Stream Processing & Analytics with Flink

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@g9yuayon

Four Kinds of Analytics

- On demand aggregation and pattern detection
- Clustering
- Forecasting
- Pattern detection on geo-temporal data

Two Ingredients

Geo/Spatial

Time

Real-time aggregation and pattern matching

Complex Event Processing

Examples

How many cars enter and exit a user defined area in past 5 minutes

CEP with full historical context

Notify me if a partner completed her 100th trip in a given area just now?

Patterns in the future

How many first-time riders will be dropped off in a given area in the next 5 minutes?

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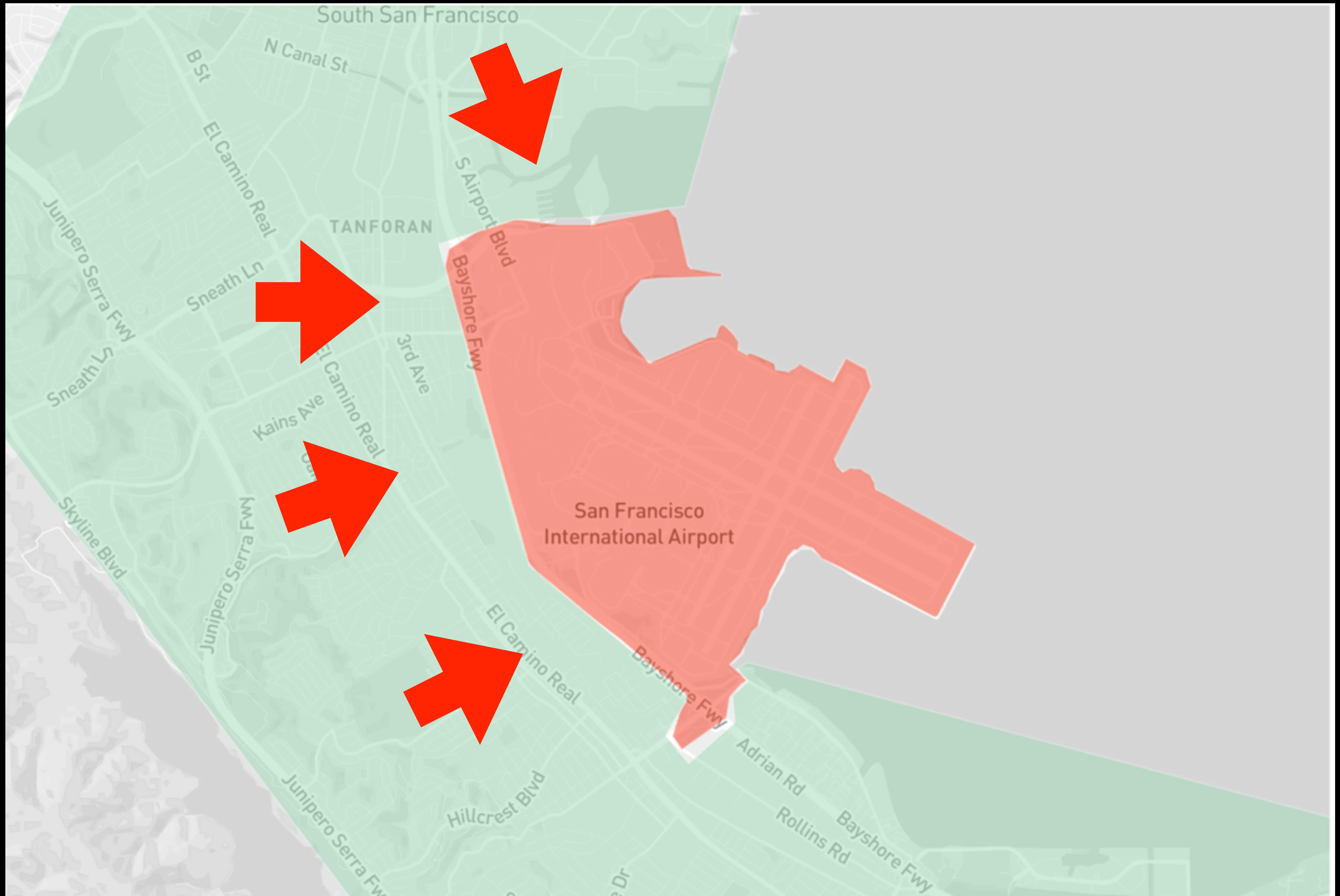

Geo: user flexibility is important

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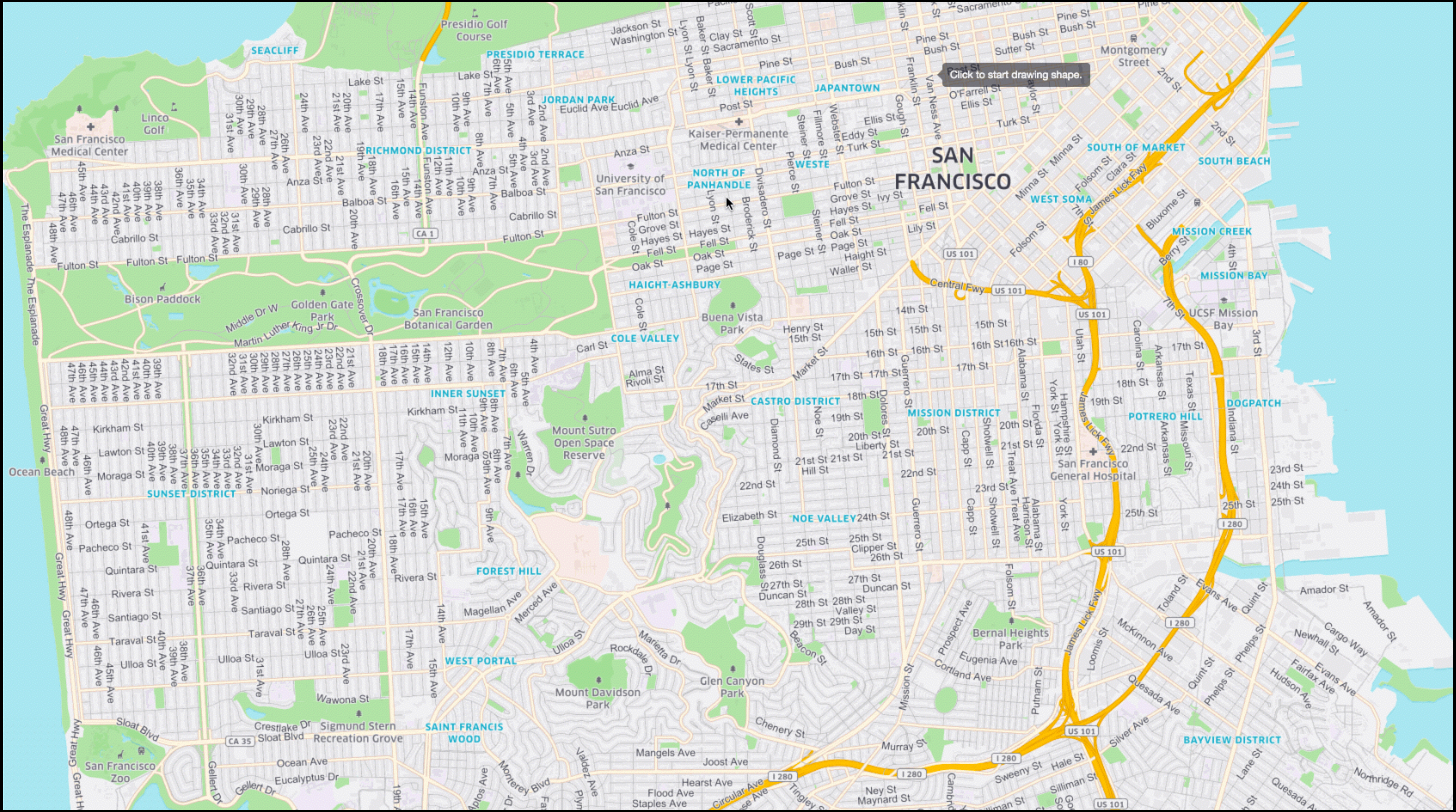

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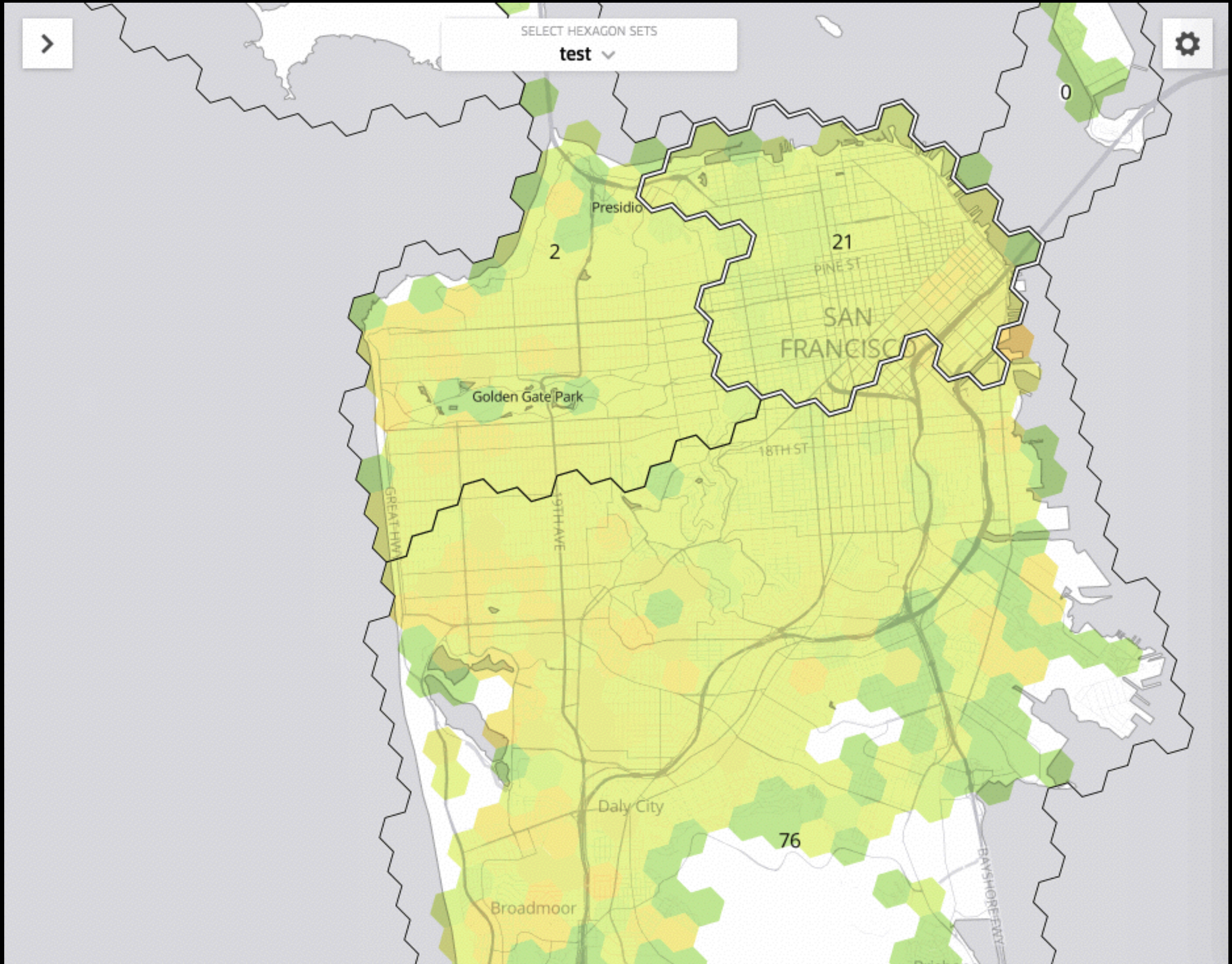

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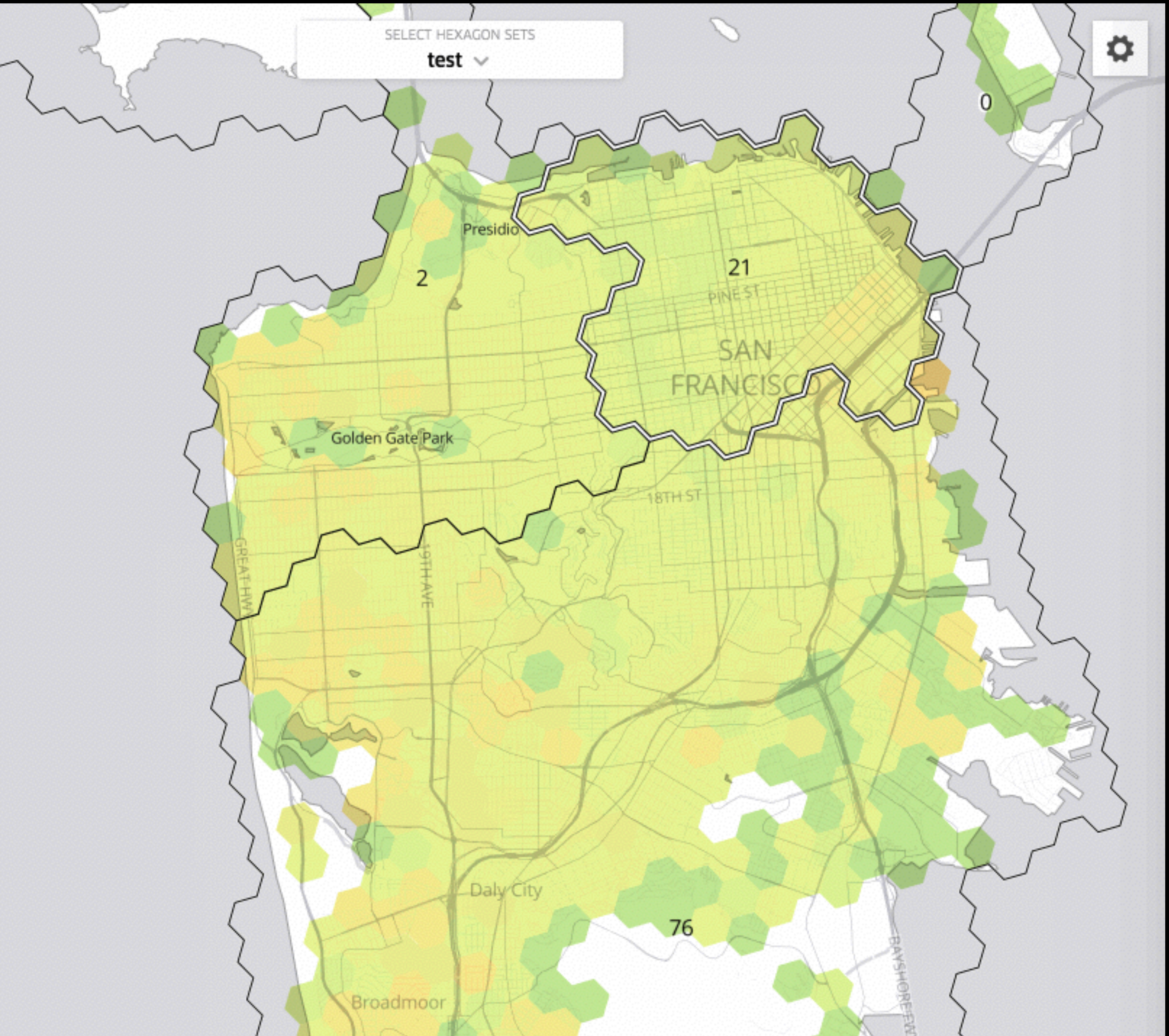
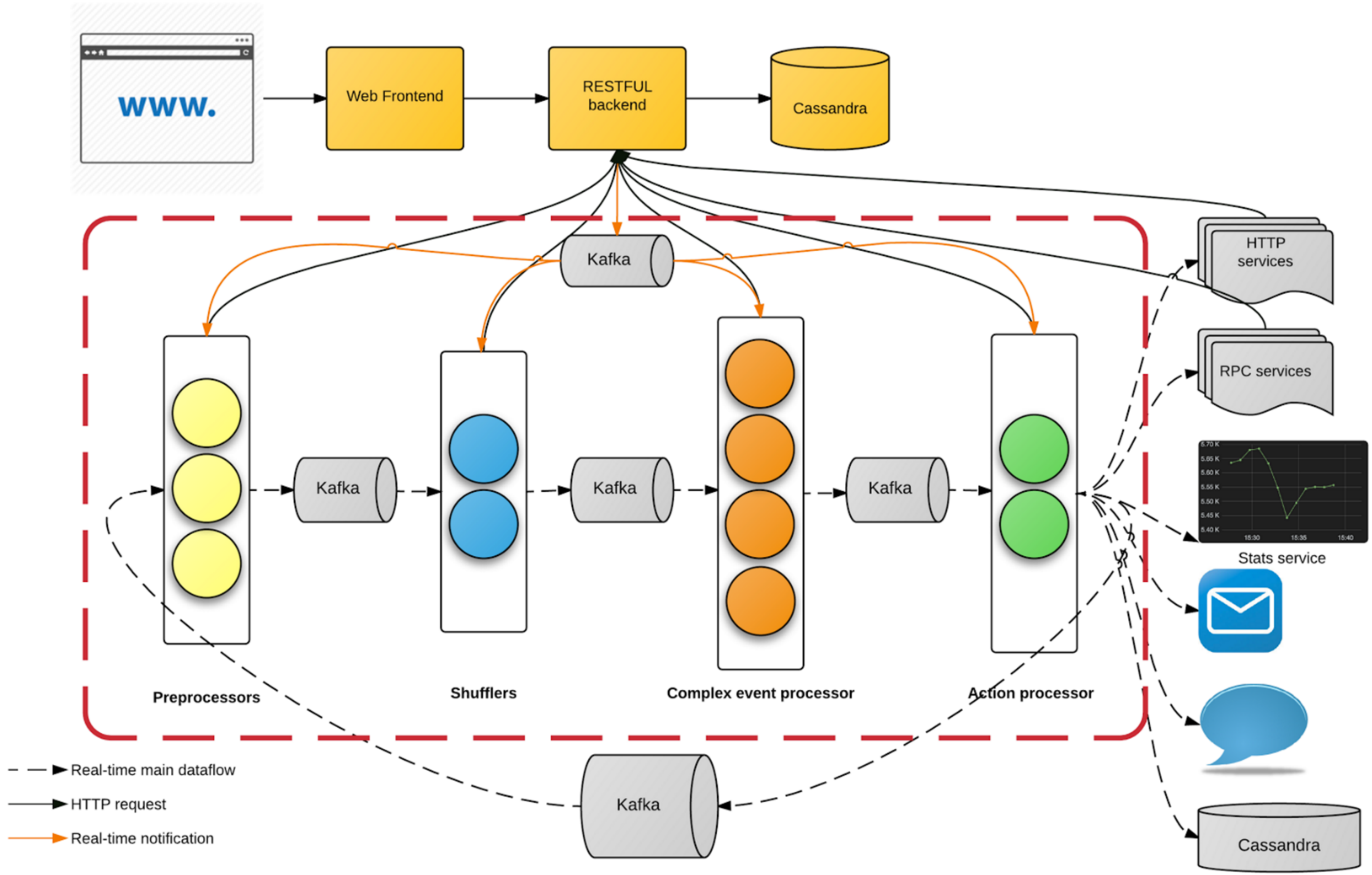


- Every hexagon
- Every driver/rider

CEP Pipeline Built on Samza

- No hard-coded CEP rules
- Applying CEP rules per individual entity: topic, driver, rider, cohorts, and etc
- Flexible checkpointing and statement management



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RESTFUL backend
Cassandra
Kafka
HTTP services
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Shufflers
Complex event processor
Action processor
Kafka
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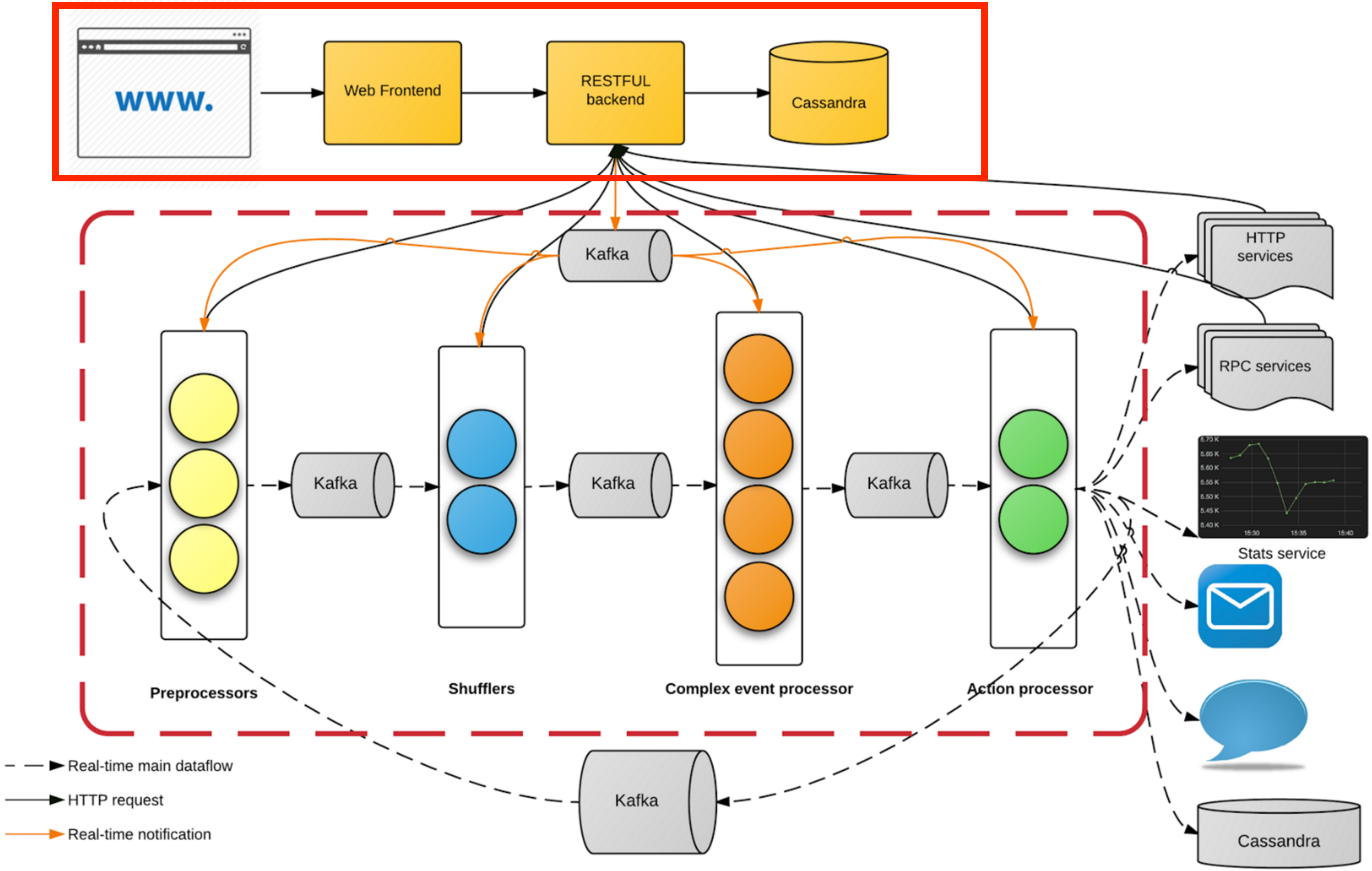
Real-time main dataflow
HTTP request
Real-time notification



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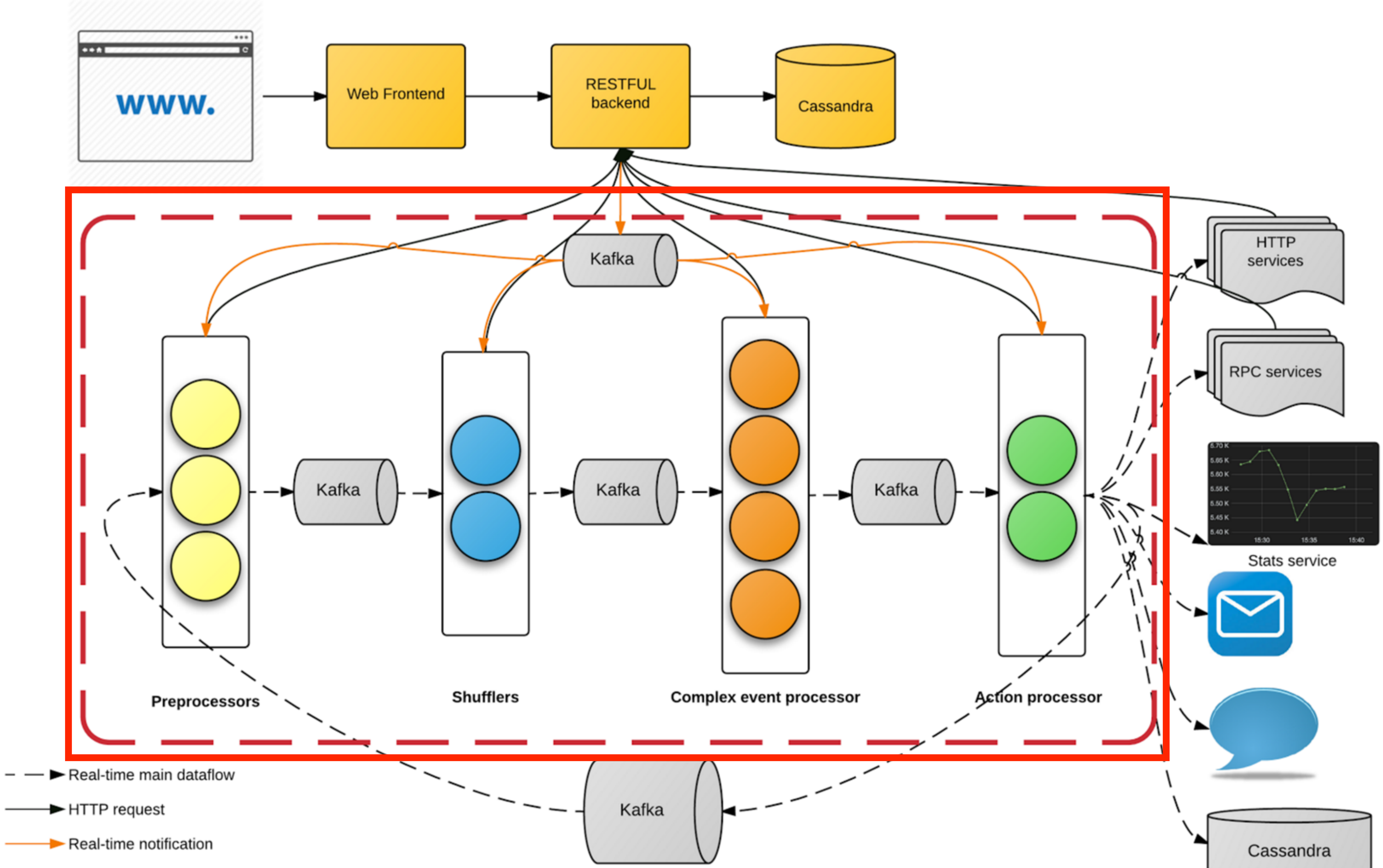

