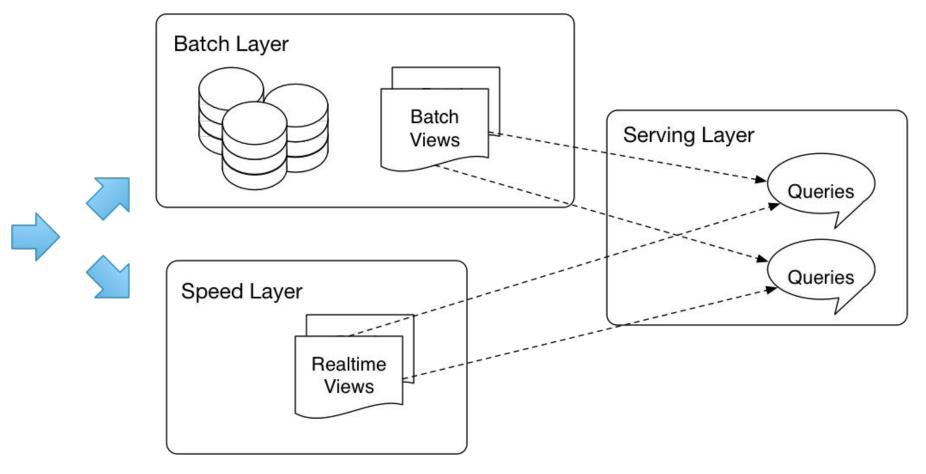
Cloud Computing and Big Data

Realtime Big Data

Oxford University
Software Engineering
Programme
July 2020



Recap on the Lambda Architecture





Streaming

- Continuous data flow
 - "Unbounded streams of data"
- Usually uses a message distribution system
 - JMS
 - Apache Kafka
 - MQTT
 - Etc
- An unbounded set of events with time
 - <t1, E1>, <t2, E2>,, <tn, En>,



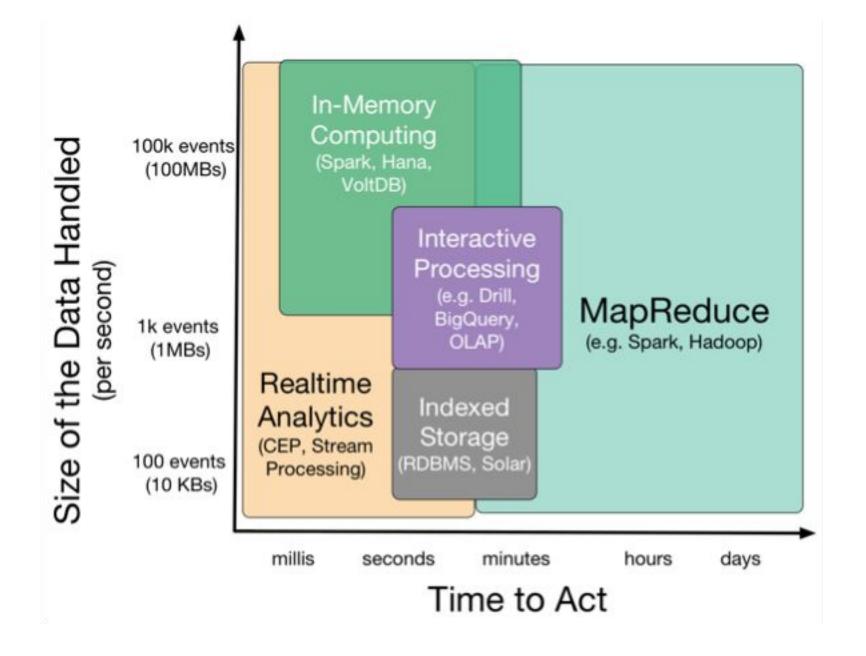
Stream processing categorization

- Simple event processing
 - Working on an event at a time
 - e.g. filter out all events where the wind speed > 50 mph
- Event stream processing
 - Time-based processing of a single stream of events
 - Average wind speed over the last hour compared to the average over the last day
- Complex Event Processing
 - Correlation of events across different streams
 - Emergency calls correlated with wind speed in real time



Comparing Databases with Real-Time systems

	Database Applications	Event-driven Applications	
Query Paradigm	Ad-hoc queries or requests	Continuous standing queries	
Latency	Seconds, hours, days	Milliseconds or less	
Data Rate	Hundreds of events/sec	Tens of thousands of events/sec or more	





Approaches to Streaming

- Pure streaming
 - Each event is processed as it comes in
- Micro-batch
 - Small batches of events are processed
 - Typically trades flexibility for performance
- Shared nothing
 - You can process events on any system in the cluster
- Stateful / Partitioned
 - The event must be processed on a system that has the correct state in memory

