LDBC

The LDBC Financial Benchmark: Transaction Workload

VLDB 2025, London, United Kingdom

Research 60 - Database Engine Performance and Manageability II

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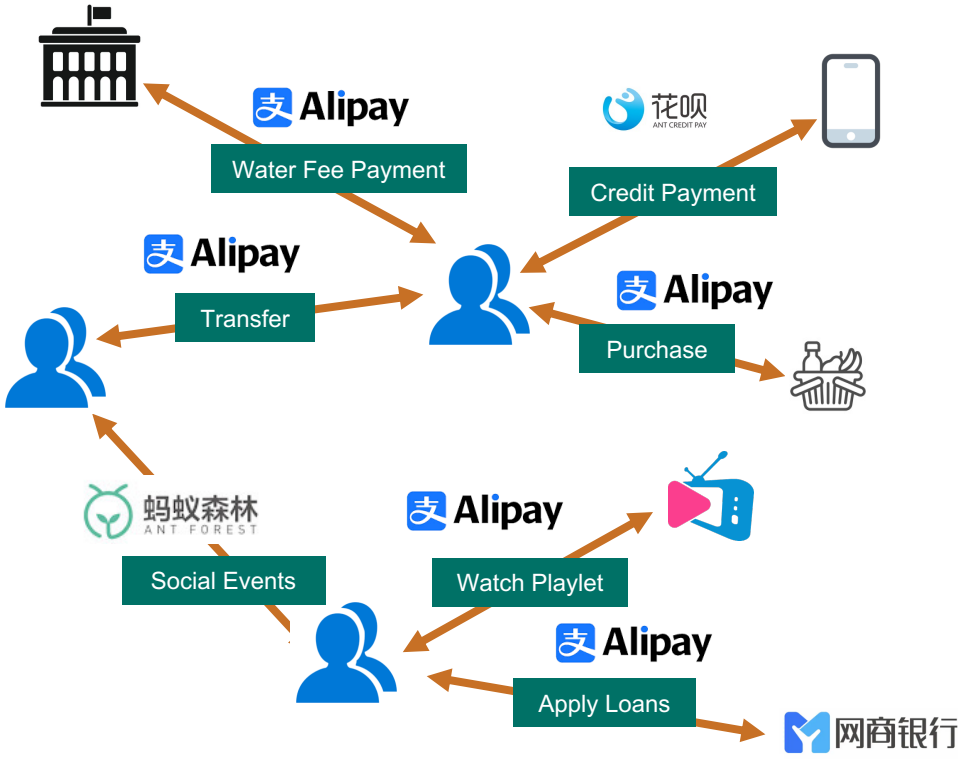
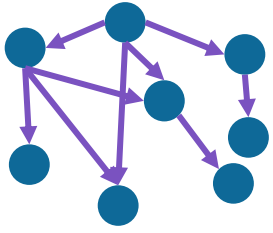
(with contributions from members of the FinBench Working Group)

