Unified Stream & Batch Processing with Apache Flink

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Hadoop Summit Dublin
April 13, 2016

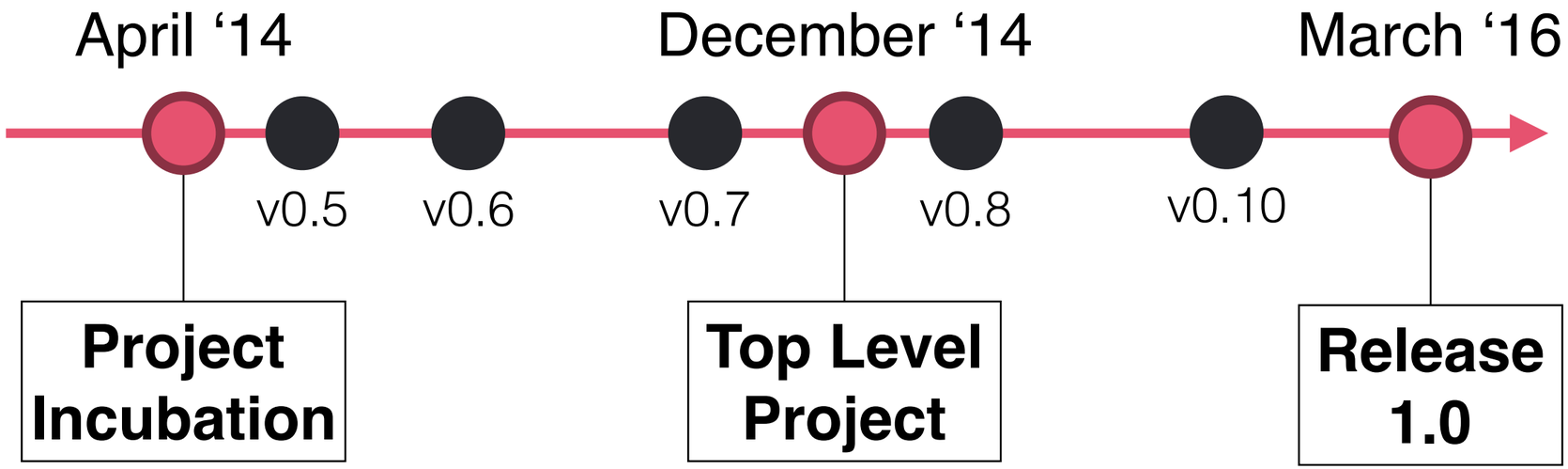
What is Apache Flink?

Apache Flink is an open source *stream processing* framework.

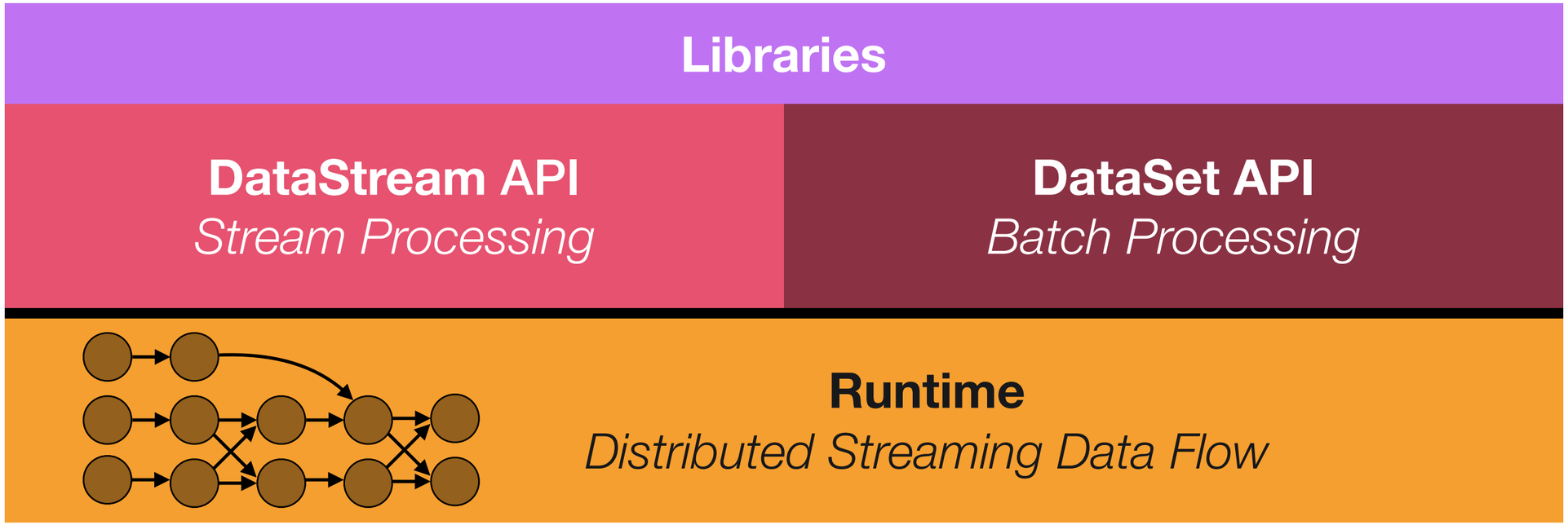
- Event Time Handling
- State & Fault Tolerance
- Low Latency
- High Throughput

Developed at the *Apache Software Foundation*.

Recent History

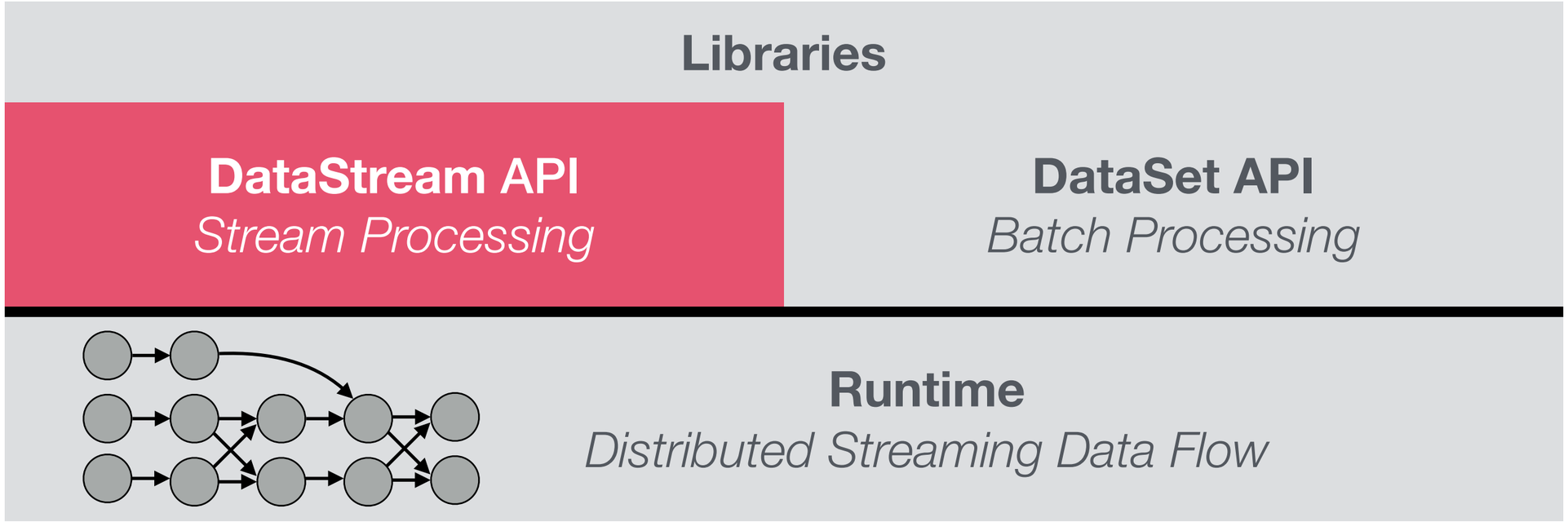


Flink Stack



Streaming and **batch** as **first class citizens**.

Today



Streaming and **batch** as **first class citizens**.

Counting

Seemingly **simple application**:
Count visitors, ad impressions, etc.

But **generalizes** well to other problems.

Batch Processing

All Input

Hadoop,
Spark,
Flink

All Output

Batch Processing

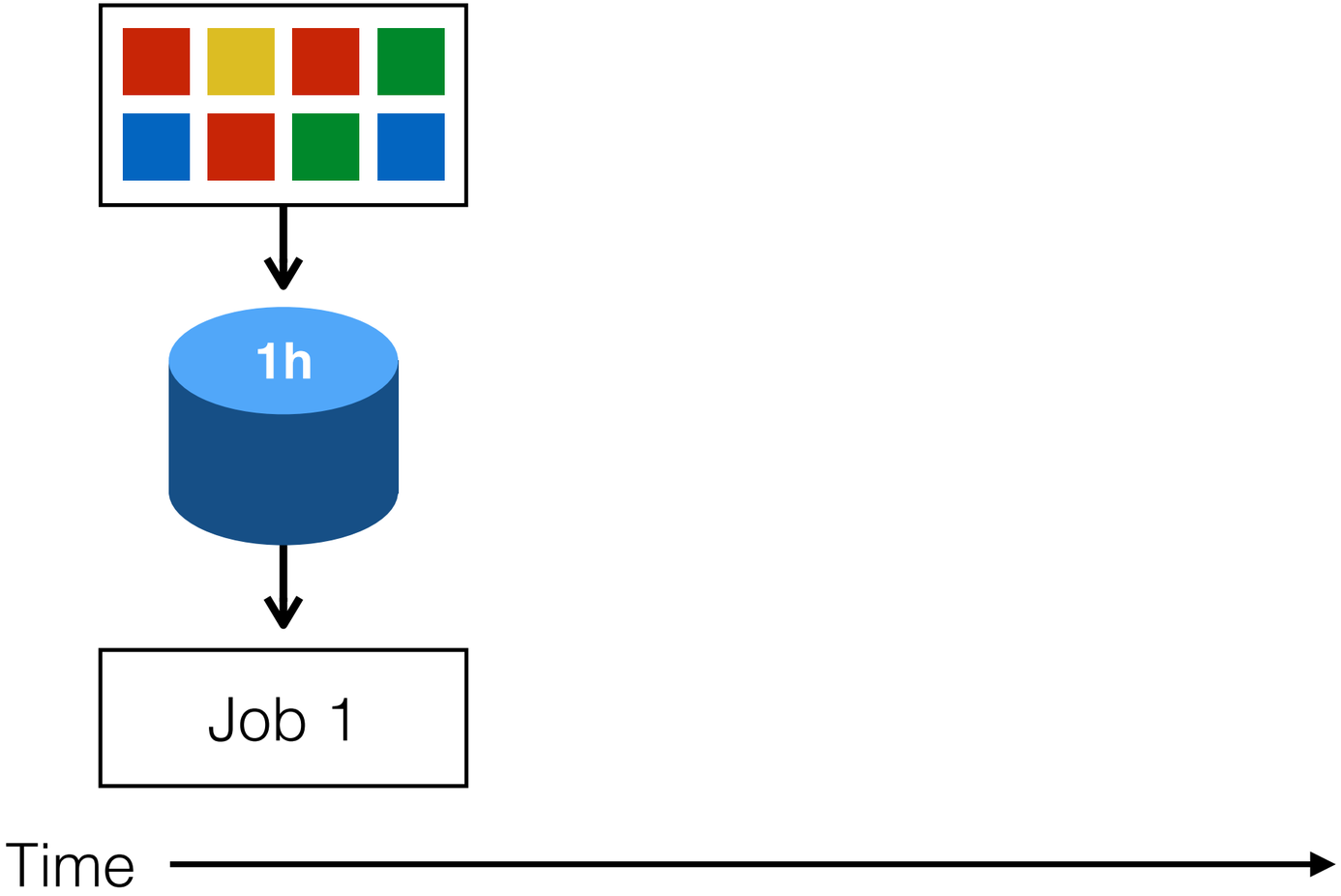
```
DataSet<ColorEvent> counts = env
  .readFile("MM-dd.csv")
  .groupBy("color")
  .count();
```

