SamzaSQL

Scalable Fast Data Management with *Streaming SQL*

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Fast Data

Data has to be processed as it arrives, so that we can react immediately to changing conditions.

> **BIG DATA ISN'T JUST BIG; IT'S ALSO FAST.**
>
> Big data is often data that is generated at incredible speeds, such as click-stream data, financial ticker data, log aggregation, and sensor data.

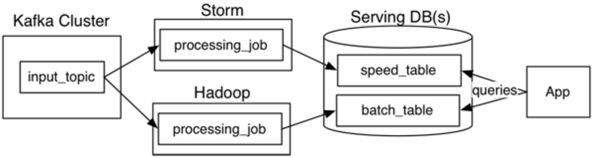
*John Hugg, **"Fast data: The next step after big data"***

Applications

- Real-time distributed tracing for website performance and efficiency optimizations
- Calculating click-through rates
- Data stream enrichment
  - Count page views by group key where group key is retrieved from a key/value storage
  - Enriching data streams related to use activities with user's information such as location and company
- **At the time of writing LinkedIn uses 90 Kafka clusters deployed across 1500 nodes to process 150TB of input data daily**

Lambda Architecture (LA)

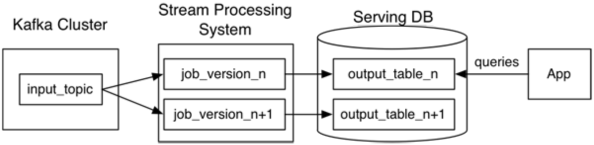
LA is a technology agnostic data processing architecture that attempts to balance latency, accuracy, throughput and fault-tolerance by providing a unified serving layer on top of batch and stream processing sub-systems.



From: `https://www.oreilly.com/ideas/questioning-the-lambda-architecture`

Kappa Architecture (KA)

Simplification of *Lambda Architecture* is KA that uses append-only immutable log as the canonical data store; batch processing is replaced by stream replay.



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Motivation

Programming APIs for LA and KA

Summingbird is a well known abstraction for writing *LA* style applications. *KA* style applications are mainly written in a **stateful stream processing APIs** provided by frameworks such as Apache Samza.

Limitations

- Need to maintain two complex distributed systems
- Users need to understand complex programming abstractions
- Long turnaround times

Word Count

```scala
def wordCount[P <: Platform[P]]
    (source: Producer[P, String], store: P#Store[String, Long]) =
      source.flatMap { sentence =>
        toWords(sentence).map(_ -> 1L)
      }.sumByKey(store)
```

More examples at `https://github.com/twitter/summingbird`

Samza API

Window Aggregation

```
public class WikipediaStatsStreamTask implements StreamTask, InitableTask, WindowableTask {
  ...
  private KeyValueStore<String, Integer> store;
  public void init(Config config, TaskContext context) {
    this.store = (KeyValueStore<String, Integer>) context.getStore("wikipedia-stats");
  }
  @Override
  public void process(IncomingMessageEnvelope envelope, MessageCollector collector,
                      TaskCoordinator coordinator) {
    Map<String, Object> edit = (Map<String, Object>) envelope.getMessage();
    ...
  }
  @Override
  public void window(MessageCollector collector, TaskCoordinator coordinator) {
    ...
    collector.send(new OutgoingMessageEnvelope(new SystemStream("kafka", "wikipedia-stats"), counts));
    ...
  }
```

SQL for Big Data

There are several well known SQL-on-Hadoop solutions and most organizations that use Hadoop use one or more SQL-on-Hadoop solutions.

- Apache Hive
- Presto
- Apache Drill
- Apache Impala
- Apache Kylin
- Apache Tajo
- Apache Phoenix

Motivating Research Questions

- Can the same low barrier and the clear semantics of SQL be extended to queries that execute simultaneously over data **`streams`** (in movement) and **`tables`** (at rest)?
- Can this be done with minimal and well-founded extensions to SQL?
- And with minimal latency overhead over a non-SQL-based LA/KA?

SamzaSQL

Streaming SQL - Data Model

- **Stream:** A stream S is a possibly indefinite partitioned sequence of temporally-defined elements where an element is a tuple belonging to the schema of S.
- **Partition:** A partition is a time-ordered, immutable sequence of elements existing within a single stream.
- **Relation:** Analogous to a relation/table in relational databases, a relation R is a bag of tuples belonging to the schema of R.

