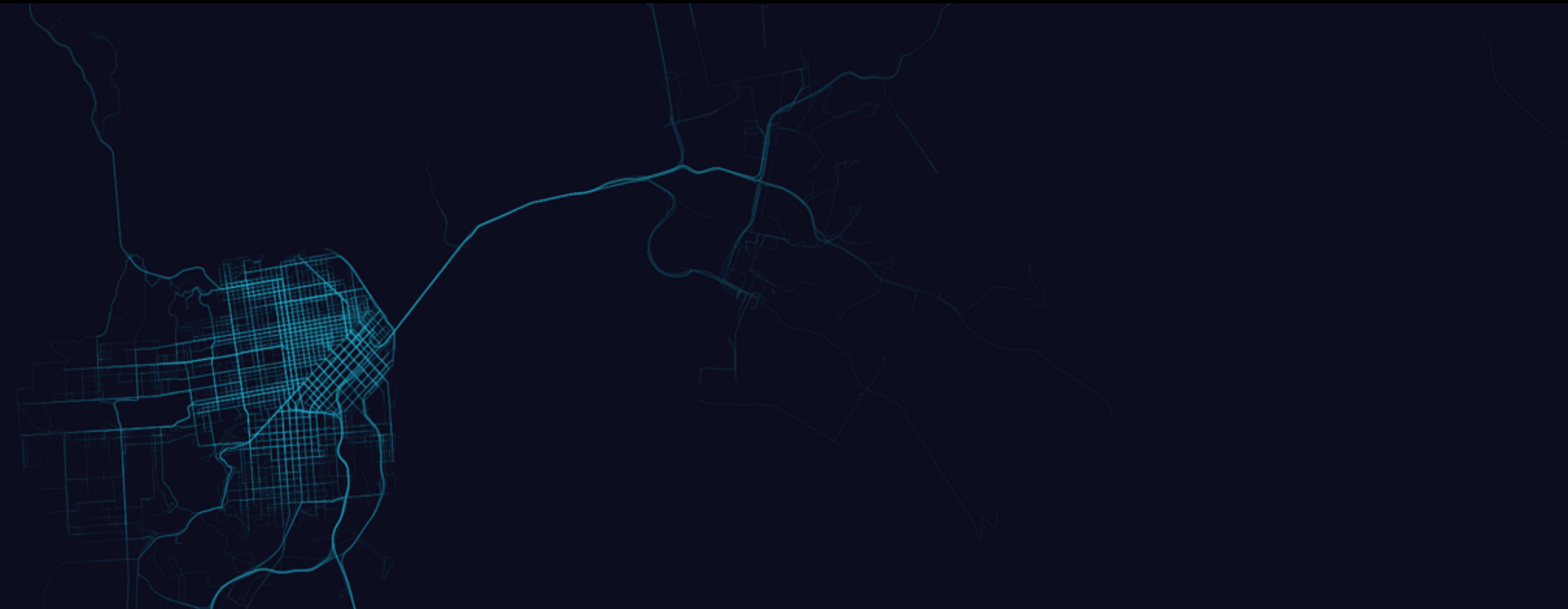
Stream Computing & Analytics At Uber

Sudhir Tonse, Uber Engineering

@stonse

Mar 7, 2016

UBER

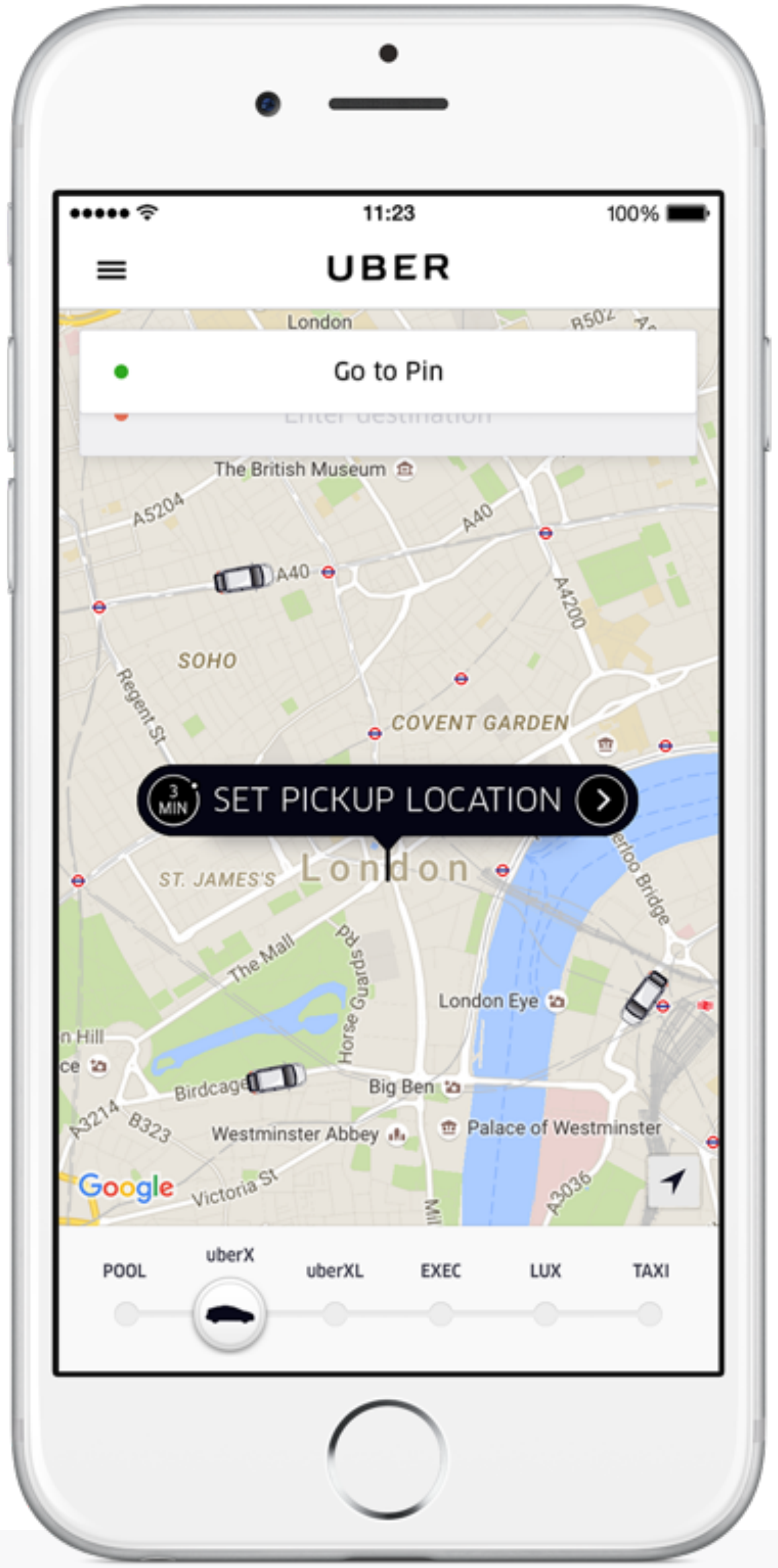


UBER

Get There

Your day belongs to you

- ~ 68 countries / 350+ cities
- Transportation as reliable as running water, everywhere, for everyone



Who am I

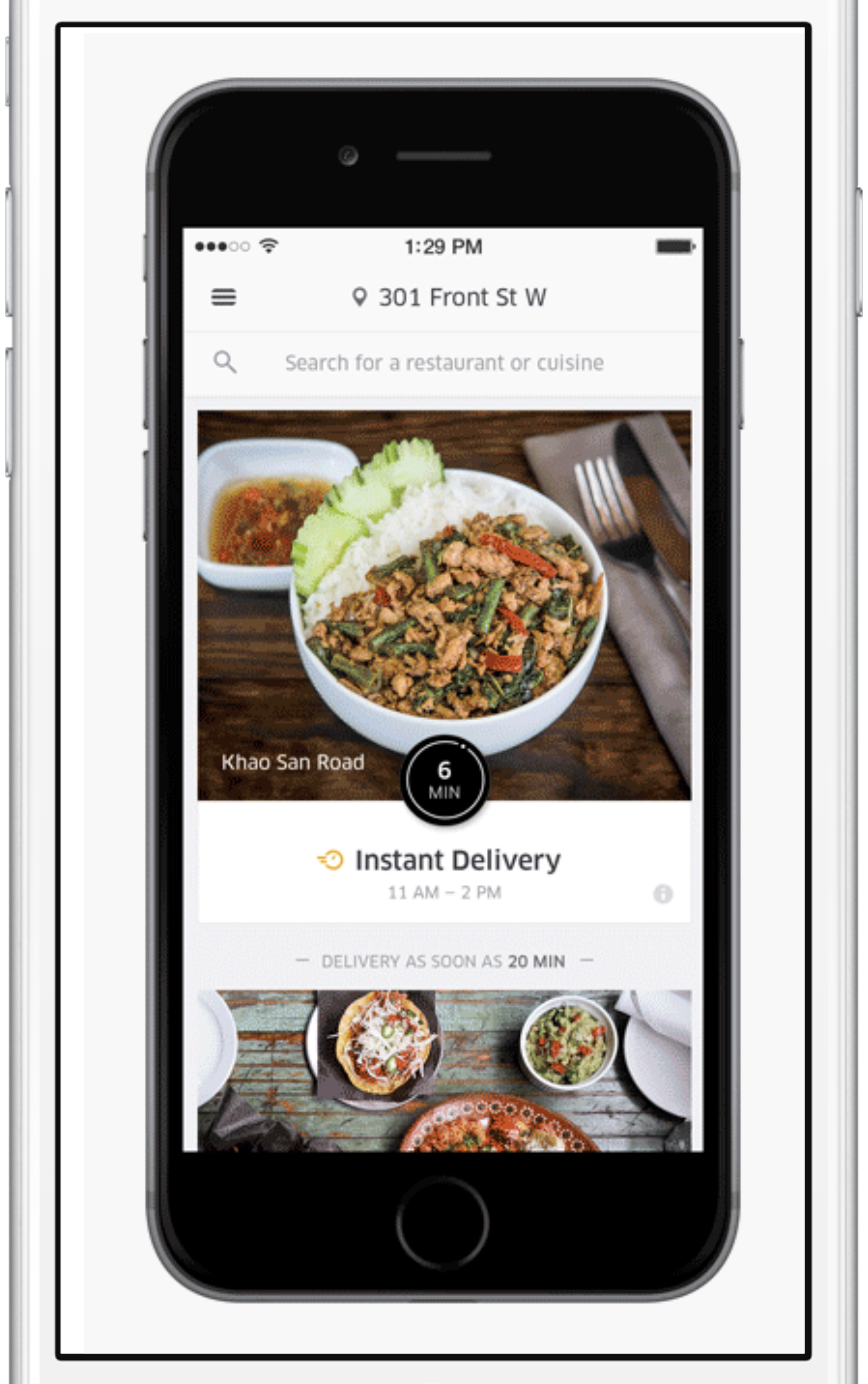
Engineering Leader, Marketplace Data at Uber

- Marketplace Dynamics
  - Realtime Data Processing
  - Analytics
  - Forecasting
- Previously managed Cloud Platform at Netflix
- Twitter @stonse

Agenda

What's on the menu?

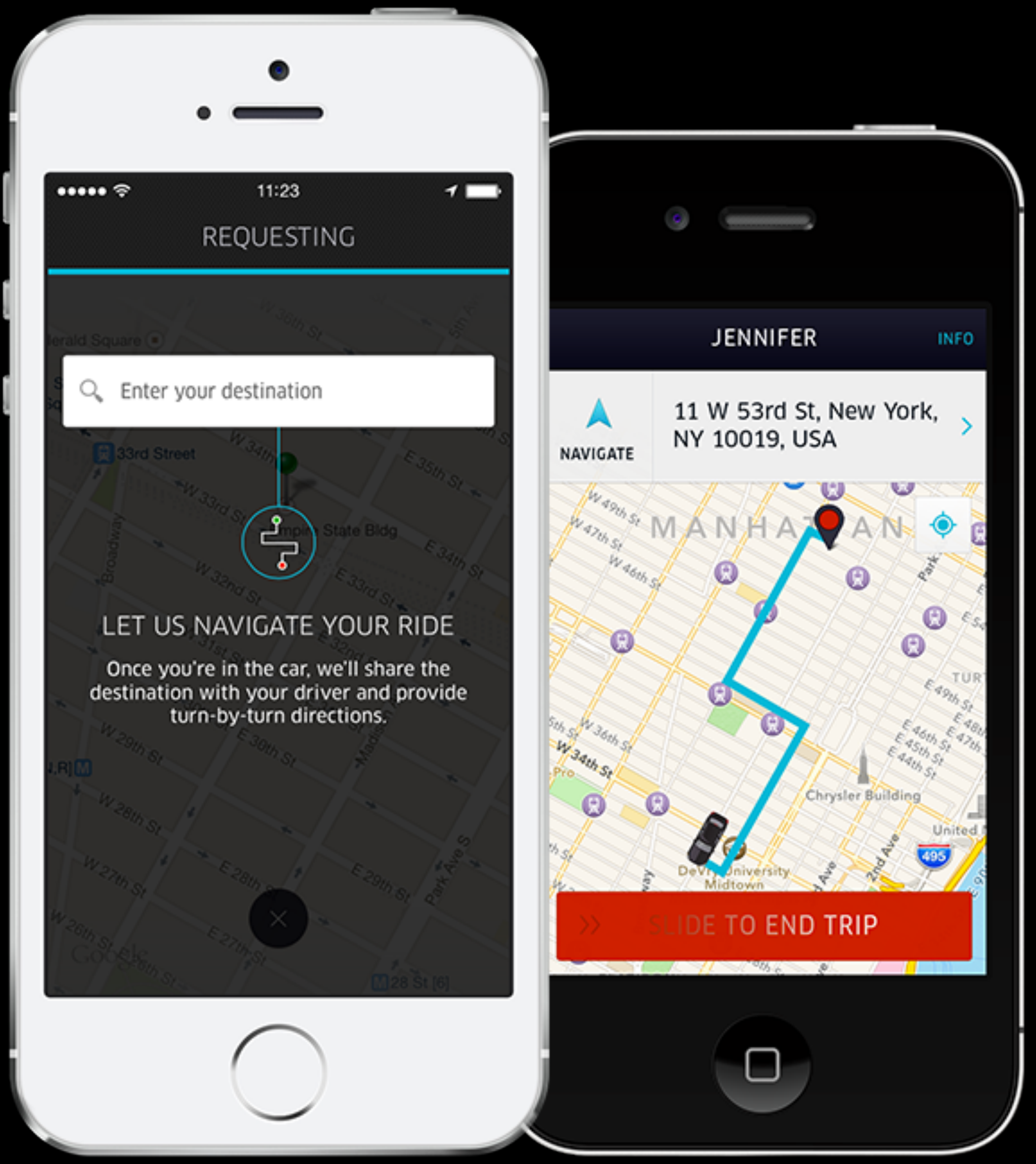
- Use Cases
- Problem Space
- Overall Architecture
- Choices & Tradeoffs
- Q & A

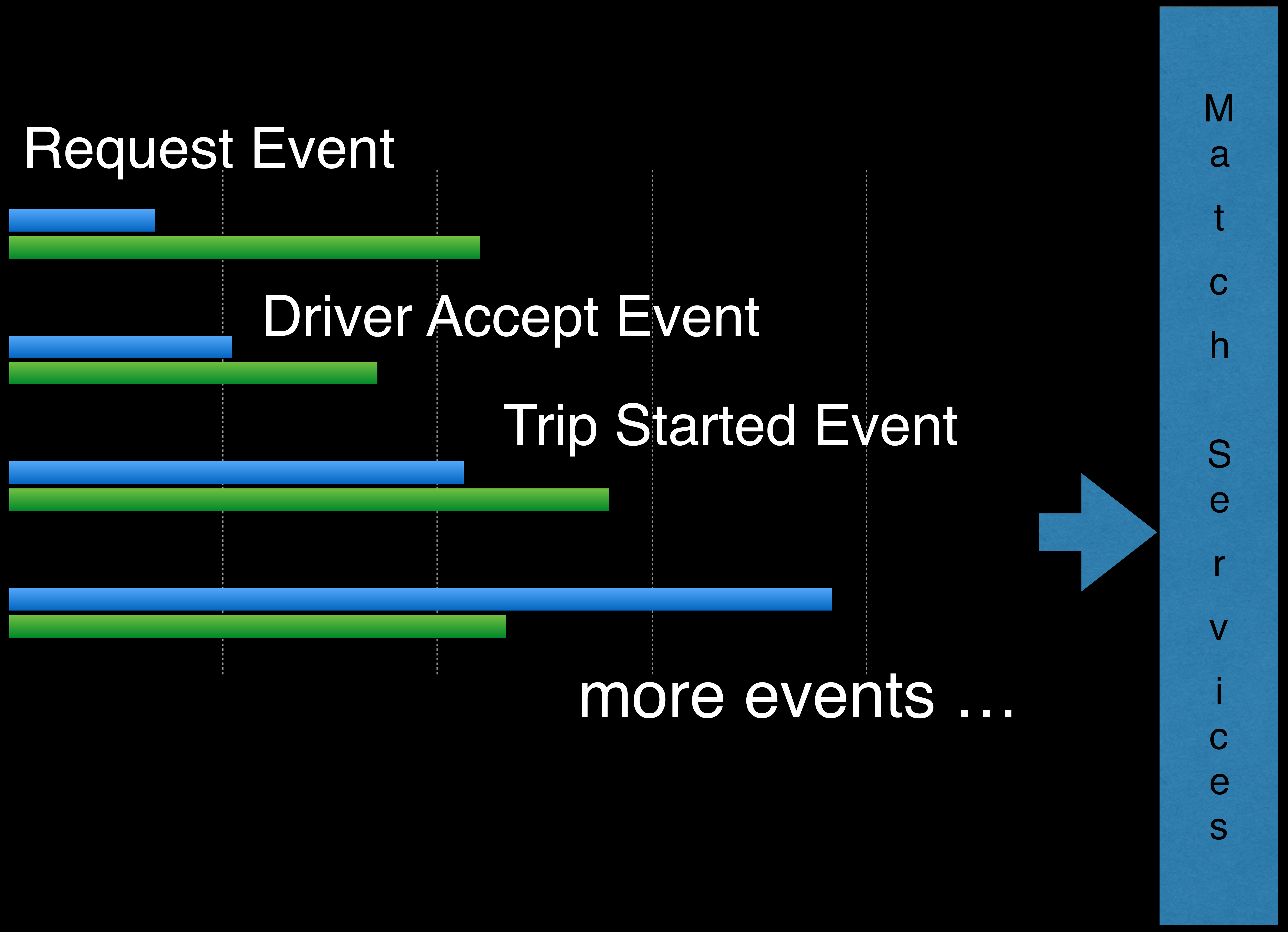


Use Cases

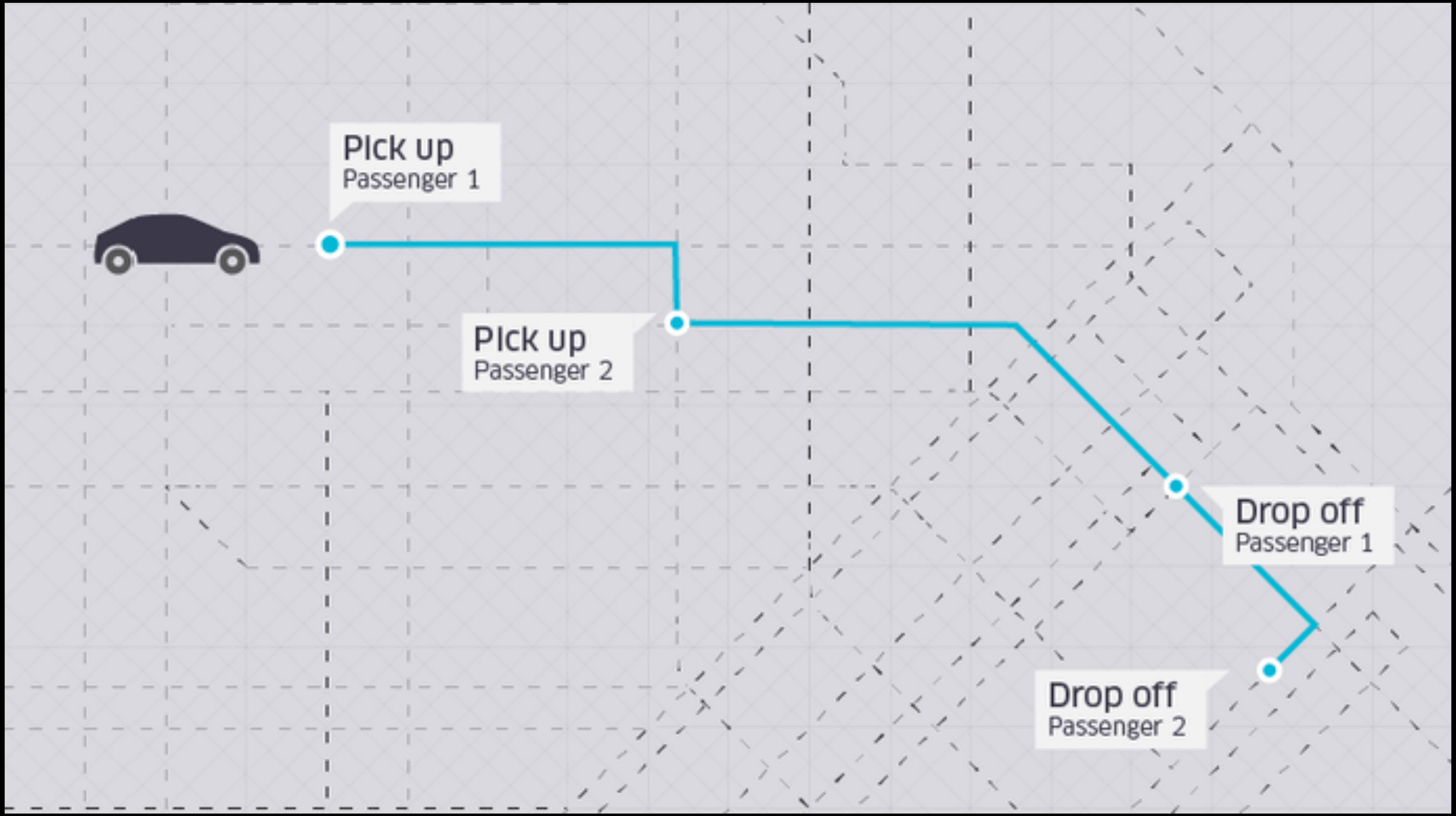
Some examples of what we work on

Stream Processing …





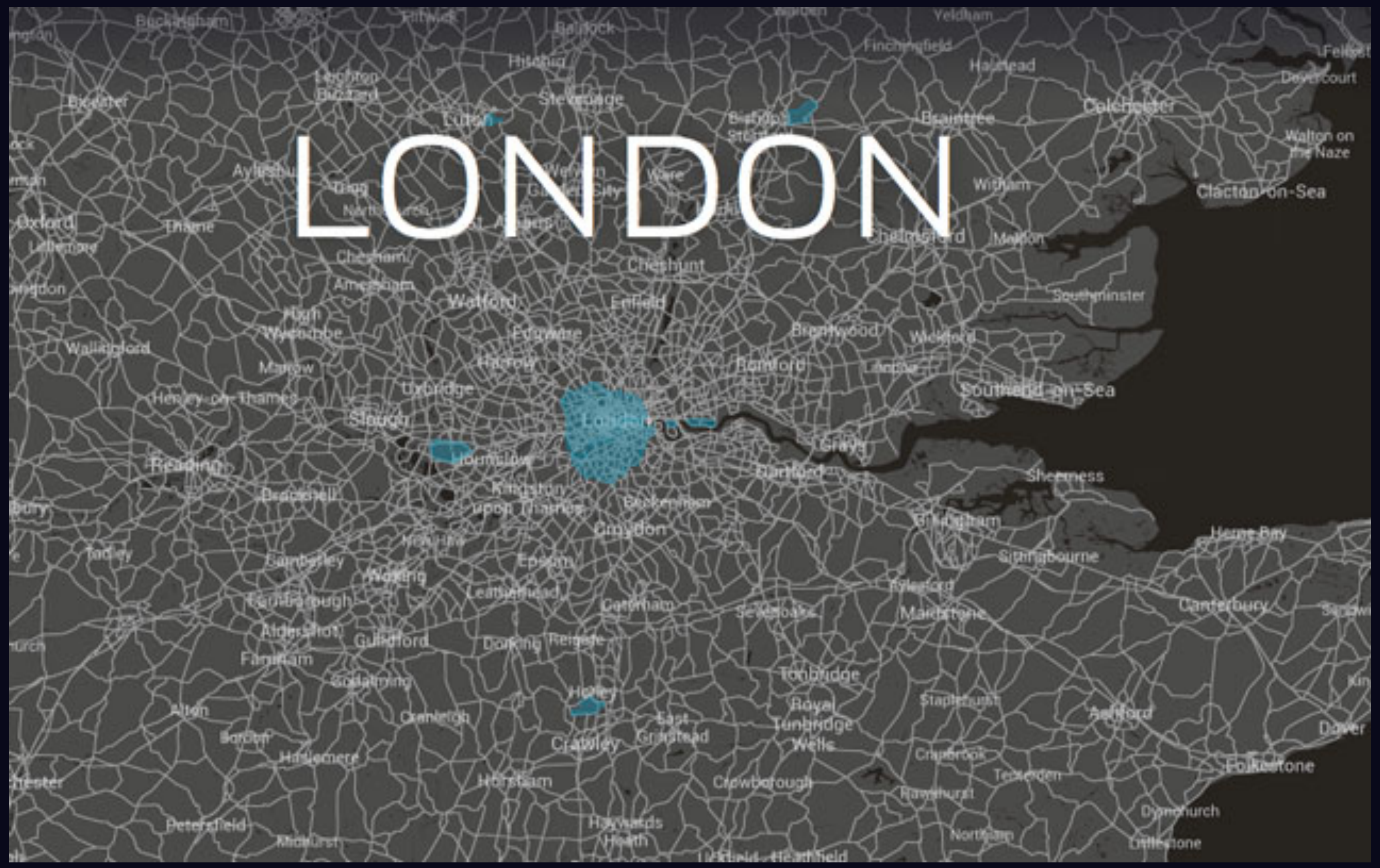
Trip States


Pick up
Passenger 1
Pick up
Passenger 2
Drop off
Passenger 1
Drop off
Passenger 2