Continuous Counting

Continuous ingestion

Periodic files

Periodic batch jobs



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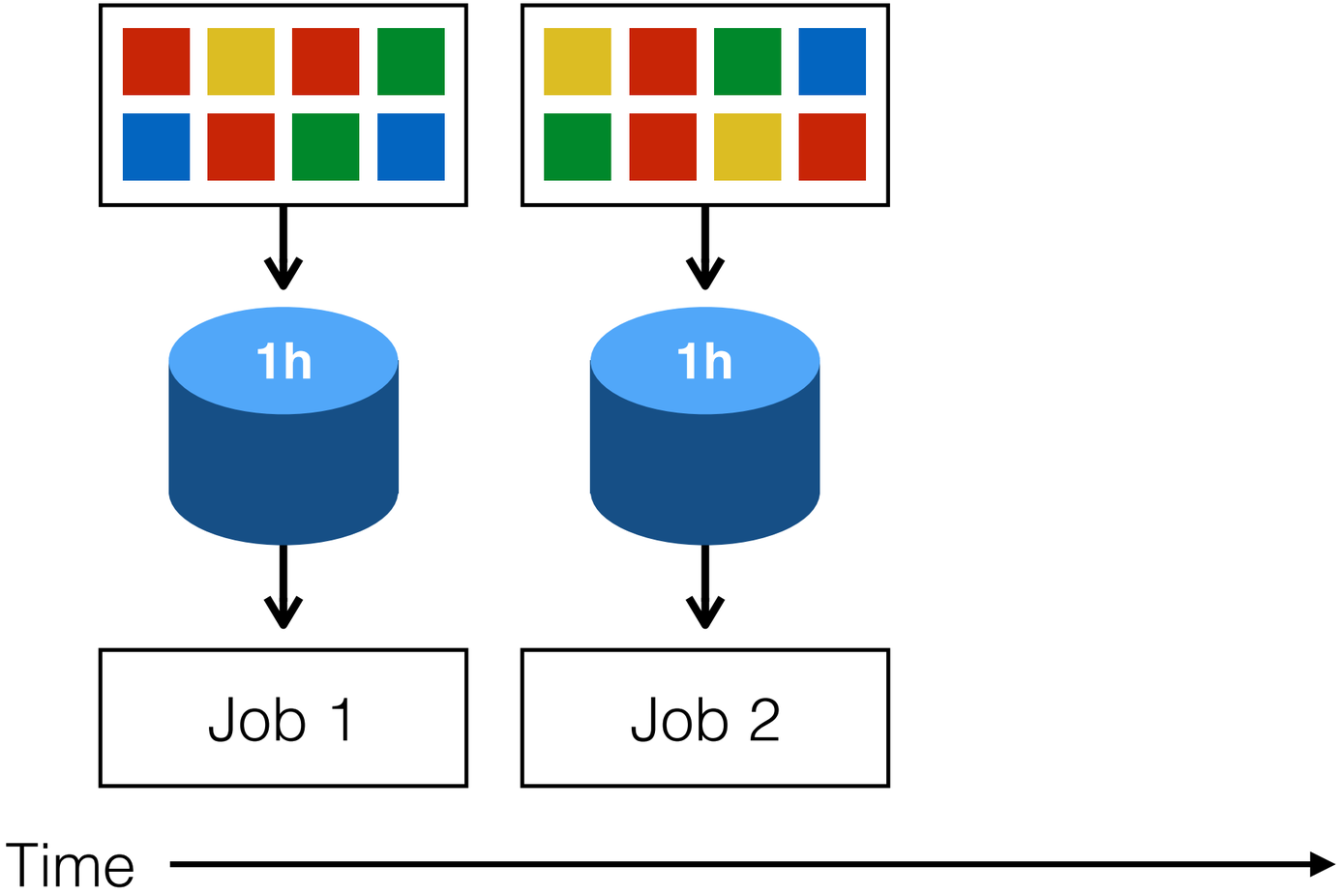
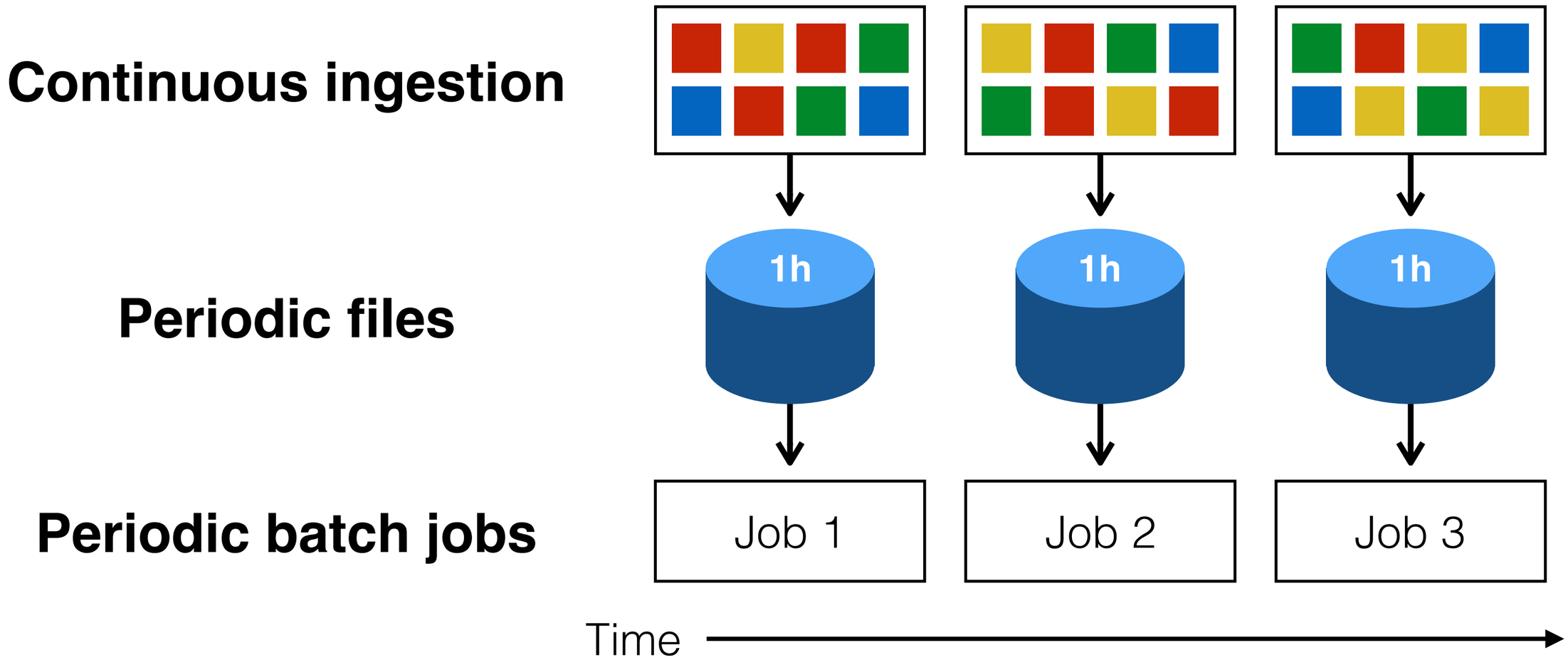
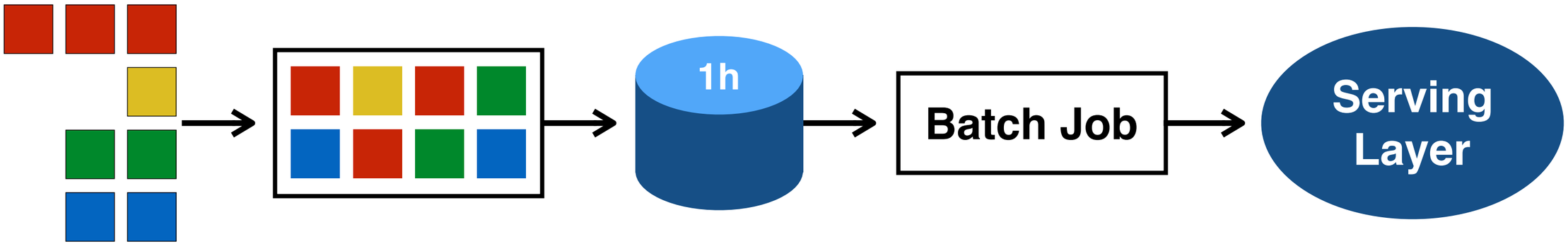


Continuous Counting



Many Moving Parts



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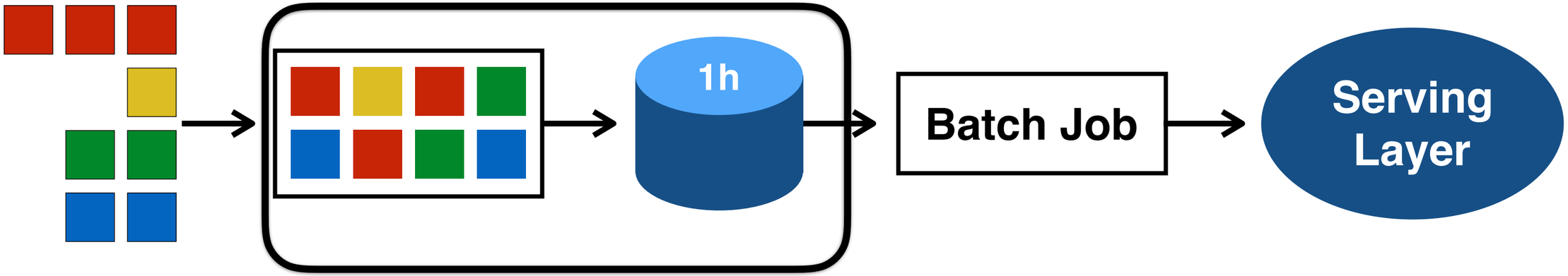
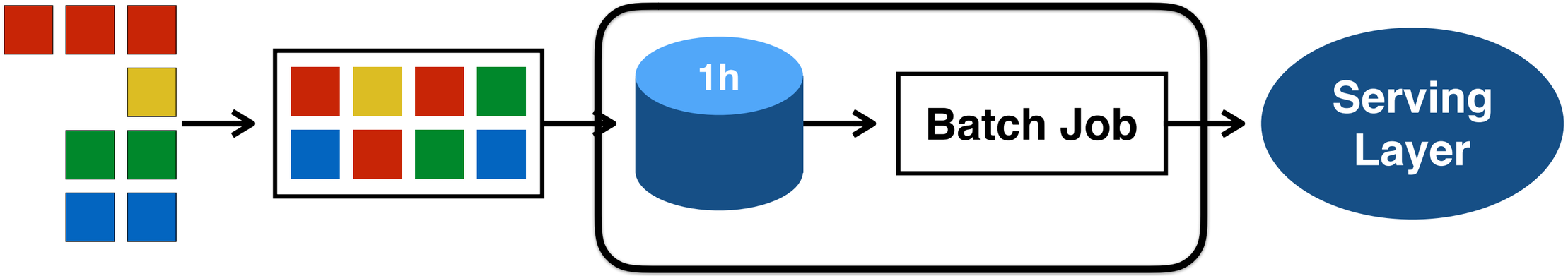


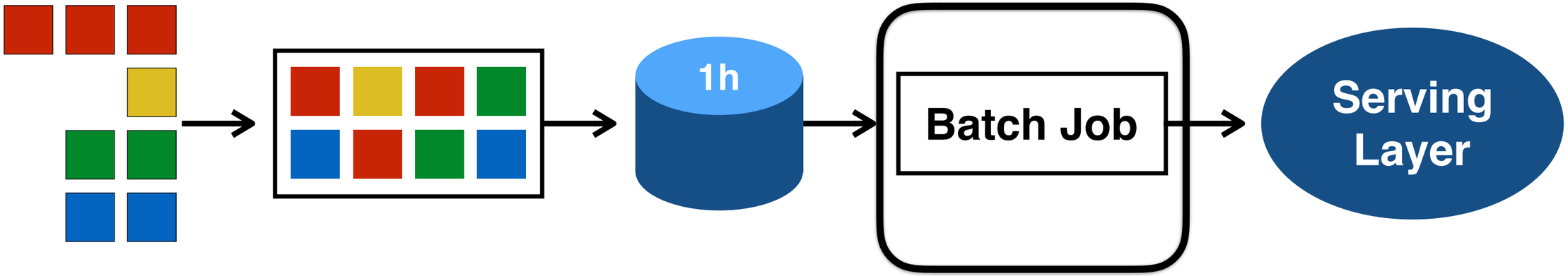
Data loading into HDFS
(e.g. Flume)