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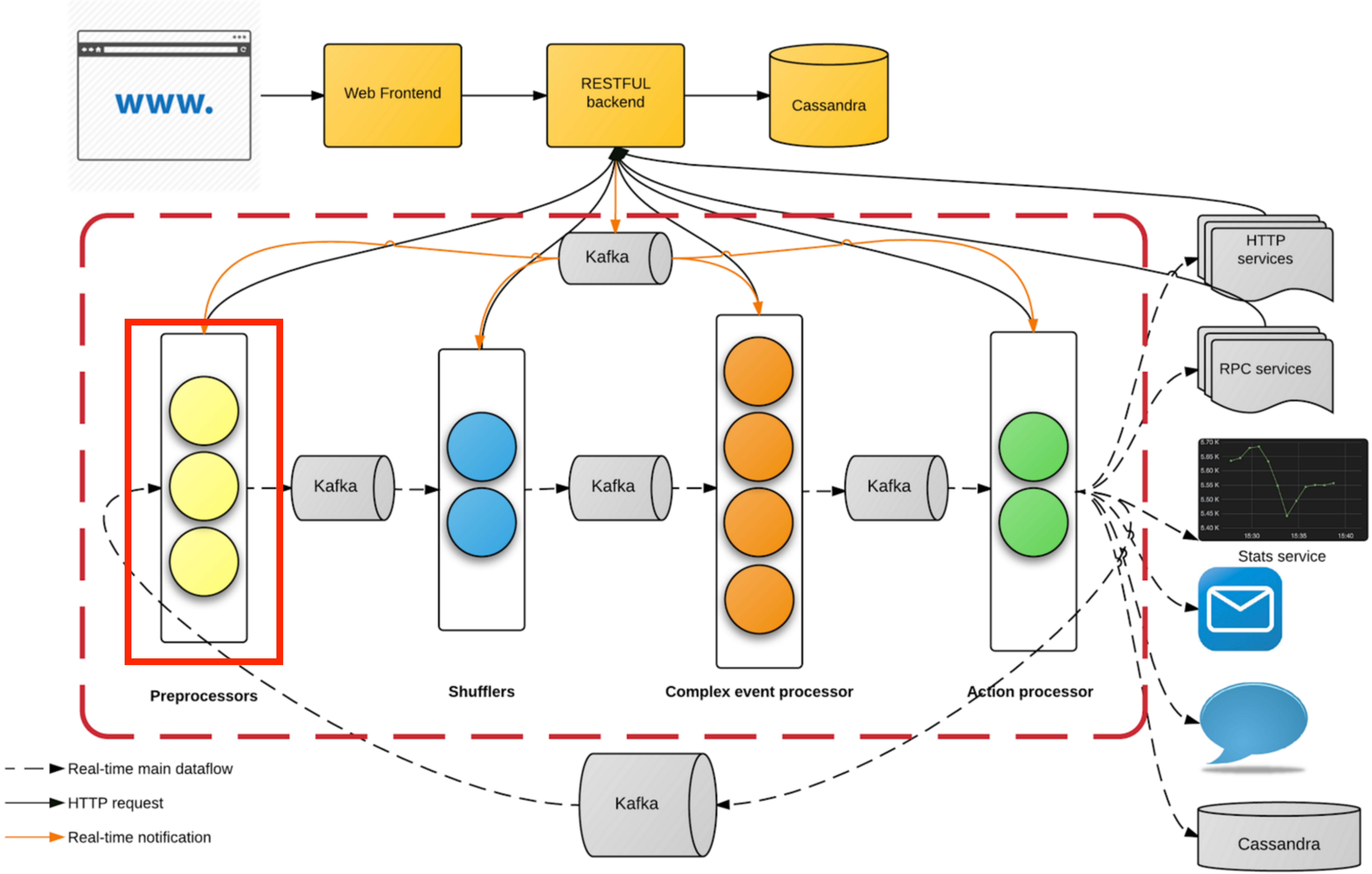
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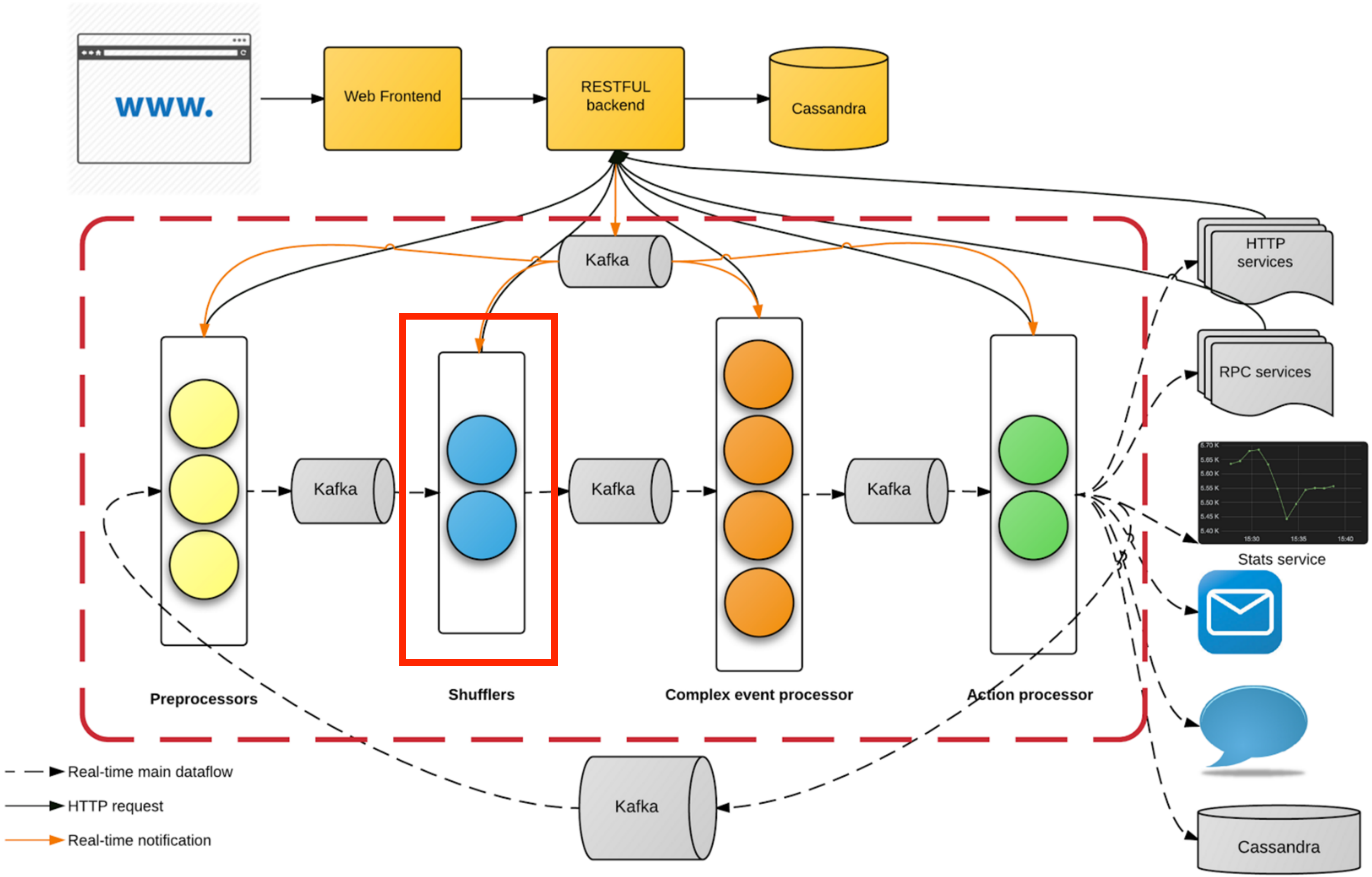
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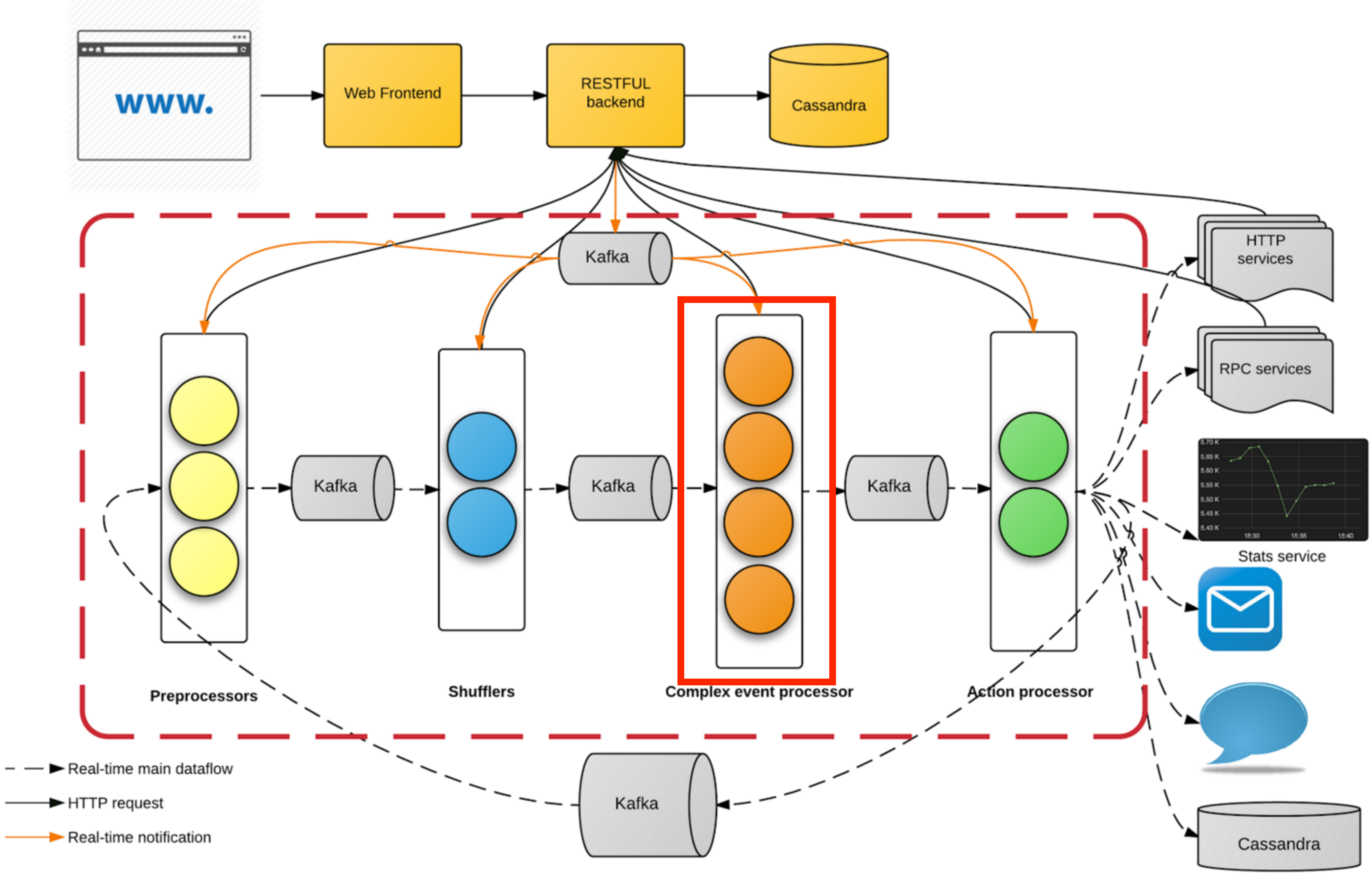
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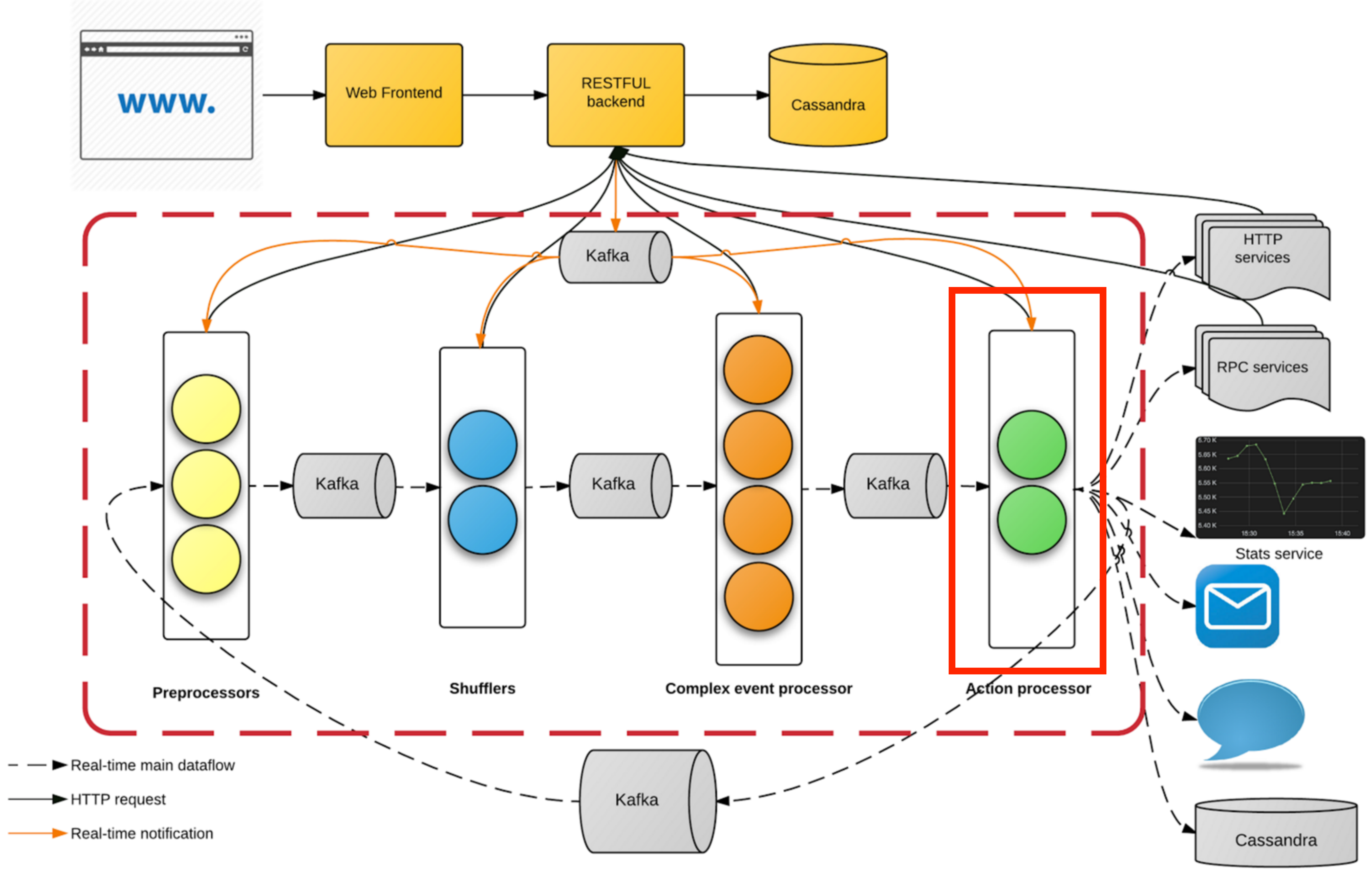
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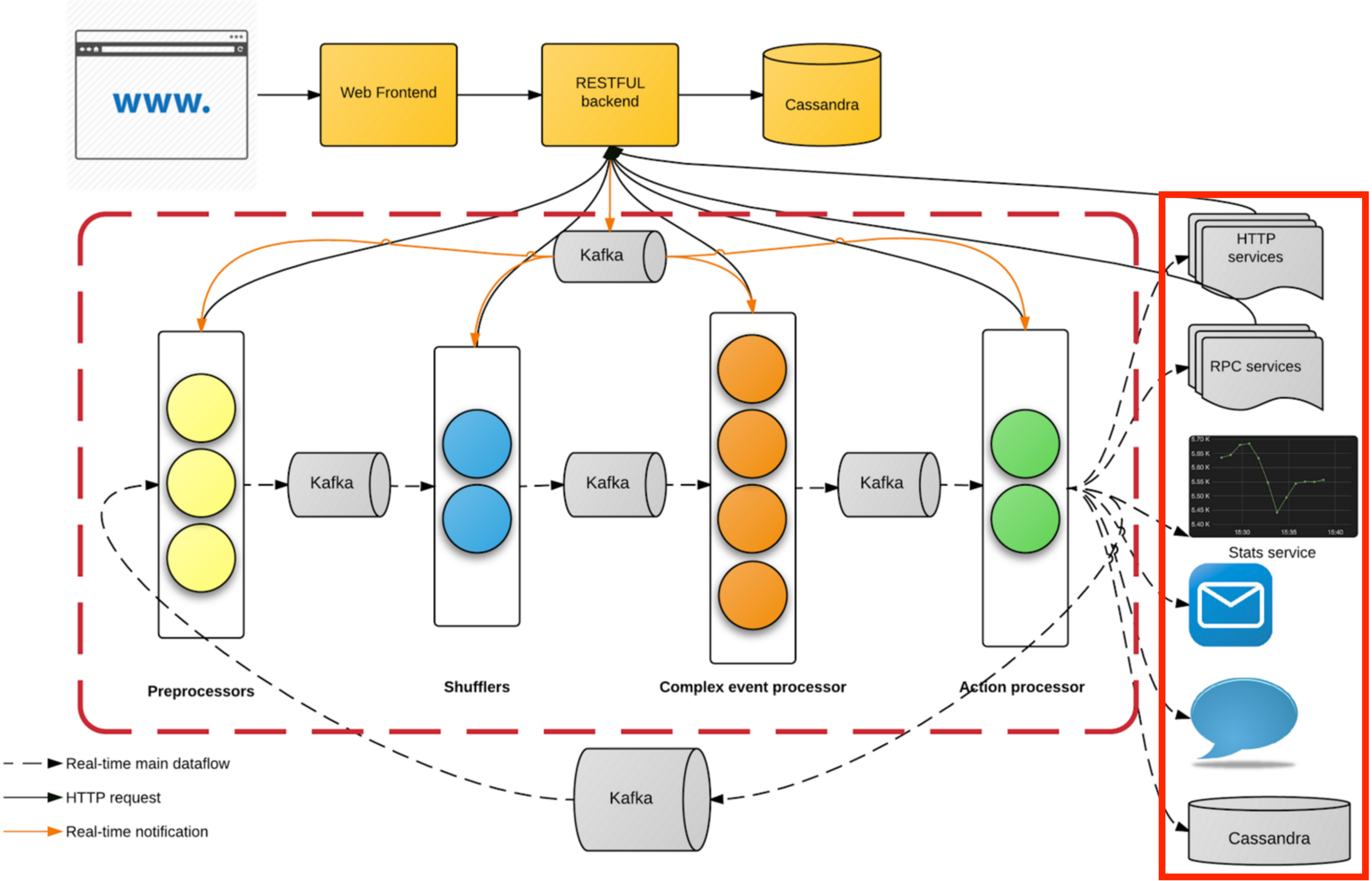

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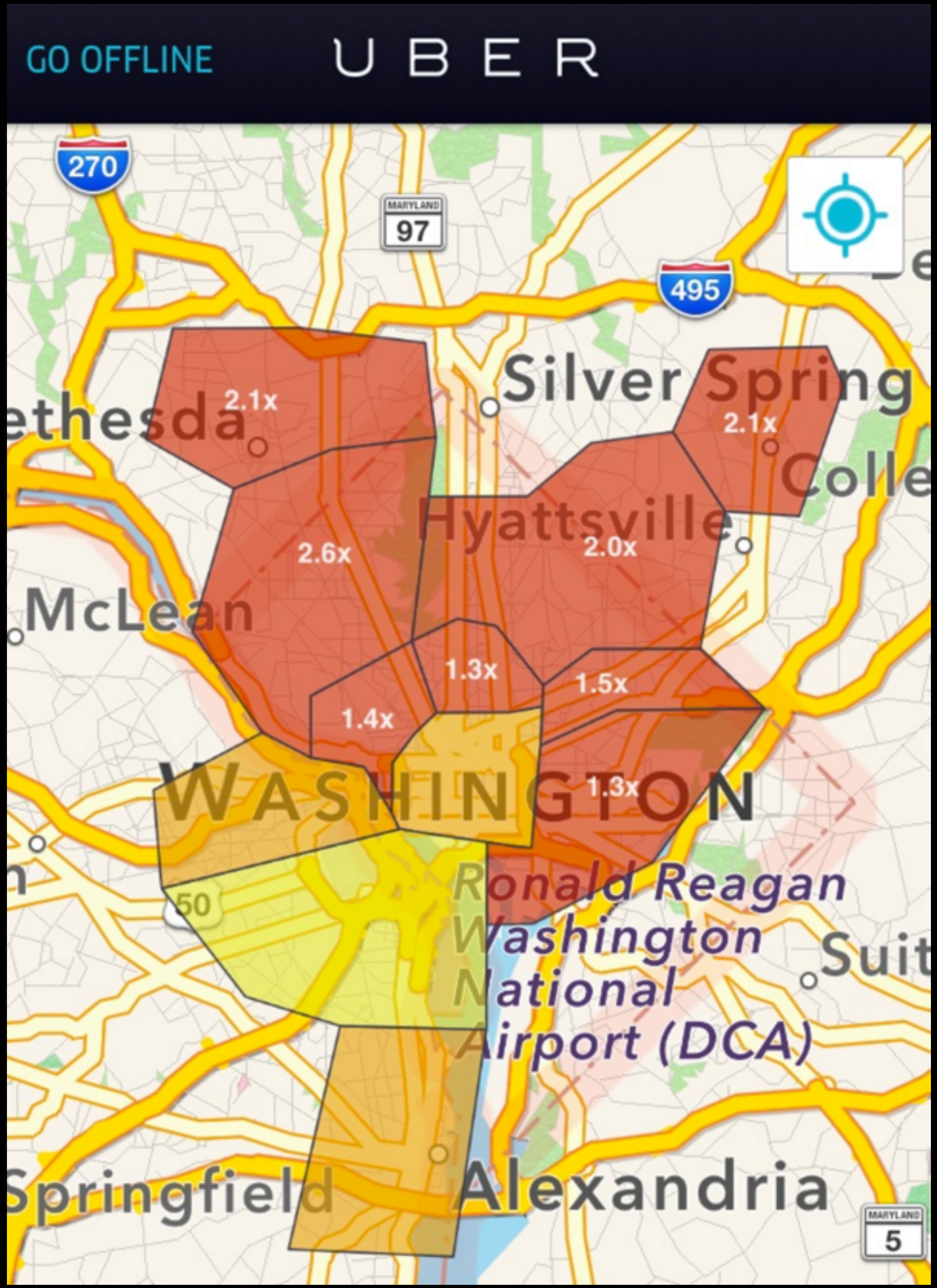
We need to evolve our architecture for other analytics

Clustering

Manually Created Cluster

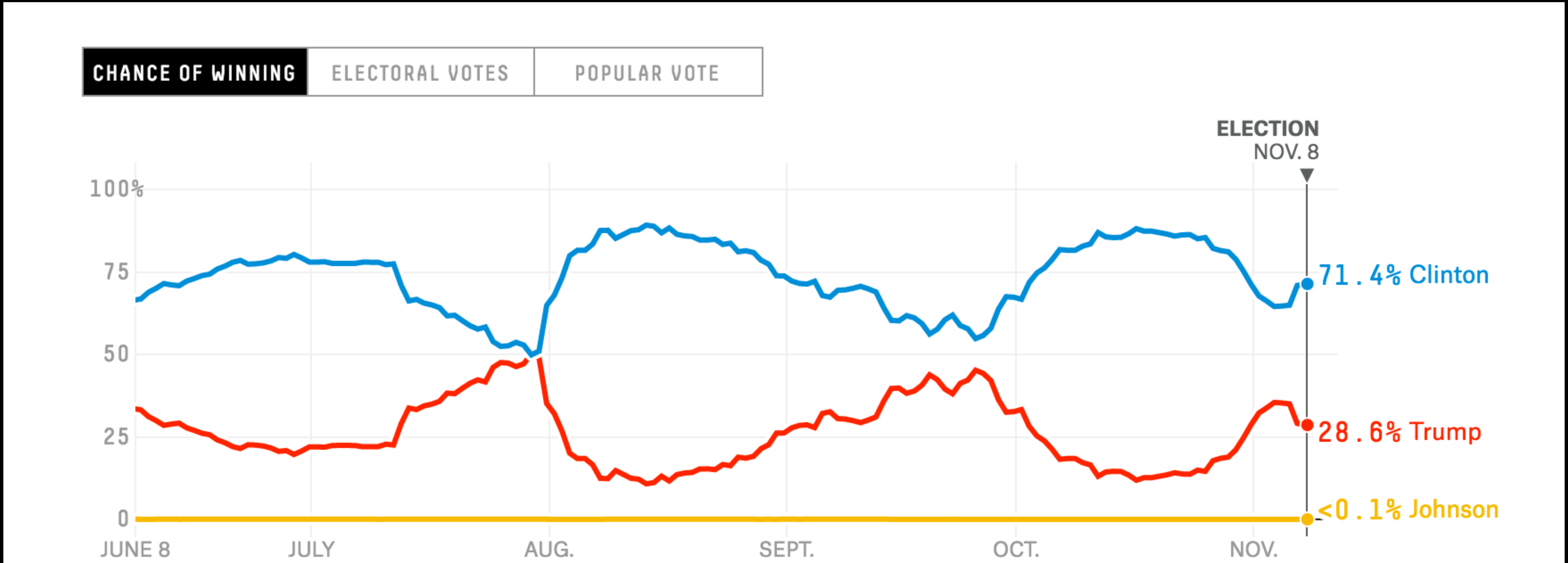


Call for algorithmically created clusters

- Clustering based on key performance metrics

Call for algorithmically created cluster

- Clustering based on key performance metrics
- Continuously measure the clusters



Call for algorithmically created clusters

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- Different clustering for different business needs