Realtime OLAP/Exploration

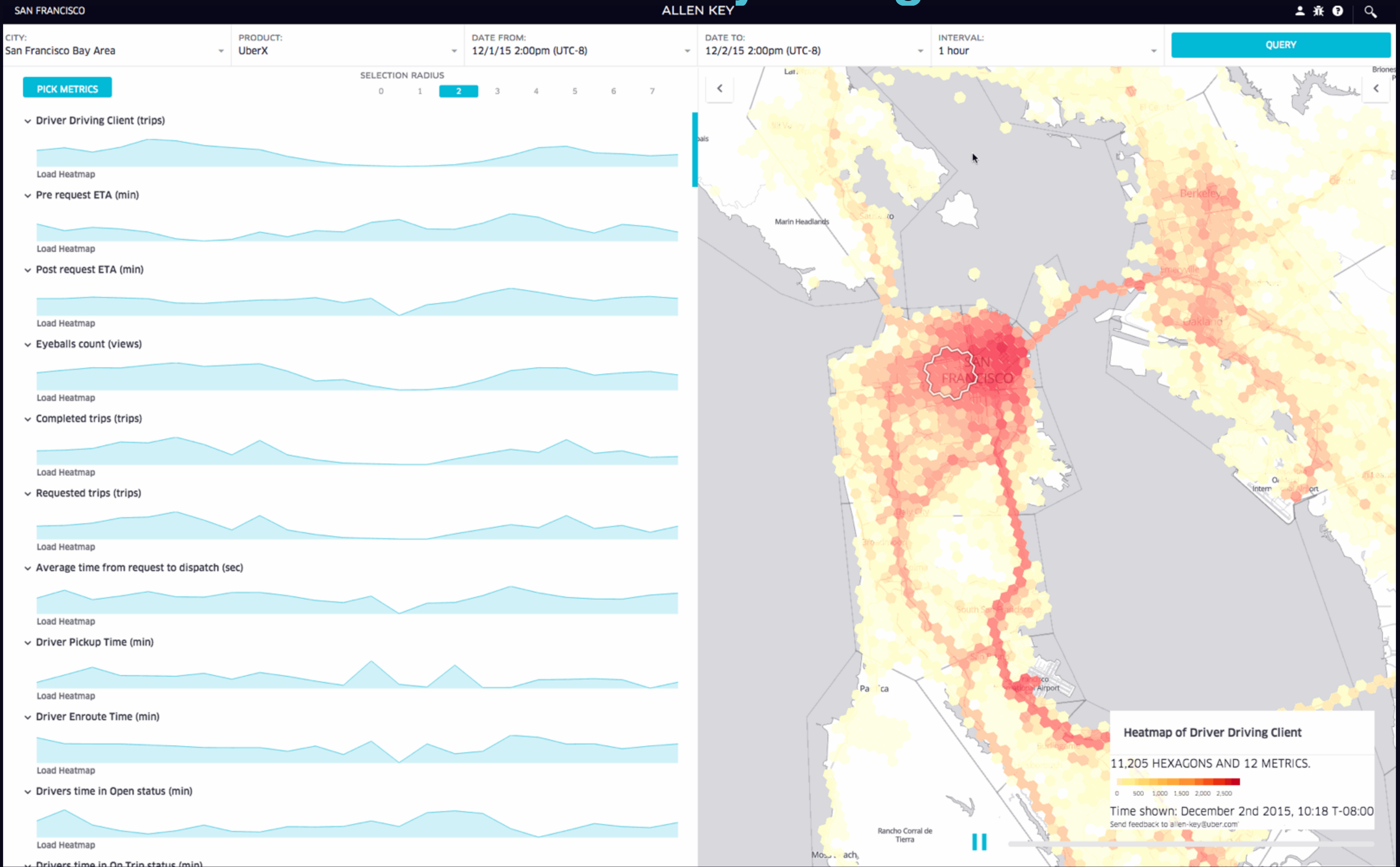
There is always a need for quick exploration

How many open cars in London, right NOW?



Estimated Pickup time, Driving Time and etc over time by geographic area

KPIs over time by hexagon area



Behaviour/Gaming/Fraud

How many drivers cancel a request > 3 times in a row within a 10-minute window?

Detect riders requesting a pickup 100 miles apart within a half hour window?

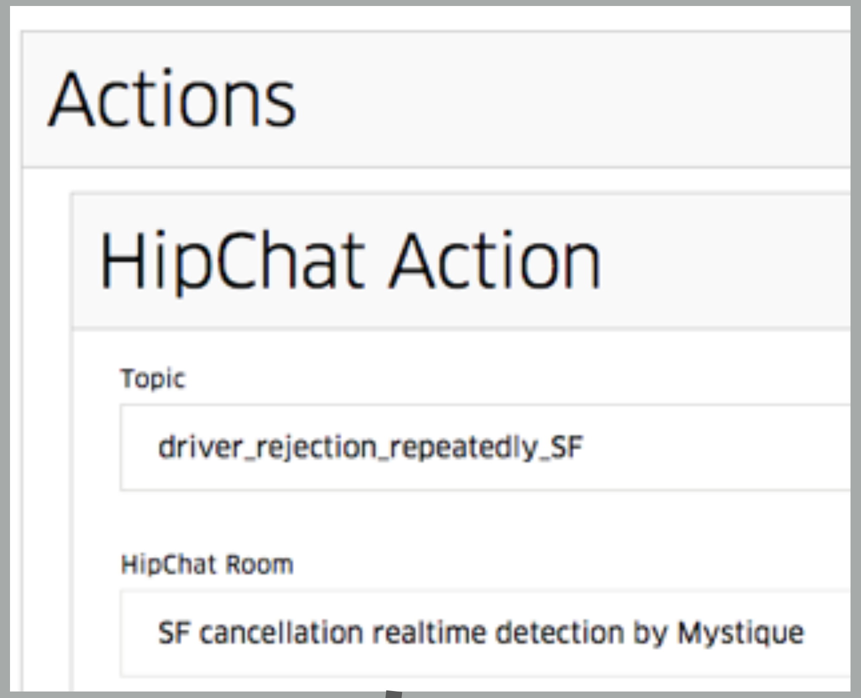
Complex Event Processing

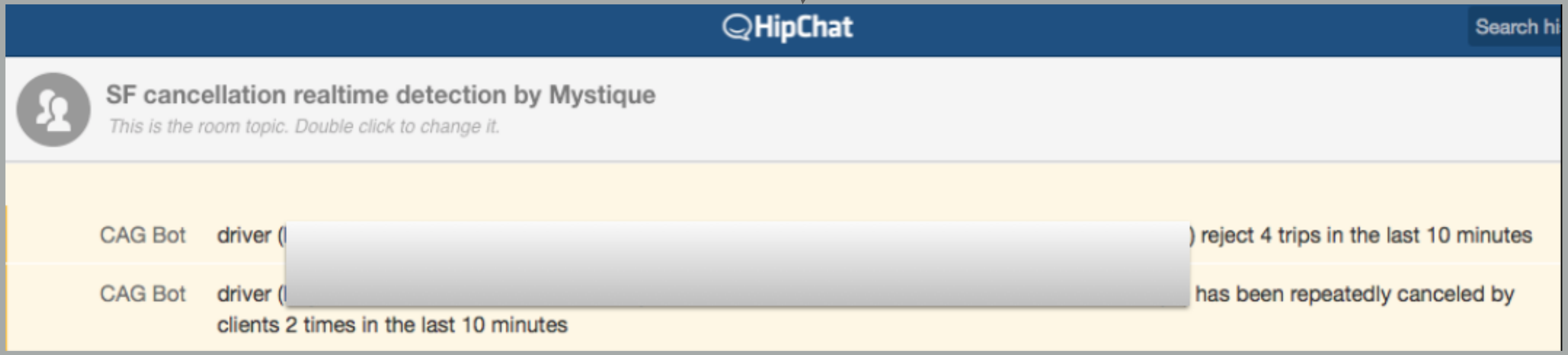
IF

This ->

```
FROM driver_canceled#window.time(10 min)
SELECT    clientUUID,    count(clientUUID) as cancelCount
GROUP BY clientUUID HAVING cancelCount > 3
INSERT INTO hipchat(room);
```

Then that ->





If This Then That

A simple SQL-like syntax!

that can take **ACTIONS**!!

In Real Time!

Supply Positioning

Clusters Of Supply & Demand

Near Term Forecasting

Airports, Stadiums, Arenas, Business districts, Transit stations, Malls, Dining ...

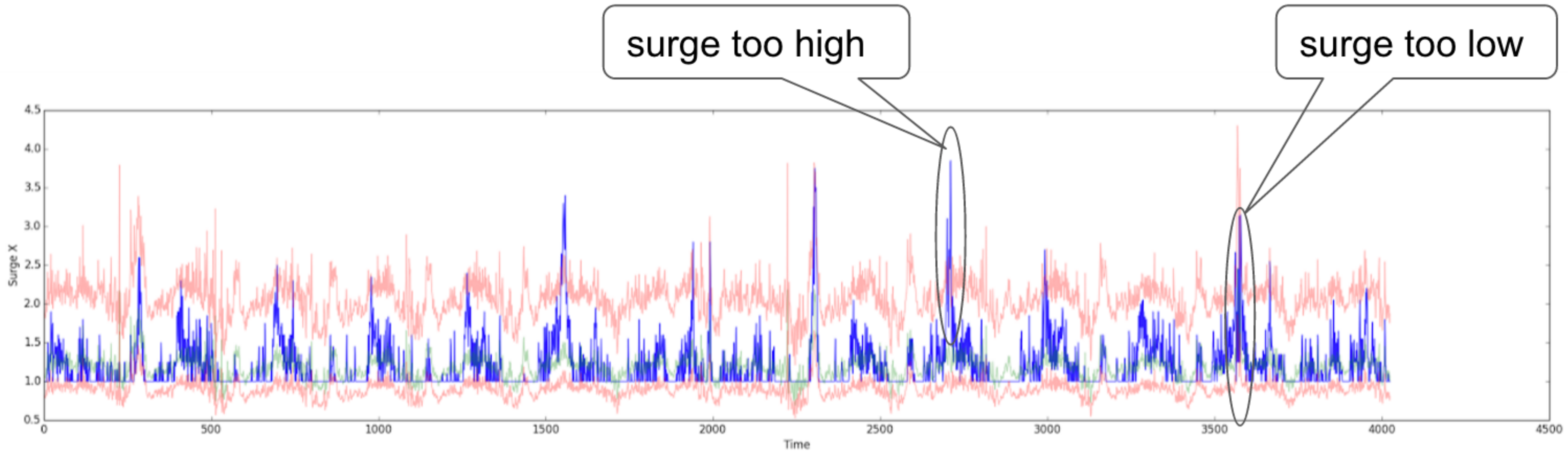
Monitoring Business Metrics

Realtime Monitoring of Business Metrics

Blue line: production surge x;

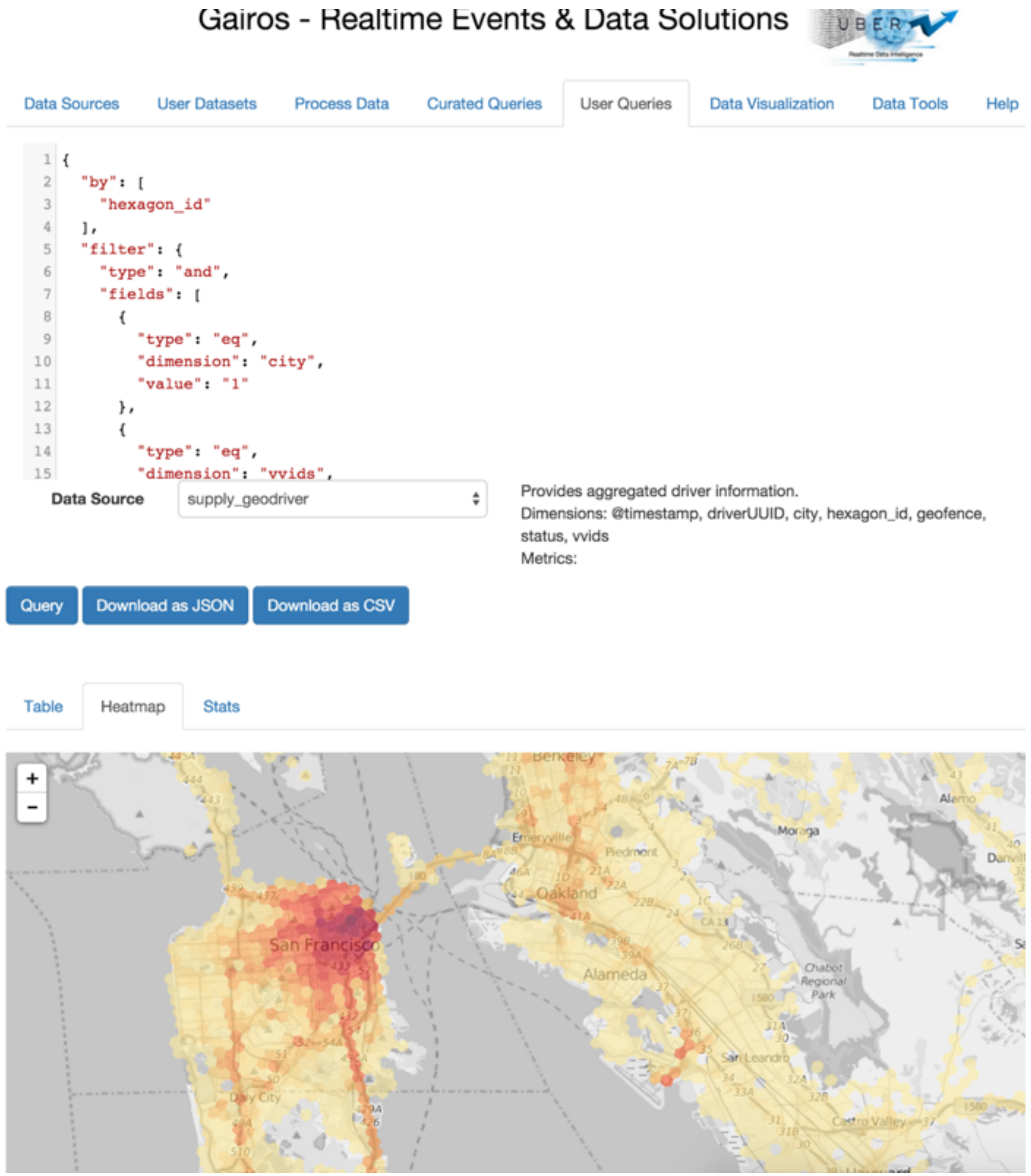
Green line: model estimated surge x;

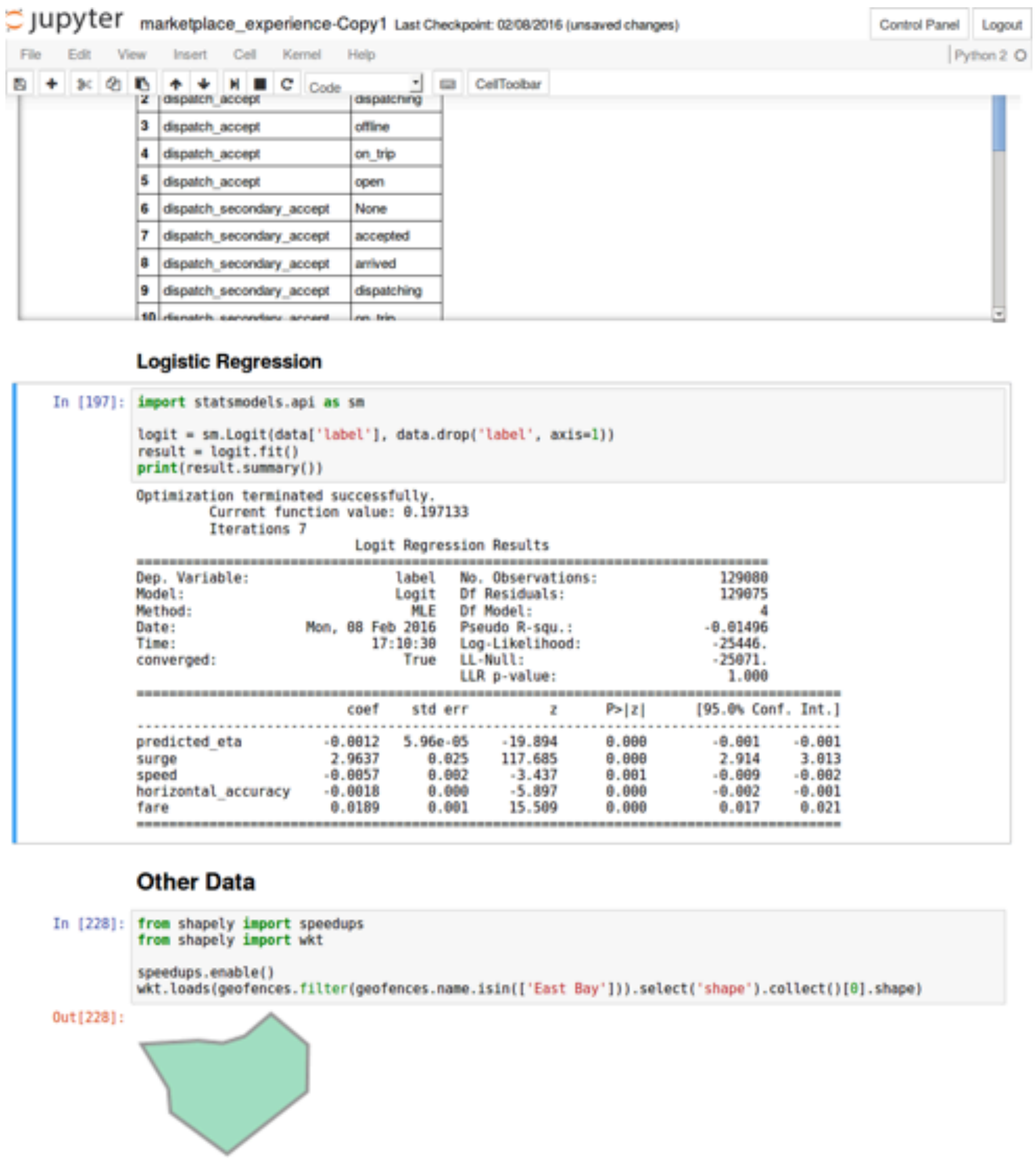
Red line: error bounding surge x



Ops & Data Scientists

Ops & Data Scientists (Dashboards & Analytics)





What’s not covered

to keep this focused

ETL Pipeline

Offline/Batch Analytics

Business Intelligence

Stream Processing fundamentals ..

…

Problem space

What are the challenges?

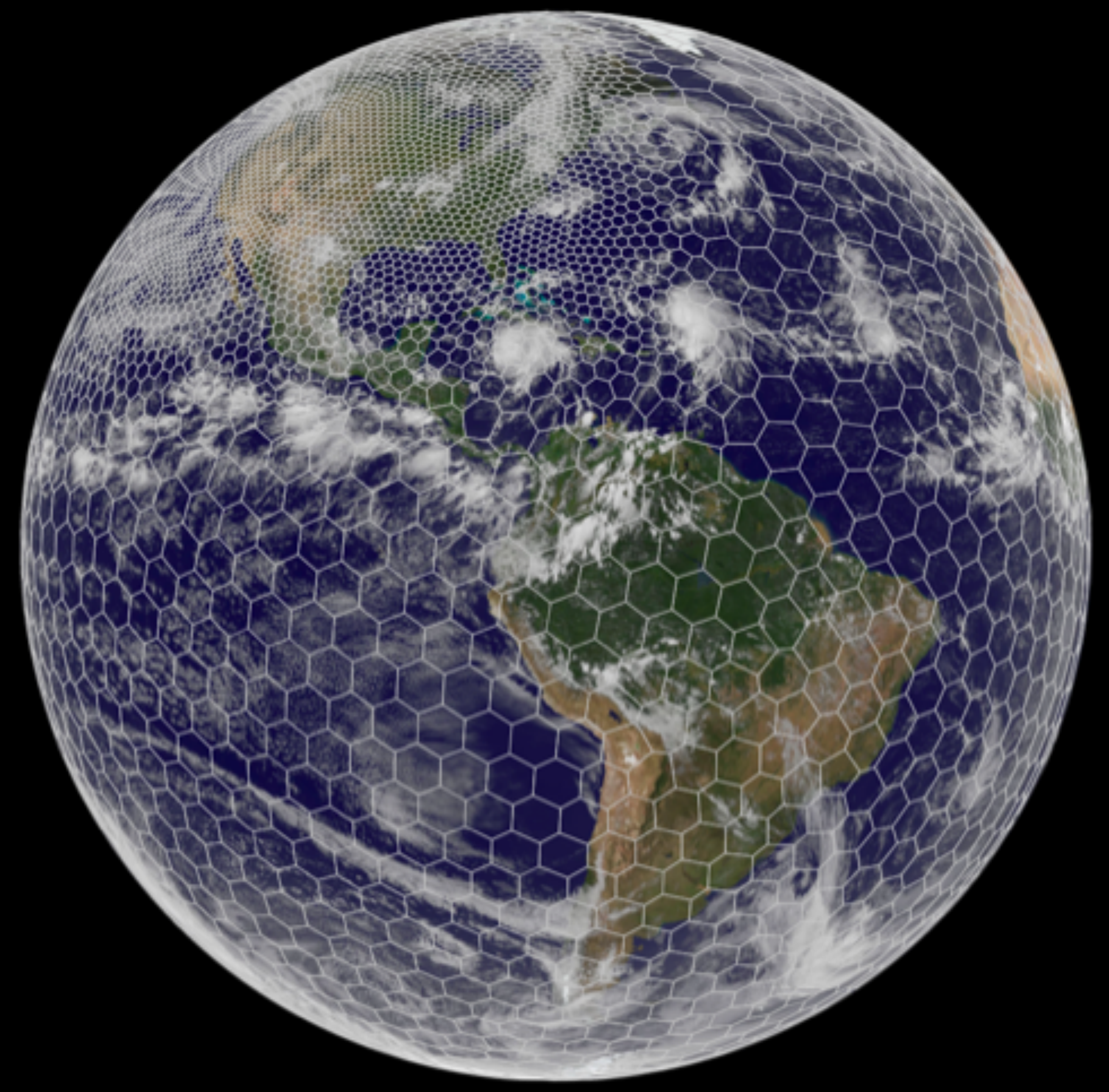
OLAP of Spacio-Temporal data

Large Scale Data

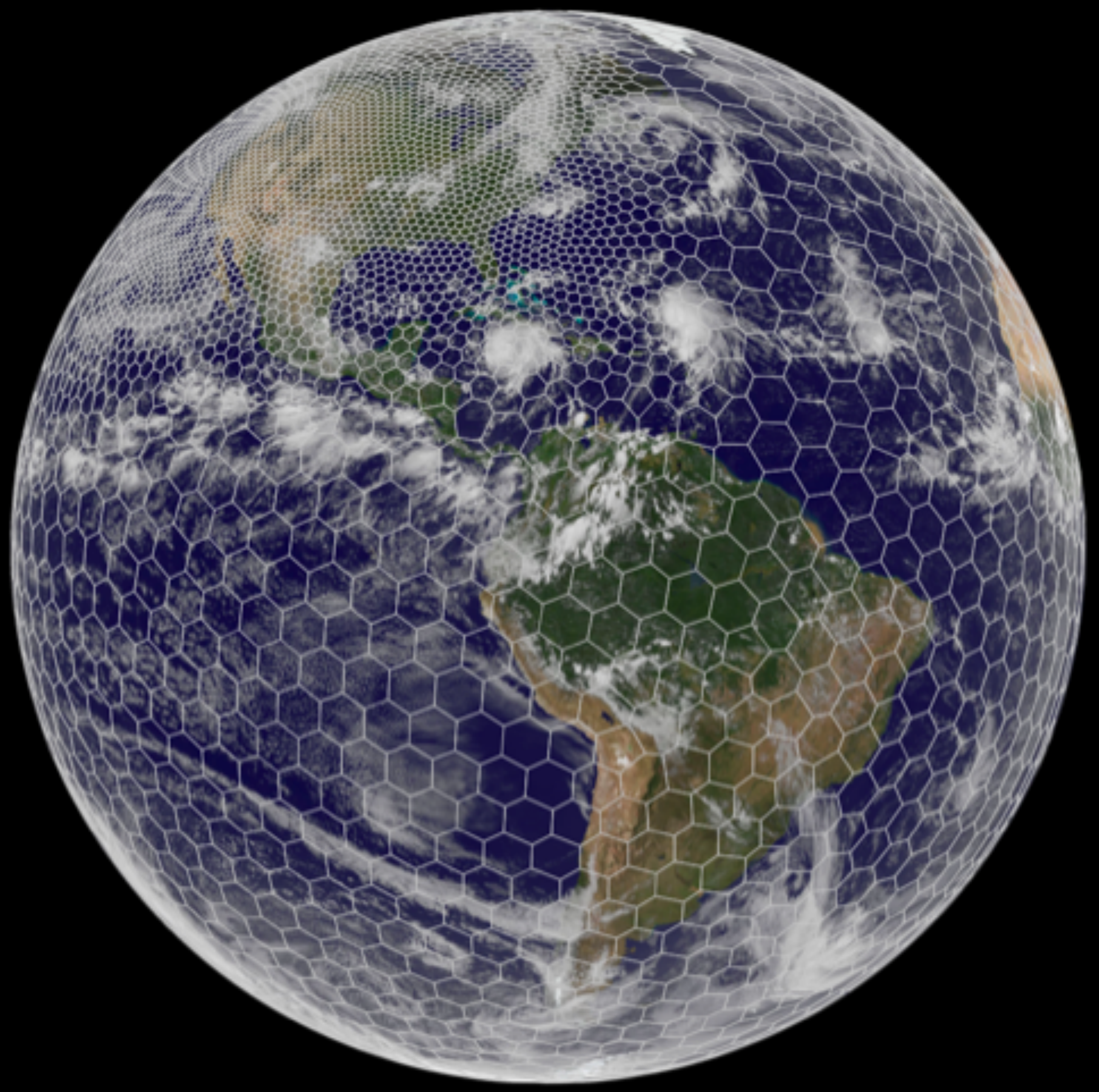
Near Real Time

Hexagons

- Indexing, Lookup, Rendering
- Symmetric Neighbors
- Convex & Compact Regions
- Equal Areas
- Equal Shape



