Microsoft

Microsoft Azure Data
Gray Systems Lab

From Paper to Practice: Leveraging LST-Bench to Evaluate Lake-Centric Data Platforms

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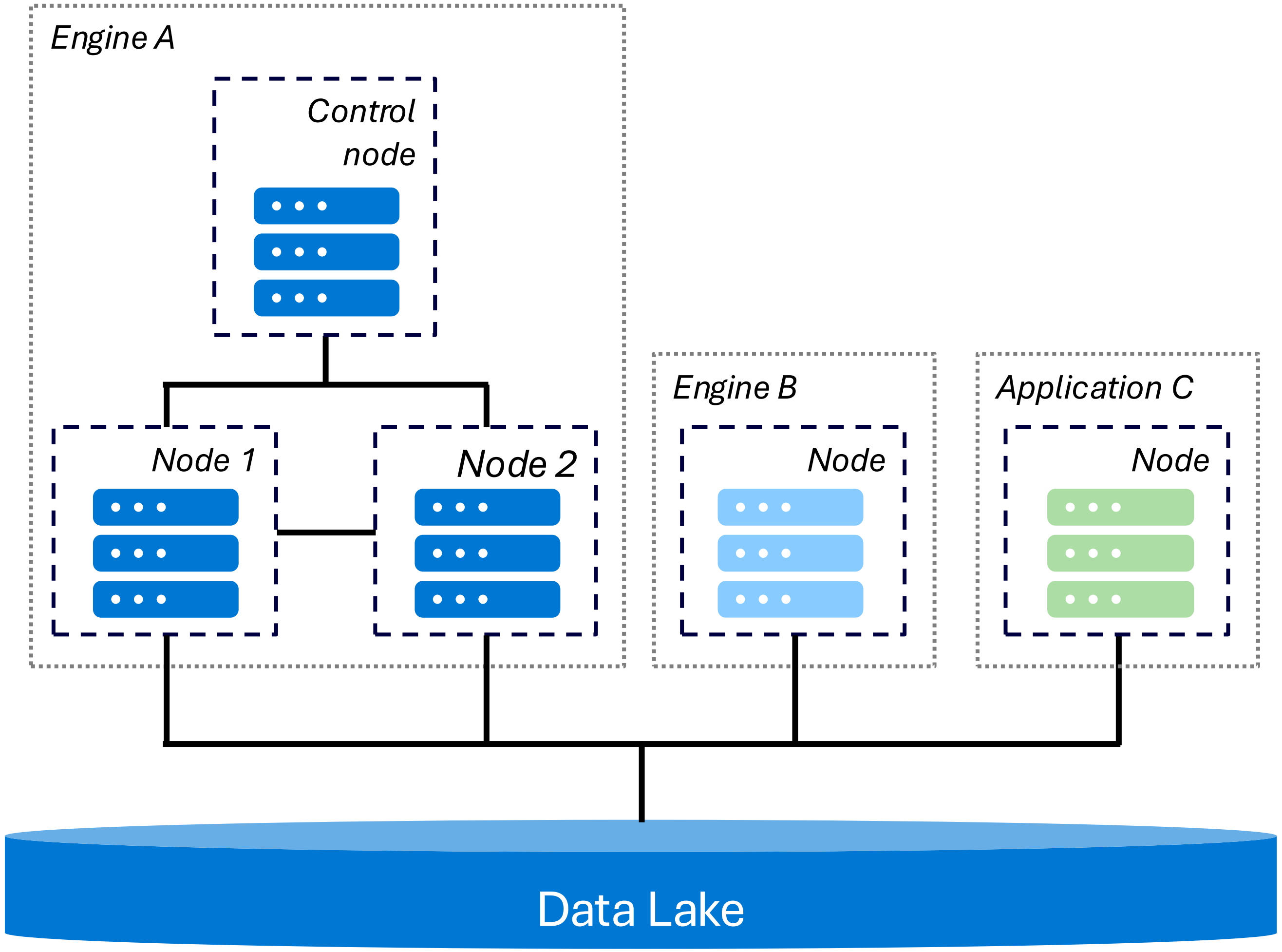
1. Data Lake-Centric Architectures and LSTs
2. Motivation
3. Tool and Benchmark Design
4. Implementation
5. Results
6. Status, Road Ahead, and Key Takeaways

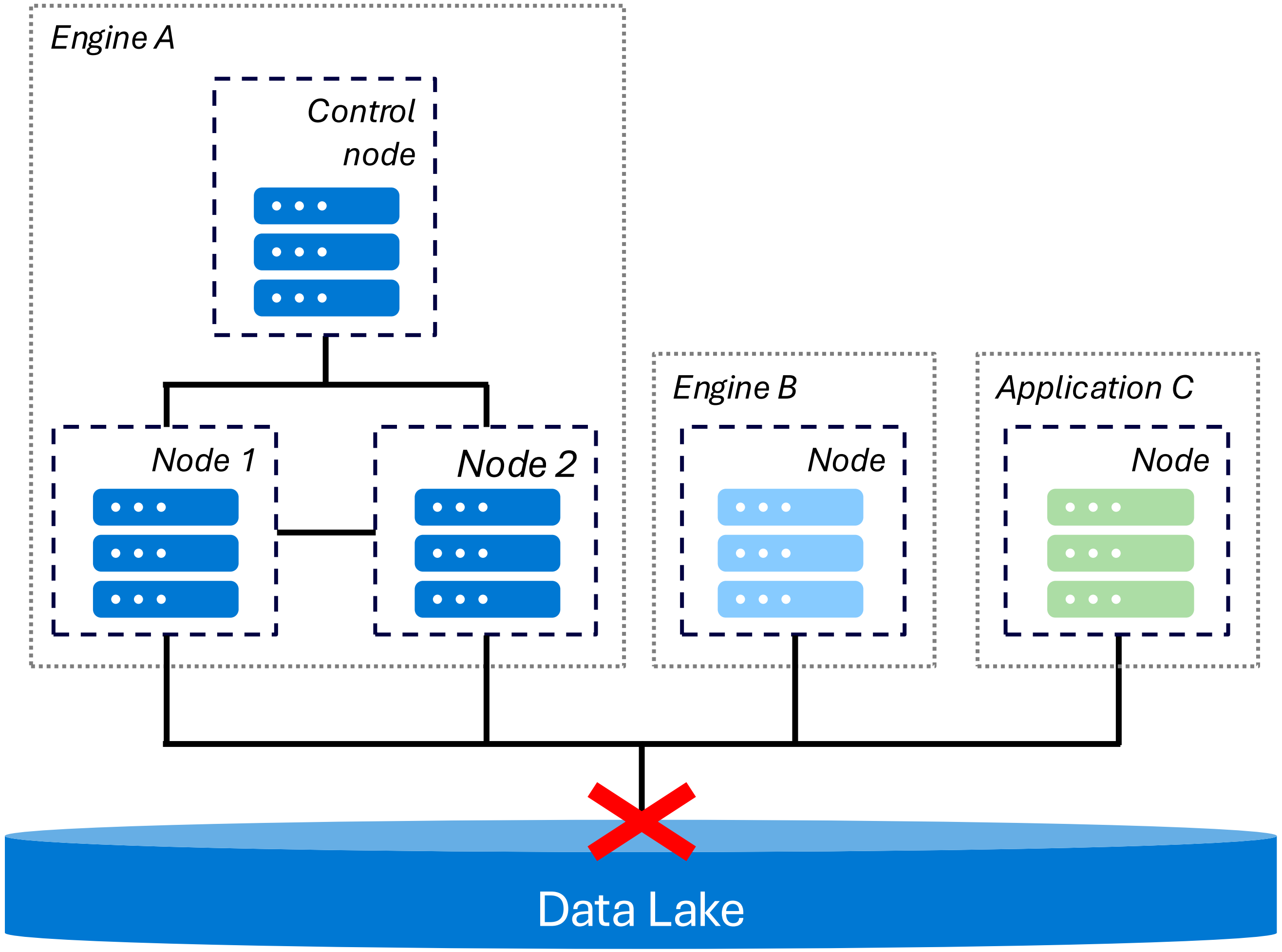
Data Lake-Centric Architecture



Benefits

- **Flexible Scalability:**
  Scale storage and compute independently for better efficiency and cost savings
- **Streamlined Workflows:**
  Eliminate data silos for simpler data movement across systems
- **Reduced Lock-In:**
  Allow any engine to directly access data storage, offering flexibility to choose the best solution for each application

Data Lake-Centric Architecture



Challenges

- Ensuring consistency and isolation of complex read and write transactions
- Data lakes excel in scalability and durability but lack necessary concurrency and recovery capabilities