Inherently connected data in Ant Group





~1 billion
Total registered users of Alipay

~100 billion
Total transaction count of Alipay

10 thousands ~ 1 trillion
Actual graph size we face

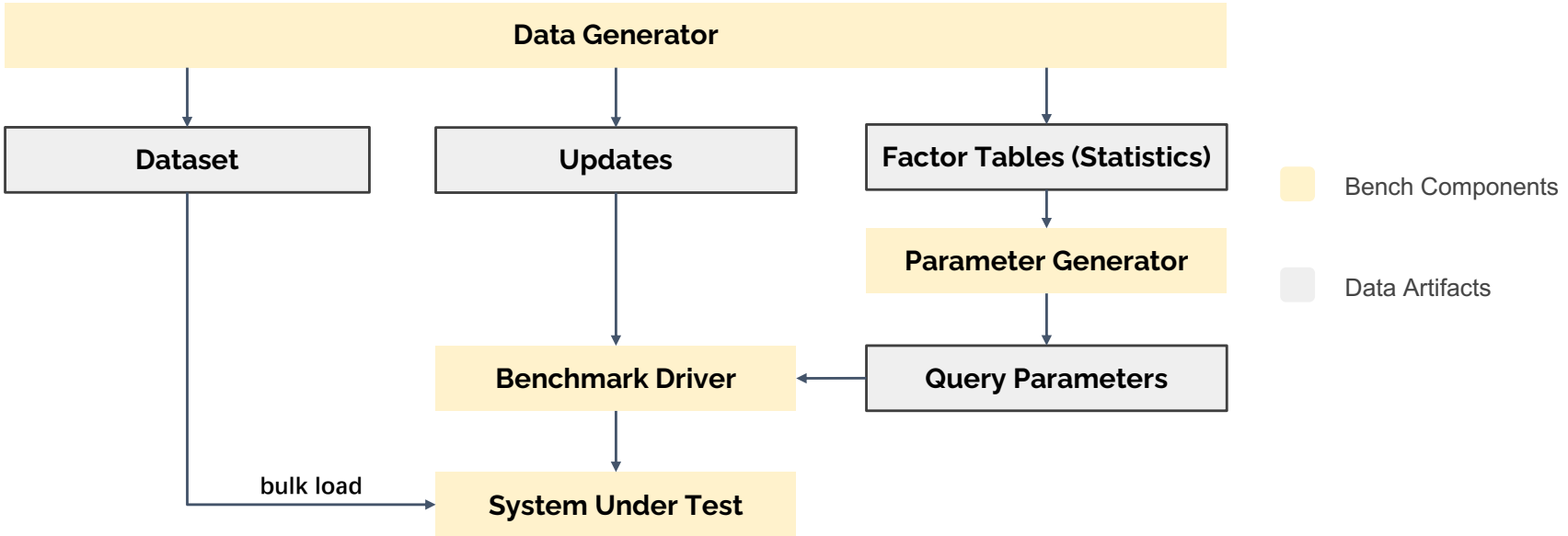
Motivation

Previous graph benchmarks fail to capture the characteristics of financial scenarios.

LDBC benchmarks	FinBench Transaction	SNB Interactive v1*	LinkBench	SNB BI	Graphalytics
labelled property graph	⊗	⊗	⊗	⊗	○
temporal property graph	⊗	⊗	○	⊗	○
edge multiplicity	⊗	○	○	○	○
insert operations	⊗	⊗	⊗	⊗	○
delete operations	⊗	○	⊗	⊗	○
query footprint	small	small	small	large	all data
inter-query parallelism	required	required	required	optional	not applicable
path finding	⊗	○	○	⊗	⊗
time-window queries	⊗	○	○	○	○
recursive path filtering	⊗	○	○	○	○
truncated traversal	⊗	○	○	○	○
read-write queries	⊗	○	○	○	○
workload type	OLTP	OLTP	OLTP	OLAP	graph algorithms
query mix	⊗	⊗	⊗	⊗	not applicable
time-biased query mix	⊗	○	○	○	not applicable

Benchmark Design Overview

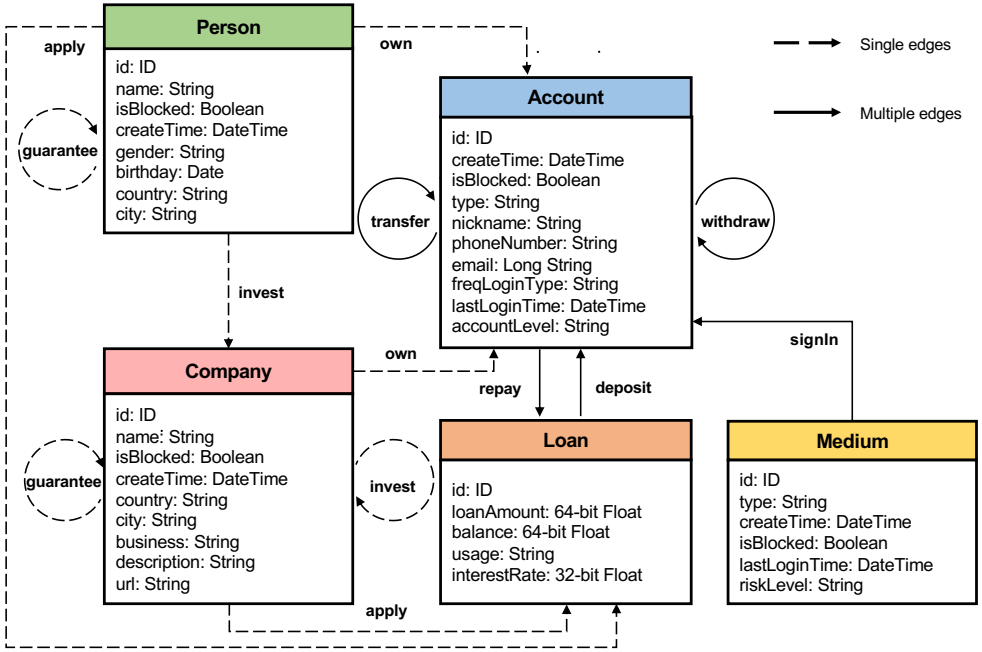
- Design philosophy: "**choke point driven methodology**"[1] to balance between the real-world business complexity and benchmark abstraction
- Key aspects: **dataset** (including schema and distribution), **query**, and **workload**