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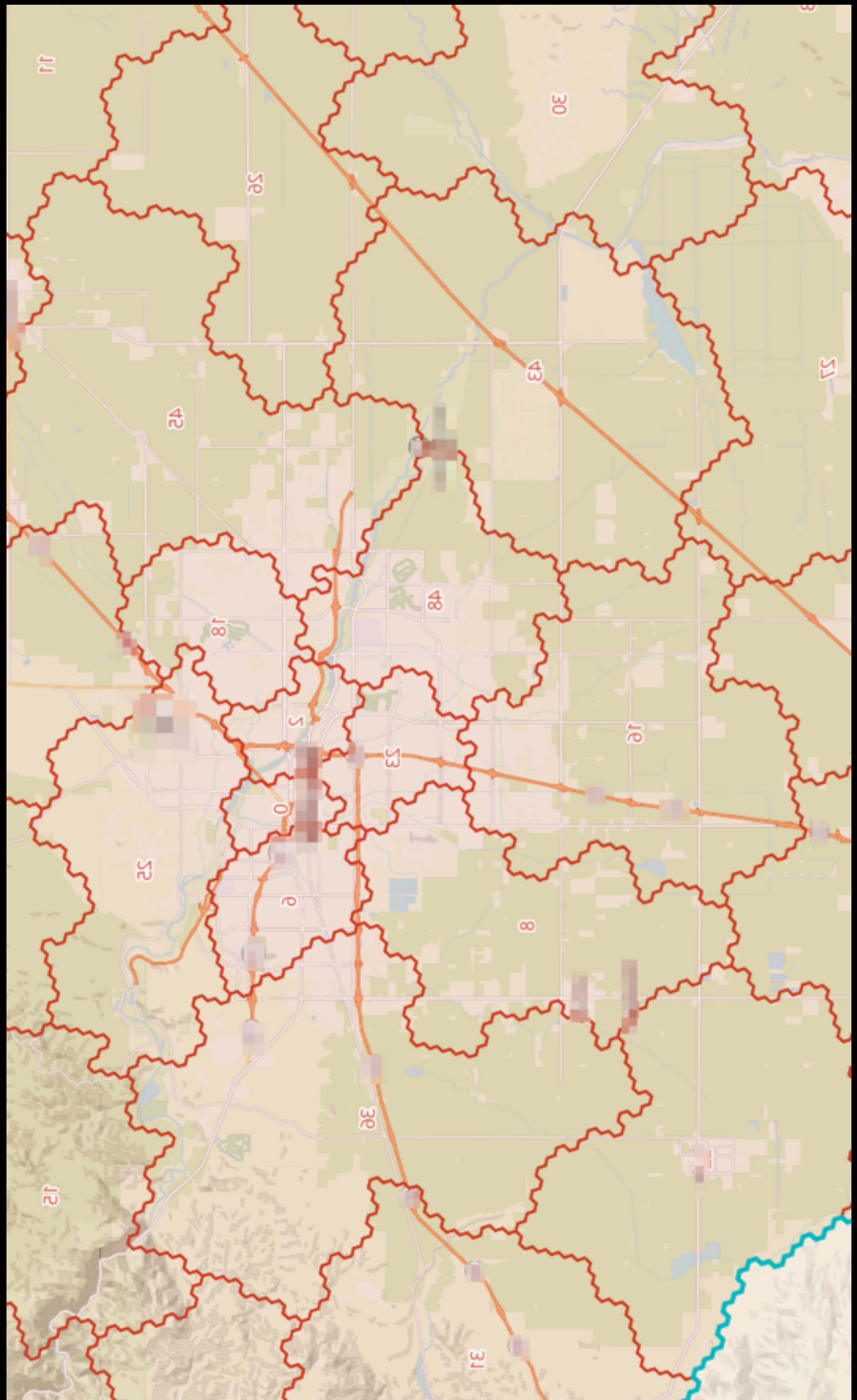
Call for algorithmically created clusters

- Clustering based on key performance metrics
- Continuously measure the clusters
- Different clustering for different business needs
- Create clusters in minutes for all cities
- Foundation for other stream analytics

Home-grown Clustering Service



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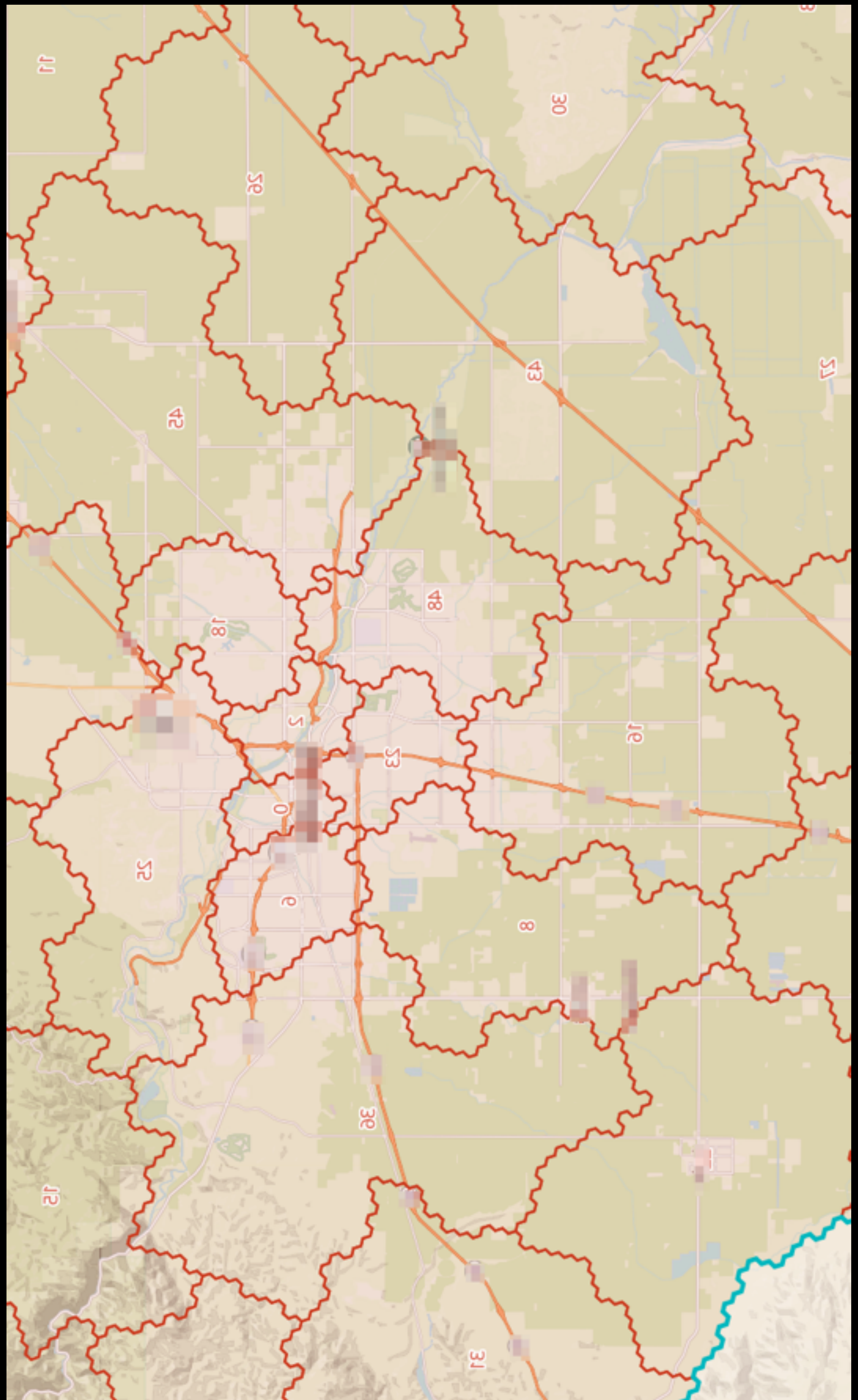

- All cities under 3 minutes

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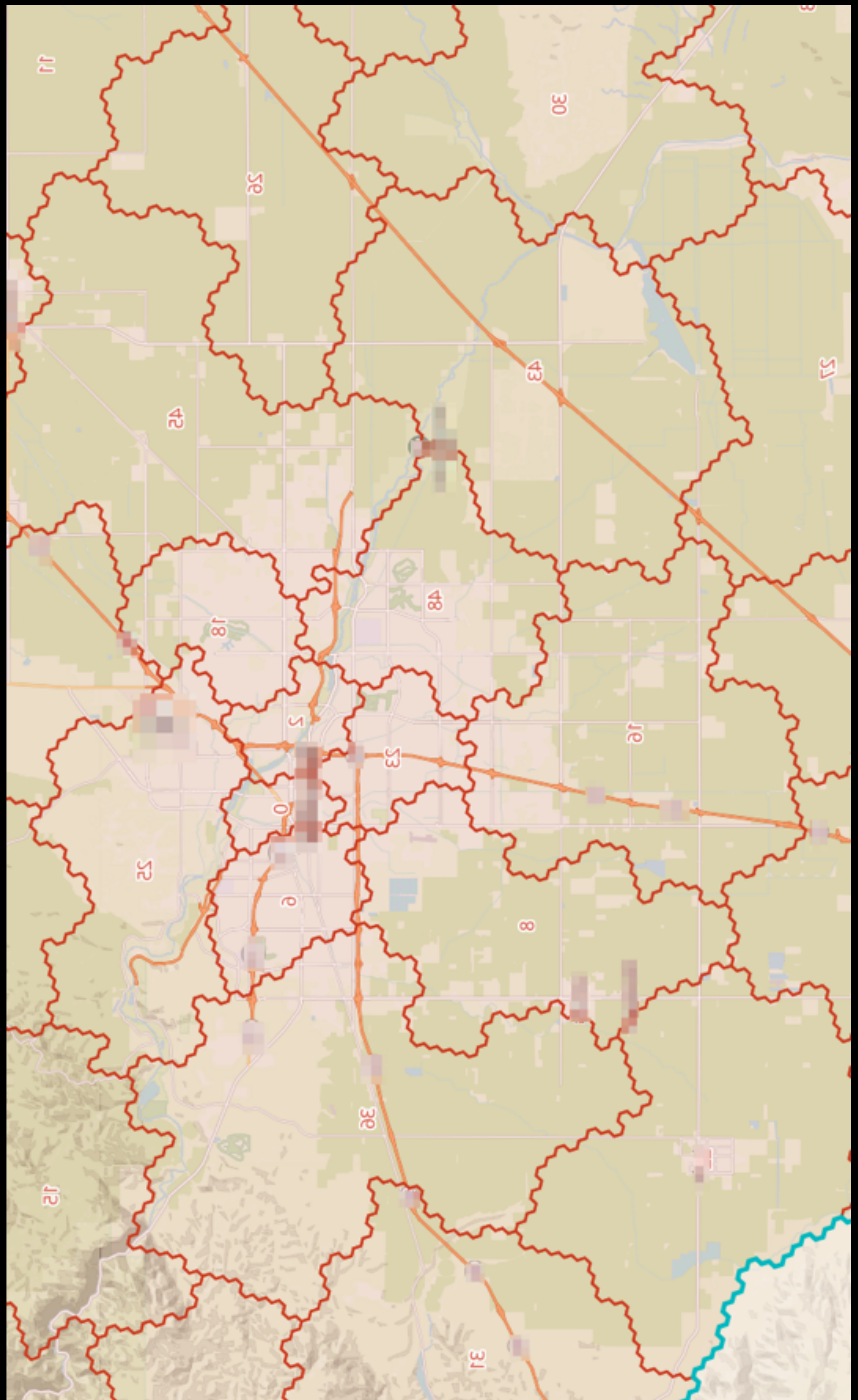

- All cities under 3 minutes
- Pluggable algorithms and measurements

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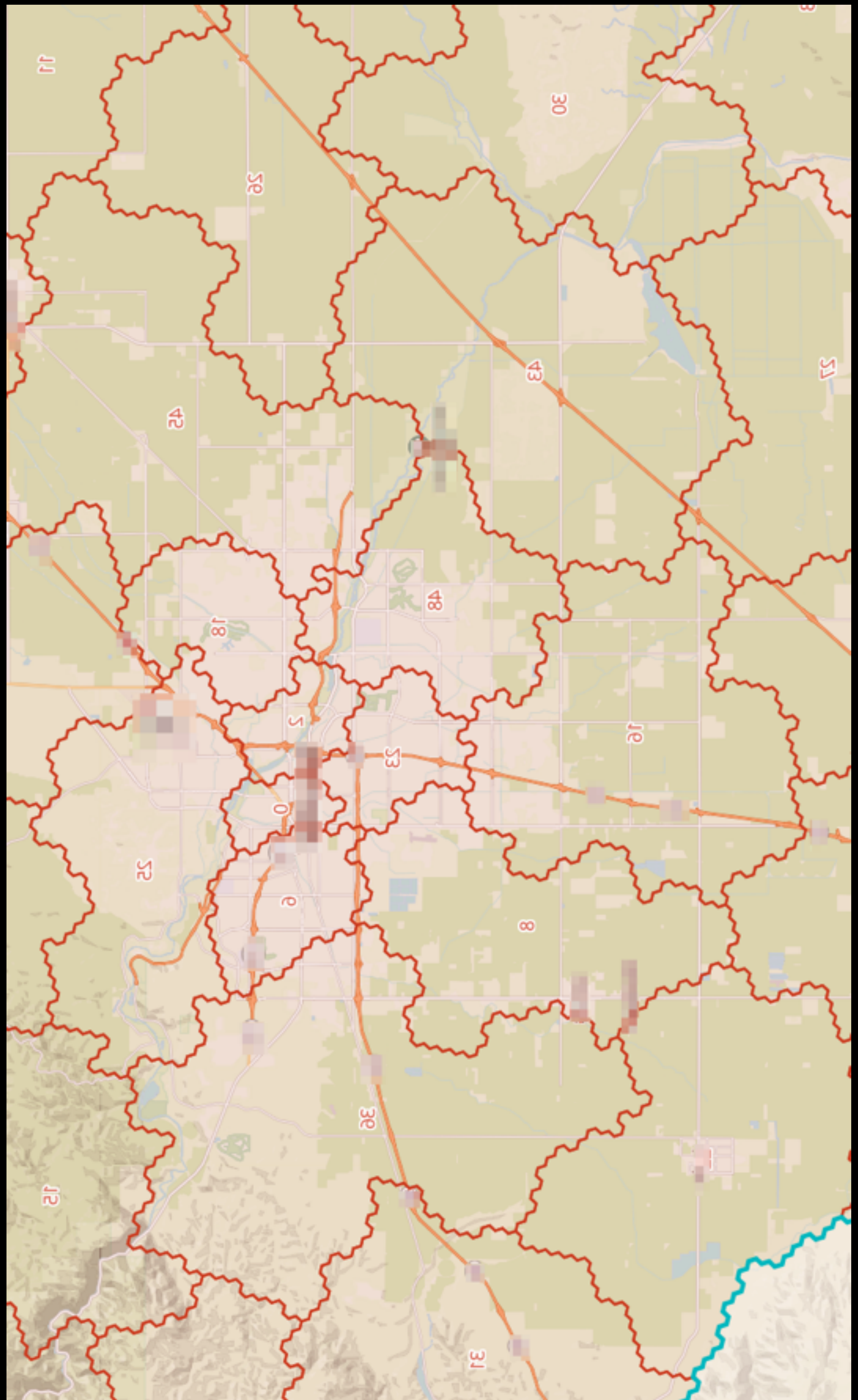

- All cities under 3 minutes
- Easily pluggable algorithms and measurements
- Historical geo-temporal data for clustering

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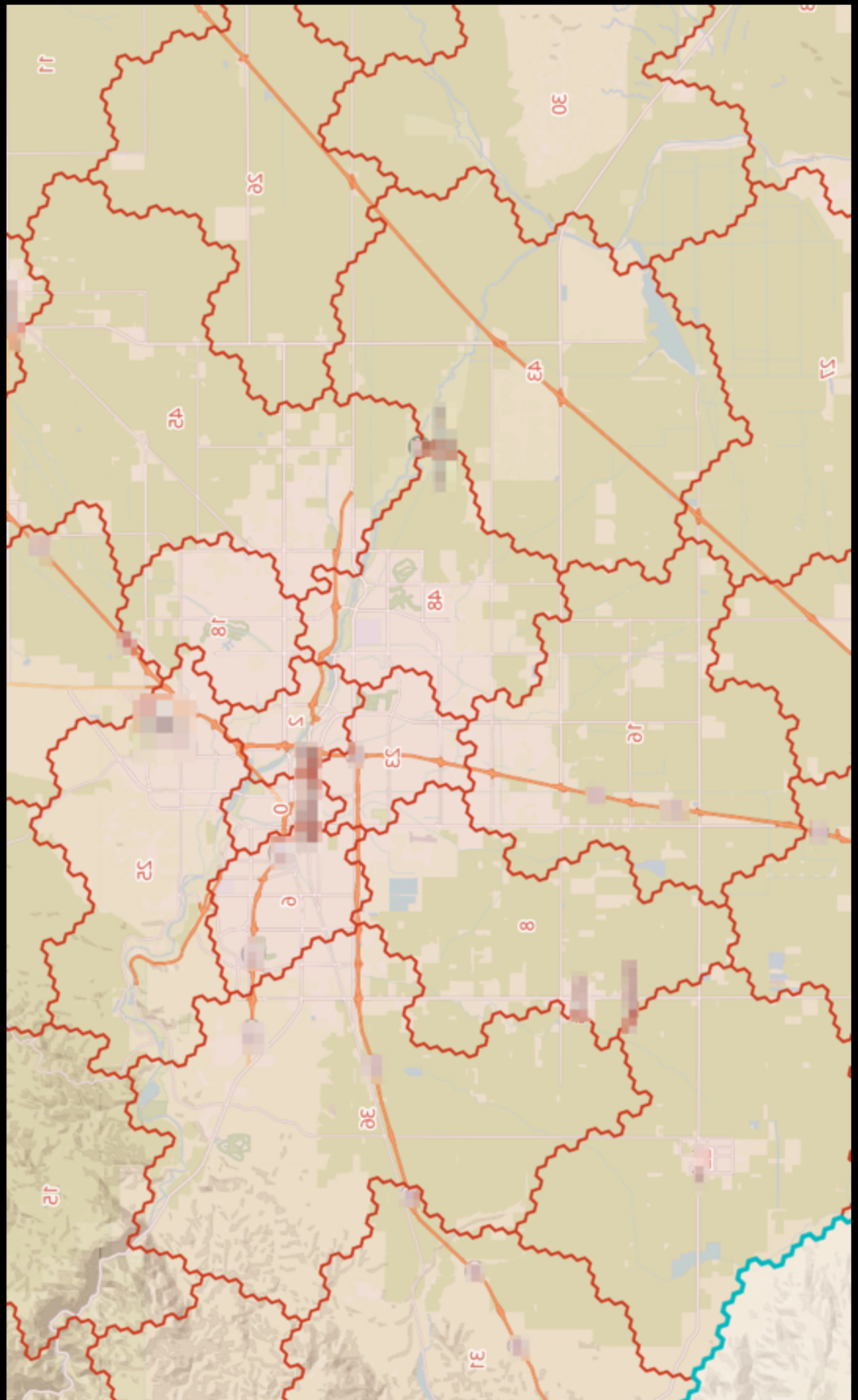

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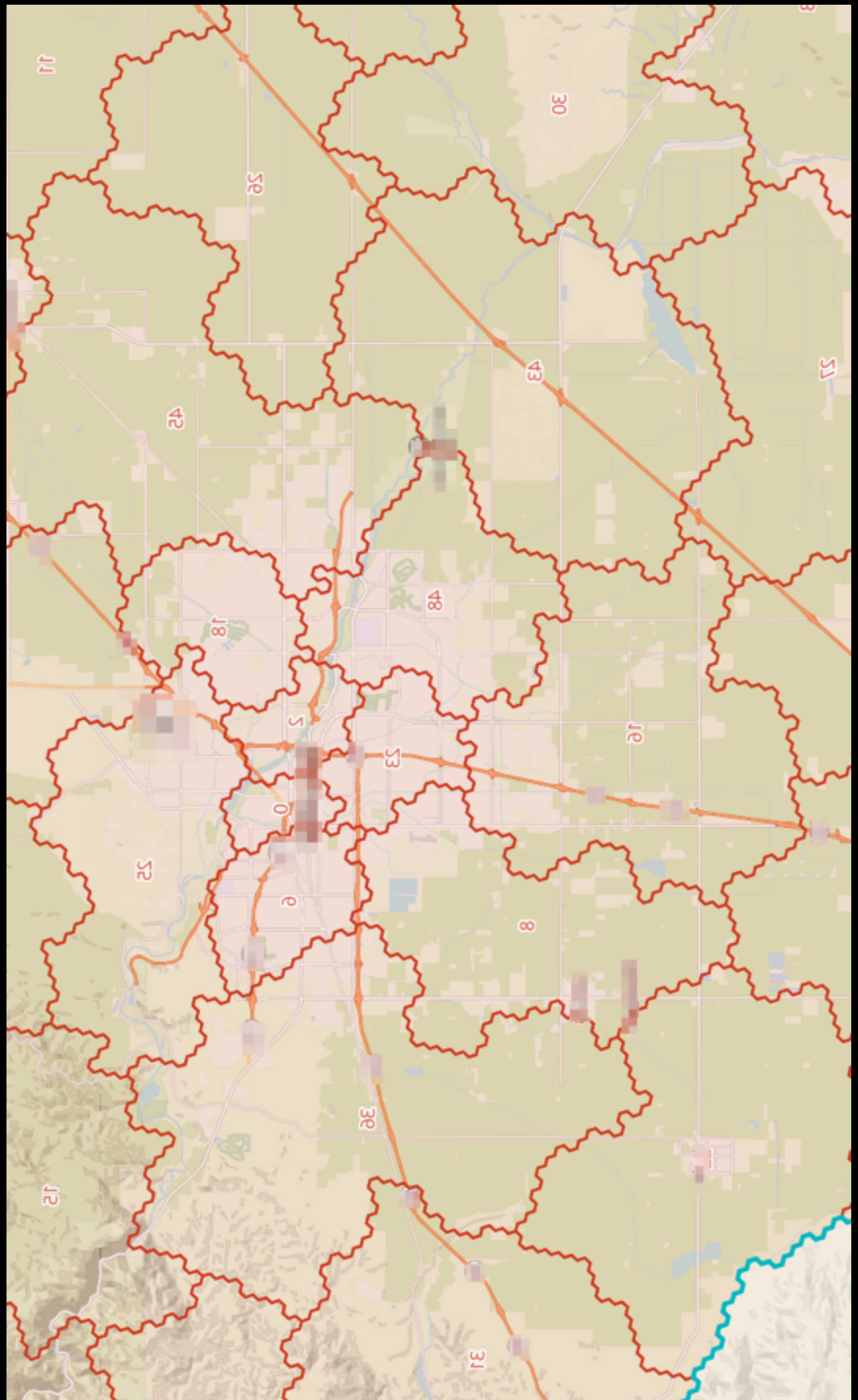

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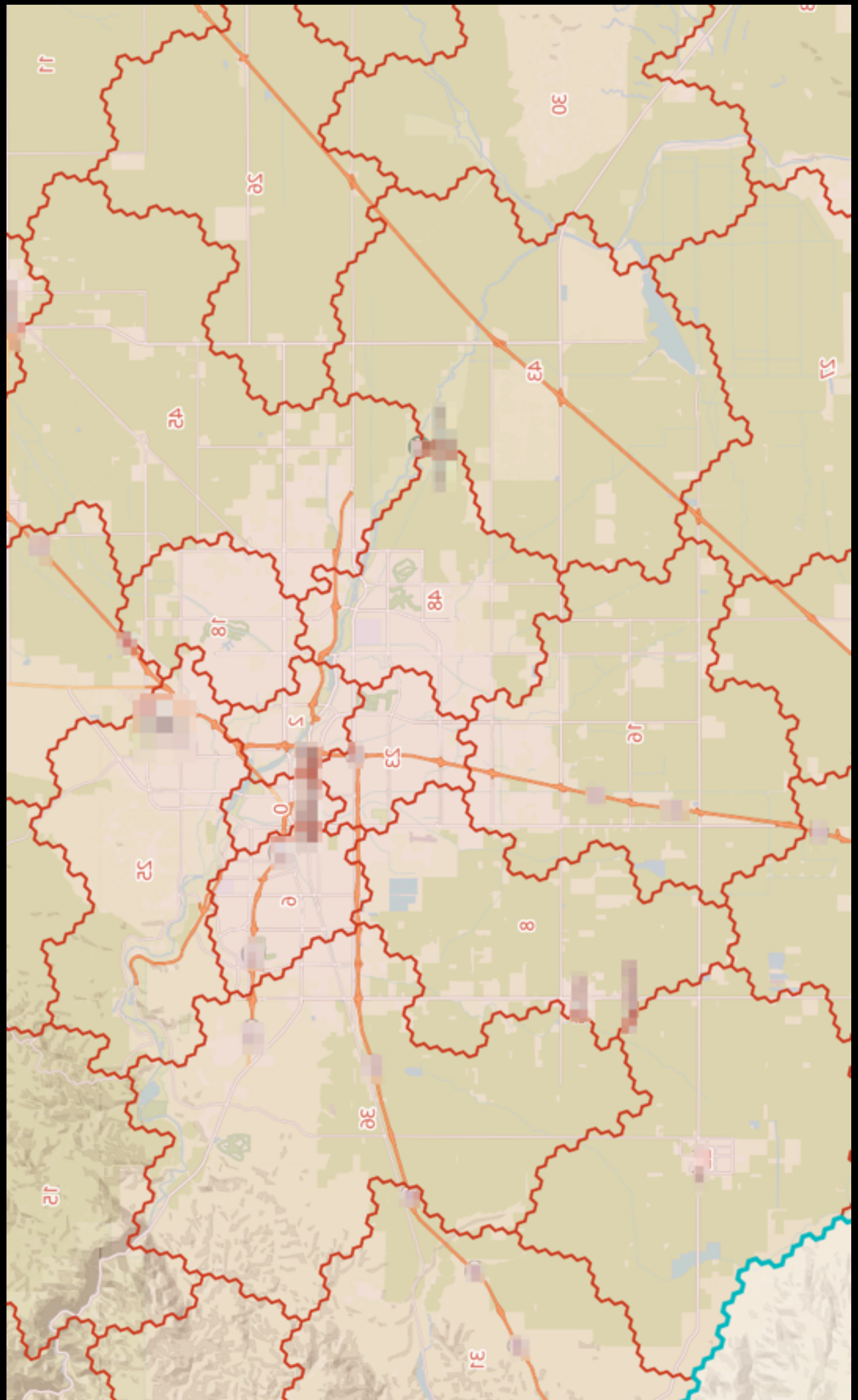
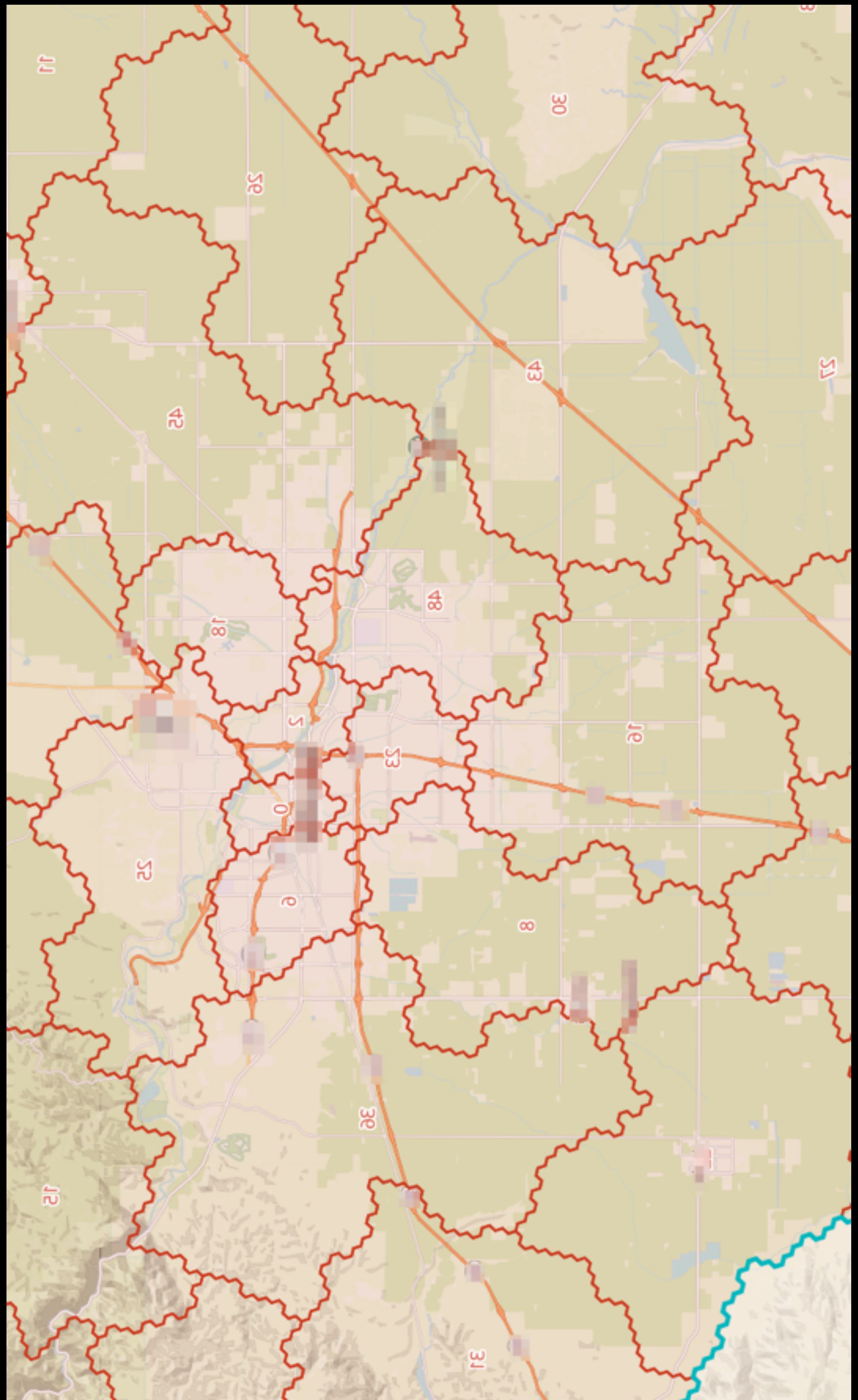


- All cities under 3 minutes
- Easily pluggable algorithms and measurements
- Historical geo-temporal data for clustering
- Real-time geo-temporal data for measurement
- Shared optimizations. To put things in perspective:
    - 70,000 hexagons in SF
    - Naive distance function requires at least 70,000 x 70,000 = 4.9 billion pairs!