Log Structured Tables (LSTs) – Overview

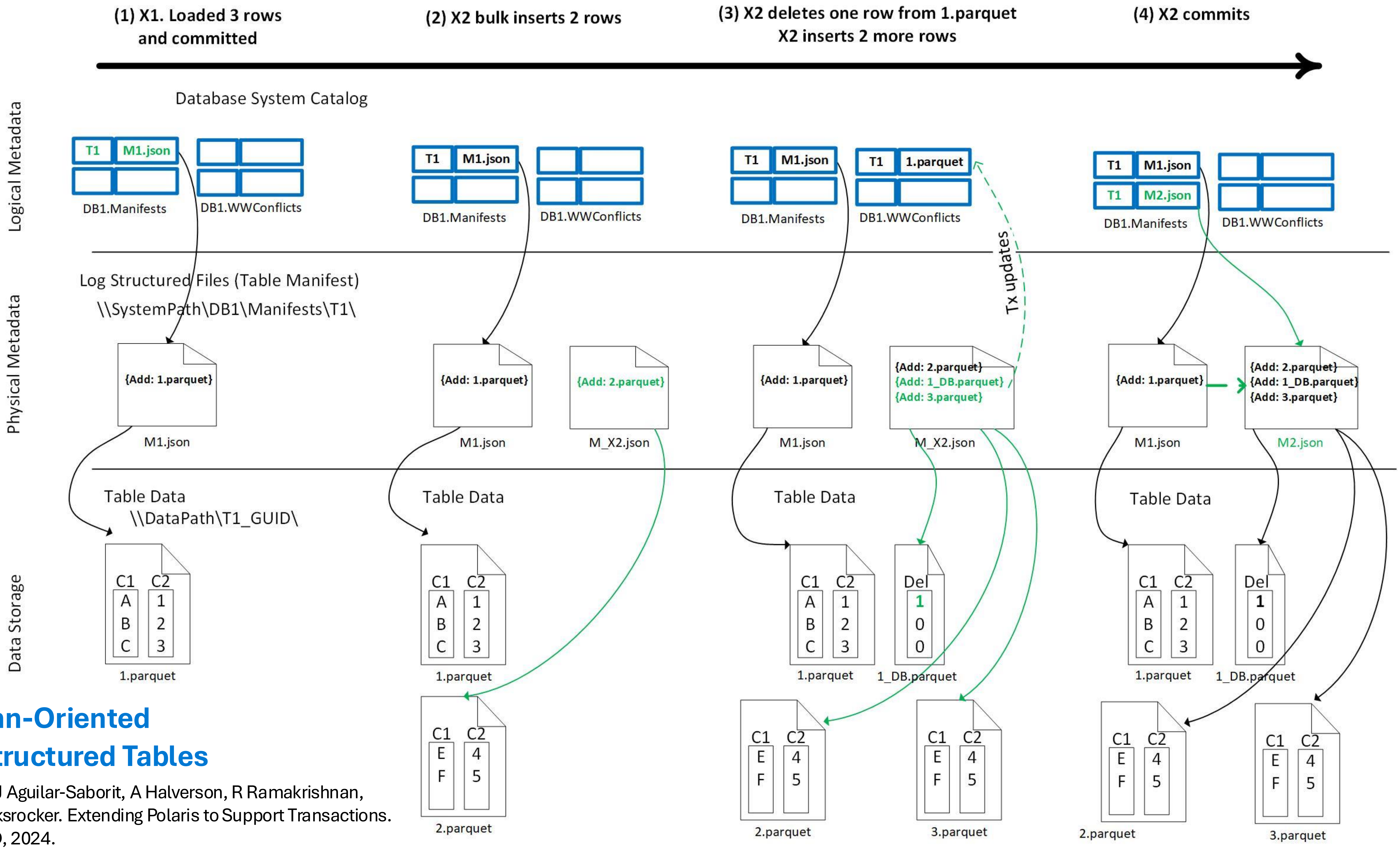
- Popular OSS projects for updatable tables: **Delta Lake**, **Apache Hudi**, **Apache Iceberg**, and **Apache Paimon (Incubating)**
  - **Goal:** Provide additional functionality (transactions, indexes, time travel, cloning) on top of immutable files (Parquet) stored in the data lake

LSTs – Data and Protocol

- Many types of data are required to represent a LST
  - Logical metadata (e.g., table definitions)
  - Physical metadata (how to find data for a table)
  - Data files (Parquet type, column oriented, store user data)
  - Delete bitmaps (describes which rows are deleted)
  - Clone info (reference counting for files)

- Where this data is stored
  - Files in cloud storage

- Approach to updates — NOT in-place in page-files!
  - Copy-on-Write (CoW) — Affected data files copied over with changes reflected
  - Merge-on-Read (MoR) — For affected data files, ONLY changes recorded; reads must merge changes



Column-Oriented Log-Structured Tables

[AHR+24] J Aguilar-Saborit, A Halverson, R Ramakrishnan, and K Bocksrocker. Extending Polaris to Support Transactions. In SIGMOD, 2024.

LSTs, Engines, and Platforms

- While LSTs share the same goal, their architecture and implementation vary
  - CoW and MoR support, metadata caching, distributed planning, storage optimizations

- Performance depends on numerous factors

LSTs	Policies	Engines
DELTA LAKE	databricks	Apache Spark
Apache hudi	AWS Glue Data Catalog	Power BI
ICEBERG	Tabular	trino
Apache Paimon™	AutoOptimize	DuckDB
	OpenHouse	presto
		Synapse Data Warehousing

- Limited work on a **comprehensive framework for LSTs evaluation**

Existing Approaches to Evaluate LSTs

- Experimental Evaluation: LH-Bench [JKP+23], Brooklyn Data, DataBeans
  - Ad-hoc approaches
  - Typically rely on **TPC-DS**, standard OLAP benchmark
  - Subset of standard queries or handcrafted queries

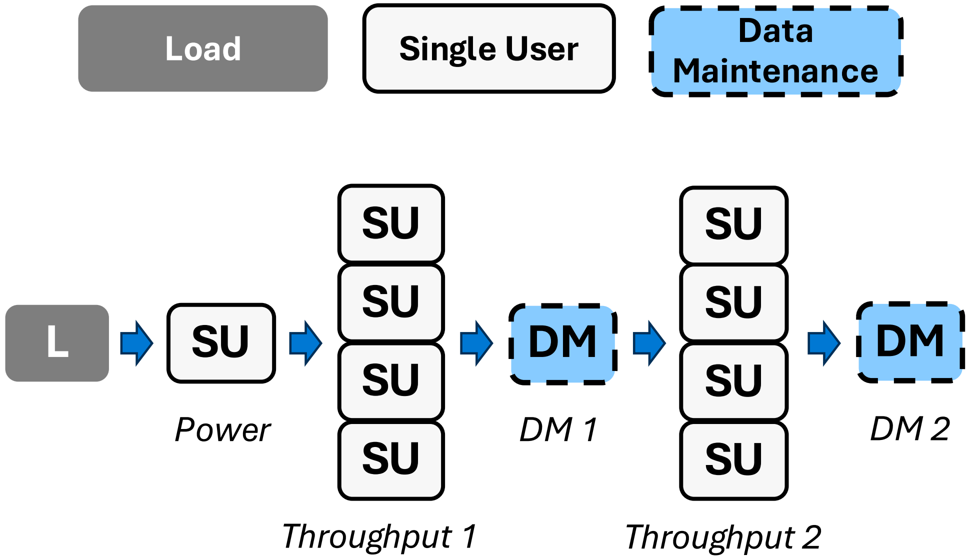
Limitation 1: Unable to extend to new engines, datasets, and scenarios beyond traditional OLAP tasks, despite the continuous expansion of data-lake centric architectures with new use cases

[JKP+23] P Jain, P Kraft, C Power, T Das, I Stoica, and M Zaharia.
Analyzing and Comparing Lakehouse Storage Systems. In CIDR, 2023.

TPC-DS Overview

Workload:

Up to 99 ~~analytical~~ queries ?



Performance Metric:

Total ~~execution~~ latency ?

Normalized *query throughput per hour*

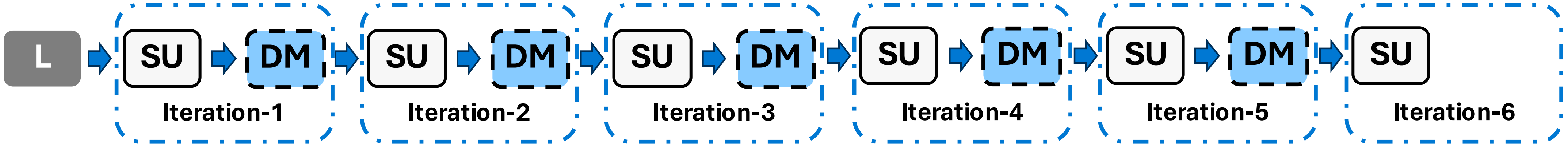
Product of total # of queries executed and scale factor

$$QphDS@SF = \left\lfloor \frac{SF * Q}{\sqrt[4]{T_{PT} * T_{TT} * T_{DM} * T_{LD}}} \right\rfloor$$

