SnappyData

A Unified Cluster for Streaming, Transactions, & Interactive Analytics

Version 0.7 |

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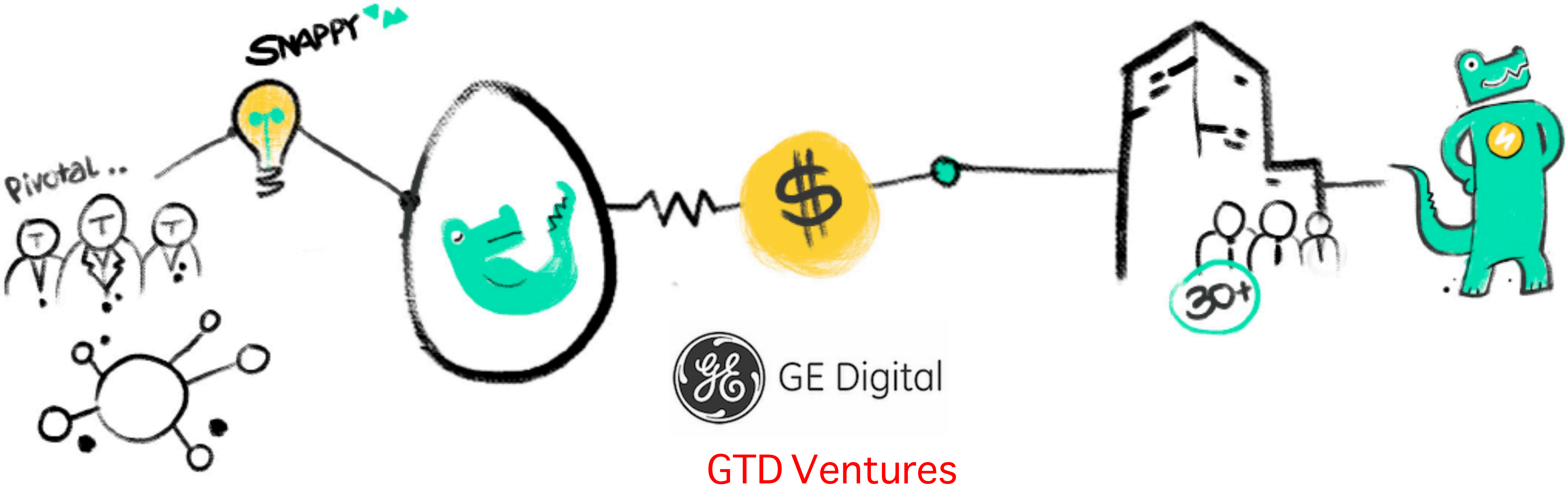
www.Snappydata.io

