Data-Intensive Distributed Computing

CS 451/651 431/631 (Winter 2018)

Part 9: Real-Time Data Analytics (1/2)

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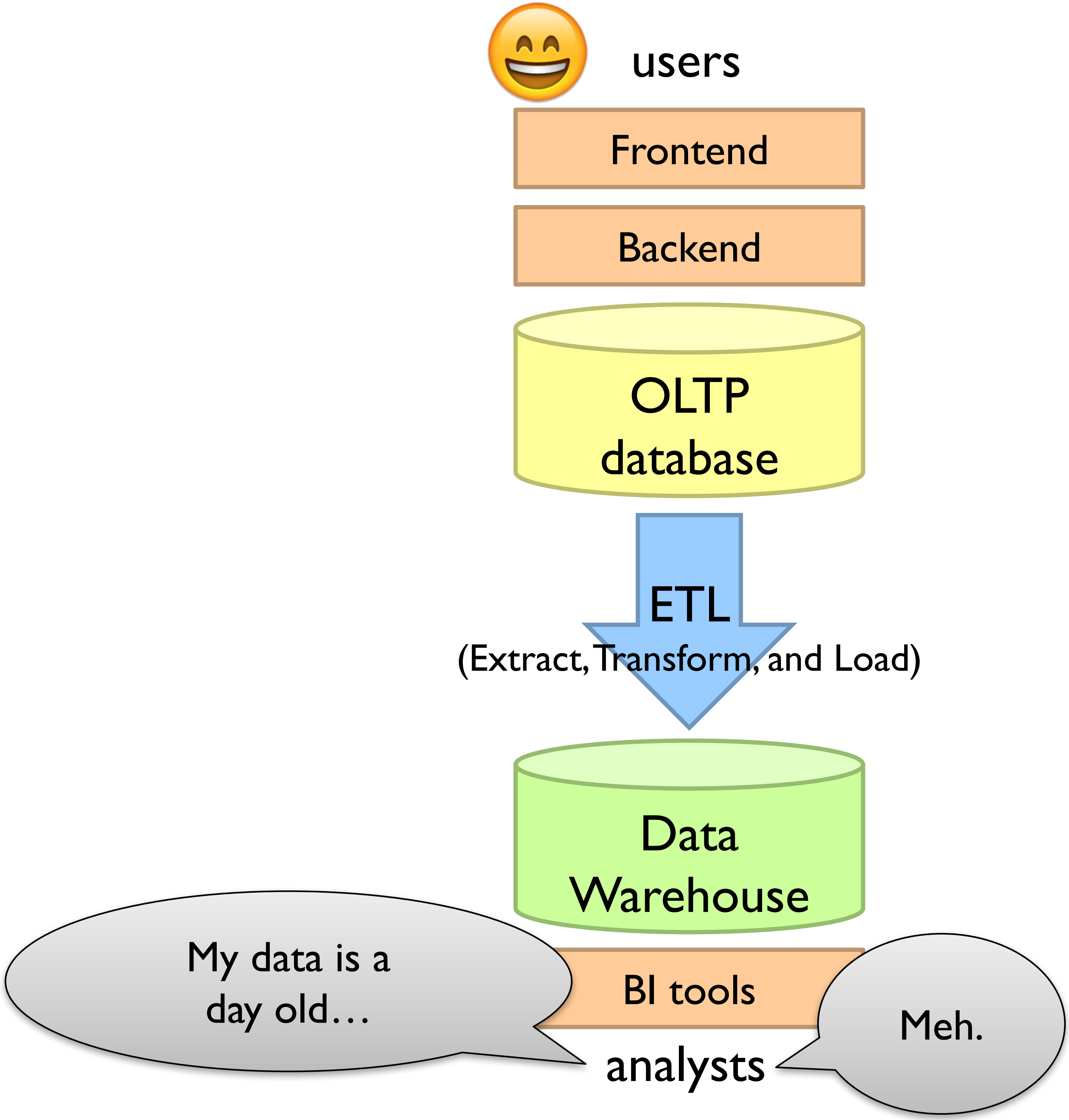
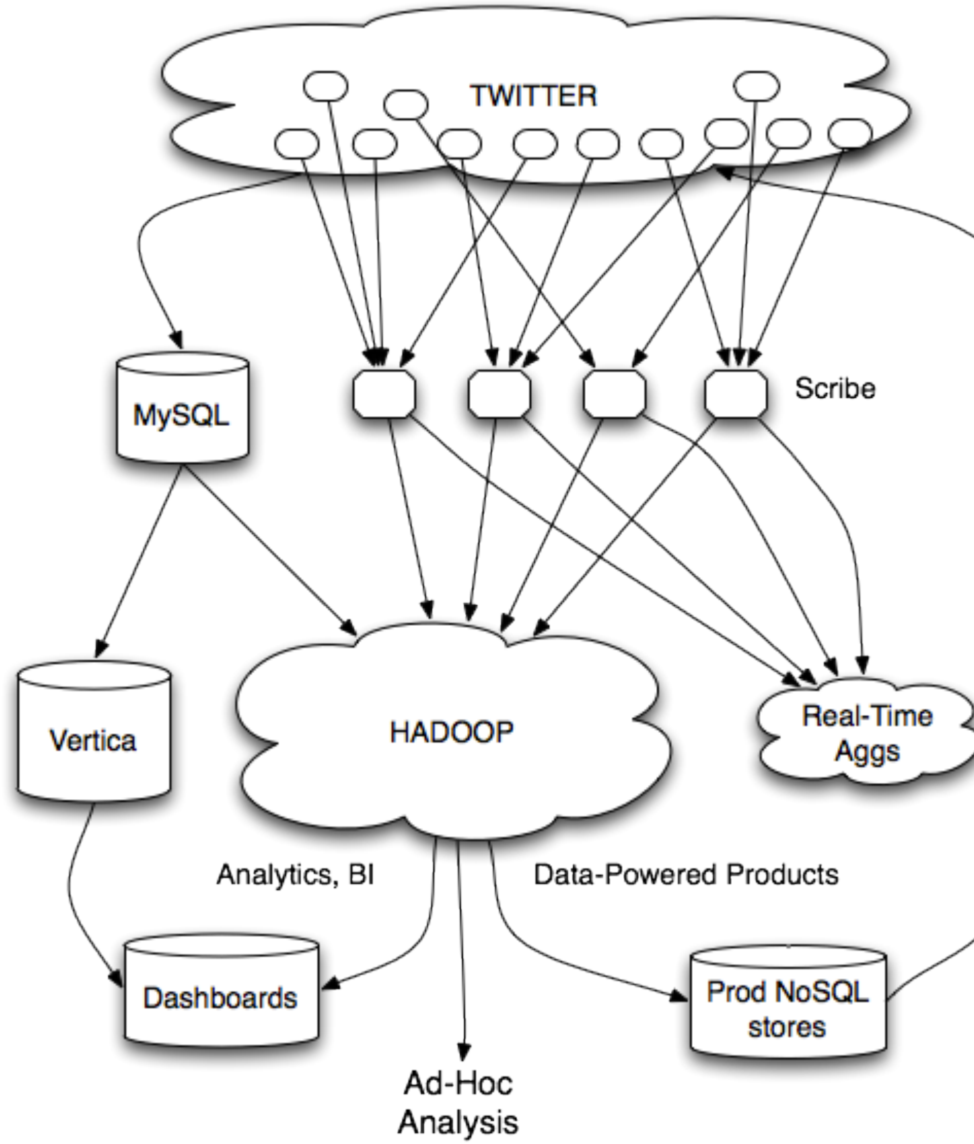
