ISTC BIG DATA

S-Store: Streaming meets Transaction Processing

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joint work with

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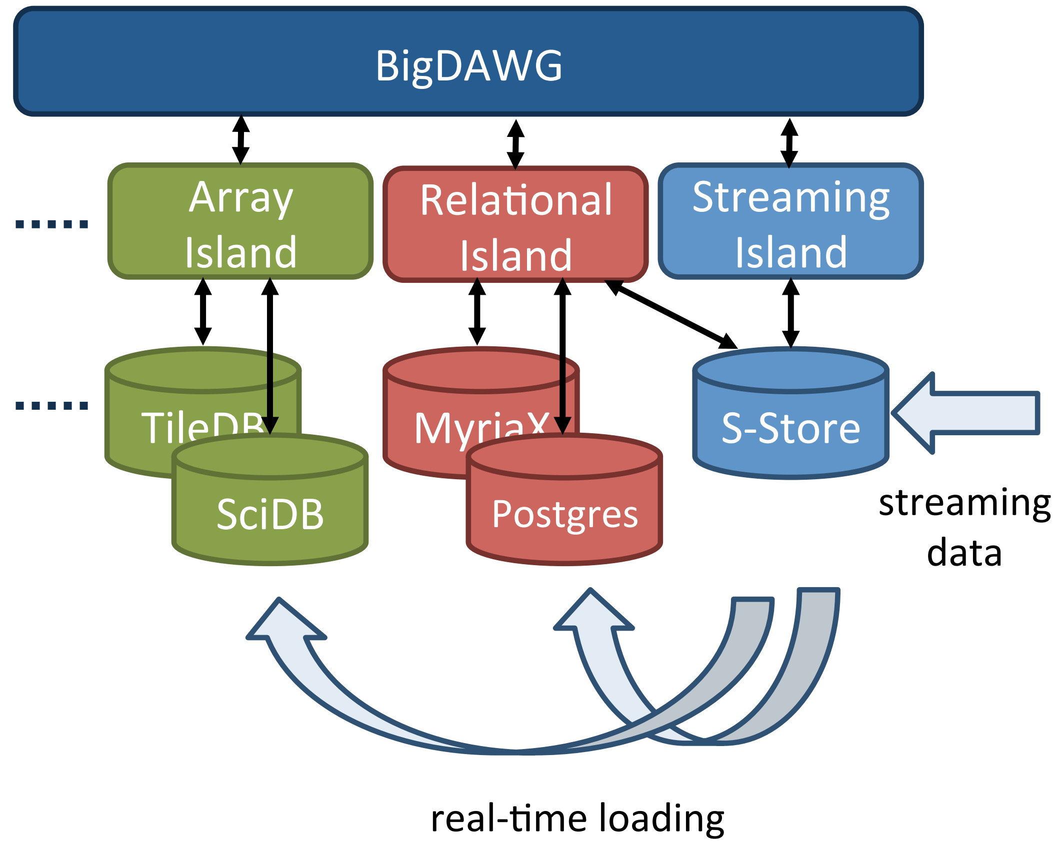
ISTC for Big Data

- One of Intel's 4 current Science and Technology Centers in the US (+6 similar ones world-wide)
- MIT as main hub + 8 other universities
- Launched in 2012, 3+2 years of funding
- Research themes:
  - Data analytics & processing platforms
  - Scalable math & algorithms
  - Visualization
  - Architecture
  - Benchmarks & testbeds
  - **Integration across multiple data processing systems**

The BigDAWG Polystore System

S-Store: BigDAWG's Streaming Data Store

- Reliable, real-time ingest of streaming data
- In-memory processing of all streaming analytics workloads
- Support for transactional state management and relational OLTP workloads
- Real-time ETL of new data into other BigDAWG stores
- Critical enabler for joining current data with past data



The Big Velocity Challenge

- Data is coming too fast!
  - Sensors, Smart phones, Internet of Things, Web clicks, Stock tickers, Social media feeds, News feeds, …
- Applications need:
  - scalable data ingest, processing, and storage
  - real-time, complex data analytics
  - high-throughput, transactional processing
  - data-driven, continuous, incremental processing models

State of the Art & Recent Trends

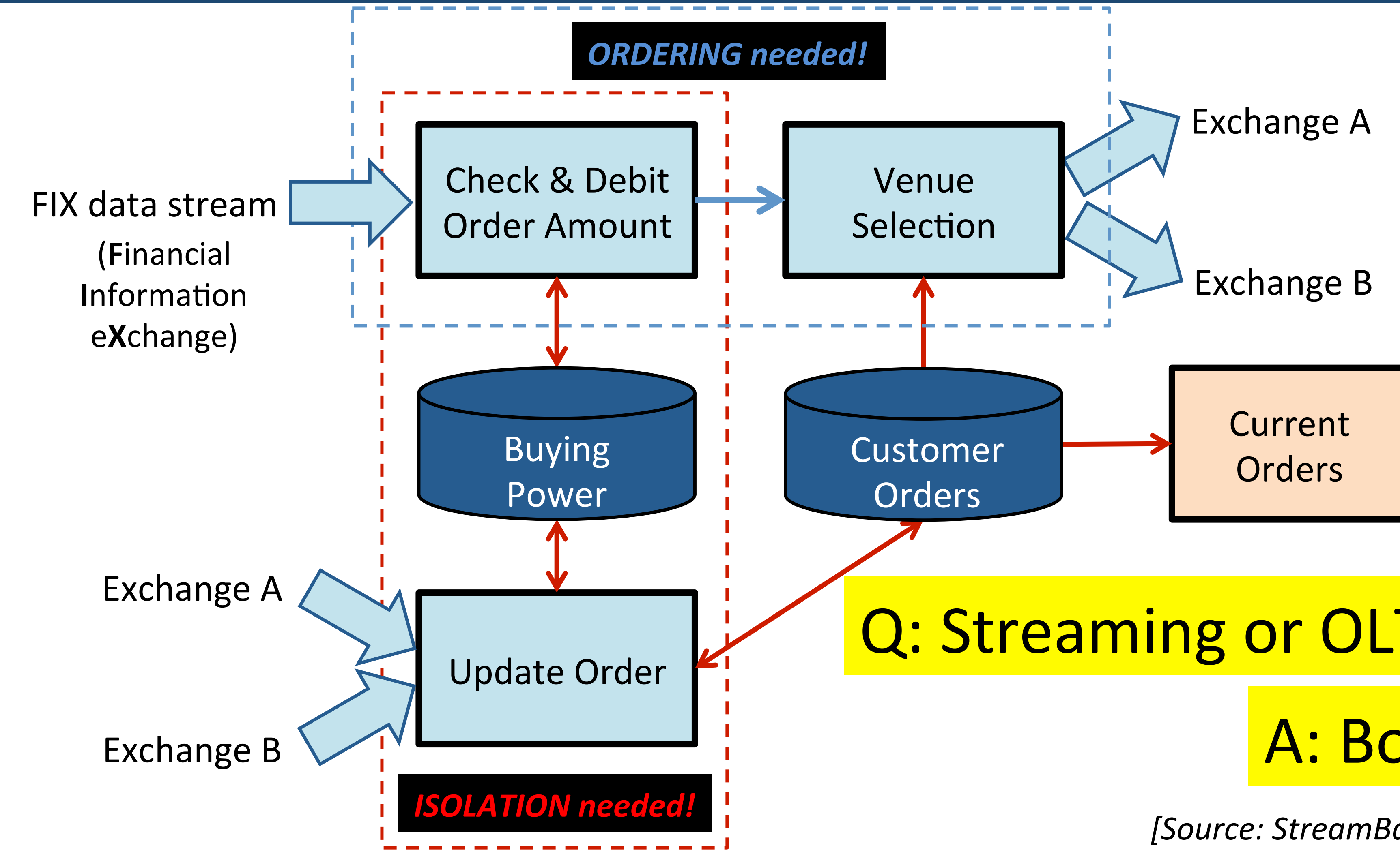
- Stream processing
  - in-memory, low-latency processing
  - fine-grained batching of inputs, complex datafl … utations
  - scalab … s

....