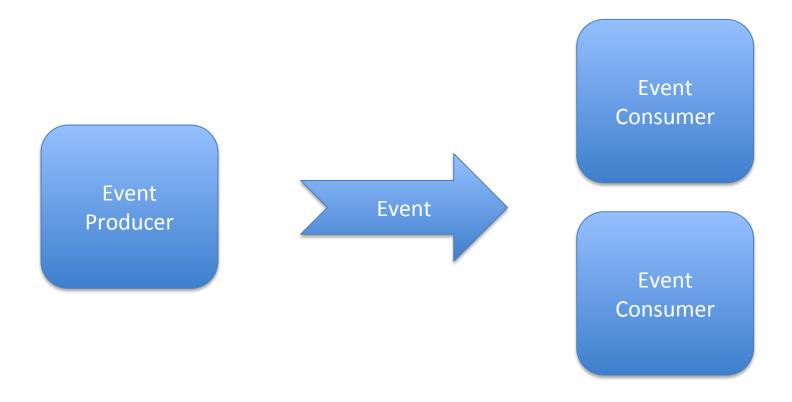


Data distribution

You need to get the events to the processing systems

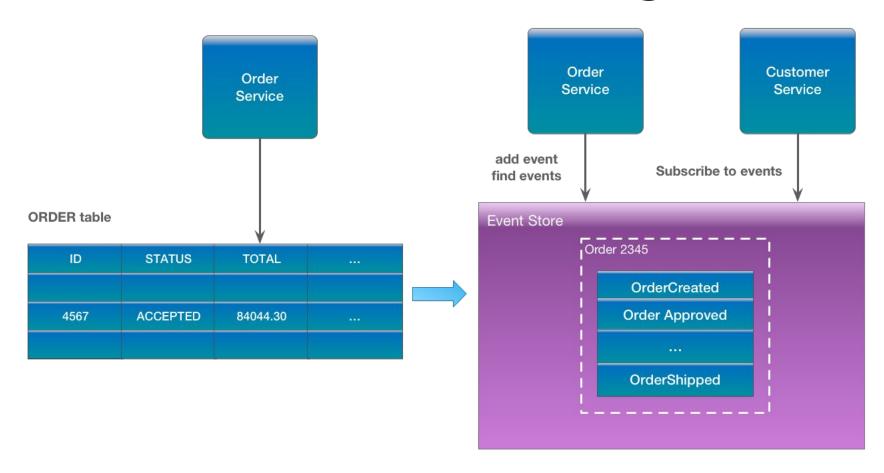


Event Driven Architecture





Event Sourcing



https://eventuate.io/whyeventsourcing.html

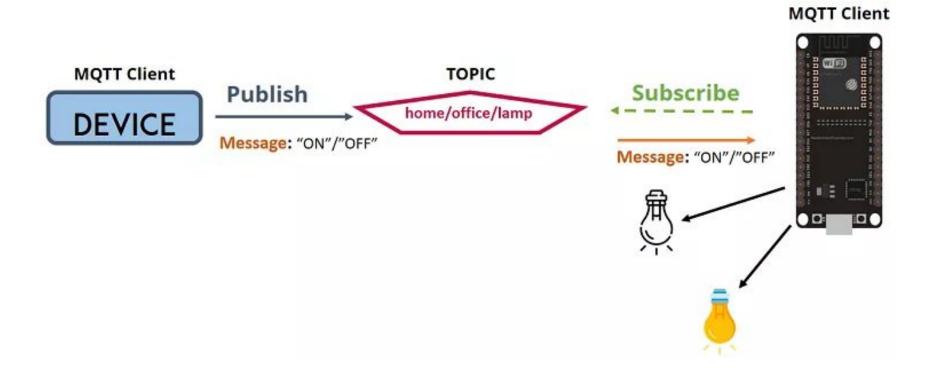


MQTT

- Very lightweight binary protocol
 - 2-byte overhead
- Widely used in IoT scenarios
- Pub-sub only until MQTT5
- QoS levels
 - Fire and forget QoS0
 - At least once QoS1
 - Exactly once QoS2