Our Pedigree

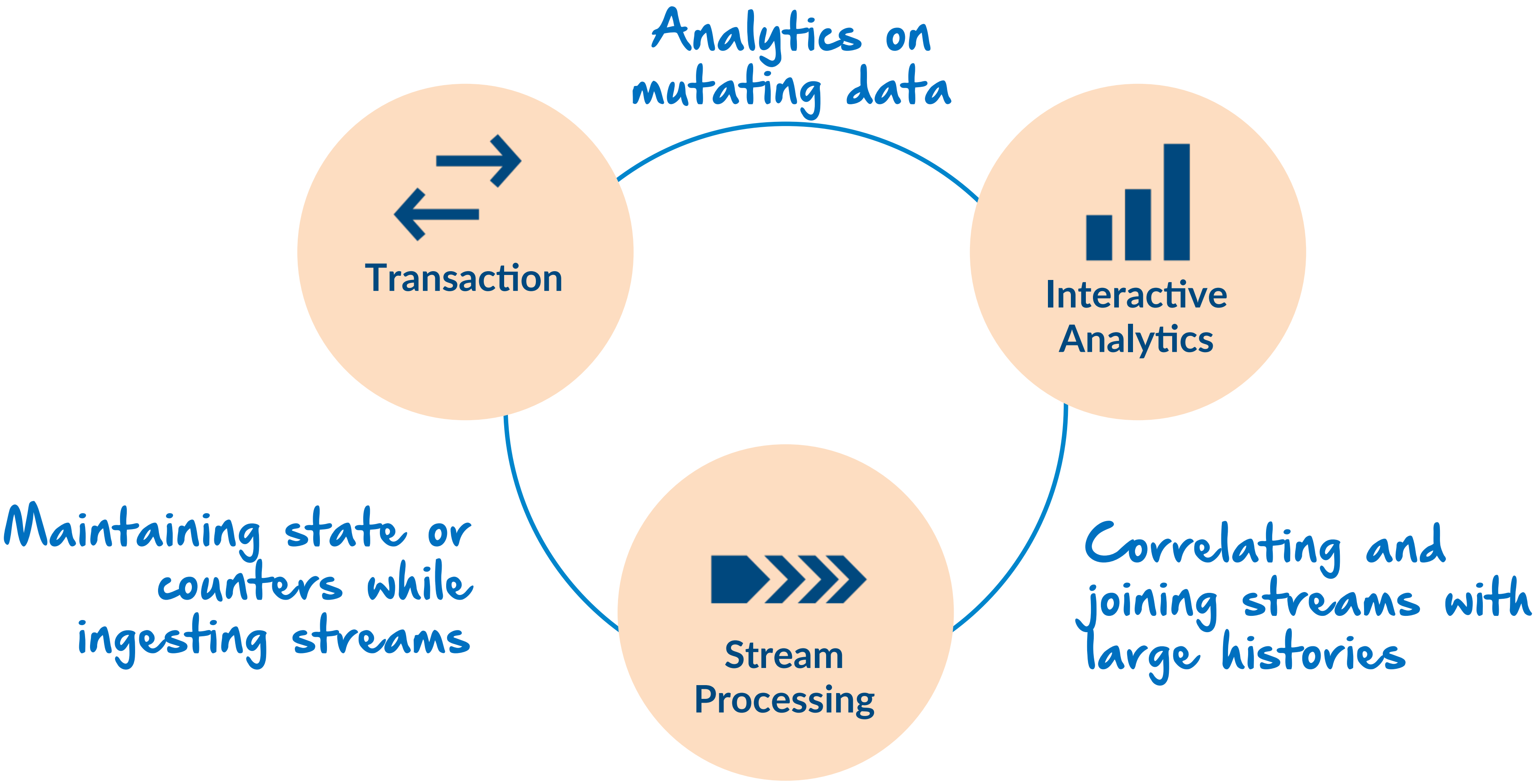


GE Digital

GTD Ventures

Pivotal

Mixed Workloads Are Everywhere



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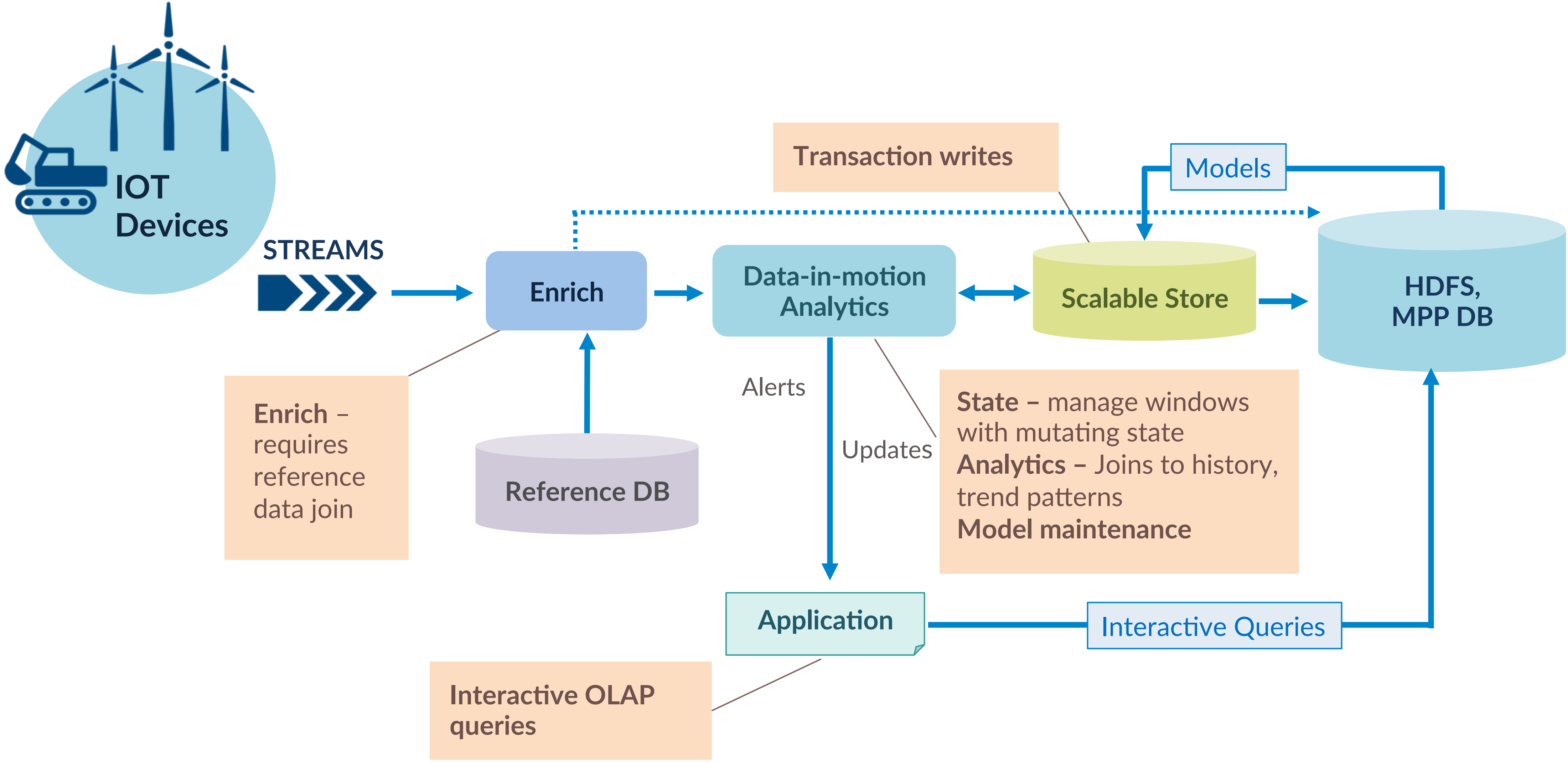
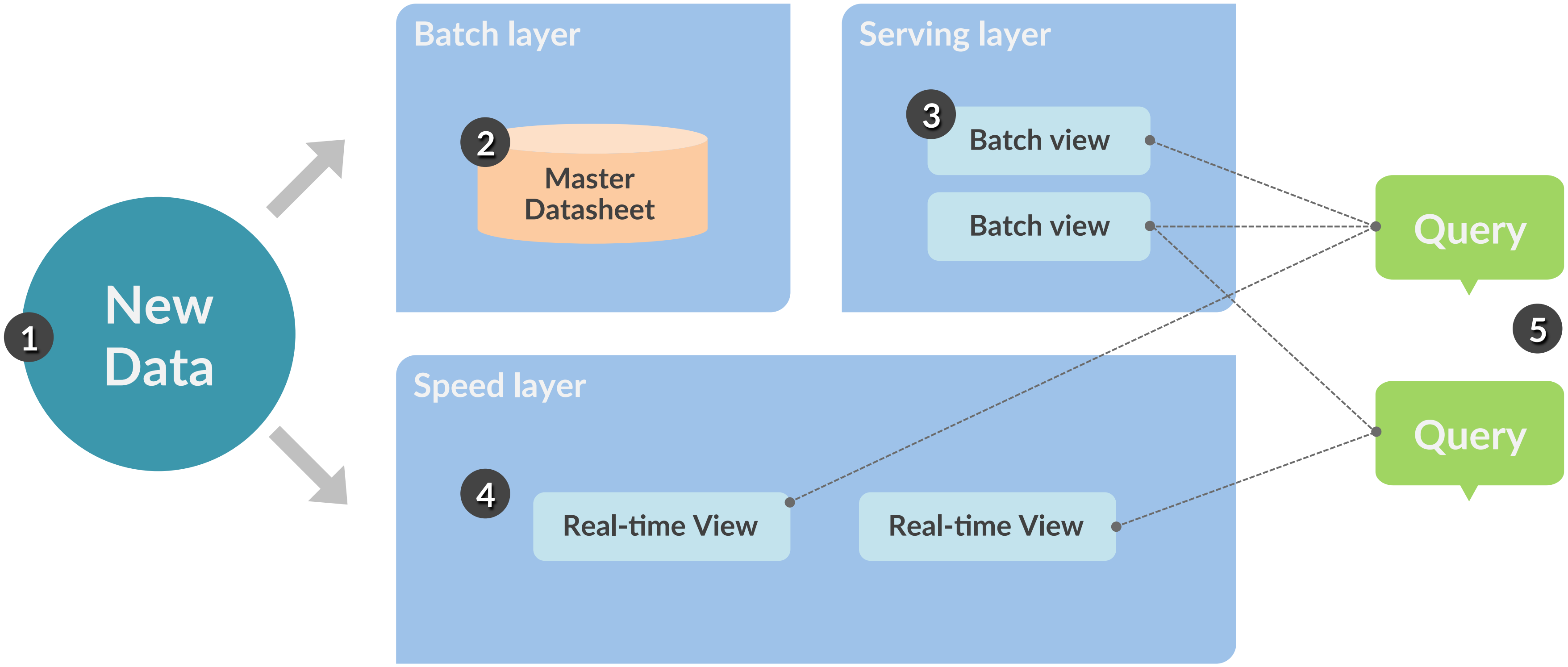


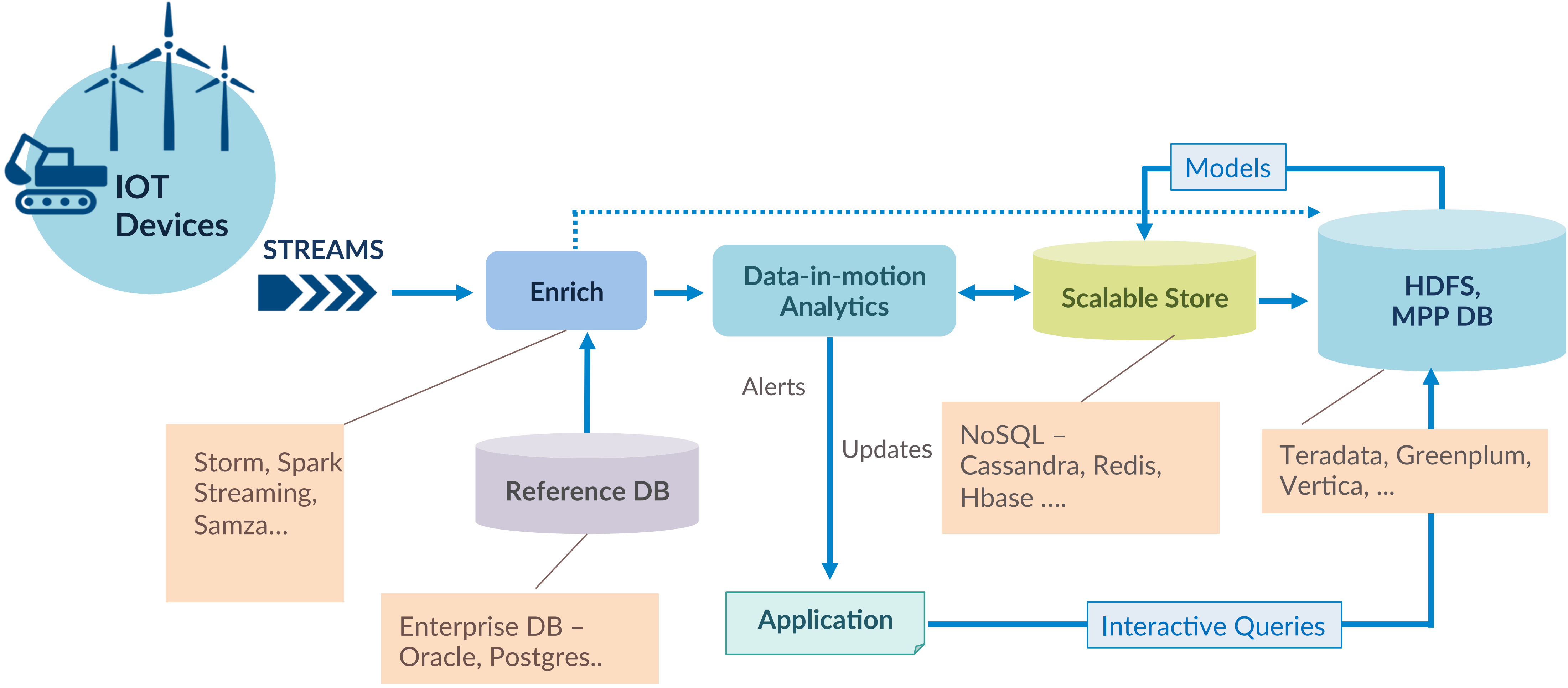
Why Supporting Mixed Workloads is Difficult?

Data Structures	Columnar	Row stores	Sketches
Query Processing Paradigm	Batch Processing	Point Lookups	Delta / Incremental
Scheduling & Provisioning	Long-running	Short-lived	Bursty

Lambda Architecture



Lambda Architecture is Complex



Lambda Architecture is Complex

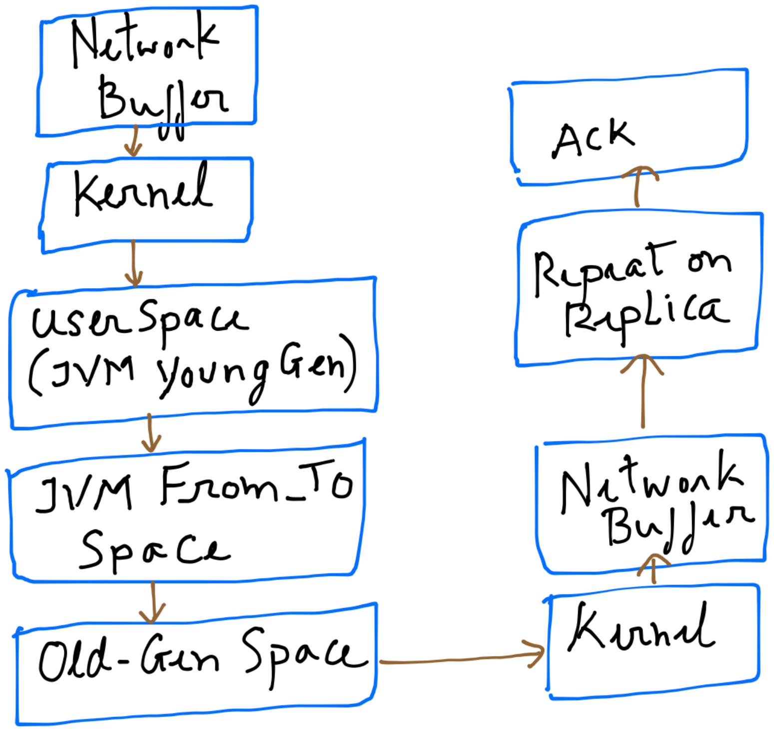
- **Complexity**

  - Learn and master multiple products, data models, disparate APIs & configs

- **Wasted resources**

- **Slower**

  - Excessive copying, serialization, shuffles
  - Impossible to achieve interactive-speed analytics on large or mutating data



Can We Simplify & Optimize?

