

Challenges & Lessons at Uber Engineering





Quick Introduction



Chinmay Soman



- Staff Software Engineer @ Uber
- Tech Lead on Streaming Platform
- Background in distributed storage and filesystems
- Apache Samza Committer, PMC

Apache Kafka at Uber

Billion to Trillions

Messages/day

~ PB

bytes/day

Near Real-Time Analytics at Uber

Billions

Messages Processed / day

100s of TB - PB

Bytes Processed / day



What is near real-time?



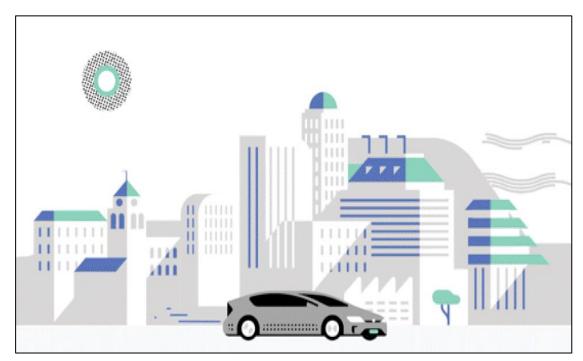
Agenda

- Evolution of Business Needs
- The case for SQL as building block
- New ecosystem using Flink
- The road ahead

Evolution of Business Needs



Case I - Growth Metrics



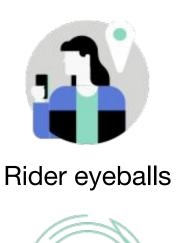
"How many cars are active right now?"

"What % of trips have been delayed in the last 5 mins?"

"What is the % of Uber X trips taken by Android users?"