Many Moving Parts



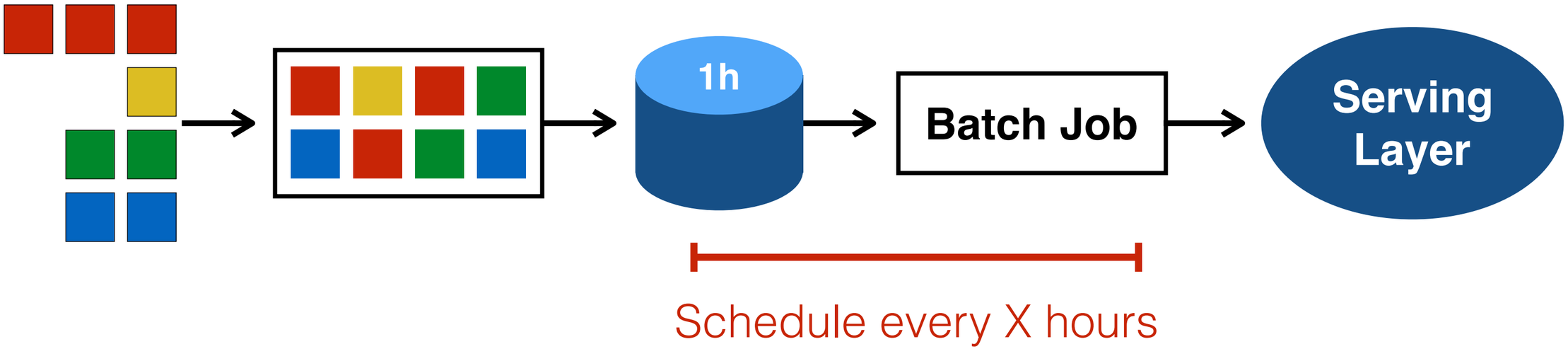
Periodic job scheduler
(e.g. Oozie)

Many Moving Parts



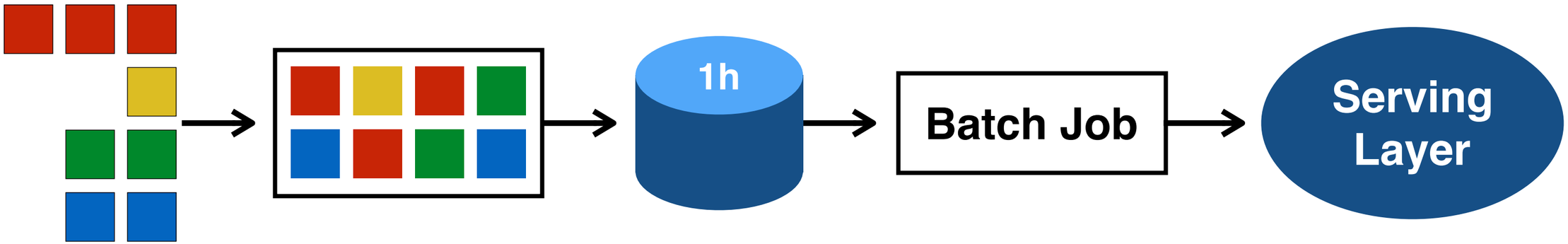
Batch processor
(e.g. Hadoop, Spark, Flink)

High Latency



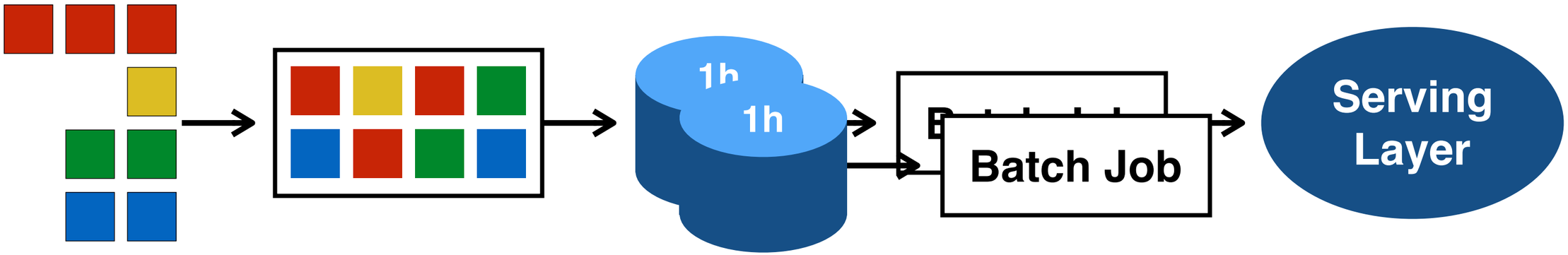
Latency from *event to serving layer* usually in the **range of hours.**

Implicit Treatment of Time



Time is treated **outside** of your application.

Implicit Treatment of Time



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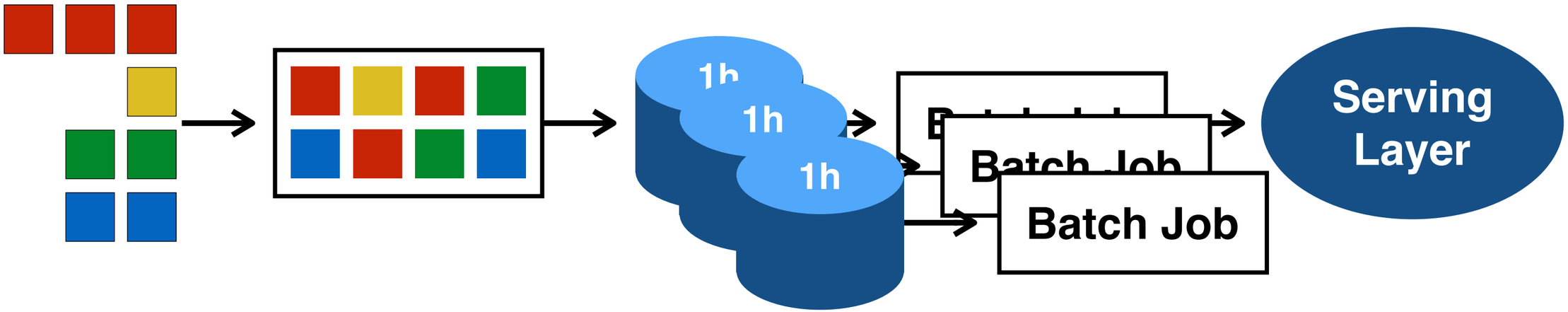


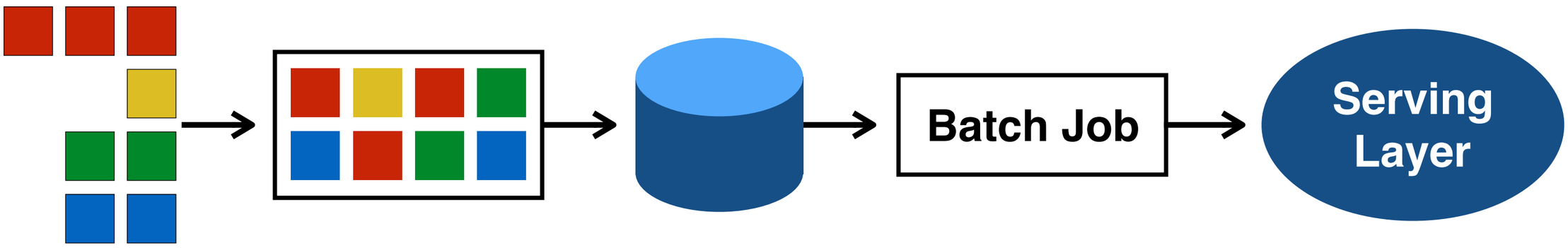
Time is treated **outside** of your application.

Implicit Treatment of Time

```
DataSet<ColorEvent> counts = env
  .readFile("MM-dd.csv")
  .groupBy("color")
  .count();
```

Time is **implicit**
in input file

Streaming over Batch



Continuously produced

Files are **finite streams**

Periodically executed

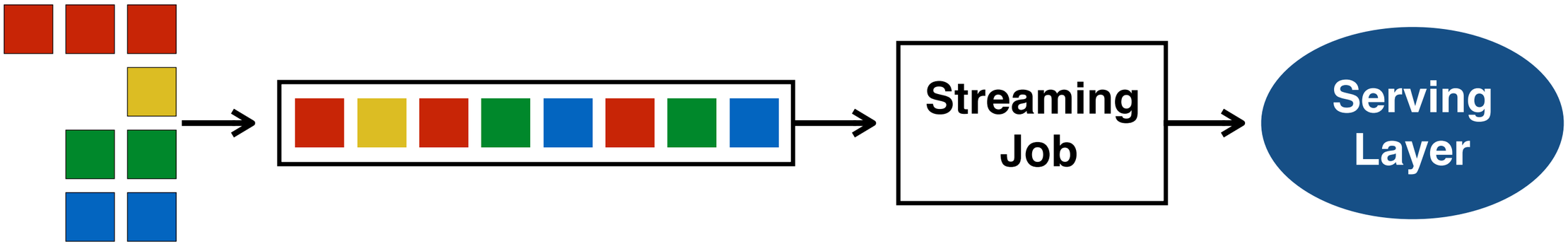
Streaming

Until now, **stream processors** were **less mature** than their batch counterparts. This led to:

- **in-house solutions**,
- **abuse of batch processors**,
- **Lambda architectures**

This is **no longer** needed with new generation stream processors like Flink.

Streaming All the Way



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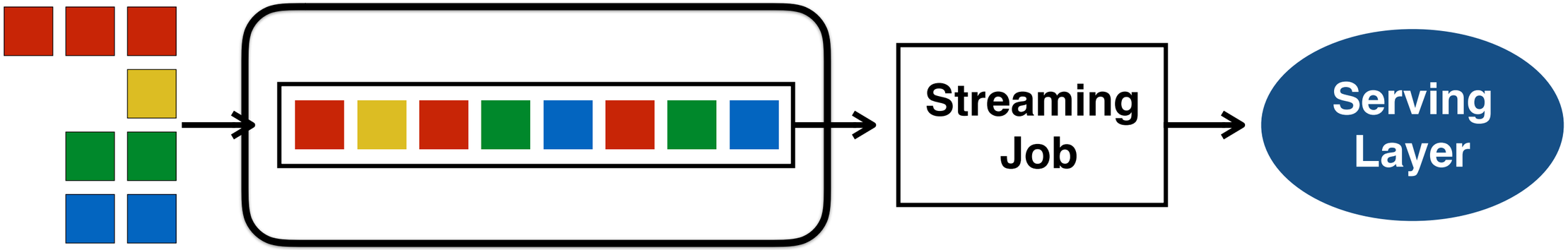
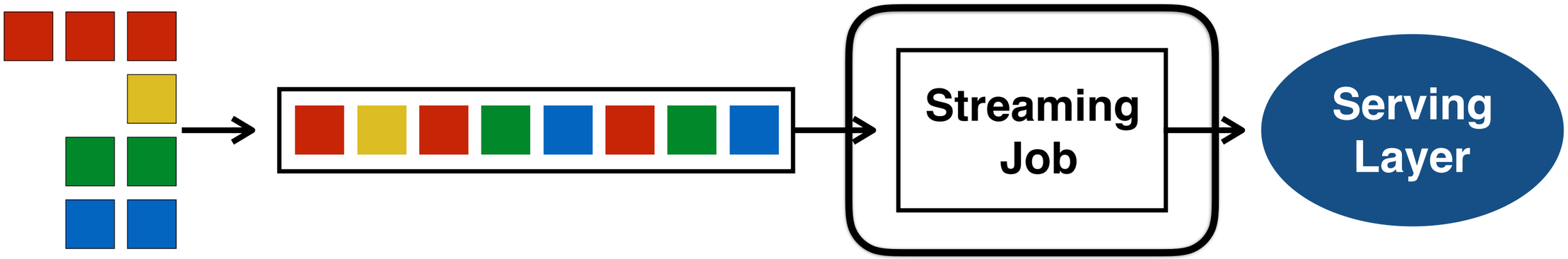