Our Solution: SnappyData

Single Unified HA Cluster

OLTP + OLAP + Streaming for Real-time Analytics

Spark

Batch design, high throughput

Rapidly Maturing

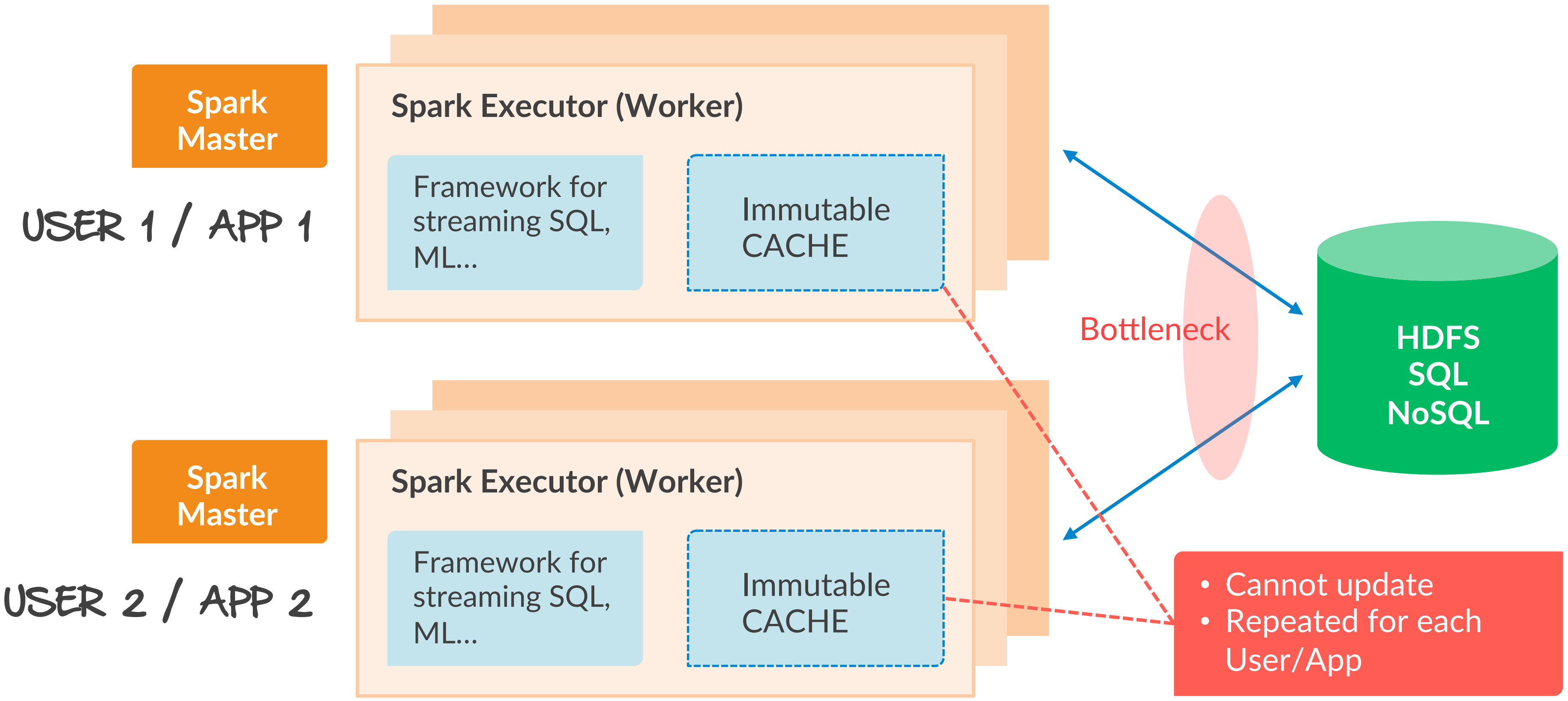
GemFire

Real-time design

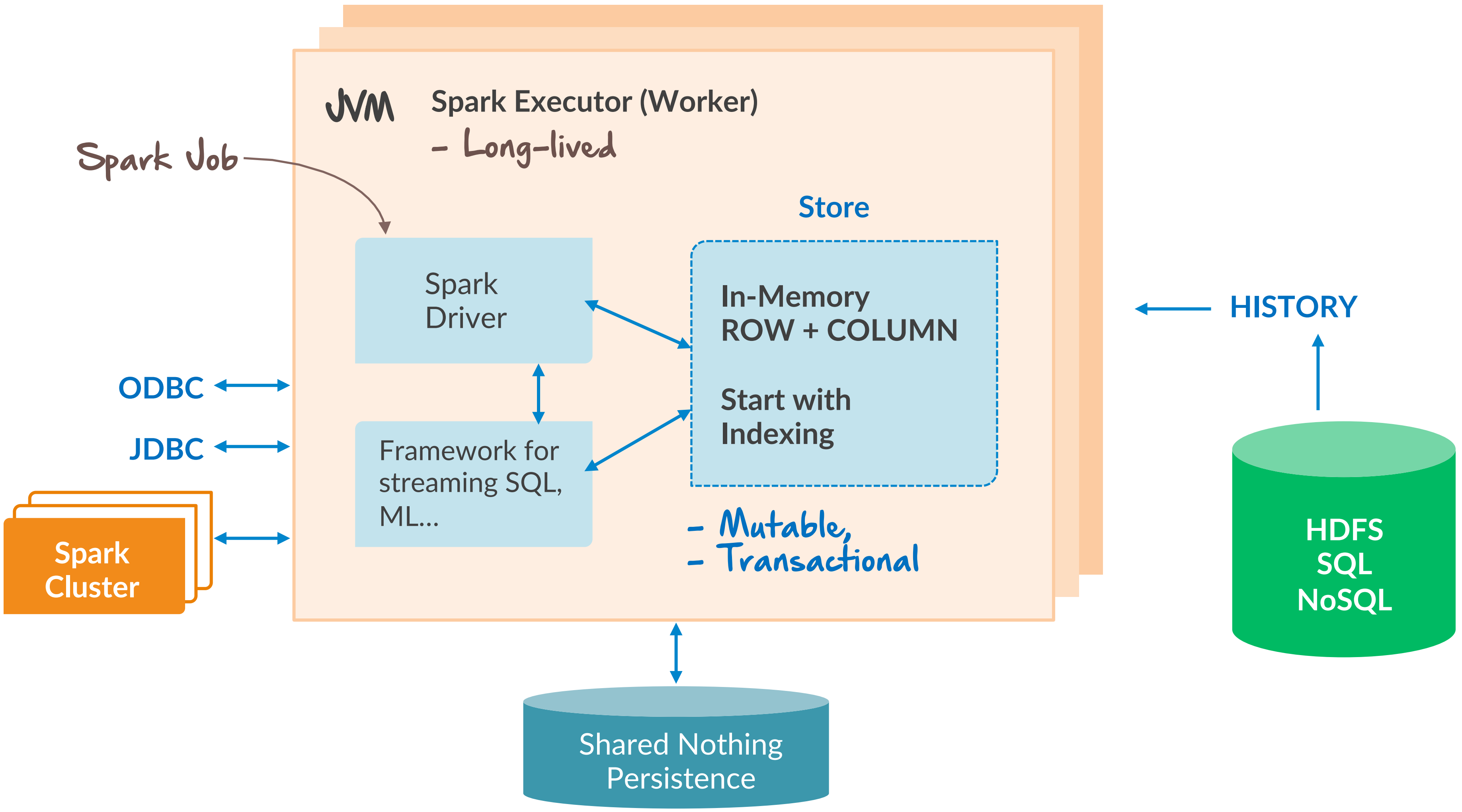
Low latency, HA, concurrency

Matured over 13 years

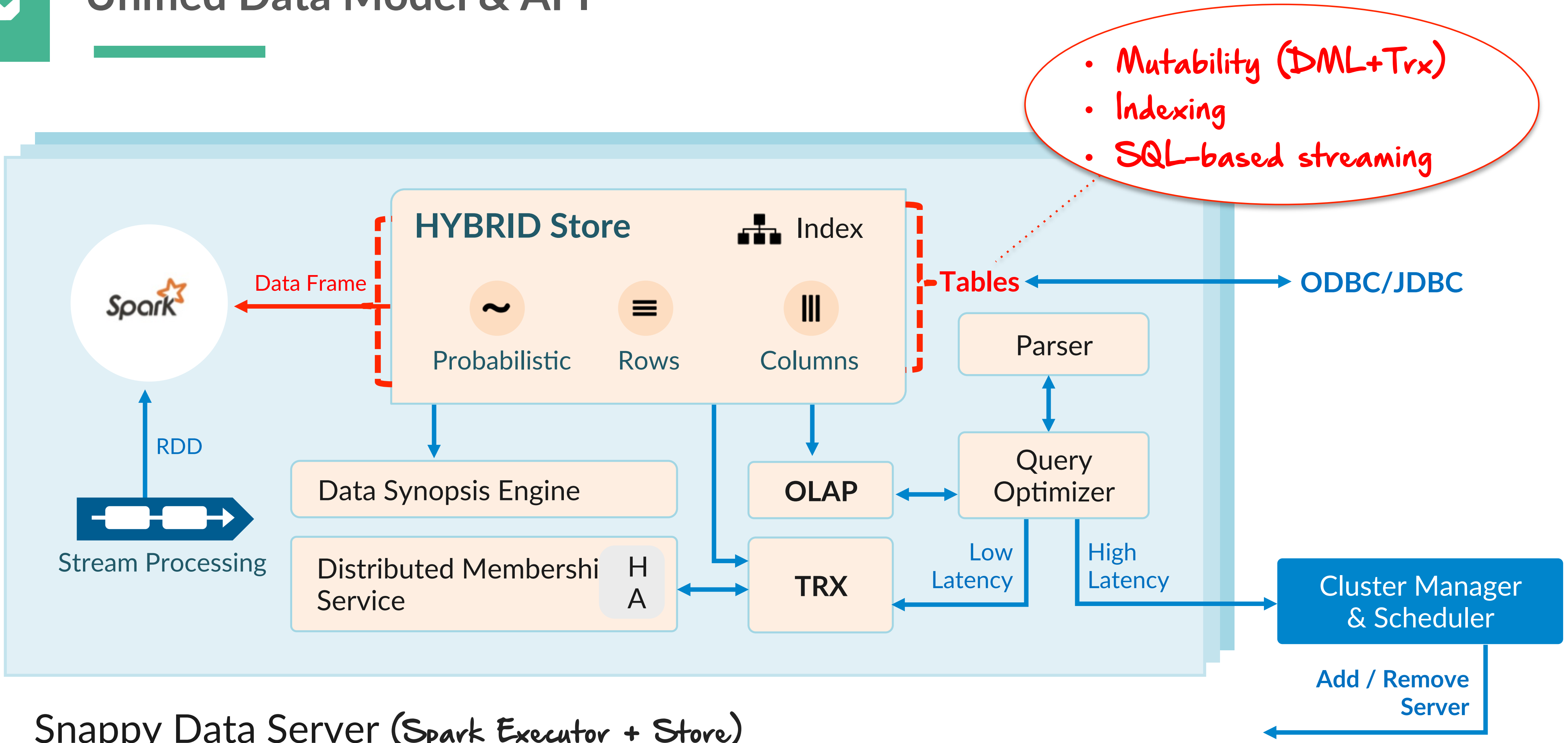
We Transform Spark from This …



... Into an "Always-On" Hybrid Database !

