Big Data Engineering

Realtime Big Data Processing

Streaming

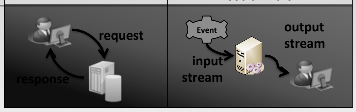
- Continuous data flow
  - "Unbounded streams of data"
- Usually uses a message distribution system
  - JMS, Apache Kafka, ZeroMQ, MQTT
- An unbounded set of events with time
  - <t1, E1>, <t2, E2>, ….., <tn, En>, ….

Stream processing categorization

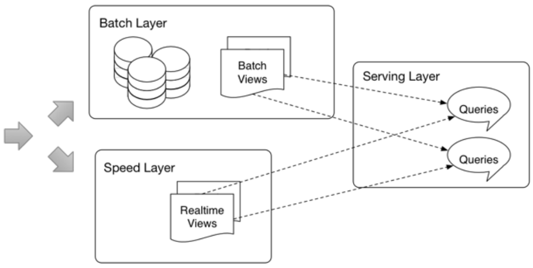
- Simple event processing
  - Working on an event at a time
    - e.g. filter out all events where the wind speed > 50 mph
- Event stream processing
  - Time-based processing of a single stream of events
    - Average wind speed over the last hour compared to the average over the last day
- Complex Event 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



Lambda Architecture



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

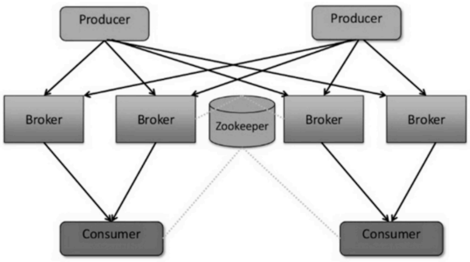
Data distribution

- You need to get the events to the processing systems

MQTT

- Very simple, lightweight, fast
- No built in support for clustering / big-data
  - But can make up for it by being very fast
- Used a lot in IoT

Apache Kafka

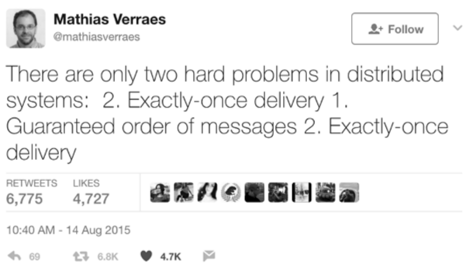


Source: http://www.slideshare.net/charmalloc/

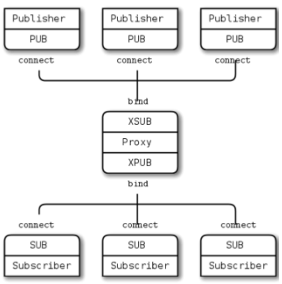
Kafka

- Many of the approaches we've seen:
  - Partitioning
  - Multiple brokers
  - Elastically scalable
  - Supports clusters of co-ordinated consumers
  - Automatic re-election of leaders

Kafka exactly-once semantics

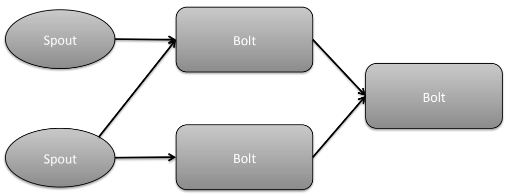


ZeroMQ



Processing the data

Apache Storm



Note: another DAG

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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

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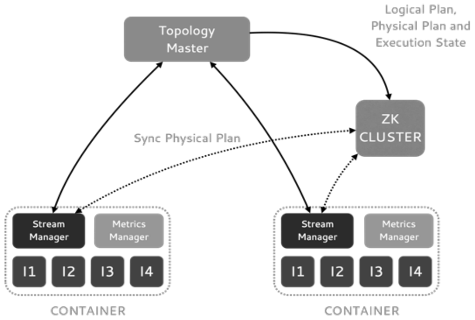
Heron



Heron: Key Features

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

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Heron

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

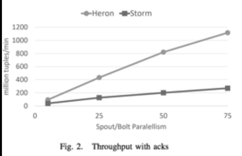


Fig. 2. Throughput with acks

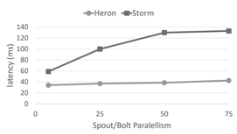
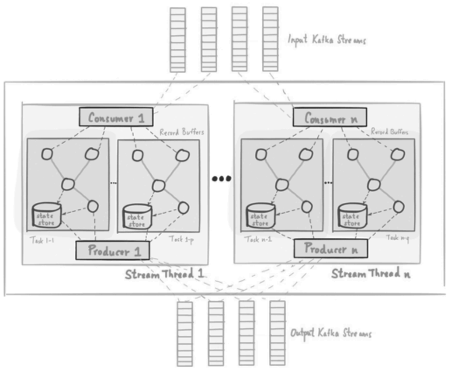