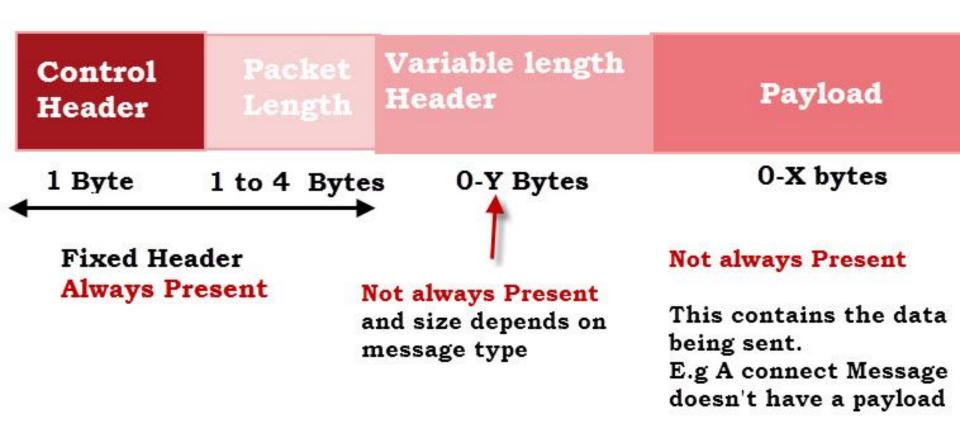


MQTT



MQTT Packets

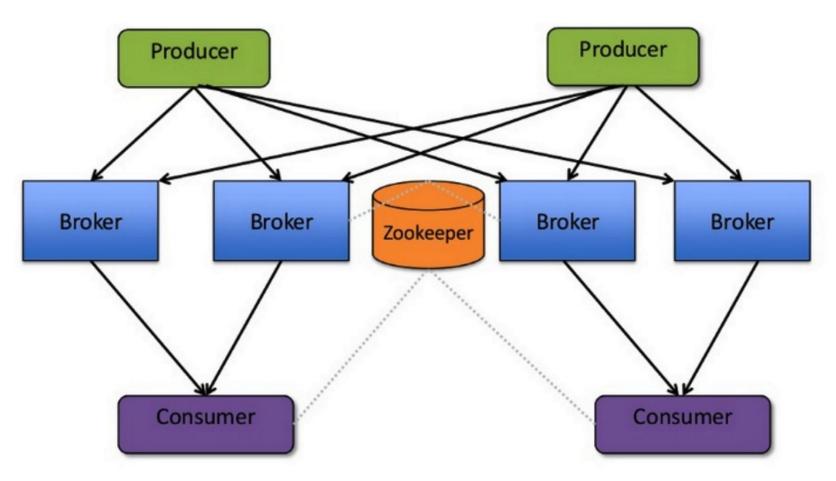
http://www.steves-internet-guide.com/matt-protocol-messages-overview/



MQTT Standard Packet Structure



Apache Kafka





Kafka

- Applying "big data" approaches to messaging:
 - Partitioning
 - Multiple brokers
 - Elastically scalable
 - Supports clusters of co-ordinated consumers
 - Automatic re-election of leaders



Kafka exactly-once semantics



Mathias Verraes @mathiasverraes



There are only two hard problems in distributed systems: 2. Exactly-once delivery 1. Guaranteed order of messages 2. Exactly-once delivery

RETWEETS

LIKES

6,775 4,727















10:40 AM - 14 Aug 2015





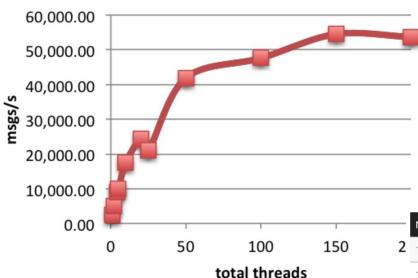
13 6.8K

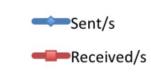




Kafka Performance

Apache Kafka





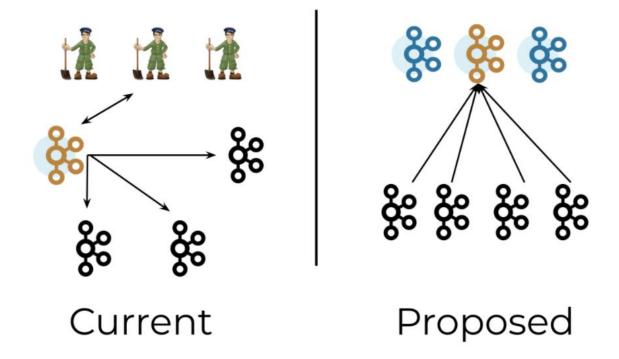
53 696

_	Nodes	Threads	Send msgs/s	Receive msgs/s	Processing latency	Send latency
2	1	1	2 391	2 391	48	48
	1	5	9 917	9 917	48	48
	1	25	20 982	20 982	46	48
	2	1	4 957	4 957	47	
	2	5	17 470	17 470	47	
	2	25	41 902	41 901	45	48
	4	1	9 149	9 149	47	
	4	5	24 381	24 381	47	48
	4	25	47 617	47 618	47	48
s	6	25	54 494	54 494	47	48

53 697



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Roadmap

Removing ZooKeeper from Kafka's administrative tools

Several administrative tools shipped as part of the Kafka release still allow direct communication with ZooKeeper. Worse still, there are still one or two operations that can't be done except through this direct ZooKeeper communication.

We have been working hard to close these gaps. Soon, there will be a public Kafka API for every operation that previously required direct ZooKeeper access. We will also disable or remove the unnecessary —zookeeper flags in the next major release of Kafka.