Events logged to Kafka

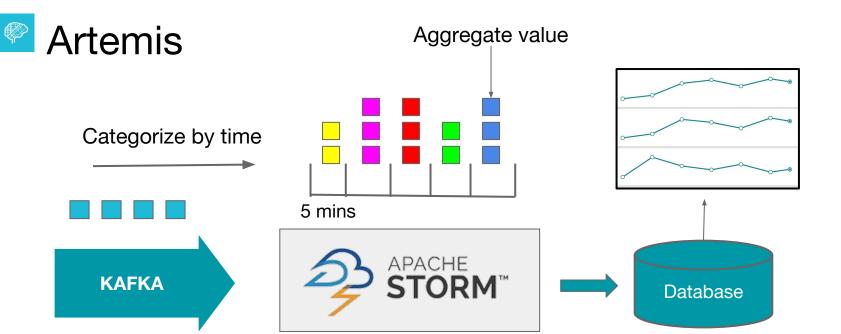




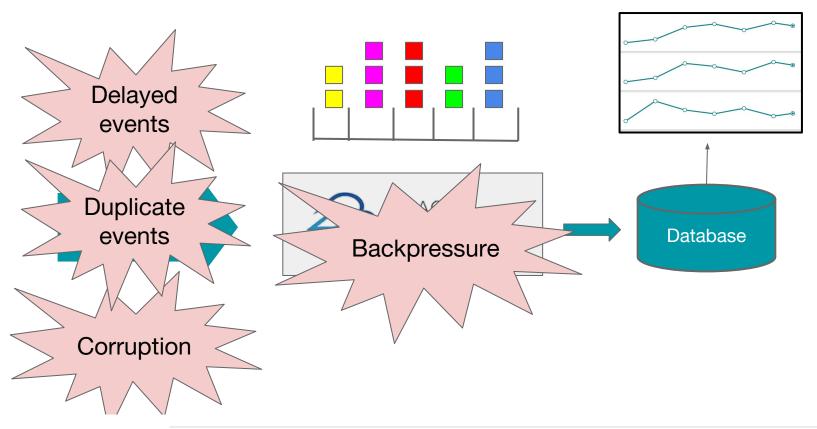




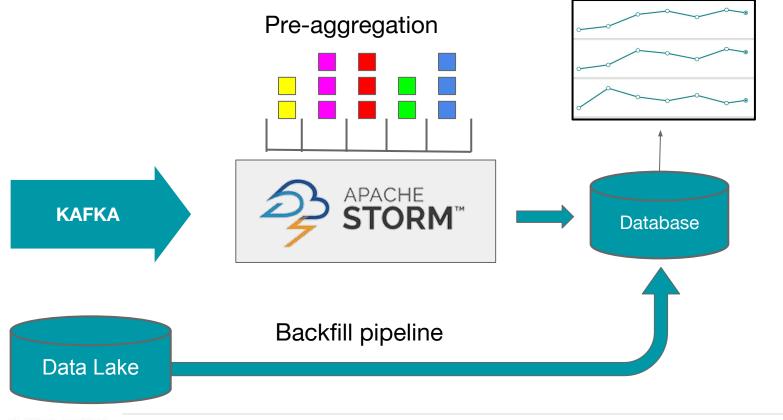
Trip updates



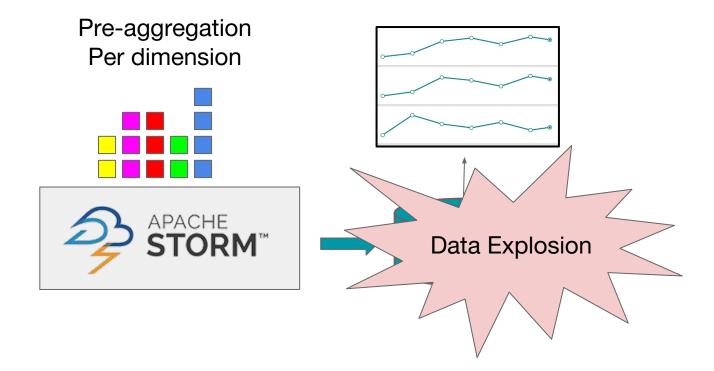












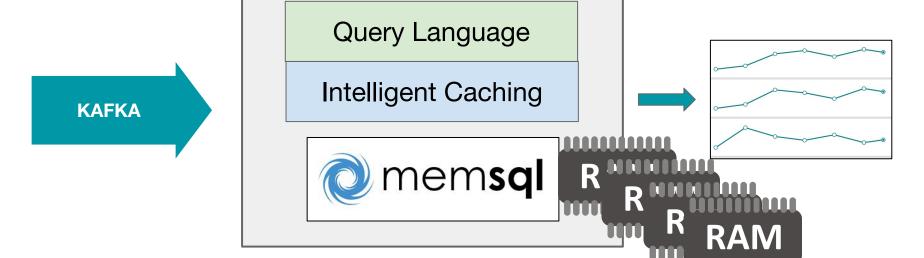






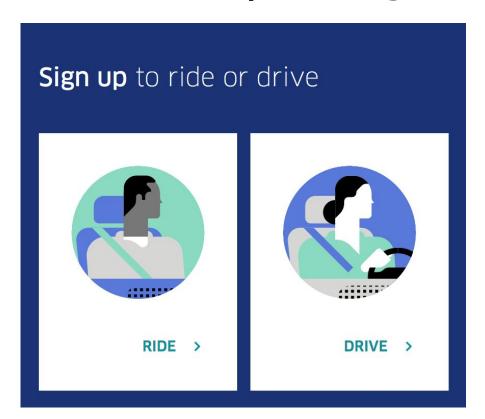








Case II - Event processing

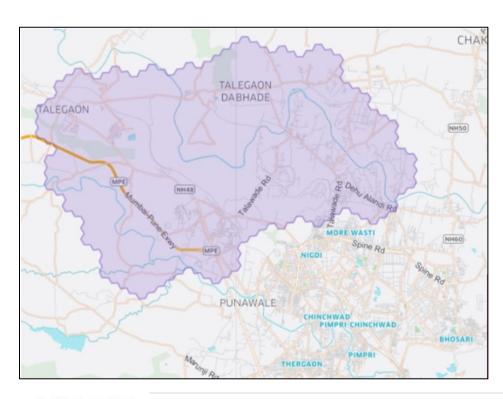


FRAUD

"If # Signups per device look suspicious -> Ban the driver/rider"



Case II - Event processing



INTELLIGENT ALERTS

"Send me an alert if a leased vehicle leaves a geo-fence"