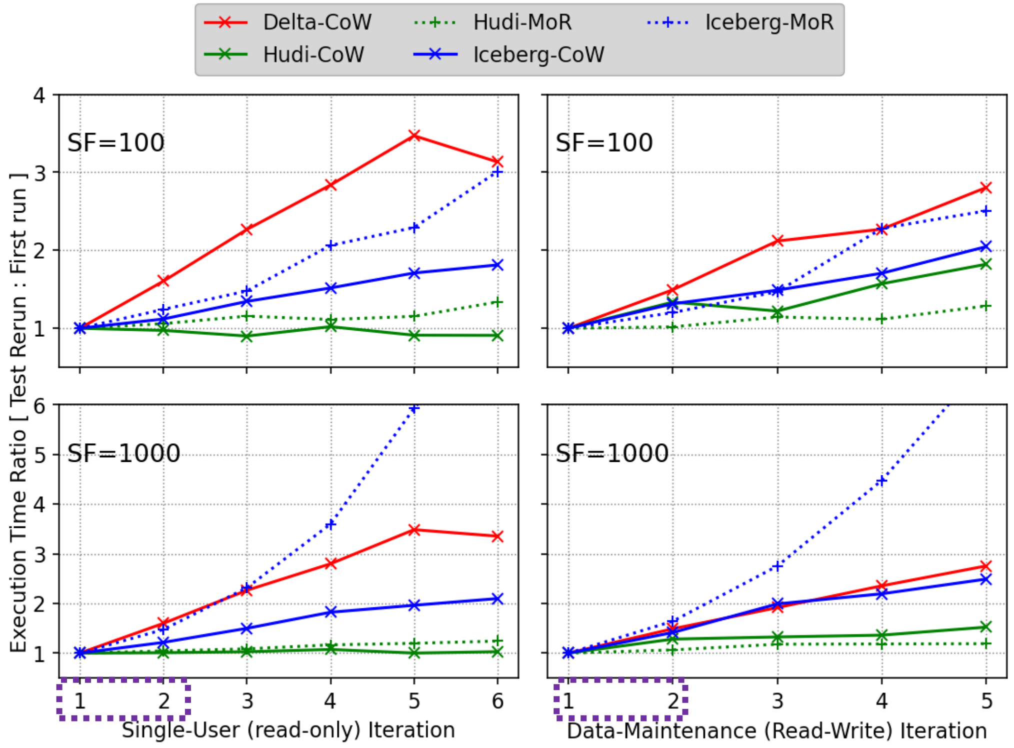
Geometric mean of elapsed time for load, power, throughput, and data maintenance phases

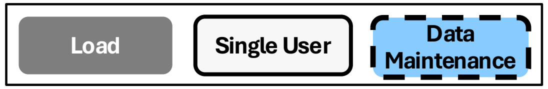
TPC-DS Workload

Question: Regarding trickle updates, is TPC-DS a representative workload?

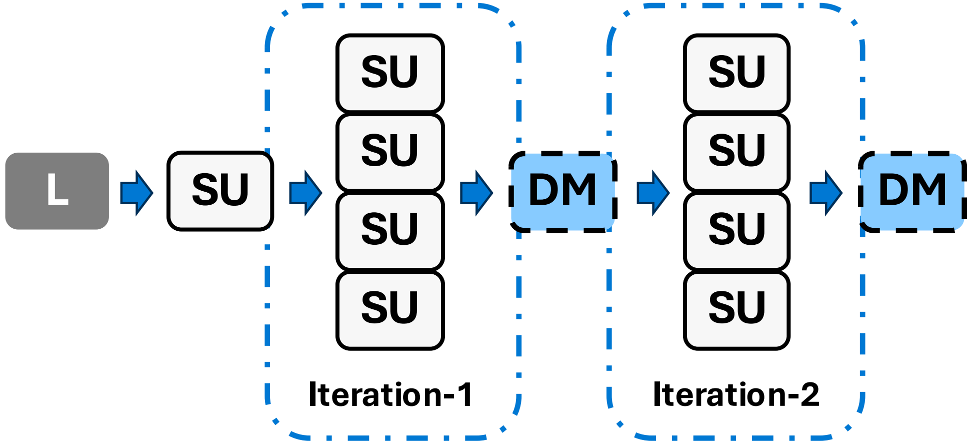


Limitation 2: Failure to expose important characteristics of LSTs that are crucial in real customer scenarios





TPC-DS Metrics



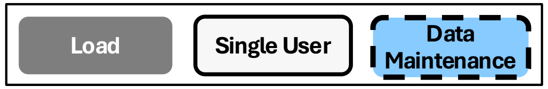
Limitation 3: Lack of metrics to expose important aspects when comparing different LST implementations

$$QphDS@SF = \left\lfloor \frac{SF * Q}{\sqrt[4]{T_{PT} * T_{TT} * T_{DM} * T_{LD}}} \right\rfloor$$

LST	Throughput-QphDS	Inter-test Degradation
Delta	511K	2.7 -> 5.2 hrs **(92%)**
Hudi-CoW*	262K	6.2 -> 6.5 hrs **(5%)**
Hudi-MoR⁑	112K	23 -> 24 hrs **(6%)**
Iceberg-CoW*	549K	2.7 -> 4 hrs **(45%)**
Iceberg-MoR⁑	493K	2.9 -> 5 hrs **(73%)**

* Copy-on-Write mode ⁑ Merge-on-Read mode

SF=1000
Spark (3.3.1), 16 workers, 8 cores, 64 GB
Delta (2.2.0), Iceberg (1.1.0), Hudi (0.12.2)



❶ Data Lake-Centric Architectures and LSTs

❷ Motivation

❸ Tool and Benchmark Design

❹ Implementation

❺ Results

❻ Status, Road Ahead, and Key Takeaways

LST-Bench

- A benchmark tool specifically tailored to evaluate LSTs

Limitation 1: Unable to extend to new engines, datasets, and scenarios beyond traditional OLAP tasks, despite the continuous expansion of data-lake centric architectures with new use cases	➡	**Flexible Workload Representation** Can represent existing benchmarks but easily extends to new scenarios
Limitation 2: Failure to expose important characteristics of LSTs that are crucial in real customer scenarios	➡	**Enhanced Workloads** Introduces *diverse workload patterns*
Limitation 3: Lack of metrics to expose important aspects when comparing different LST implementations	➡	**Relevant Metrics** Includes *metrics extensions* relevant for LSTs

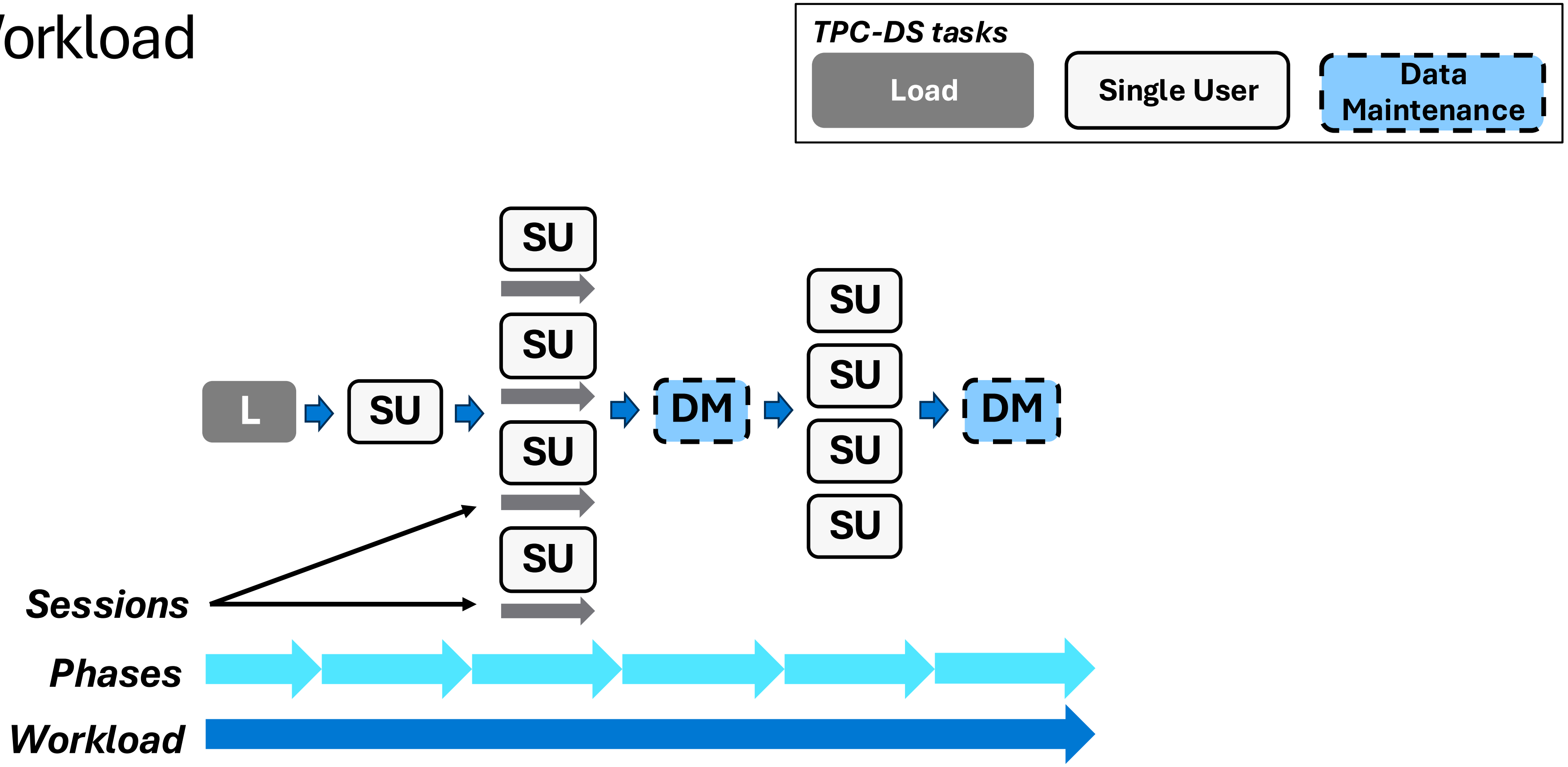
[CAG+24] J Camacho-Rodriguez, A Agrawal, A Gruenheid, A Gosalia, C Petculescu, J Aguilar-Saborit, A Floratou, C Curino, and R Ramakrishnan. LST-Bench: Benchmarking Log-Structured Tables in the Cloud. In SIGMOD, 2024.