Message Queue
(e.g. Apache Kafka)

Durability and Replay

Streaming All the Way



Stream Processor
(e.g. Apache Flink)

Consistent Processing

Building Blocks of Flink

Explicit Handling of Time

State & Fault Tolerance

Performance

Building Blocks of Flink

Explicit Handling of Time

State & Fault Tolerance

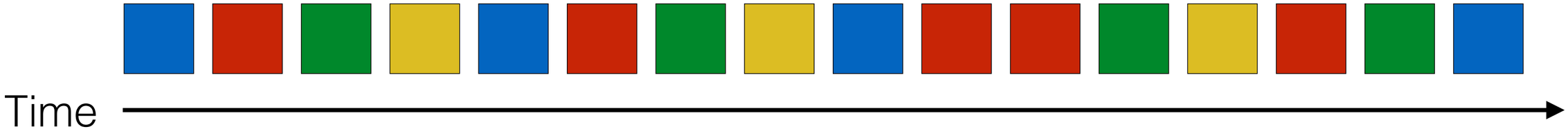
Performance

Windowing

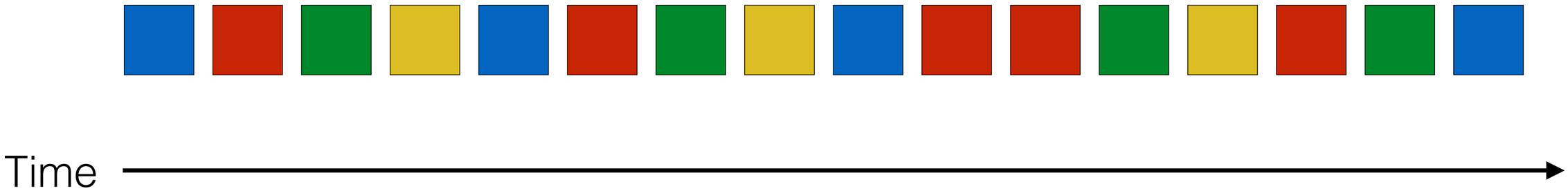
Aggregates on **streams**
are scoped by **windows**

Time-driven
e.g. last X minutes

Data-driven
e.g. last X records



Tumbling Windows (No Overlap)



e.g. *"Count over the **last 5 minutes**",*

*"Average over the **last 100 records**"*

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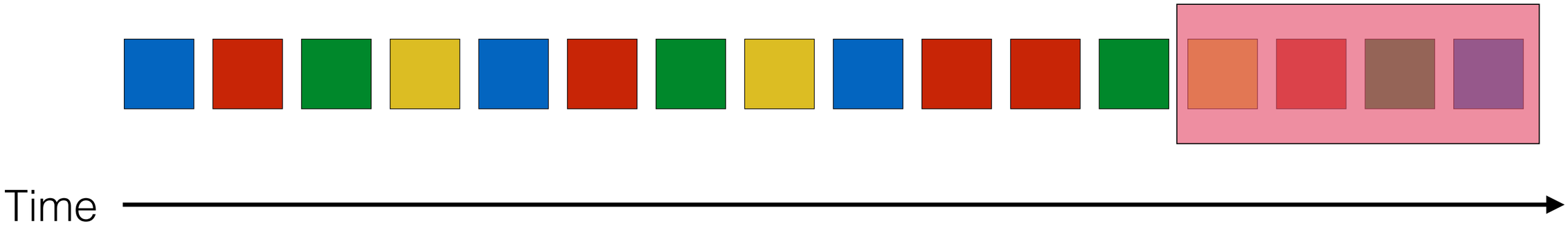

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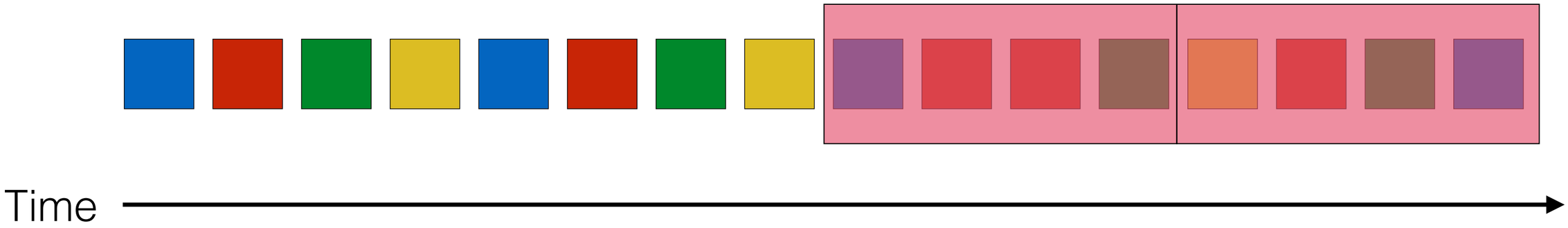

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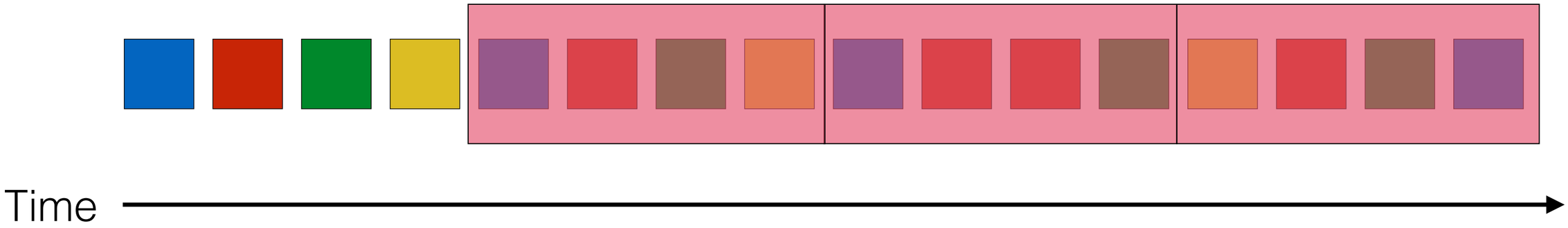

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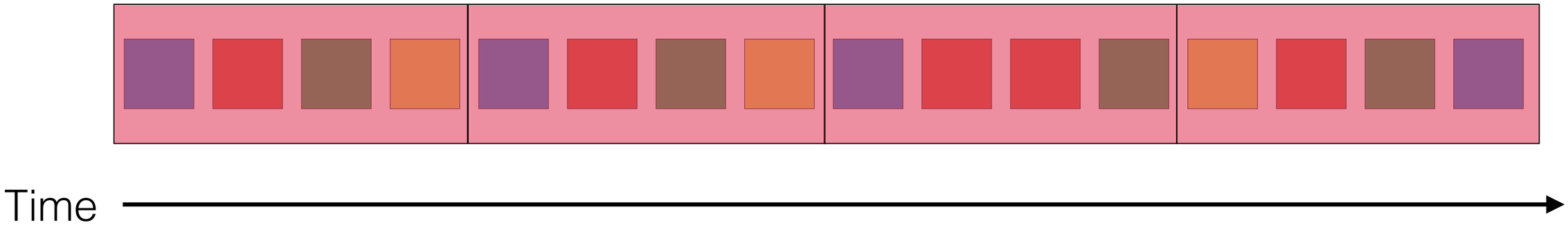
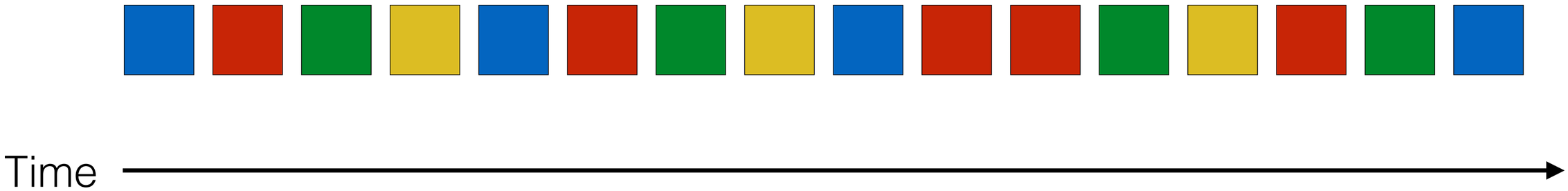


e.g. *"Count over the* ***last 5 minutes****"*,

"Average over the ***last 100 records****"*

Sliding Windows (with Overlap)



e.g. *"Count over the **last 5 minutes**, updated **each minute**."*,

*"Average over the **last 100 elements**, updated every **10 elements**"*

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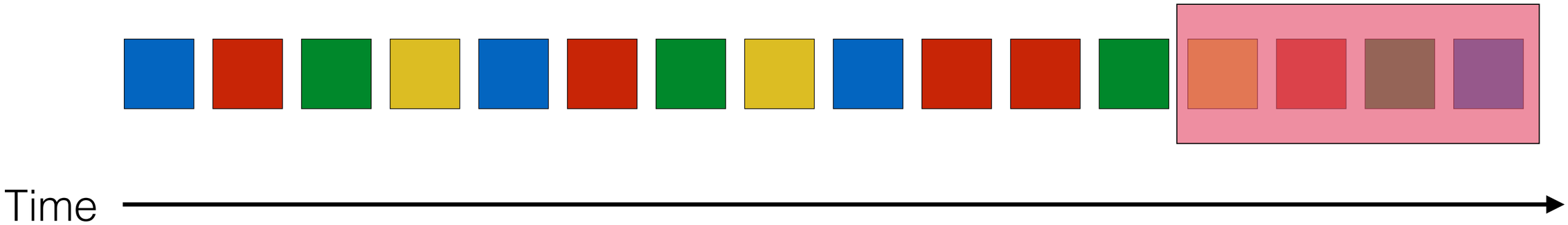

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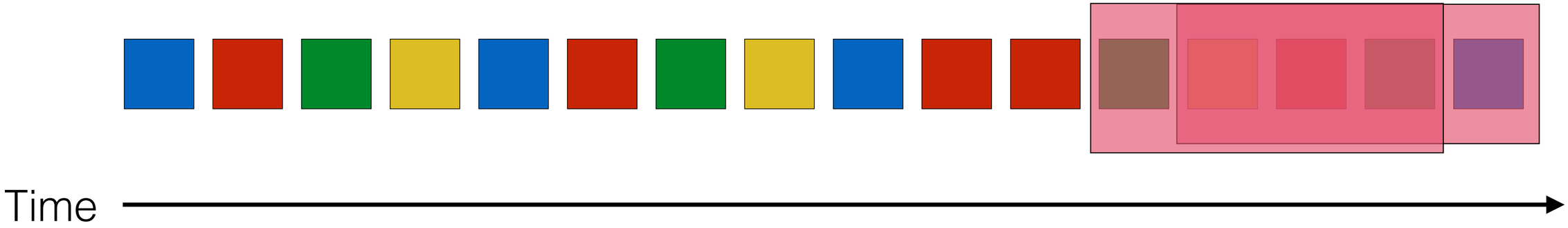