Home-grown Clustering Service



- All cities under 3 minutes
- Easily pluggable algorithms and measurements
- Historical geo-temporal data for clustering
- Real-time geo-temporal data for measurement
- Shared optimizations
  - Incremental updates
  - Compact data representation
  - Memoization
  - Avoid anything more complex than O(nlog(n))

Forecasting

- Every decision is based on forecasting

Forecasting

- Forecasting based on both historical data and stream input

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Forecasting

- Spatially granular forecasting - down to every hexagon

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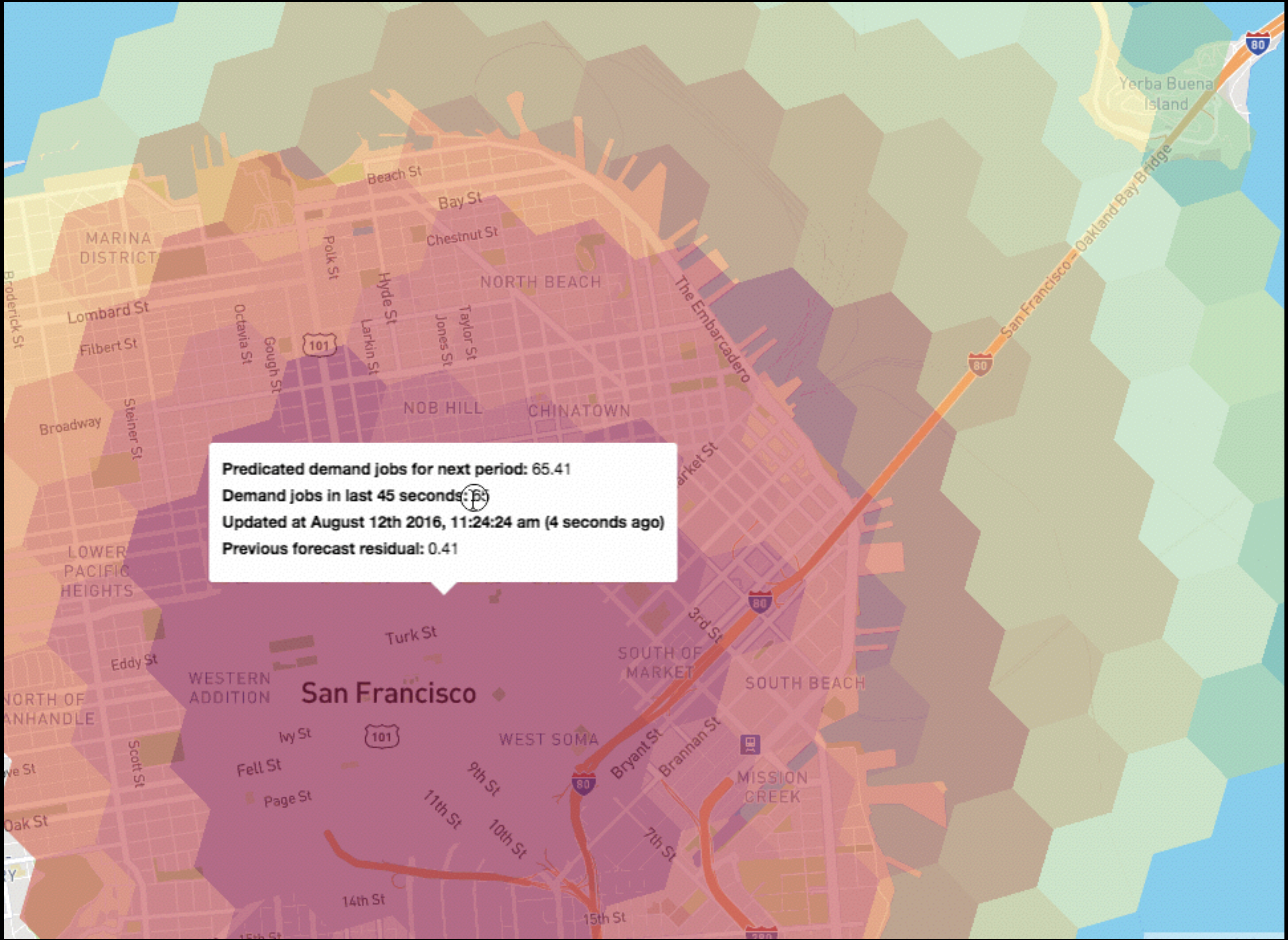

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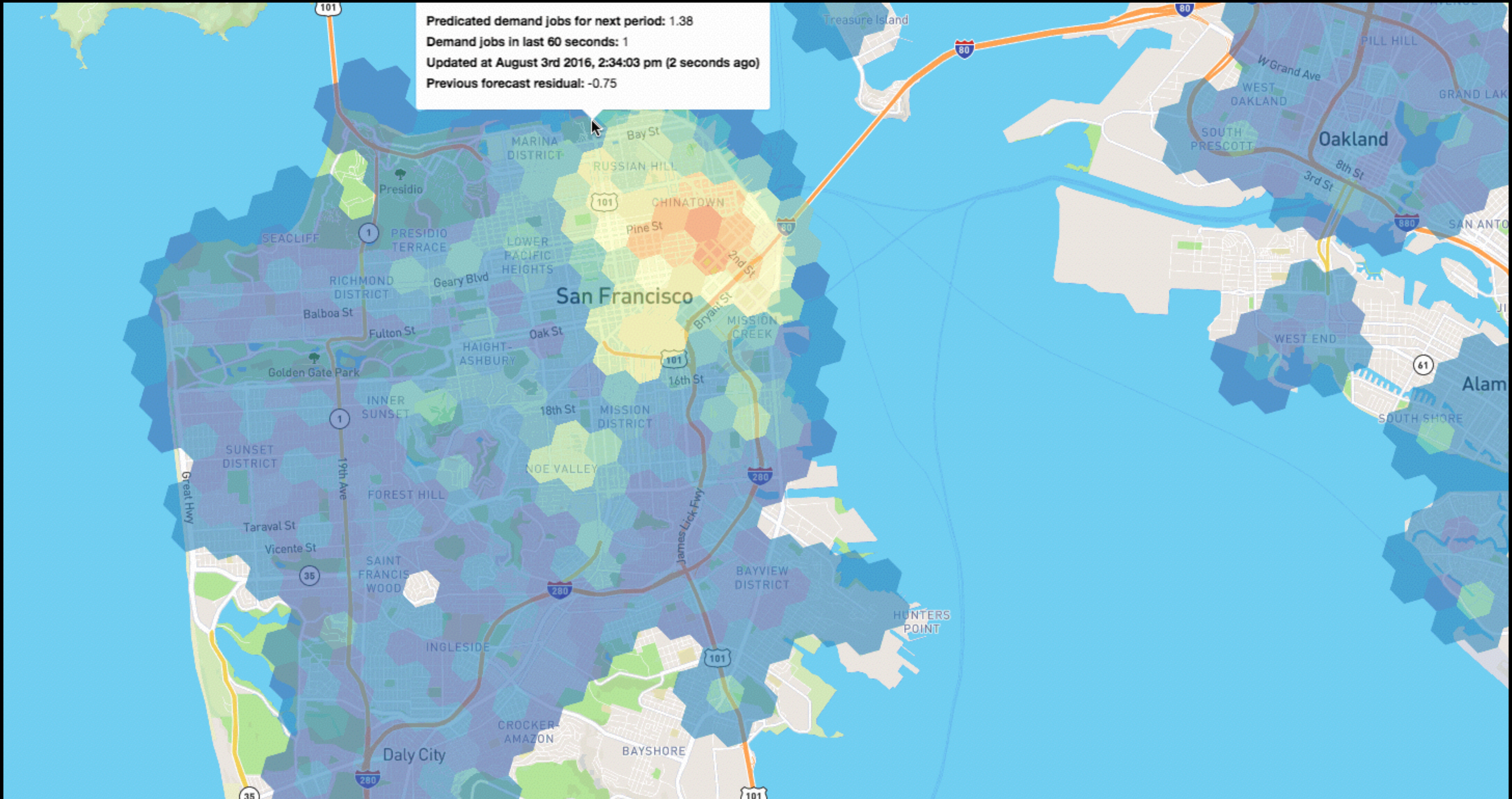


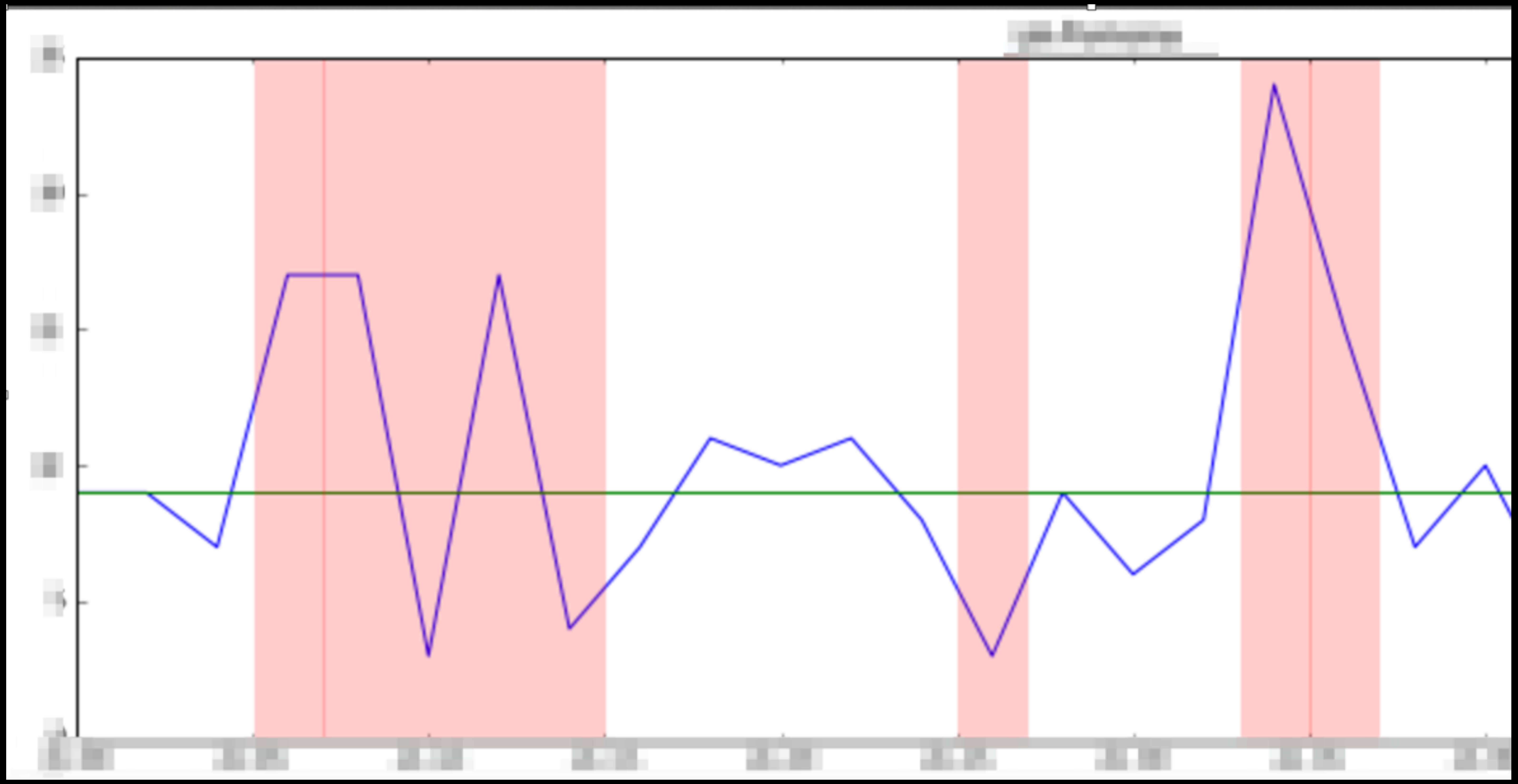
Pattern Detection

- Similarity of different metrics across geolocation and time
- Metric outliers across geolocations and time
- Frequent occurrences of certain patterns
- Clustered behavior
- Anomalies

Common Requirements in Pattern Detection

- Not just traditional time series analysis
- Incorporating insights on marketplace data
- Required both historical data and real-time input
- Spatially granular patterns - down to every hexagon
- Temporally granular patterns - down to every minute

Example: Anomaly Detection



- Simple time series analysis
- For a single geo area
- Can be noisy

A More Realistic Anomaly Detection

Example: Anomaly Detection

Example: Anomaly Detection

What’s the right architecture to support the analytics use cases?

Shared abstraction: multi-dimensional geo-temporal data

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- Time series by event time

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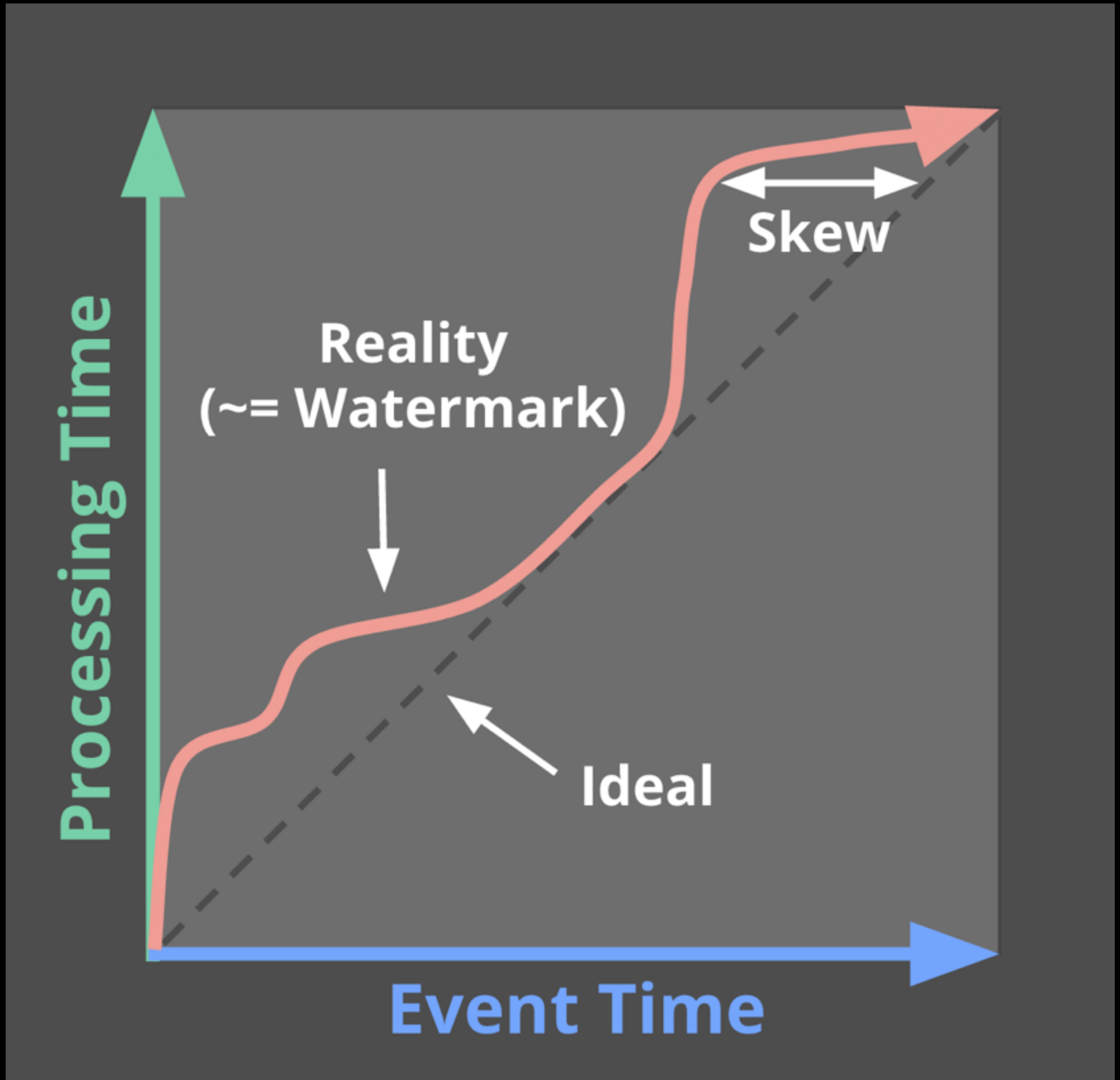

https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-101

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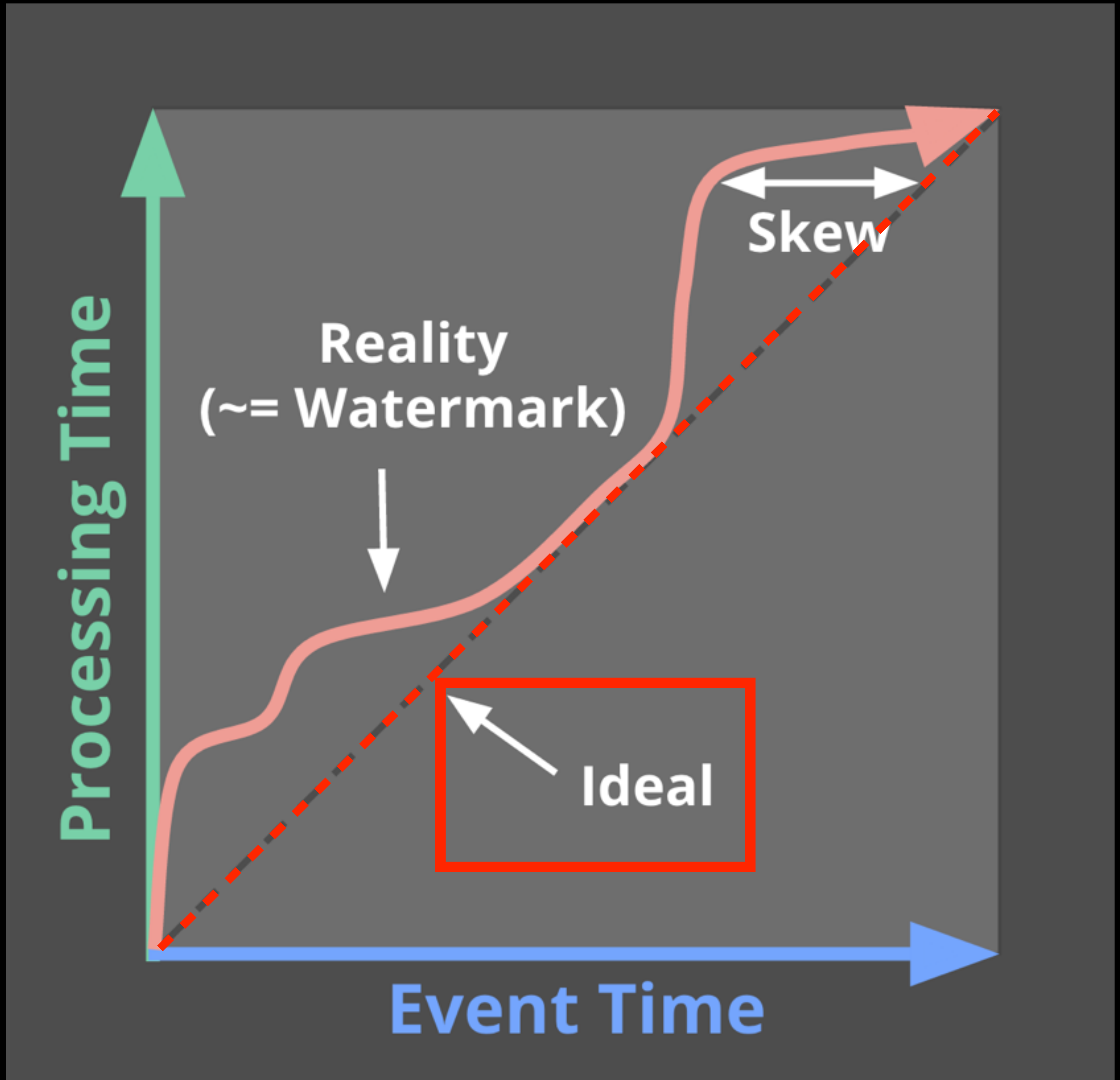

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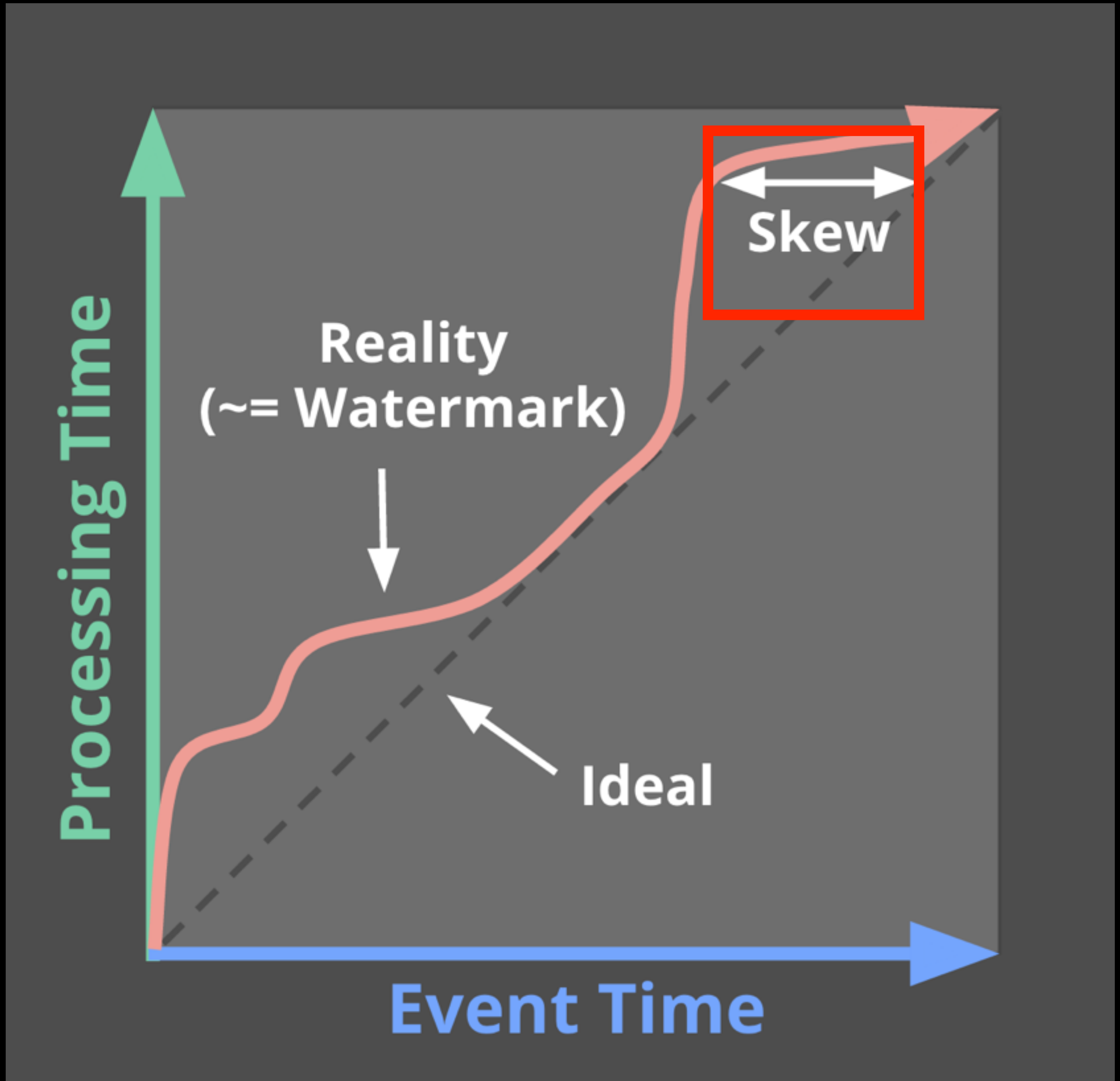

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  - e.g. event-based triggers
  - e.g., triggers of computation results