Workload Representation

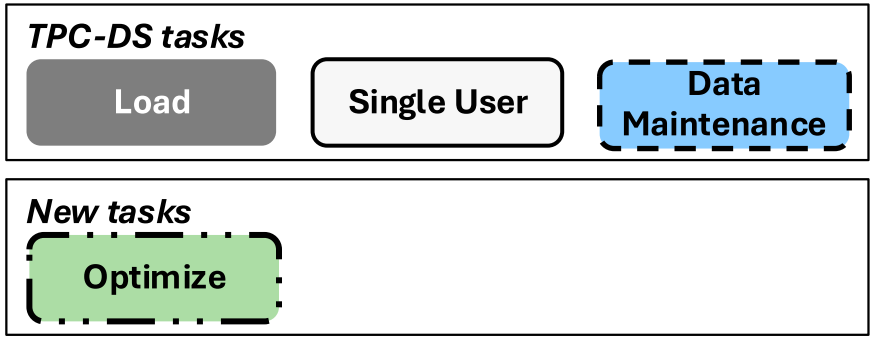
- Adaptable to both standard and custom workloads prevalent in practice
  - Driven by diverse and extensive internal user feedback
  - Facilitates the mapping of existing workloads, such as TPC-DS
  - Aligns with the concept of sessions in JDBC
  - Ensures ease of reusability

Extending Workloads Beyond TPC-DS

- ***W0:*** TPC-DS Workload



LST-Bench Workload Patterns

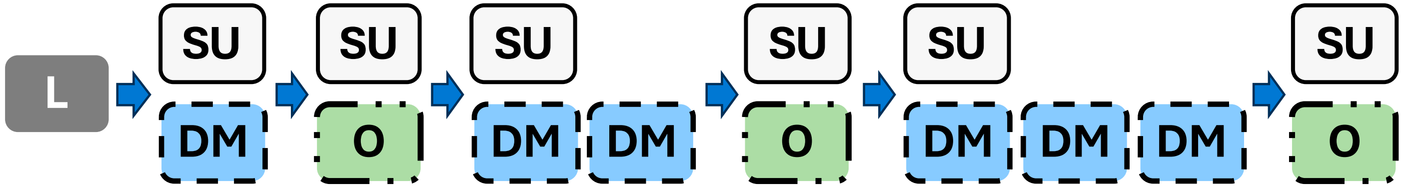


Gain insights into LST aspects overlooked by TPC-DS

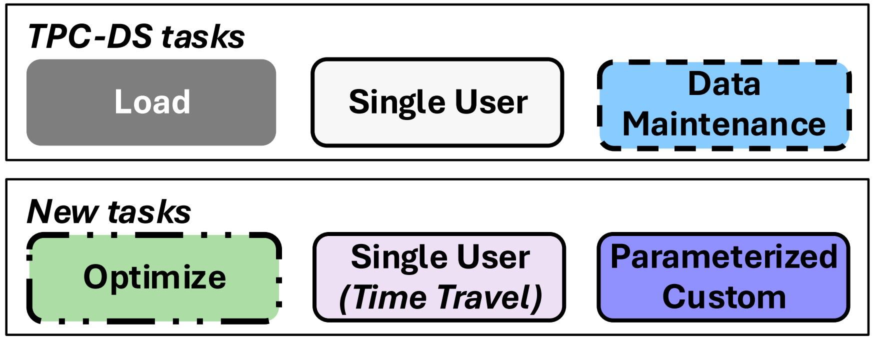
- ***W1:*** How are frequent data modifications handled over a long period of time?

- ***W2:*** How are multiple data modifications of varying sizes handled within a regularly optimized table?

- ***W3:*** How are simultaneous reading and writing sessions handled, potentially across multiple compute clusters?

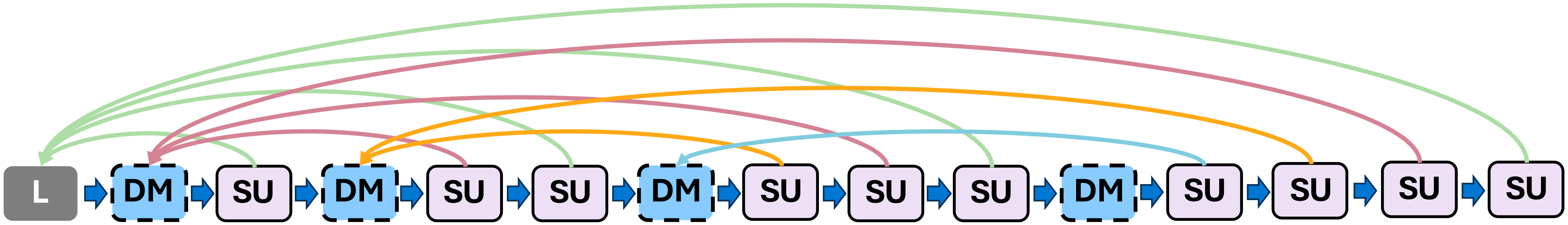


LST-Bench Workload Patterns

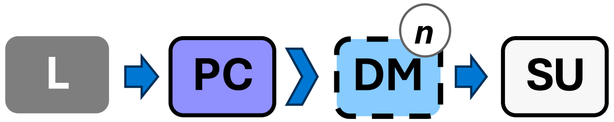


Gain insights into LST aspects overlooked by TPC-DS

- ***W4:*** How is data querying across different points in time handled?



- ***W5:*** How does updating or deleting the same data volume in different batch sizes influence read query performance?



n tasks dynamically generated by parameterized custom task

LST-Bench Metrics

Traditional Metrics

- Performance: *Latency, Throughput*
- Cloud Storage Efficiency: *Capacity Utilization, API Call Count, Total IO*
- Compute Engine Efficiency: *CPU Utilization, Memory Utilization, Disk Utilization*

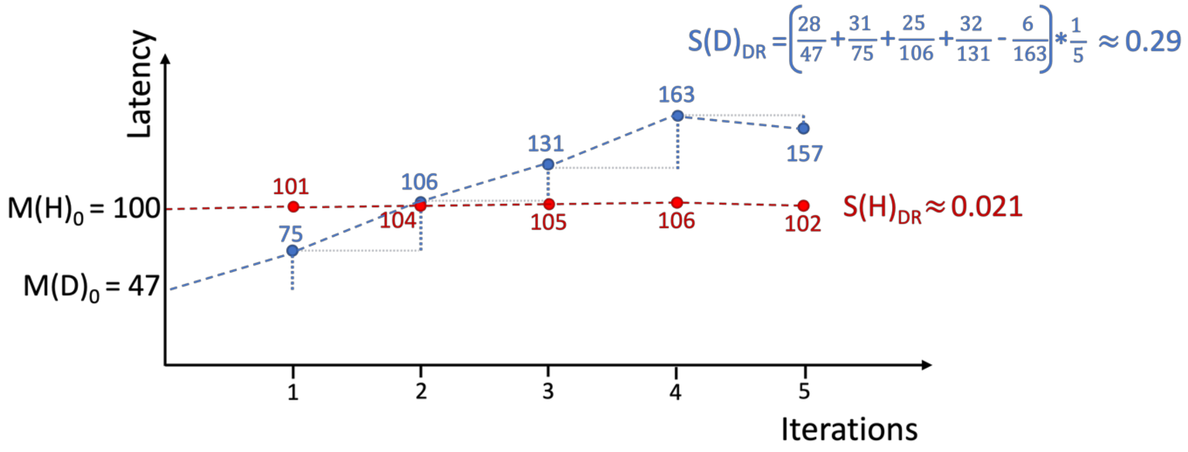
Other Metrics

- Stability - System's ability to sustain consistent performance and efficiency with minimal degradation: *Degradation Rate*

$$S_{DR} = \frac{1}{n}\sum_{i=1}^{n} \frac{M_i - M_{i-1}}{M_{i-1}}$$

where

- M_i is metric value of the i^{th} iteration of a workload phase,
- n is the number of iteration of the phase, and
- S_{DR} is the degradation rate.