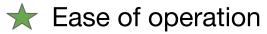




Athena platform using Apache Samza







★ No backpressure issues

* Built in state management





Event processing - Apache Samza







Fraud Rule Engine

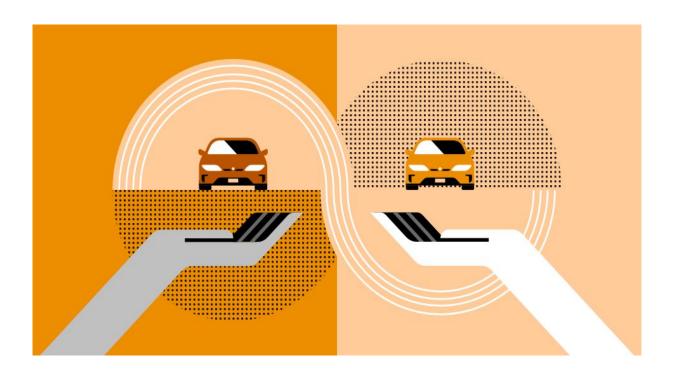
> Ban fraudsters in real-time

Track count # of sign_ups categorized by device_imei





Case III - OLAP (OnLine Analytical Processing)



A / B Tests

See progress of tests in real-time





Case III - OLAP use case



FORECASTING

"How many first time riders will be dropped off in a given geofence?"





Our integrated platform



- Filter events
- Merge streams
- Decorate with external data



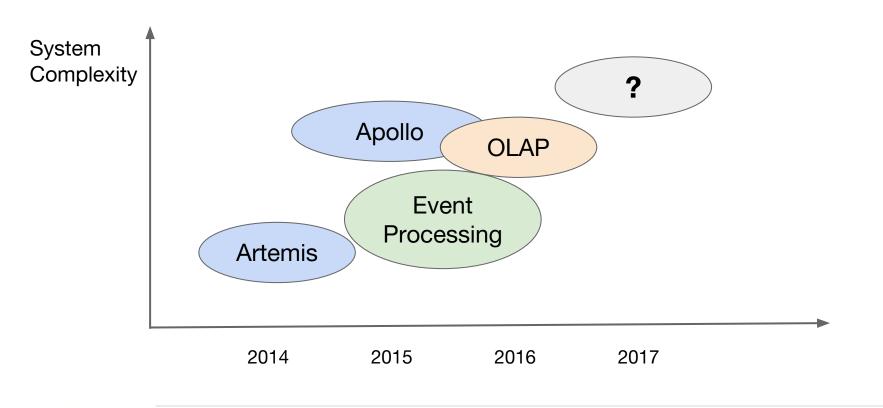








Are we there yet?





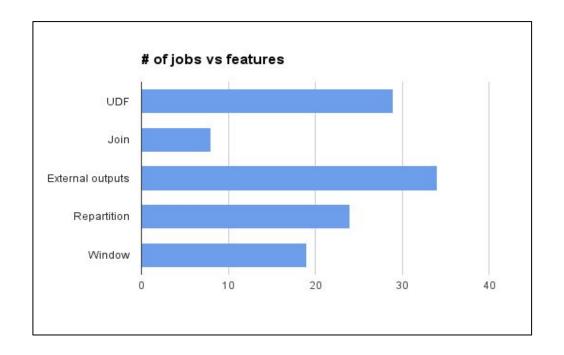
What's missing?

- Cumbersome for data scientists / Ops people
- Redundant code
- Custom backfill pipelines

SQL as the building block



SQL + Stream Processing



70-80% of jobs can be implemented via SQL



Intelligent Promotions

Rule

"All trips worth > 10\$ in San Francisco between Friday 5 pm and Sunday 9 pm

Threshold

> 100

Action

"Give bonus of \$500"



Complicated rules

- "If number of hours online > 10 ..."
- "If amount earned > 700 in a given week, then ..."
- "If # uberPOOL rides >10, then ..."
- "If trip happens over some geo-fence 10 times in a given weekend, then ..."