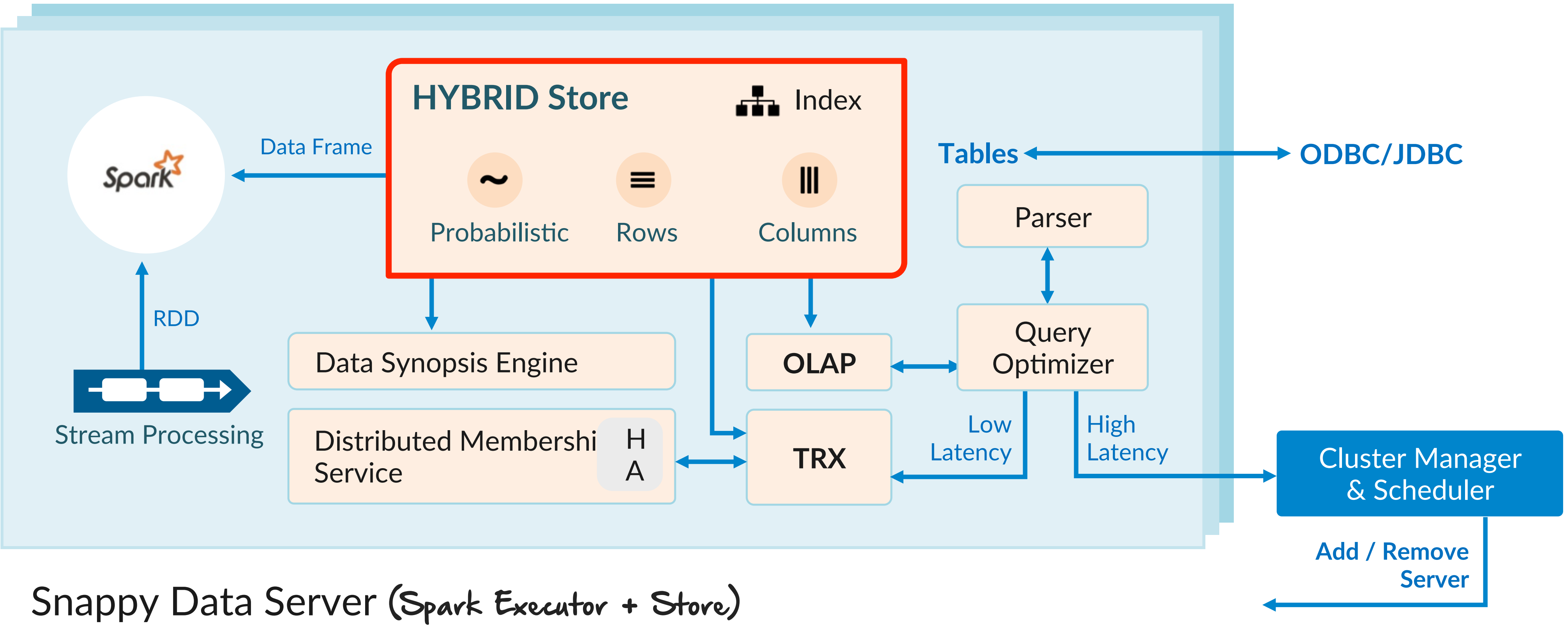


Unified Data Model & API



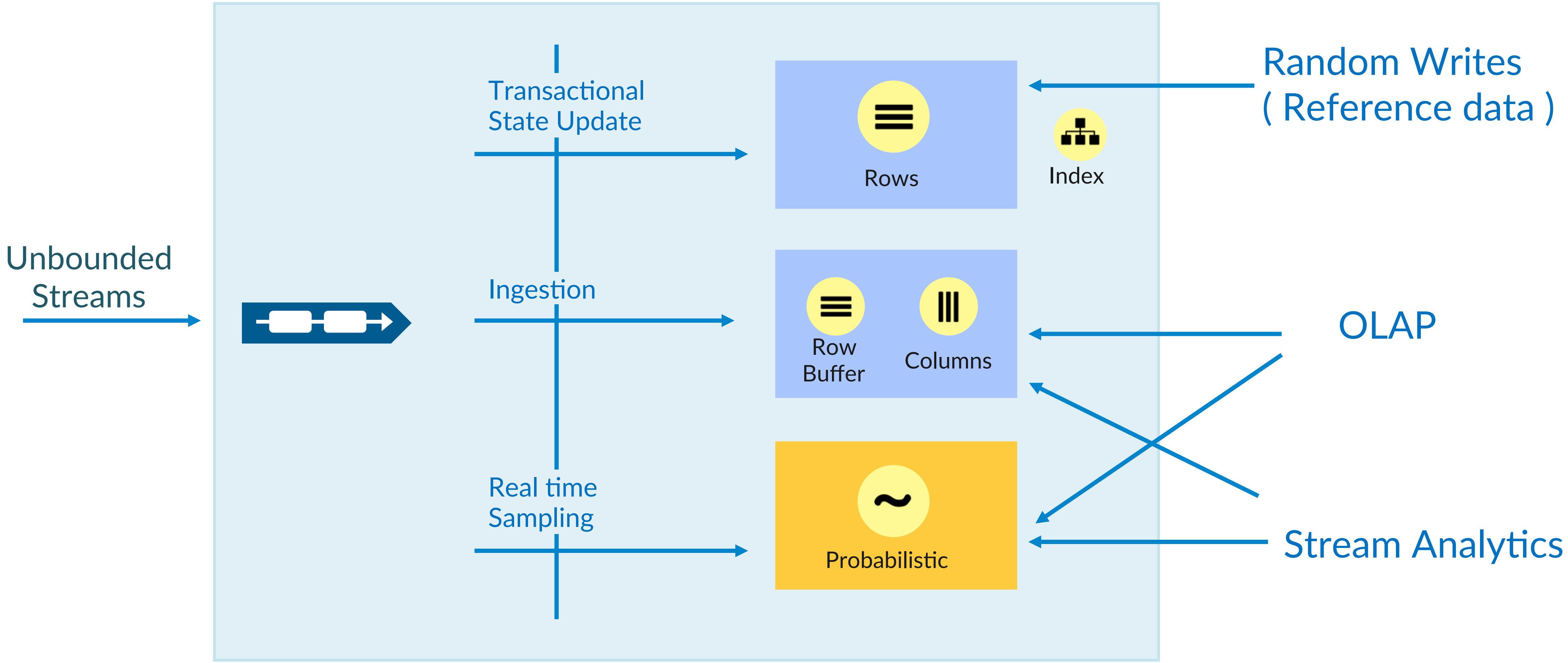
Snappy Data Server (Spark Executor + Store)