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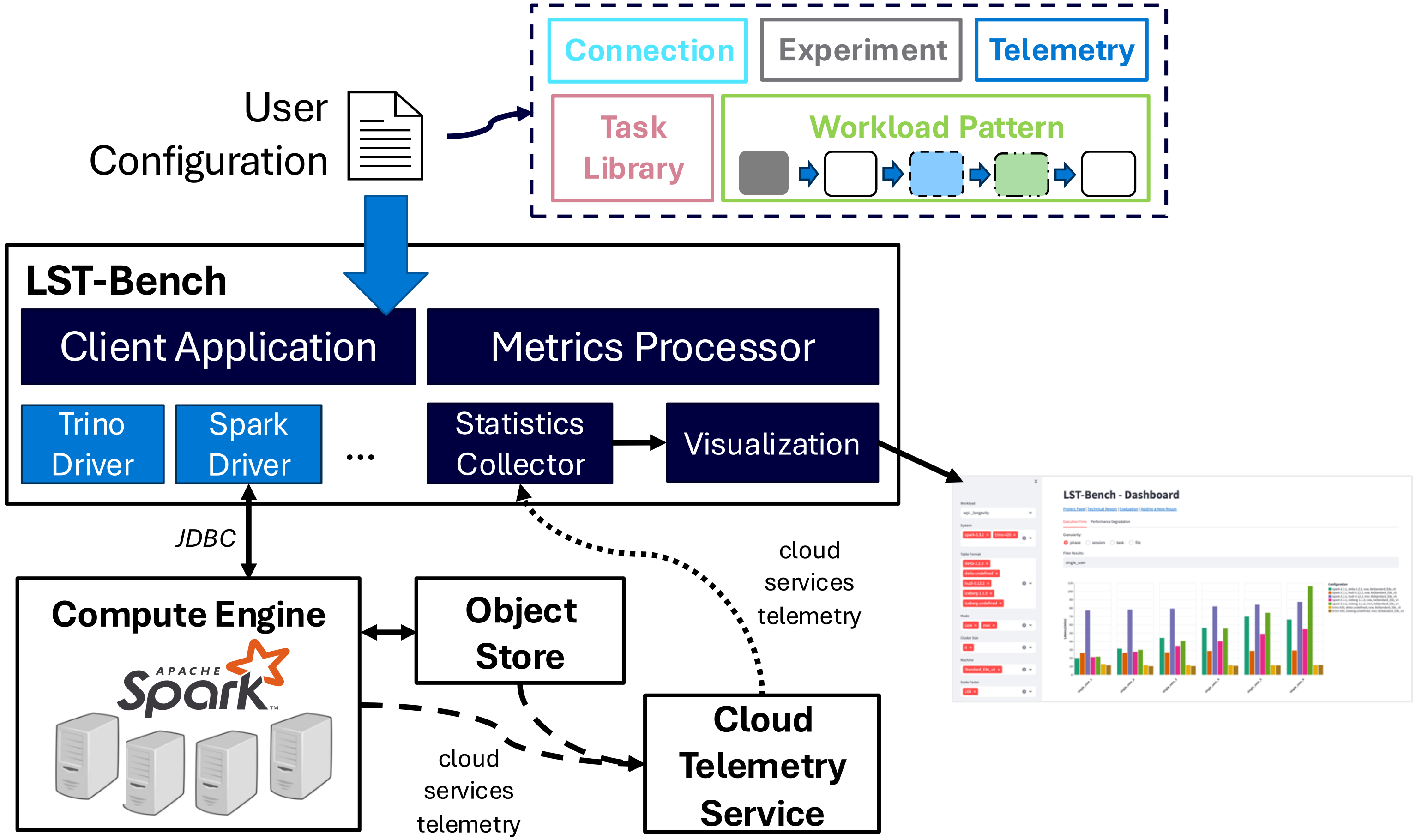
LST-Bench Implementation

- Java Client Application
  - Customizable / extensible via config files
  - Connects to engine via JDBC or Spark session client
- Python Metrics Processor
  - Visualization via notebook or Streamlit web app
- Open-source available under Apache License 2.0: https://github.com/microsoft/lst-bench



LST-Bench Configuration, Libraries, and Workloads

- Configuration-driven approach
  - YAML/JSON file support
  - Input validation against JSON Schema

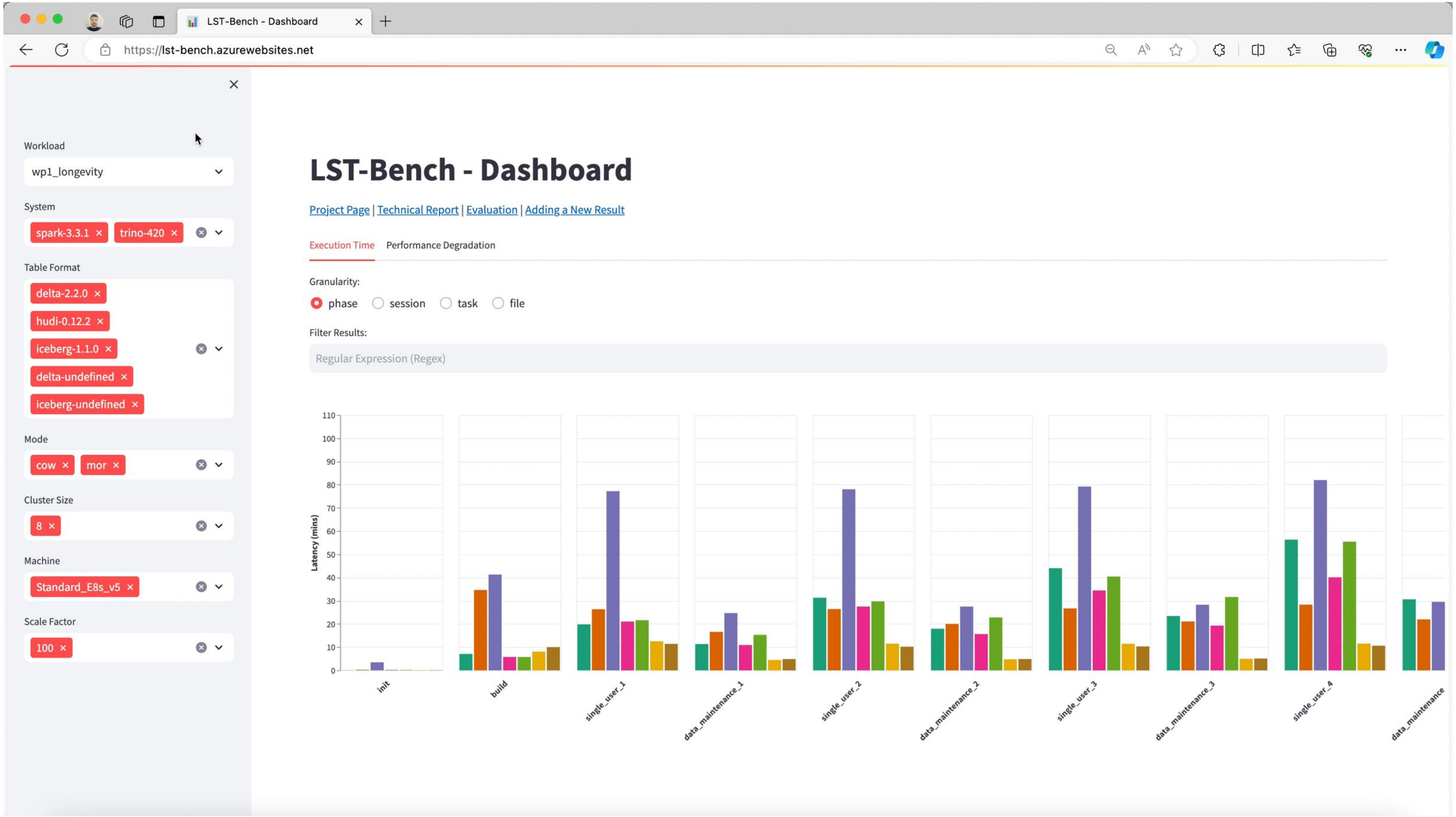
- Workload options
  - **Self-contained:** All tasks, sessions, and phases defined within the workload file
  - **Library-based:** Define tasks, sessions, and phases in a library and reference these entities from the workload definition

```yaml
- id: throughput_simple_phase
  sessions:
  - tasks:
    - template_id: single_user_simple
      permute_order: true
    target_endpoint: 0
  - tasks:
    - templ
      permu
    target_
  - tasks:
    - templ
      permu
    target_
  - tasks:
    - templ
      permu
    target_
```

```yaml
id: my_first_workload
phases:
- id: warm_up
  sessions:
  - tasks:
    - template_id: single_user_simple
    target_endpoint: 0
  - tasks:
    - template_id: single_user_simple
    target_endpoint: 1
- id: throughput_simple
  template_id: throughput_simple_phase
```

workload.yaml

LST-Bench Web UI



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Evaluation

- Azure VMSS cluster with 1 head and 16 worker nodes
  - Each node with 8 virtual cores and 64GB RAM
- Data stored in Azure Data Lake Storage Gen2 (ADLS)
  - TPC-DS SF1000
- Azure Monitor to collect telemetry and Logs Analytics to execute queries against it

- <u>No special tuning</u> for any of the engines, LSTs we evaluated:
  - Apache Spark 3.3.1: Delta Lake v2.2.0, Apache Hudi v0.12.2, Apache Iceberg v1.1.0
  - Trino 420: Delta Lake, Apache Iceberg

- <u>*Important remarks*</u>
  - Results subject to change and improvements due to further tuning and future developments
  - Insights drawn for these engines may not apply to the LST on different engines

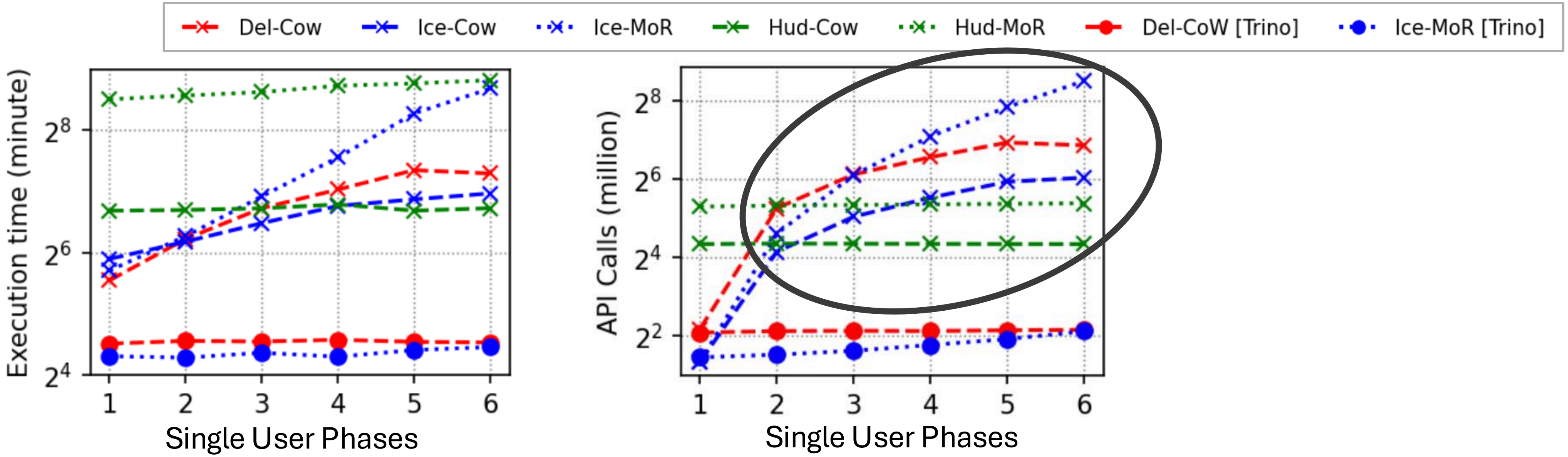
Evaluation – *W1*

Performance (Spark): Significant slowdown observed across iterations (up to 6.8x) for Iceberg-MoR. Nearly all formats show a decrease in performance.