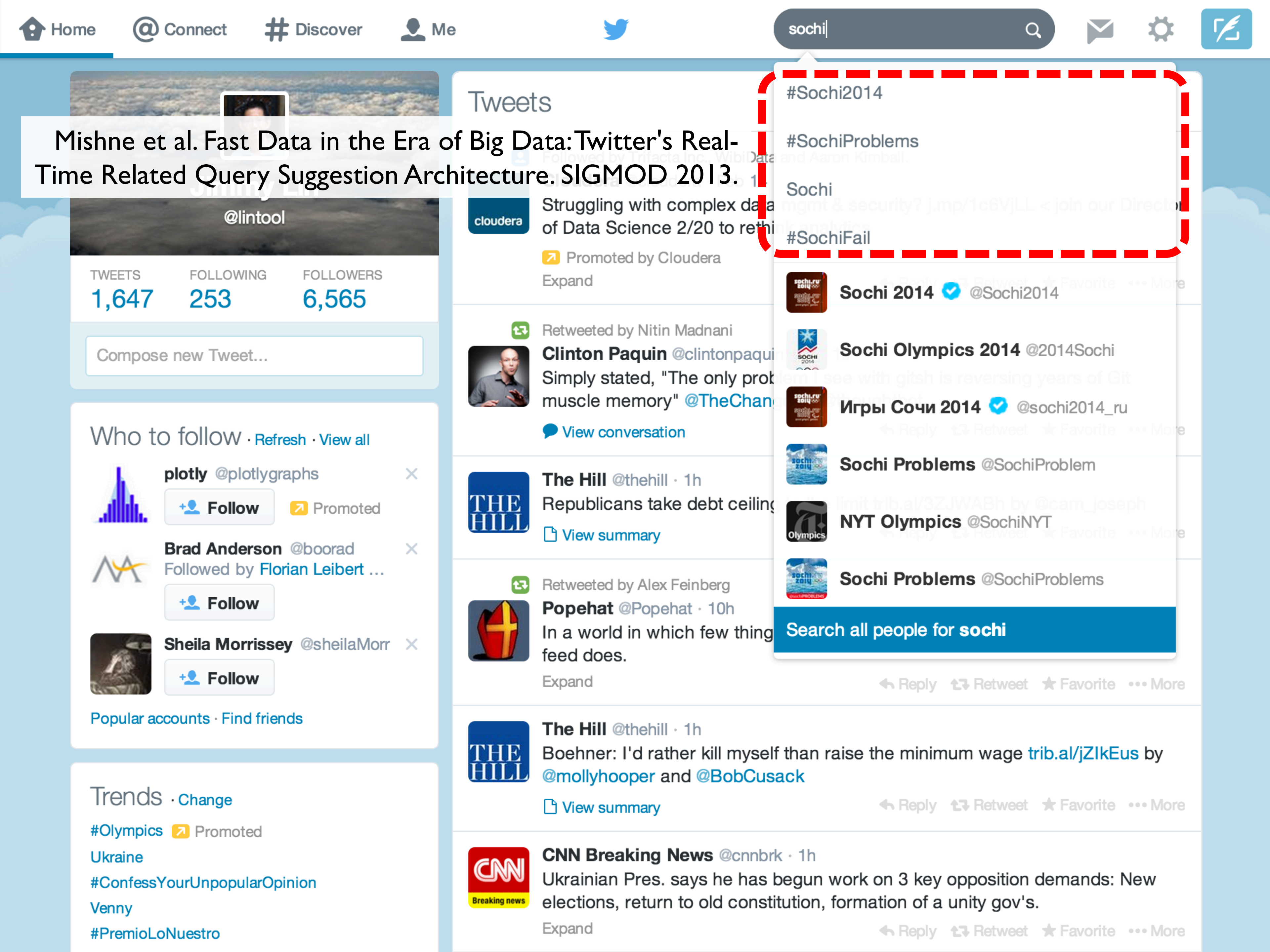
These slides are available at http://lintool.github.io/bigdata-2018w/