Fig. 3. End-to-end latency with acks

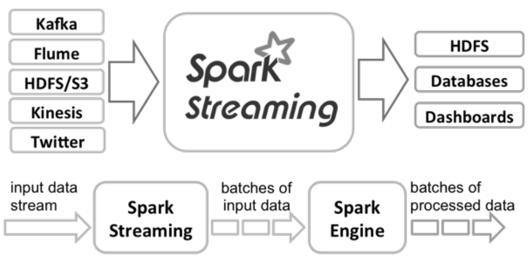
Kafka Streams



Kafka Streams

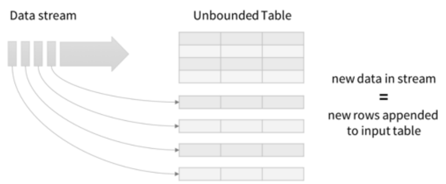
- Event-at-a-time processing (not microbatch) with millisecond latency
- Stateful processing including distributed joins and aggregations
- A convenient DSL
- Windowing with out-of-order data using a DataFlow-like model
- Distributed processing and fault-tolerance with fast failover
- Reprocessing capabilities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

Apache Spark Streaming

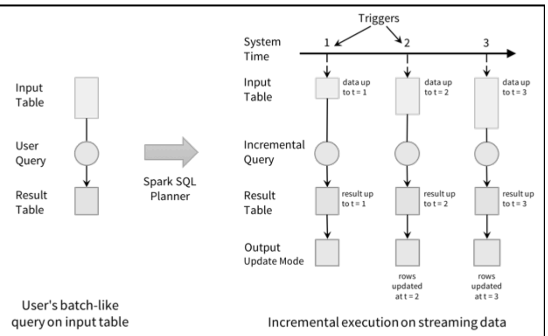


Structured Streams in Spark

- Since Spark 2.0, there is a much better approach

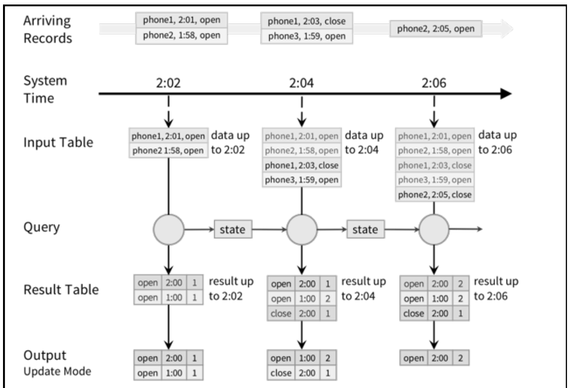


Data stream as an unbounded Input Table



Structured Streaming Processing Model

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

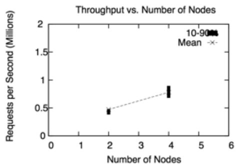


Siddhi

- 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

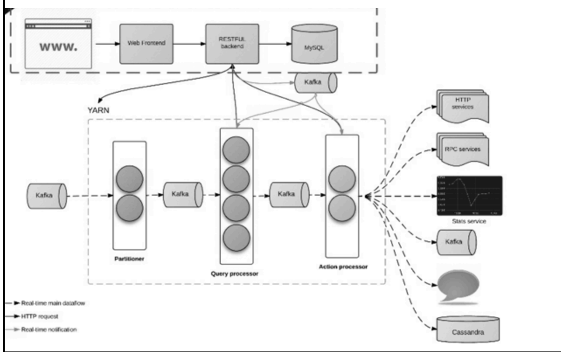
- Apache Licensed Open Source on Github
  - https://github.com/wso2/siddhi/
- Pluggable into Storm, Spark and Kafka Streams
- Supports millions of events/sec
- http://freo.me/DEBS_Siddhi



SiddhiQL

```
FROM login_stream#window.time(10 min)
SELECT ip,
       count(ip) as loginCount,
       cityId
GROUP BY ip
HAVING loginCount > 10
INSERT INTO login_attemp_repeatedly_stream;
```

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

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
  – CEP

Questions?