What about streams + transactions?

- Transaction processing
  - disk-based OLTP -> main-memory OLTP
  - multi-core, shared-nothing clusters
  - NewSQL architectures (scalable SQL and ACID)

Shared Mutable State in Streaming
A Real-World Example: Financial Order Routing



Q: Streaming or OLTP?

A: Both!

[Source: StreamBase, Inc.]

S-Store in a Nutshell

- A single system for transaction & stream processing
- A novel computational model for supporting hybrid workloads with well-defined correctness guarantees
  - **ACID** guarantees for individual transactions (OLTP + streaming)
  - **ordered execution** guarantees for dataflow graphs of streaming transactions
  - **exactly-once processing** guarantees for streams (no loss or duplication)
- A flexible and expressive programming interface
  - transactions as user-defined stored procedures (Java) w/ SQL-based data access
  - support for dataflow graphs and nested transactions
- Scalable software architecture and implementation
  - distributed main-memory OLTP system as foundation (H-Store)
  - clean and general architectural extensions (e.g., triggers, windowing)

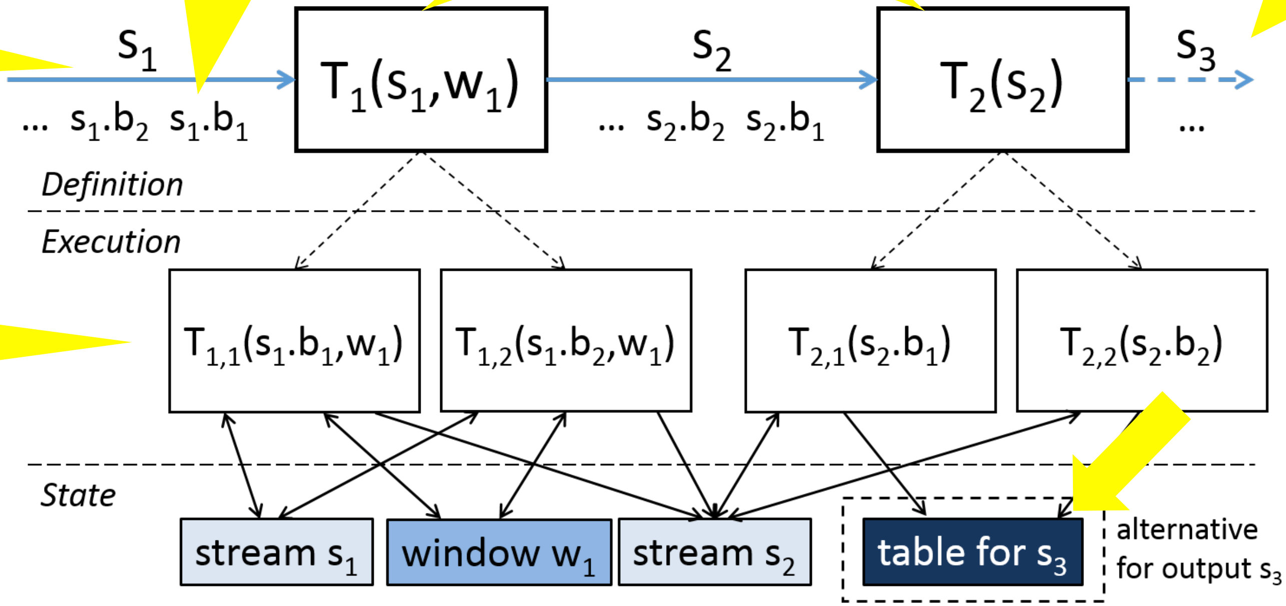
Hybrid Computational Model

Batch-id's are used to track lineage and order

Dataflow Graphs of **Streaming Transactions**

Push outputs to an external sink (or store in a Table)

Stream as a sequence of **Atomic Batches**



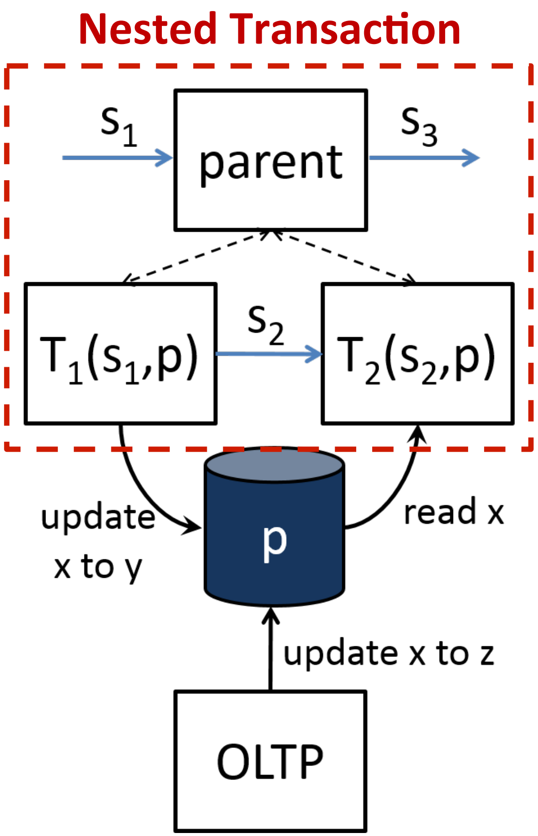
Each batch leads to a **Transaction Execution (TE)**

Three kinds of state: **Streams, Windows, and Tables**
- All physically kept as in-memory tables
- Tables can be publicly shared among all transactions (**OLTP or Streaming)**
- Streams & Windows are not publicly shareable

