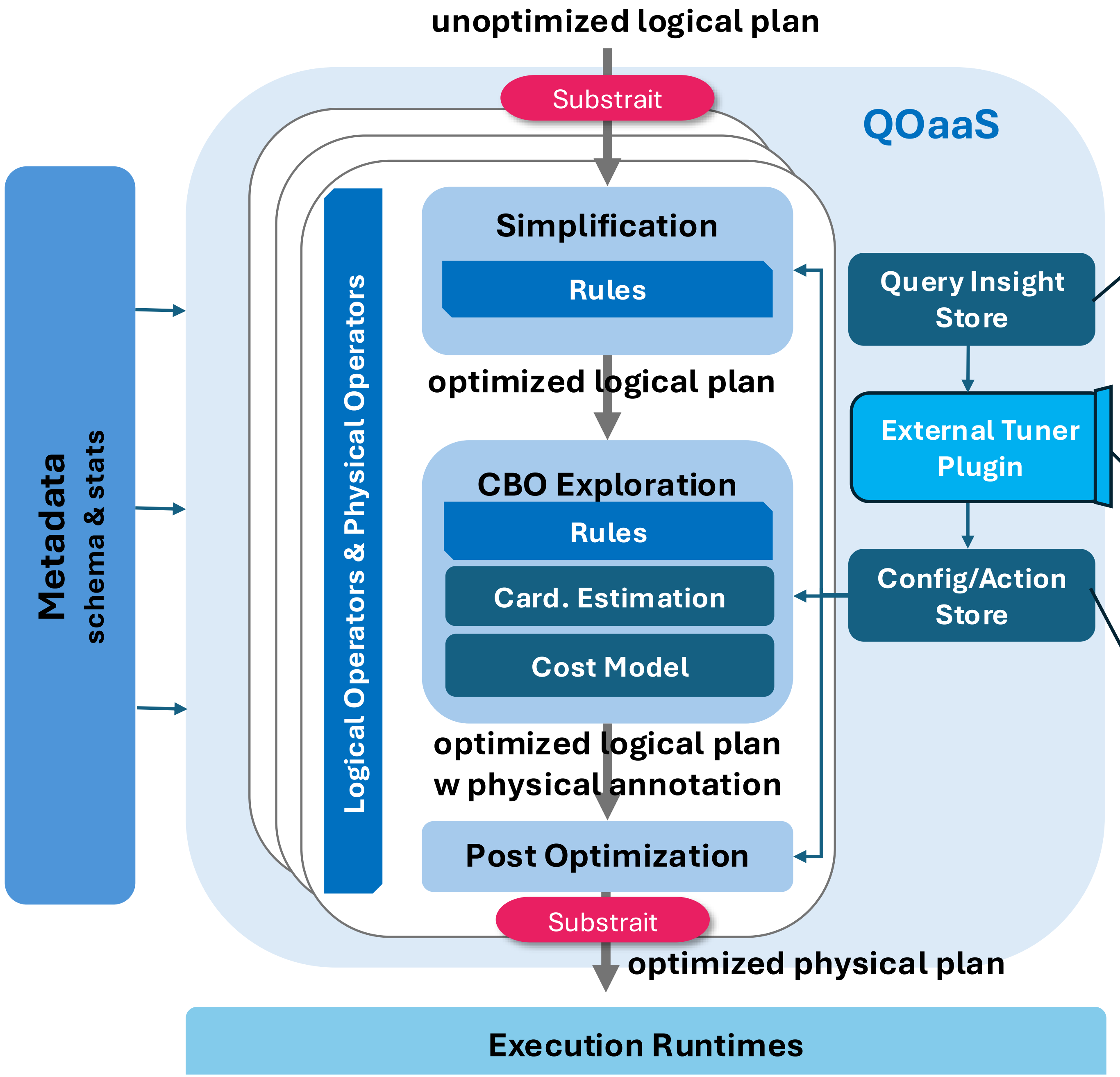


Observability

- Automatically capturing queries, plans, and runtime statistics

Pluggable External Service

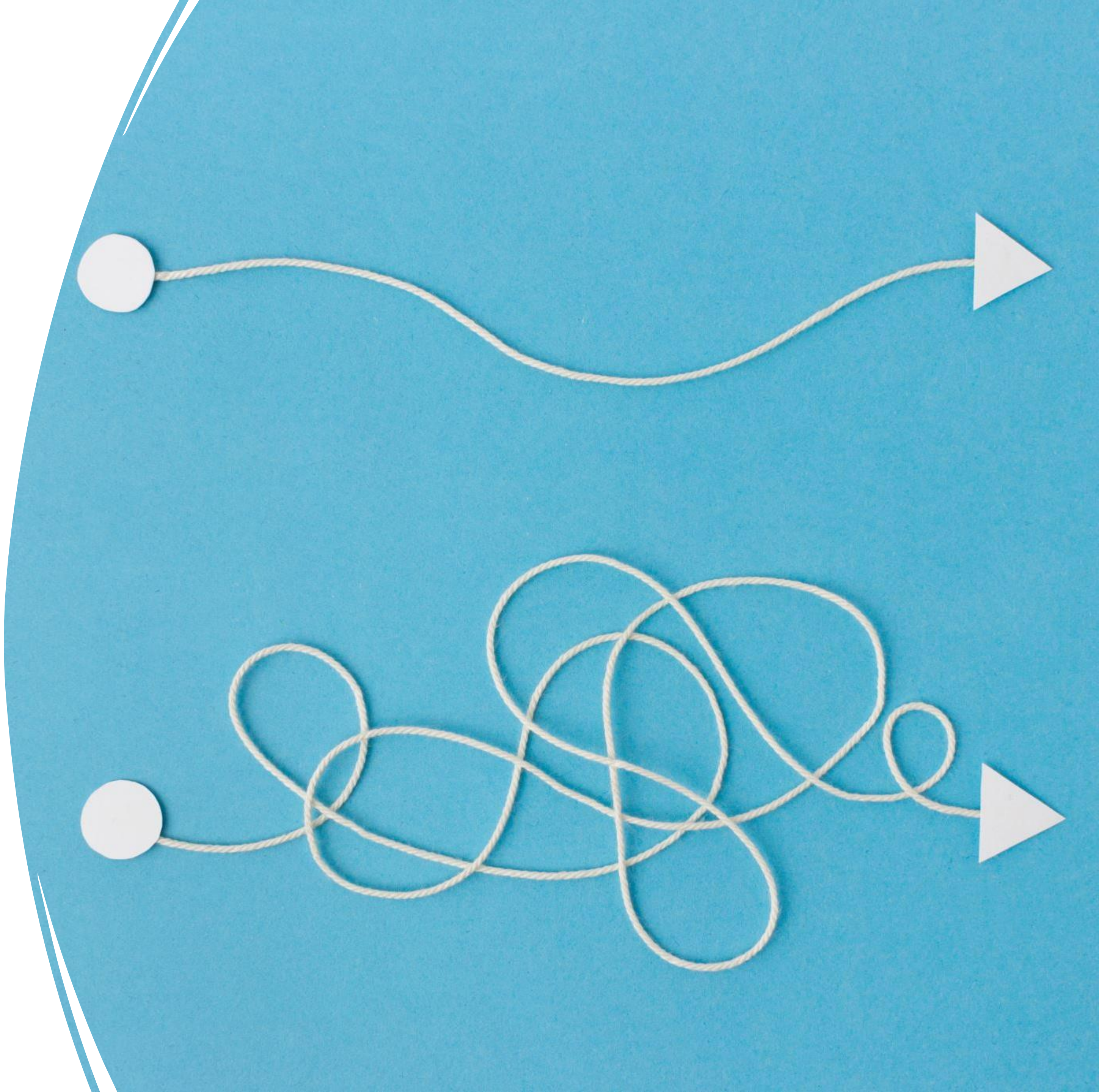
- e.g. MV/index selection, ML-based QO enhancement
- APIs to read info from Query Insight Store
- APIs to store information into the Config/Action Store

Feedback to QO

- Enhancement from the stored info

Challenges and Risks

- QO software complexity
- Learning curve for QO developers
- Coordination across teams
- Communication overhead between engines and QO
- Innovation hurdle



Open Discussion and Debate

Is QOaaS a fantasy?

Will it work?