Streaming SQL - Continuous Queries

SamzaSQL

```
SELECT STREAM rowtime, productId, units FROM Orders
  WHERE units > 25
```

CQL

```
SELECT ISTREAM rowtime, productId, units FROM Orders
  WHERE units > 25;
```

Streaming SQL - Window Aggregations

SamzaSQL

```
SELECT STREAM TUMBLE_END(rowtime, INTERVAL '1' HOUR) AS rowtime,
  productId,
  COUNT(*) AS c,
  SUM(units) AS units
FROM Orders
GROUP BY TUMBLE(rowtime, INTERVAL '1' HOUR), productId
```

CQL

```
SELECT ISTREAM ... AS rowtime, productId, COUNT(*) AS c,
  SUM(units) AS units
FROM Orders[Range '1' HOUR, Slide '1' HOUR]
GROUP BY  productId;
```

Streaming SQL - Sliding Windows

SamzaSQL

```
SELECT STREAM rowtime, productId, units,
  SUM(units)  OVER  (ORDER BY rowtime PARTITION BY productId RANGE
    INTERVAL '1' HOUR PRECEDING) unitsLastHour
FROM Orders;
```

CQL

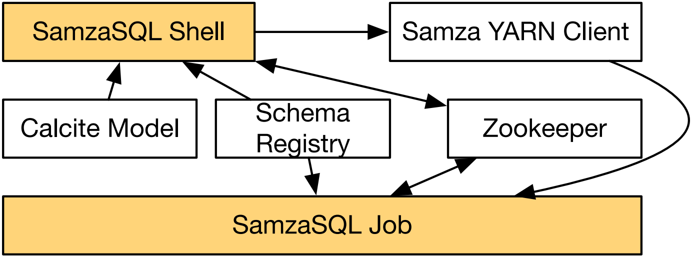
```
SELECT ISTREAM rowtime, productId, units,
  SUM(units) AS unitsLastHour
FROM Orders[Range '1' HOUR]
GROUP BY  productId;
```

Streaming SQL - Window Joins

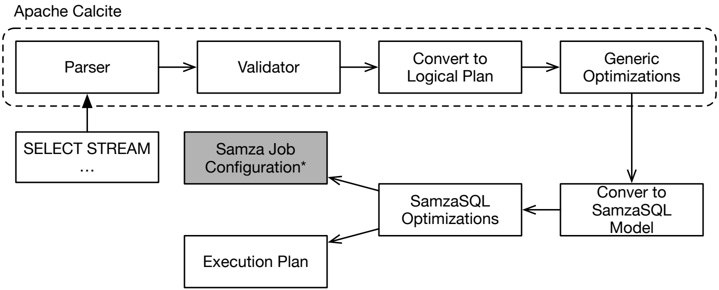
SamzaSQL

```sql
SELECT STREAM
  GREATEST(PacketsR1.rowtime, PacketsR2.rowtime) AS rowtime,
  PacketsR1.sourcetime,
  PacketsR1.packetId,
  PacketsR2.rowtime - PacketsR1.rowtime AS timeToTravel
FROM PacketsR1 JOIN PacketsR2 ON
  PacketsR1.rowtime BETWEEN
  PacketsR2.rowtime - INTERVAL '2' SECOND
  AND PacketsR2.rowtime + INTERVAL '2' SECOND
  AND PacketsR1.packetId = PacketsR2.packetId
```

SamzaSQL - Architecture



SamzaSQL - Query Planner



Evaluation

Evaluation - Environment

- 100 byte messages (based on previous Kafka benchmarks)
- 3 node (EC2 r3.2xlarge) Kafka cluster
- 3 node (EC2 r3.2xlarge) YARN cluster
- Each r3.2xlarge instance has 8 vCPUs, 61GB of RAM and 160 GB SSD backed storage
- Data model
  - Stream - `Orders (rowtime, productId, orderId, units)`
  - Table - `Products (productId, name, supplierId)`

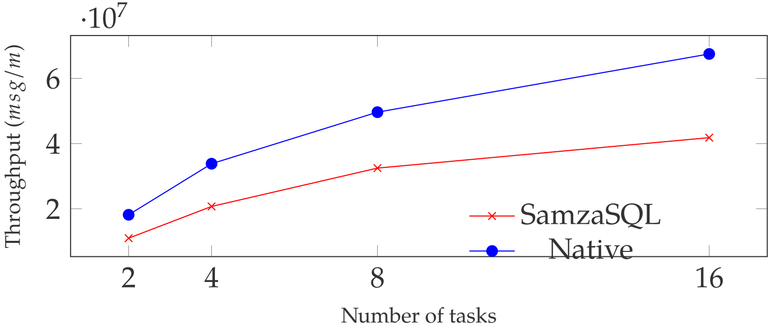
Evaluation - Results

- SamzaSQL underperform 30-40% compared to native Samza applications mainly due to message format transformations required in streaming SQL runtime
- SamzaSQL joins underperform mainly due to local store message serialization/deserialization overheads
- Local storage effects the throughputs directly