[1] Peter Boncz, Thomas Neumann, and Orri Erling. 2013. TPC-H Analyzed: Hidden Messages and Lessons Learned from an Influential Benchmark. In Revised Selected Papers of the 5th TPC Technology Conference on Performance Characterization and Benchmarking - Volume 8391. Springer-Verlag, Berlin, Heidelberg, 61–76. https://doi.org/10.1007/978-3-319-04936-6_5

Dataset Schema

Surveyed on over 20 business clusters and take typical transaction scenario as design



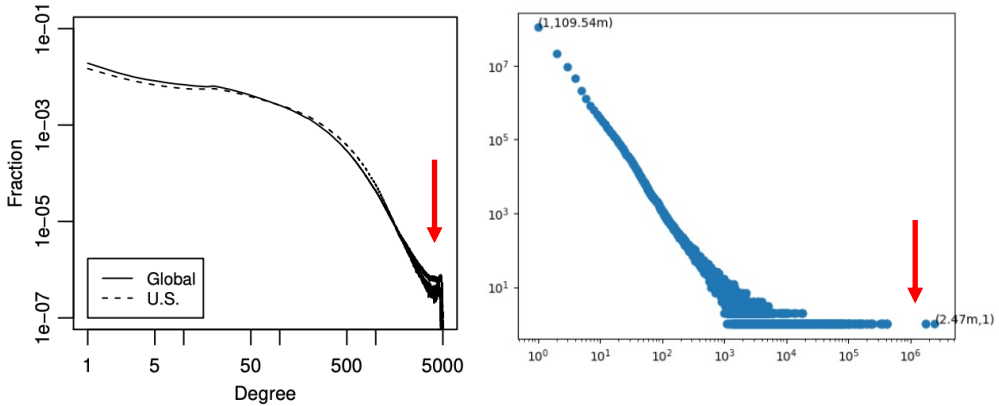
5 vertex types and 9 edge types

- Entities as vertices while activities as edges
- Timestamp frequently used
- Various subtypes of same entities
- Rich properties
- Edge multiplicity

Note: edge properties are omitted here.

Dataset Distribution

We randomly sampled three subgraphs from the online production environment by uniformly selecting vertices to ensure representative profiling



social network[2] financial graph

Power law distribution of the vertex degree

What is the difference?

Max 5000 friend limited by Facebook

↓

Social Network

↓

Bounded skewness with a shallower tail

V.S.