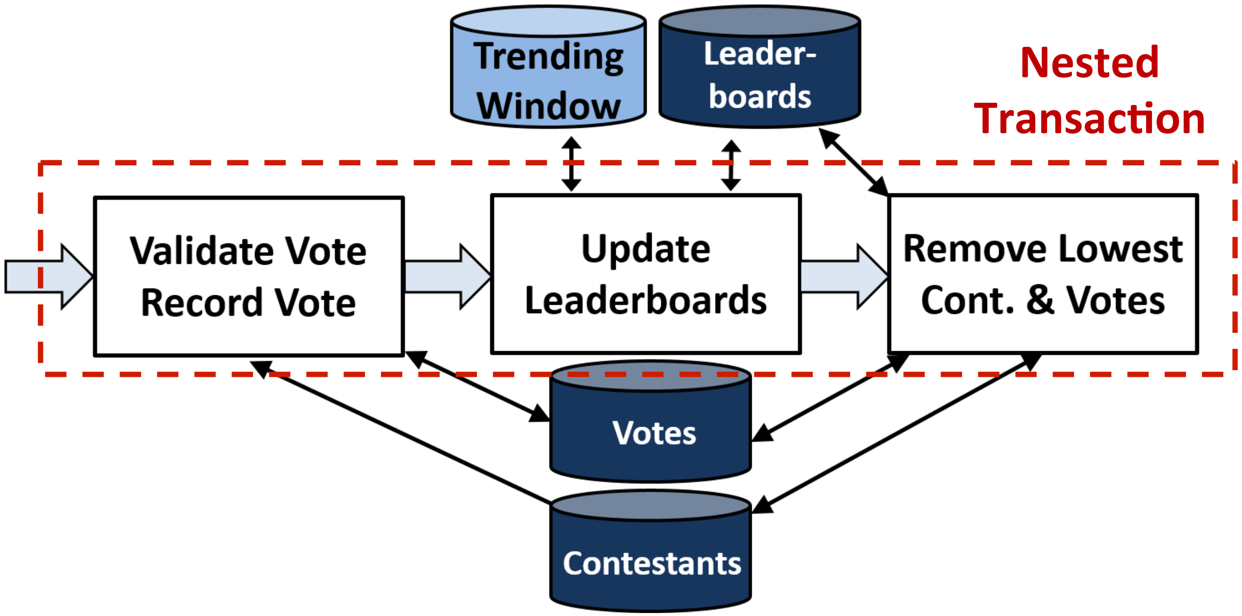
Nested Transactions for coarse-grained isolation

Example Uses for Nested Transactions

Use 1: To protect parts of a dataflow graph from other OLTP or Streaming transactions



Use 2: To protect one instance of a dataflow graph from its subsequent instances (e.g., Leaderboard Benchmark)



Triple Correctness Guarantees

- **ACID** from traditional OLTP
  - Failure recovery (Atomicity and Durability)
  - Concurrency control (Consistency and Isolation)
- **Ordered execution** from Streaming
  - Atomic batches of a stream must be processed in order (stream order constraint)
  - For a given atomic batch, transactions in a dataflow graph must be processed in topological order (dataflow order constraint)
  - Nested transactions require strict serial ordering
- **Exactly-once processing** from Streaming
  - Recovering from failures (i.e., replay of streams) should not cause lost or

➢ S-Store provides efficient scheduling and recovery mechanisms to ensure these guarantees.

H-Store as System Foundation

- main-memory OLTP system developed at Brown & MIT
- base design for the VoltDB NewSQL database system
- programming model: stored procedures (Java + SQL)
- database partitioned across multiple sites in a way to minimize the number of distributed transactions
- single-threaded transaction execution per partition
- recovery via checkpointing + command-logging
- anti-caching to disk if all data does not fit in memory

S-Store = H-Store + Streaming

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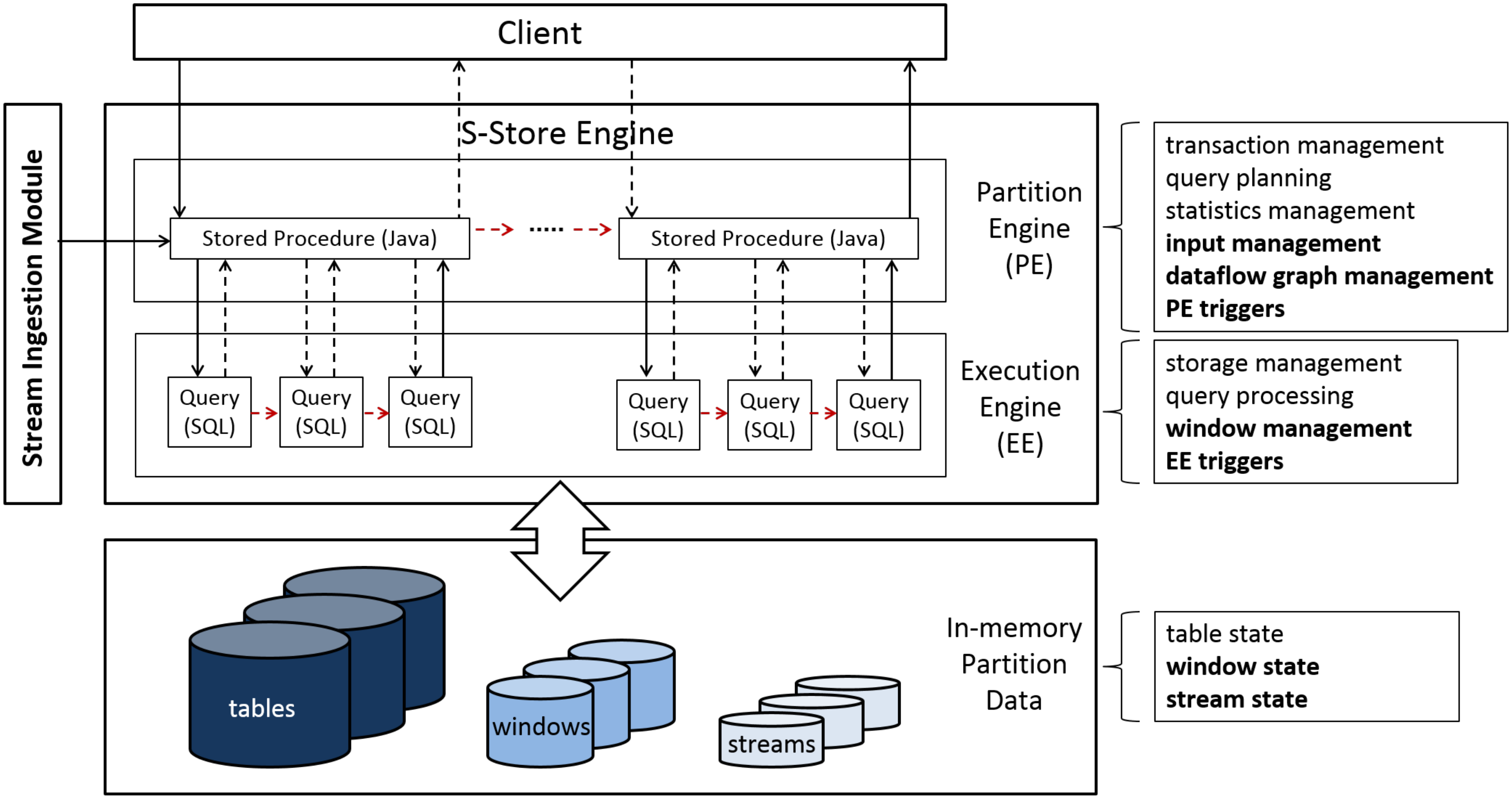
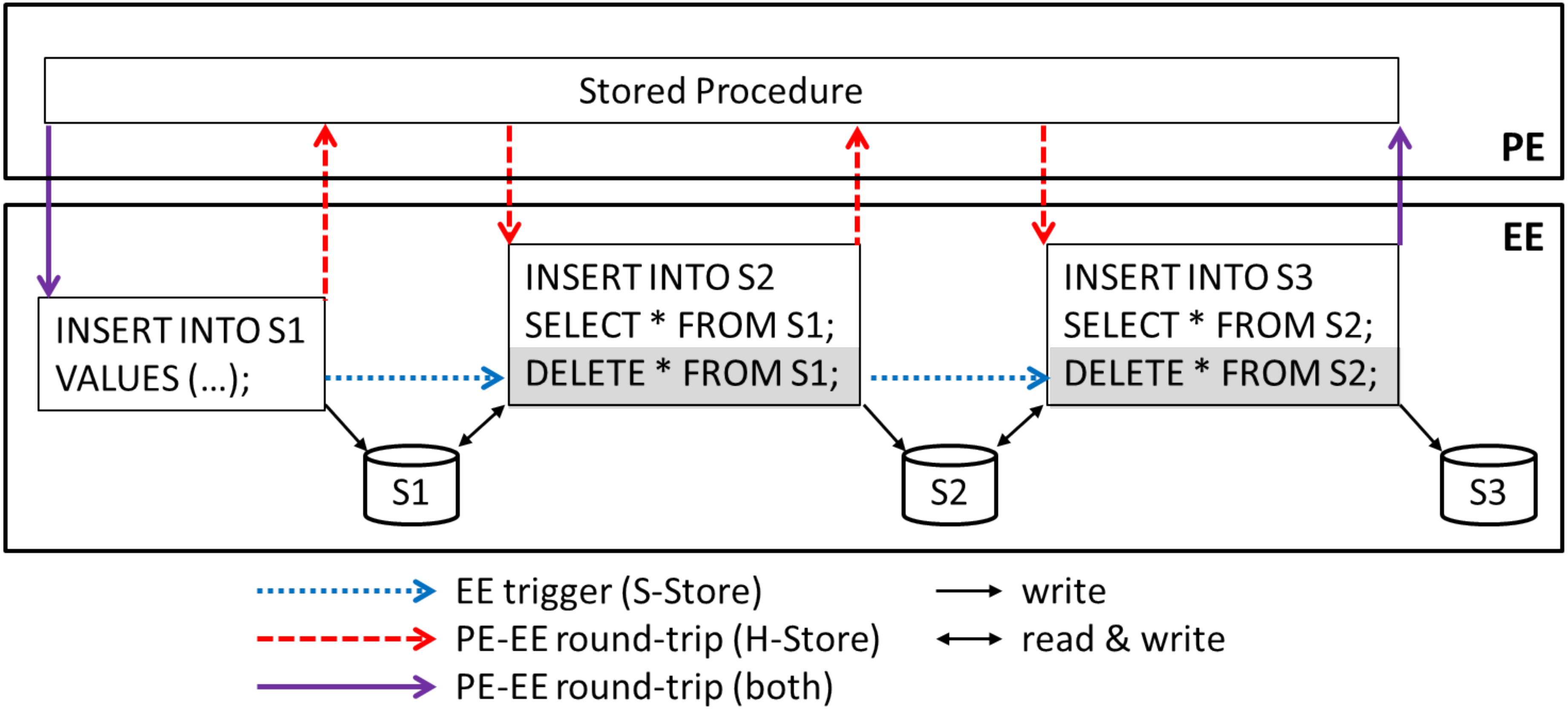
S-Store's Extended Architecture