Scale



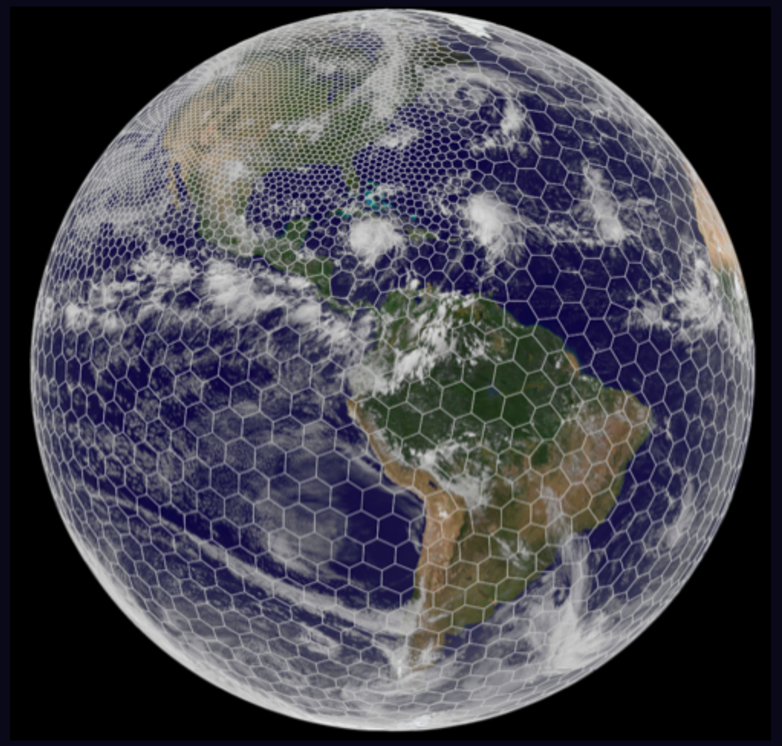
Geo Space

Vehicle Types

Time

Granular Data

Granular Data



Over 10,000 hexagons in the city

Granular Data

7 vehicle types

Granular Data

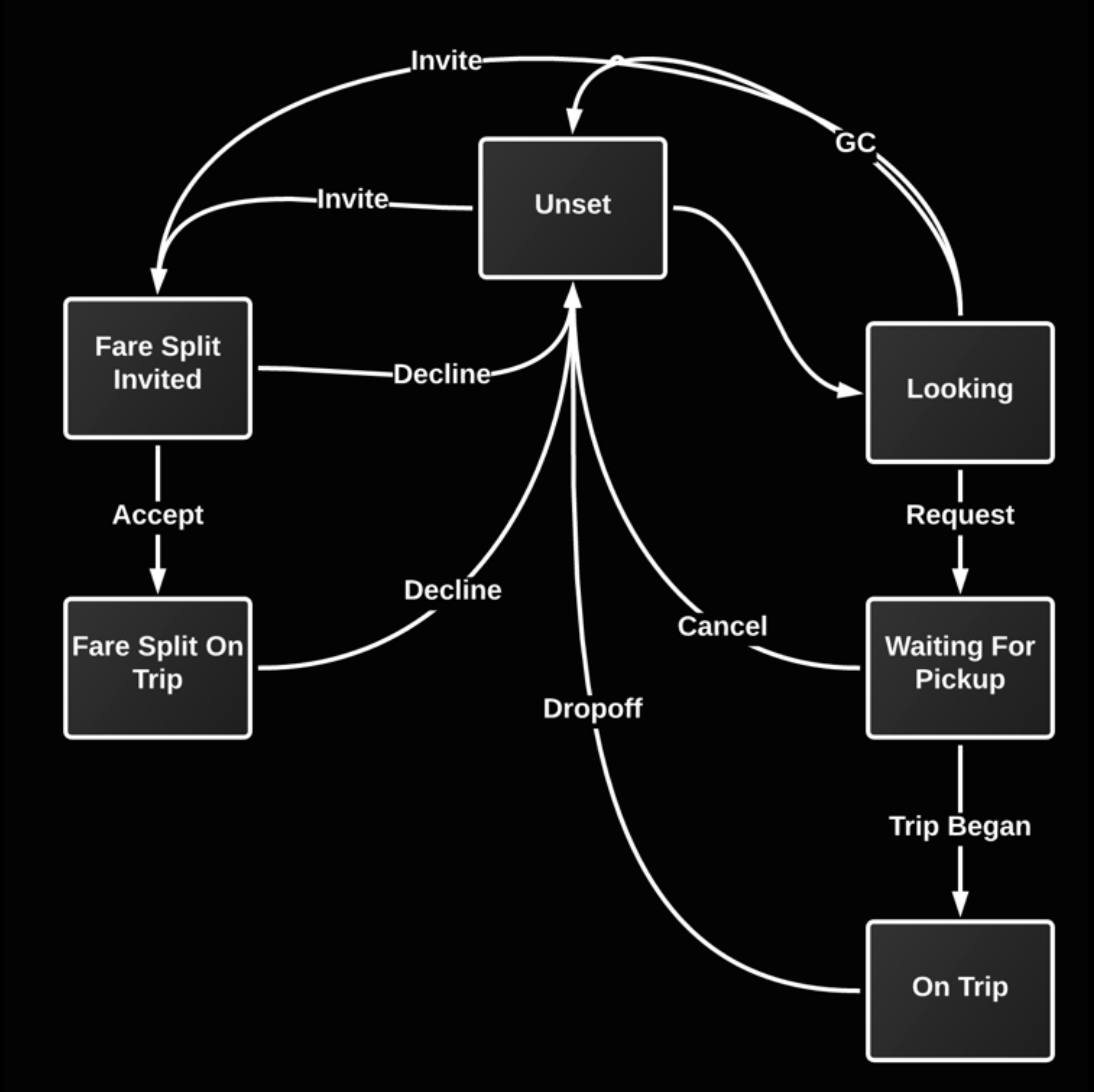
1440 minutes in a day

Granular Data

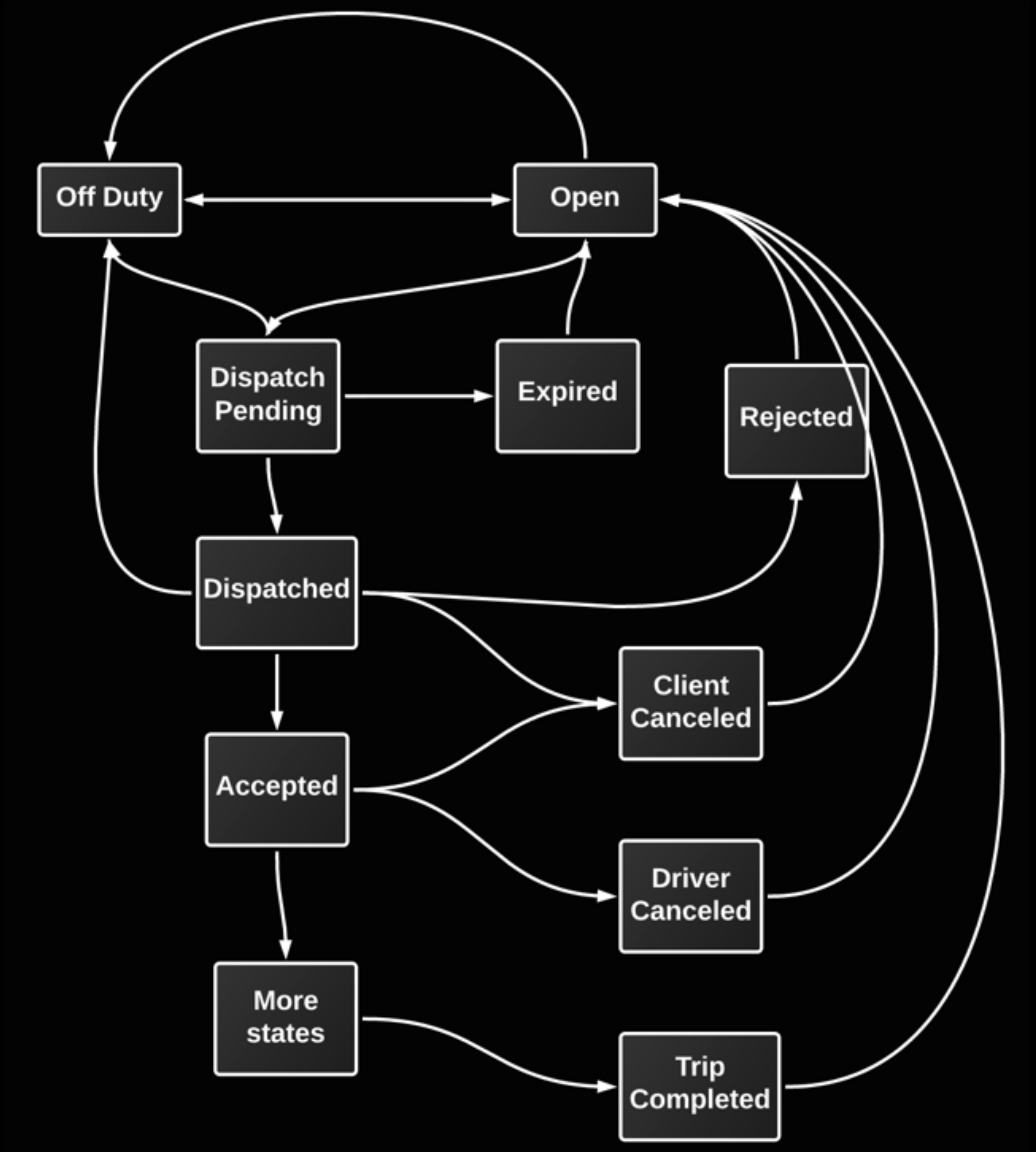
13 driver states

Events - for each action/state

Rider States



Driver States



Granular Data

300 cities

Sample Data Scale

1 day of data: 300 x 10,000 x 7 x 1440 x 13 = 393 billion possible combinations

Unknown Query Patterns

Any combination of dimensions

Talk about an example

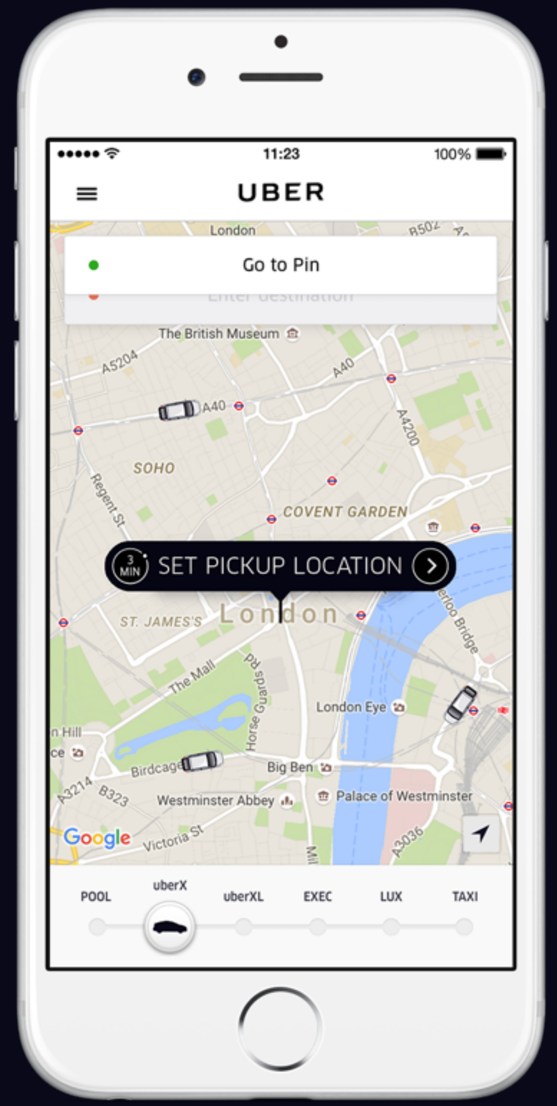
Variety of Aggregations

- Heatmap
- Top N
- Histogram
- count(), avg(), sum(), percent(), geo

Large Data Volume

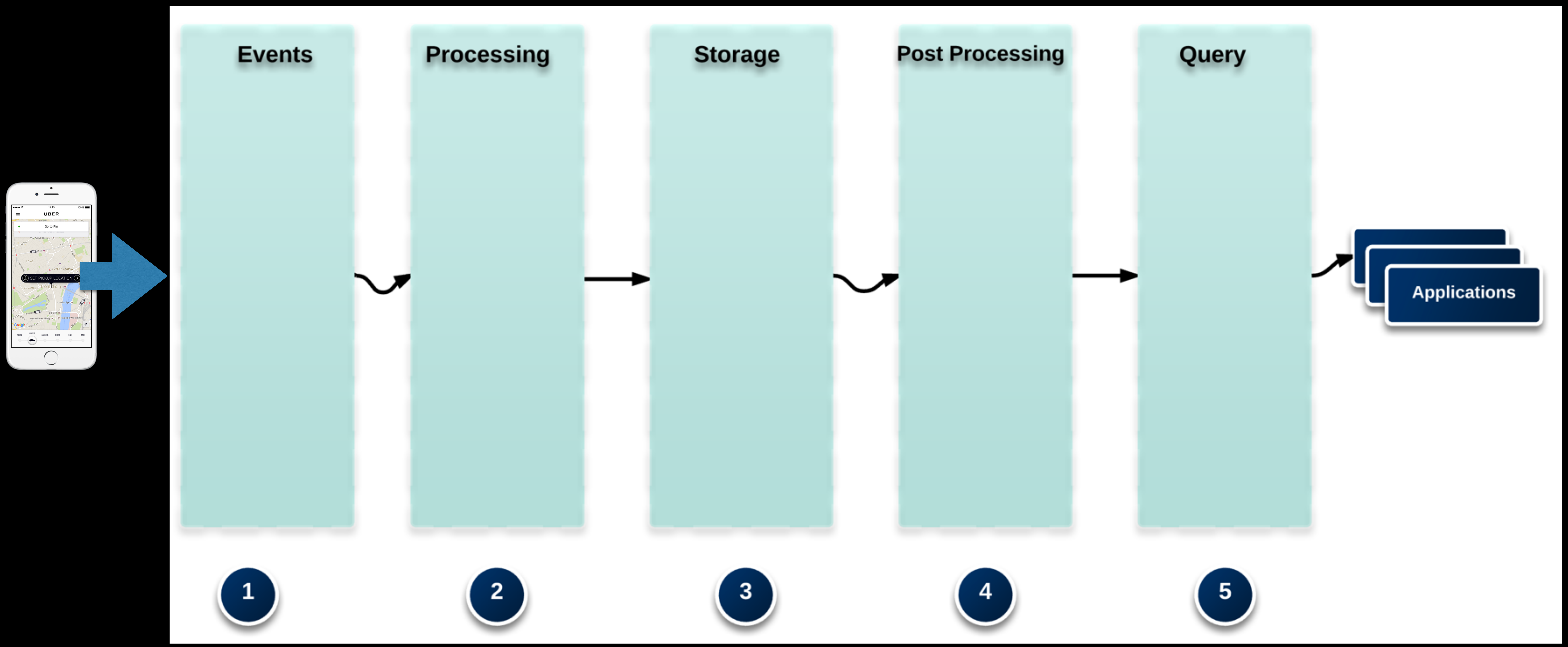
- Hundreds of thousands of events per second, or billions of events per day
- At least dozens of fields in each event

```
{
    "query": {
        "filtered": {
            "query": {
                "match_all": {}
            },
            "filter": {
                "and": [
                    {
                        "or": [
                            {
                                "term": {
                                    "dispatch.tags": "driver_accepted"
                                }
                            },
                            {
                                "term": {
                                    "dispatch.tags": "pickup_requested"
                                }
                            }
                        ]
                    },
                    {
                        "range": {
                            "@timestamp": {
                                "gte": "2015-01-20T02:52:45.582Z",
                                "lte": "2015-01-20T04:59:45.582Z"
                            }
                        }
                    },
                    {
                        "geo_distance": {
                            "distance": "10km",
                            "geo": {
                                "lat": 37,
                                "lon": -122
                            }
                        }
                    }
                ]
            }
        }
    },
    "aggs": {
        "pick_up_counts": {
            "terms": {
                "field": "tags"
            }
        }
    }
}
```



Lets Build a Stream Processing System!

Skeleton Of A System



Event Producing/Consuming

Match (Dispatch) Services Emit

Billions Of Events Per Topic

High Scale/Throughput

Events Should Be Available In

m-Seconds

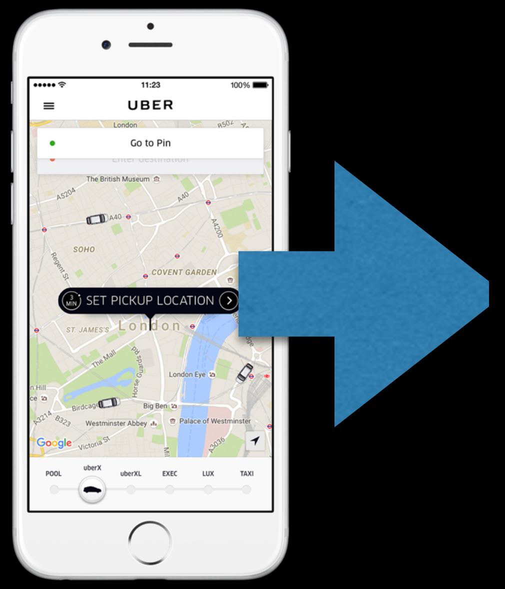
Low Latency

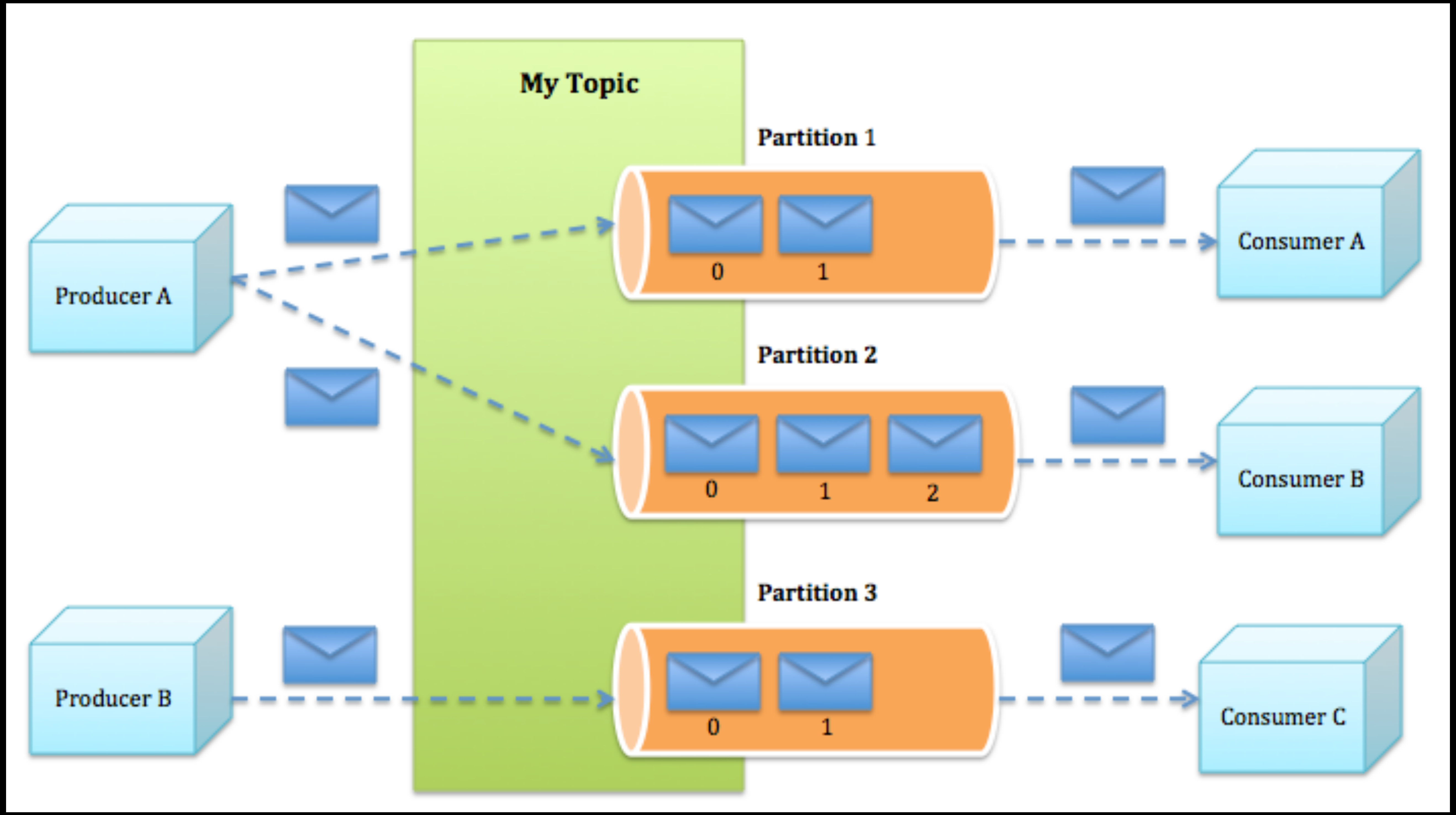
Events Should Rarely Ever Get **Lost**

Durability

Events Should Be Consumable By Many Consumers

Apache
Kafka


UBER
SET PICKUP LOCATION


My Topic
Producer A
Producer B
Partition 1
0
1
Partition 2
0
1
2
Partition 3
0
1
Consumer A
Consumer B
Consumer C

Apache Kafka

✓ High Scalability (Billions of event per day)