NATS

3Mb Docker image

Minimum HA deployment is 2 servers (automatic hot-cold)

```
3. root@nats-server: ~ (ssh)

NATS server version 1.3.0 (uptime: 6m50s)

Server:

Load: CPU: 262.0% Memory: 33.1M Slow Consumers: 0

In: Msgs: 122.1M Bytes: 1.9G Msgs/Sec: 1139740.5 Bytes/Sec: 17.4M

Out: Msgs: 557.7M Bytes: 8.7G Msgs/Sec: 5680200.0 Bytes/Sec: 86.7M

NATS Pub/Sub stats: 6,384,935 msgs/sec ~ 97.43 MB/sec

Pub stats: 1,064,543 msgs/sec ~ 16.24 MB/sec

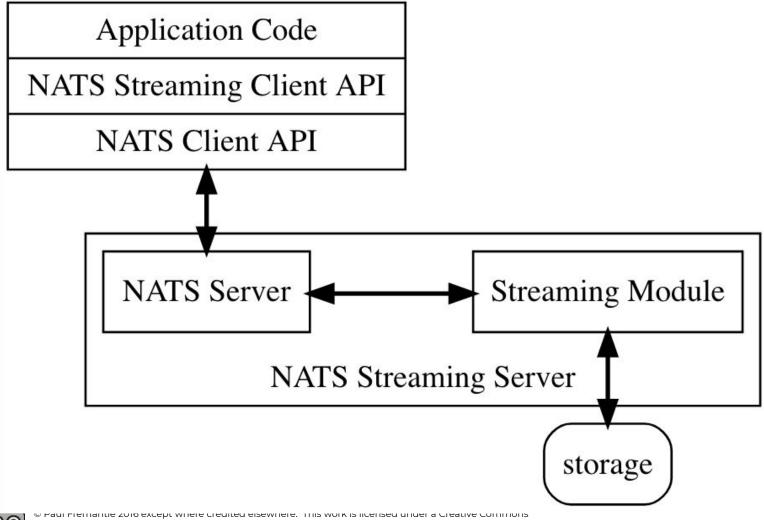
min 212,925 | avg 214,970 | max 218,169 | stddev 1,945 msgs

Sub stats: 5,320,801 msgs/sec ~ 81.19 MB/sec

min 1,064,160 | avg 1,064,283 | max 1,064,384 | stddev 72 msgs
```



NATS Streaming





NATS Streaming

- At least once delivery
- Publisher rate limiting
- Subscriber rate limiting
- Message Replay
- Durable Subscriptions



NATS security model

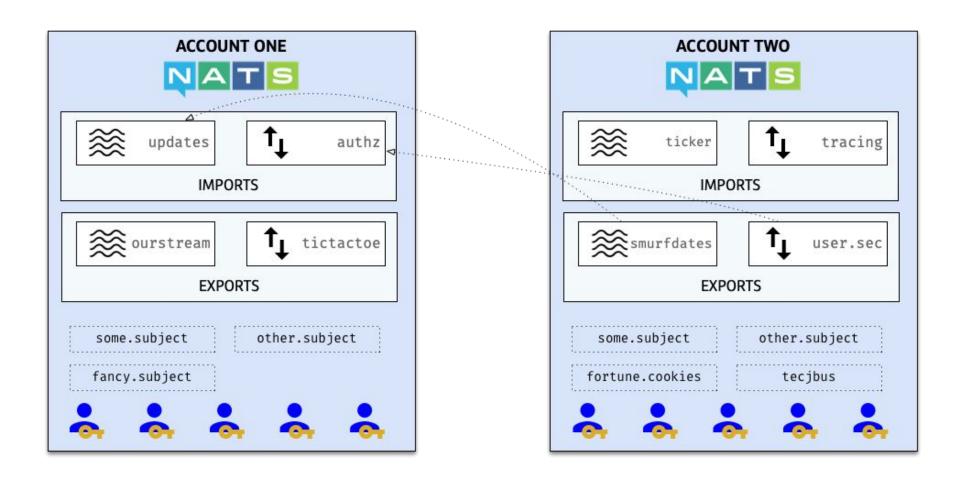
Introduction to NATS 2.0 Security



Decentralized Authorization and Authentication with JWTs

NATS is a lightweight, cloud native, open-source high-performance messaging system. In this post, I want to talk about security in the upcoming NATS 2.0 release—what it is, why you should care, and what it can do for you and your organization. But before I get into those details, I want to take a moment to explain a journey common to people adopting messaging systems and asynchronous architectures.