users
Frontend
Backend
OLTP
database
ETL
(Extract, Transform, and Load)
Data
Warehouse
BI tools
analysts
My data is a
day old…
Meh.

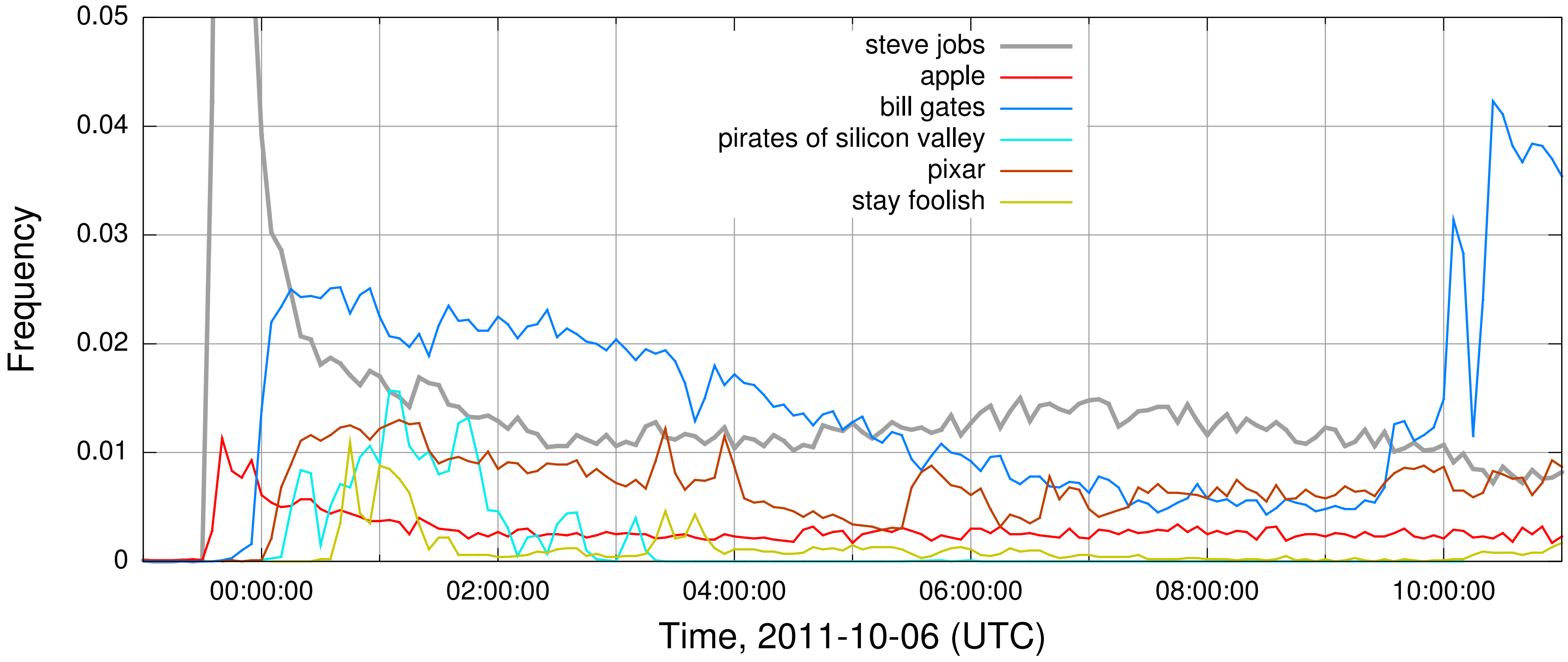


Twitter's data warehousing architecture



Mishne et al. Fast Data in the Era of Big Data: Twitter's Real-Time Related Query Suggestion Architecture. SIGMOD 2013.

Case Study: Steve Jobs passes away



Initial Implementation

Algorithm: Co-occurrences within query sessions

Implementation: Pig scripts over query logs on HDFS

Problem: Query suggestions were several hours old!

Why?