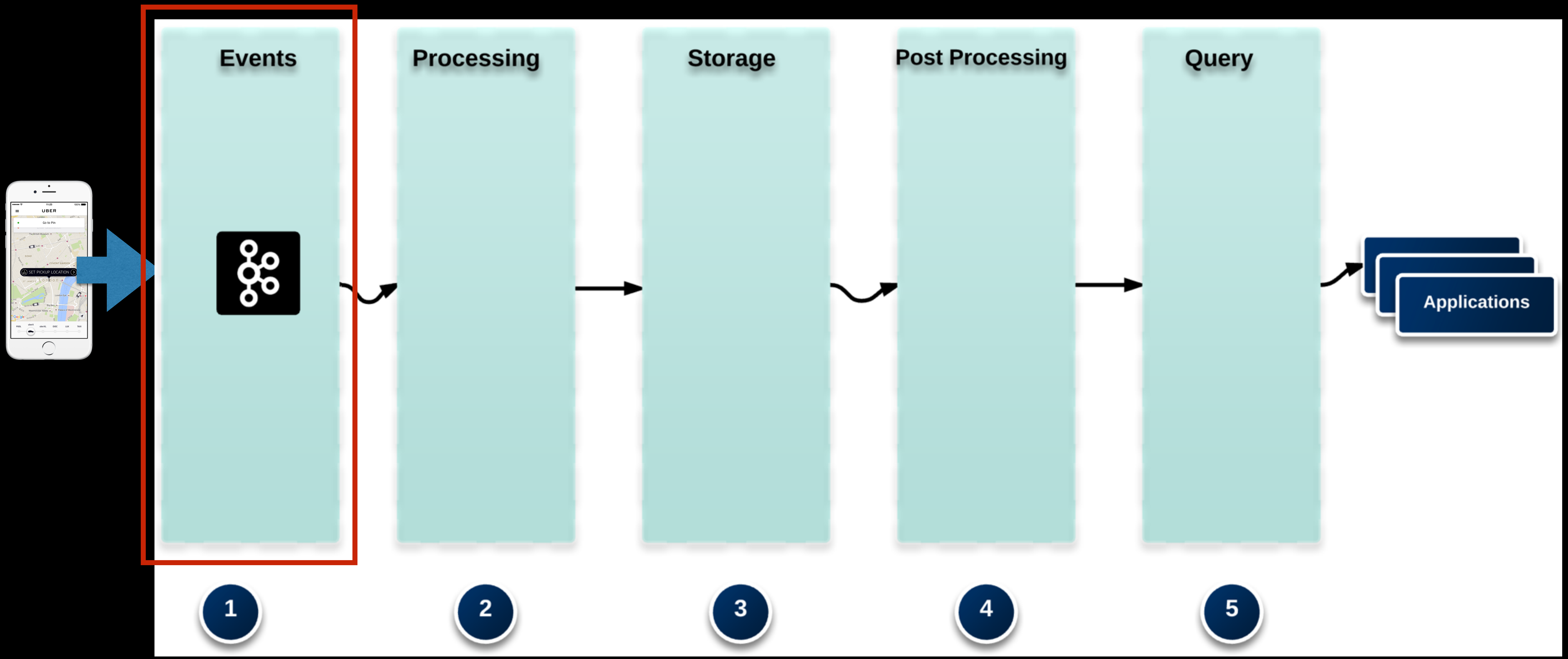
✓ Durability (no loss)

✓ Multiple Consumers

✓ Very efficient & low latency

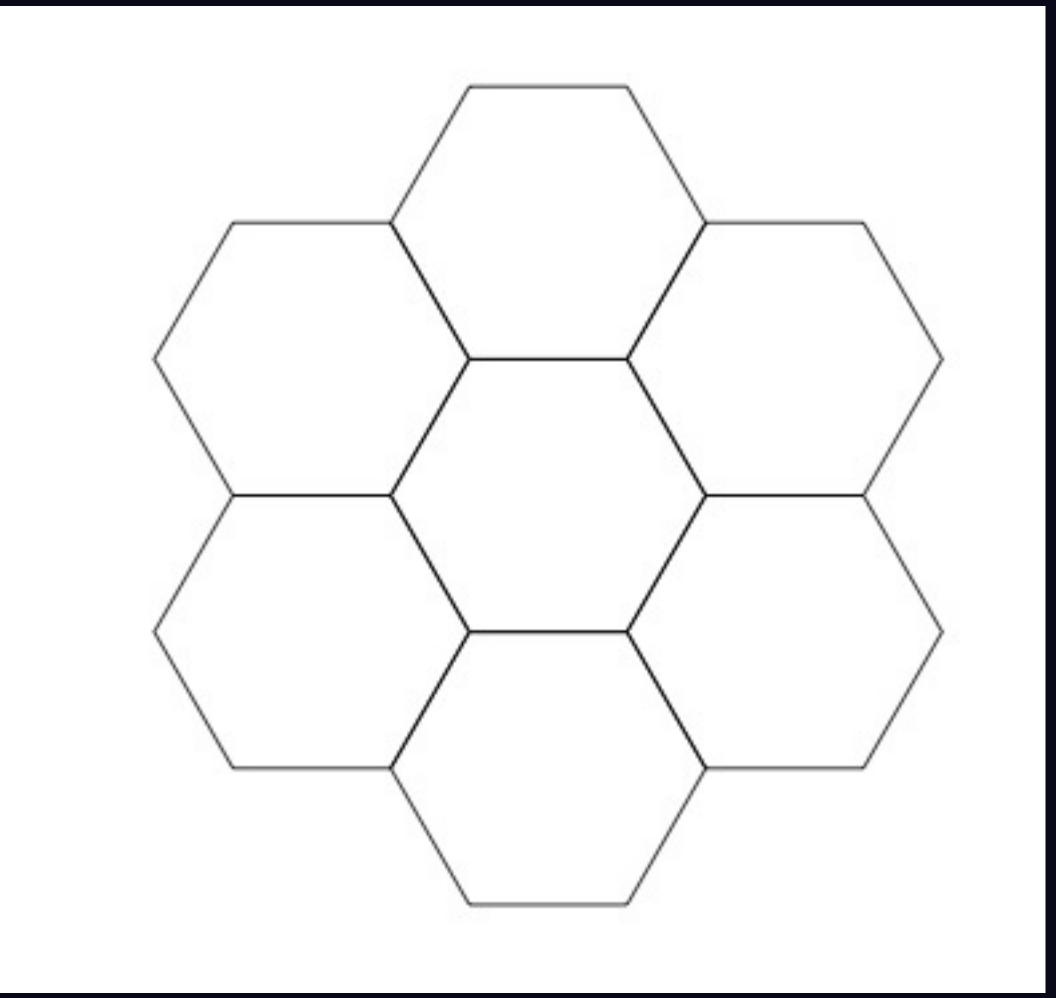
...

Stream Processing System

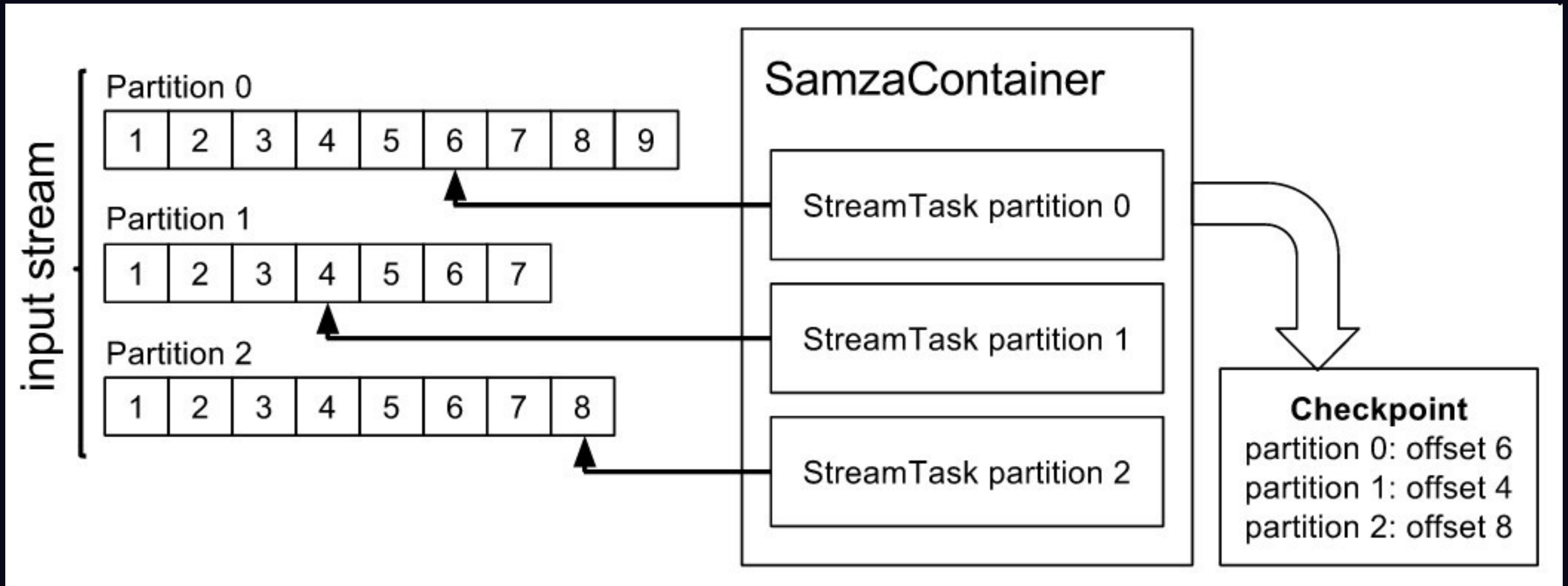


EVENT PROCESSING

Pre-aggregation



Checkpointing



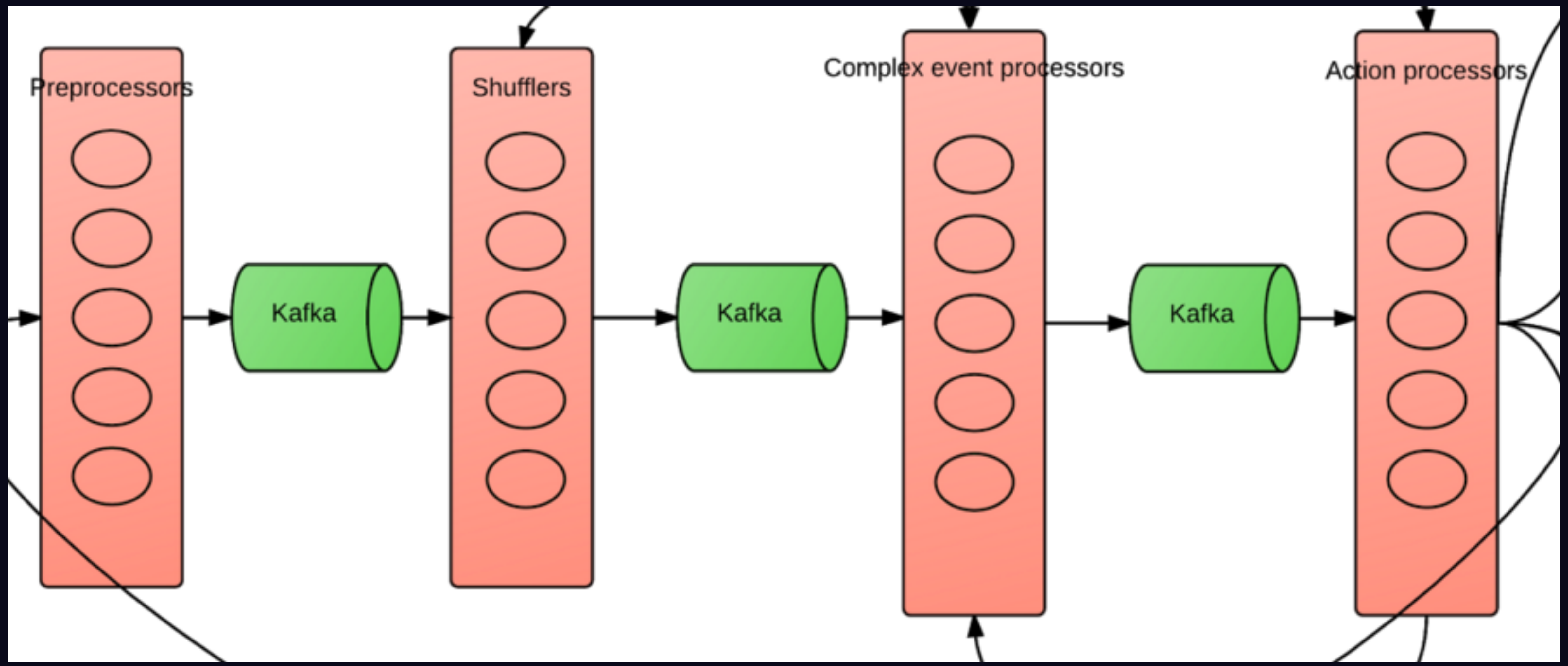
Joining Multiple Streams

Sessionization

Trips on Uber can take from few minutes to a few hours

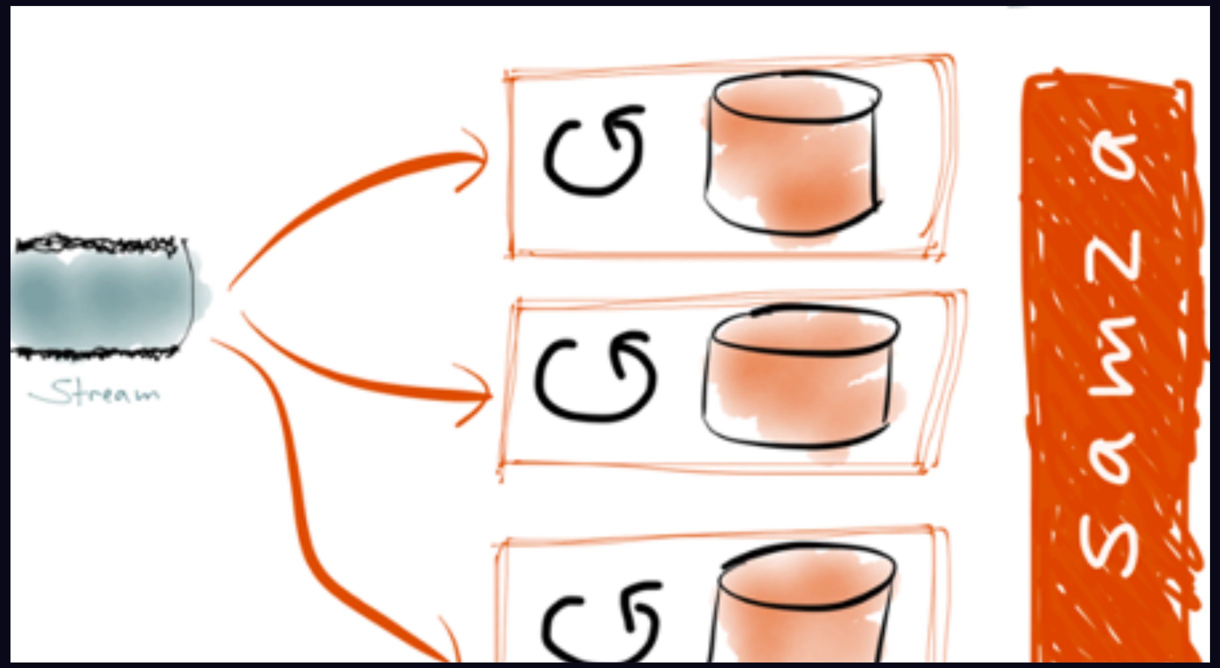
Driver Partners can be “online” from few mins to hours

Multi-Staged Processing

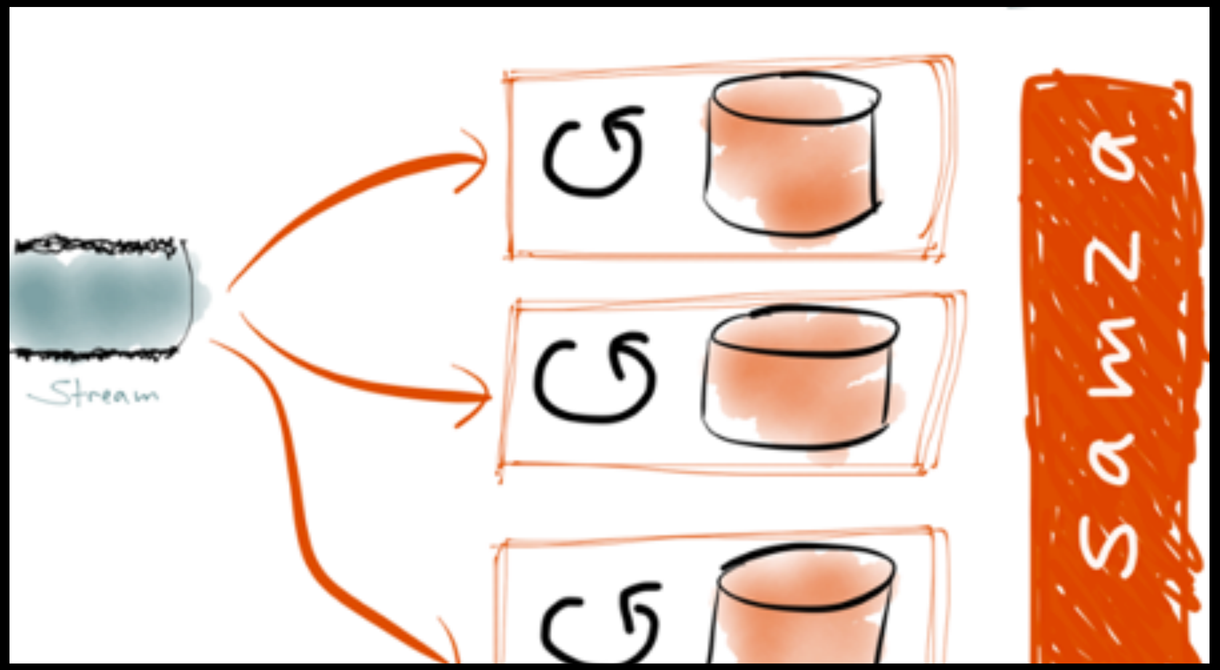


State Management

Apache Samza



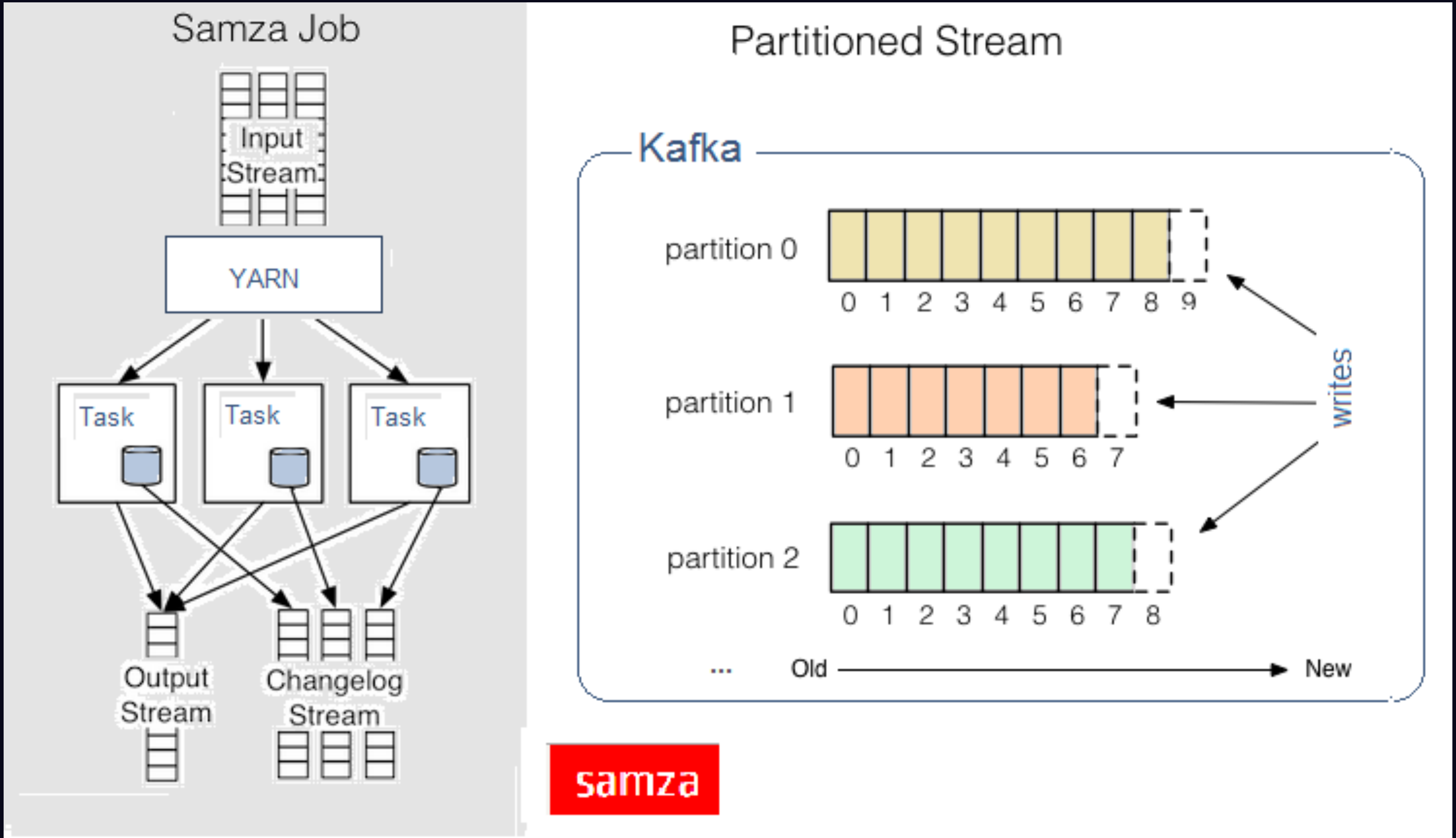
Why Apache Samza?



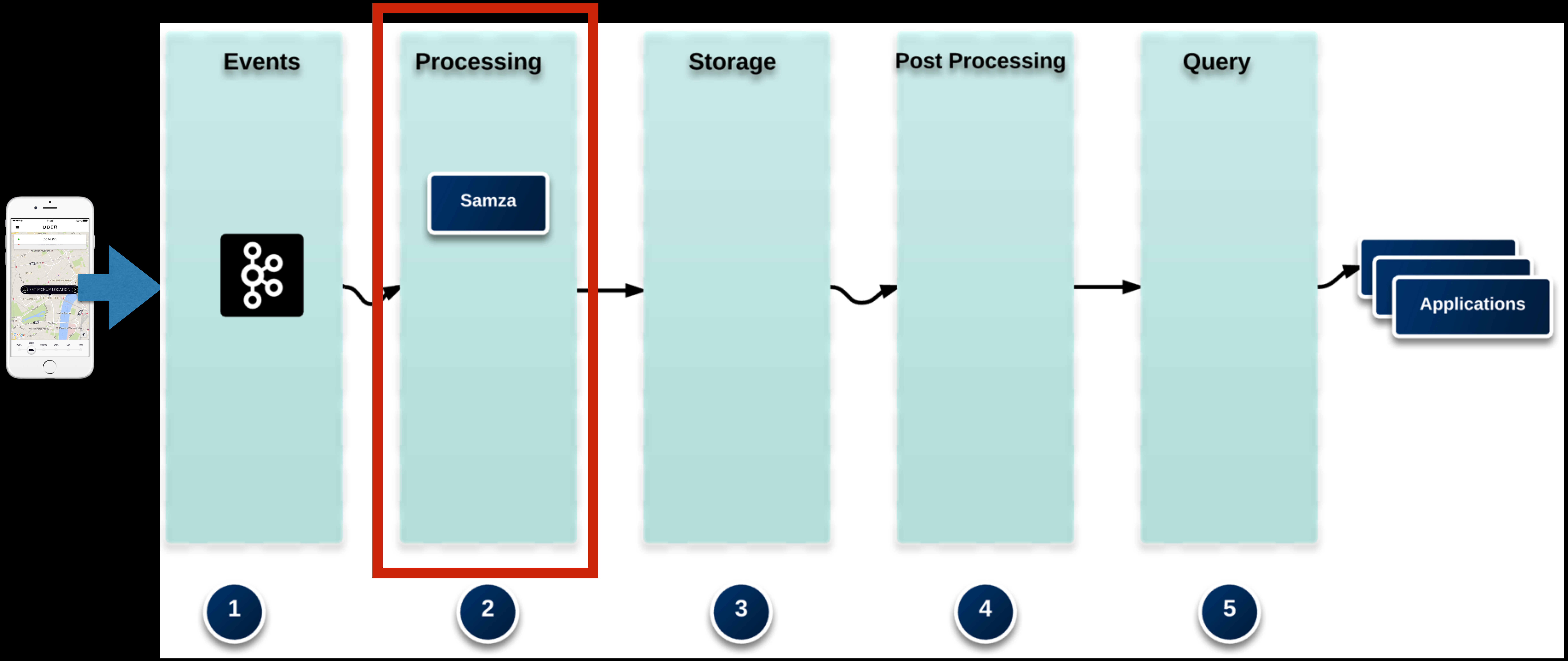
- ✓ DAG on Kafka
- ✓ Excellent integration with Kafka
- ✓ Built in checkpointing
- ✓ Built in state management
- ✓ Highly Scalable
- ✓ Fault tolerant

…

Why Apache Samza?