Message processing flow

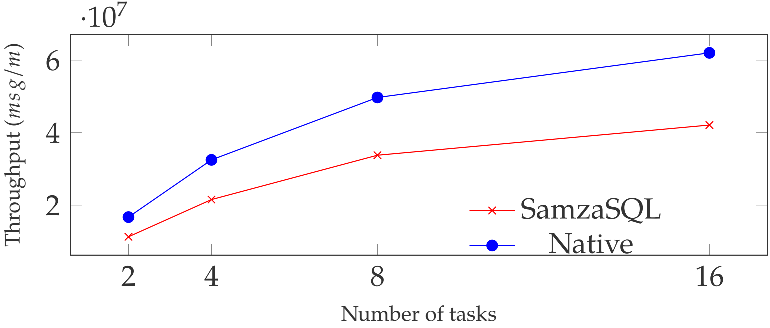
→ Decode → AvrotoArray → Process → ArraytoAvro → Encode →

Evaluation - Filter Throughput



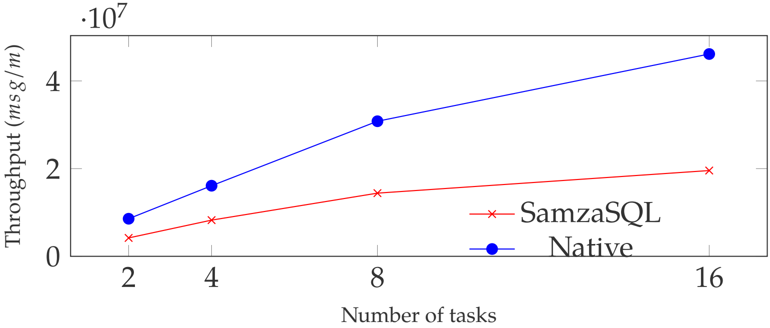
`SELECT STREAM * FROM Orders WHERE units > 50`

Evaluation - Project Throughput



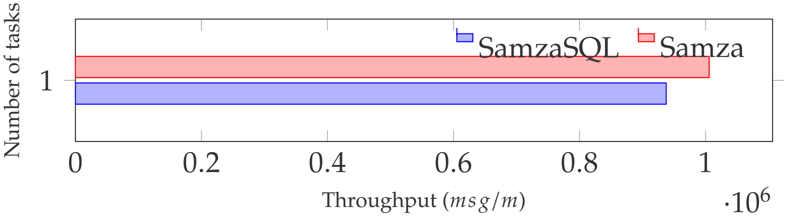

```
SELECT STREAM rowtime, productId, units FROM Orders
```

Evaluation - Stream-to-Relation Join Throughput




```
SELECT STREAM Orders.rowtime, Orders.orderId, Orders,productId, Orders.units,
Products.supplierId FROM Orders JOIN ON Orders.productId = Products.productId
```

Evaluation - Sliding Window Throughput




```
SELECT STREAM rowtime, productId, units, SUM(units) OVER (PARTITION BY
productId ORDER BY rowtime RANGE INTERVAL '5' MINUTE PRECEDING)
unitsLastFiveMinutes FROM Orders
```

Sliding window query throughput was measured in a iMac due to limitations in EC2 IO rates.

Related Work

Related Work

- Eerly work on streaming SQL - TelegraphCQ, Tribecca, GSQL
- CQL
- Streaming SQL for Apache Flink and Apache Storm based on our work in Apache Calcite

Future Work and Conclusion

Future Work

- Code generation to bring SamzaSQL generated physical plans closer to Samza Java API based queries
- Streaming query optimizations for fast data management systems
- Ordering guarantees in the presence of stream repartitioning
- Stream-to-relation queries
- Intra-query optimizations
- Handling out-of-order arrivals

Summary and Conclusion

- We propose a novel set of extensions to standard SQL for expressing streaming queries.
- SamzaSQL is a implementation of proposed streaming SQL variant on top of Apache Samza.
- We demonstrate that we can achieve decent amount of performance by utilizing existing libraries.
- Our evaluation results shows that further improvements such as code generation is needed to bring streaming SQL runtime closer to streaming queries written in imperative languages.