NATS security model



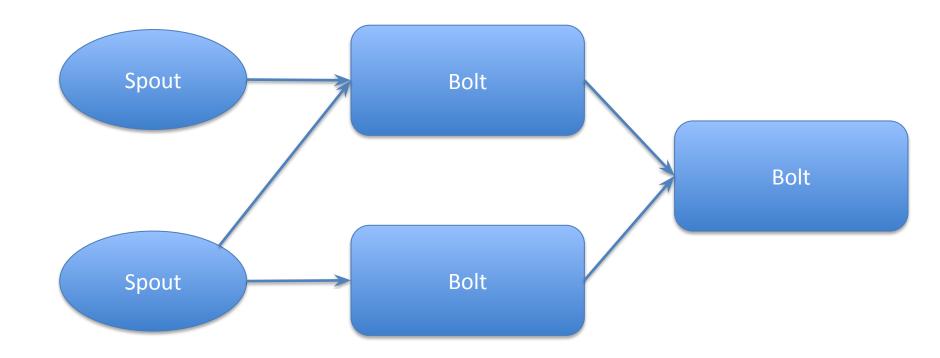


Processing the data



Apache Storm





Note: another DAG

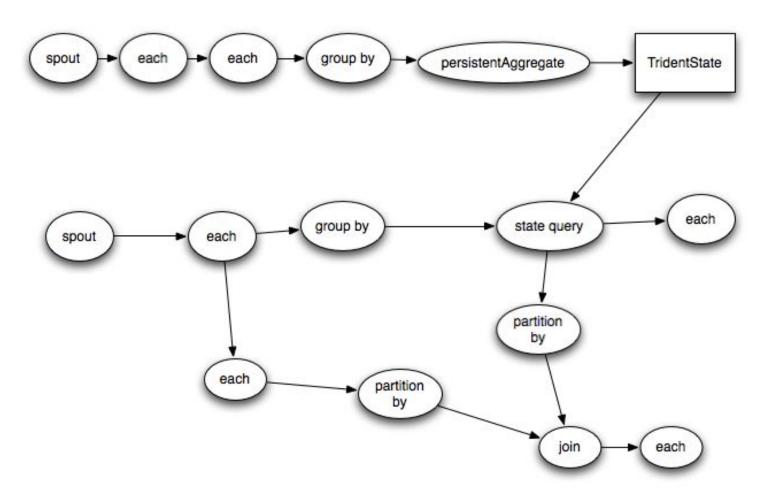


Apache Storm

- Originally developed by BackType
 - Nathan Marz
- Acquired by Twitter
- Open Sourced and then donated to Apache
- Became a top level project in 2014
 - http://storm.apache.org



Apache Storm Trident (micro-batch)



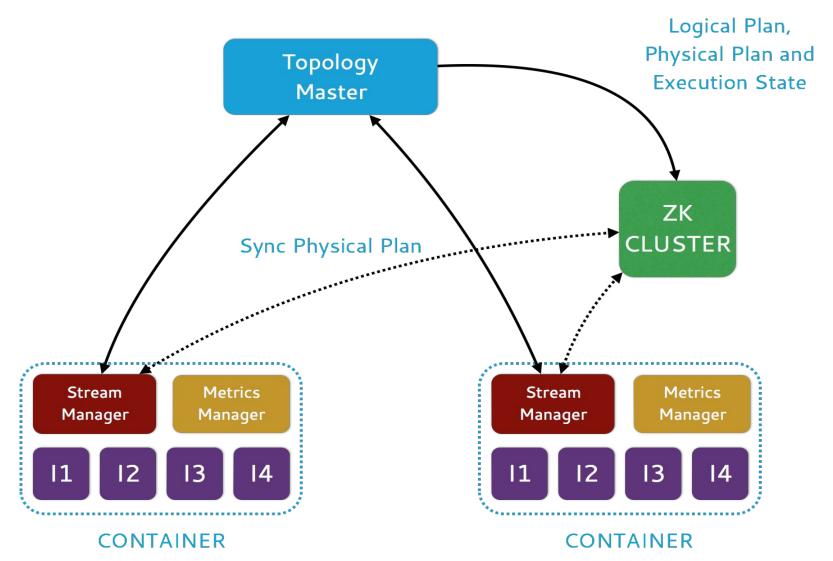


Storm vs Spark Streaming

- "Classic" Storm has no counterpart in Spark
 - Spouts and Bolts
 - Event by event processing
- Trident and Streaming both offer micro-batch models
 - More performant but less flexible
- Storm is more flexible for pure streaming systems
- Spark offers a much more unified programming model for Batch and Streaming



Heron





Heron: Key Features

- Fully API compatible with Apache Storm
- Task isolation
- Developer productivity
- Ease of manageability
- Use of mainstream languages
 C++/Java/Python

Heron

- In production at Twitter for >2 years
- Going into production at Microsoft, WeChat
- Donation to CNCF