Intelligent Promotions

Rule

Threshold

Action

select count(*) from hp_api_created_trips

WHERE city_id = 1

AND fare > 10

AND request_at > 1491105600

AND request_at <= 1491177600

> 100

trigger_payment()



Complicated rules

- "If number of hours online > 10 ..."
- "If amount earned > 700 in a given week, then ..."
- "If # Uber Pool rides >10, then ..."
- "If trip happens over some geo-fence 10 times in a given weekend, then ..."

What if we created specific rules for specific driver partners?



Can be used for alerts as well:

"If a driver X is outside a geofence, then ..."

New eco-system: Athena X

Enter Flink



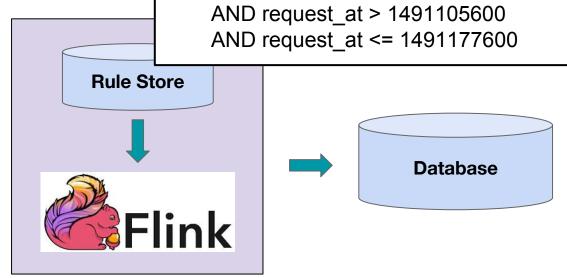
- ★ Apache Calcite (SQL) Integration
- * Easy to manage and scale
- ★ No backpressure problem
- ★ Built in state management support
- ★ HDFS integration
- ★ Not dependent on Kafka



Promotions using Flink

select count(*) from hp_api_created_trips
WHERE city_id = 1
AND fare > 10
AND request_at > 1491105600







Promotions using Flink

select count(*) from hp api created trips

WHERE city id = 1

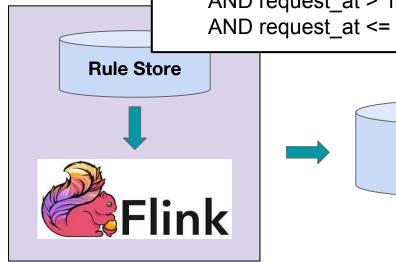
AND fare > 10

AND request at > 1491105600

AND request_at <= 1491177600

Database









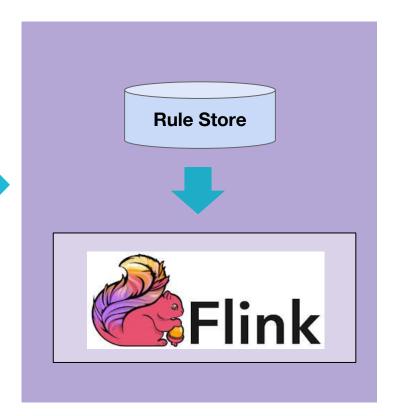
New Eco-system: Athena X

HTTP

Database Streams

Kafka Streams







Alerts



Kafka

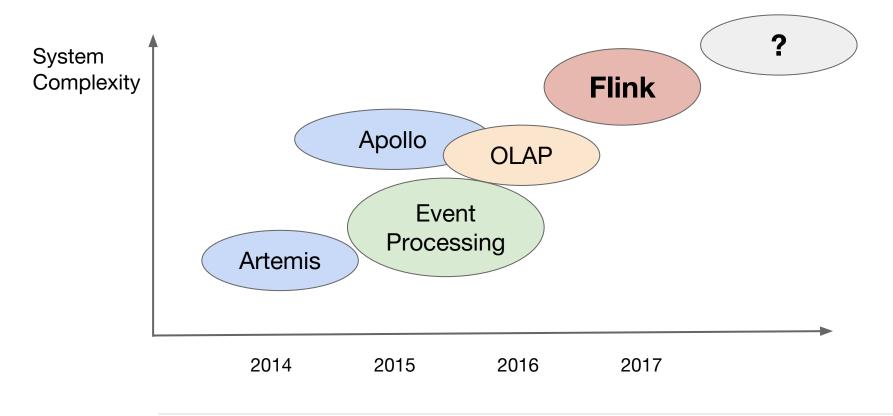
Cassandra

Other data destinations





Are we there yet?



The road ahead ...



Future Discussions

- To (Apache) Beam or not to Beam?
- Real-time Machine Learning
- Auto scaling

AthenaX - Flink deep dive Haohui Mai Bill Liu

(11:45 am)

Thank you

For more: eng.uber.com
Twitter: @UberEng