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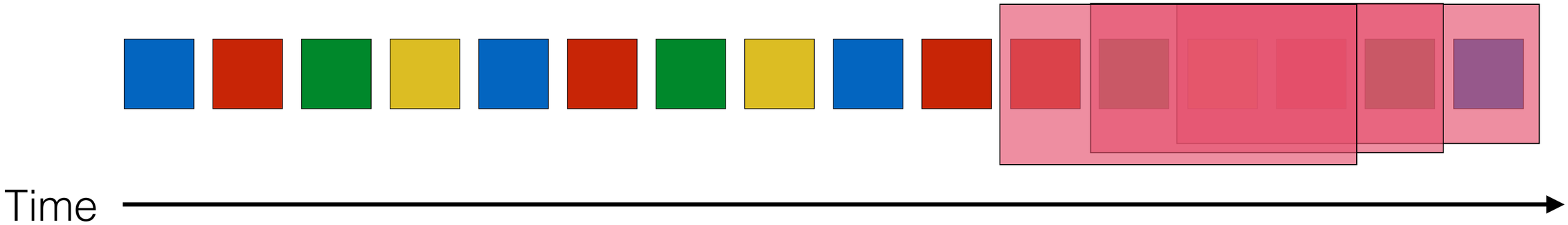

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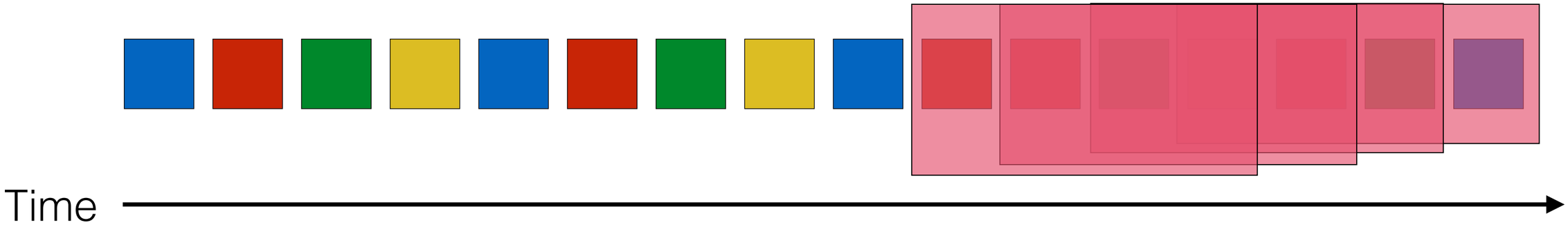


e.g. *"Count over the **last 5 minutes**, updated **each minute**."*,

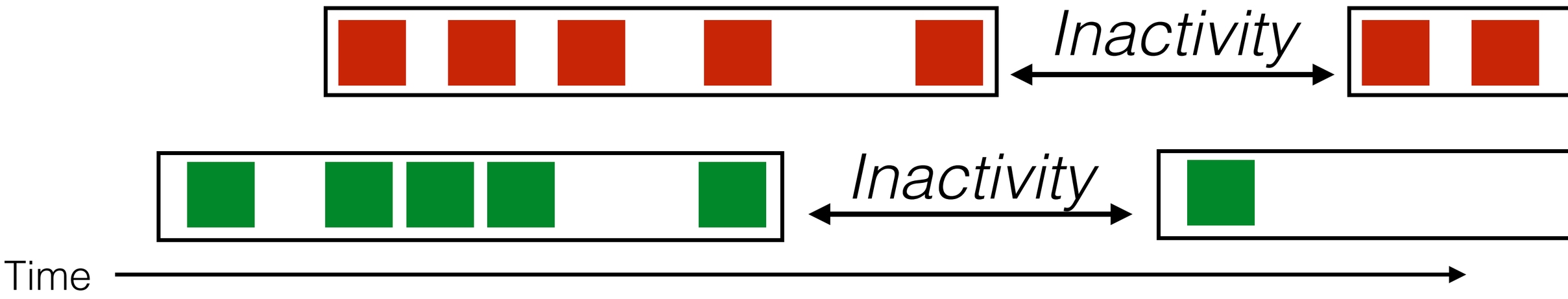
*"Average over the **last 100 elements**, updated every **10 elements**"*

Explicit Handling of Time

```
DataStream<ColorEvent> counts = env
  .addSource(new KafkaConsumer(…))
  .keyBy("color")
  .timeWindow(Time.minutes(60))
  .apply(new CountPerWindow());
```

Time is **explicit**
in **your program**

Session Windows



Sessions **close** after *period of inactivity*.

e.g. "Count activity from login until time-out or logout."

Session Windows

```
DataStream<ColorEvent> counts = env
  .addSource(new KafkaConsumer(…))
  .keyBy("color")
  .window(EventTimeSessionWindows
    .withGap(Time.minutes(10))
  .apply(new CountPerWindow());
```

Notions of Time

Event Time

Time when event happened.

12:23 am

Notions of Time

Event Time

Time when event happened.

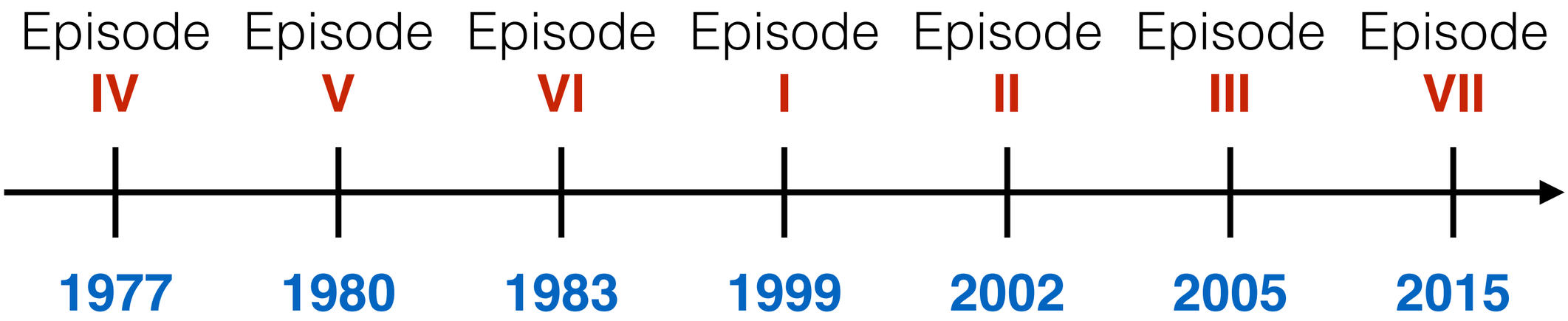
12:23 am

1:37 pm

Processing Time

Time measured by system clock

Out of Order Events



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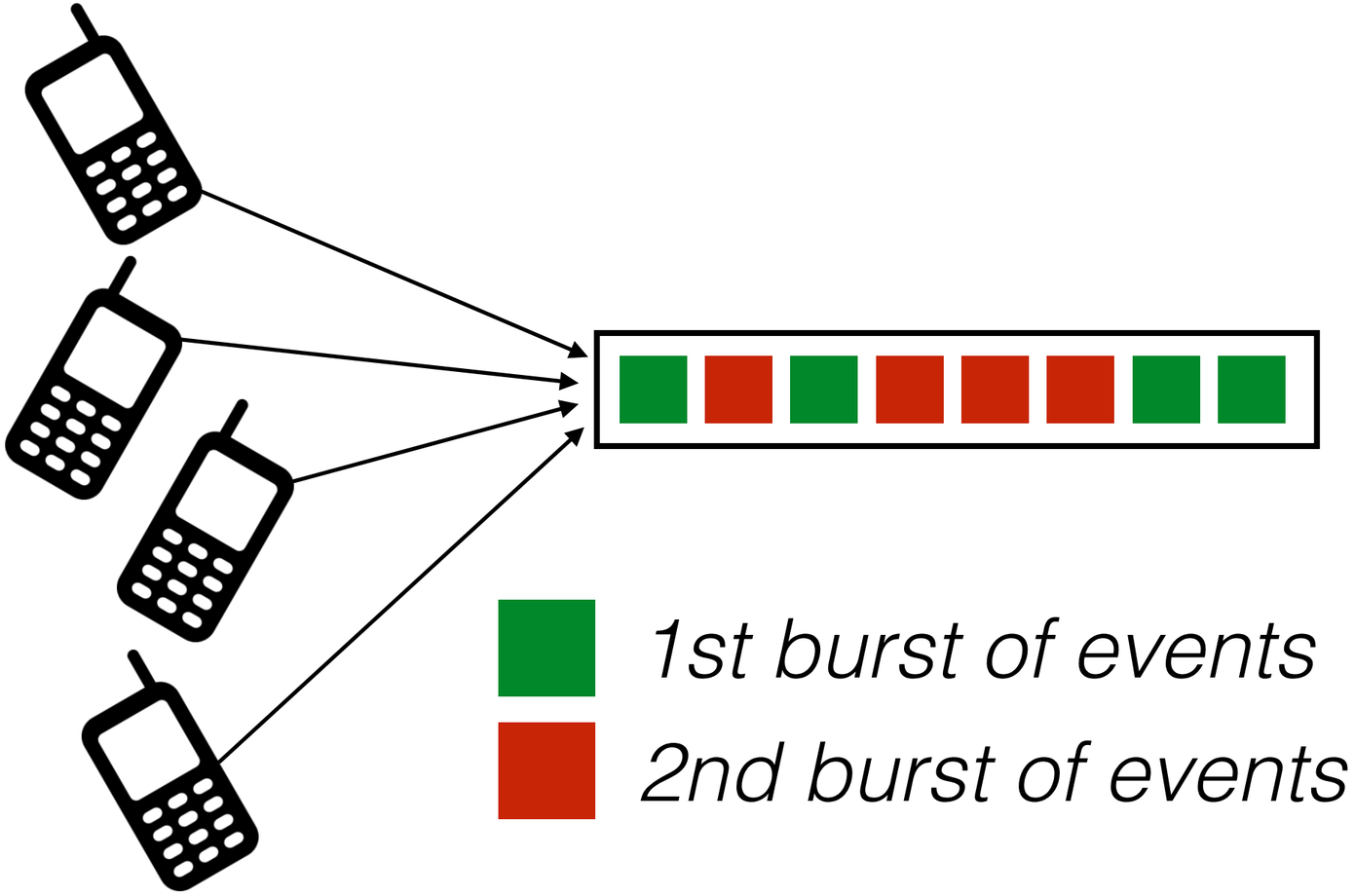
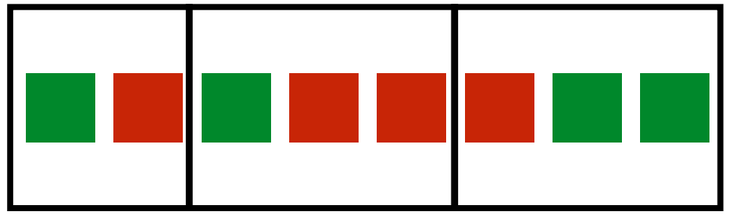
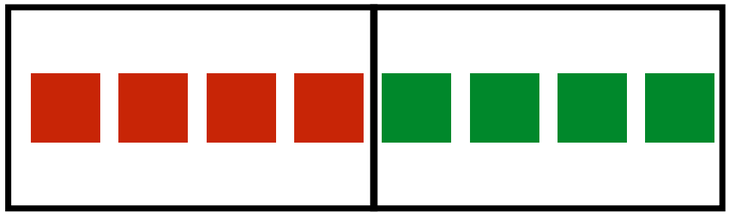




Processing Time Windows



Event Time Windows

Notions of Time

```
env.setStreamTimeCharacteristic(
  TimeCharacteristic.EventTime);

DataStream<ColorEvent> counts = env
  ...
  .timeWindow(Time.minutes(60))
  .apply(new CountPerWindow());
```

Explicit Handling of Time

1. **Expressive windowing**
2. **Accurate results** for out of order data
3. **Deterministic** results