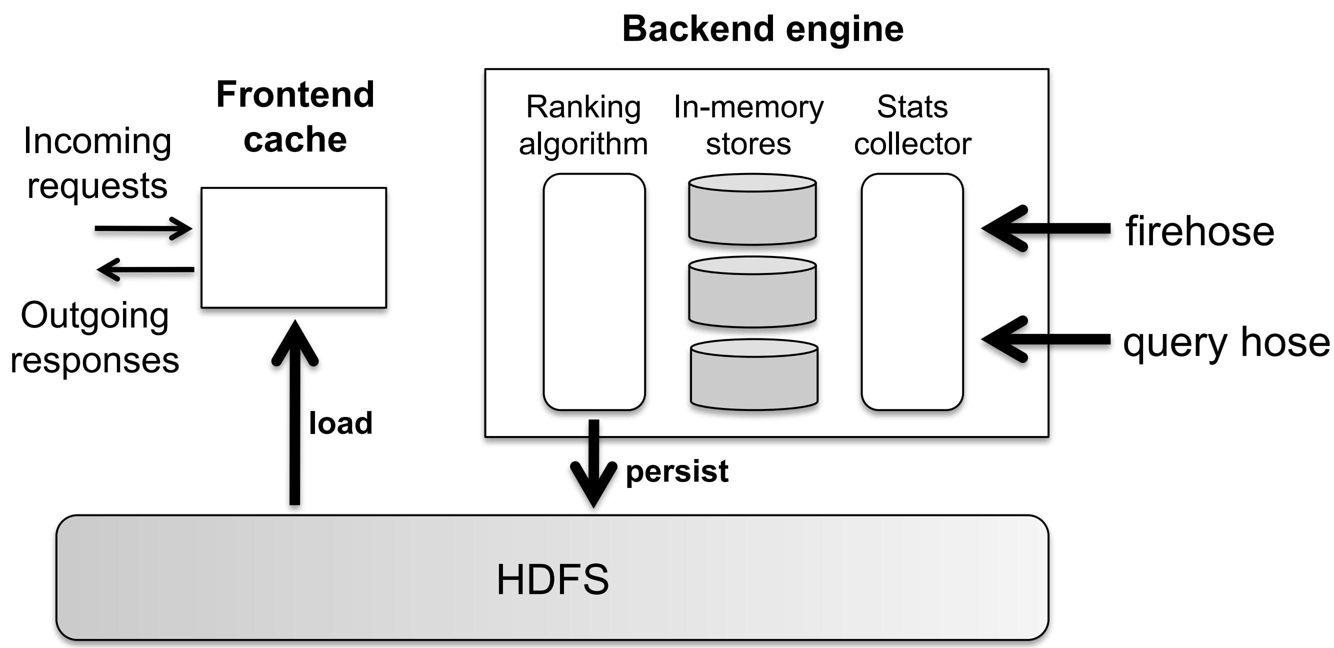
Log collection lag

Hadoop scheduling lag

Hadoop job latencies

We need real-time processing!

Solution?



Can we do better than one-off custom systems?

Stream Processing Frameworks

Source: Wikipedia (River)

real-time

vs.

online

vs.

streaming

What is a data stream?

Sequence of items:

Structured (e.g., tuples)

Ordered (implicitly or timestamped)

Arriving continuously at high volumes

Sometimes not possible to store entirely

Sometimes not possible to even examine all items

Applications

Network traffic monitoring
Datacenter telemetry monitoring
Sensor networks monitoring
Credit card fraud detection
Stock market analysis
Online mining of click streams
Monitoring social media streams

What exactly do you do?

"Standard" relational operations:

Select

Project

Transform (i.e., apply custom UDF)

Group by

Join

Aggregations

What else do you need to make this "work"?

Issues of Semantics

Group by… aggregate

When do you stop grouping and start aggregating?

Joining a stream and a static source

Simple lookup

Joining two streams

How long do you wait for the join key in the other stream?

Joining two streams, group by and aggregation

When do you stop joining?

What's the solution?

Windows

Windows restrict processing scope:

Windows based on ordering attributes (e.g., time)