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- Stateful processing

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State per key

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- Unified stream

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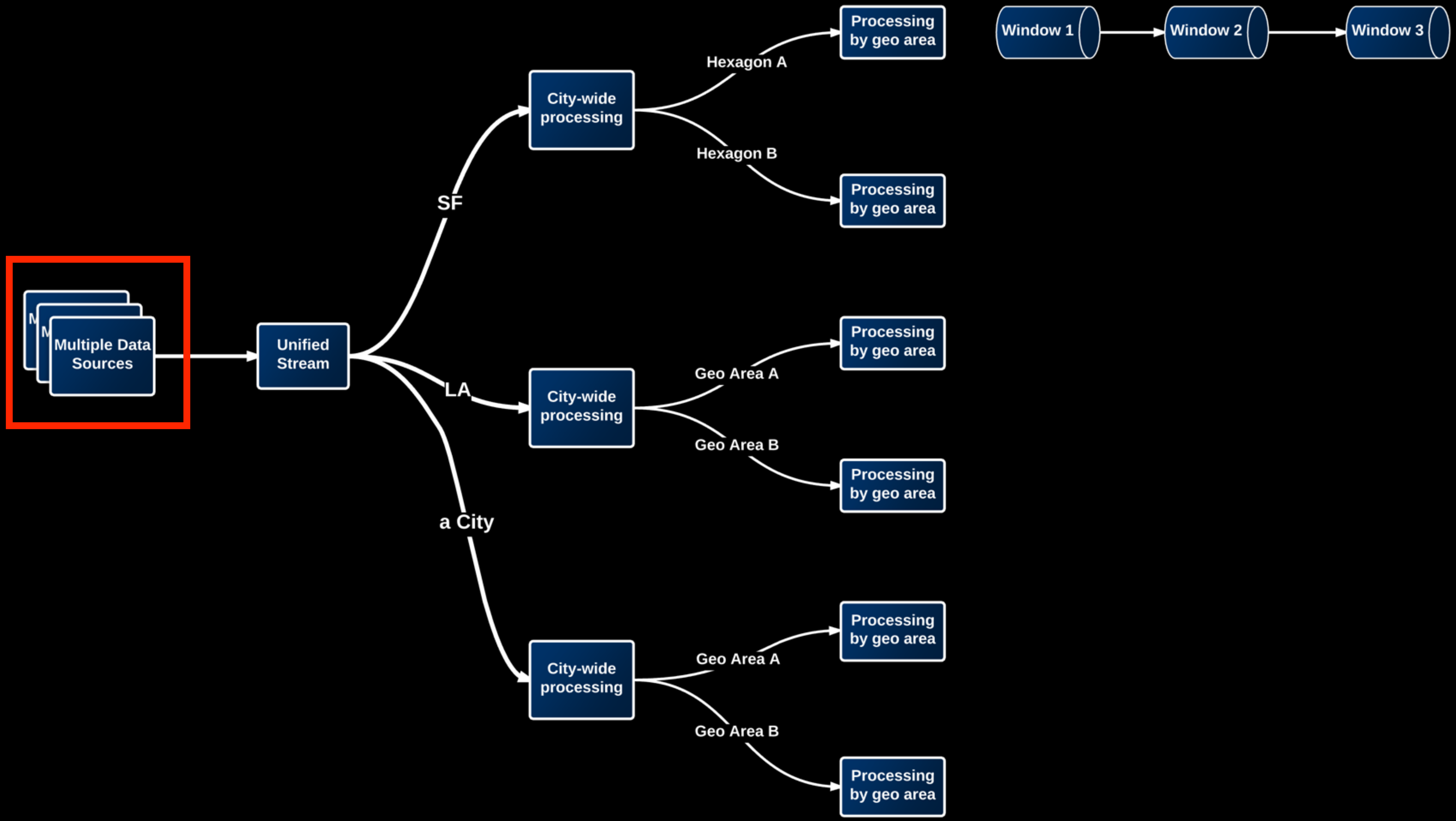
- Unified stream
    - Real-time streams: unbounded streams
    - Batch: bounded streams
    - s/lambda/kappa

Apache Flink

- Ordering by event time
- Flexible windowing with watermark and triggers
- Exactly-once semantics
- Built-in state management and checkpointing
- Nice data flow APIs

Mental Picture for Processing Geo-temporal Data



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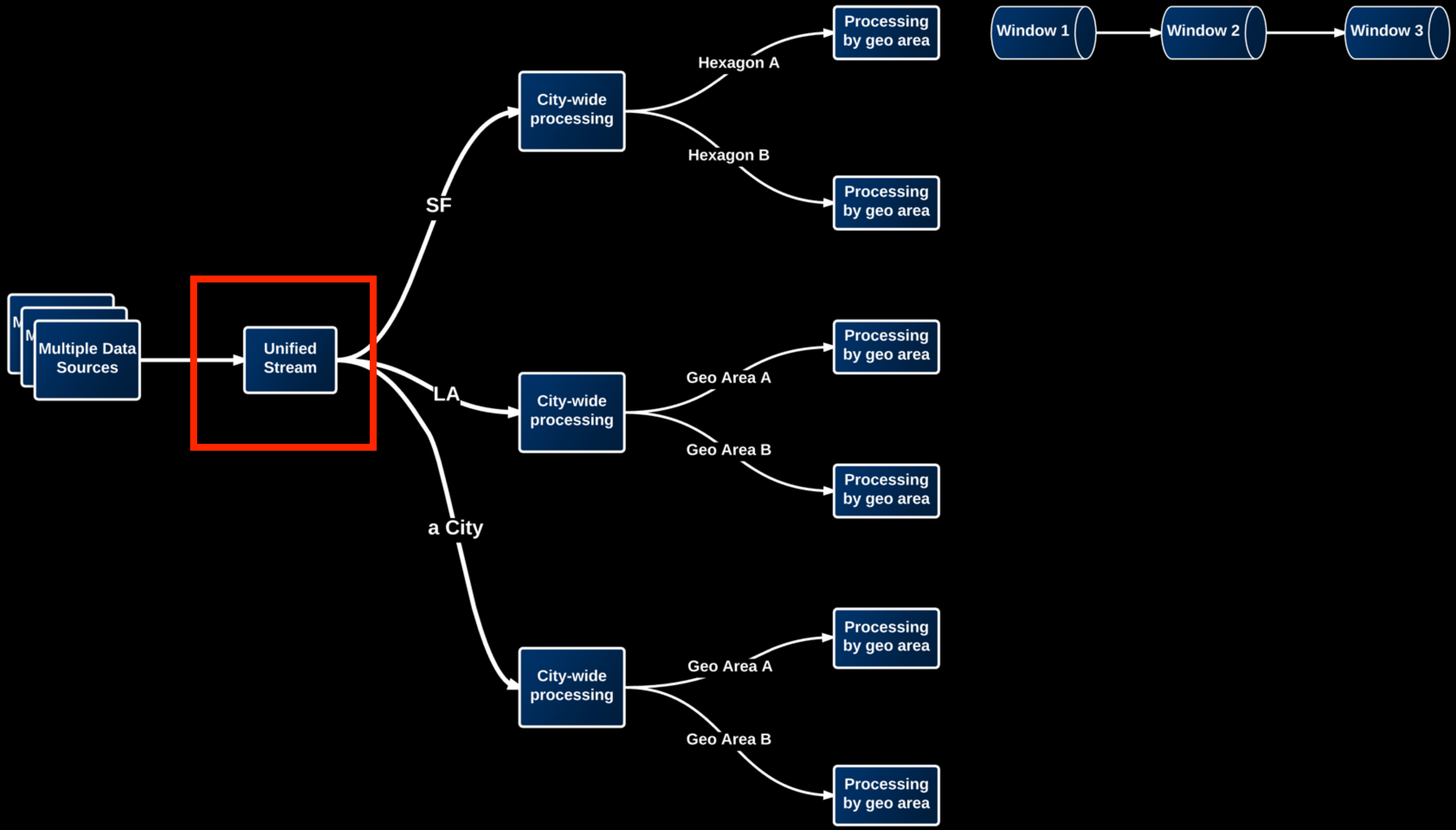

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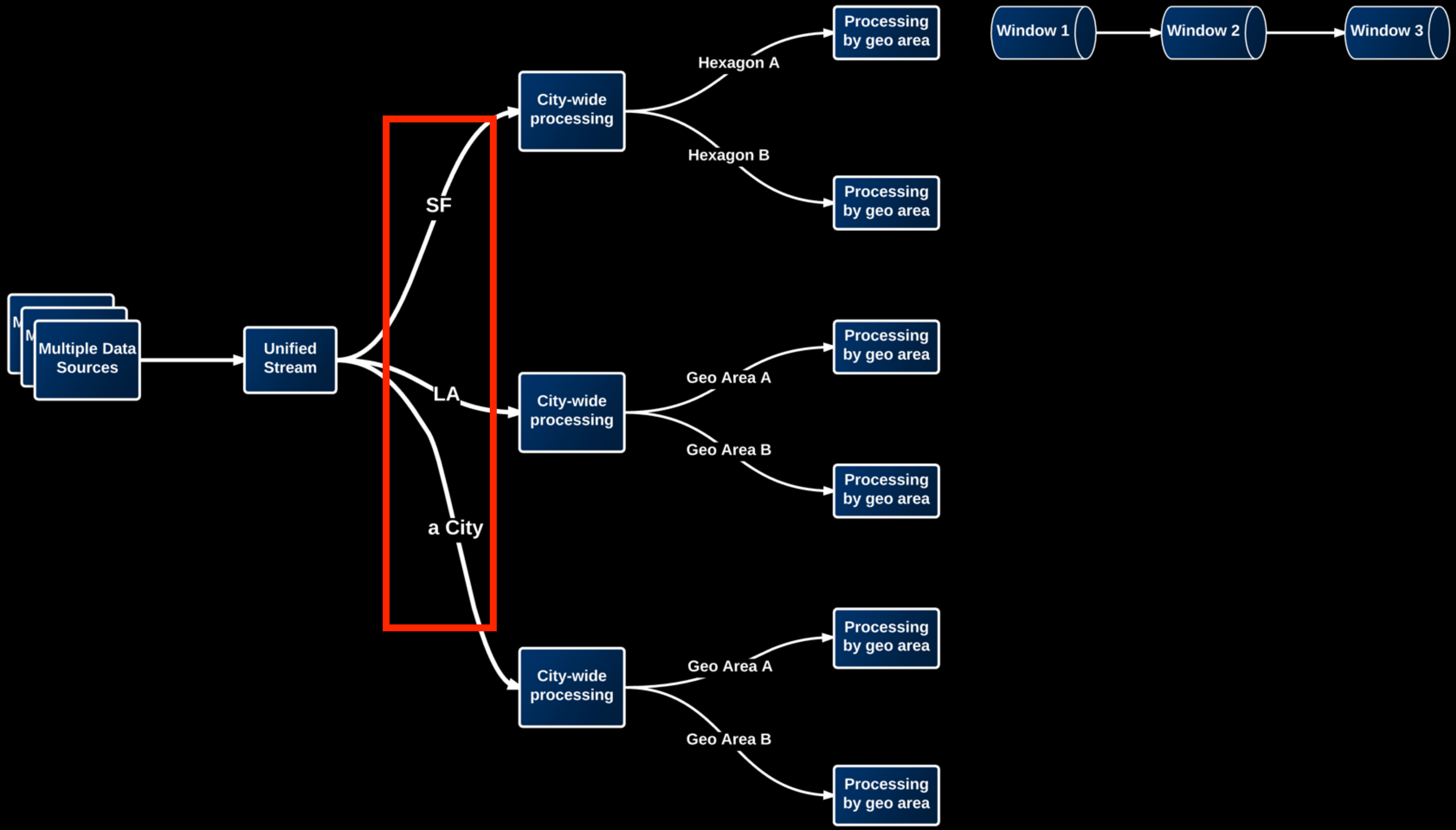

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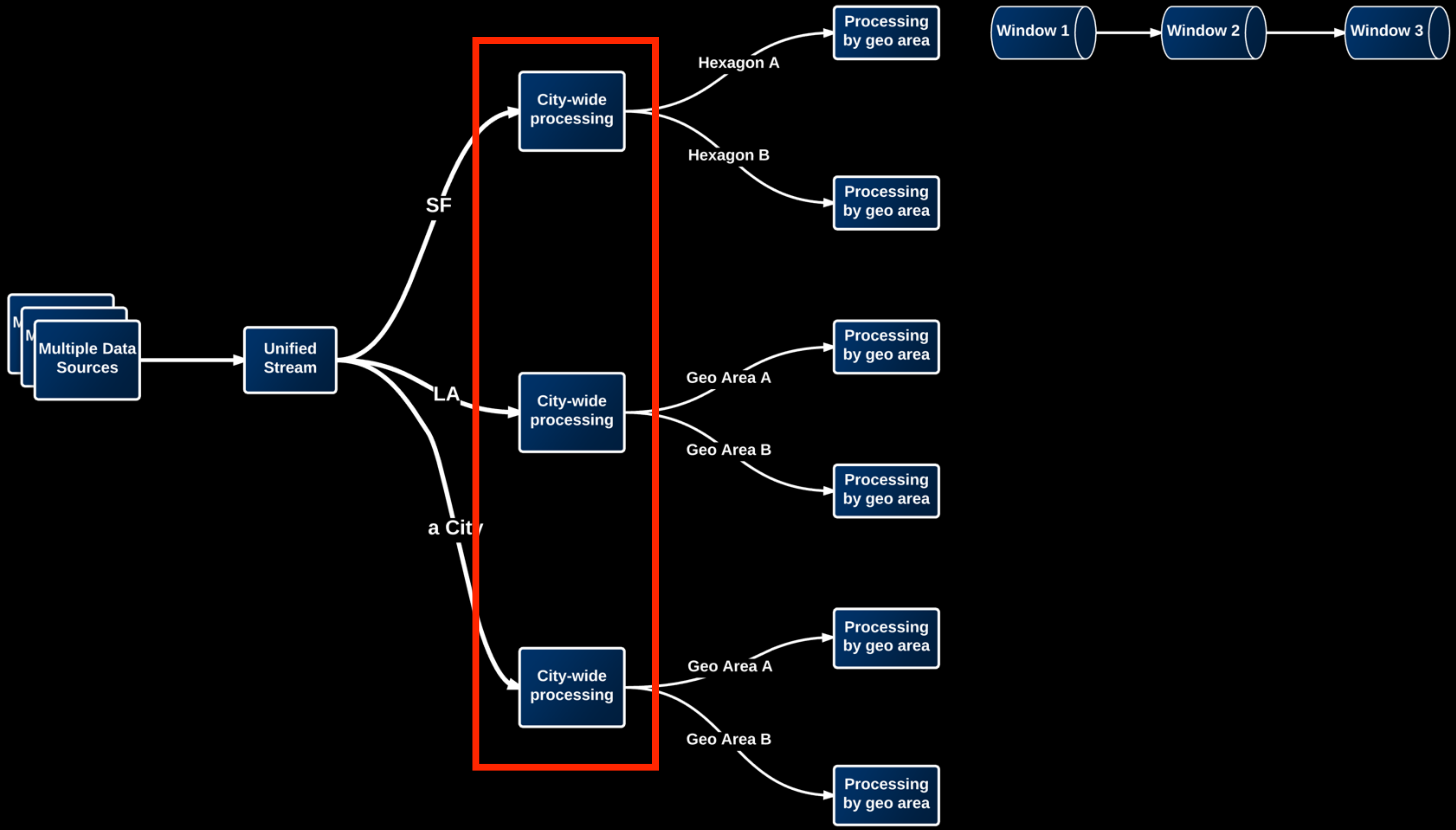

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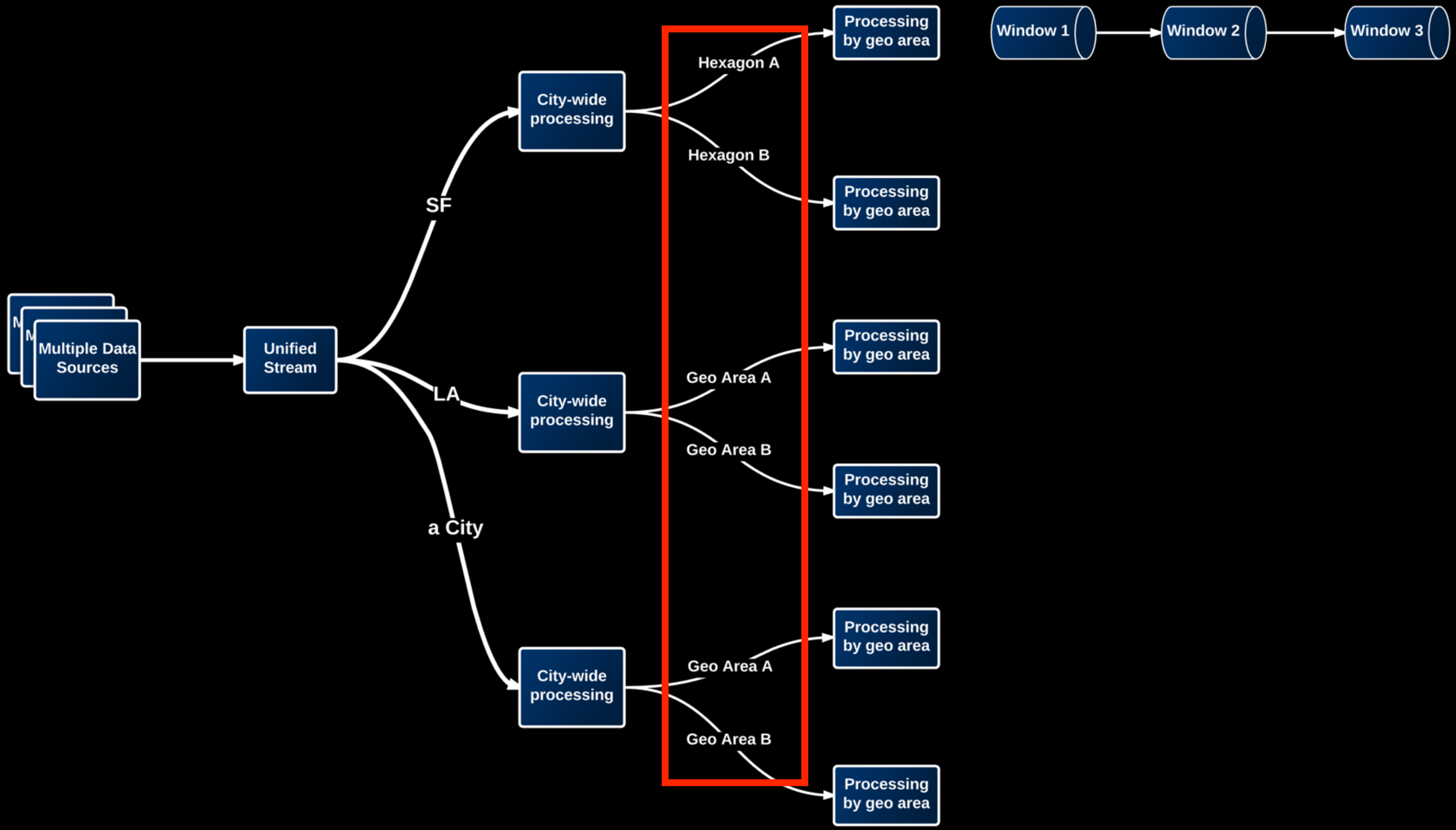

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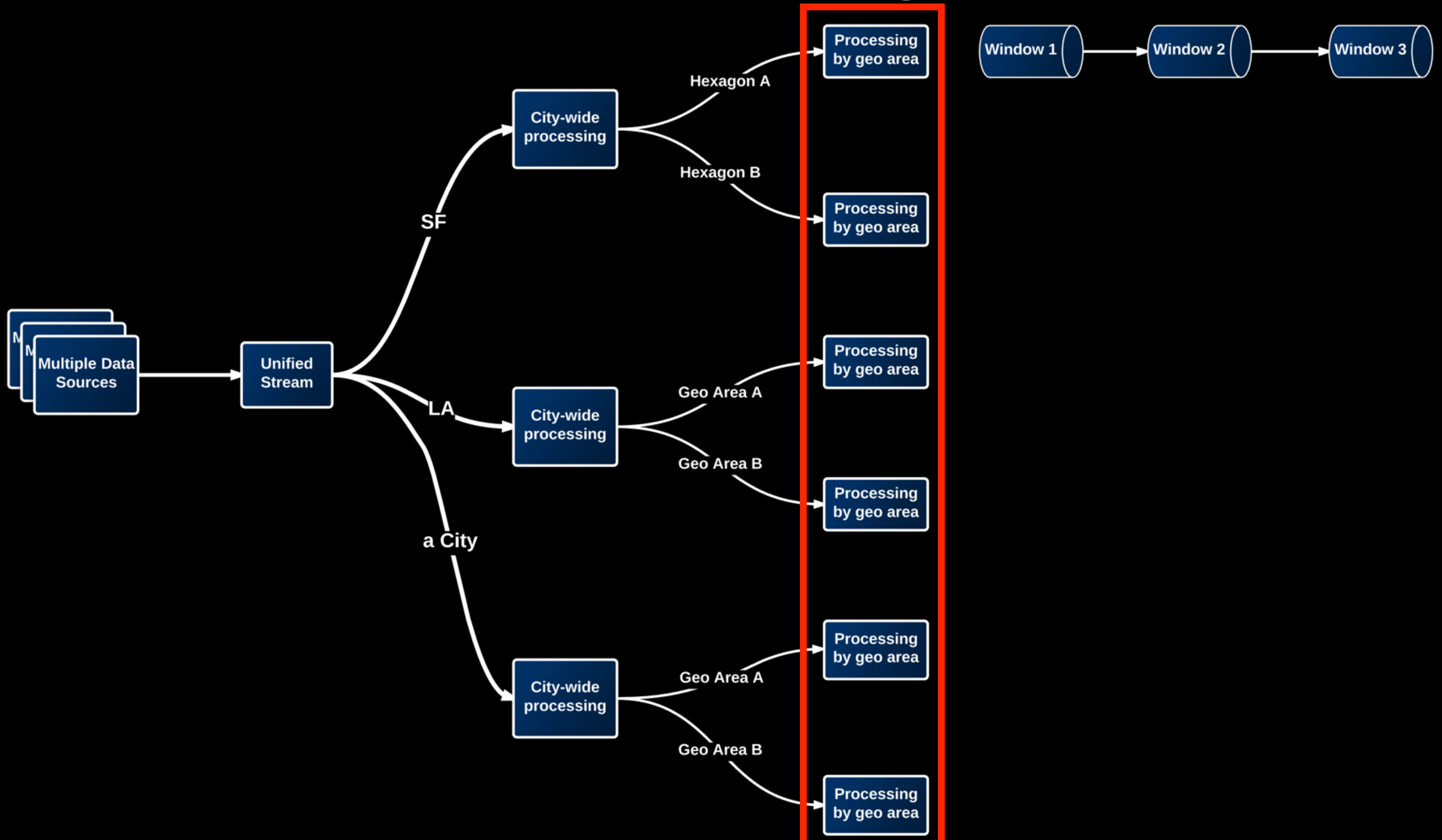

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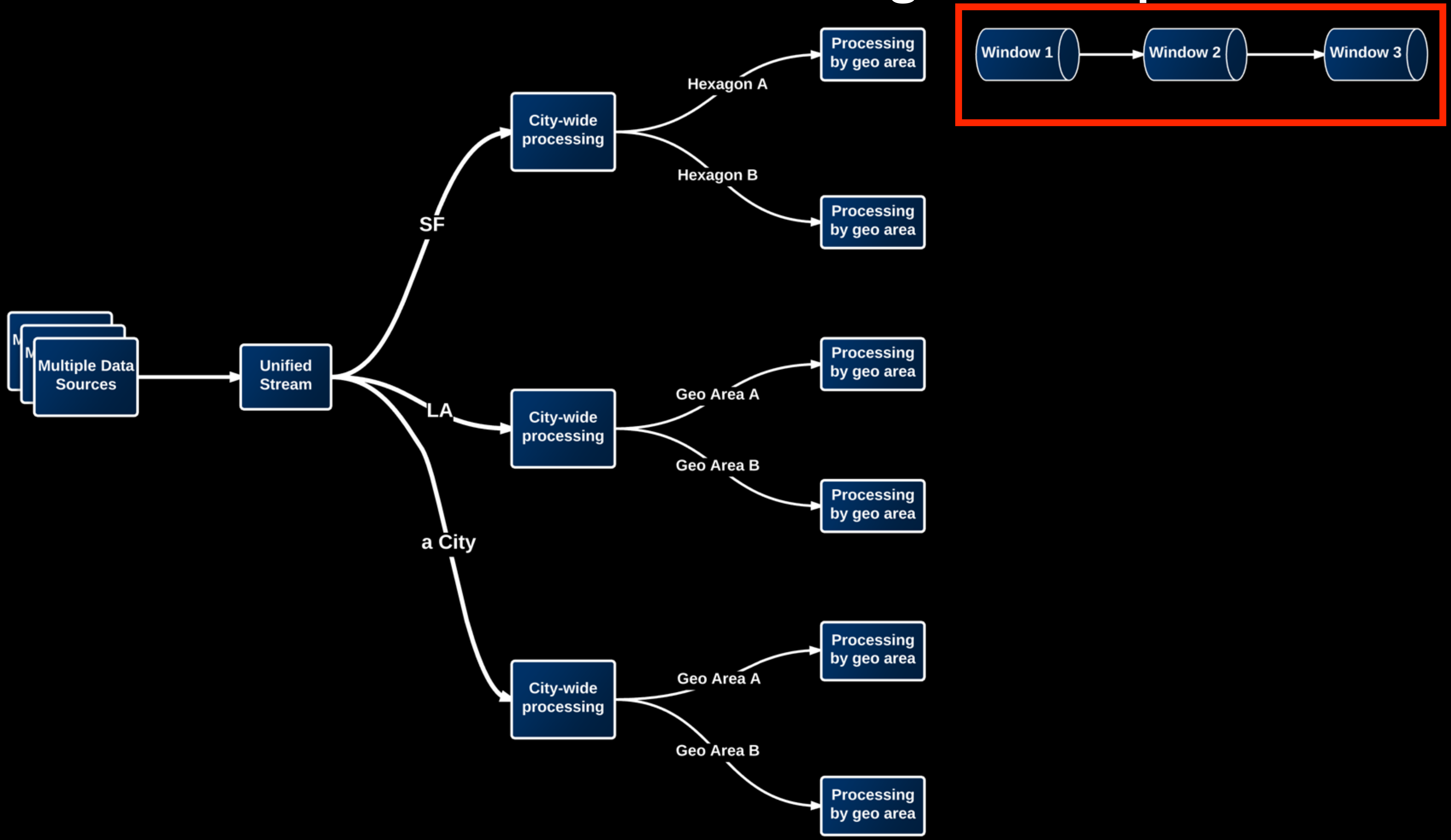


A Simple Example: simple prediction

Sources

```
.fromKafka()
.config(config)
.cluster(aCluster)
.topics(topicList)
```

A Simple Example

`assignTimestampsAndWatermarks`

A Simple Example

keyBy(...)