Unbounded skewness in FinBench

↓

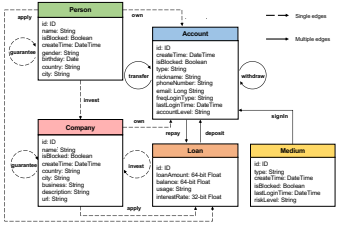
Financial Graphs

↓

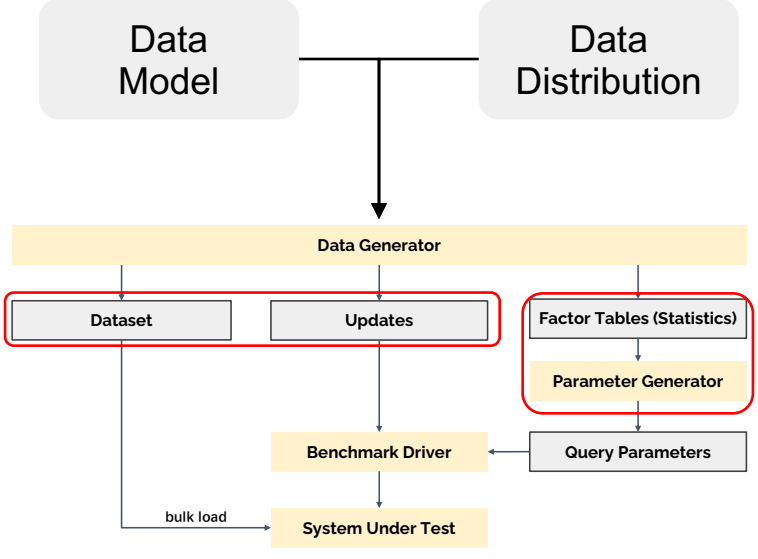
Hub vertices of **higher** degree

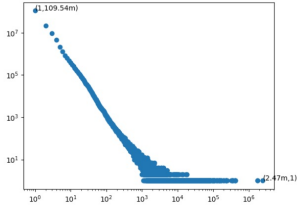
[2] Johan Ugander, Brian Karrer, Lars Backstrom, and Cameron Marlow. 2011. The Anatomy of the Facebook Social Graph. arXiv:1111.4503 [cs.SI] Retrieved June 17, 2025 from https://arxiv.org/abs/1111.4503

Dataset Generation



The scalable and configurable data generator simulates the financial activities and then segments the overall data to **snapshot data for bulk loading** and **incremental data for write queries.**





Fact: The cost of graph queries varies depending on the starting vertex. The factor tables record **statistics of query footprints**, and are used to guide the read query parameter selection to ensure the benchmark reliability.

Case Study: Temporal Queries

- **Feature**: Query usually looks back in a limited time window. They filter edges between startTime and endTime in traversal.
- **Practices**: Hot/cold storage tiering, data compaction
- **Choke point**: Query benefits from temporal access locality (for edges).

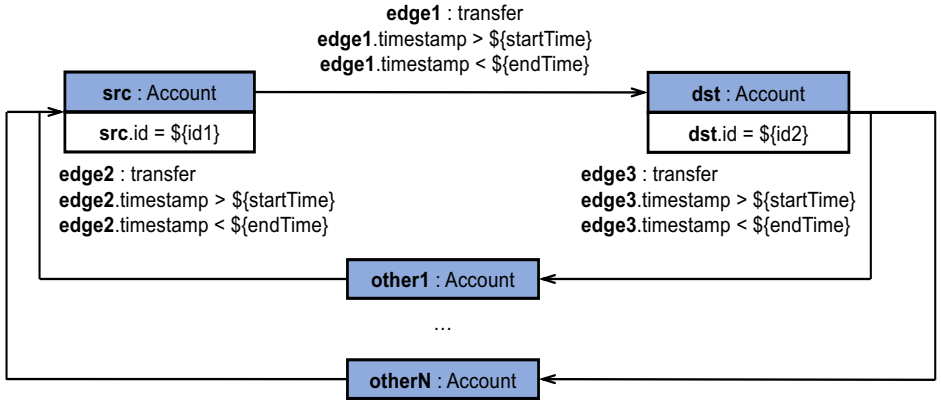


Figure 6: The pattern of complex read query 4 (TCR 4) in transaction workload.

Query Explanation:

TCR 4 matches a transfer cycle within a specified time window between *startTime* and *endTime.*

Case Study: Recursive Path Filtering

Given a path: A -[e_1]-> B -[e_2]-> ... -> X

- Timestamp order: $e_1 < \ldots < e_i$
- Amount order: $e_1 > \ldots > e_i$
- Optional: $e_i \in (e_{i-1}, e_{i-1} + k)$, k is const.

- **Feature**: Query matches paths filtered by monotonicity predicates.
- **Choke point**: Query benefits from path-level predicates push-down, pruning invalid intermediate results.