Skeleton Of A System

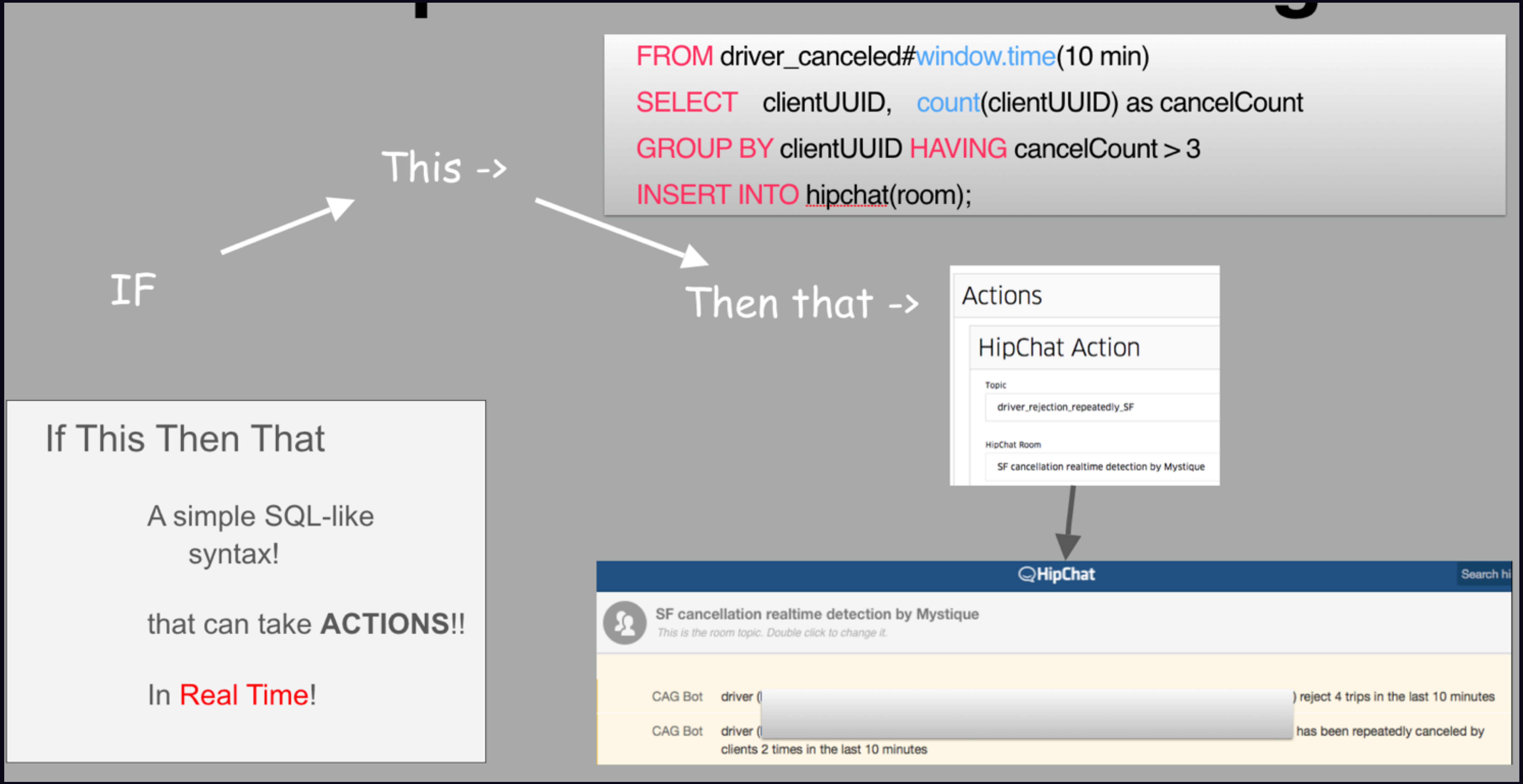


WAIT!

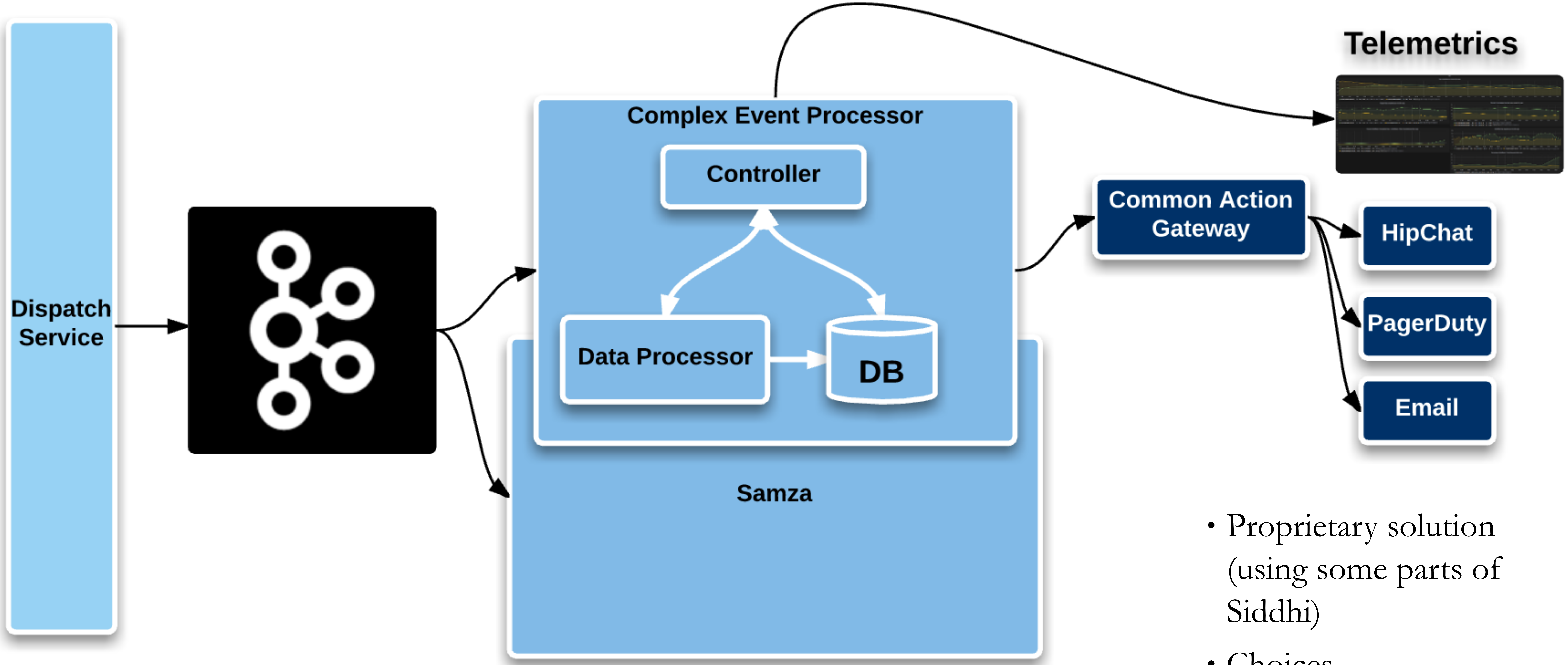
What About Complex Event Processing?

aka

Continuous Queries



Complex Event Processing



- Proprietary solution (using some parts of Siddhi)
- Choices
  - Esper
  - Siddhi

Skeleton Of A System

STORAGE

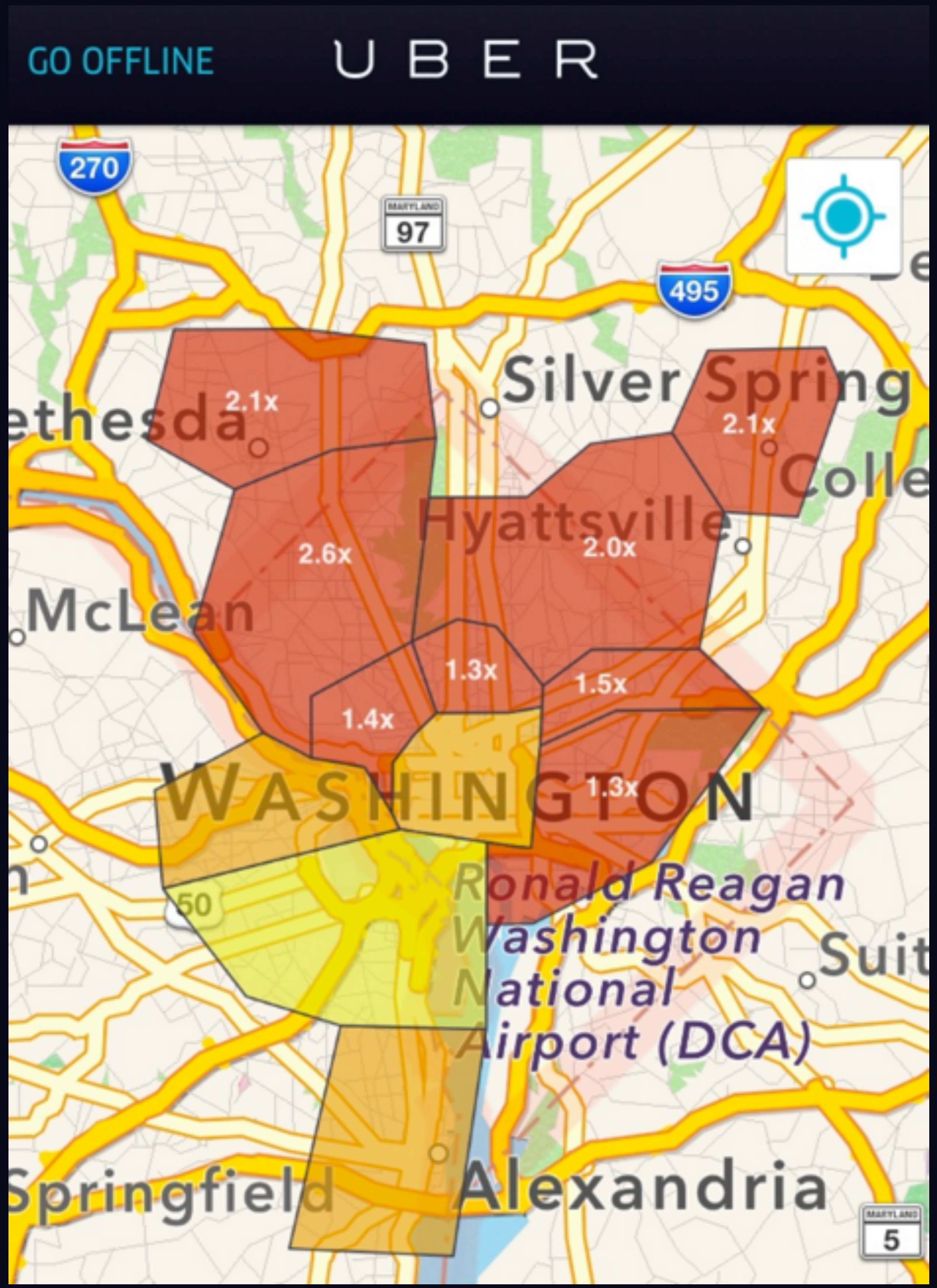
Where are the challenges?

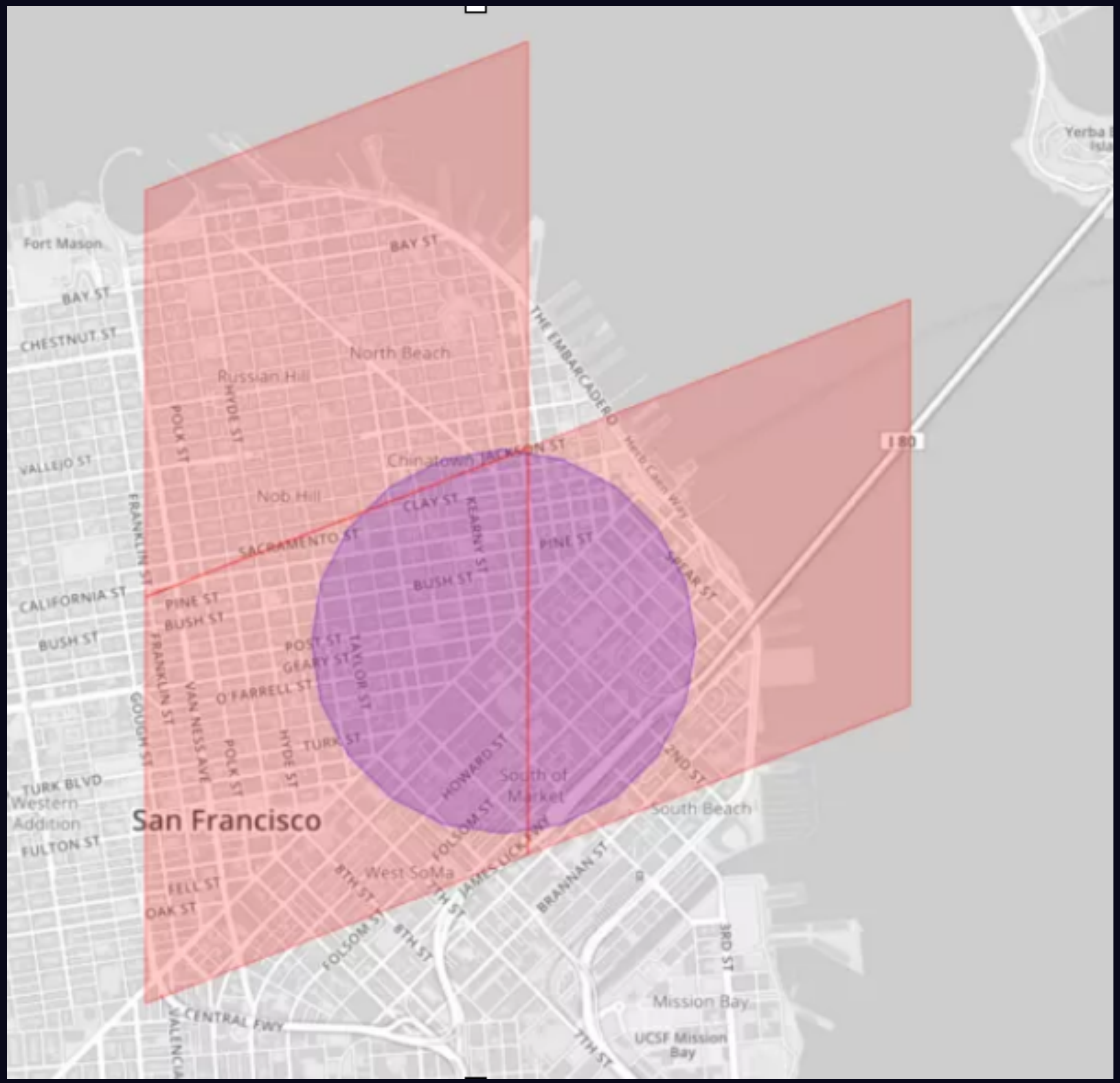
Many Dimensions

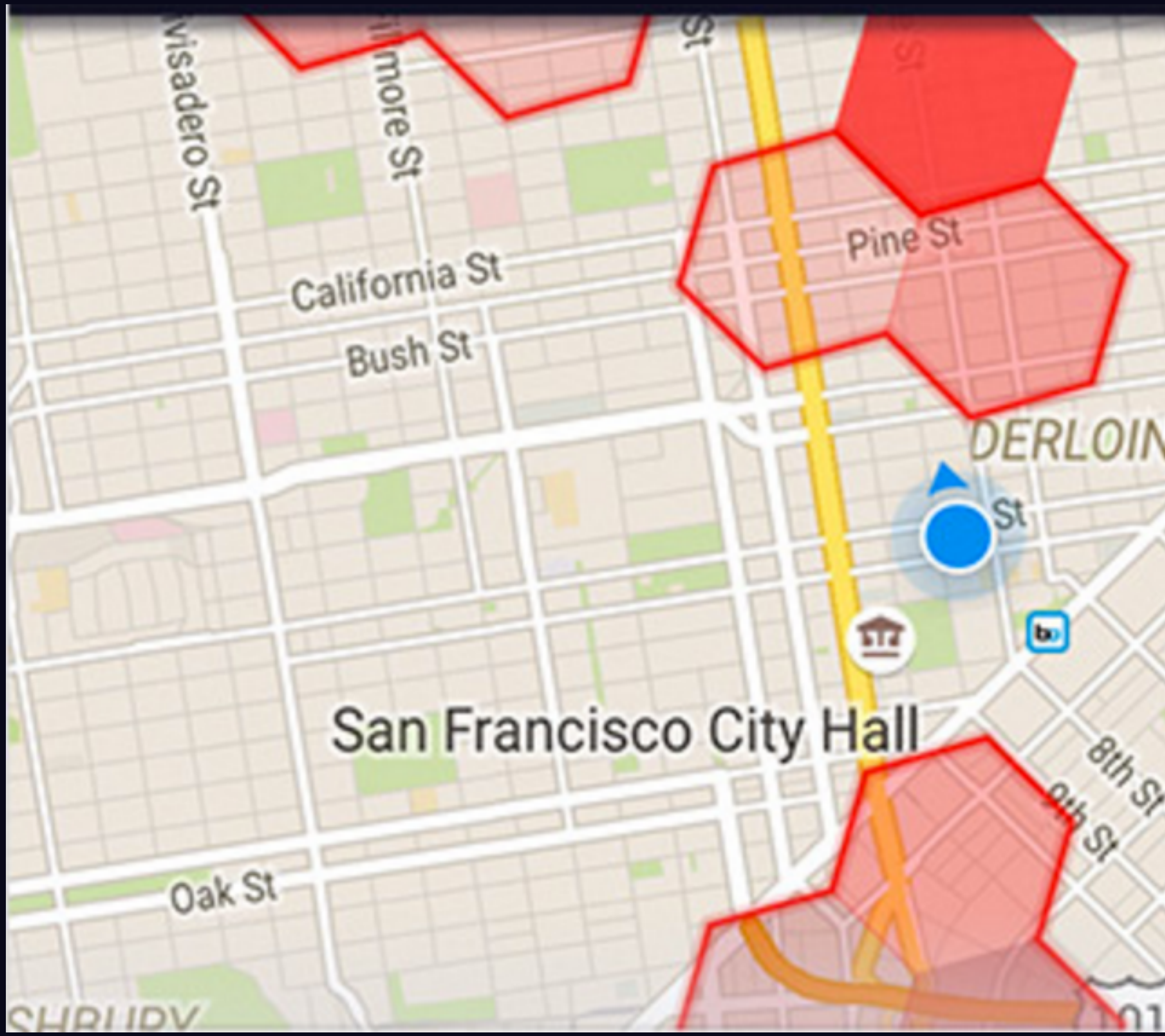
Dozens of fields per event

```
{
    "query": {
        "filtered": {
            "query": {
                "match_all": {}
            },
            "filter": {
                "and": [
                    {
                        "or": [
                            {
                                "term": {
                                    "dispatch.tags": "driver_accepted"
                                }
                            },
                            {
                                "term": {
                                    "dispatch.tags": "pickup_requested"
                                }
                            }
                        ]
                    },
                    {
                        "range": {
                            "@timestamp": {
                                "gte": "2015-01-20T02:52:45.582Z",
                                "lte": "2015-01-20T04:59:45.582Z"
                            }
                        }
                    },
                    {
                        "geo_distance": {
                            "distance": "10km",
                            "geo": {
                                "lat": 37,
                                "lon": -122
                            }
                        }
                    }
                ]
            }
        }
    },
    "aggs": {
        "pick_up_counts": {
            "terms": {
                "field": "tags"
            }
        }
    }
}
```

Different Geo Aggregation







Data Type

- Spatio-Temporal Data

Dimension	Value
state	driver_arrived
vehicle type	uber X
timestamp	13244323342
lattitude	12,23
longitude	30,00

Data Query

- OLAP on single-table spatio-temporal data

```
SELECT <agg functions>, <dimensions>
FROM <data_source>
WHERE <boolean filter>
GROUP BY <dimensions>
HAVING <boolean filter>
ORDER BY <sorting criterial>
LIMIT <n>
DO <post aggregation>
```

Data Query

- OLAP on single-table temporal-spatial data

```
SELECT <agg functions>, <dimensions>
FROM <data_source>
WHERE <boolean filter>
GROUP BY <dimensions>
HAVING <boolean filter>
ORDER BY <sorting criterial>
LIMIT <n>
DO <post aggregation>
```

```
/driverAcceptanceRate?
geo_dist(10, [37, 22])&
time_range(2015-02-04,2015-03-06)&
aggregate(timeseries(7d))&
eq(msg.driverId,1)
```

Finding the Right Storage System

Minimum Requirements

- OLAP with geospatial and time series support
- Support large amount of data
- Sub-second response time
- Query of raw data

It can’t be a KV store

How many keys?

Dimension	Value
A	a
B	b

How many keys?

Dimension	Value
A	a
B	b

- All boolean operators: AND, OR, NOT

How many keys?

Dimension	Value
A	a
B	b

- All boolean operators: AND, OR, NOT
  - A and (not B)
  - B and (not A)
  - A or B
  - not (A or B)

How many keys?

Dimension
A
B

- {A}
- {B}
- {A, B}
- {}

Challenges to KV Store

Pre-computing all keys is $O(2^n)$ for both space and time

e.g. 2^10 = 1024

Sure, K-V Stores Are Fast

Being Fast Is Not Enough

Number of cars per hexagon in a city => 18,000 lookups

Mean latency: 1ms

99.99%-ile latency: 2s

Failure rate: 0.001%

Being Fast Is Not Enough

Probability that a request will experience 99.99%-ile: $(1 - 0.9999^{18000})$ x = 83%

Probability that a single query will succeed: $(1 - 0.00001)^{18000}$ = 84%

Lesson: Don’t play the probability game

Can we use a relational database?

Challenges to Relational DB

- Managing multiple indices is painful
- Scaling Is Hard

We Need A System That Supports

- Fast scan
- Arbitrary boolean queries
- Raw data
- Wide range of aggregations

A System That Optimizes

- Data segmentations
- Parallel queries
- Bitset-based set operations
- Index compressions
- Fast range queries

Is there such a system?