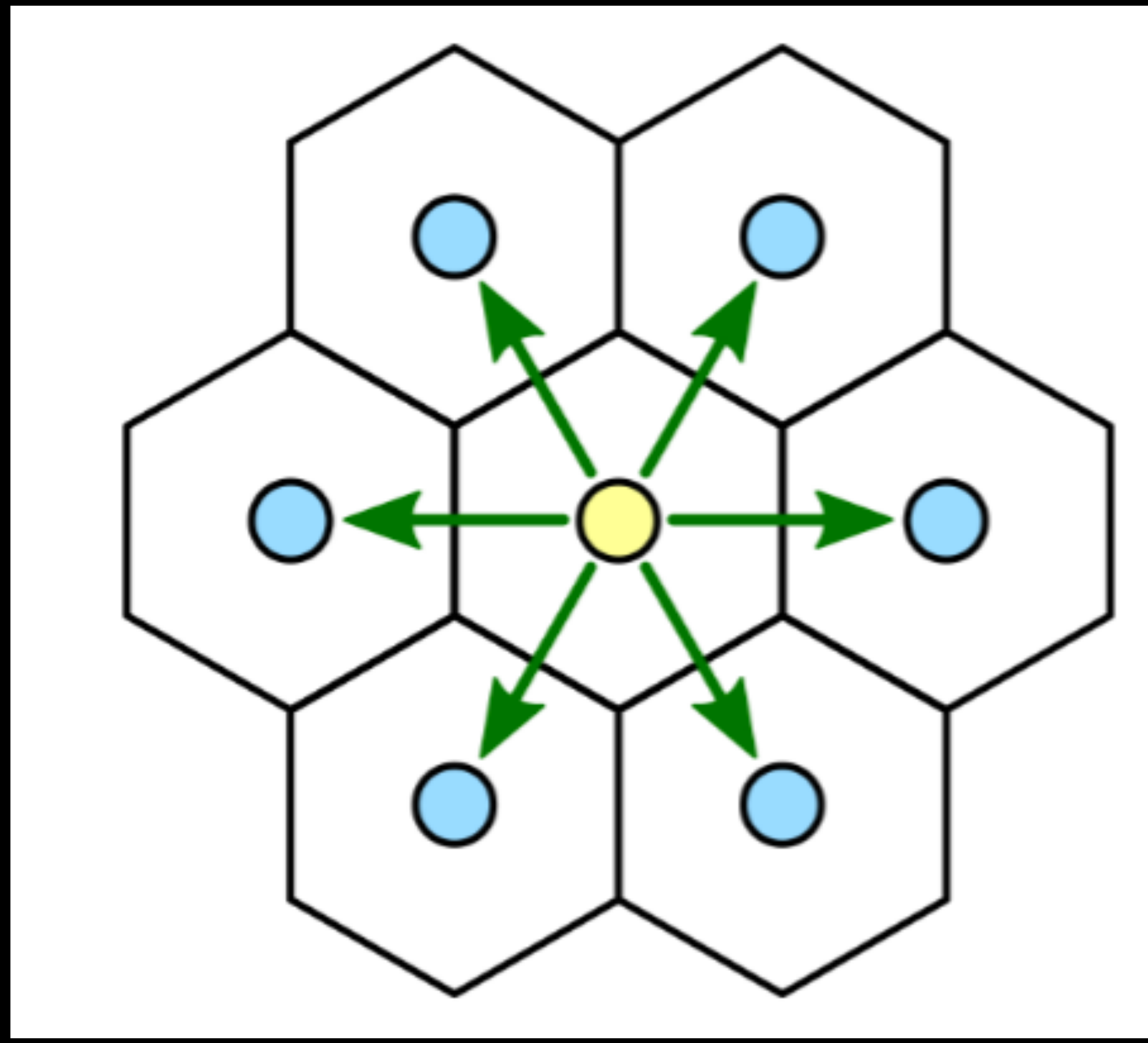
A Simple Example

`.timeWindow(…)`

A Simple Example

Kafka → Extract/decode timestamp → Key by city → Window by event time → Spatial Smoothing → Key by hex → Stateful prediction → Sink

.flatMap(…)



A Simple Example

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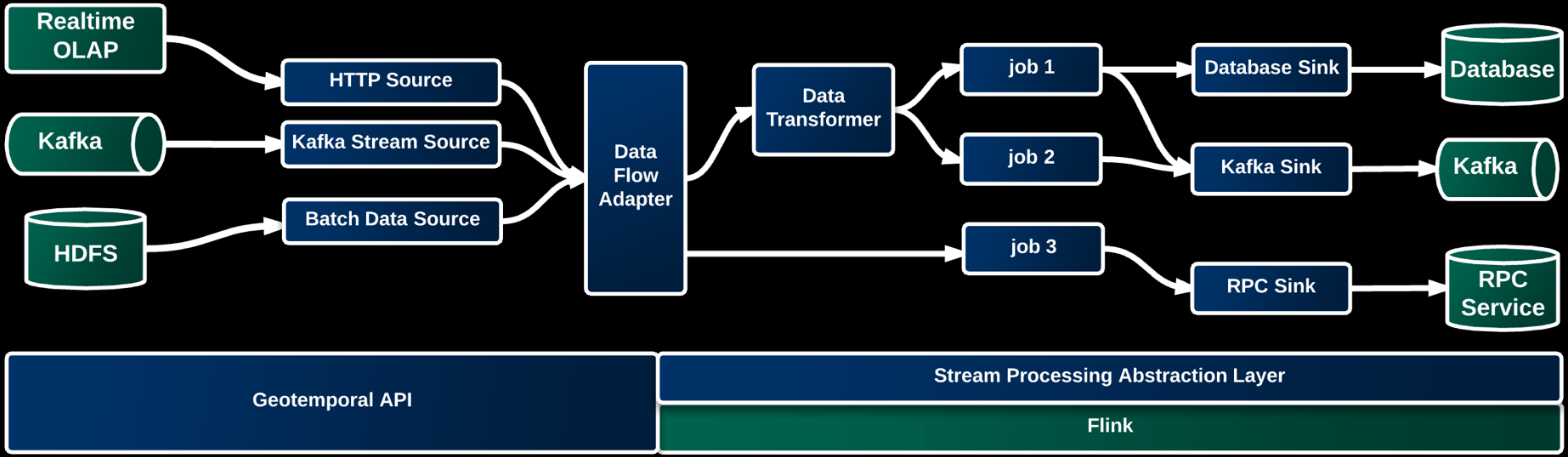
`.addSink(…)`

High Level Data Flow



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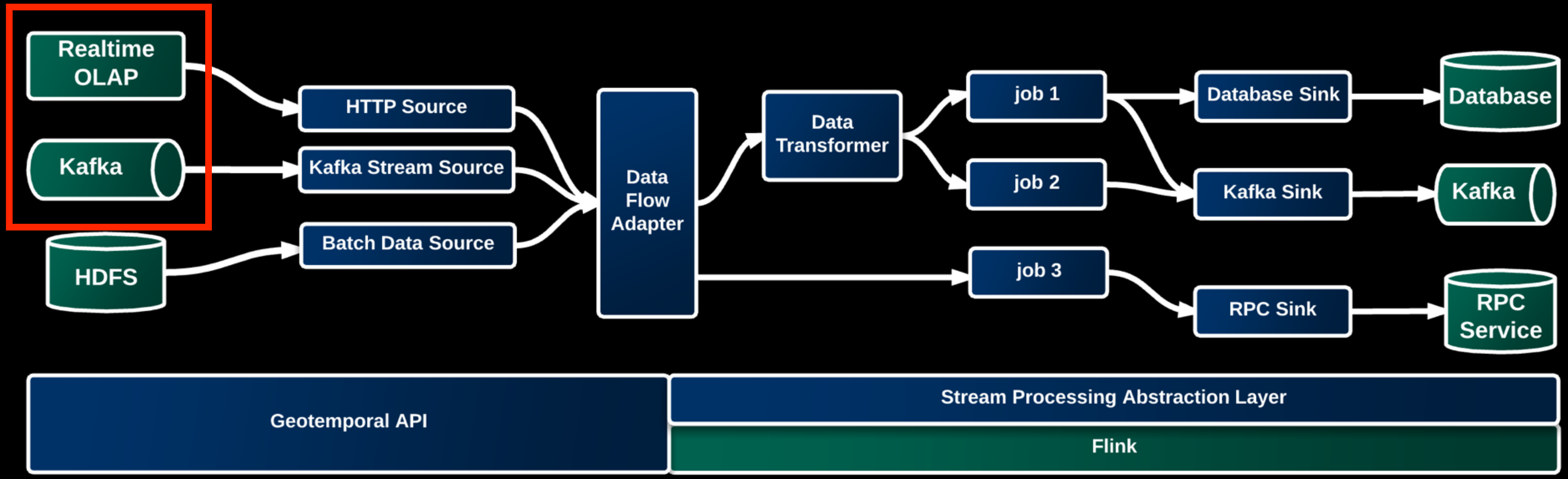

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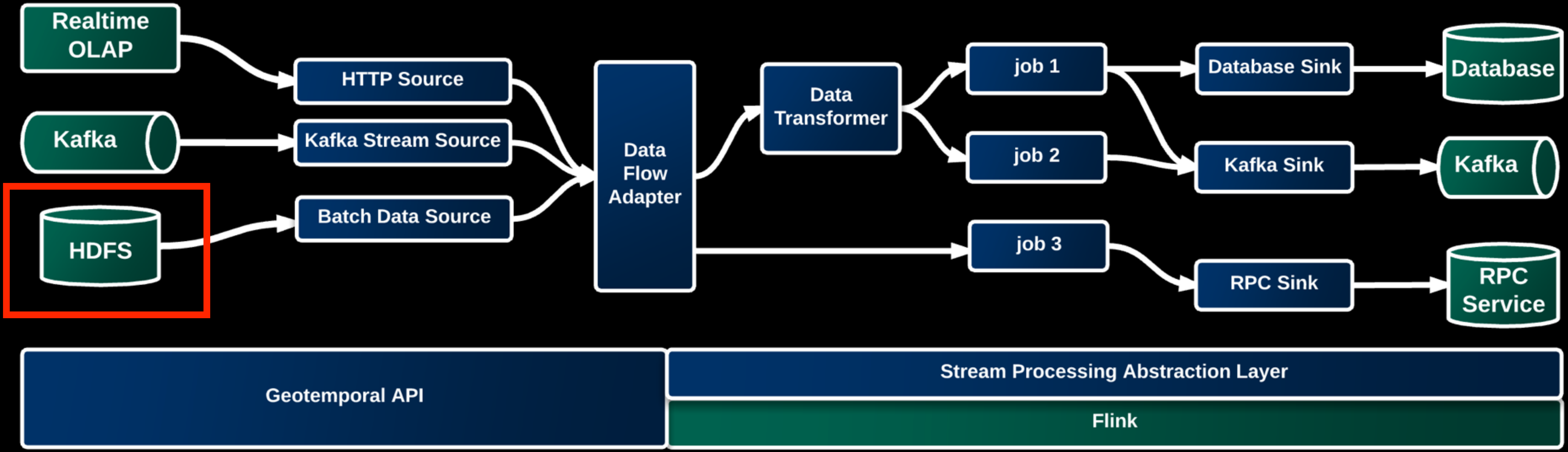

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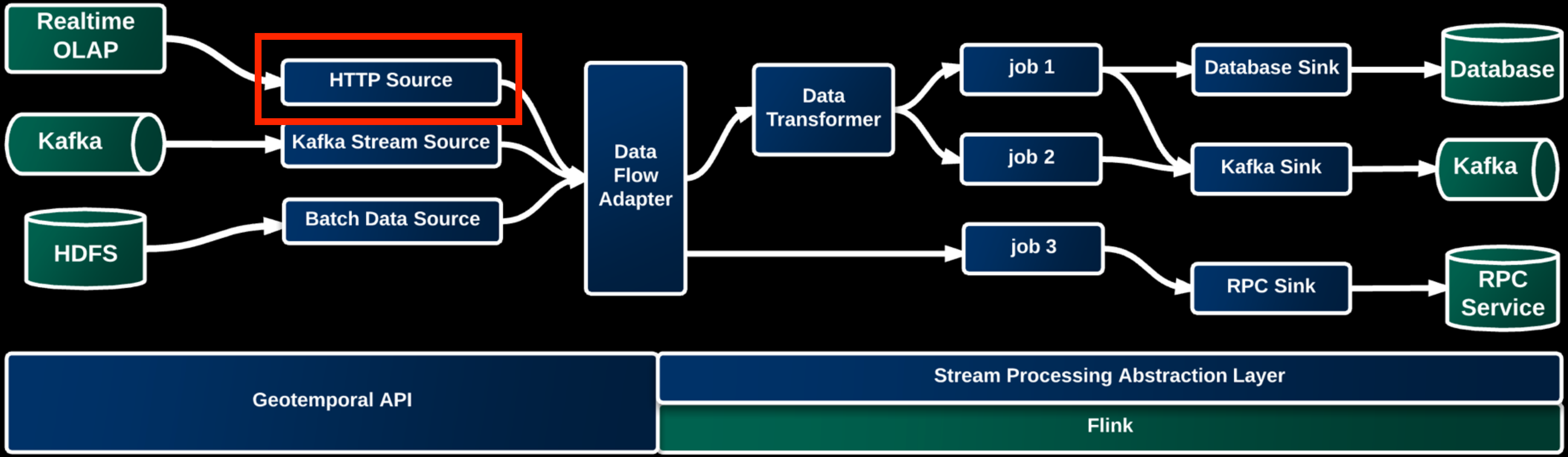

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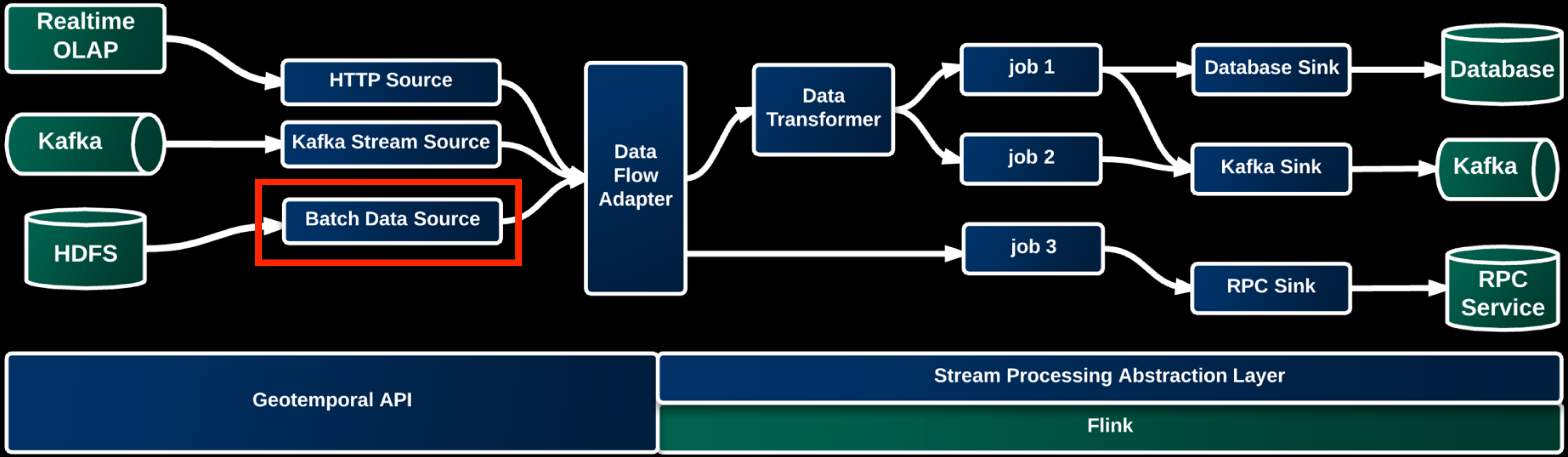

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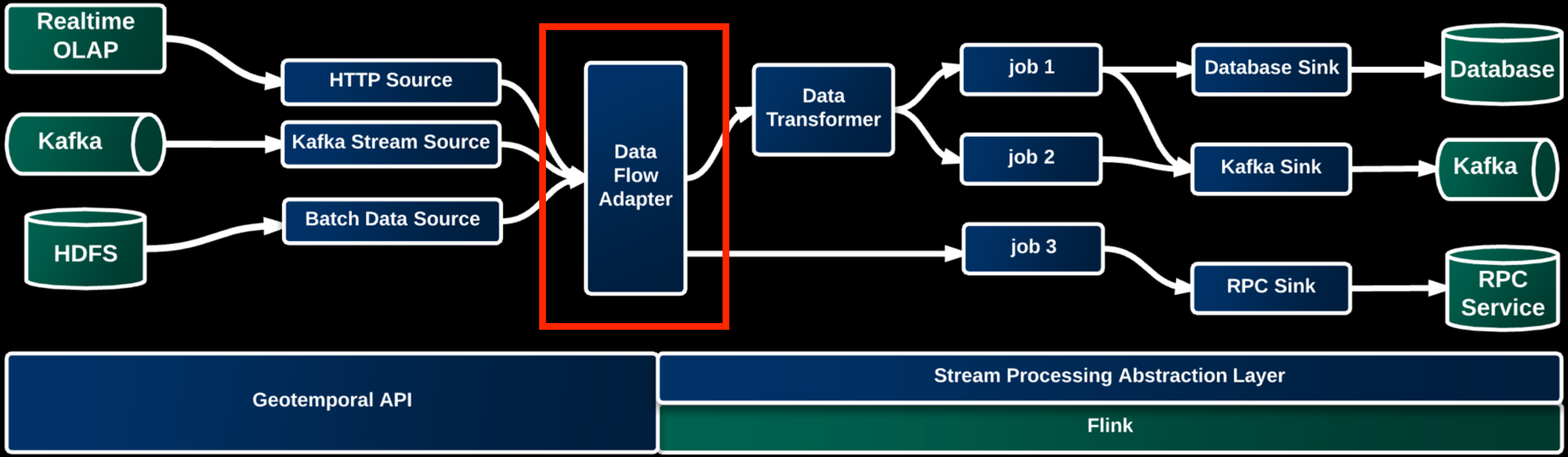

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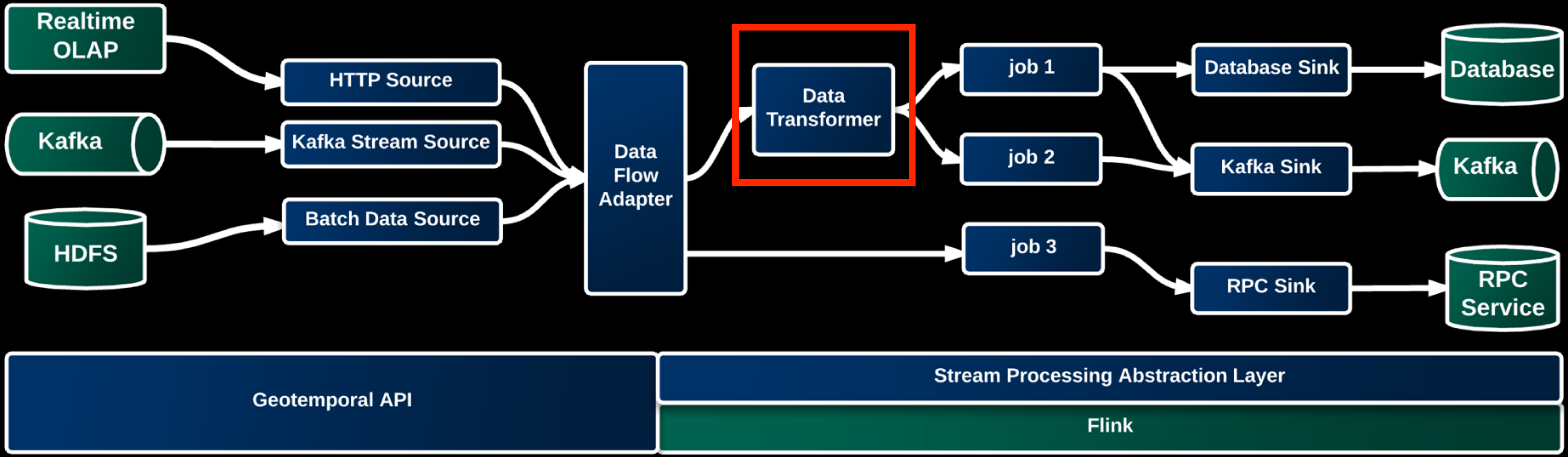

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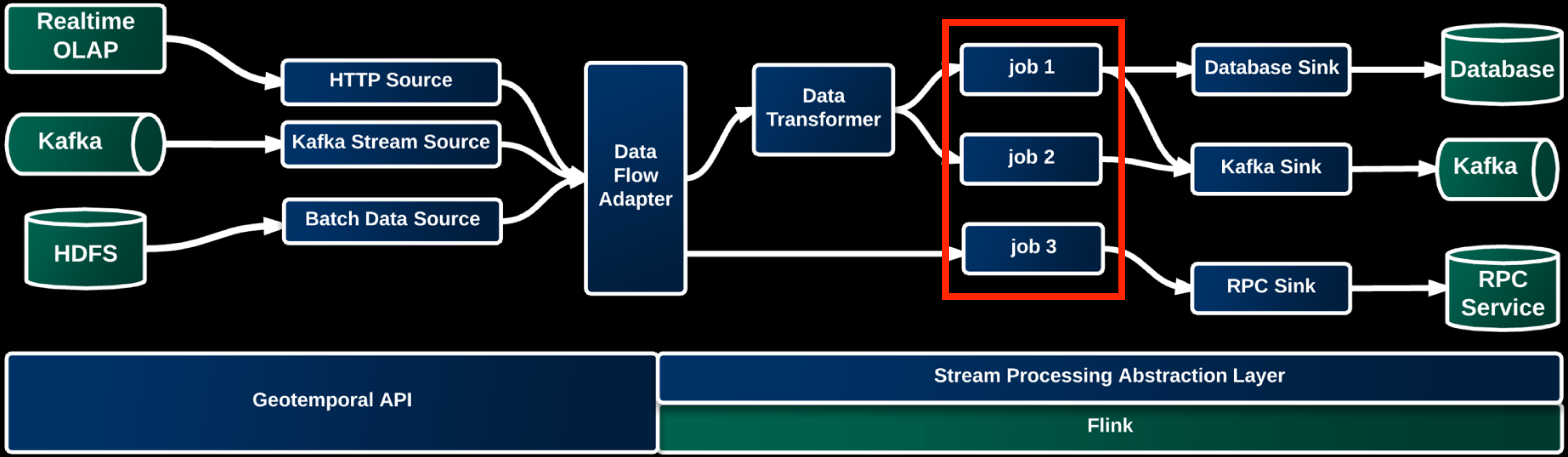

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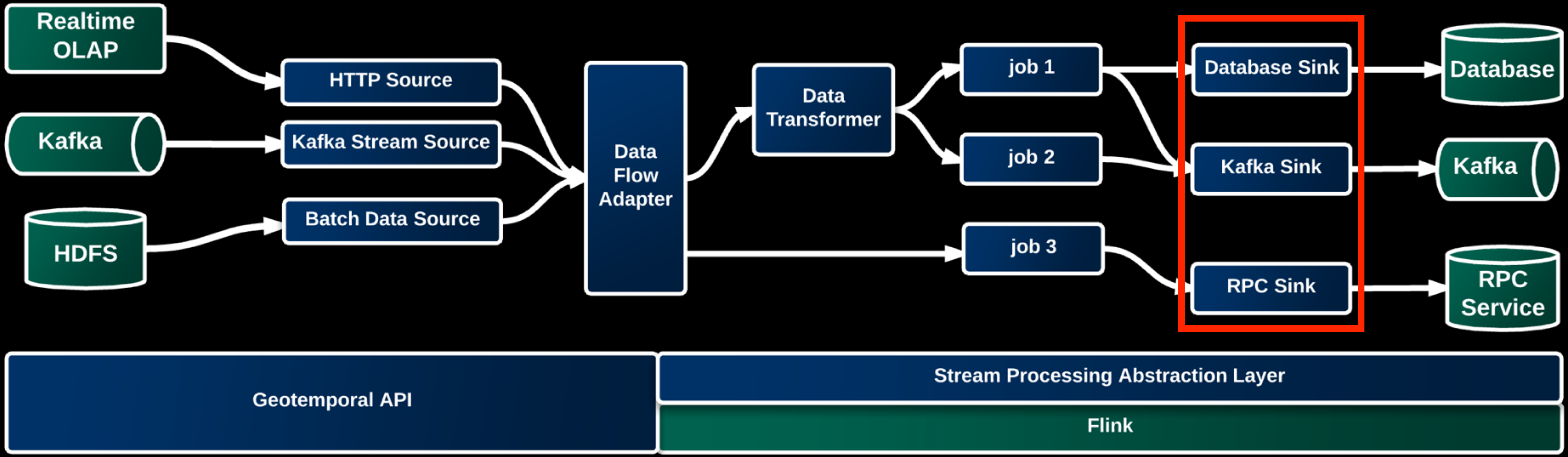