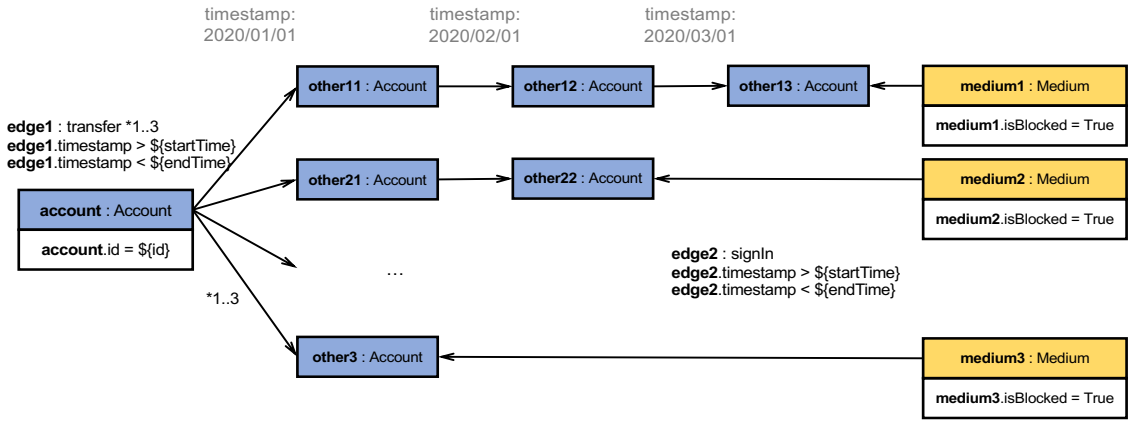


Figure 7: The pattern of complex read query 1 (TCR 1) in transaction workload.

Query Explanation:

TCR 1 matches transfer paths in ascending temporal order, tracing the divergence/downstream of a fund flow.

Case Study: Read-Write Query

- **Query Explanation:** Query usually checks graph pattern indicating illegal activities before write operation execution.
- **Feature**: Query is a complex read (the risk strategies) wrapped in transactions
- **Choke point**: Query benefits from optimization on write operation contention and conflicts.

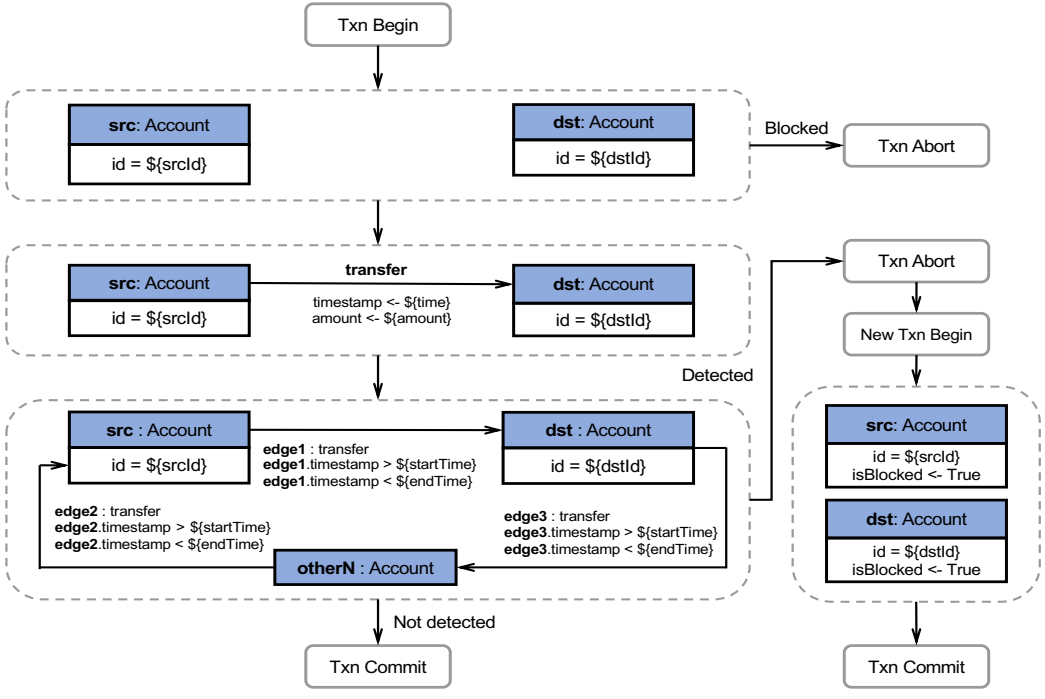


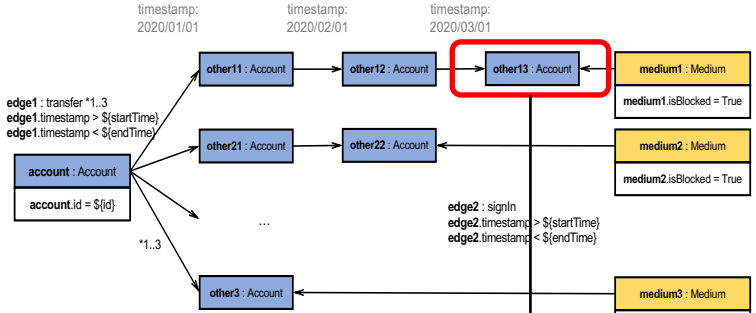
Figure 8: The pattern of read-write query 1 (TRW 1) in transaction workload.