Building Blocks of Flink

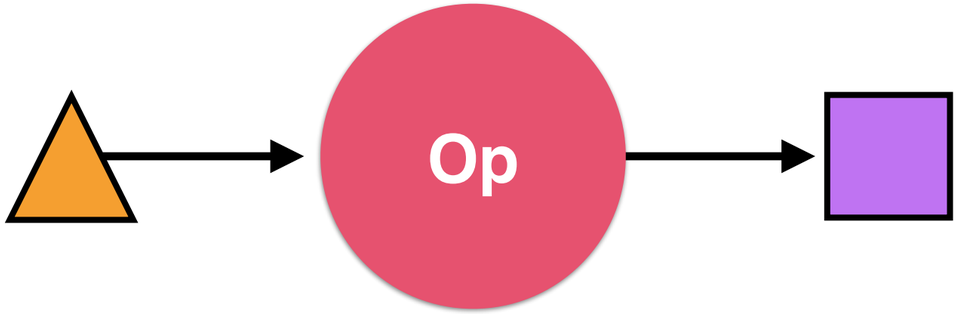
Explicit Handling of Time

State & Fault Tolerance

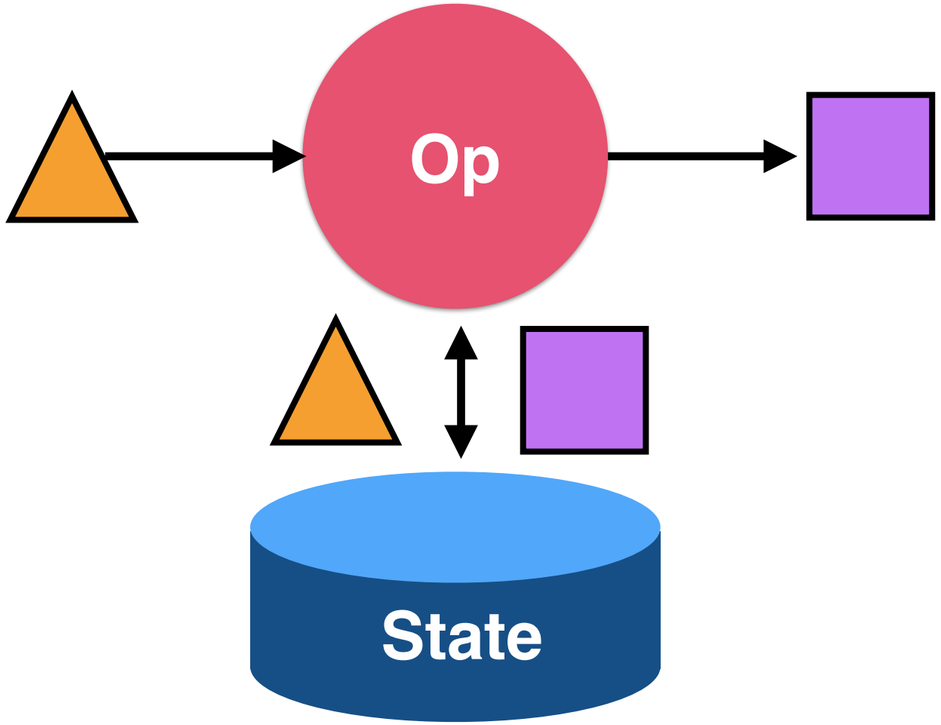
Performance

Stateful Streaming

Stateless Stream Processing



Stateful Stream Processing



Processing Semantics

At-least once
May over-count
after failure

Exactly Once
Correct counts
after failures

End-to-end exactly once
Correct counts in external system
(e.g. DB, file system) after failure

Processing Semantics

- Flink guarantees **exactly once** (can be configured for *at-least once* if desired)
- **End-to-end exactly** once with specific sources and sinks (e.g. Kafka -> Flink -> HDFS)
- Internally, Flink periodically takes **consistent snapshots** of the state without ever stopping computation

Building Blocks of Flink

Explicit Handling of Time

State & Fault Tolerance

Performance

Yahoo! Benchmark

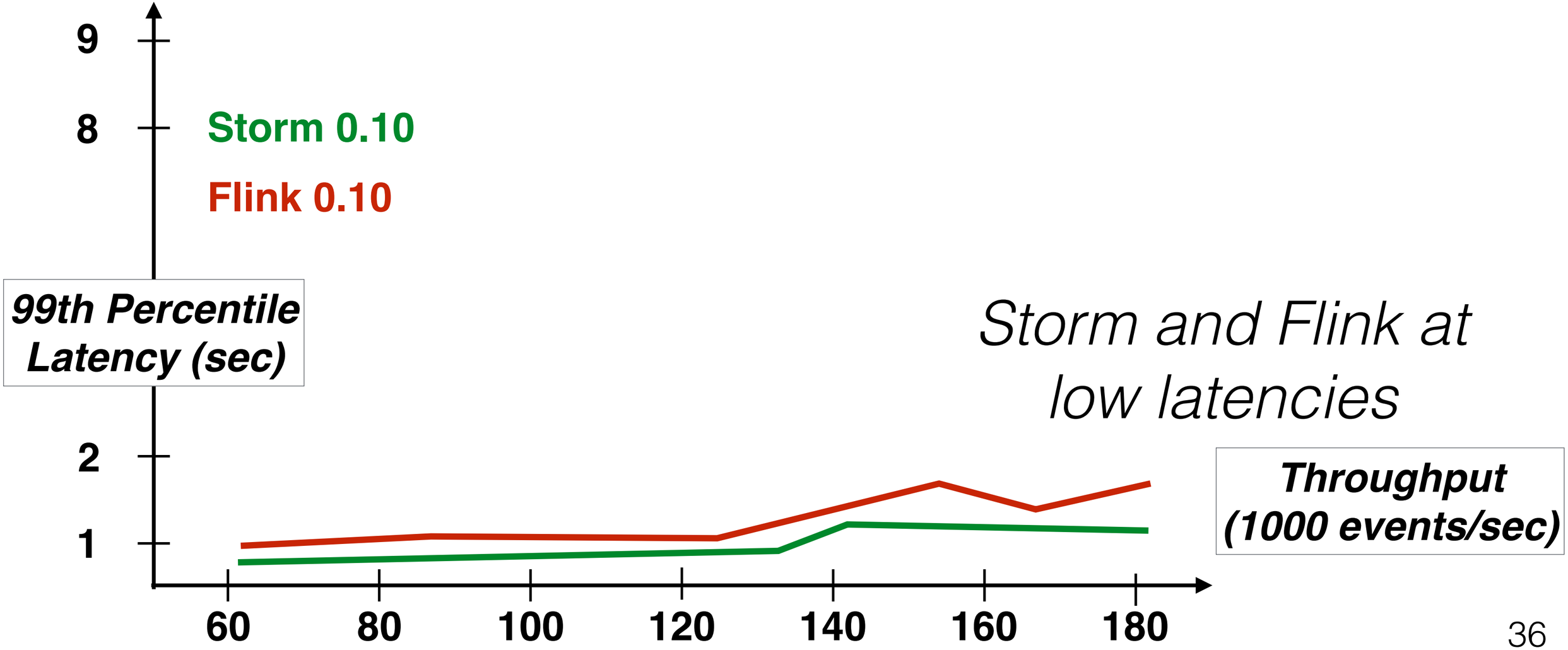
- **Storm 0.10**, **Spark Streaming 1.5**, and **Flink 0.10** benchmark by Storm team at Yahoo!
- Focus on measuring **end-to-end latency** at **low throughputs** (~ 200k events/sec)
- First benchmark modelled after a **real application**

https://yahooeng.tumblr.com/post/135321837876/benchmarking-streaming-computation-engines-at

Yahoo! Benchmark

- **Count ad impressions** grouped by campaign
- Compute **aggregates** over last 10 seconds
- Make aggregates available for **queries** in Redis

Latency (Lower is Better)



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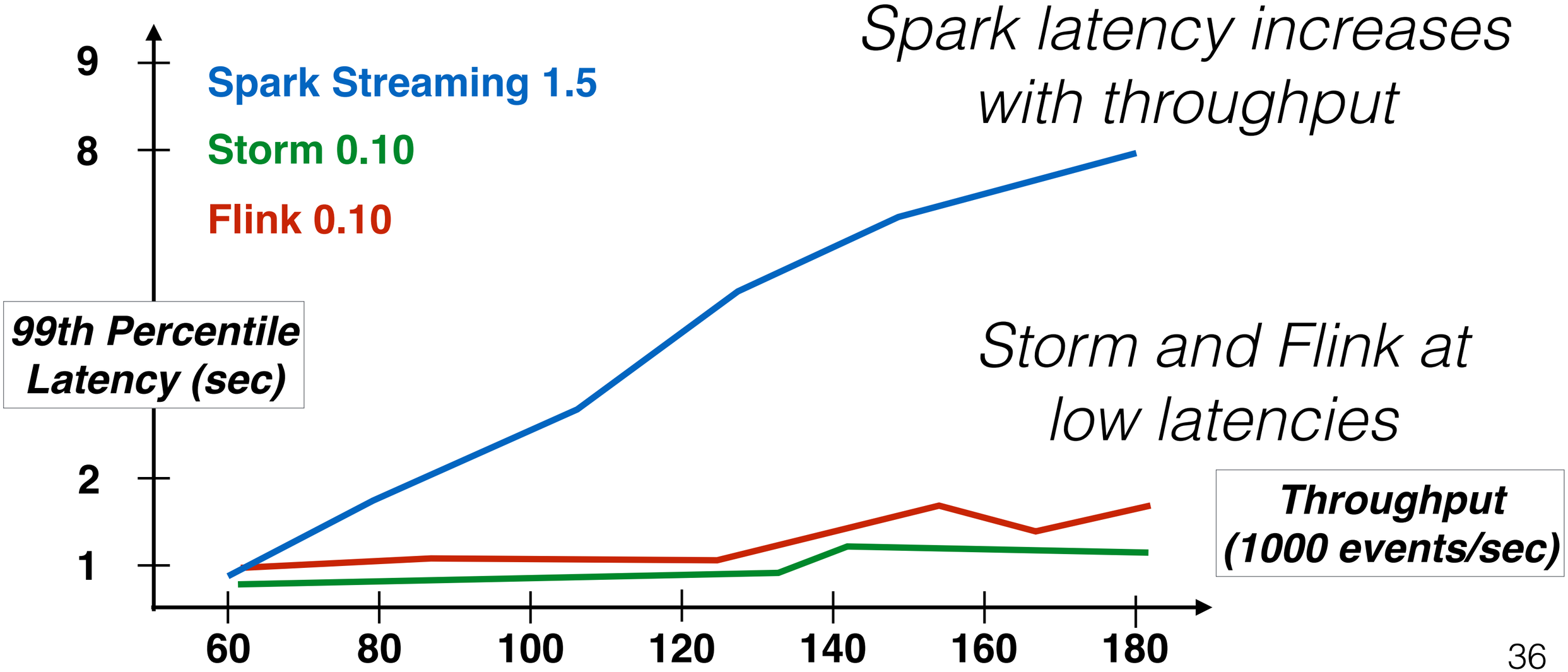
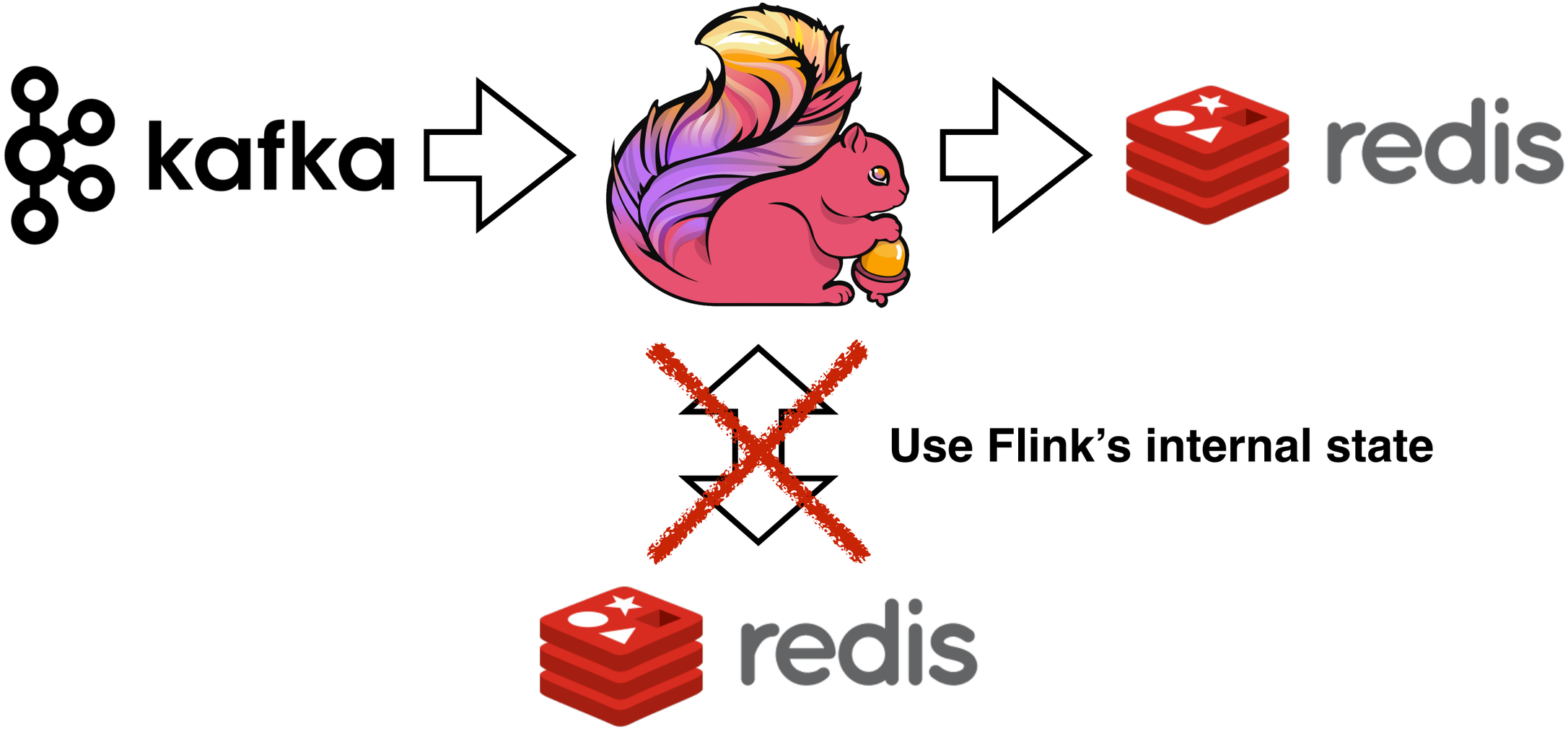