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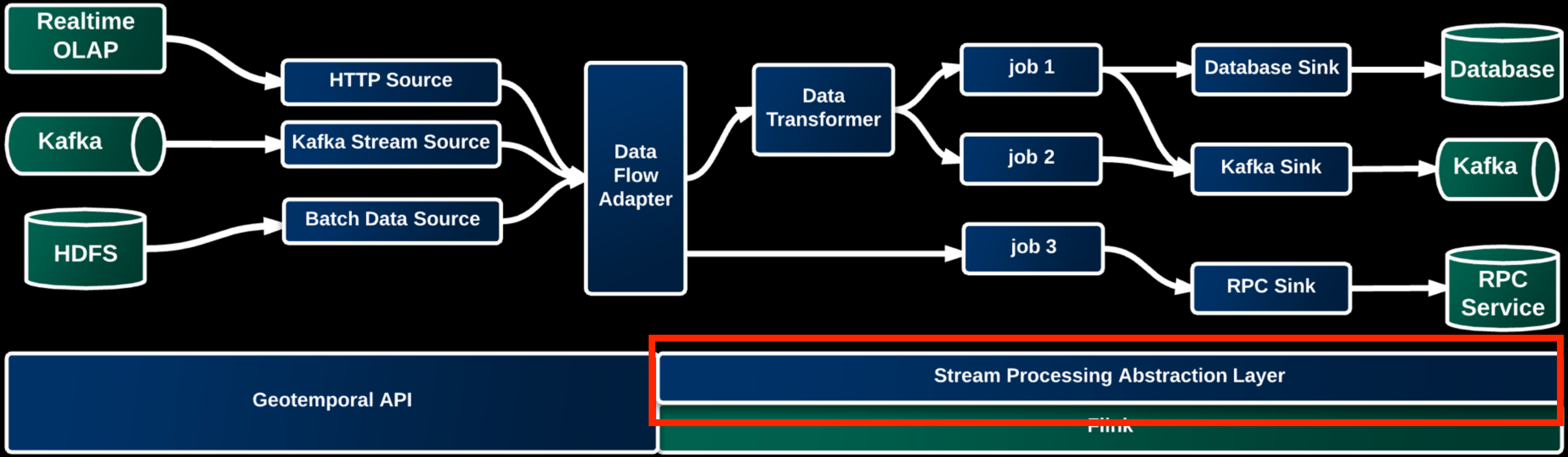
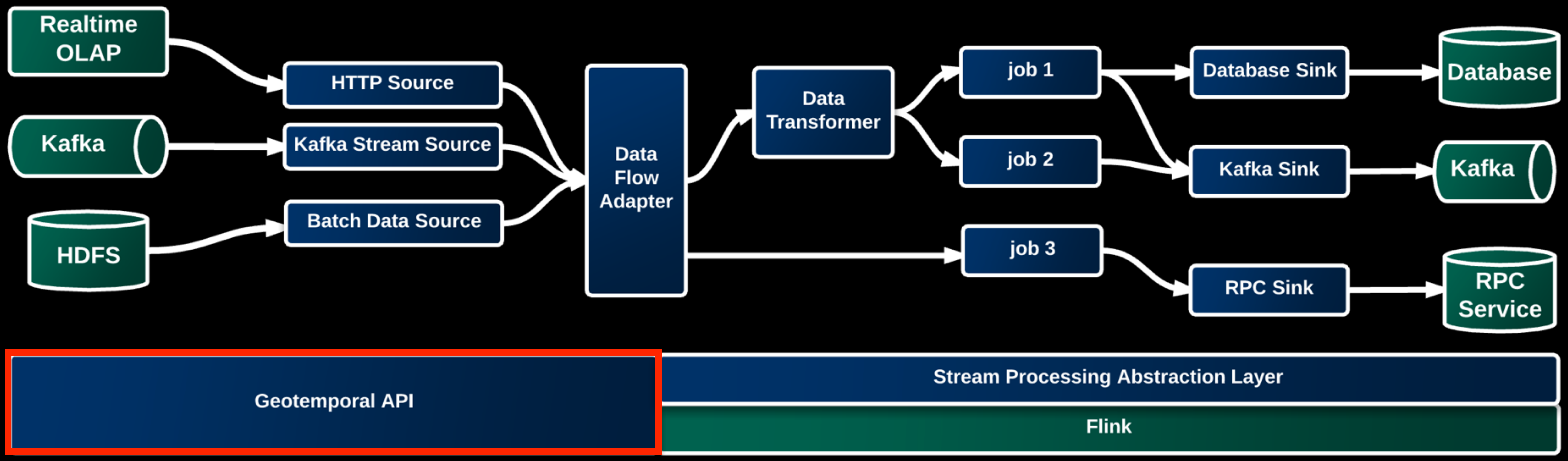
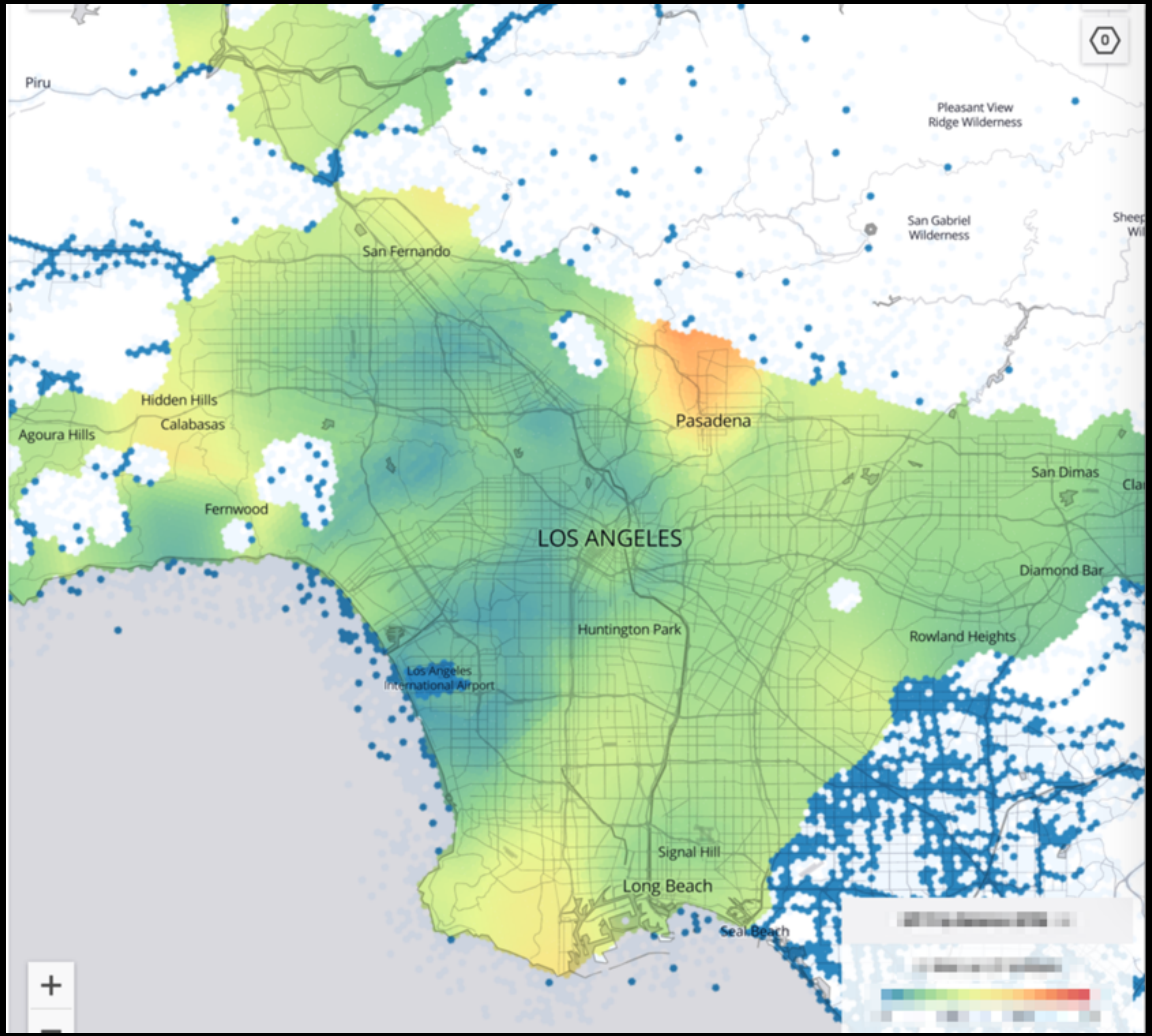
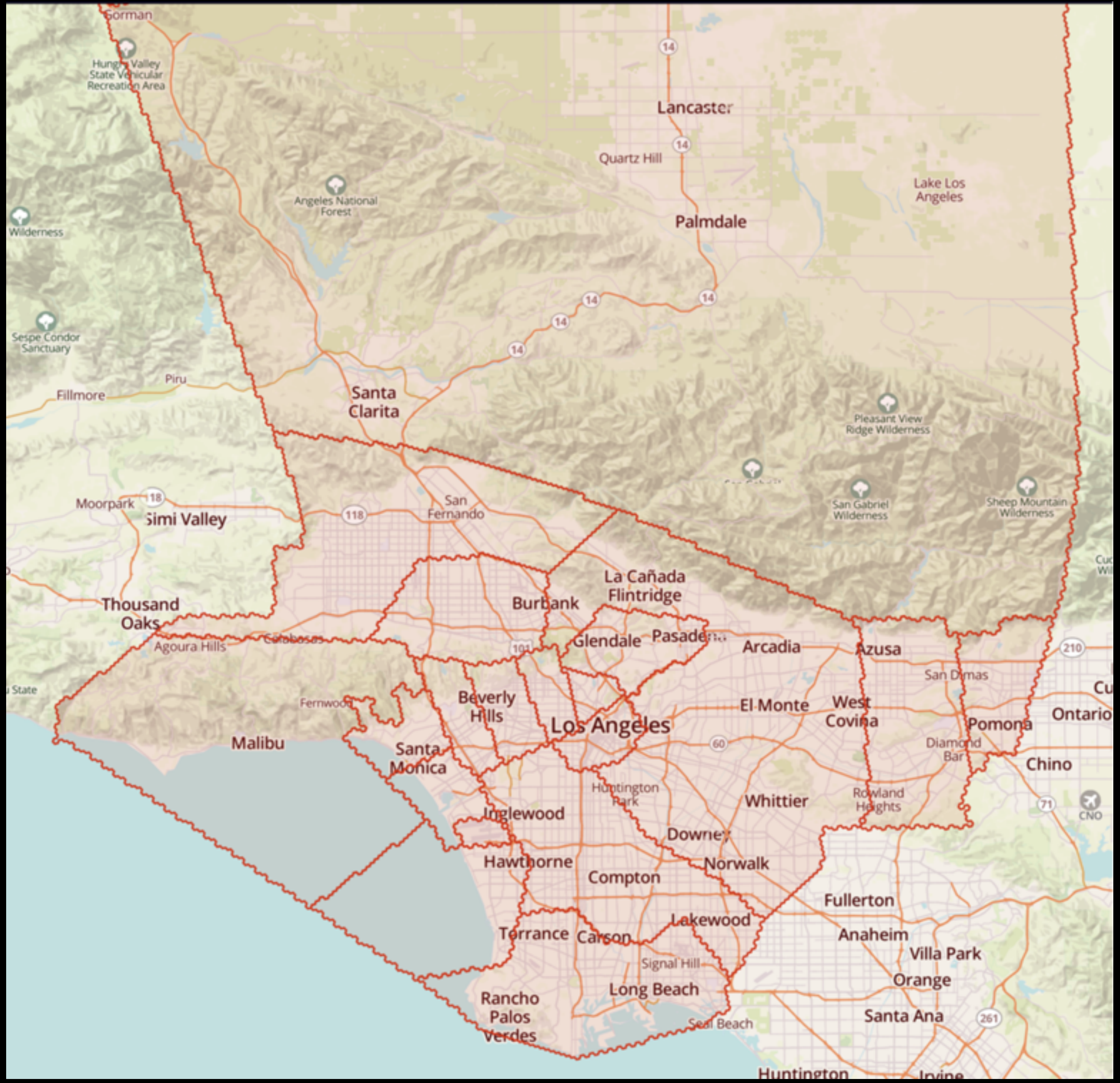


High Level Data Flow



Geotemporal API for efficiency





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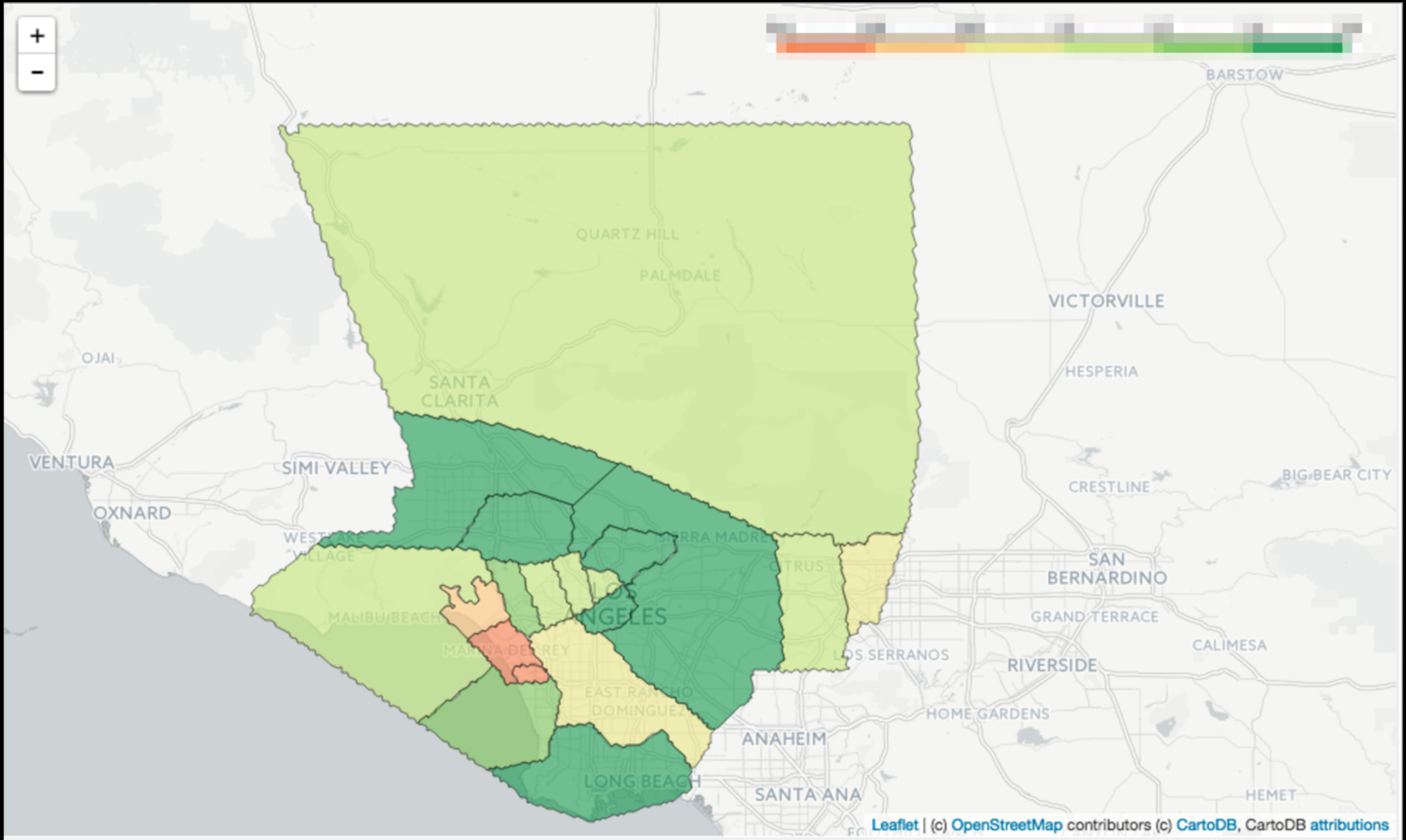

Geotemporal API for productivity

```java
private static ForkJoinPool fjPool = new ForkJoinPool();

@Override
public void postProcessResult(QueryResult result) {
    ImmutableMap<HexagonCoord, BucketWrapper> hexagons = HexagonAggregationUtility.buildHexagonMap(result, hexField);

    List<BucketWrapper> buckets = Lists.newArrayList(hexagons.values());

    fjPool.invoke(new KRingProcessor(SEQUENTIAL_THRESHOLD, hexagons, buckets, 0, buckets.size()));
}

private class KRingProcessor extends RecursiveTask<List<BucketWrapper>> {
    private int sequentialThreshold;
    private int low;
    private int high;

    private ImmutableMap<HexagonCoord, BucketWrapper> data;
    private List<BucketWrapper> buckets;

    KRingProcessor(int sequentialThreshold,
                   ImmutableMap<HexagonCoord, BucketWrapper> data,
                   List<BucketWrapper> buckets,
                   int low, int high) {
        this.sequentialThreshold = sequentialThreshold;
        this.data = data;
        this.buckets = buckets;
        this.low = low;
        this.high = high;
    }

    @Override
    protected List<BucketWrapper> compute() {
        if (high - low <= sequentialThreshold) {
            for (int i = low; i < high; ++i) {
                BucketWrapper bucket = buckets.get(i);
                Map<String, Object> values = bucket.getBucket().getValues();
                if (values.containsKey(hexField) && values.containsKey(metric)) {
                    processBucket(data, bucket);
                }
            }

            return buckets;
        } else {
            int mid = low + (high - low) / 2;
            KRingProcessor left = new KRingProcessor(sequentialThreshold, data, buckets, low, mid);
            KRingProcessor right = new KRingProcessor(sequentialThreshold, data, buckets, mid, high);
            left.fork();
            right.compute();
            left.join();

            return buckets;
        }
    }

    private void processBucket(Map<HexagonCoord, BucketWrapper> hexagons, BucketWrapper bucket) {
        [redacted]
    }
}
```

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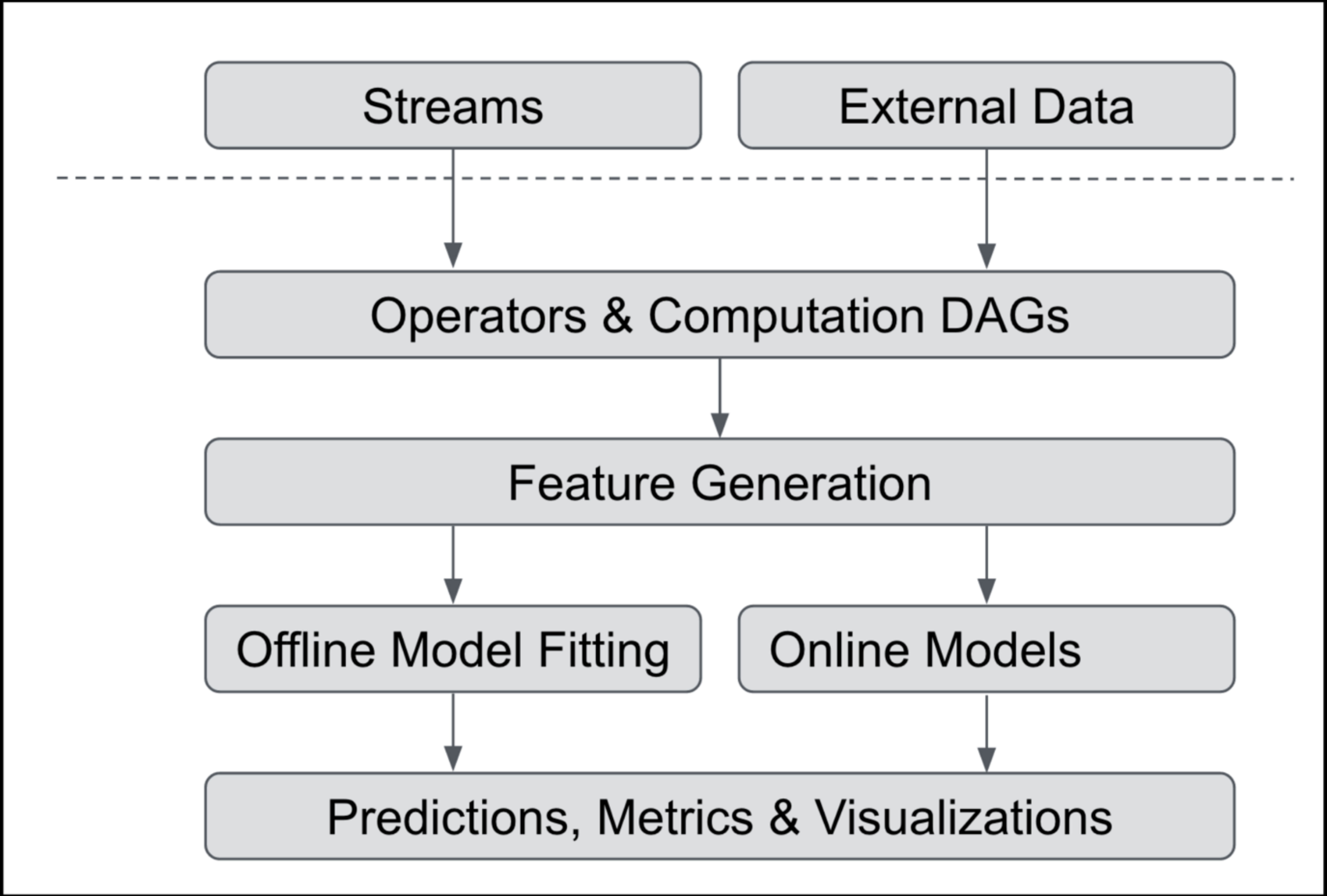
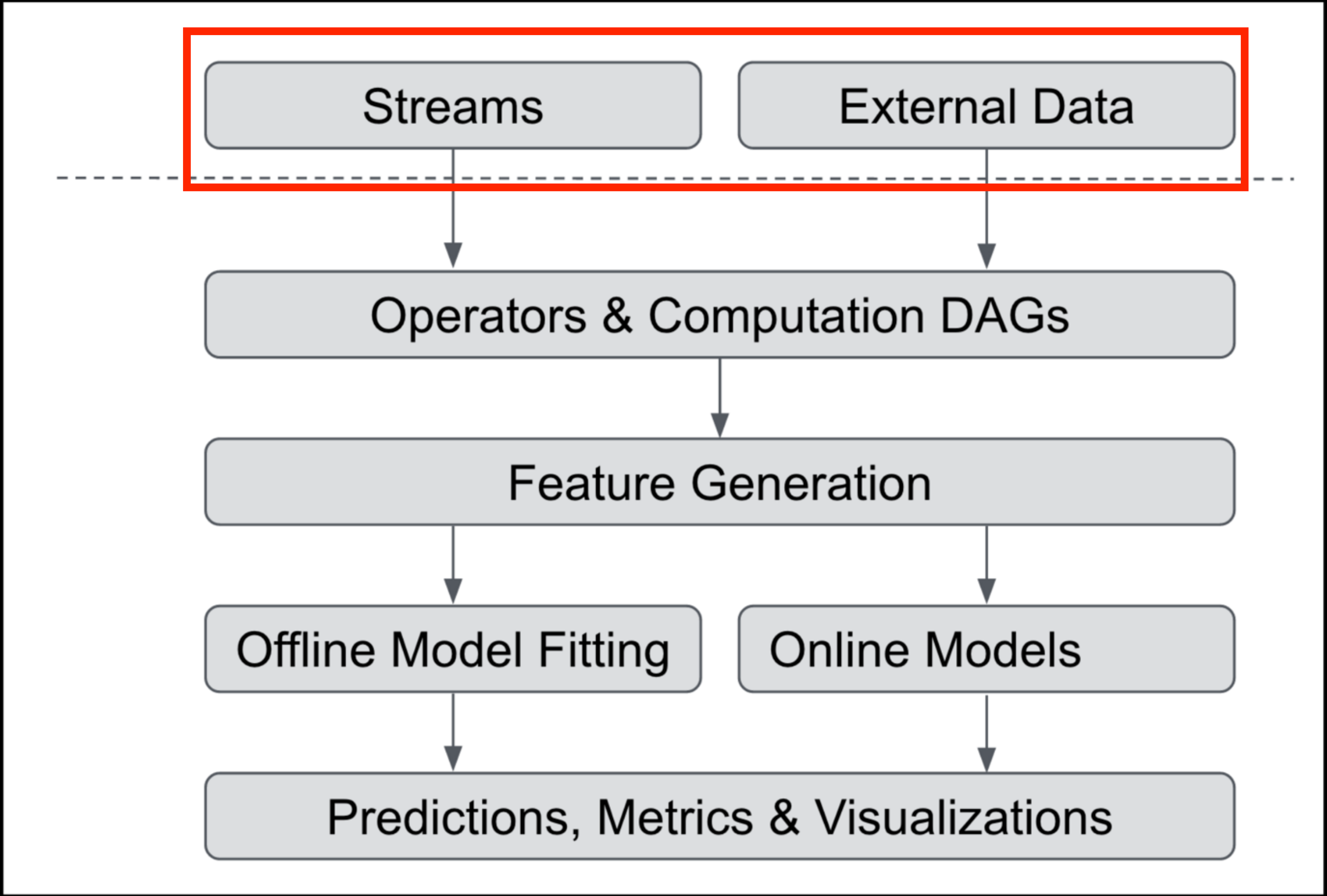
    private void processBucket(Map<HexagonCoord, BucketWrapper> hexagons, BucketWrapper bucket) {
        HexagonCoord hexCoord = bucket.getCoord();
        ...
    }
}
```