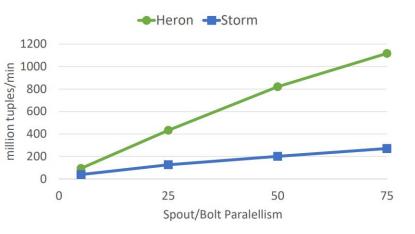


Fig. 2. Throughput with acks

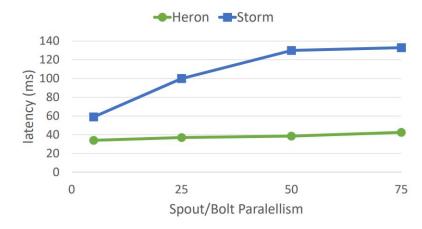
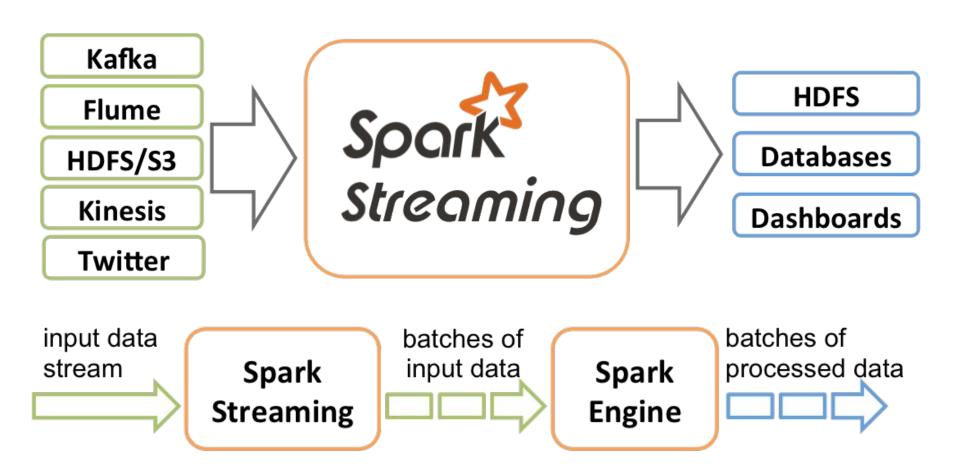


Fig. 3. End-to-end latency with acks



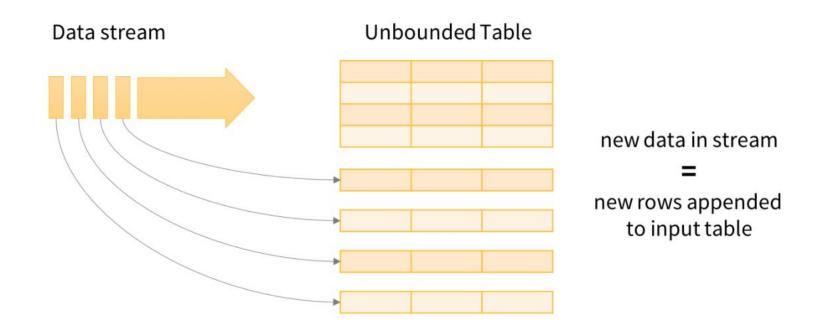
Apache Spark Streaming





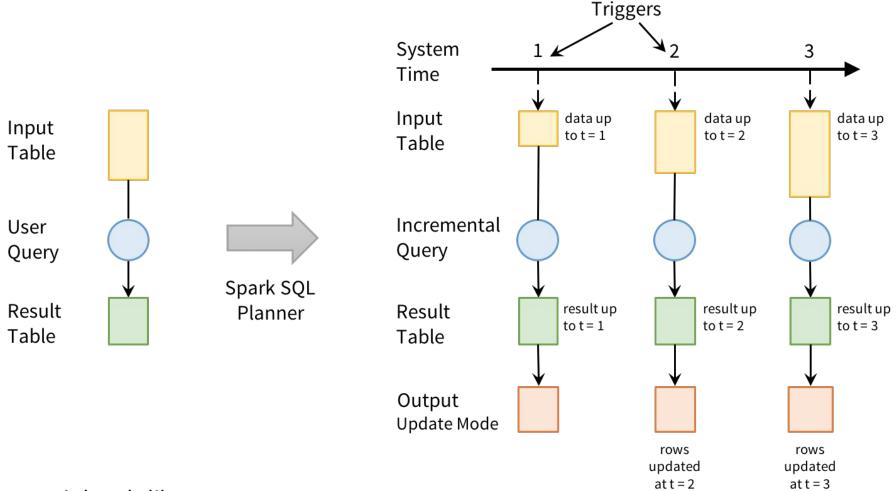
Structured Streams in Spark

Since Spark 2.0, there is a much better approach



Data stream as an unbounded Input Table





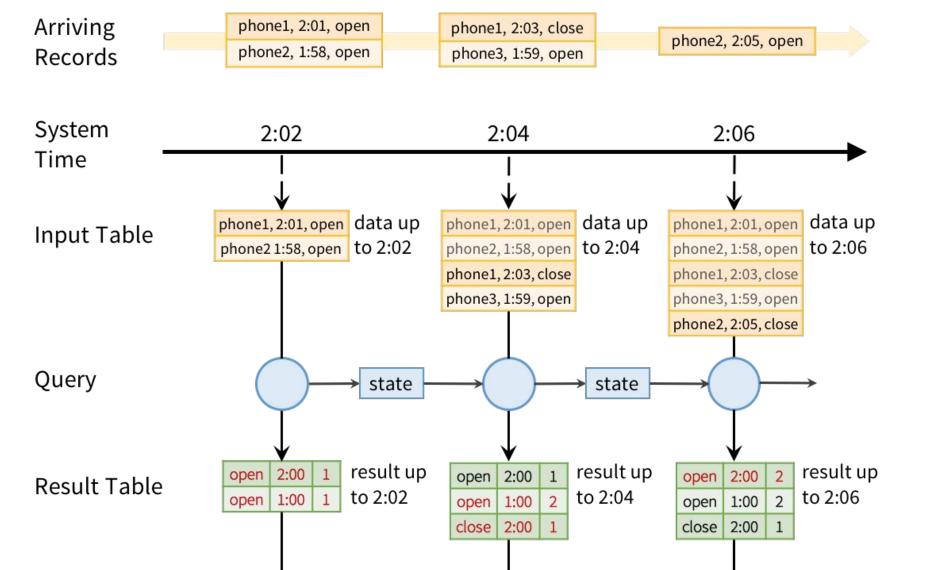
User's batch-like query on input table

Incremental execution on streaming data

Structured Streaming Processing Model

Users express queries using a batch API; Spark incrementalizes them to run on streams