S-Store vs. H-Store: EE Triggers



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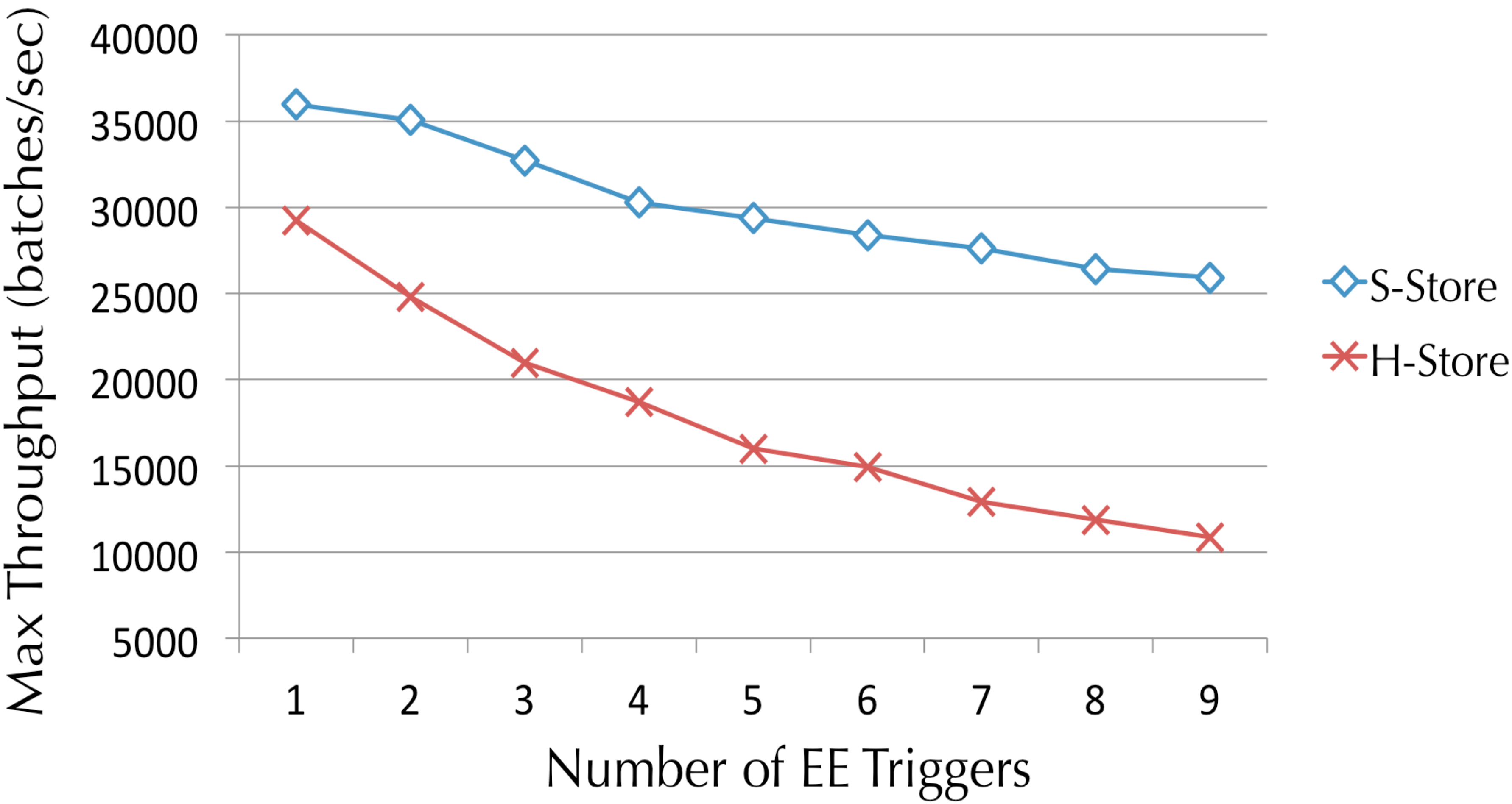