```java
return hexagonContext.mapGeoArea(
    (context, area) -> {
        double incrementalValue = 0;
        ...
    }
```

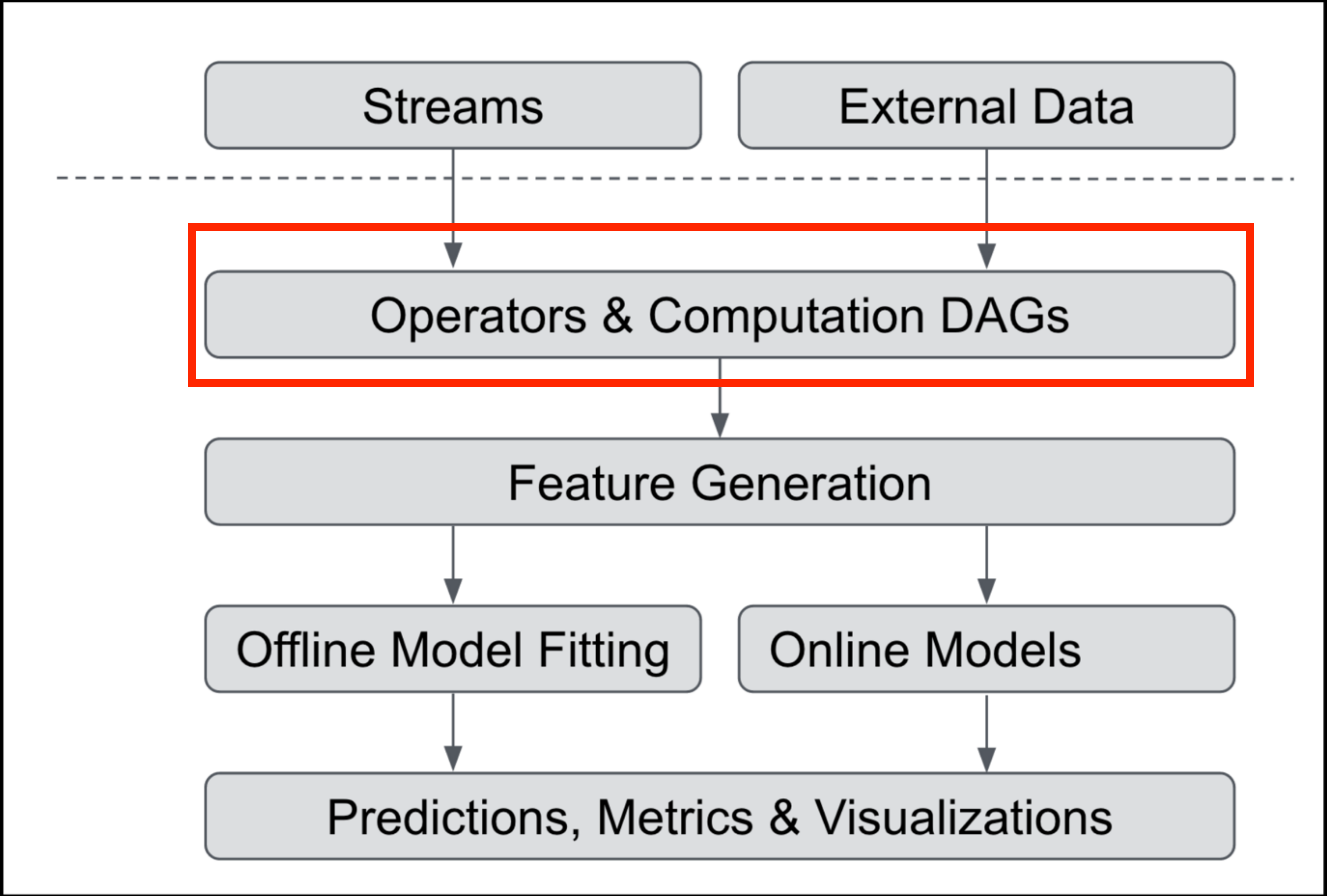
Forecasting as an example



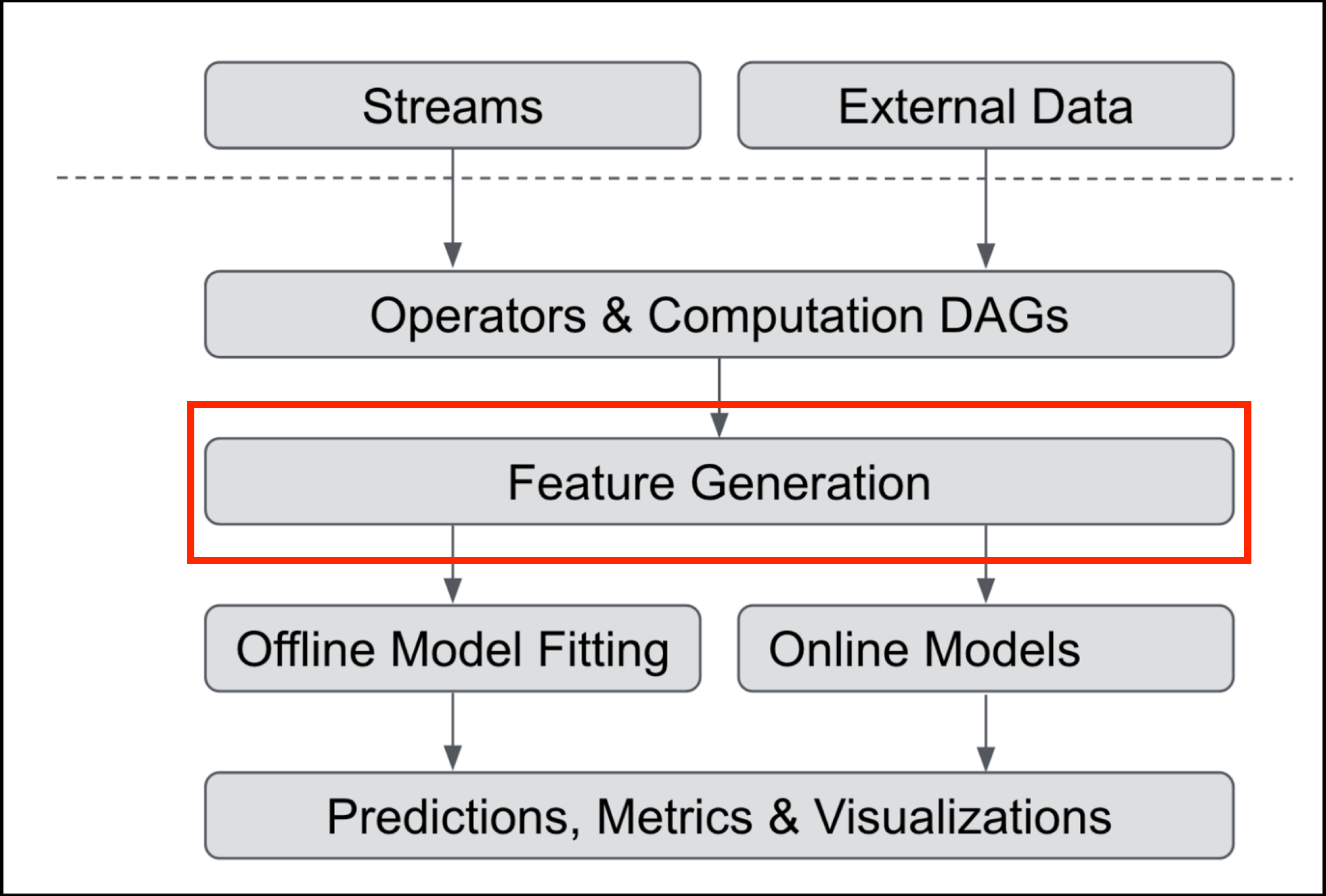
Forecasting as an example



Forecasting as an example



Forecasting as an example



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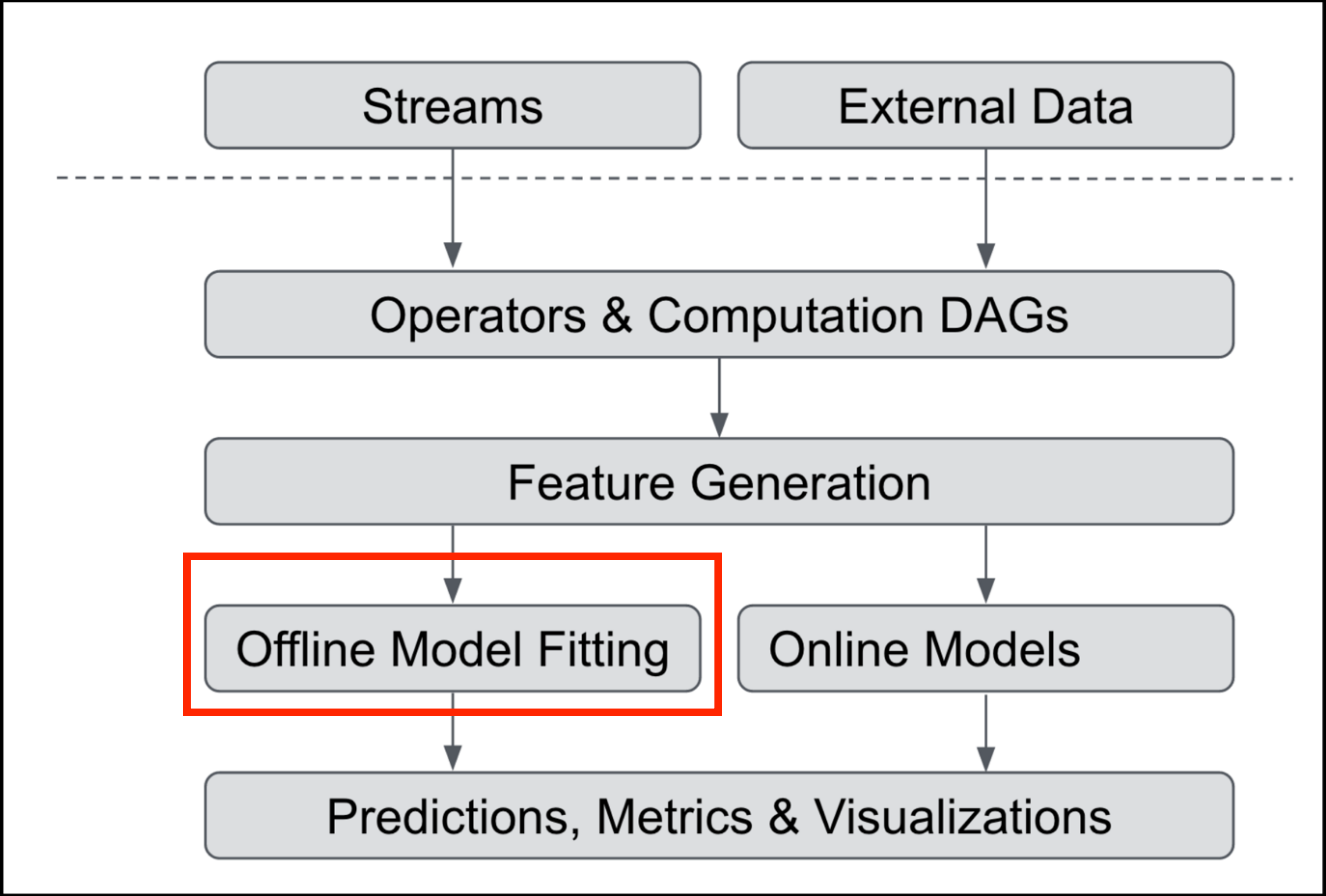

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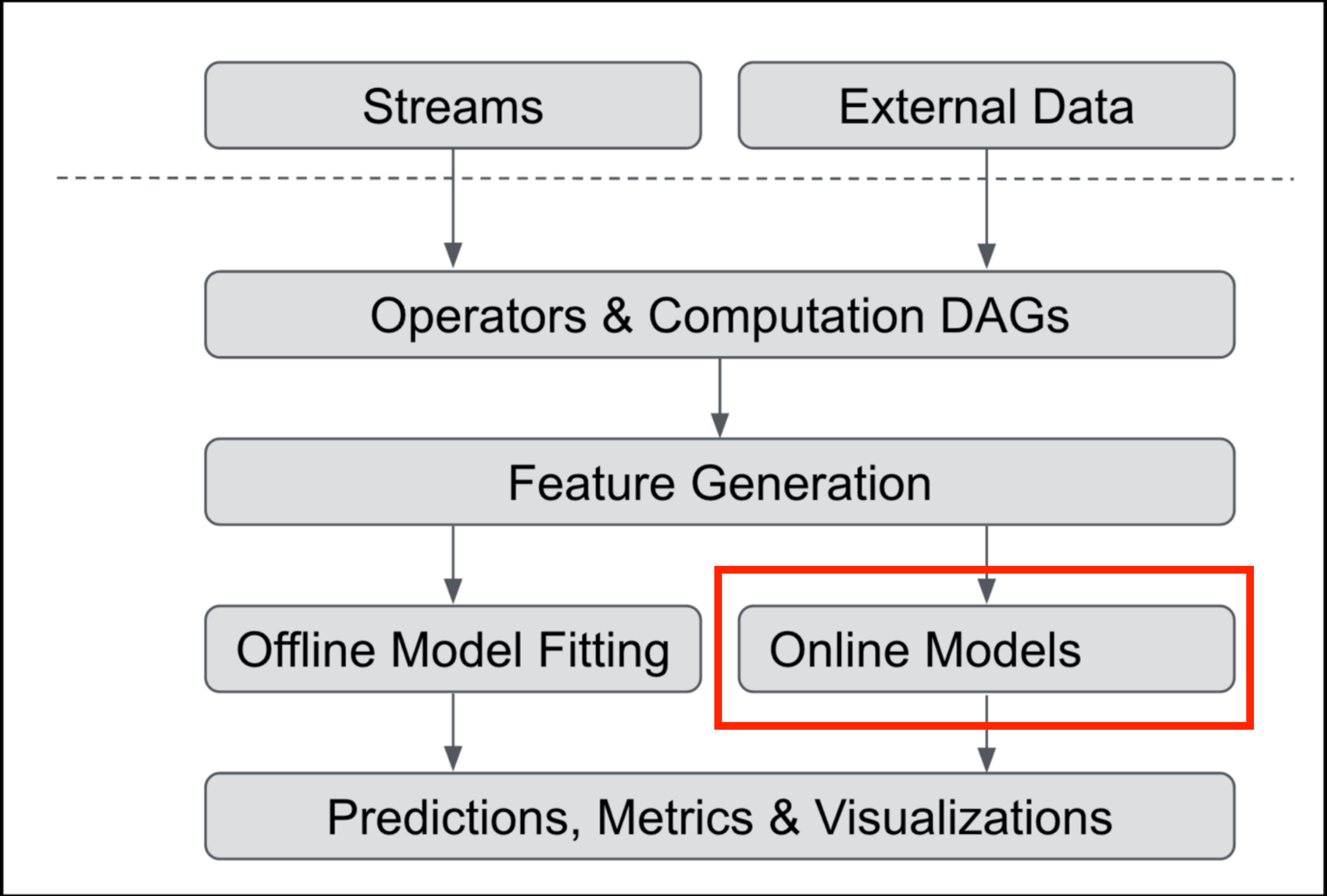

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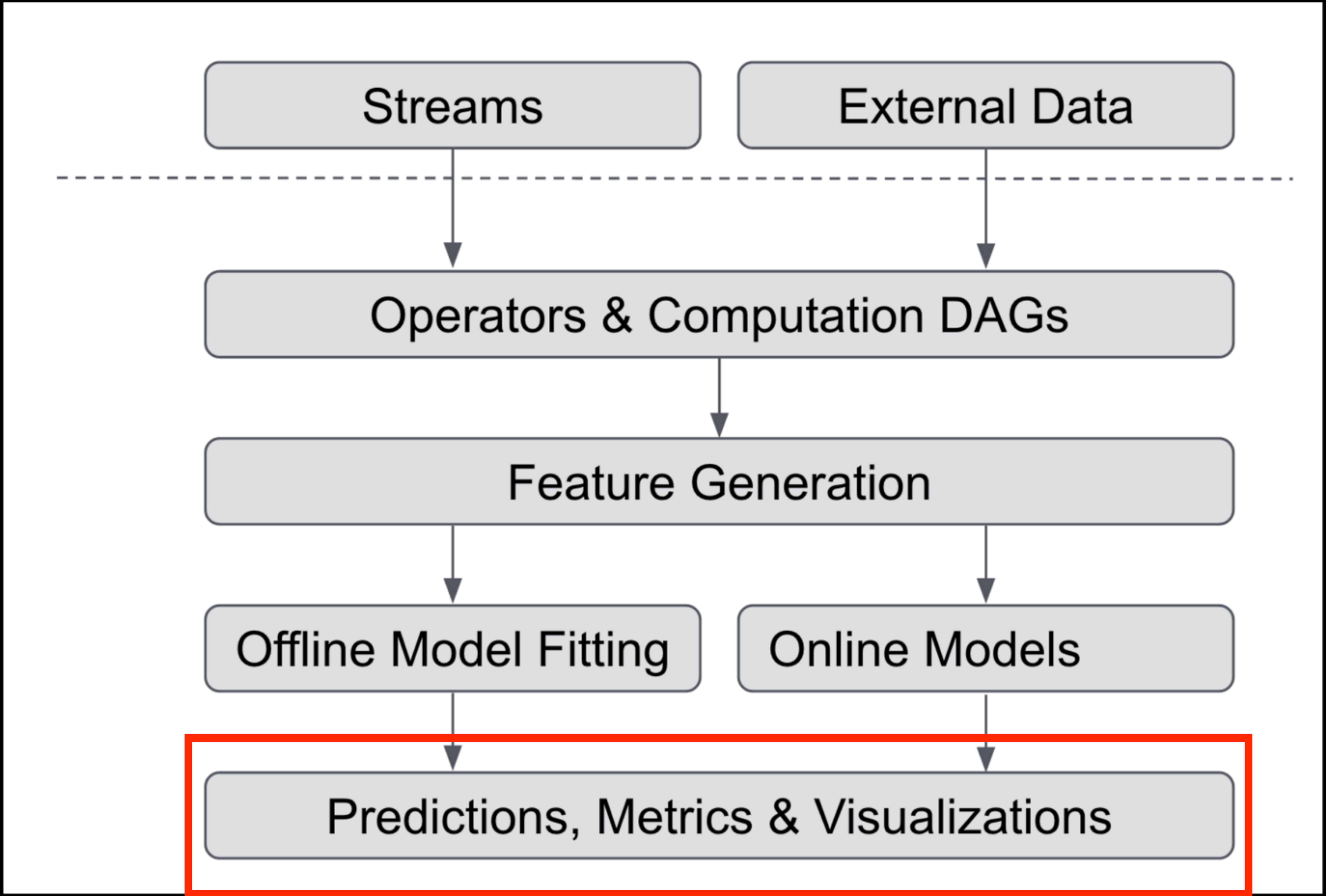

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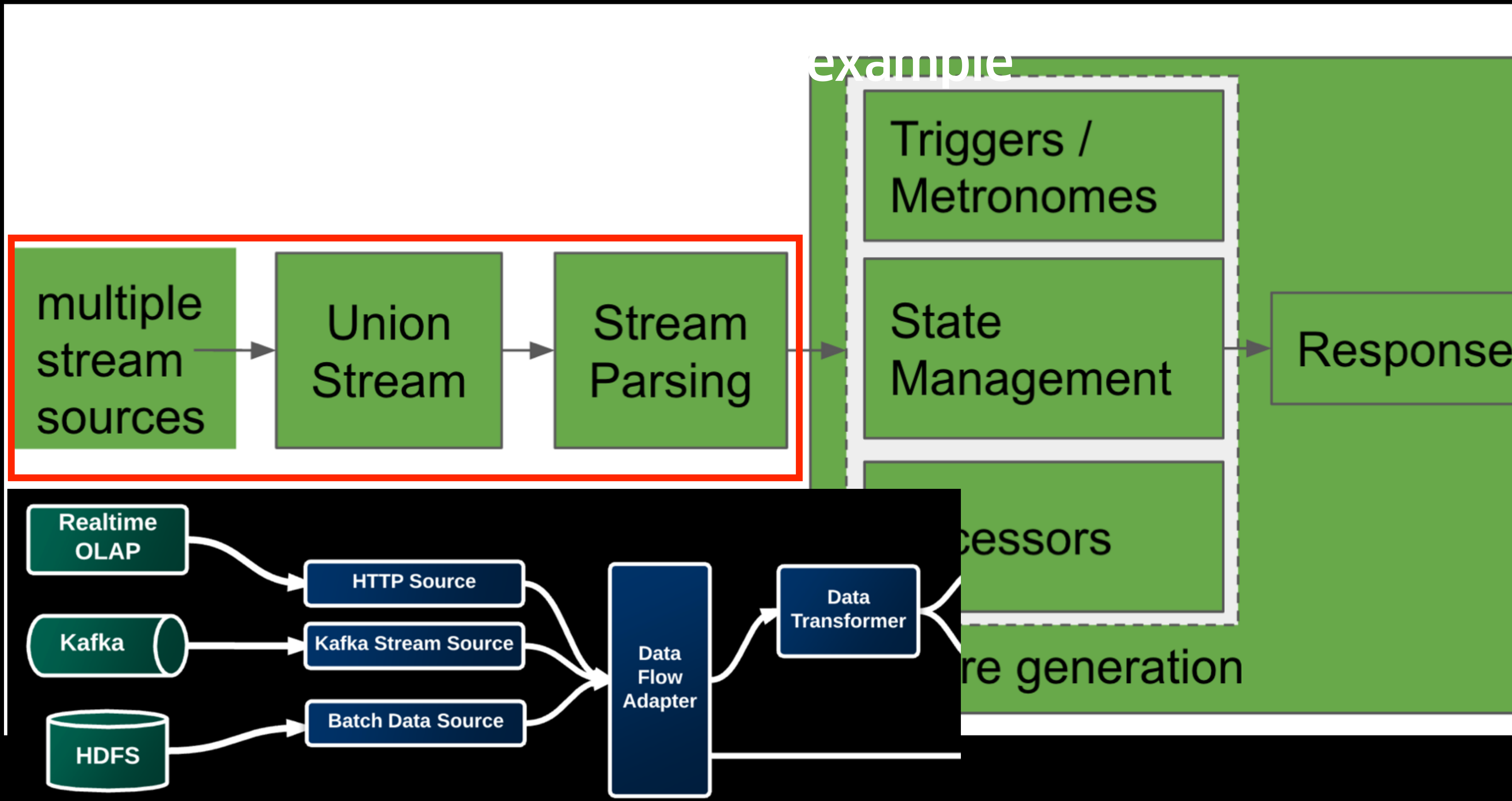
example
multiple stream sources
Union Stream
Stream Parsing
Triggers / Metronomes
State Management
cessors
re generation
Response
Realtime OLAP
Kafka
HDFS
HTTP Source
Kafka Stream Source
Batch Data Source
Data Flow Adapter
Data Transformer

Forecasting as an example

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Lessons Learned

- Make sure you have robust infrastructure support
- Scaling up, namely single-node optimization matters
- Ensure exactly-once by proper data modeling
- Use external state store to avoid too much snapshotting
- Standardize monitoring and data validation

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Stream System

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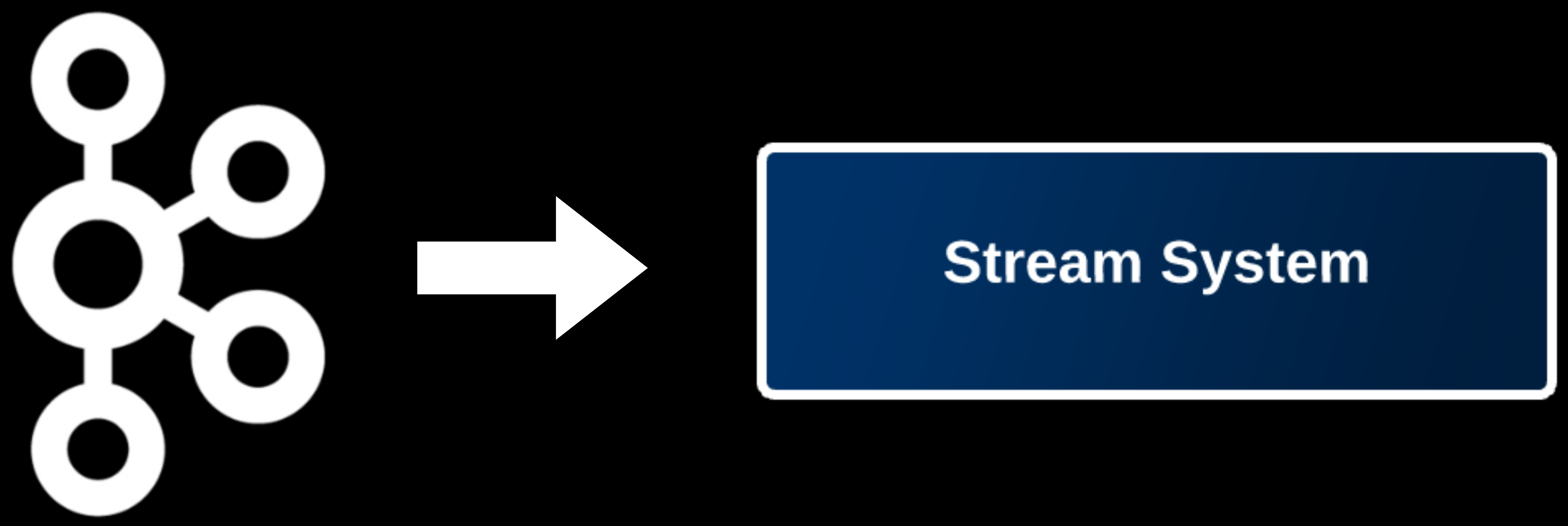

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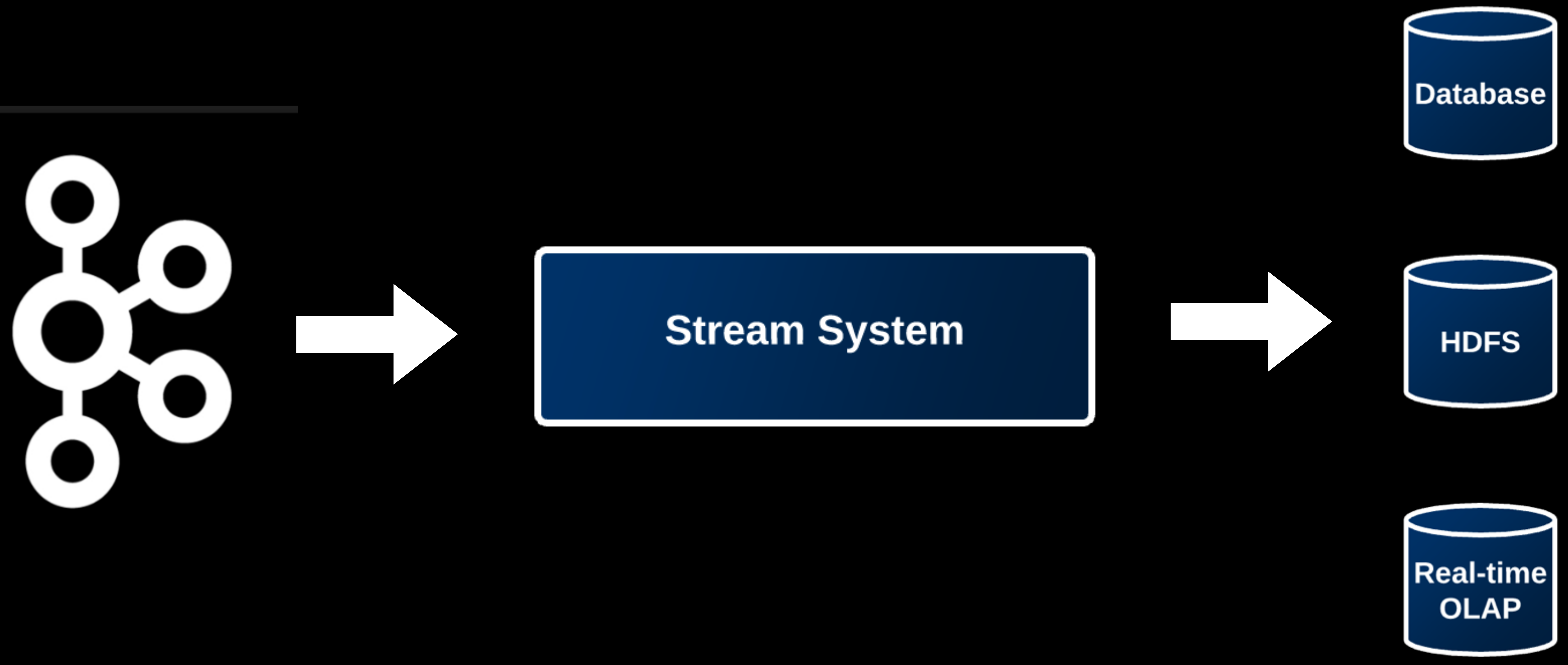

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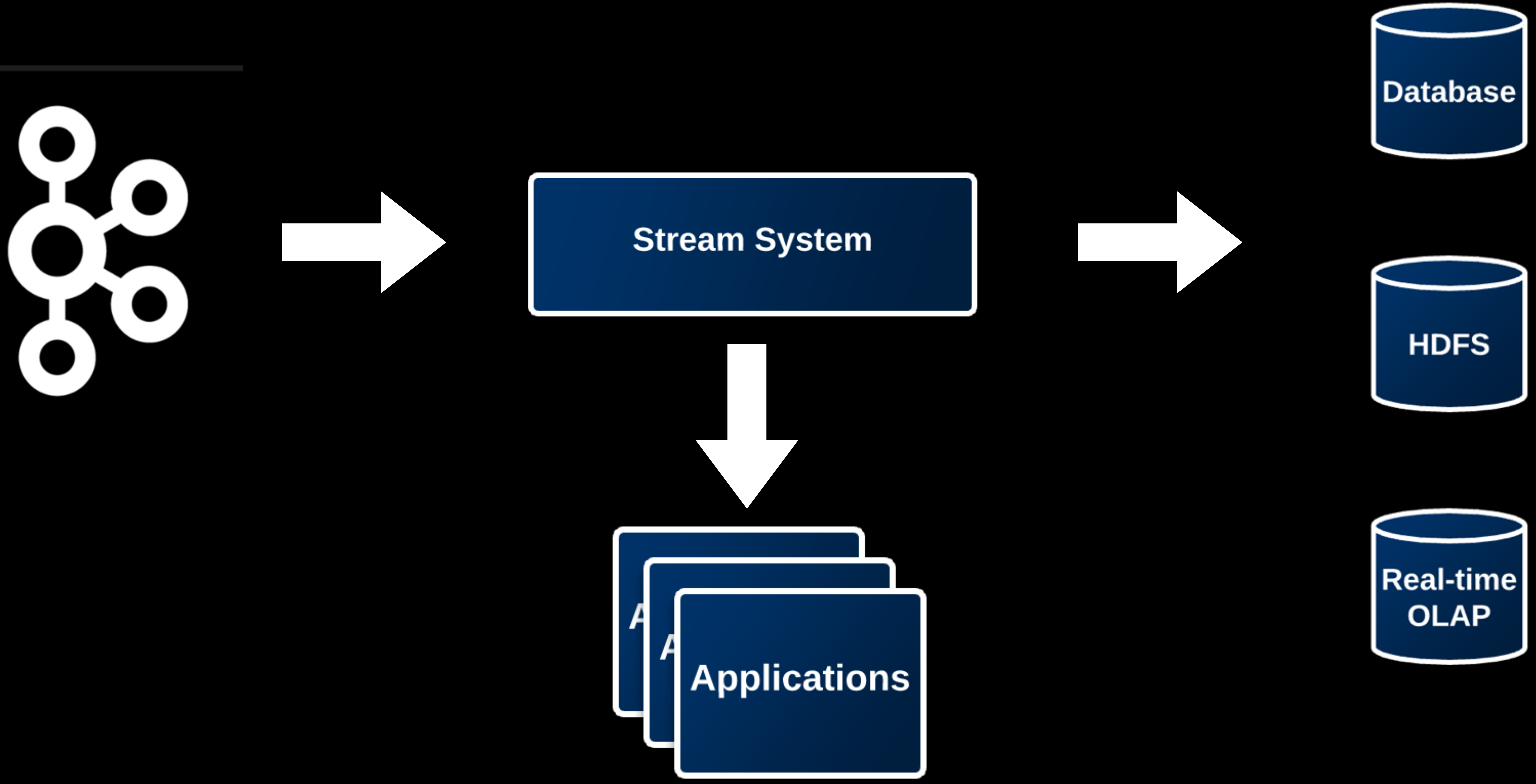

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Choose a Stream Processing Platform

samza

Spark

beam

Thank You