1:00

2:00

open

close

2

open

2:00

2



Update Mode

Output

2:00

1:00

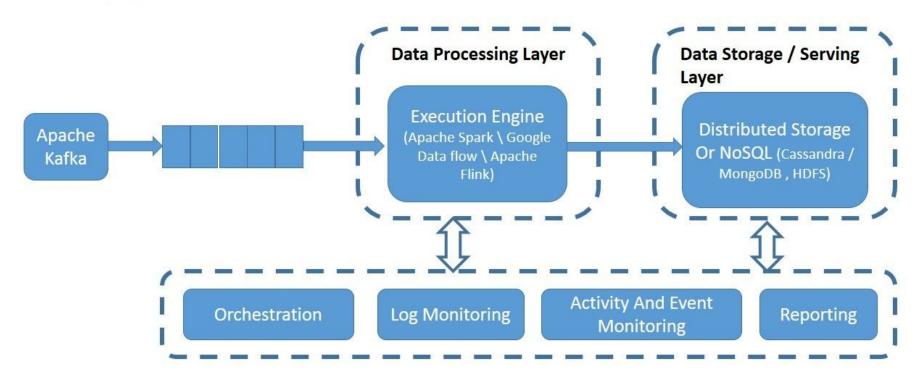
open

open

1

Kappa Architecture

Kappa Architecture

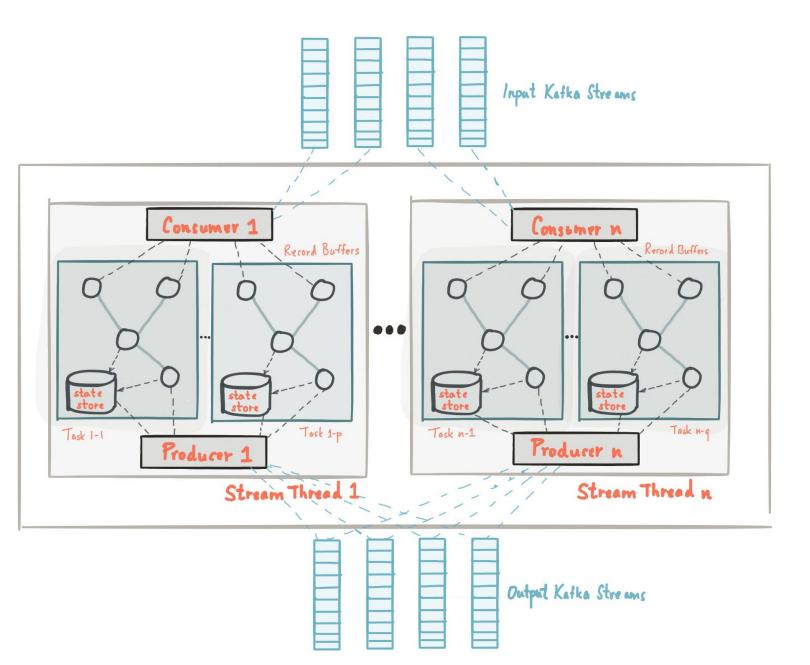


https://jonboulineau.me/blog/architecture/kappa-architecture

Siddharth Mittal



Kafka Streams

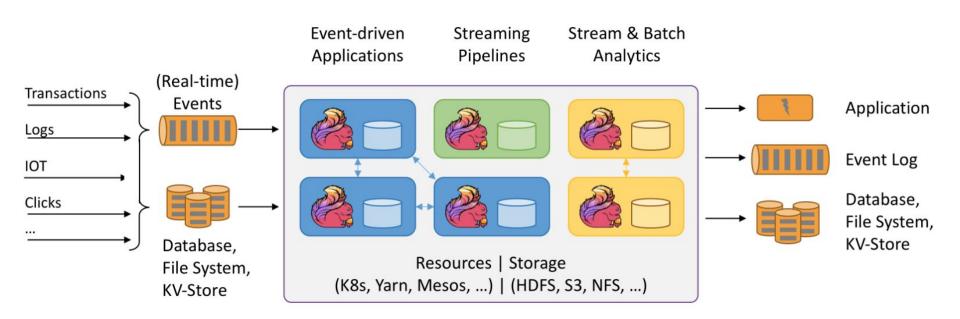


Kafka Streams

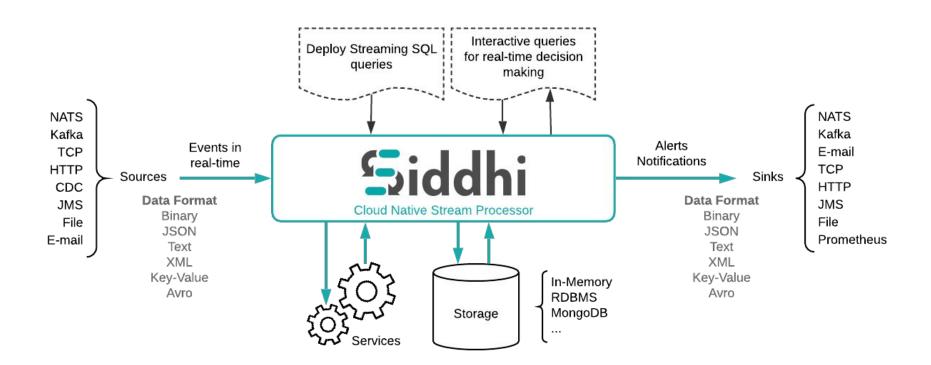
- Event-at-a-time processing (not microbatch) with millisecond latency
- Stateful processing including distributed joins and aggregations
- A convenient DSL
- Windowing with out-of-order data using a DataFlow-like model
- Distributed processing and fault-tolerance with fast failover
- Reprocessing capabilities so you can recalculate output when your code changes
- No-downtime rolling deployments



Apache Flink



siddhi.io



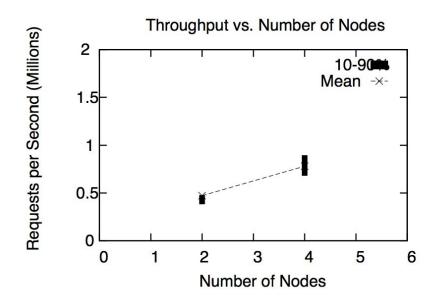
Siddhi

- A stateful query model
- SQL-like language for querying streams of data
 - Extended with windows
 - Time, Event count, batches
 - Partitioned
 - Based on data in the events
 - Pattern matching
 - A then B then C within window



Siddhi