Elasticsearch

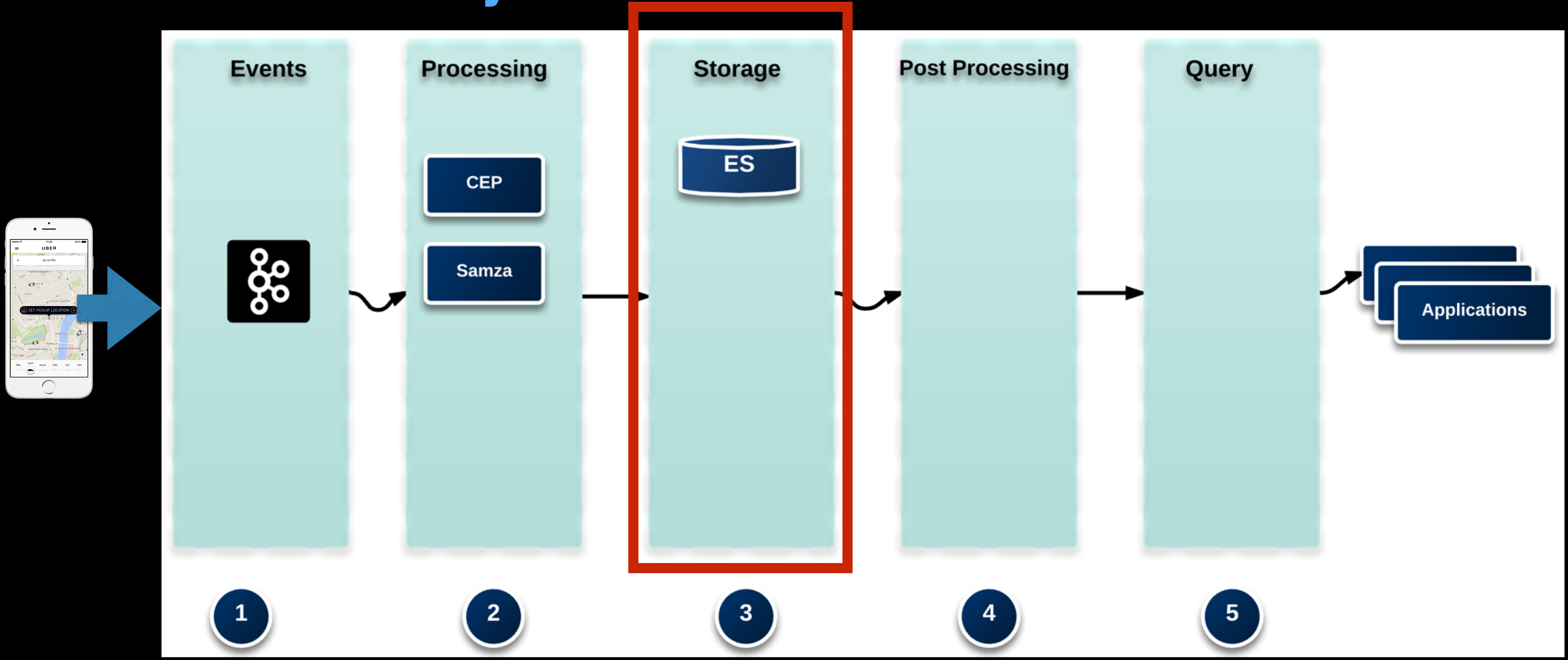
```
{
    "query": {
        "filtered": {
            "query": {
                "match_all": {}
            },
            "filter": {
                "and": [
                    {
                        "or": [
                            {
                                "term": {
                                    "dispatch.tags": "driver_accepted"
                                }
                            },
                            {
                                "term": {
                                    "dispatch.tags": "pickup_requested"
                                }
                            }
                        ]
                    },
                    {
                        "range": {
                            "@timestamp": {
                                "gte": "2015-01-20T02:52:45.582Z",
                                "lte": "2015-01-20T04:59:45.582Z"
                            }
                        }
                    },
                    {
                        "geo_distance": {
                            "distance": "10km",
                            "geo": {
                                "lat": 37,
                                "lon": -122
                            }
                        }
                    }
                ]
            }
        }
    },
    "aggs": {
        "pick_up_counts": {
            "terms": {
                "field": "tags"
            }
        }
    }
}
```

Highly Efficient Inverted-Index For Boolean Query

Built-in Distributed Query

Fast Scan with Flexible Aggregations

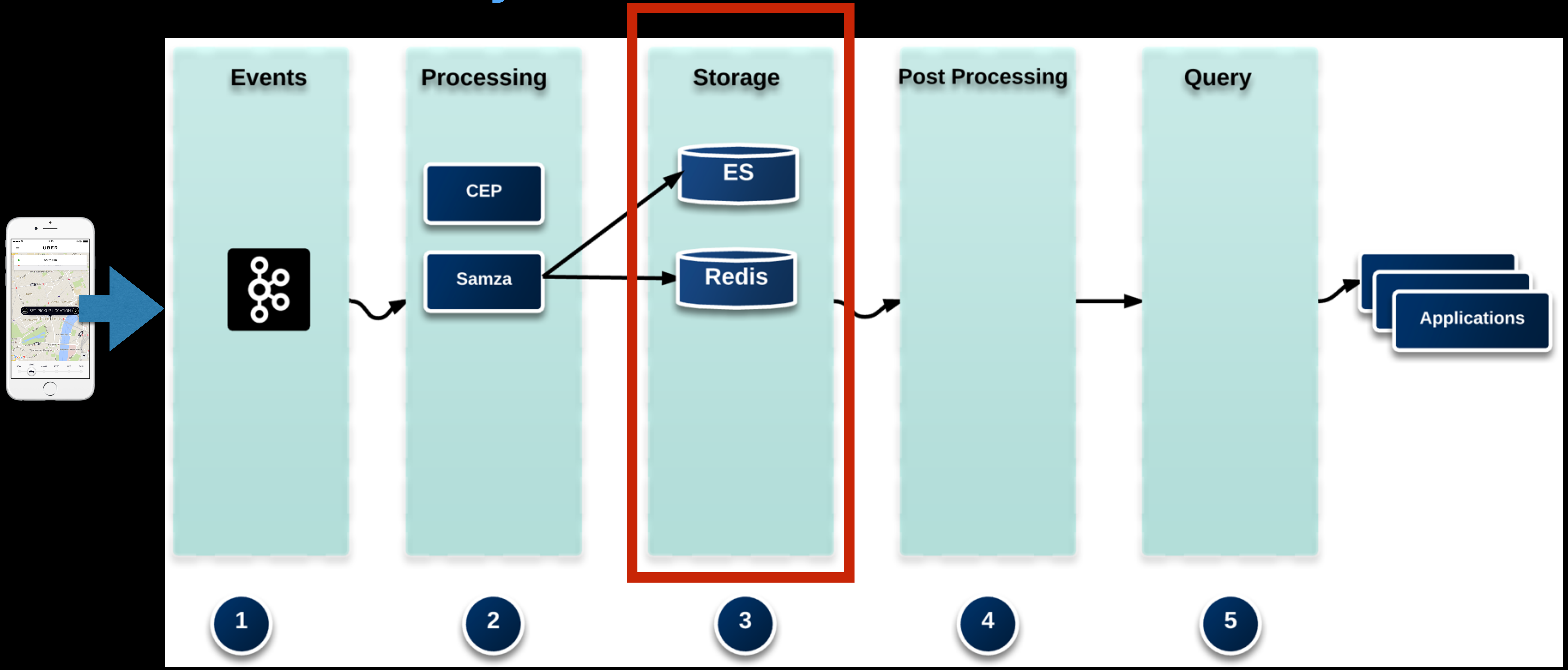
Skeleton Of A System



What About Really Fast Lookups?

redis

Skeleton Of A System



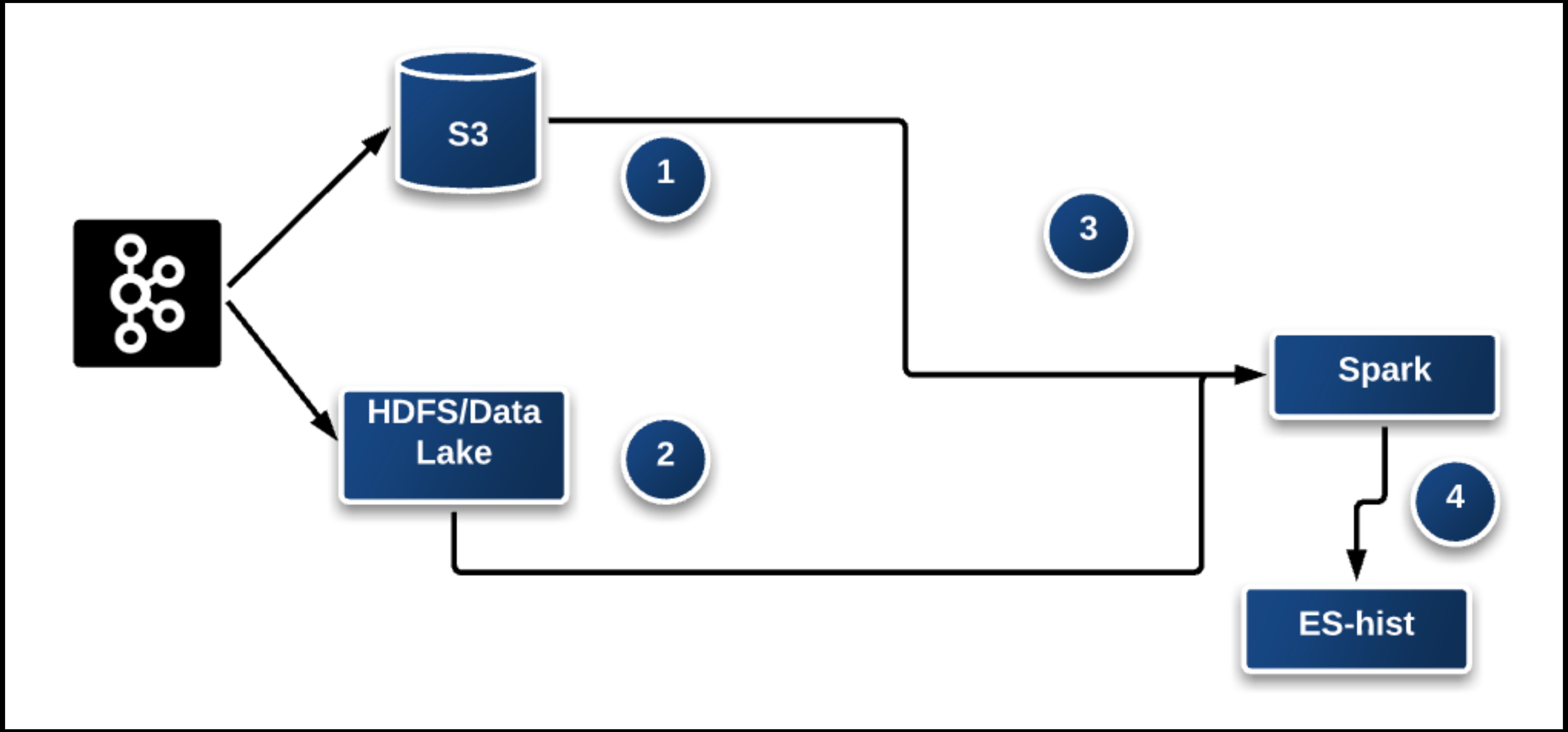
What If there is data corruption?

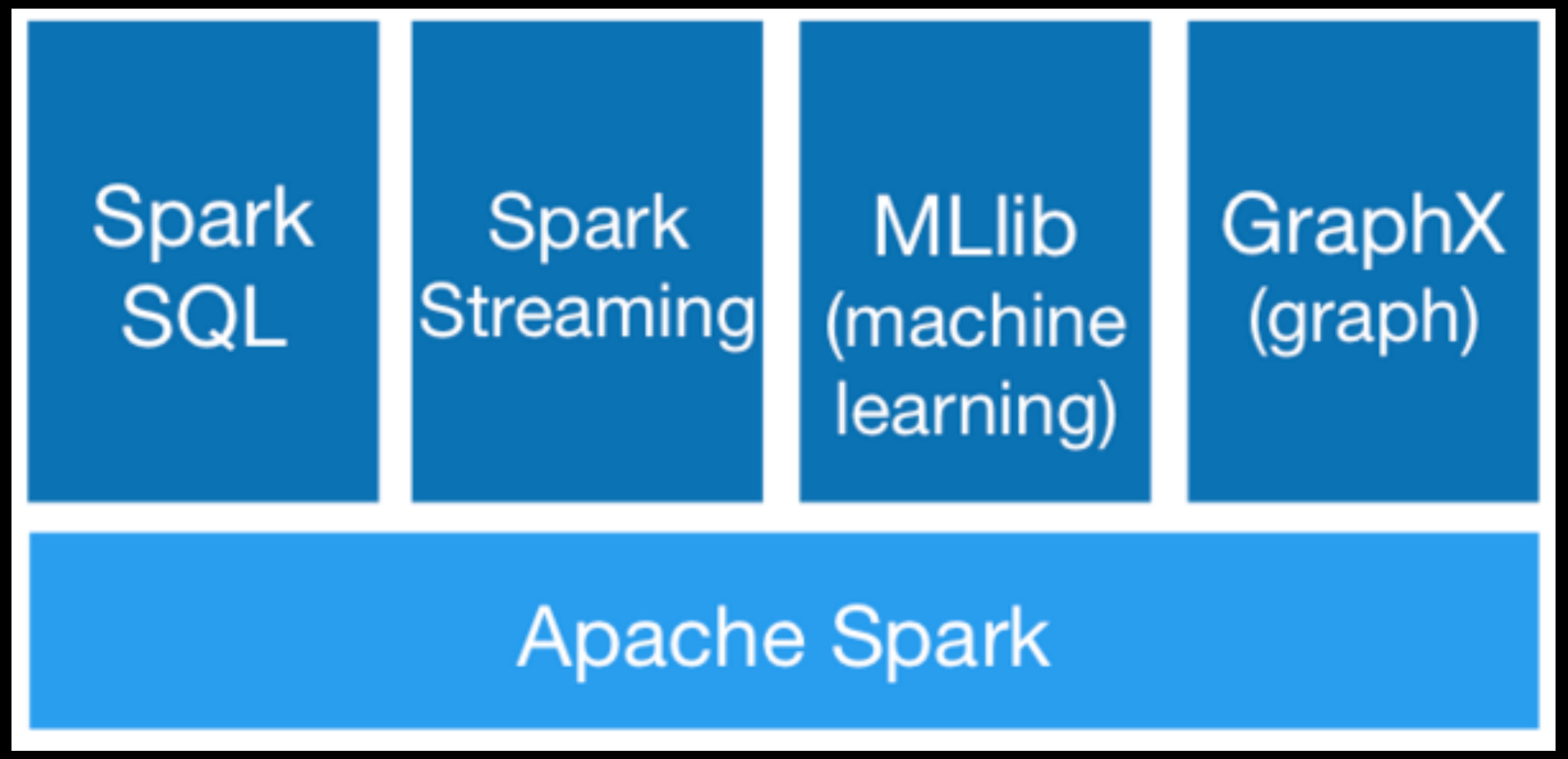
or

There was a bug in the Event Processing Job?

We Would Want To Backfill Data!

Backfill Data

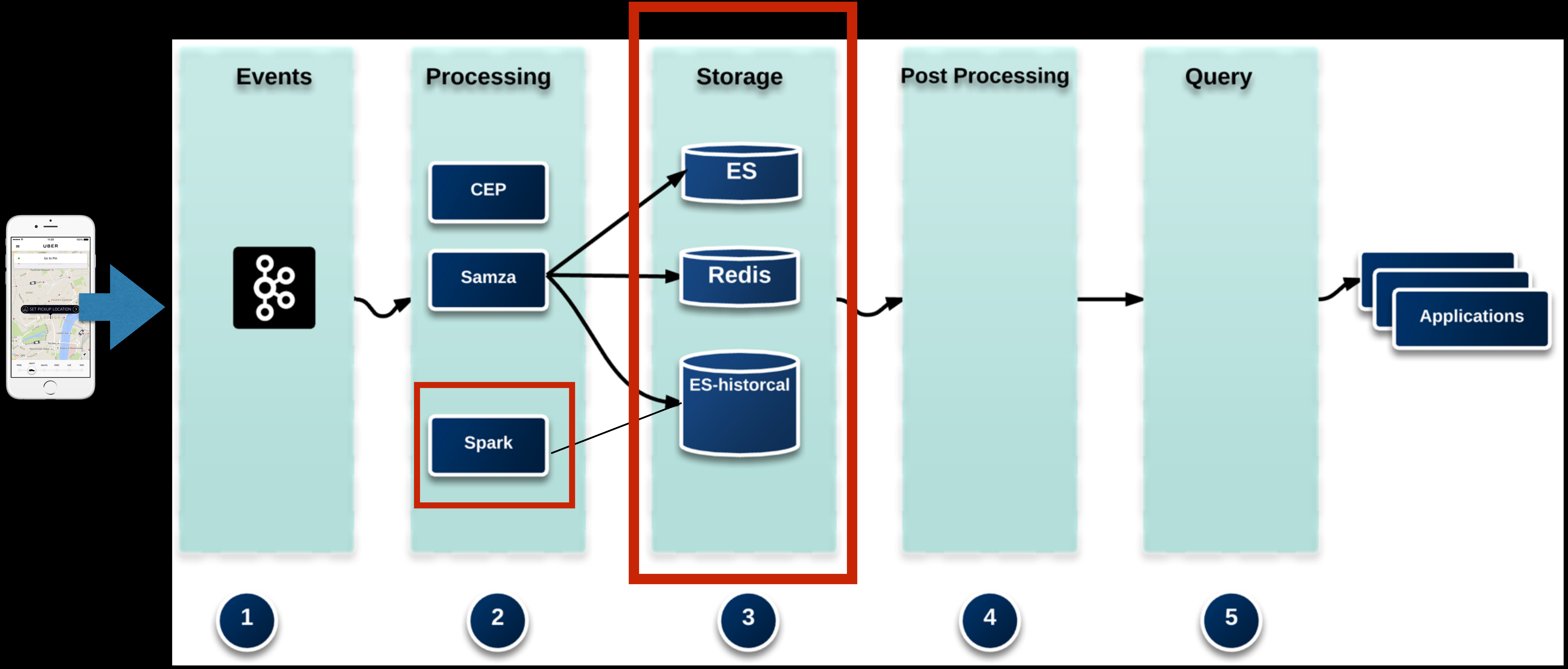




- ✓ HDFS or S3 ..
- ✓ “exactly once” processing**
- ✓ ML support (for our Data Scientists)
- ✓ Batch and Streaming (well, micro batching) support

…

Skeleton Of A System

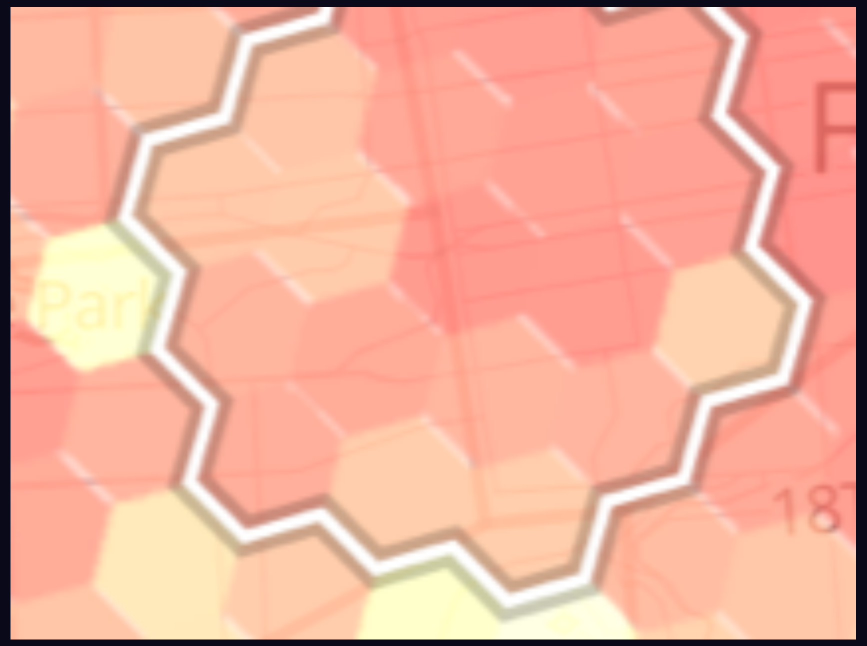


Query Pipelining

Aggregation By Ring Size (Hexagons)


SELECTION RADIUS
0 1 2 3 4 5 6 7
Presidio
PINE ST
SAN FRANCISCO
18TH ST
GREAT HWY

Results Transformation and Smoothing



Scale

10,000 hexagons in a city

Scale

331* neighboring hexagons to look at

*For a ring size of 9

Scale

331 x 10,000 = 3.1 Million Hexagons to Process for a Single Query

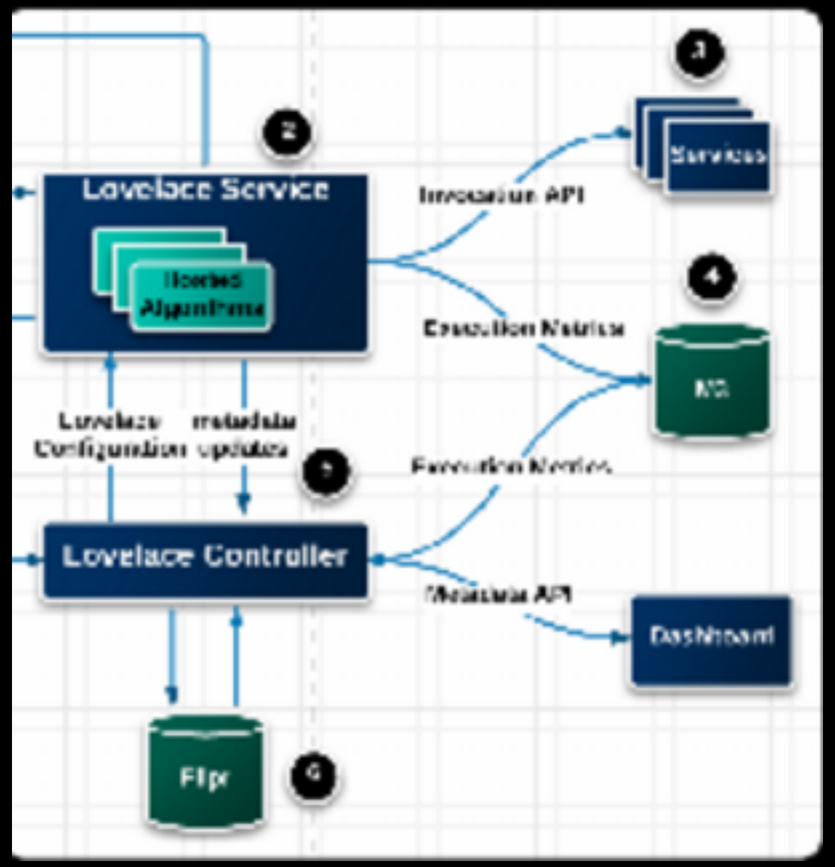
Scale

99%-ile Processing Time: 100ms

Requirements

- Highly parallelized execution
- Pipelining

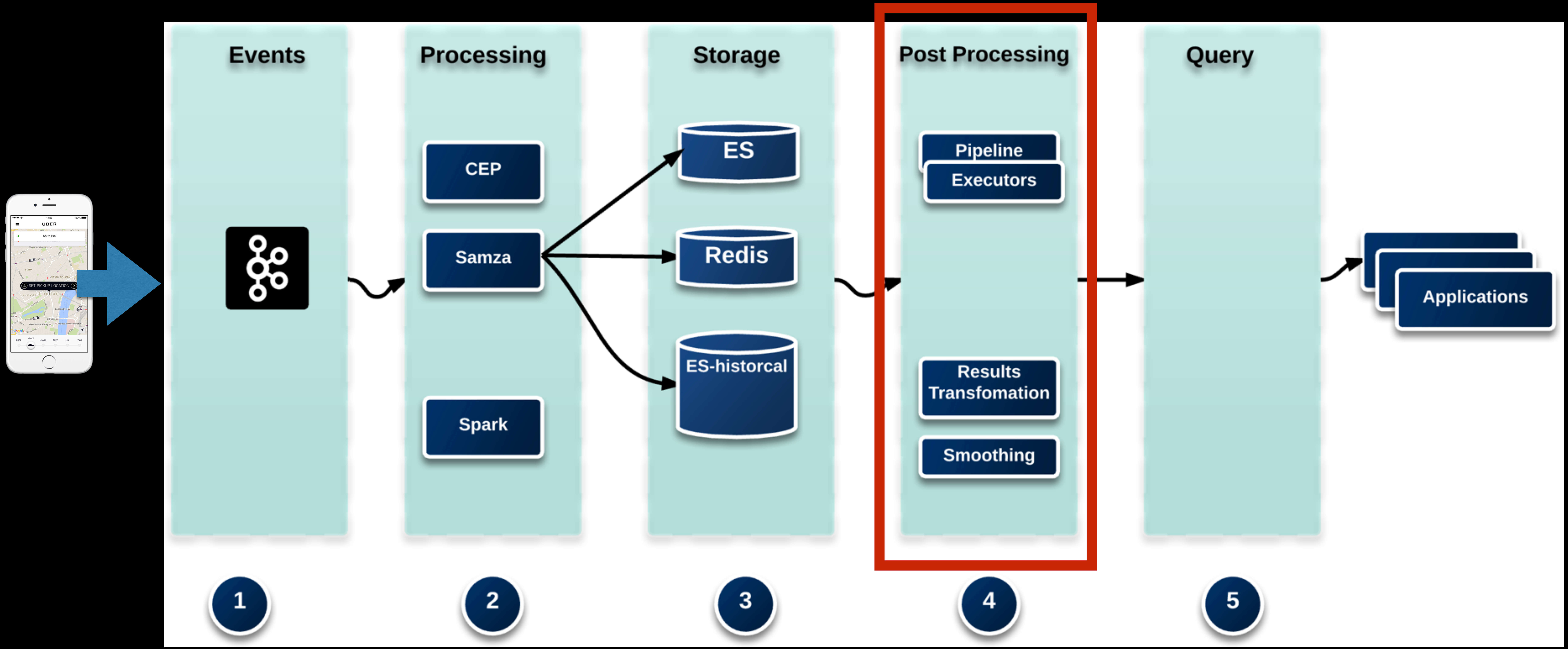
Is there an Open source solution ? :-)



✓ any out-of-box solution?

…

Stream Processing Flow



Querying

Elasticsearch Query Can Be Complex

```
/driverAcceptanceRate?
geo_dist(10, [37, 22])&
time_range(2015-02-04,2015-03-06)&
aggregate(timeseries(7d))&
eq(msg.driverId,1)
```

```
    }
  },
  "aggs": {
    "pick_up_counts": {
      "terms": {
        "field": "tags"
      }
    }
  }
}
```

Also, we need to stitch data from ES Realtime, Redis, ES Historical & any other DBs we add in the future

elasticsearch. redis Cassandra ?