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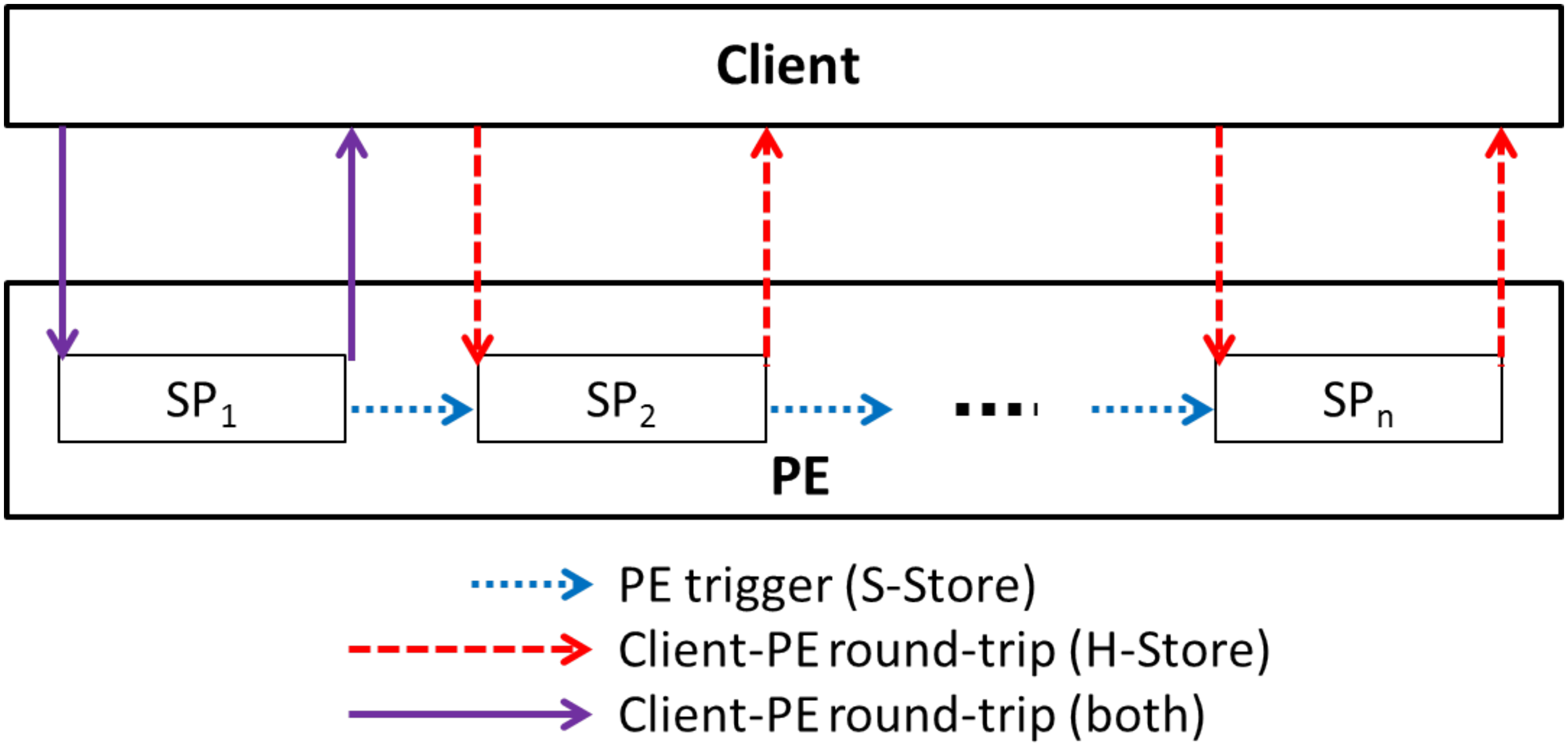
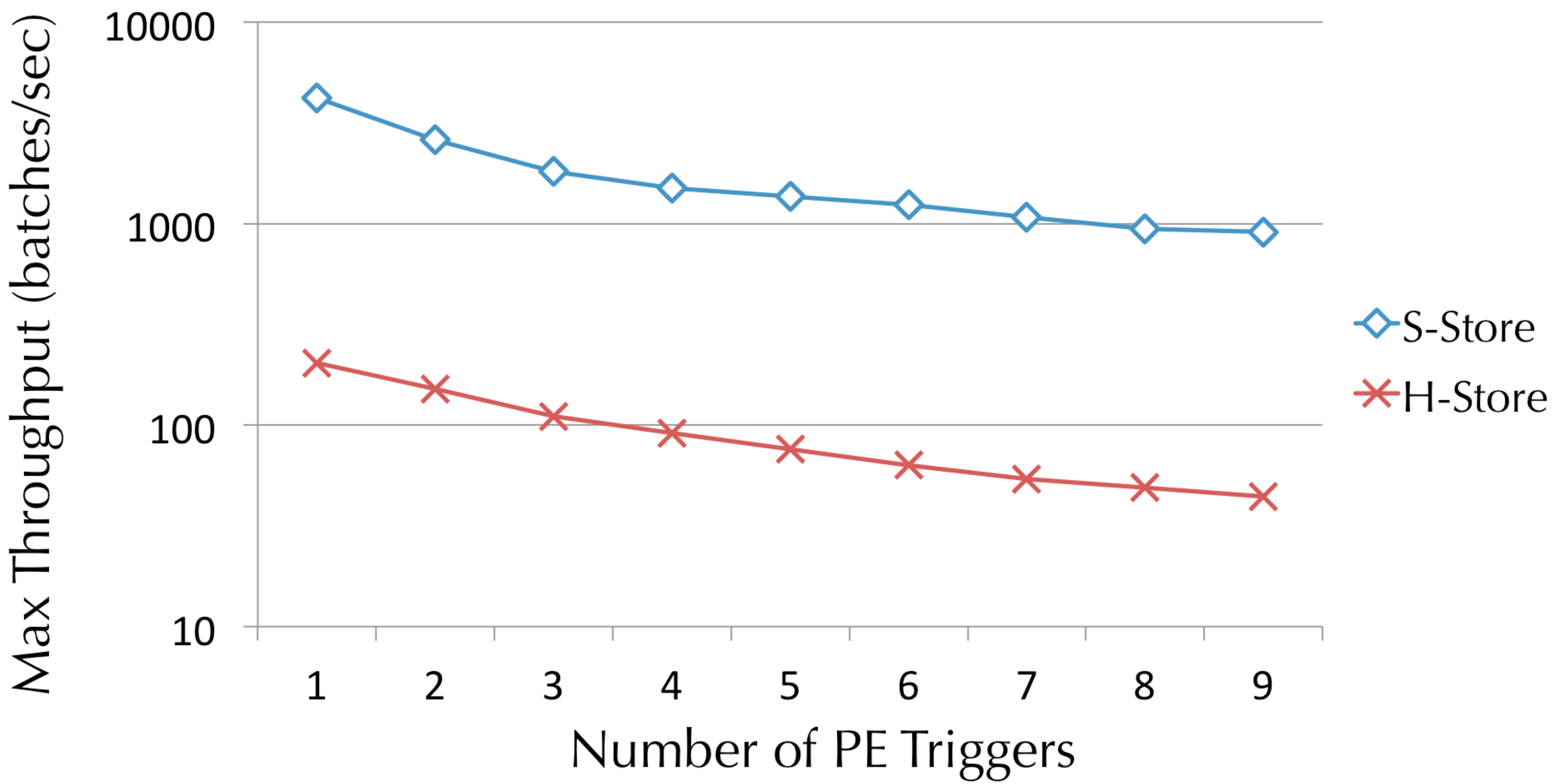
S-Store vs. H-Store: PE Triggers