Evaluation – *W1*

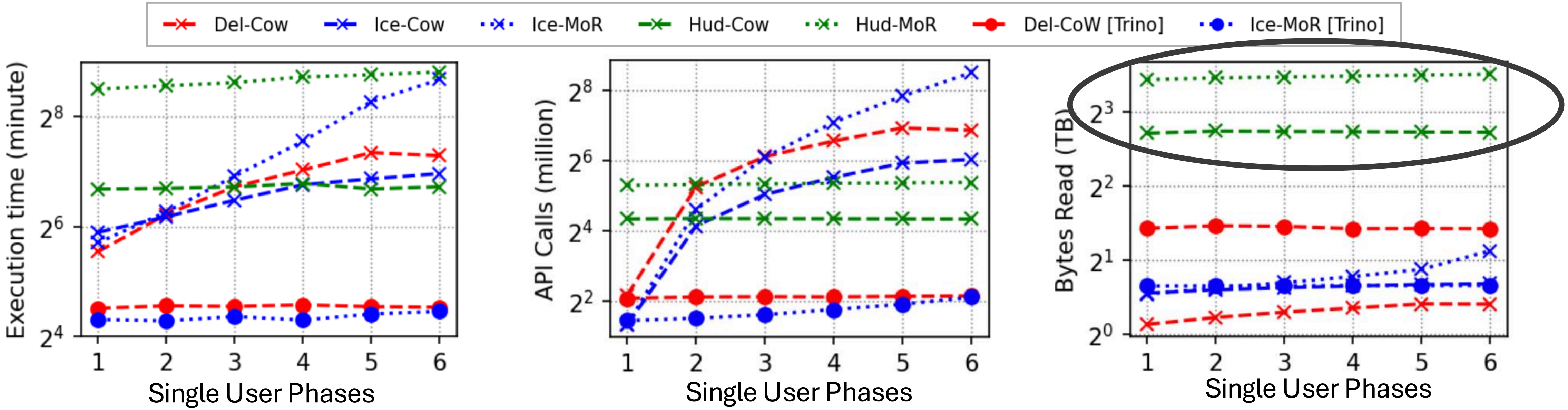
Performance (Trino compared to Spark): Nearly double the speed for both Delta and Iceberg tables after load. Higher stability.

Evaluation – *W1*



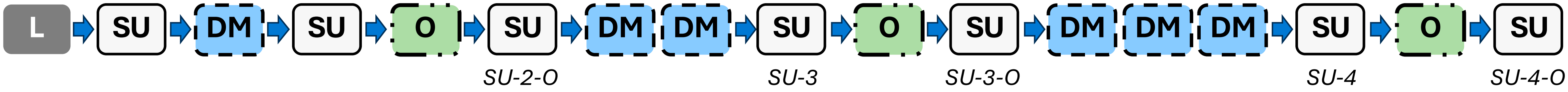
Storage Layer Calls: Increased API calls due to a higher number of (small) files that need to be read.

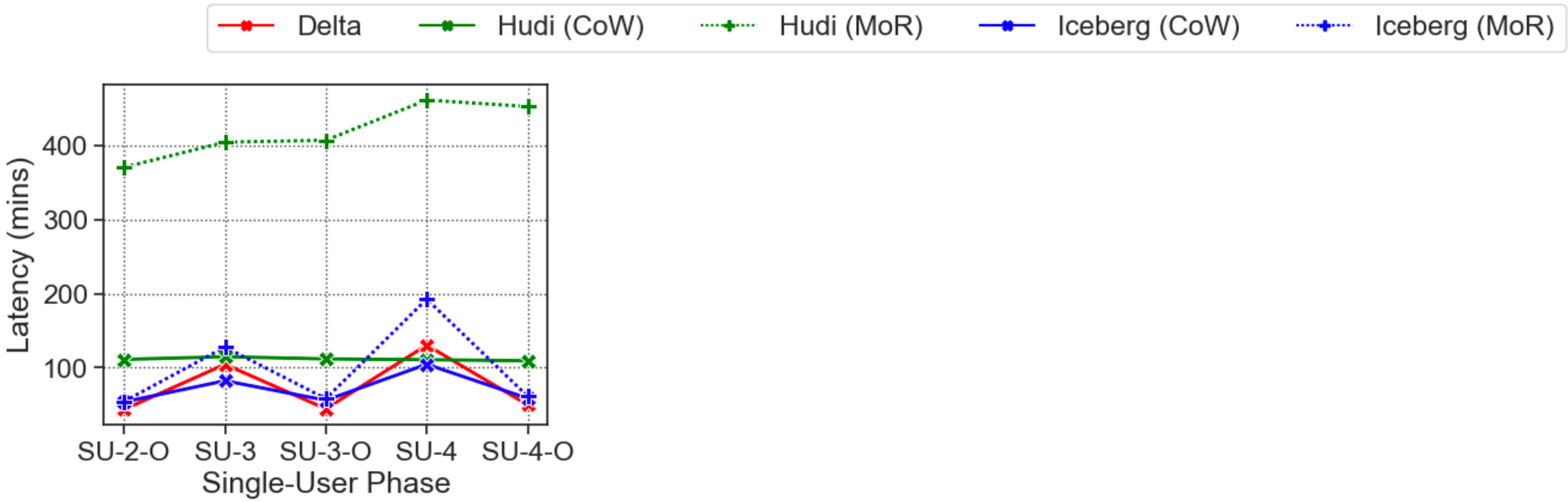
Evaluation – *W1*



I/O Volume: Comparatively high I/O volume for Hudi due to its default configuration, resulting in a higher number of small files.

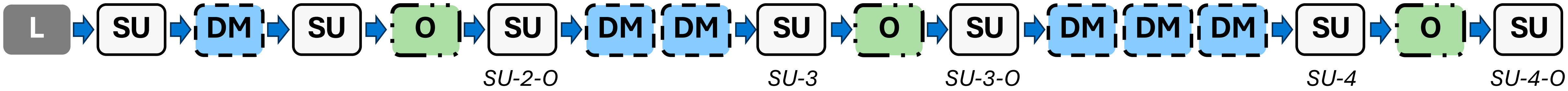
Evaluation – ***W2***

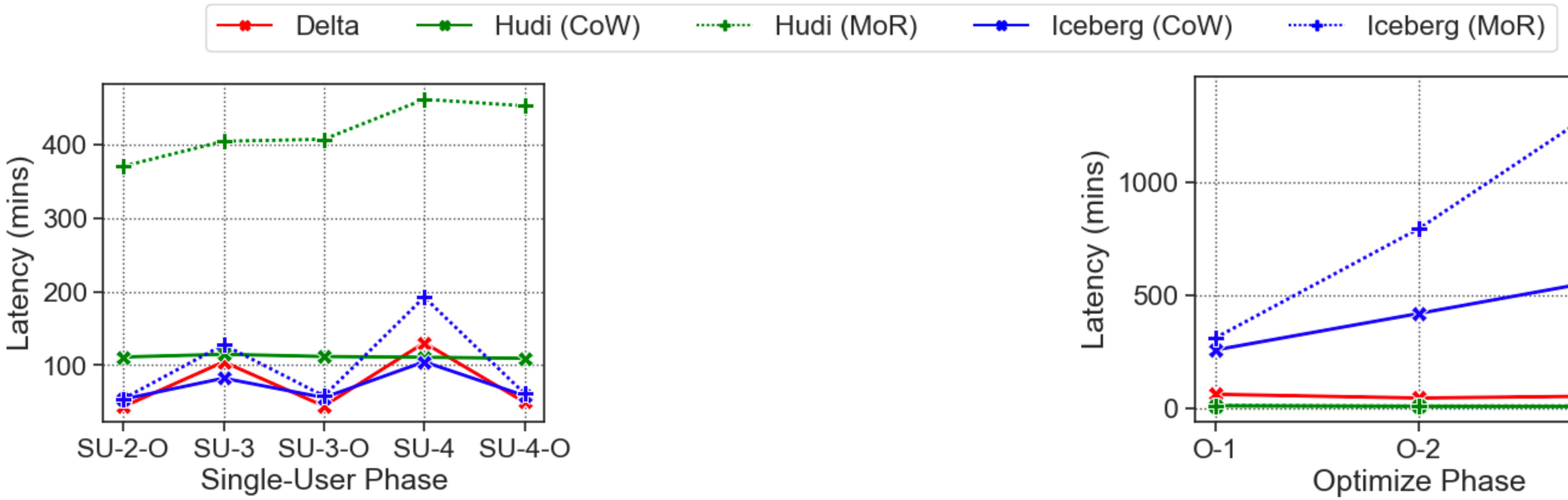




1. Table maintenance has a big impact on Delta and Iceberg performance stability (*zig-zag pattern*).
2. Hudi maintains stable performance without user-triggered maintenance by doing work upfront.