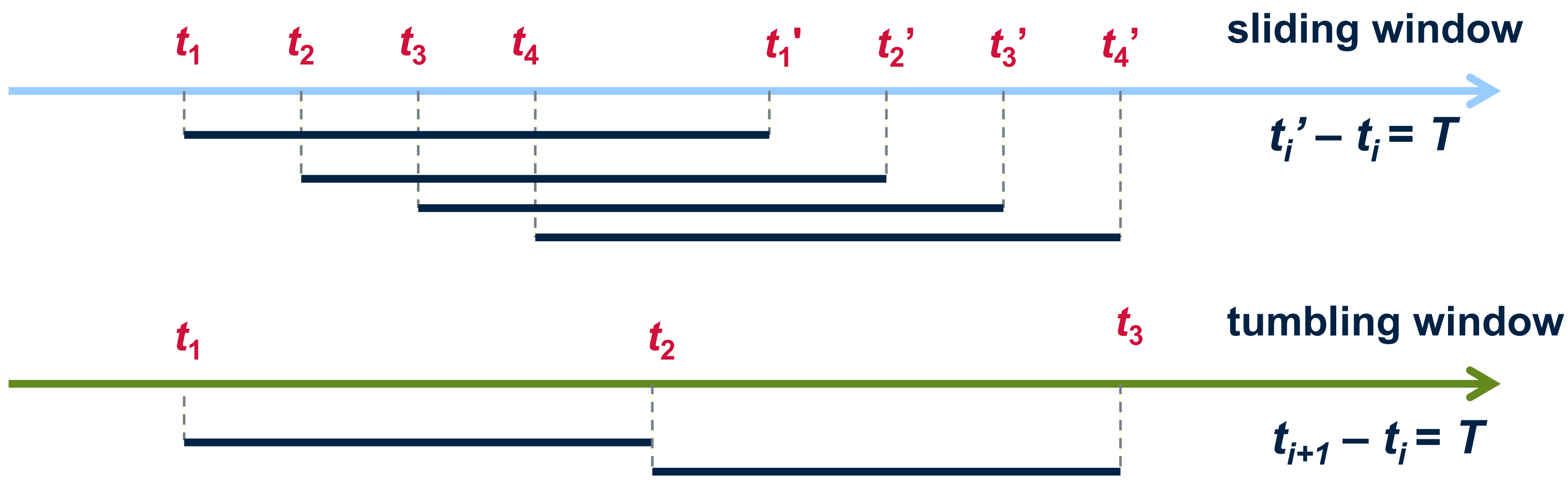
Windows based on item (record) counts

Windows based on explicit markers (e.g., punctuations)

Windows on Ordering Attributes

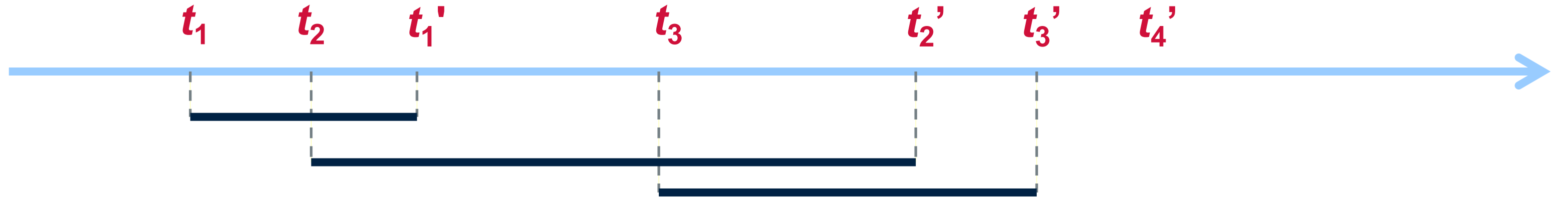
Assumes the existence of an attribute that defines the order of stream elements (e.g., time)

Let *T* be the window size in units of the ordering attribute



Windows on Counts

Window of size N elements (sliding, tumbling) over the stream



Windows from “Punctuations”

Application-inserted “end-of-processing”

Example: stream of actions… “end of user session”

Properties

Advantage: application-controlled semantics

Disadvantage: unpredictable window size (too large or too small)

Streams Processing Challenges

Inherent challenges

Latency requirements

Space bounds

System challenges

Bursty behavior and load balancing

Out-of-order message delivery and non-determinism

Consistency semantics (at most once, exactly once, at least once)

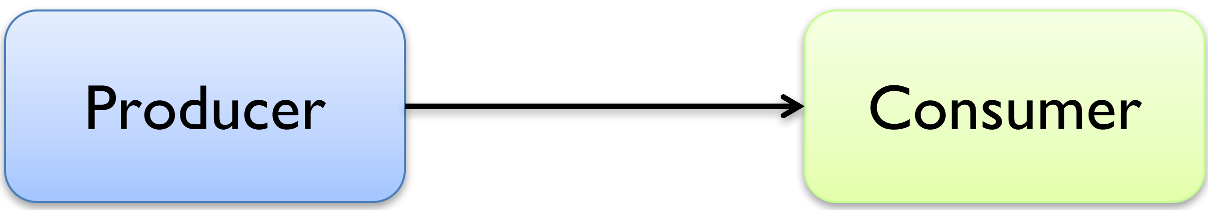
Stream Processing Frameworks

Source: Wikipedia (River)

Producer/Consumers

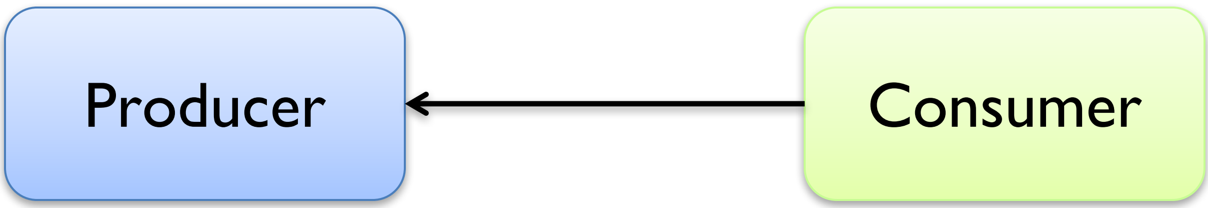
How do consumers get data from producers?