Overview

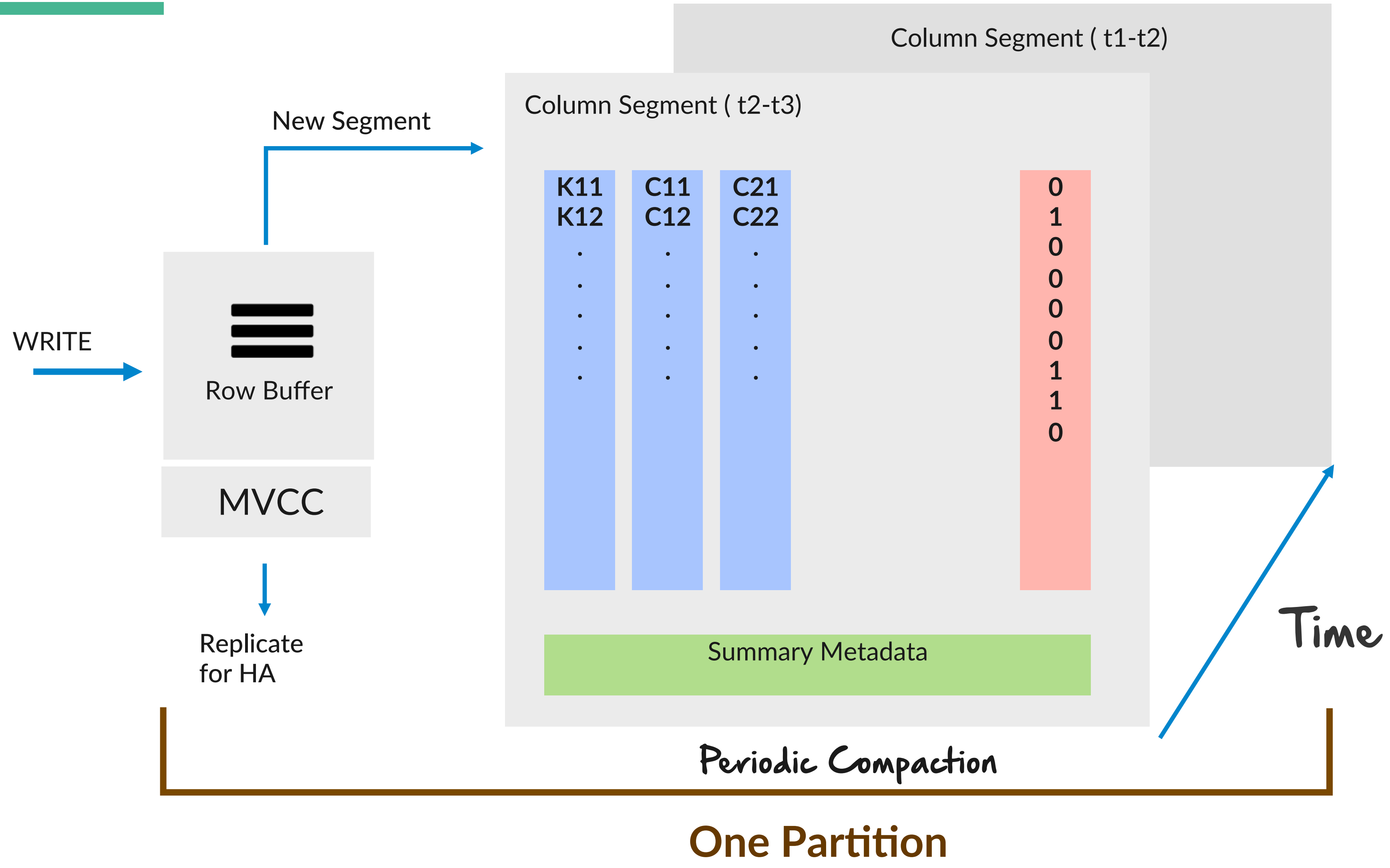


HYBRID Store
Index
Probabilistic
Rows
Columns
Data Frame
Spark
RDD
Stream Processing
Data Synopsis Engine
Distributed Membershi
Service
H
A
OLAP
TRX
Tables
ODBC/JDBC
Parser
Query
Optimizer
Low
Latency
High
Latency
Cluster Manager
& Scheduler
Add / Remove
Server
Snappy Data Server (Spark Executor + Store)

Hybrid Store



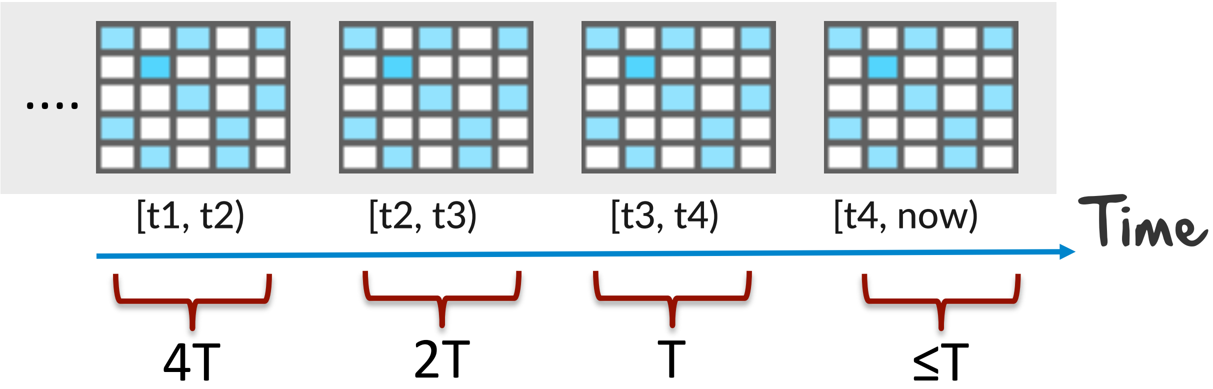
Updates & Deletes on Column Tables



Probabilistic Store: Synopses + Uniform & Stratified Samples

1. Streaming CMS (Count-Min-Sketch)

Higher resolution for more recent time ranges



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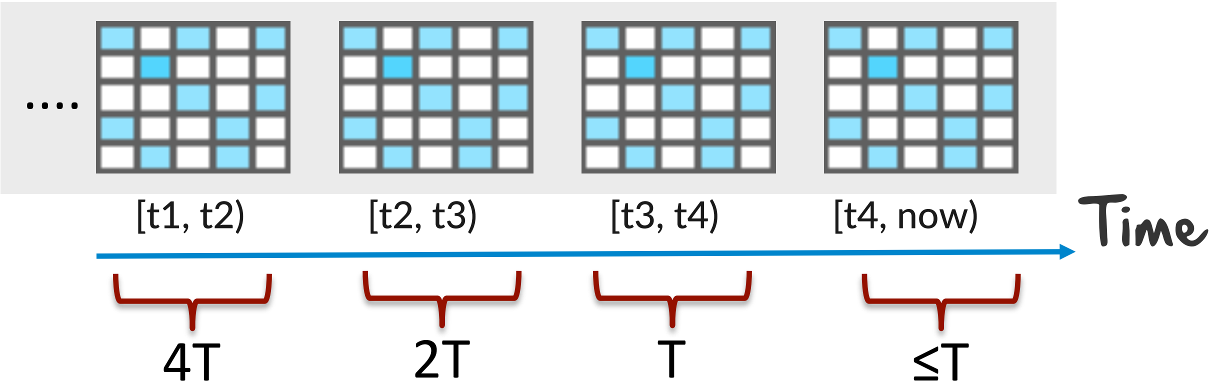

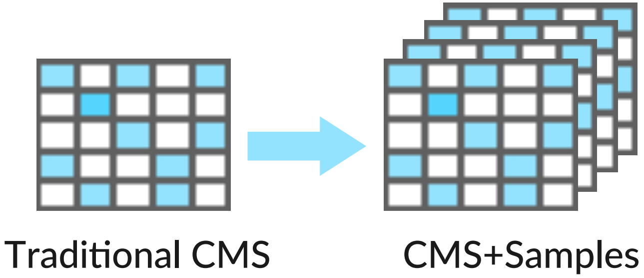

2. Top-K Queries w/ Arbitrary Filters

Maintain a small sample at each CMS cell

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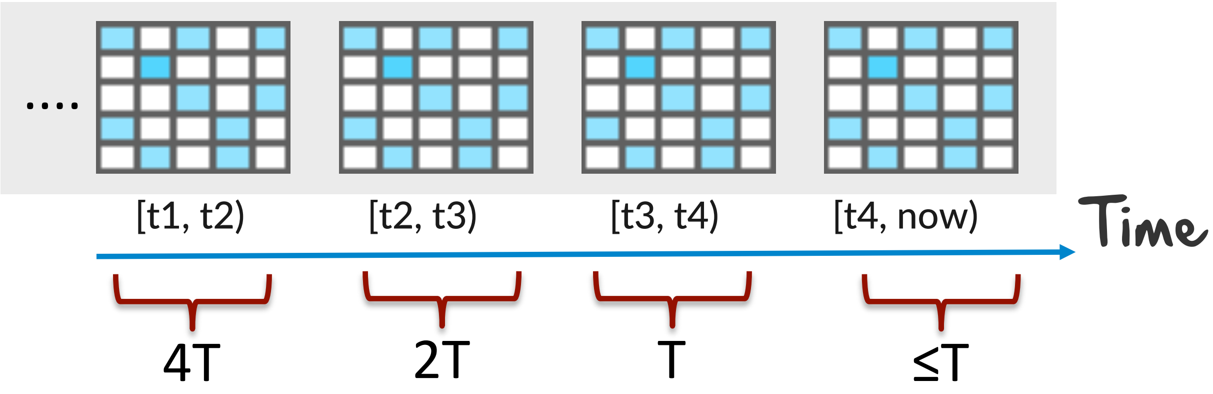

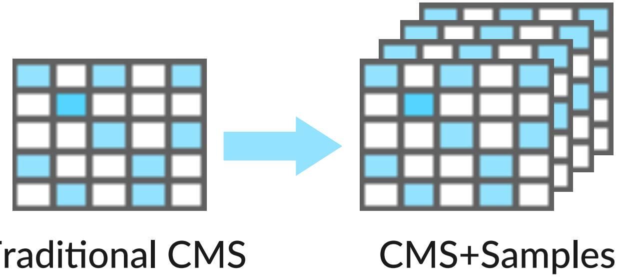

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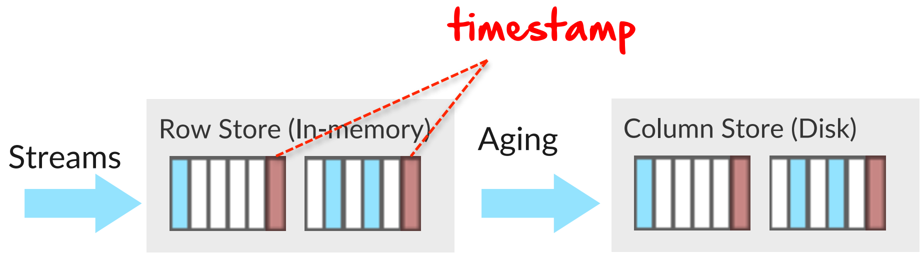
3. Fully Distributed Stratified Samples