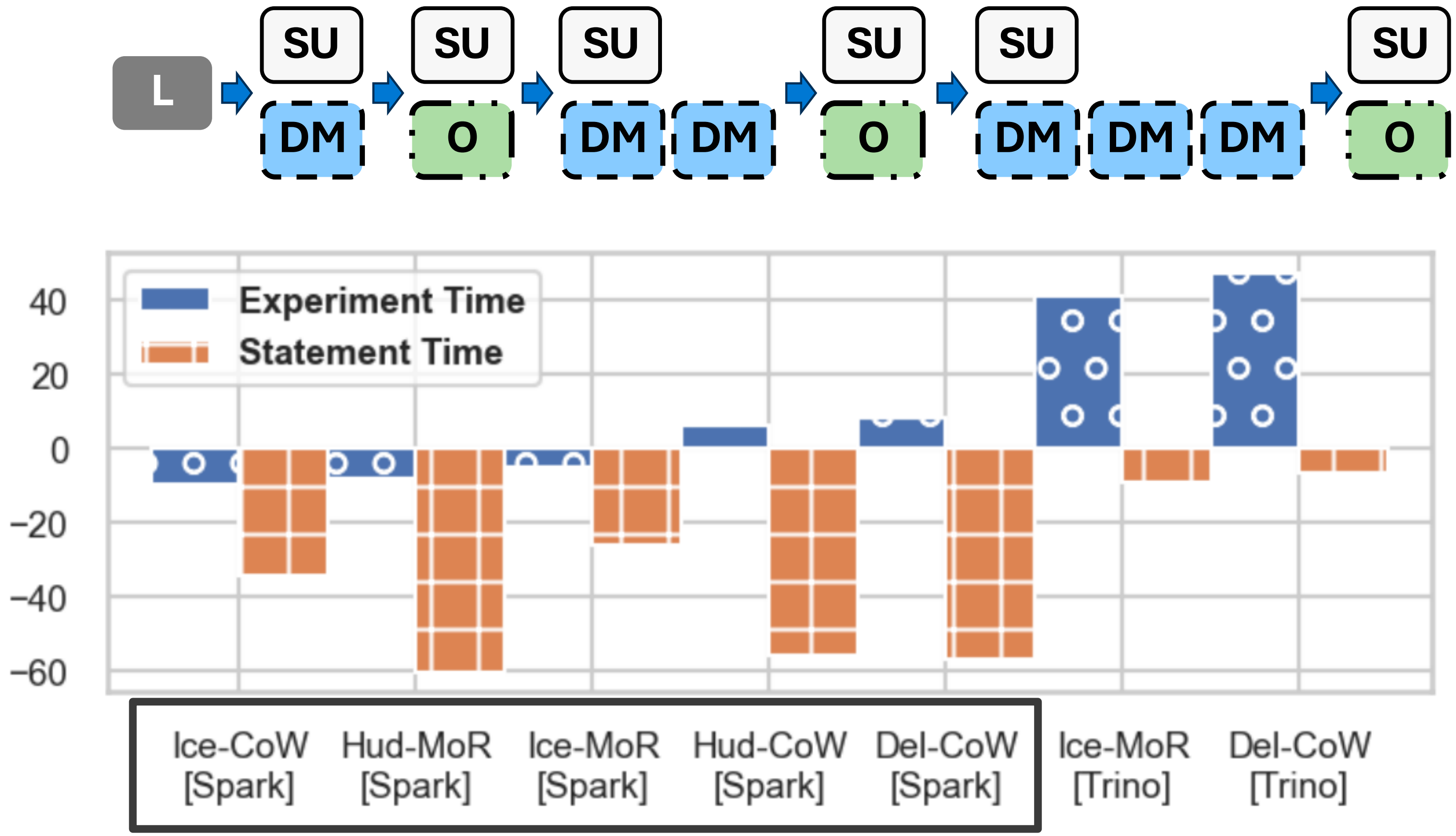
Evaluation – *W2*





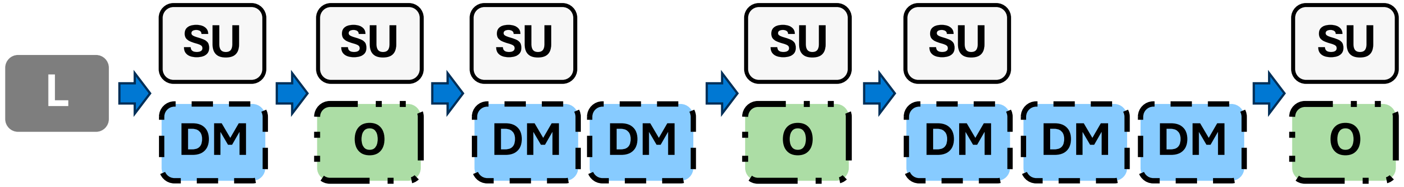
Iceberg's default file grouping for compaction *significantly increases compaction time* (potentially *minimizes read query disruptions*) ➡ Tuning LSTs involves trade-offs based on user goals

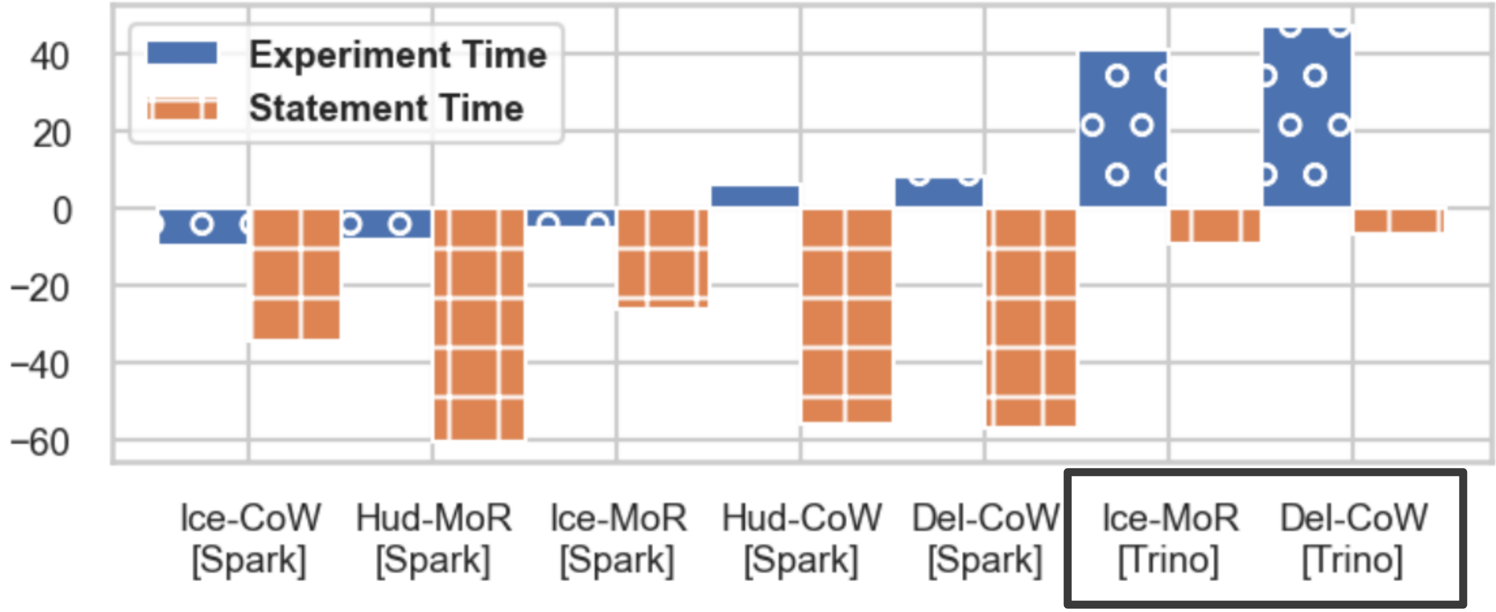
Evaluation – ***W2 vs W3***



Spark: Concurrent session execution does not lead to significant performance improvements due to resource contention.