S-Store vs. H-Store: PE Triggers

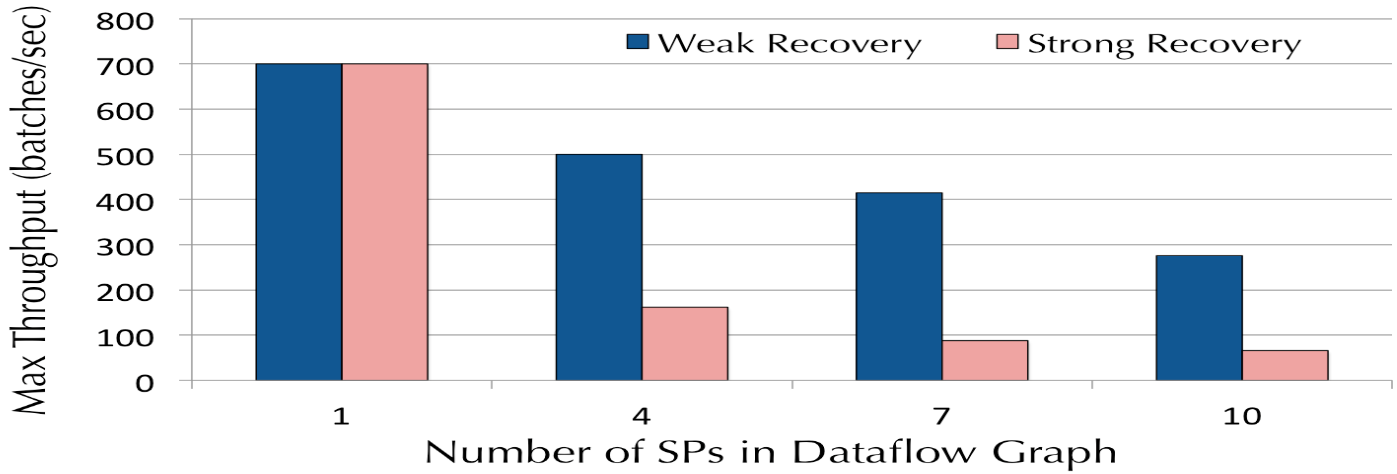


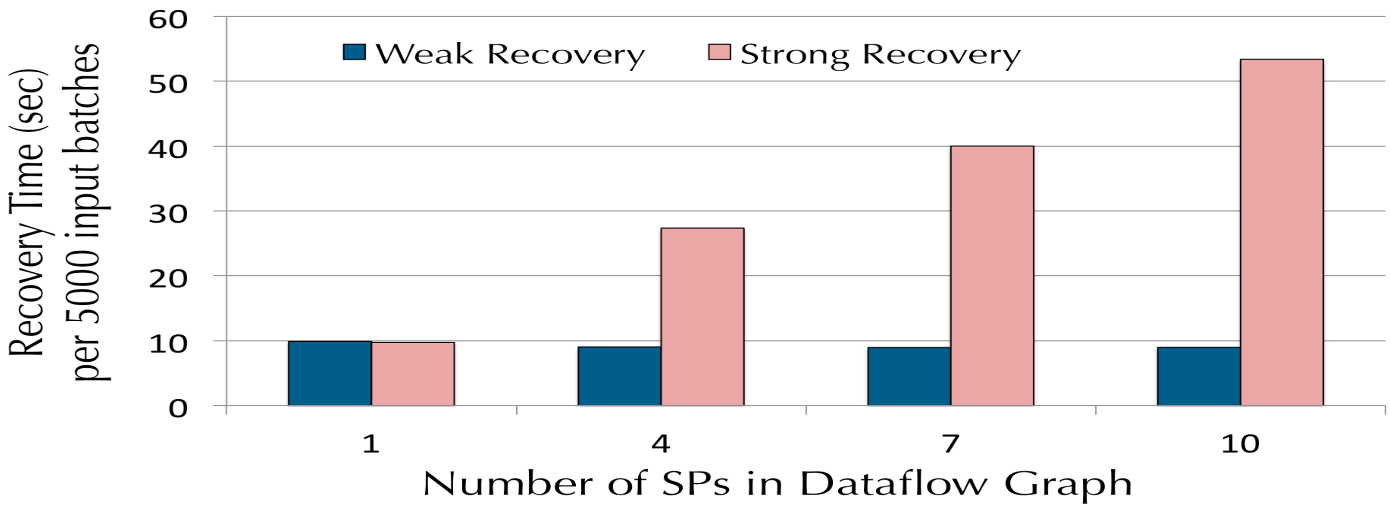
Fault Tolerance in S-Store

Check-pointing + Command-logging + Upstream backup

- Periodic check-pointing of in-memory tables to disk
- Strong recovery
  - Log all committed transactions (OLTP + streaming)
  - Upon failure, log replay reproduces the exact pre-failure state
  - To avoid redundancy, must turn off triggers during recovery
- Weak recovery
  - Log transactions selectively (all OLTP + "border" streaming)
  - Upon failure, log replay may lead to a different, but correct state
  - No need to turn off triggers
- Upstream backup for streaming inputs that have not yet been accounted for in downstream logs

Weak Recovery vs. Strong Recovery





S-Store vs. State of the Art

Better Correctness Guarantees & Better Performance

Correctness Guarantees (ACID, Order, Exactly-Once)

	System	ACID	Order	Exactly-Once	Max Tput (batches/sec)
OLTP variants	H-Store (async)	✓	×	×	5300
OLTP variants	H-Store (sync)	✓	✓	×	210
SPE variants	Esper+ VoltDB	✓	✓	×	570
SPE variants	Storm+ VoltDB	✓	✓	✓	600
	S-Store	✓	✓	✓	2200

~ 10 x OLTP
~ 4 x SPE

Leaderboard Benchmark on a single-node Intel® Xeon® E7-4830 at 2.13 GHz

"S-Store: Streaming Meets Transaction Processing", Research Track, PVLDB Vol. 8 No. 13, September 2015.

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Current Work in Progress
Scaling to Multiple Nodes