Always include timestamp as a stratified column for streams



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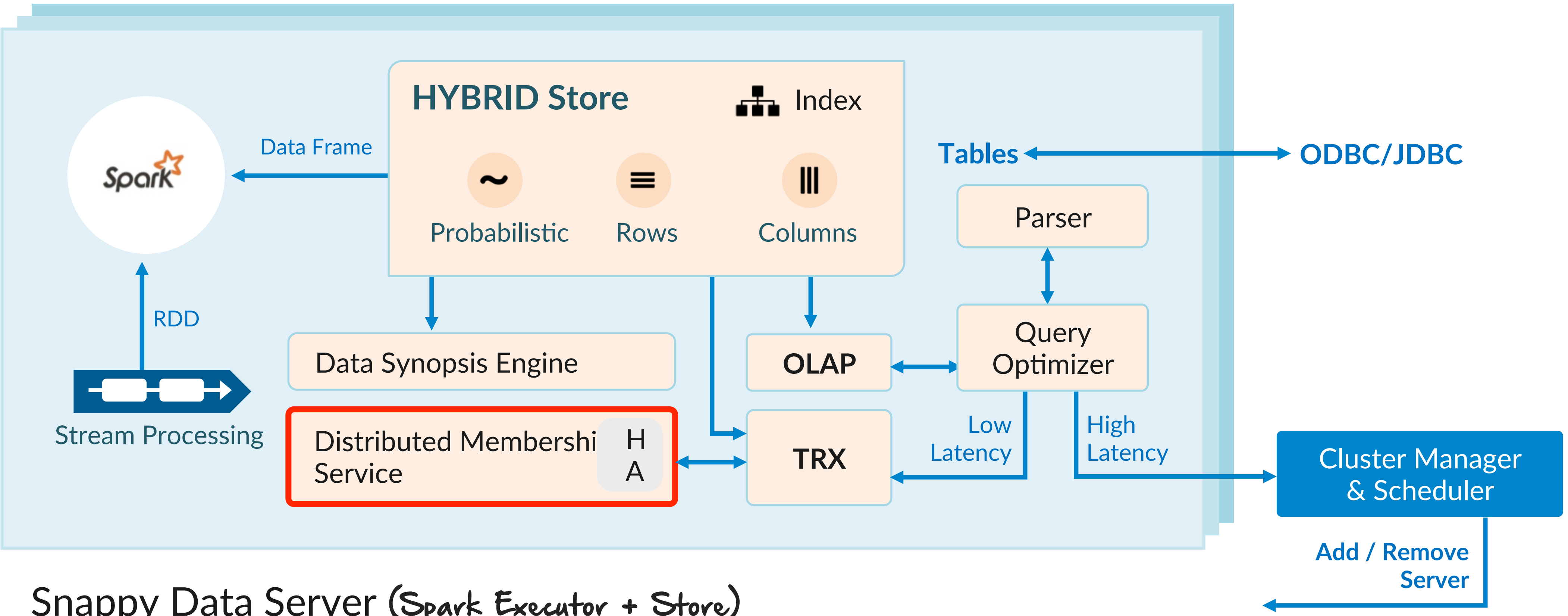
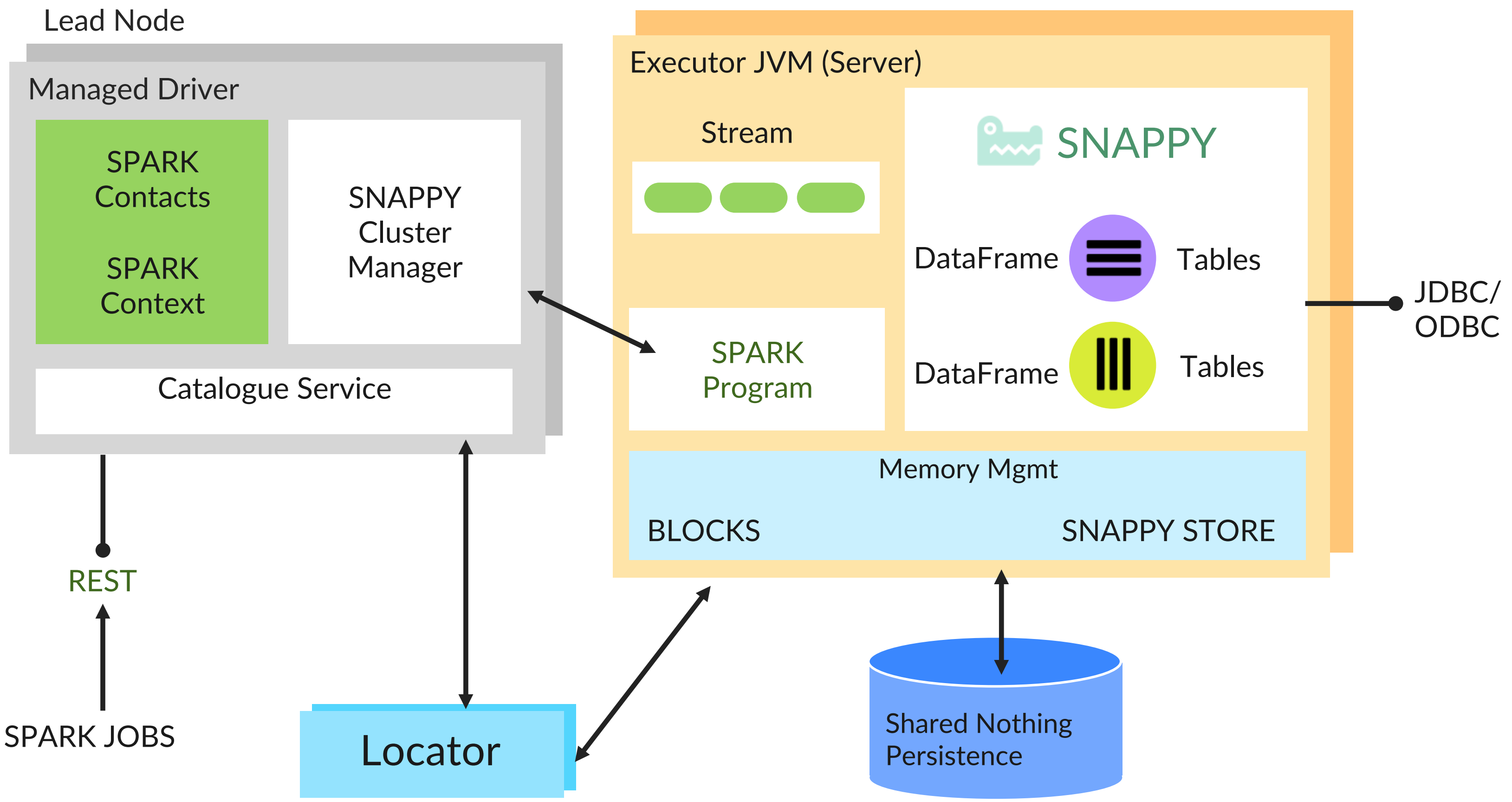


Snappy Data Server (Spark Executor + Store)

Supporting Real-time & HA

- **Spark Executors are long running.** Driver failure doesn't shutdown Executors
- **Driver HA** – Drivers are “Managed” by SnappyData with standby secondary
- **Data HA** – Consensus based clustering integrated for eager replication



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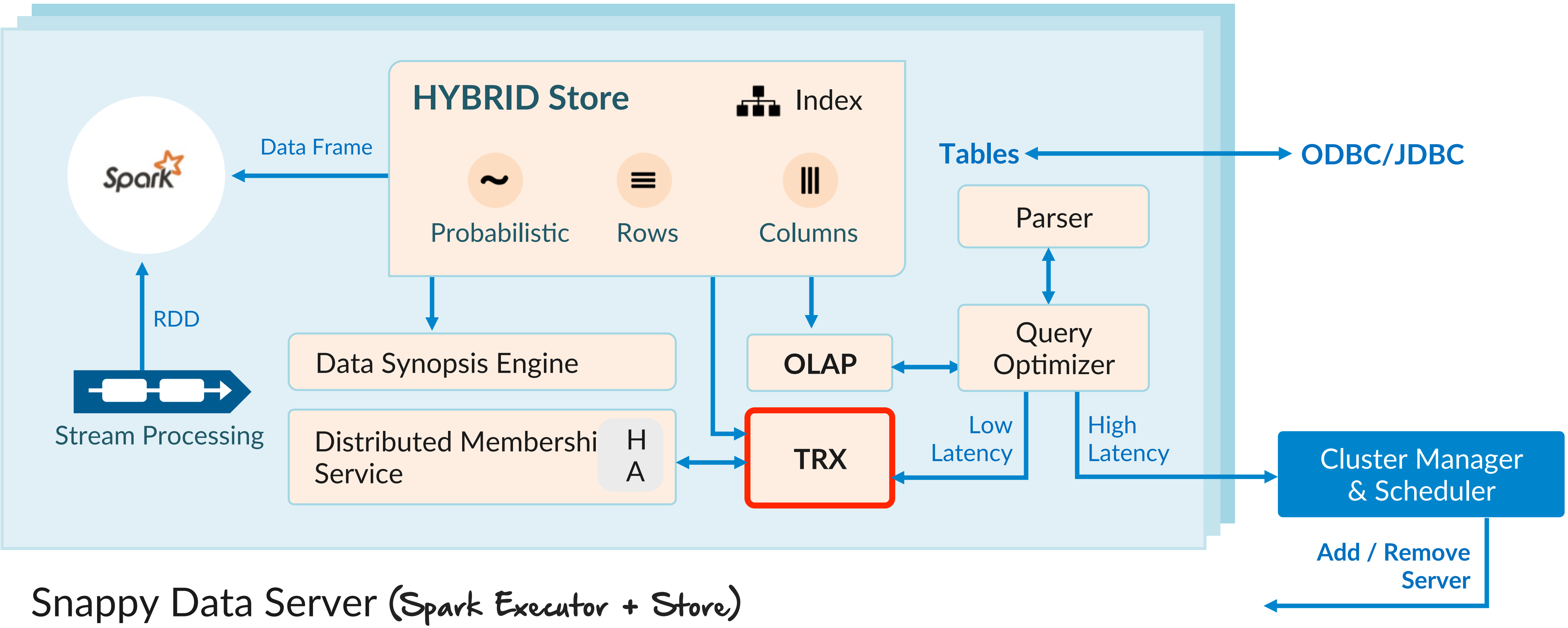
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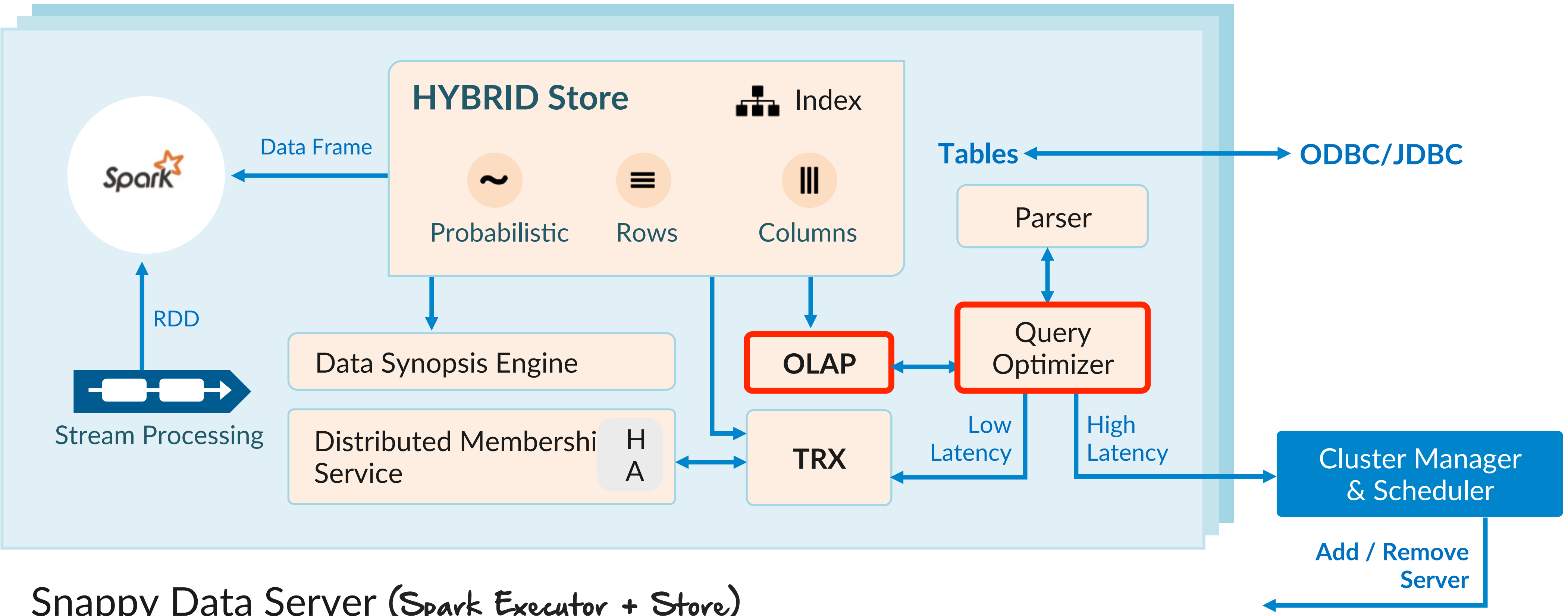