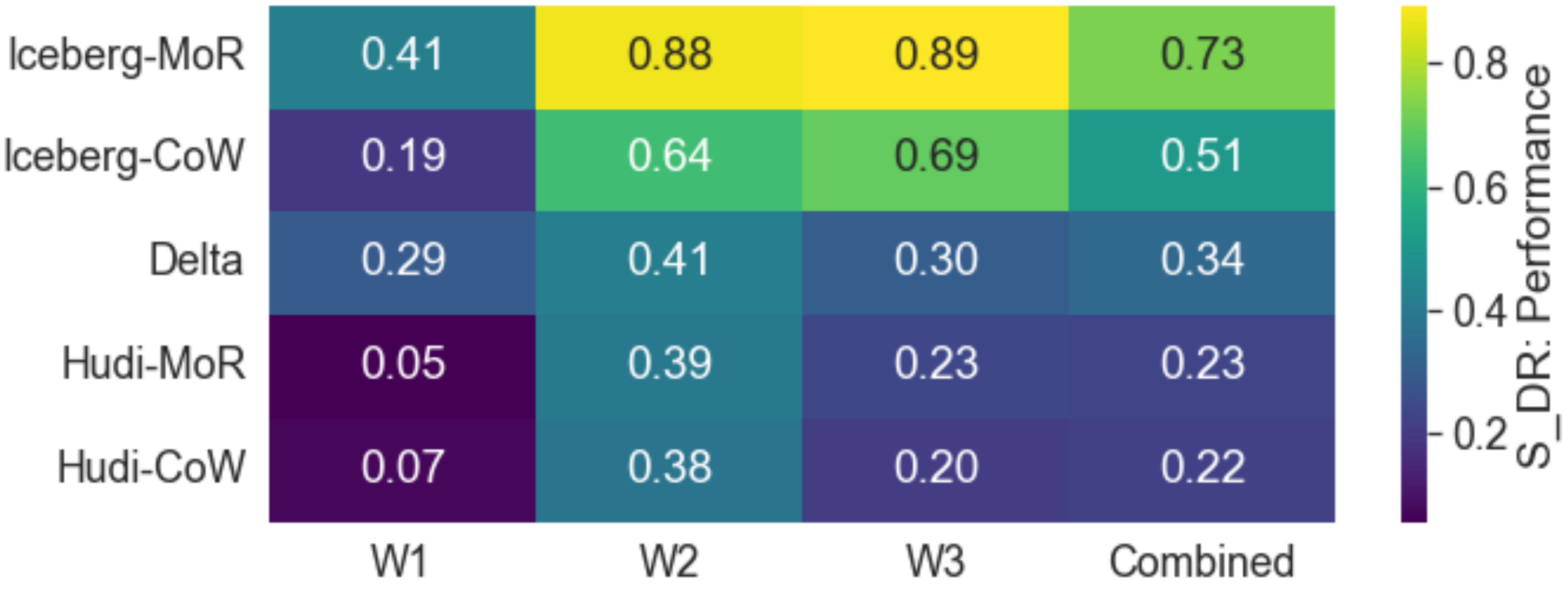
Evaluation – *W2 vs W3*



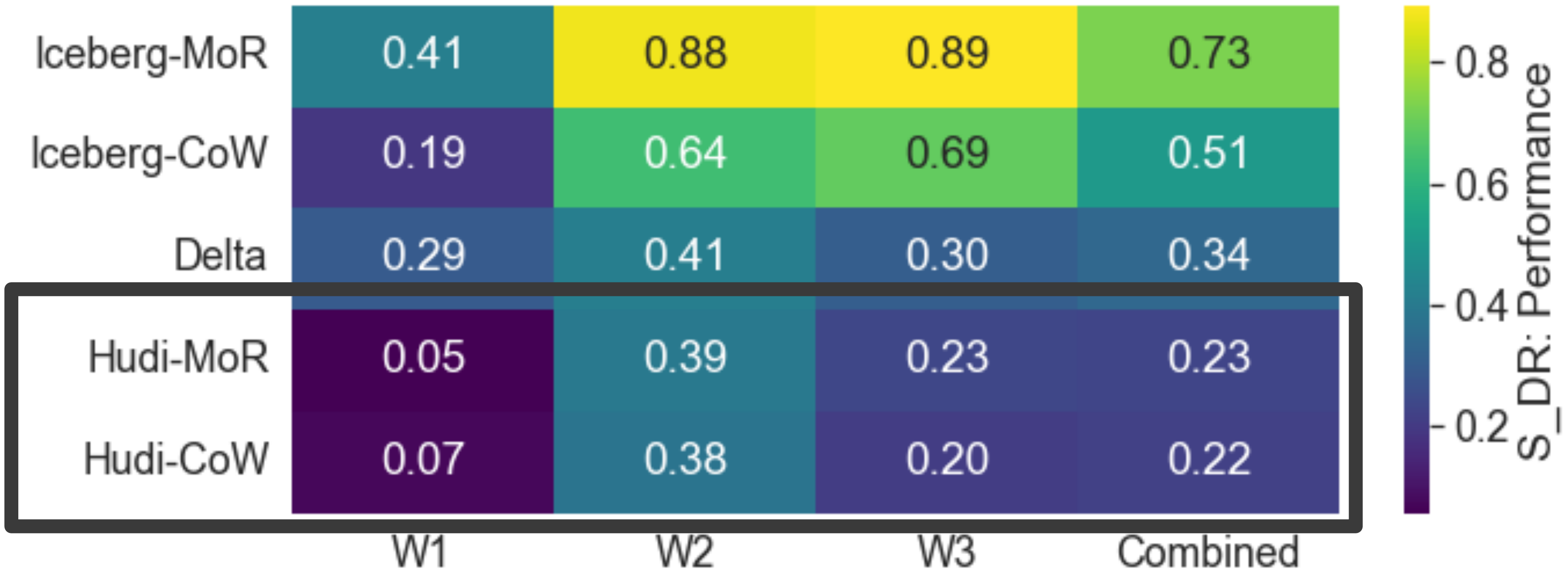


Trino: Efficient utilization of cluster resources results in significant end-to-end experiment runtime gains, despite minor slowdowns in individual statements.

Stability Evaluation



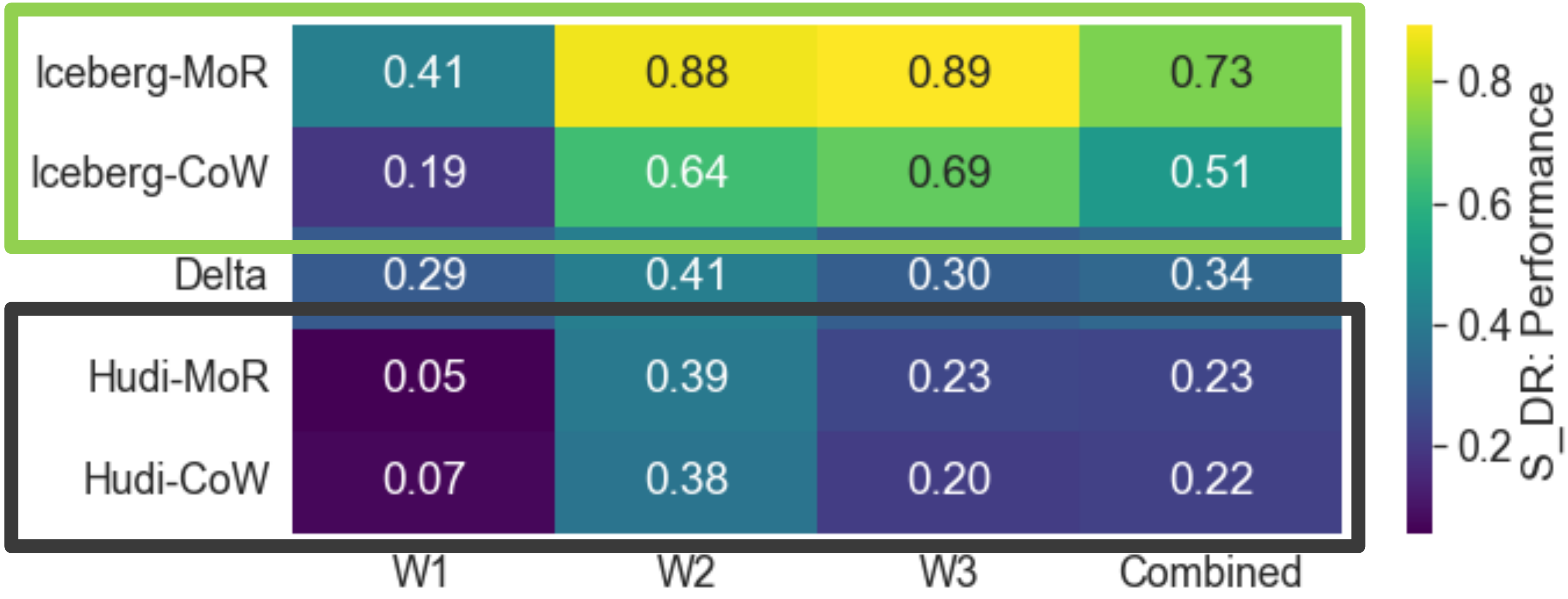
Stability Evaluation



Hudi shows highest stability

Stability Evaluation

Iceberg shows lowest stability



Hudi shows highest stability

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Status and Road Ahead

- LST-Bench @ Microsoft
  - Integrated into Microsoft Fabric Warehouse's testing workflow
  - Foundational tool for various ongoing initiatives:
    - Automatic tuning and maintenance policies for LSTs
    - Performance evaluation of LSTs converted using Apache XTable (Incubating)

- Open-source LST-Bench
  - Support for other engines, platforms, cloud providers (Apache Flink, Snowflake, AWS)
  - New scenarios: Data cleaning, CDC with transactional consistency guarantees
  - Integration with OpenTelemetry

  - Others? Contributions welcome!

Key Takeaways

- Evolving Benchmarks:
  - Traditional OLAP benchmarks like TPC-DS are not representative of modern analytic data lake workloads, e.g., lack of trickle updates
- Flexible and Extendable Tools:
  - **Modular, flexible benchmarking tools** are essential for evaluating new engines, datasets, and scenarios in the ever-expanding landscape of data lake architectures
- Comprehensive Metrics and Observability:
  - One representative metric can simplify decision-making, but **enhanced metrics and 360-degree observability** are crucial for understanding system characteristics
  - Achieving this level of observability is **challenging**, especially across multiple engines and cloud environments

Microsoft

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Gray Systems Lab

Acknowledgements

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Avrilia Floratou

Carlo Curino

Raghu Ramakrishnan

LST-Bench paper @ ACM SIGMOD 2024

Open-source available (Apache License 2.0)

Thank you! Questions?