Workload Orchestration

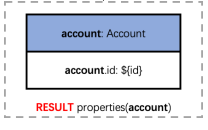
Transaction Workload includes 12 Complex Reads, 6 Simple Reads, 17 Writes, 3 Read-Writes

- Write queries and read-write queries are incremental data.
- Read queries are mixed as random walks on the graph.

Complex Read 1



Simple Read 1
find the properties of exact account



Time-biased random walk: $Prob(x) = 1 - U^{k \cdot t}$

- U is a random variable uniformly distributed in the interval [0, 1).
- t is the time window length for the complex read query.
- k is a coefficient that adjusts the time window

Longer temporal window in Complex Read Queries indicates more Simple Read Queries following it.

Chokepoint Analysis Experiments

Experiments are conducted on TuGraph-DB (open-source) to demonstrate choke point analysis

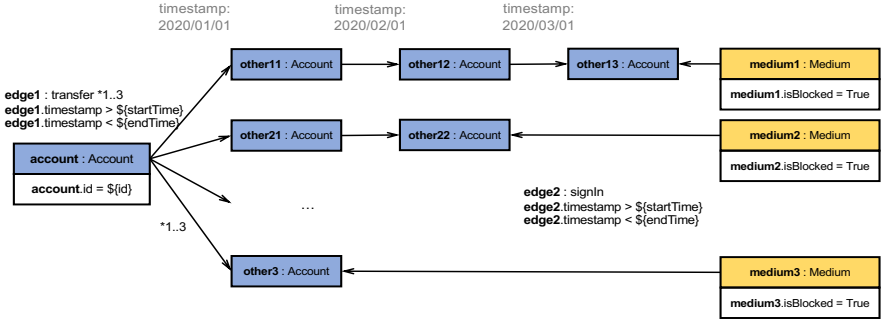
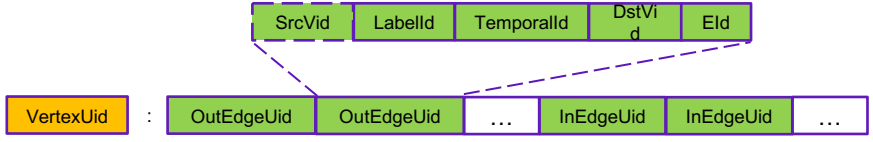


Figure 7: The pattern of complex read query 1 (TCR 1)

```
Produce Results
  Distinct
    Expand(All) [other <-- medium EdgeFilter e2]
      VarLen Expand(All) [acc -->*1..3 other EdgeFilter isAsc]
        Node Index Seek [acc]  IN []
```

Simplified logical plan of TCR 1



Experiment 1: Achieved ~41% query execution speedup on TCR 1 with temporal edge storage

Complex Read Query	Push-down Speedup
TCR 1	70.3%
TCR 2	87.4%
TCR 5	83.3%

Experiment 2: Achieved at least 70% query execution speedups with path filters pushed down

Note: Please refer to the paper for the end2end experiments

Takeaways & Future Work

- Profiled financial graphs and found features including timestamp properties, edge multiplicity and unbounded skewness.
- Provided a scalable (currently SF100) and configurable data generator conforming to the data features to simulate financial graphs.
- Identified several choke points embedded in queries and designed a Transaction Workload with 4 query categories.
- Provided a benchmark driver and reference implementations for demonstration and validation.
- Conducted choke point analysis experiments for further system optimization.

Future plan: Larger dataset scales and a new workload for OLAP (like SNB BI) in financial scenarios

Thanks!

- ldbc/ldbc_finbench_docs
- ldbc/ldbc_finbench_datagen
- ldbc/ldbc_finbench_driver
- ldbc/ldbc_finbench_transaction_impls