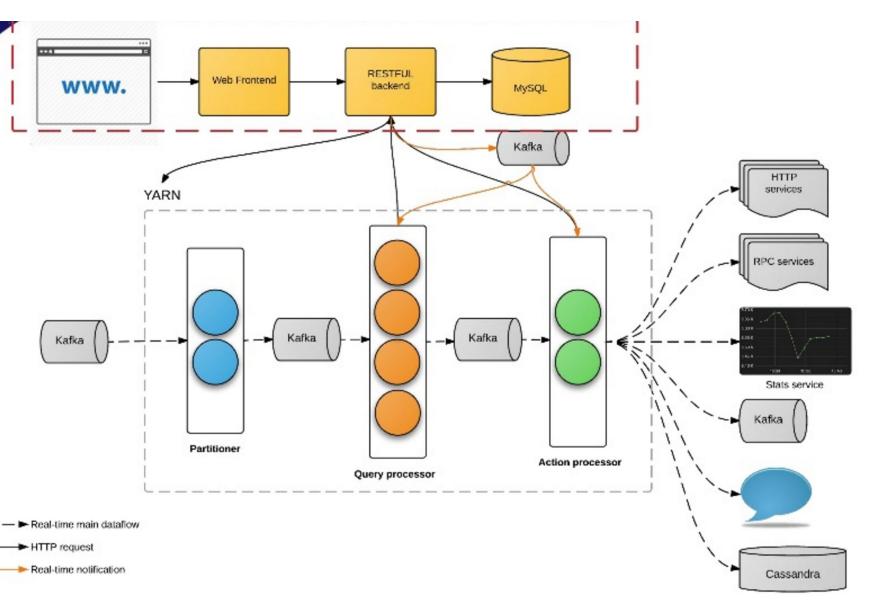
- Apache Licensed Open Source on Github
 - https://github.com/wso2/siddhi/
- Pluggable into Storm, Spark and Kafka Streams
- Supports millions of events/sec
- http://freo.me/DEBS_Siddhi



SiddhiQL



Siddhi at Uber



Siddhi at Uber

- 100+ production apps
- 30 billion messages / day
- Fraud, anomaly detection
- Marketing, promotion
- Monitoring, feedback
- Real time analytics and visualization

https://freo.me/siddhi-uber



Long-running aggregation

```
define aggregation SweetProductionAggregation

from SweetProductionStream

select name, sum(amount) as totalAmount

group by name

aggregate every hour...year
```

```
from GetTotalSweetProductionStream as b join SweetProductionAggregation as a
  on a.name == b.name
  within b.duration
  per b.interval
select a.AGG_TIMESTAMP, a.name, a.totalAmount
insert into HourlyProductionStream;
```



Summary

- Realtime processing is hard
 - Requires large memory and state
 - The lambda architecture splits the problem into batch and realtime challenges
- Multiple approaches:
 - Pure Streaming
 - Micro-batch
 - Stateful Stream Processing



Questions?