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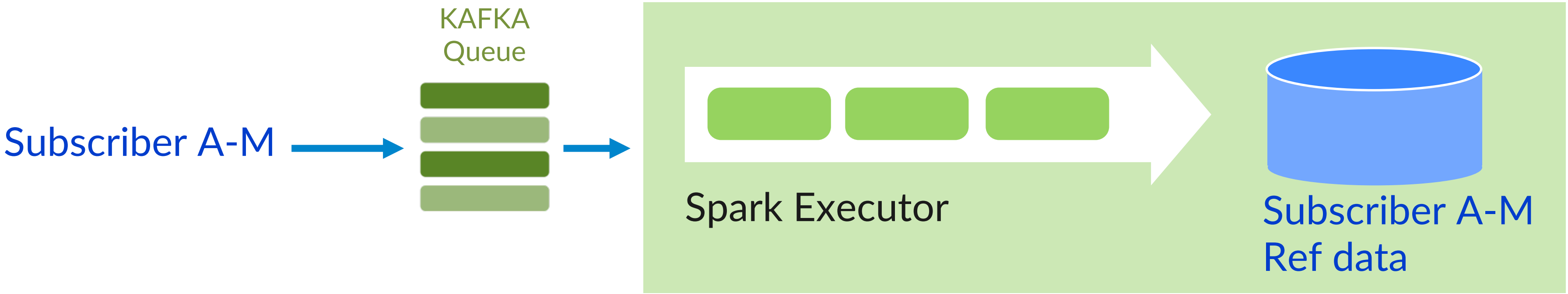
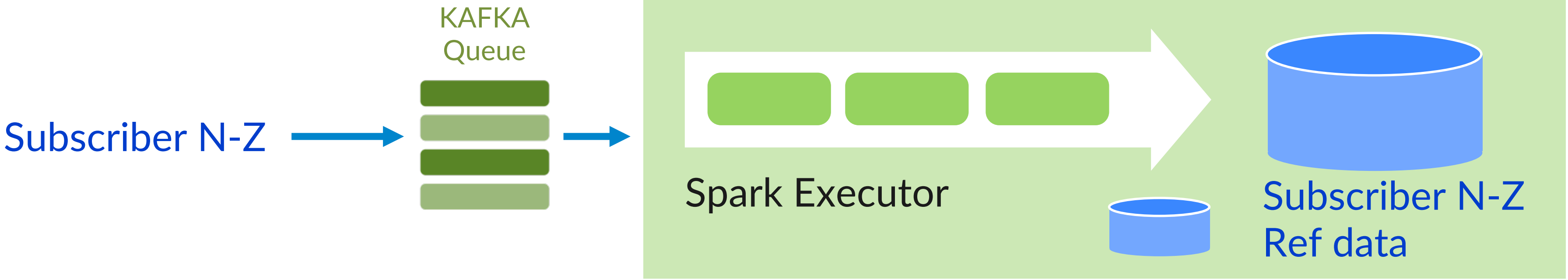
Query Optimization

- **Bypass the scheduler for transactions and low-latency jobs**
- **Minimize shuffles aggressively**
  - Dynamic replication for reference data
  - Retain ‘join indexes’ whenever possible
  - Collocate and co-partition related tables and streams
- **Optimized ‘Hash Join’, ‘Scan’, ‘GroupBy’ compared to Spark**
  - Use more variables (eliminate virtual funcs) to generate better code
  - Use vectorized structures
  - Avoid Spark’s single-node bottlenecks in broadcast joins
- **Column segment pruning through metadata**

Co-partitioning & Co-location



Linearly scale with partition pruning



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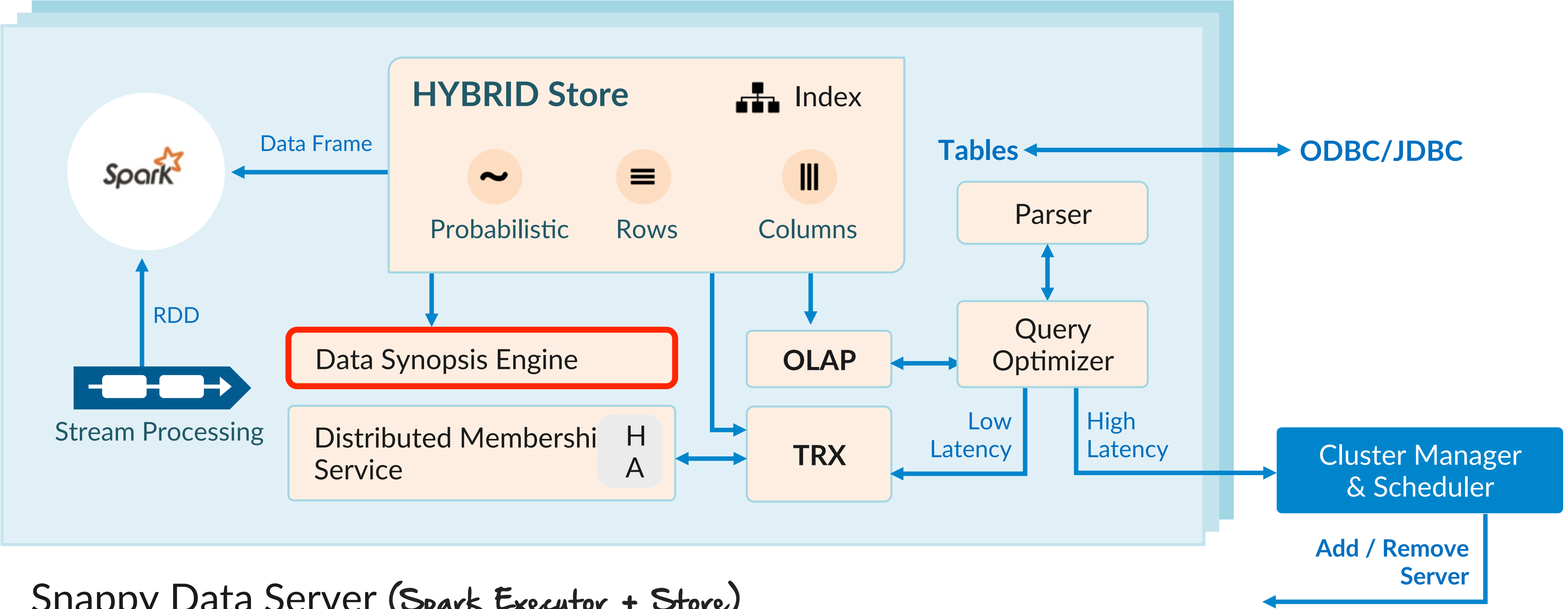

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Approximate Query Processing (AQP): Academia vs. Industry

25+ yrs of successful research in academia

AQUA, Online Aggregation, MapReduce Online, STRAT, ABS, BlinkDB / G-OLA, ...

BUT:

User-facing AQP almost non-existent in commercial world!

Some approximate features in Infobright, Yahoo's Druid, Facebook's Presto, Oracle 12C, ...

WHY ?

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WHY ?

select geo, avg(bid)
from adImpressions
group by geo having avg(bid)>10
with error 0.05 at confidence 95

geo	avg(bid)	error	prob_existence
MI	21.5	± 0.4	0.99
CA	18.3	± 5.1	0.80
MA	15.6	± 2.4	0.81
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1. Incompatible w/ BI tools
2. Complex semantics
3. Bad sales pitch!