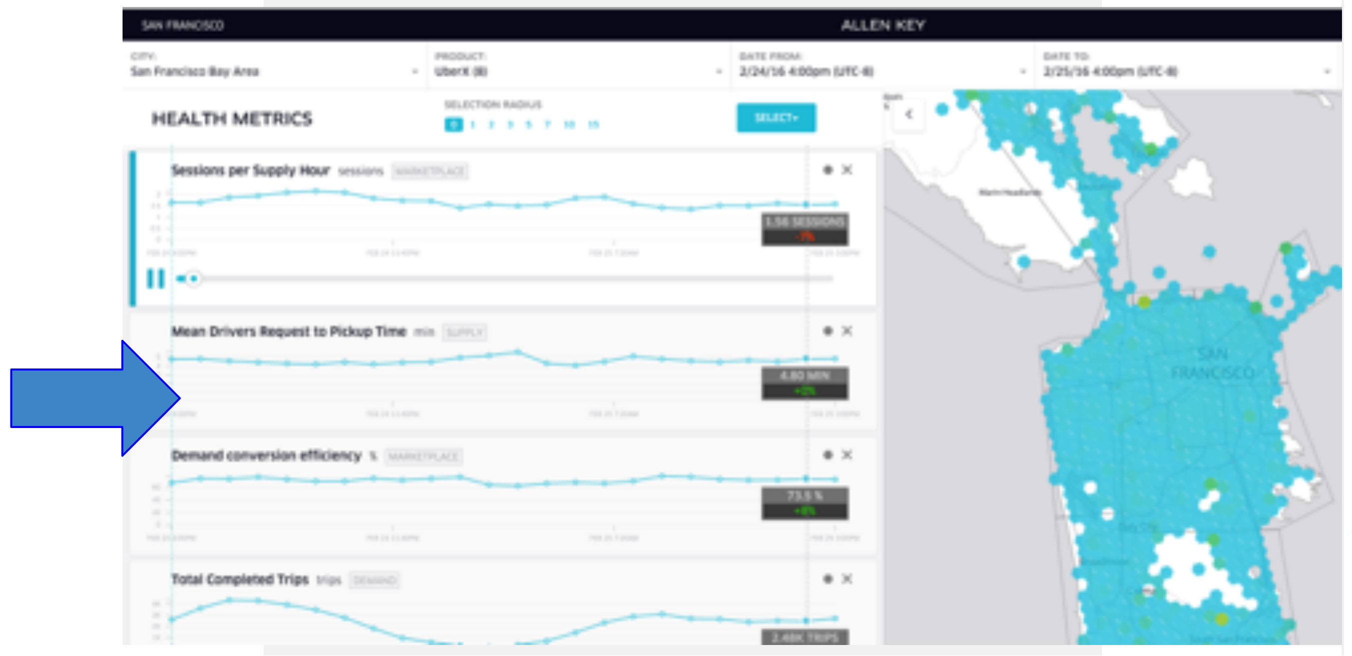
Optimizing Queries

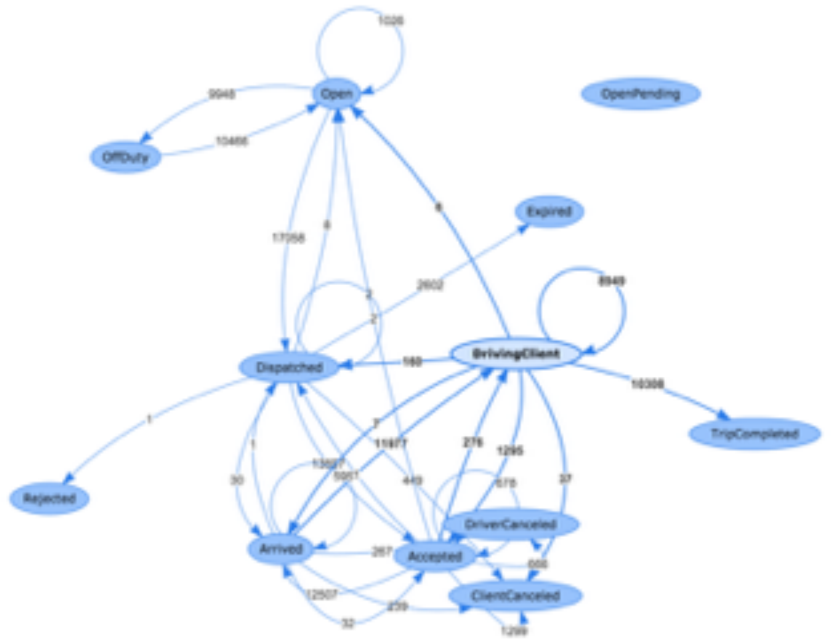
- Pipelining
- Validation
- Throttling

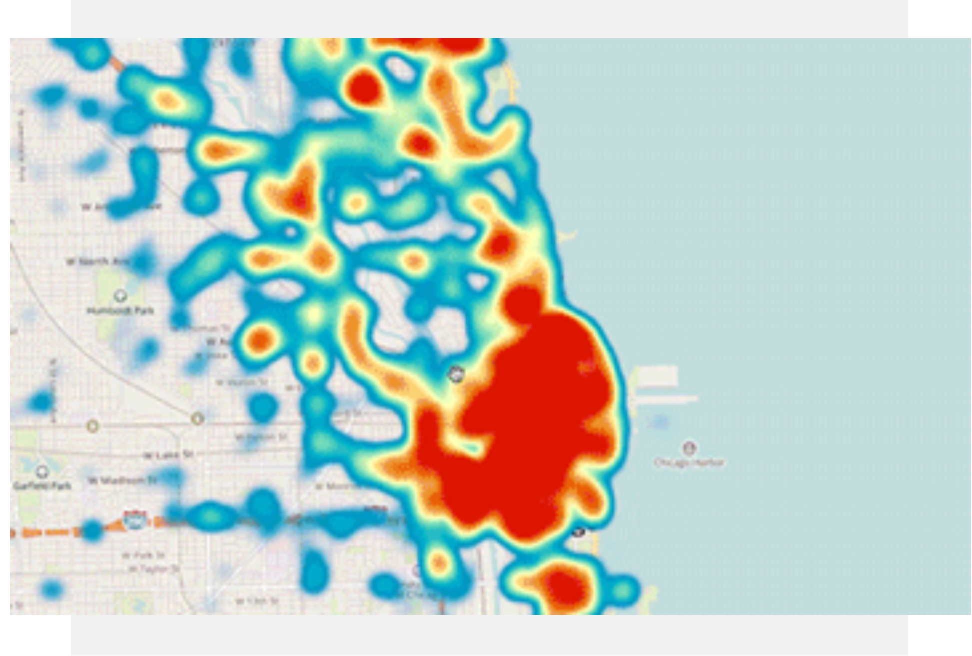
Skeleton Of A System

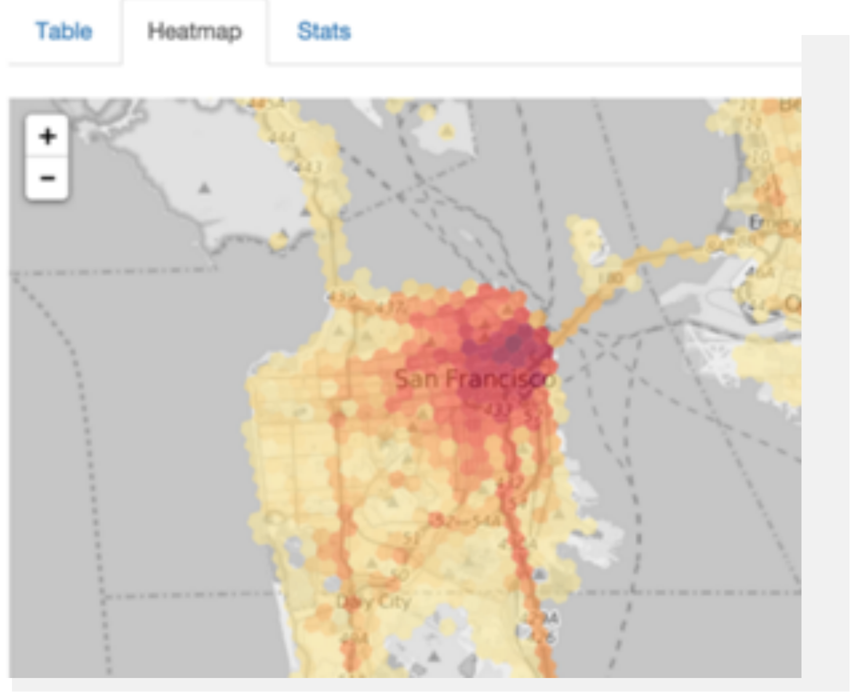
Applications that use the Query Engine

Uber Marketplace Data Query Applications









Dashboards

Business Metrics Dashboards

State Transitions/Raw Query

Querying data in flexible ways

Streaming

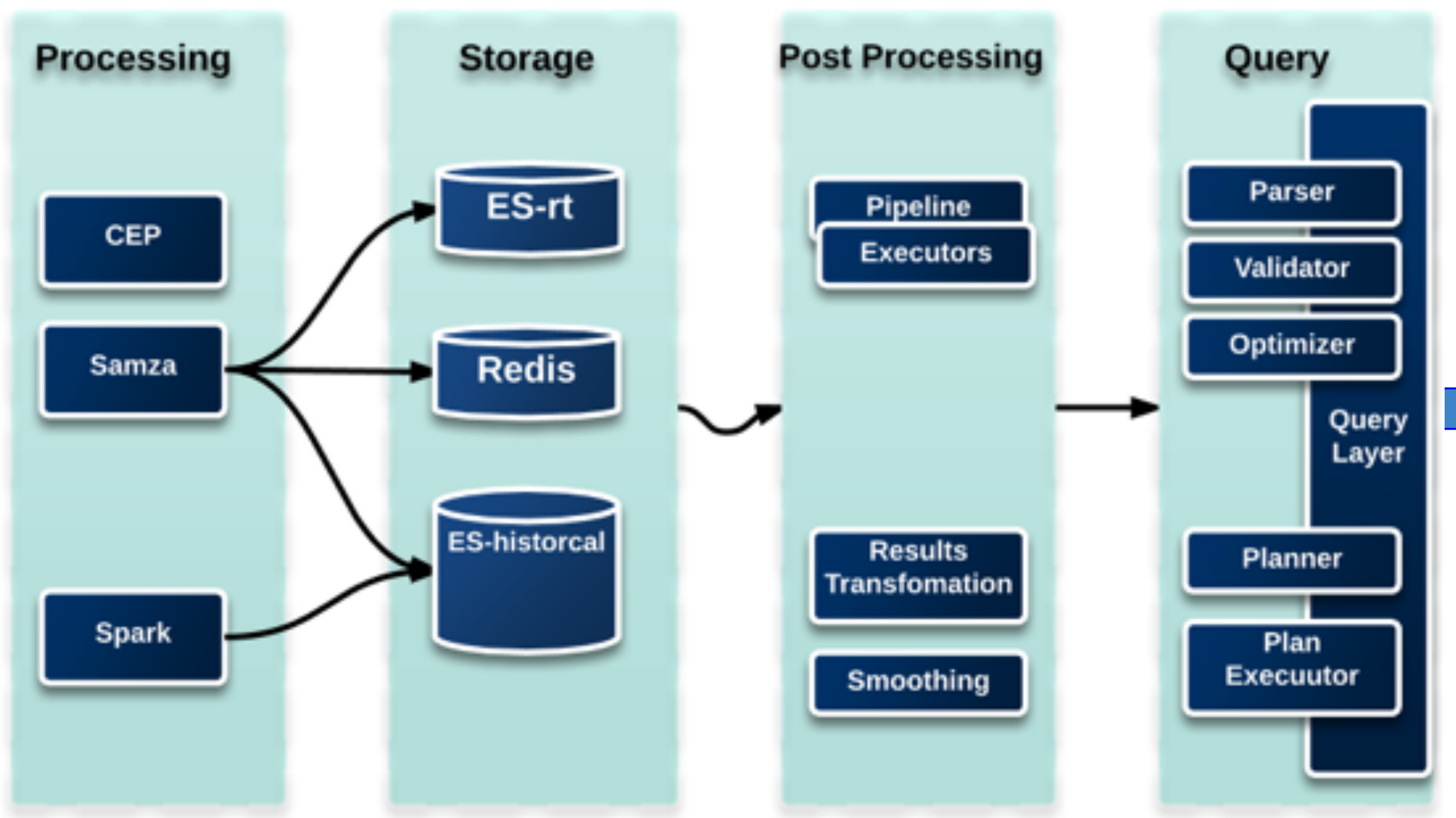
Seeing what's happening now, continuously

Visual Exploration

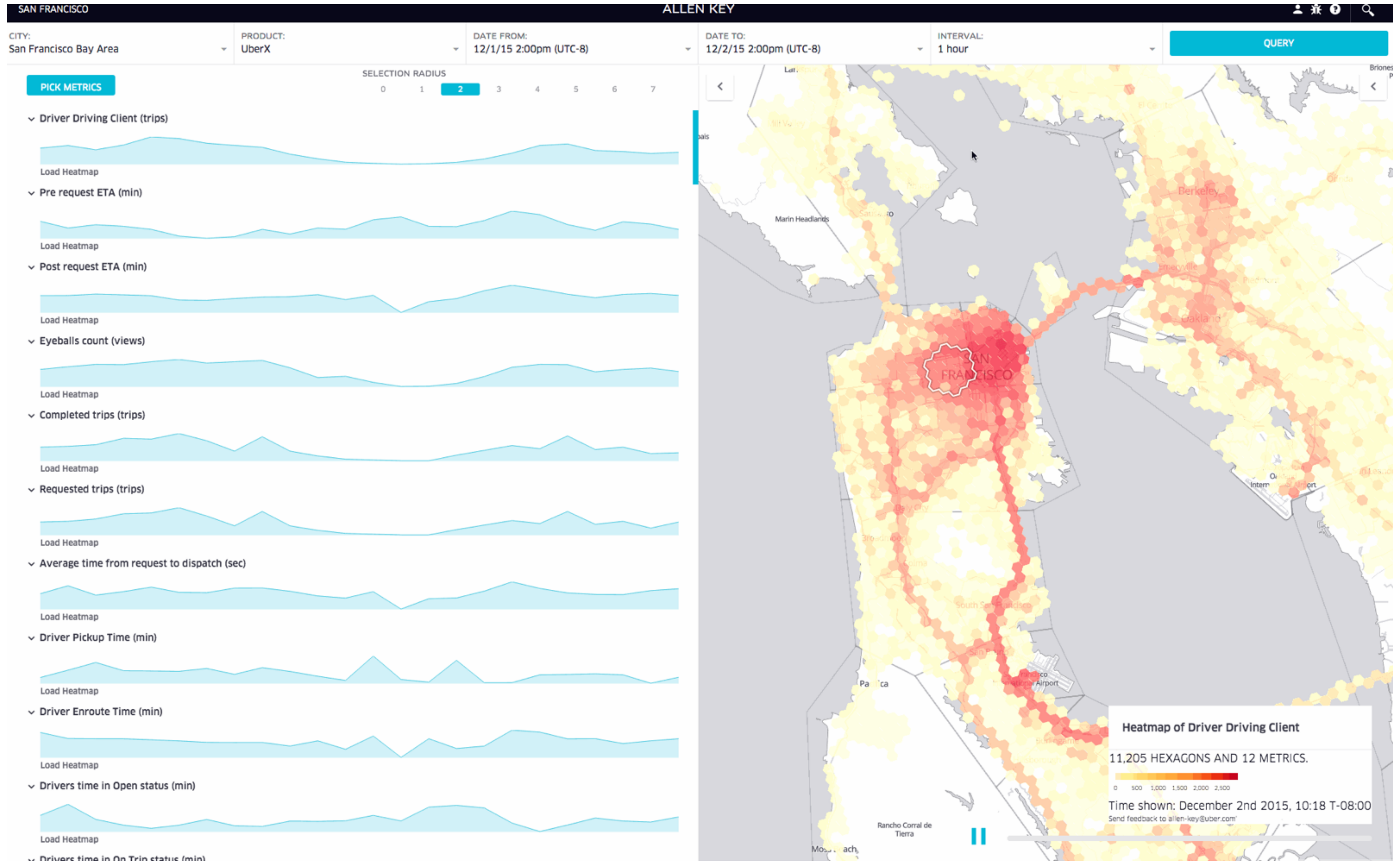
Explore your data via Geo Visualization tools

Business Metrics Dashboards

Kafka



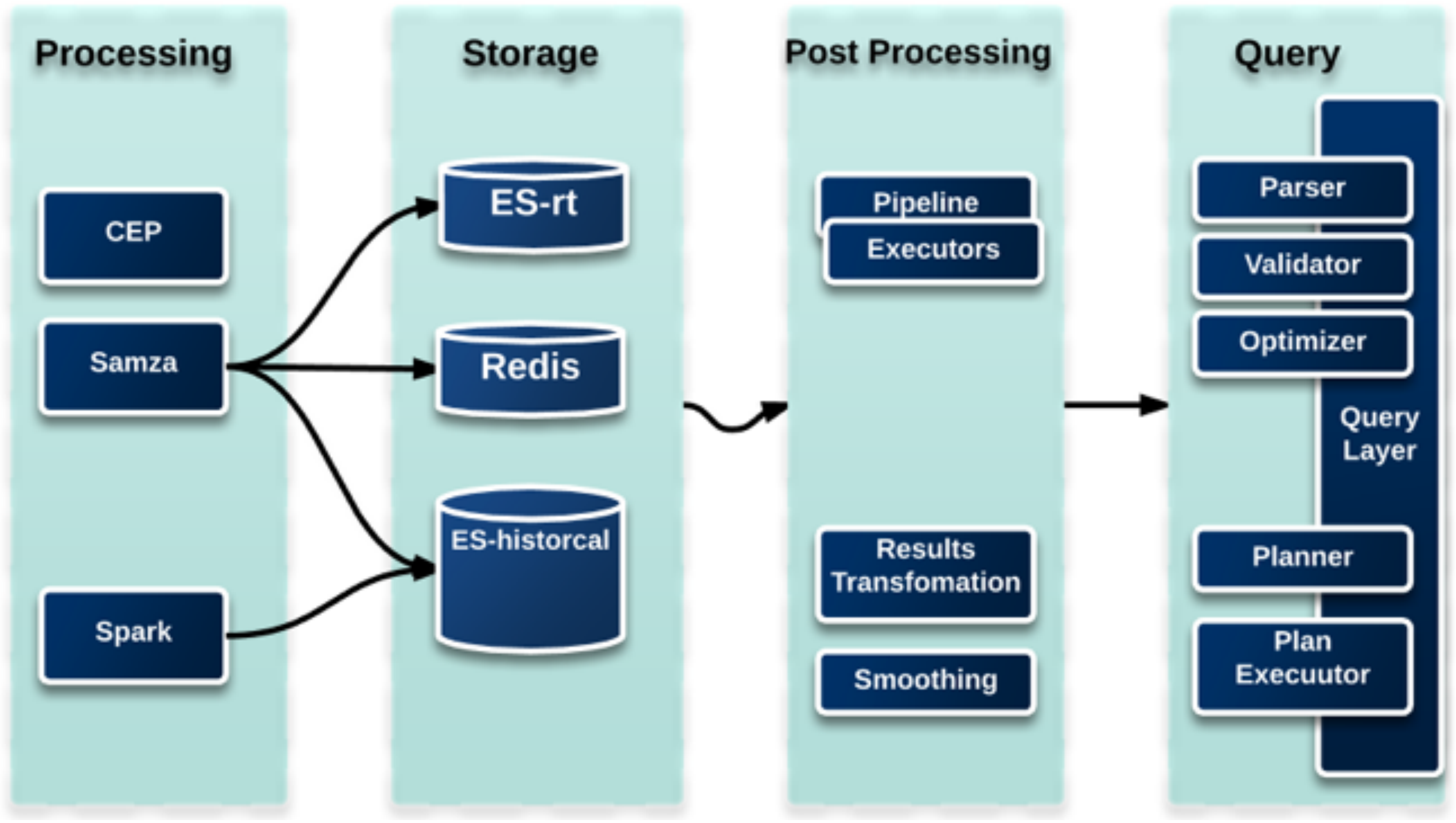
Realtime
Analytics



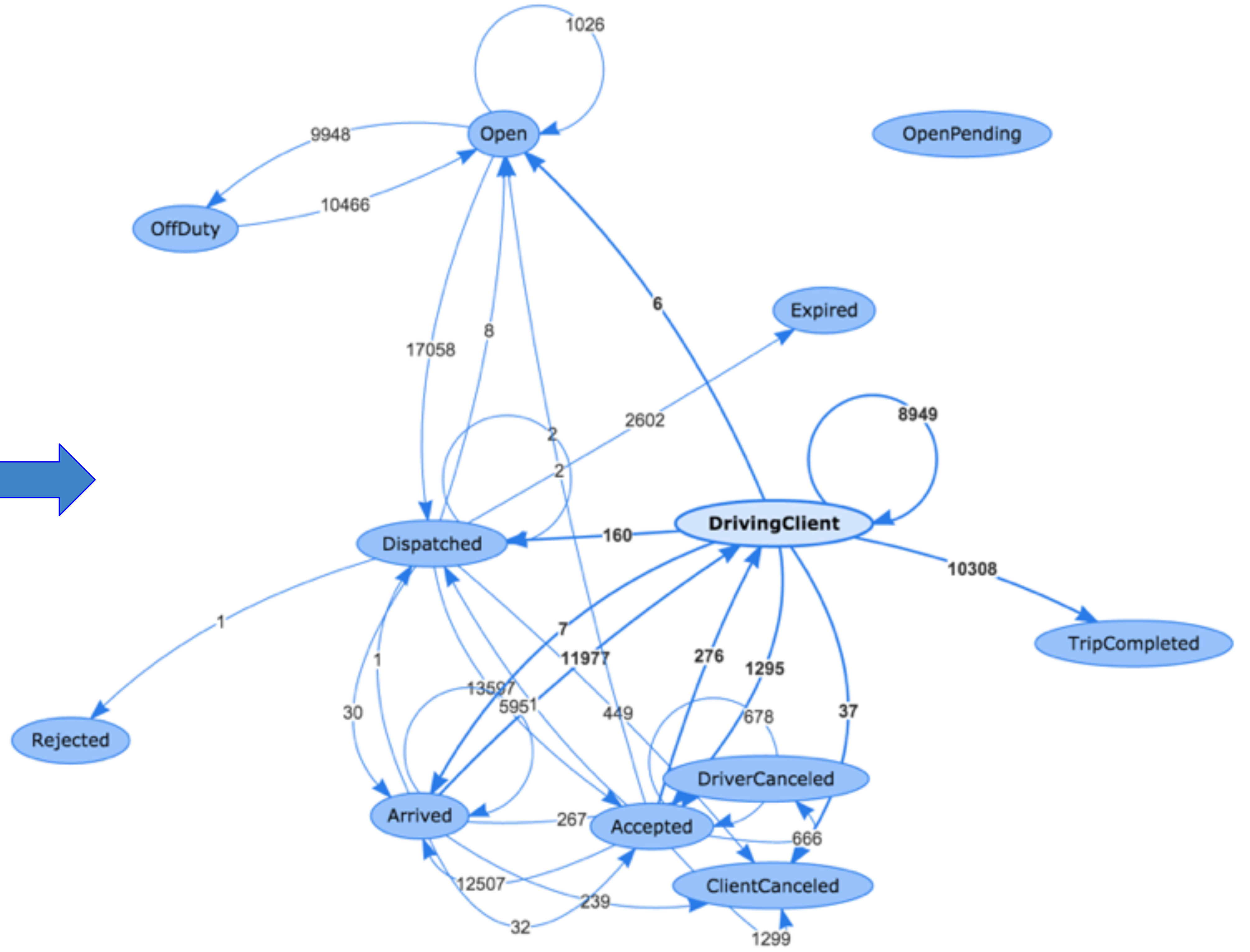
Explore Business Metrics
Per City/Vehicle Type