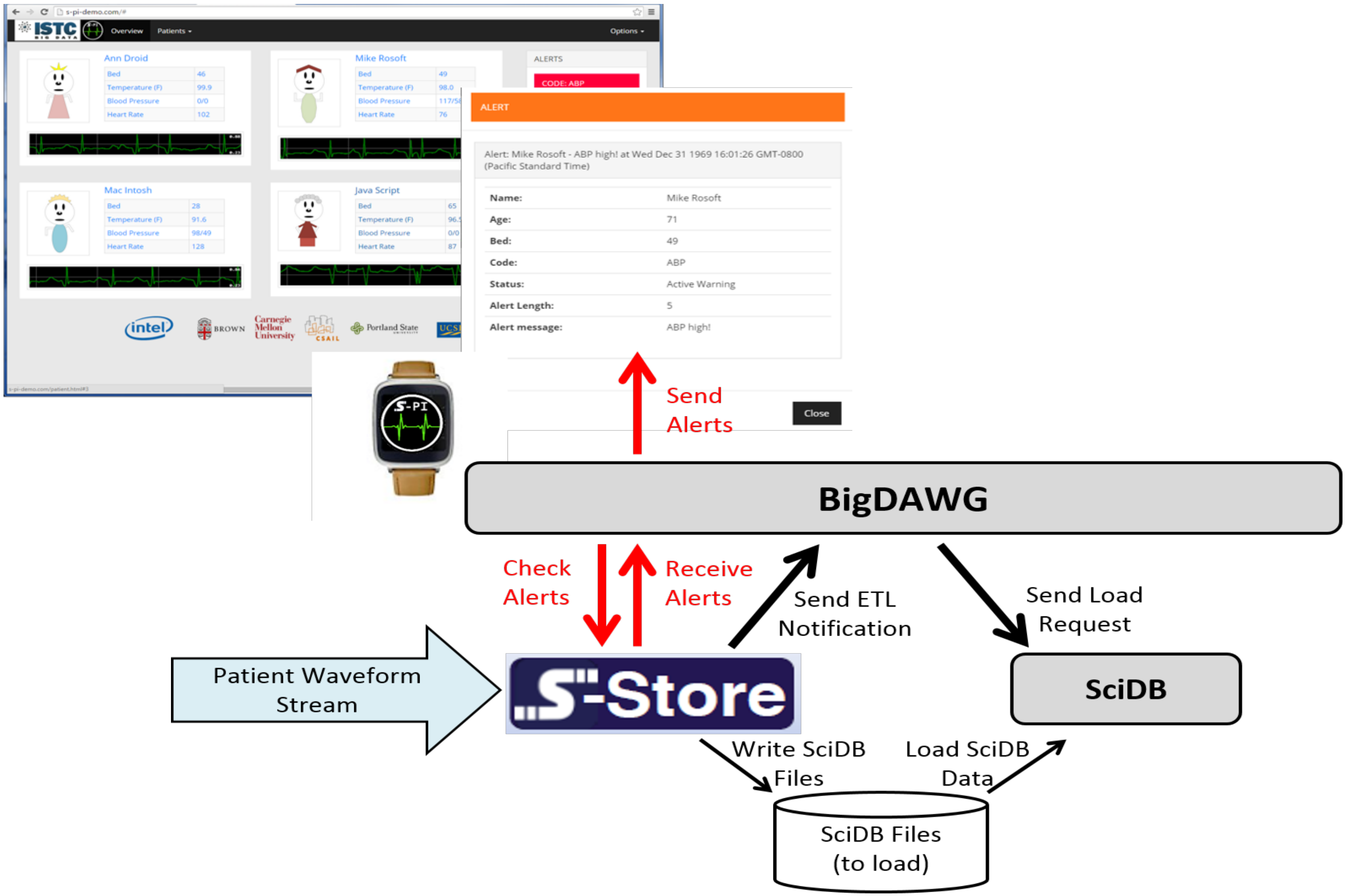
- Three basic primitives to partition a streaming workload:
  - **Move:** Move a stream from one node to another (distributed transaction)
  - **Demux:** Split a stream into multiple partitions
  - **Mux:** Merge multiple streams into one
- Both pipelined (Move) & partitioned parallelism (Demux+Move)
- Research question #1: Given a dataflow graph and a set of processing nodes, where to place Move/Demux/Mux + how to partition public Tables in order to maximize performance and load balance?
- Research question #2: How to ensure correct and efficient scheduling and recovery at all nodes?

Future Directions

- Extend our support for streaming analytics
- Tighter integration with BigDAWG (e.g., optimizing cross-system workloads)
- Hardware-aware S-Store (NVM, many-core, fast networks)
- Handling mixed and dynamic workloads
- Building novel and challenging use cases