A First Industrial-Grade AQP Engine

1. Highlevel Accuracy Contract (HAC)

- User picks a single number p, where 0≤p≤1 (by default p=0.95)
- Snappy guarantees that s/he only sees things that are at least p% accurate
- Snappy handles (and hides) everything else!

geo	avg(bid)
MI	21.5
WI	42.3
NY	65.6
…	…

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- Set HAC behavior at JDBC/ODBC connection level

tableau ZOOMDATA

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tableau

ZOOMDATA

3. Better marketing!

- Concurrency: 10's of queries in shared clusters
- Resource usage: everyone hates their AWS bill
- Network shuffles
- Immediate results while waiting for final results

iSight (Immediate inSight)

Benchmarks

Benchmarks

- Mixed Benchmark: Ad Analytics

Streaming
- Ad impressions arrive on a message bus
- Aggregate by publisher and geo
- Report avg bid, # of impressions, and # of uniques every few secs

Trx
- Write to a partitioned store
- Transactionally update the profiles during ingestion

OLAP
- Q1: Top-20 ads receiving most impressions per region
- Q2: Top-20 ads receiving largest bids per geo
- Q3: Top-20 publishers receiving largest sum of bids overall

- TPC - H

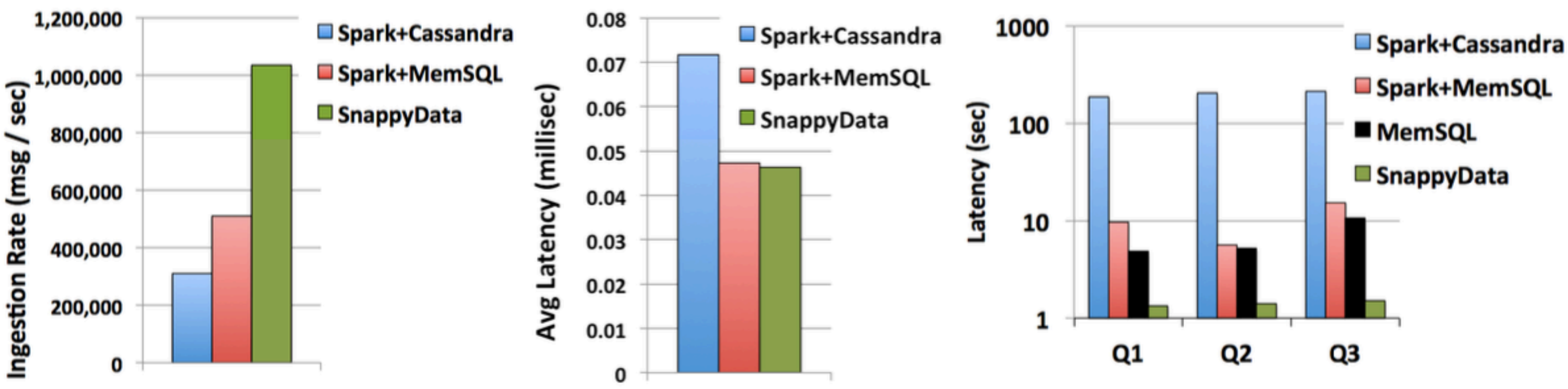
Setup

- HW: 5 c4.2xlarge EC2 instances
  - 1 coordinator + 4 workers
- Software: Latest GA versions avalable:
  - Kafka 2.10_0.8.2.2
  - Spark 2.0.0
  - Cassandra 3.9
    w/ Spark-Cassandra connector 2.0.0_M3
  - MemSQL Ops-5.5.10 Community Edition
    w/ Spark-MemSQL Connector 2.10_1.3.3
  - SnappyData 0.6.1

Ad Analytics

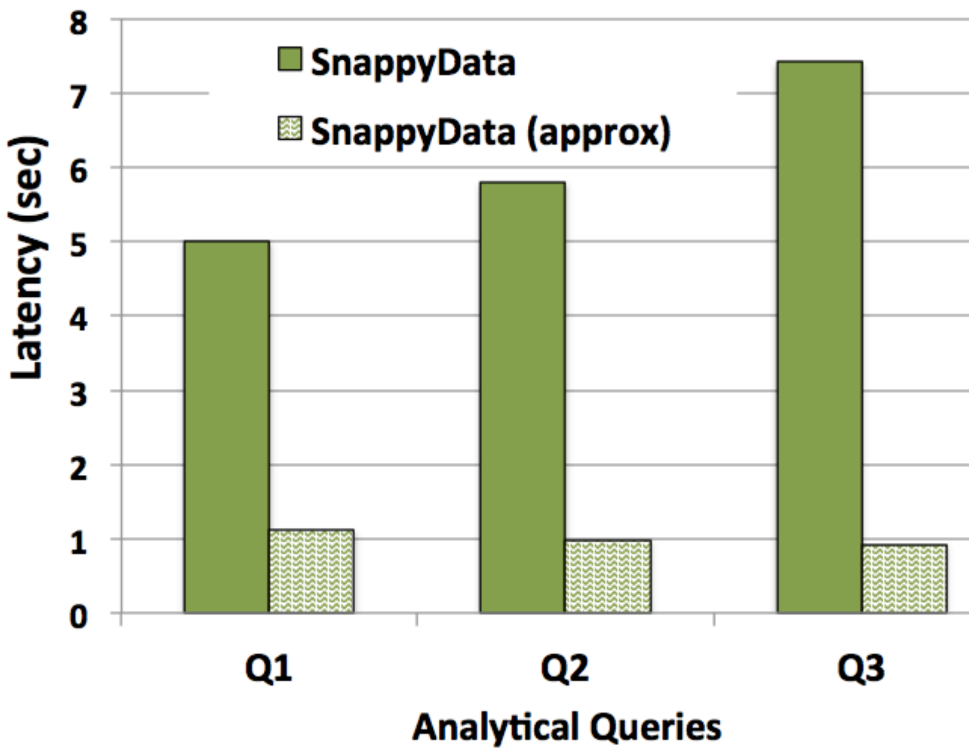
1.5-2x faster ingestion

7-142× faster analytics (at 300M records)



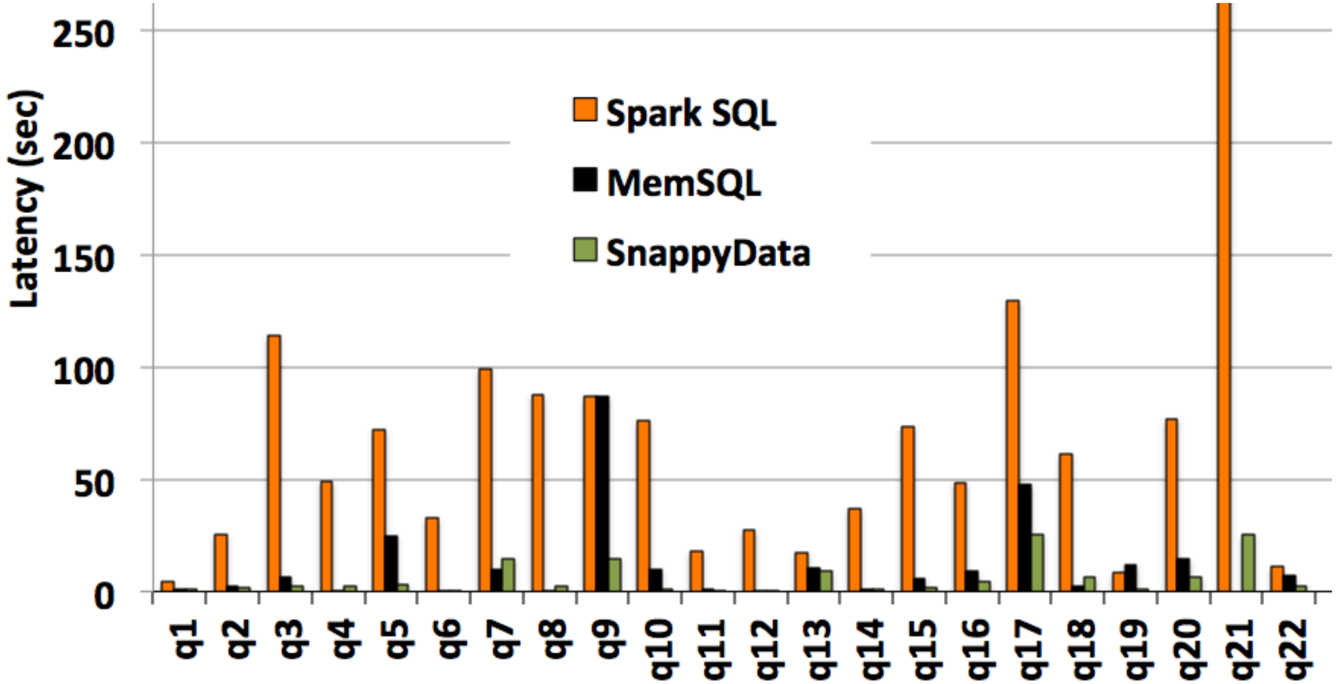
(a) Streaming (b) Transactions (c) Analytical Queries

Data Synopsis Engine



TPC-H

100 GB	Avg	Median
SnappyData	5.7s	2.5s
MemSQL	12.0s	6.4s
Spark	66.9s	55.1s



SnappyData was 2.6x faster than MemSQL & 22.4x faster than Spark 2.0

Conclusion

Where Are We Today ?

- Current customers
  - Investment banking, Industrial IoT, Telco, Ad Analytics, & healthcare
- Current release
  - 0.7 (GA 1.0 in Q1-2017)
- Next funding round
  - Q2-2017
- Upcoming features
  - Integration of Spark ML w/ our Data Synopsis Engine
  - Cost-based query optimizer
  - Physical designer & workload miner (http://CliffGuard.org)

Lessons Learned

1. A unique experience marryings two different breeds of distributed systems

lineage-based for high-throughput vs. (consensus-) replication-based for low-latency

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- By sharing state across apps, we decouple apps from data servers and provide HA
- Save memory, data copying, serialization, and shuffles
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4. Commercializing academic work is lots of work but also lots of fun

Try our iSight cloud for free:
http://snappydata.io/iSight

THANK YOU !