Extending the Benchmark

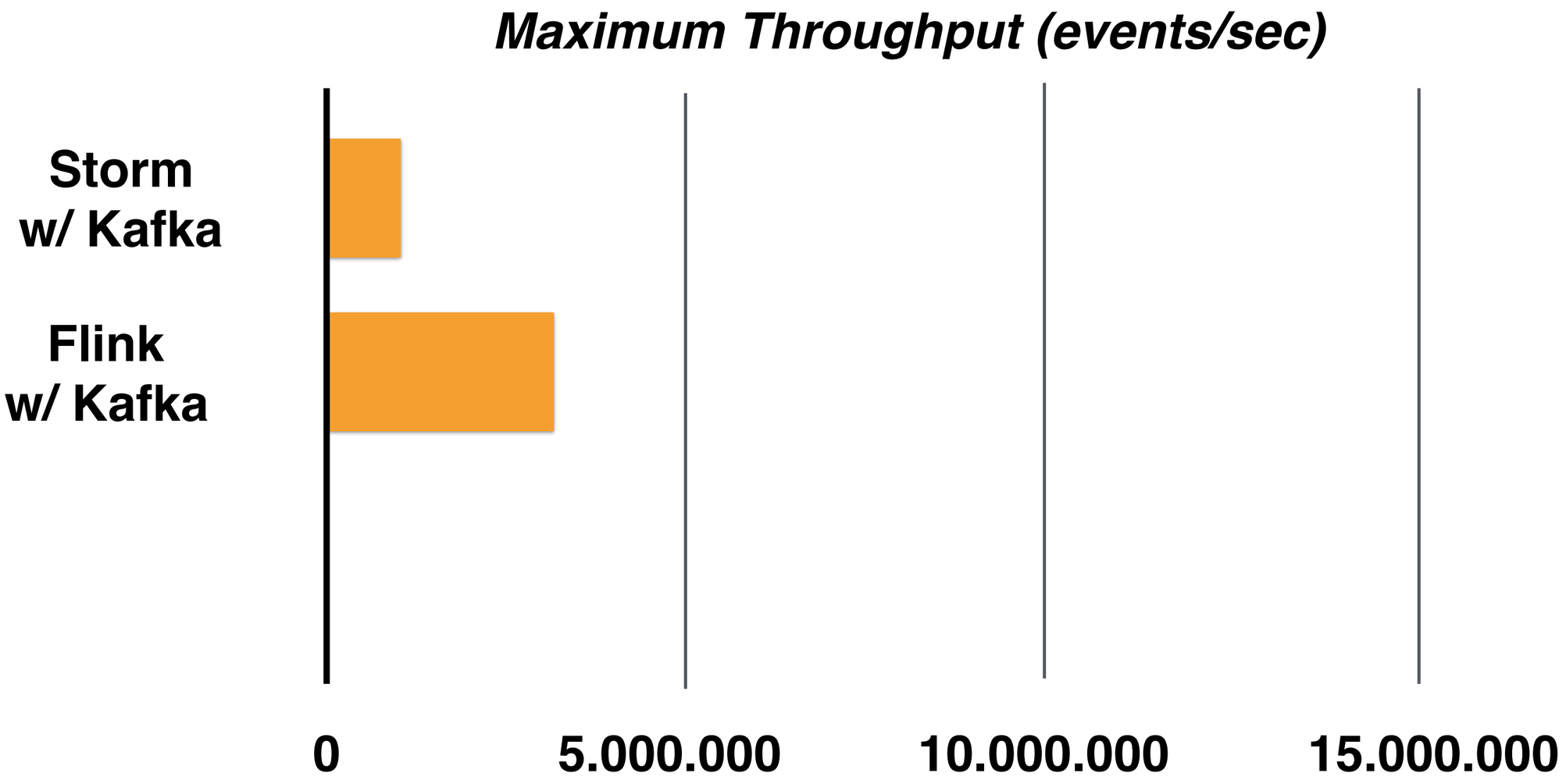
- Great starting point, but benchmark stops at **low write throughput** and programs are **not fault-tolerant**
- Extend benchmark to **high volumes** and Flink's built-in **fault-tolerant state**

http://data-artisans.com/extending-the-yahoo-streaming-benchmark/

Extending the Benchmark



Throughput (Higher is Better)



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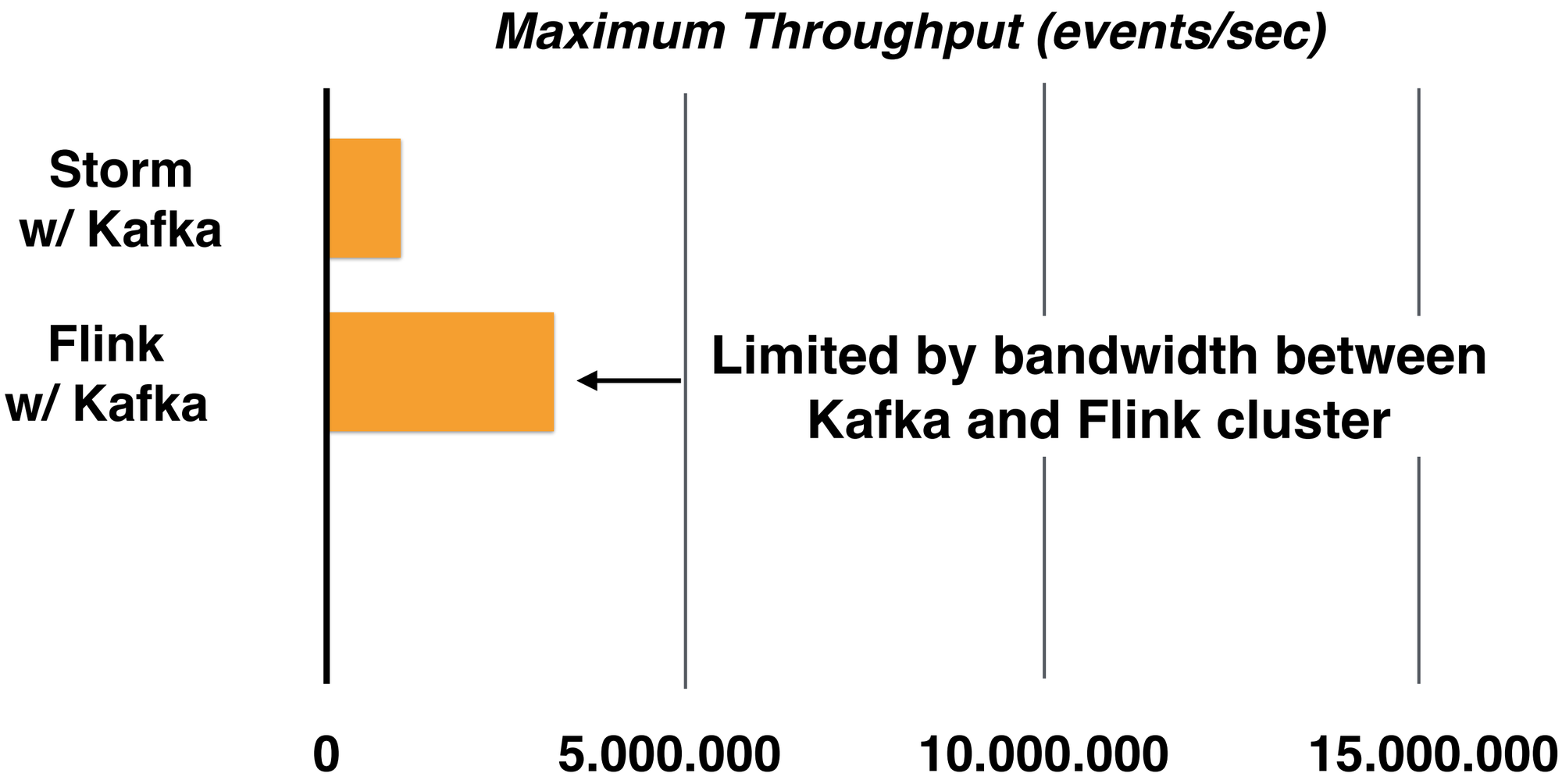