Query

Kafka

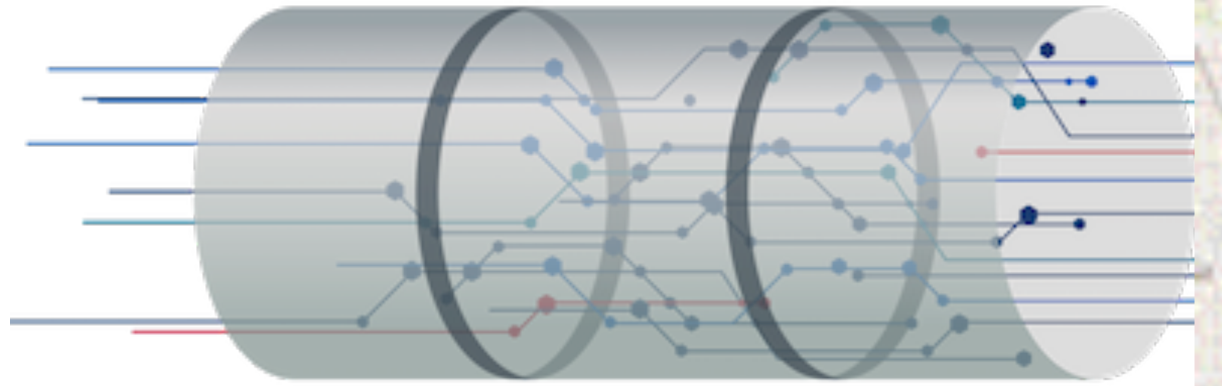


Gairos Processing

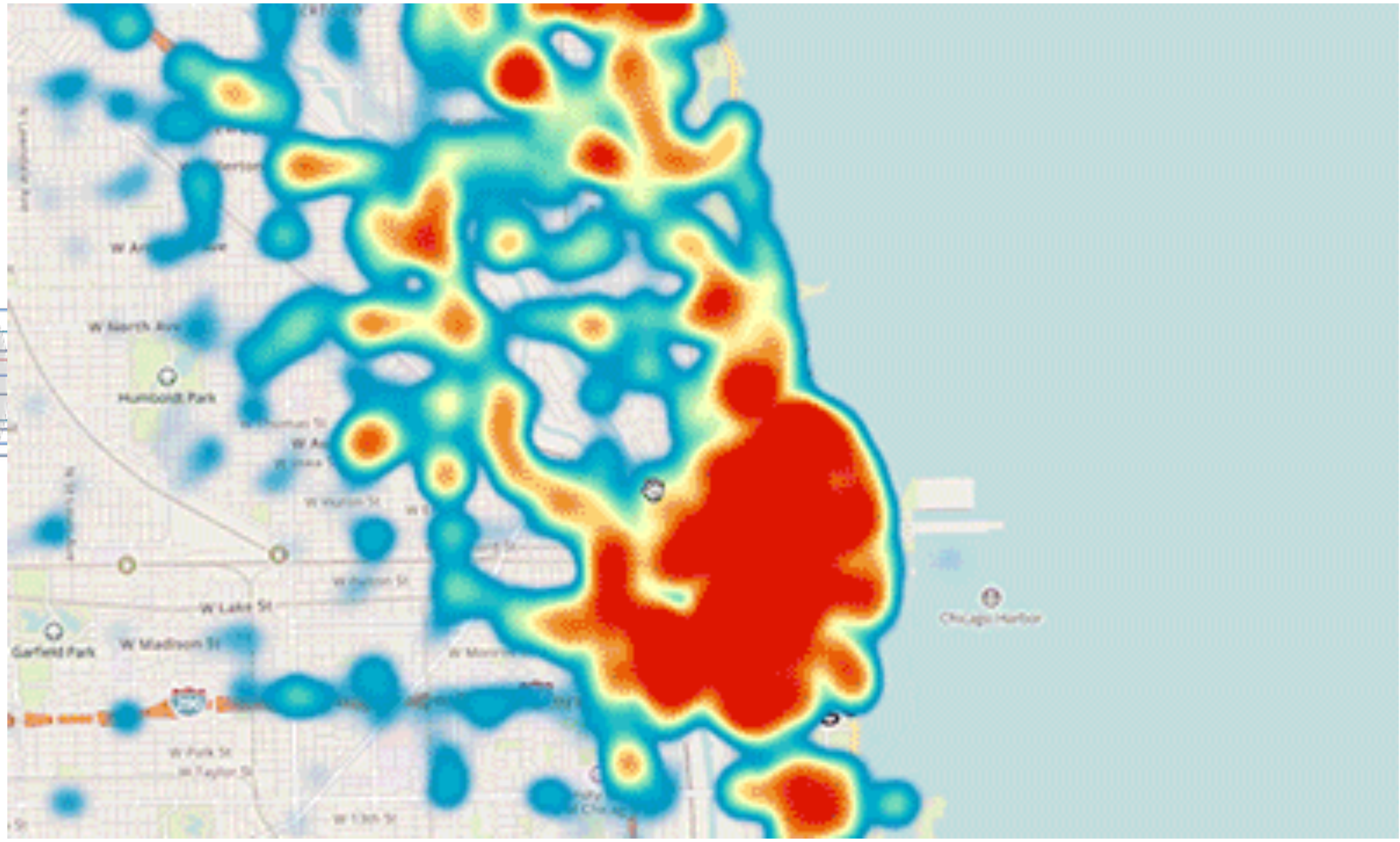


Streaming

Kafka



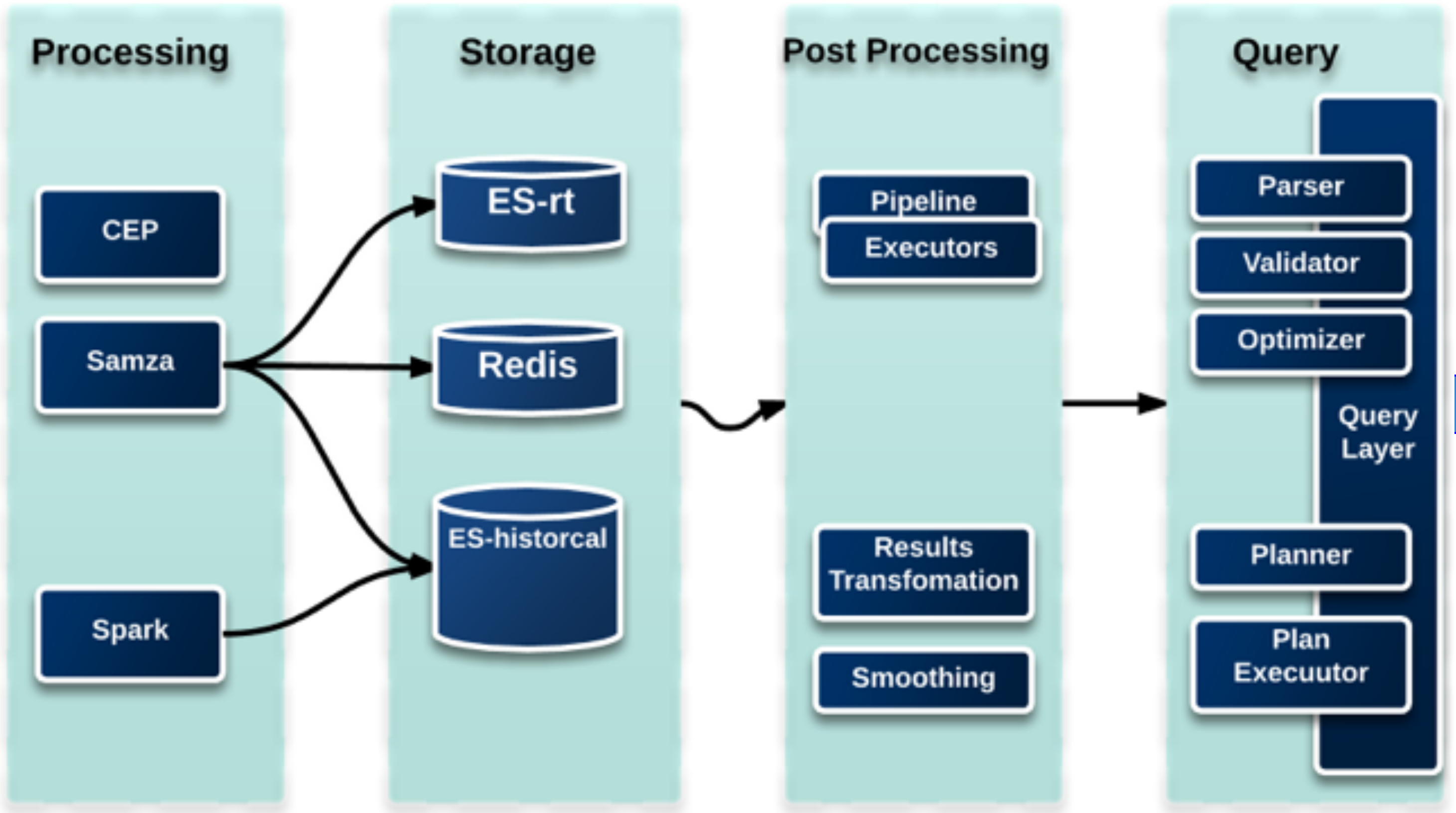
Query /
Streaming



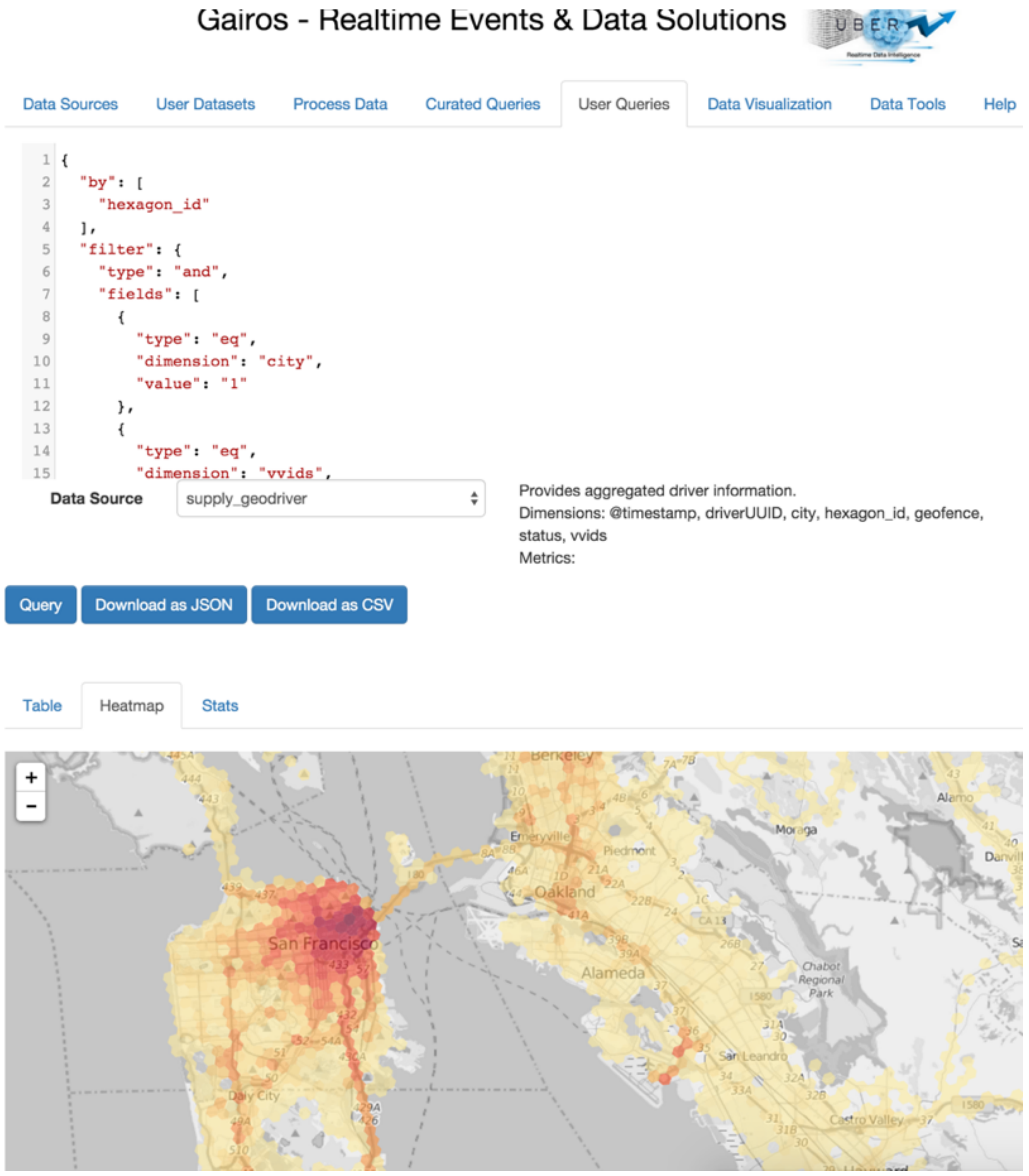
Realtime
Visualization

Exploration

Kafka



Realtime Analytics



Gairos Dashboard

Overall Architecture

To facilitate exploring, real-time analytics, backfilling, monitoring, …

Overall Analytics System


Telemetrics
HipChat
PagerDuty
Email
Common Action Gateway
Applications
Complex Event Processor
Controller
Data Processor
DB
Dashboard
ES-Realtime
Master Cluster
Data Cluster
Query Cluster
Samza
Dispatch Service
Kafka
Realtime Compute Engine
Query Layer
Query Parser
Query Validator
Query Planner
Plan Optimizer
Plan Executor
Redis Cluster
Spark
ES-Historical
Master Cluster
Data Cluster
Query Cluster
Applications
Telemetrics
Notebook

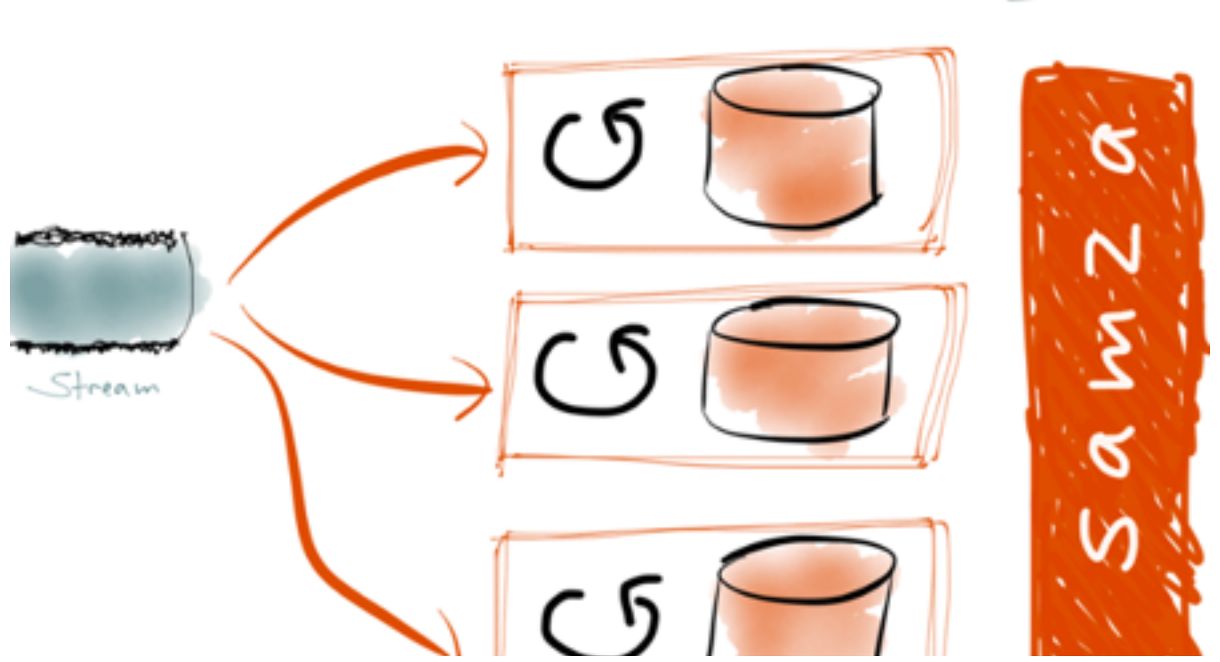
Choices/Tradeoffs

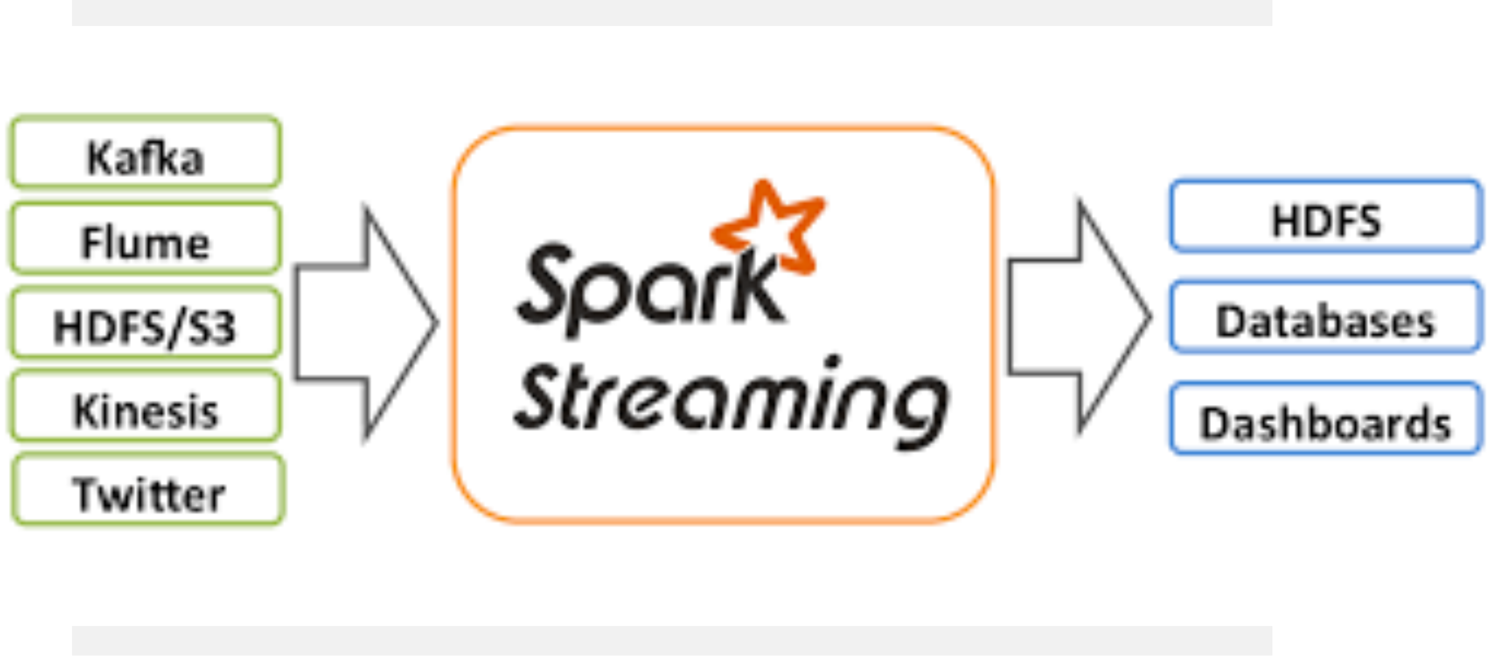
What were some of the choices considered?

How did we settle down on the final choice?

Stream Processing

Some Choices





Storm

Was our original choice
Initial systems built on Storm
However
Twitter moving away from Storm
Unbalanced topologies were problematic
Operational complexities

Samza

Our current choice

Well integrated with Kafka
Built in State Management
Built in Checkpointing

Spark Streaming

Looking at this actively

Micro Batch based processing
Good integration with HDFS & S3
Exactly once semantics

Kinesis Dataflow Flink

Persistence

Some Choices

Elasticsearch

Distributed Indexes & Queries
Versatile aggregations

memsql

In-memory database
Fast Analytic Engine

Druid

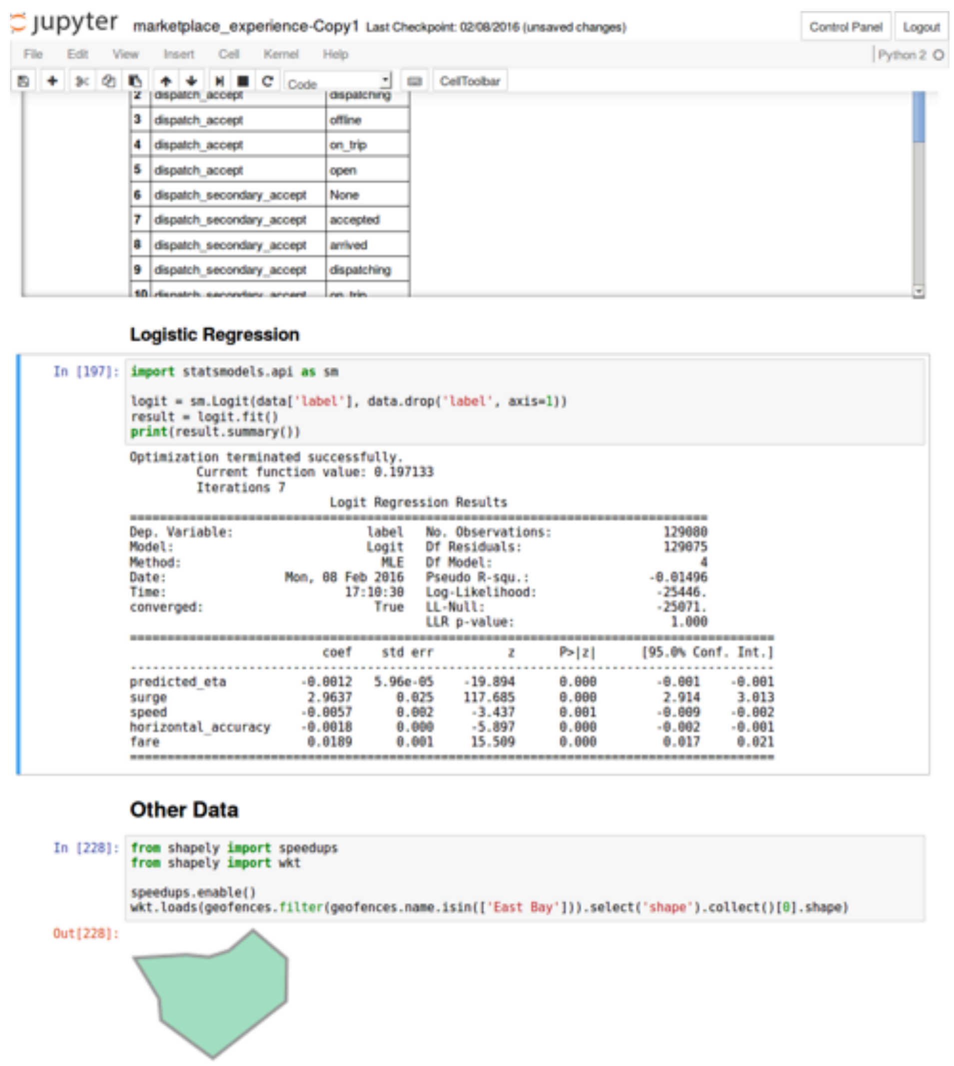
Highly scalable
Designed for Realtime OLAP
    However
Operationally Complex

Analytics/Dashboards etc.

Some Choices

Jupyter/IPython

Great community support
Data Scientists familiar with Python



Zeppelin

Integrated with Spark
Offer many language support (Python, Scala, ..)

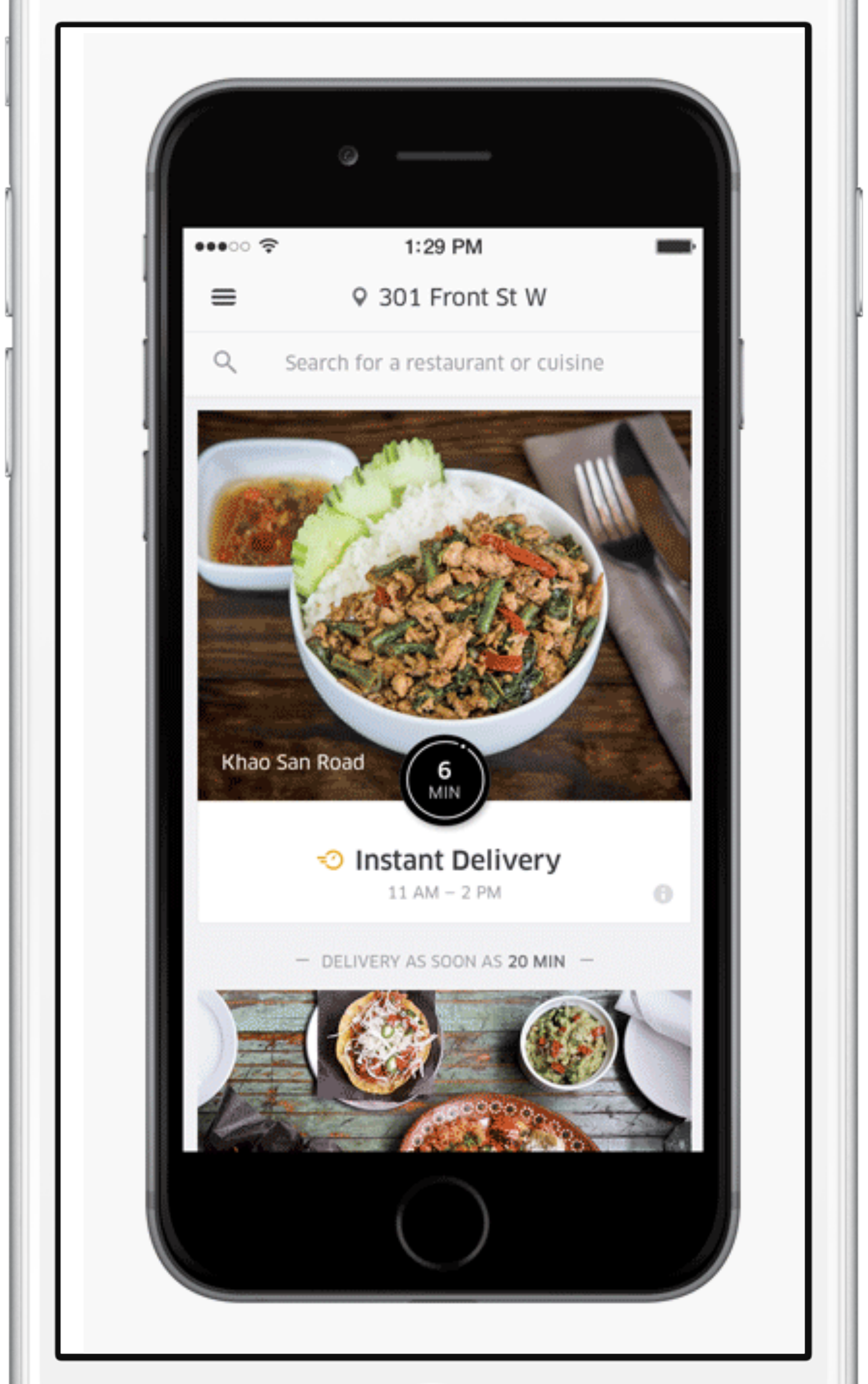
Kibana

Integration with ElasticSearch

Links

Thank you!

- Realtime Monitoring with Uber's Argos (https://eng.uber.com/argos/)
- Spark at Uber (http://www.slideshare.net/databricks/spark-meetup-at-uber)
- Career at Uber (https://www.uber.com/careers/)
-



Q & A

Happy to discuss design/architecture

No product/business questions please :-)

@stonse

Thank you

Sudhir Tonse

@stonse

UBER