Demos

S-Store in Action
The MIMIC Demo



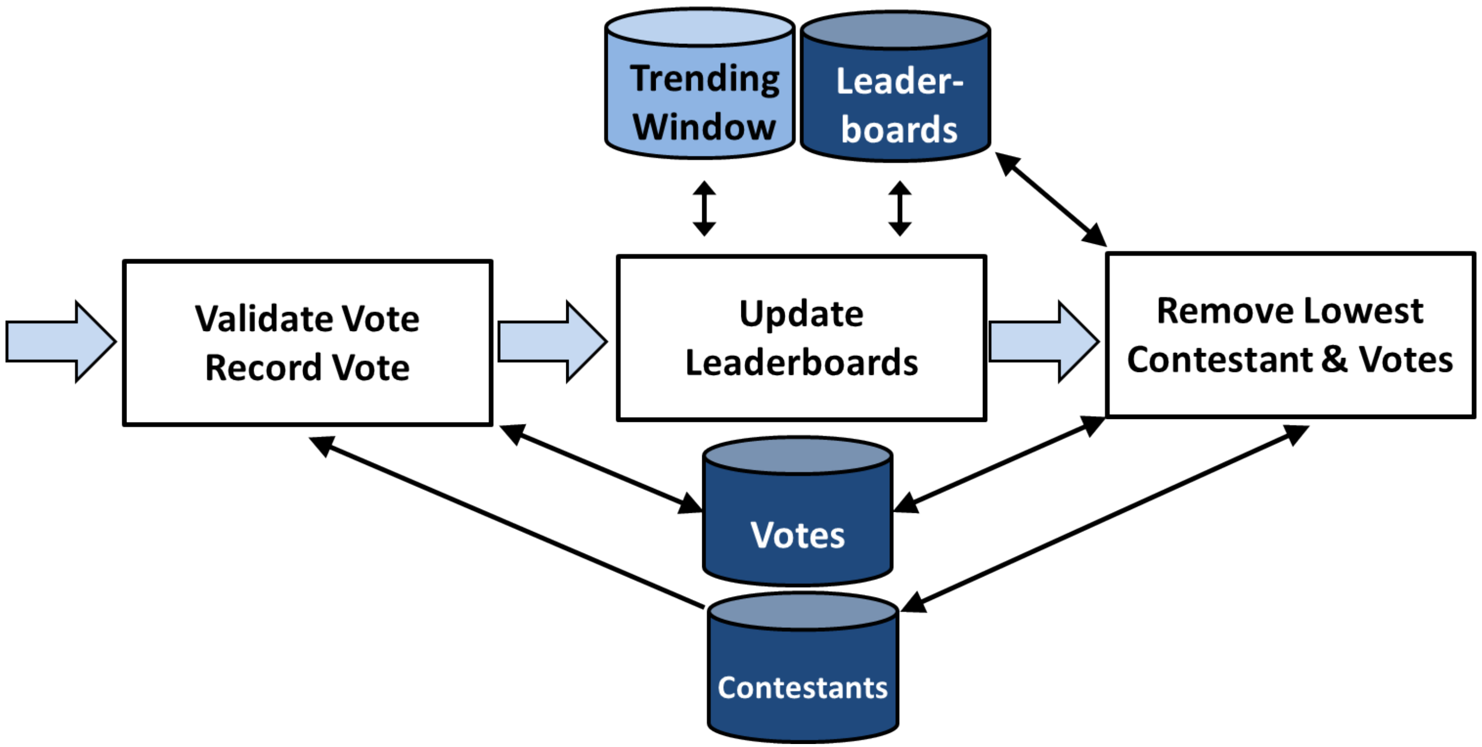
S-Store in Action

The MIMIC Demo

S-Store

S-Store in Action

The Canadian Dreamboat Demo



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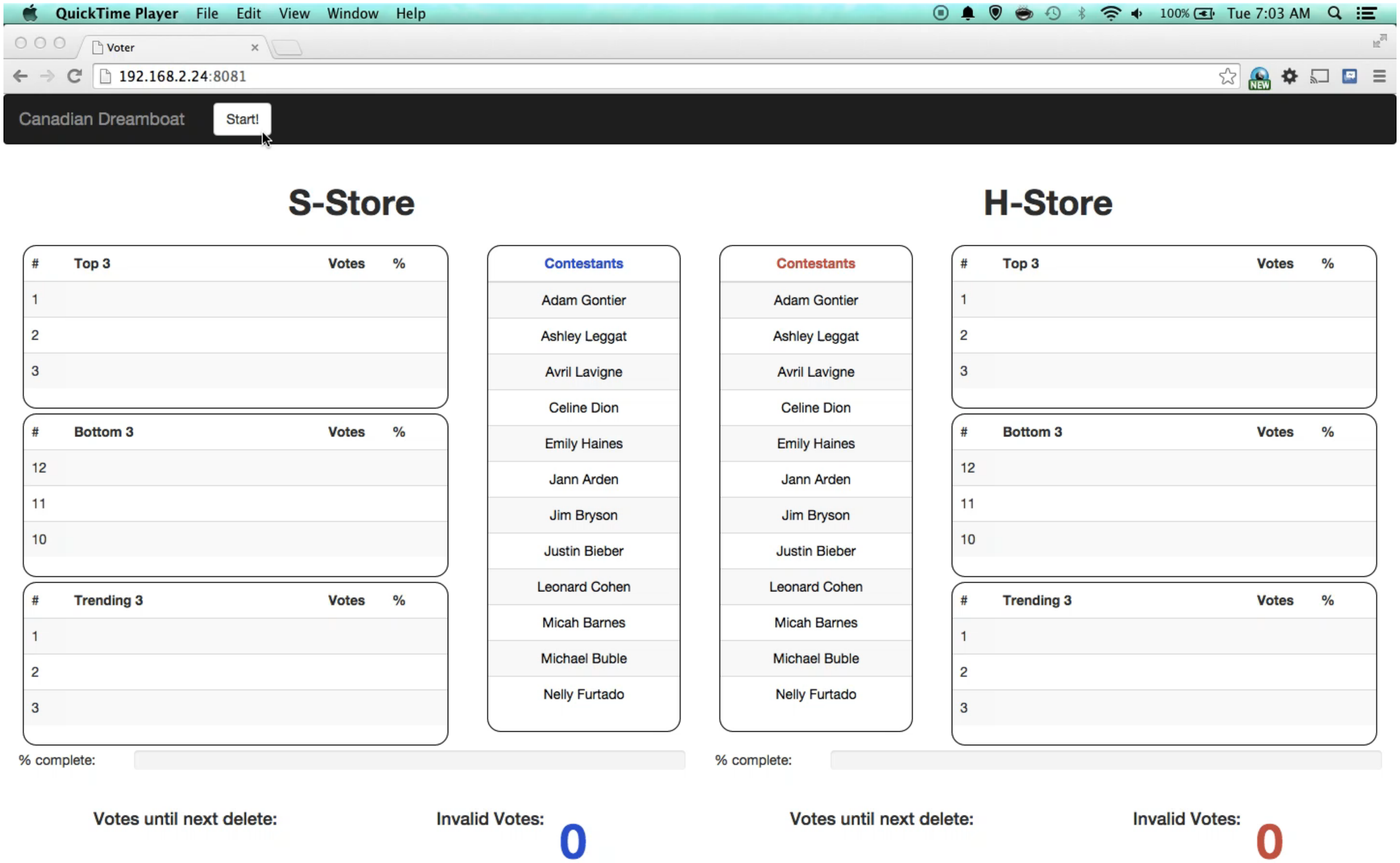

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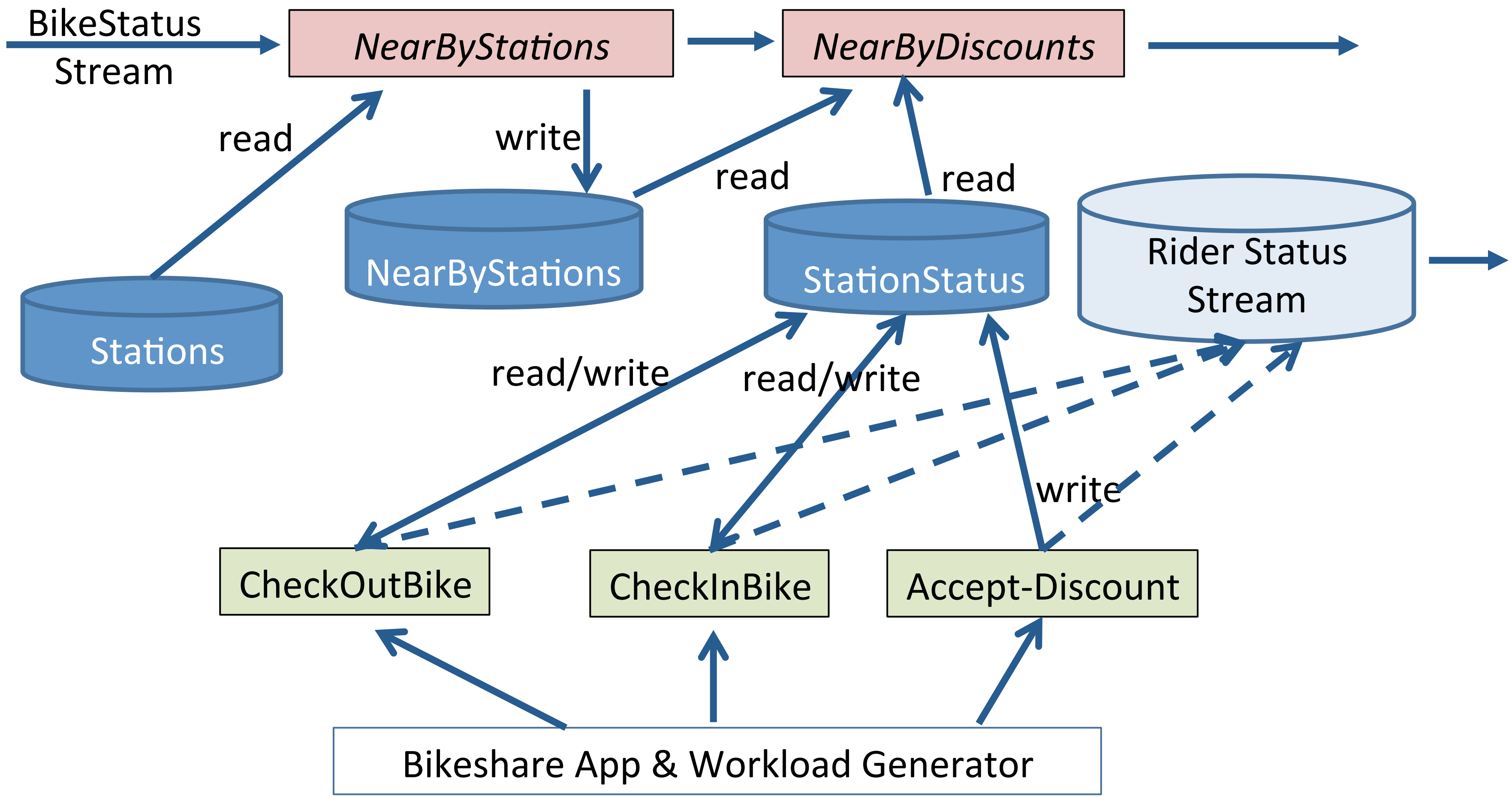
S-Store in Action

The BikeShare Demo



S-Store in Action

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