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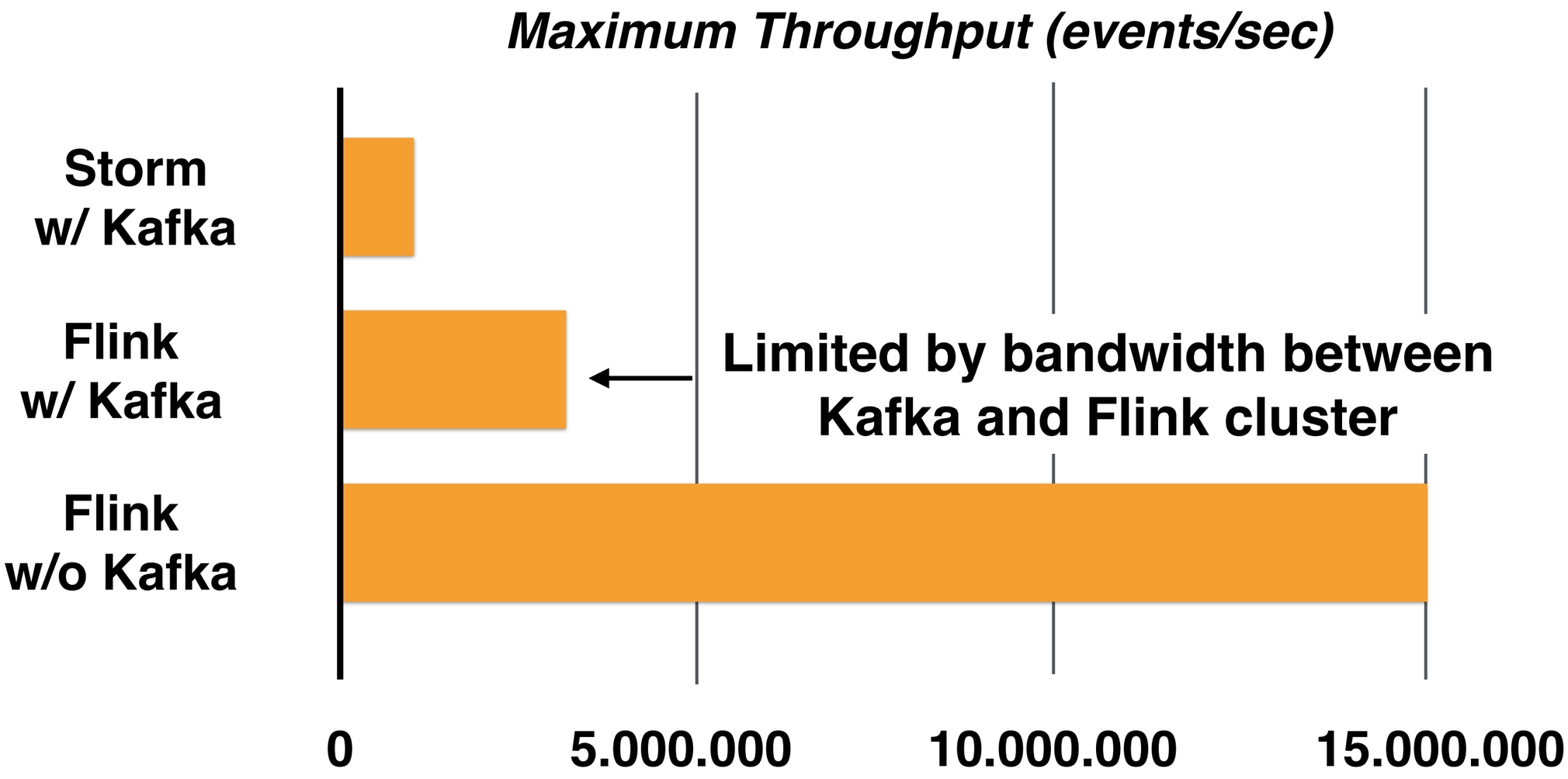
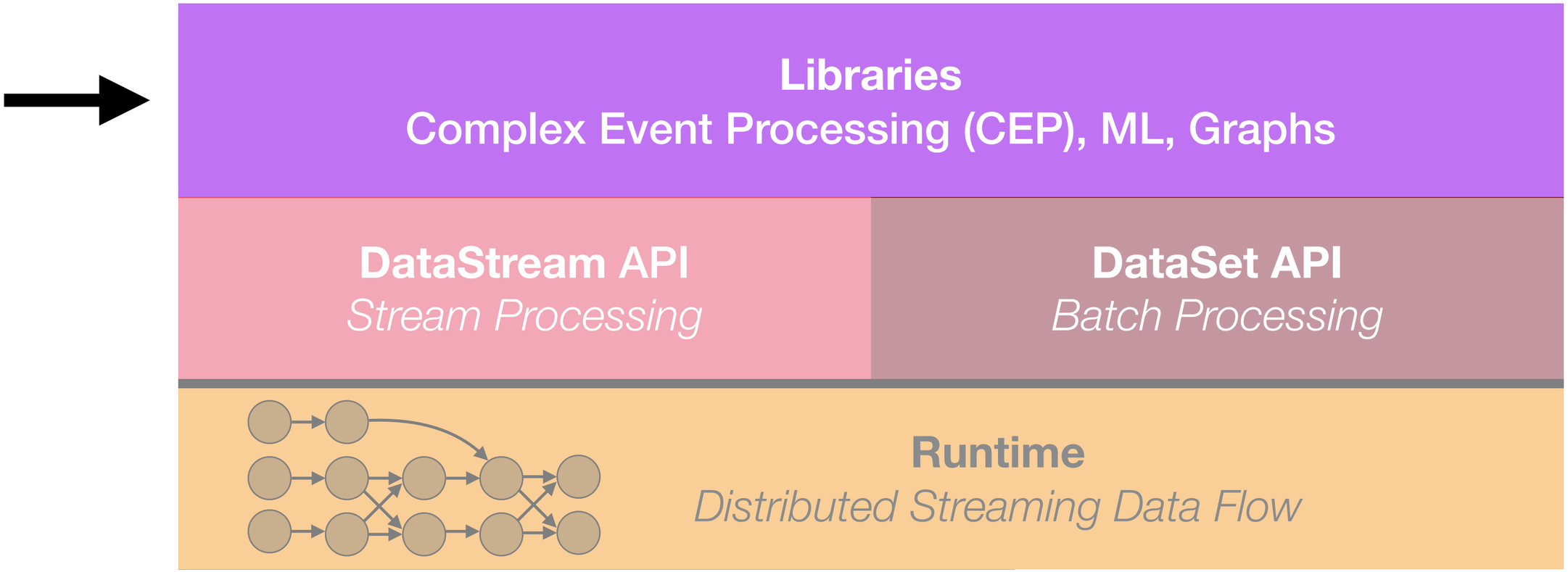


Summary

- Stream processing is gaining momentum, the **right paradigm** for continuous data applications
- Choice of **framework is crucial** – even seemingly simple applications become complex at scale and in production
- **Flink** offers **unique combination** of *efficiency*, *consistency* and *event time handling*

Libraries


Libraries
Complex Event Processing (CEP), ML, Graphs
DataStream API
Stream Processing
DataSet API
Batch Processing
Runtime
Distributed Streaming Data Flow

Complex Event Processing (CEP)

```
Pattern<MonitoringEvent, ?> warningPattern =
  Pattern.<MonitoringEvent>begin("First Event")
    .subtype(TemperatureEvent.class)
    .where(evt -> evt.getTemperature() >= THRESHOLD)
    .next("Second Event")
    .subtype(TemperatureEvent.class)
    .where(evt -> evt.getTemperature() >= THRESHOLD)
    .within(Time.seconds(10));
```

Upcoming Features

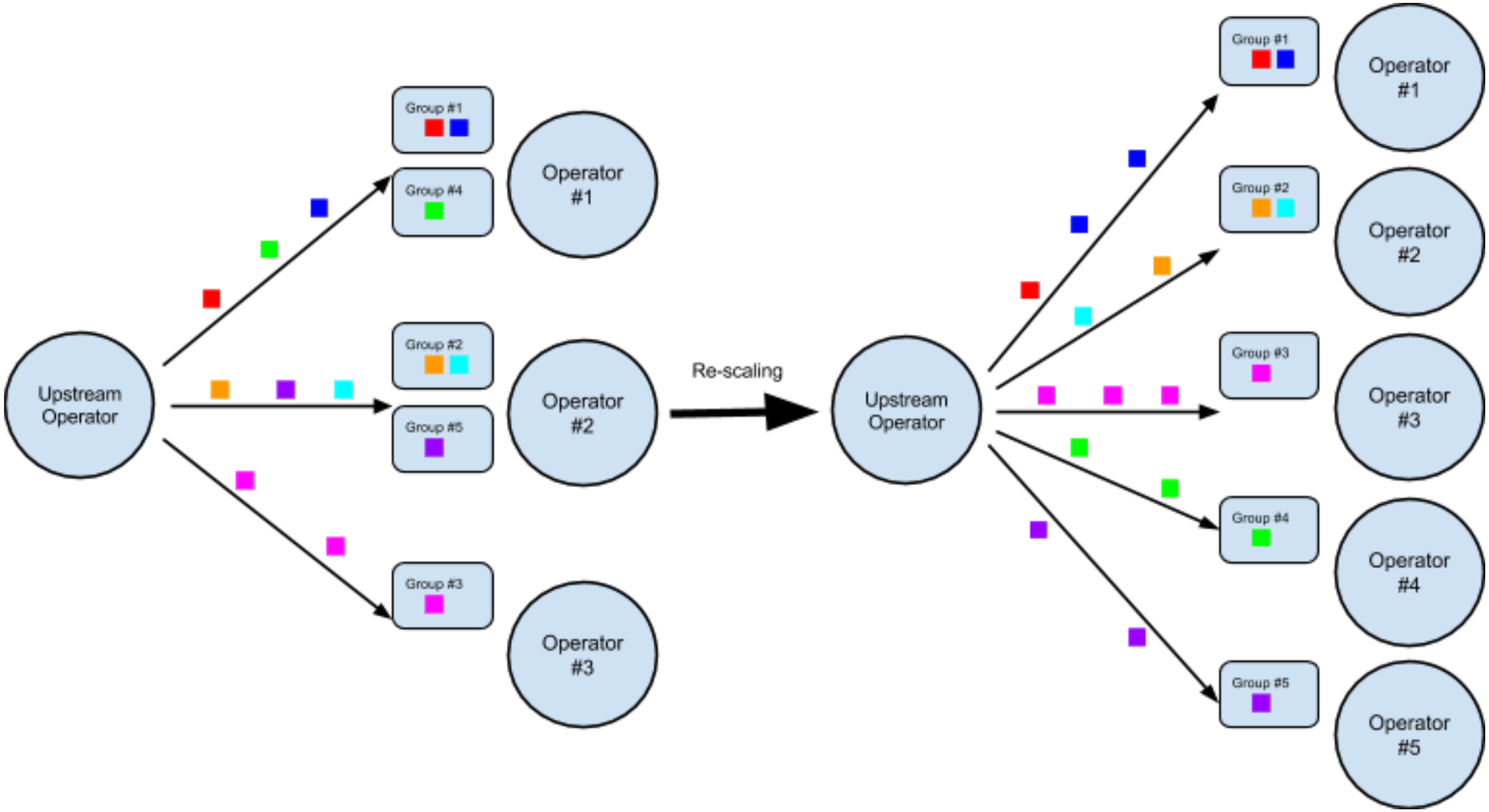
- **SQL**: ongoing work in collaboration with Apache Calcite
- **Dynamic Scaling**: adapt resources to stream volume, scale up for historical stream processing
- **Queryable State**: query the state inside the stream processor

SQL

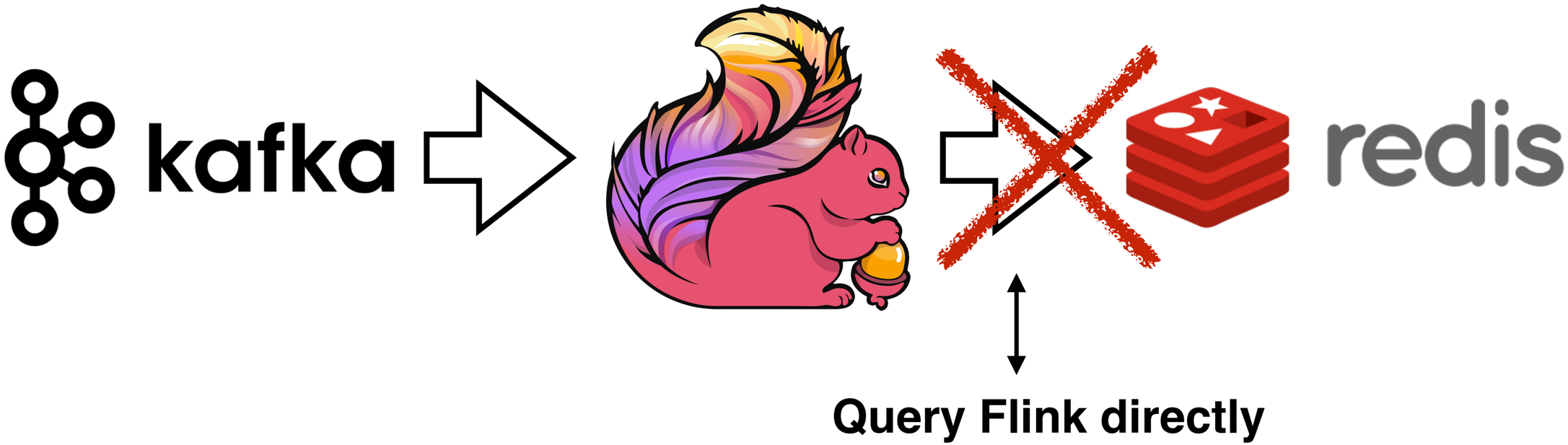
```
SELECT STREAM * FROM Orders WHERE units > 3;
```

rowtime	productId	orderId	units
10:17:00	30	5	4
10:18:07	30	8	20
11:02:00	10	9	6
11:09:30	40	11	12
11:24:11	10	12	4
…	…	…	…

Dynamic Scaling



Queryable State



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