Producer/Consumers



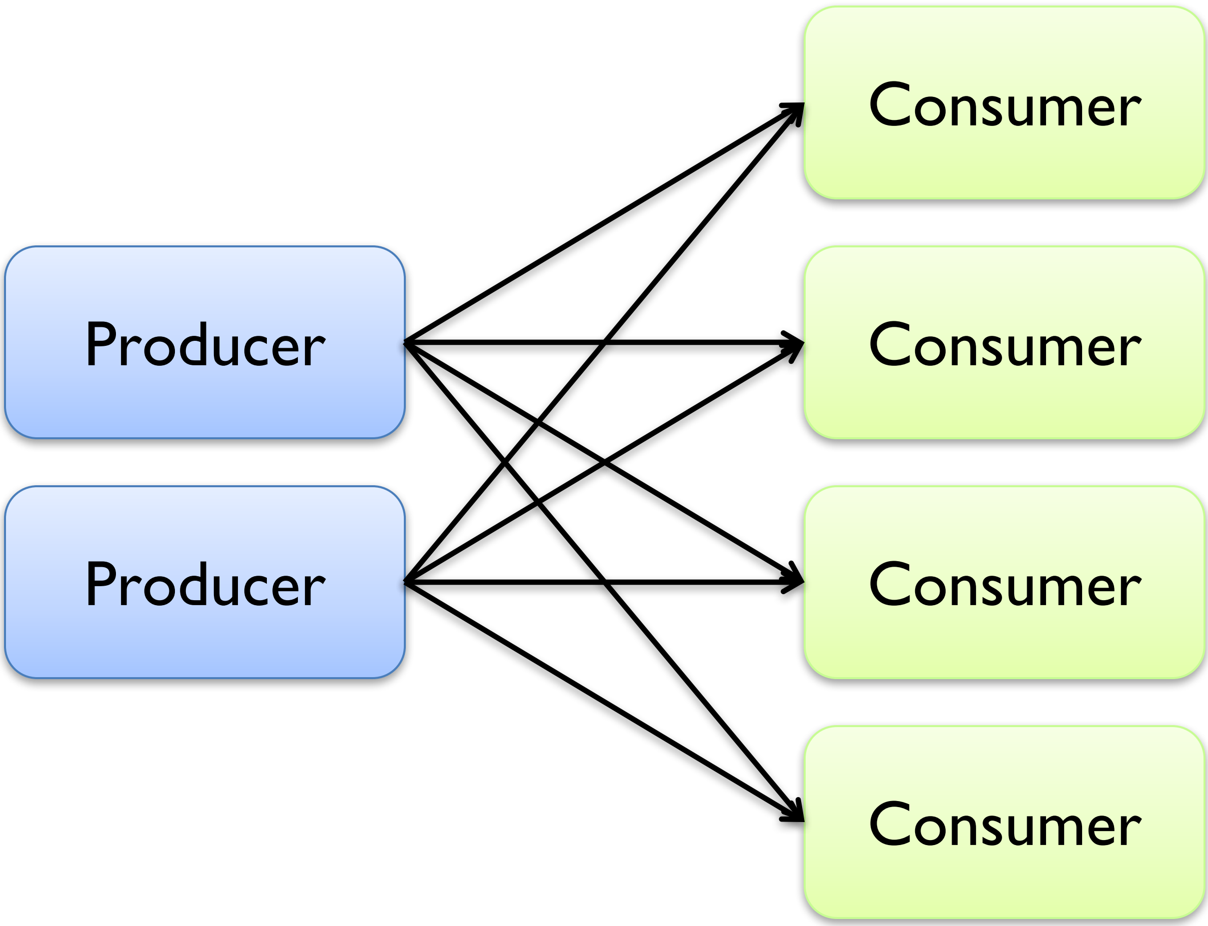
Producer pushes
e.g., callback

Producer/Consumers

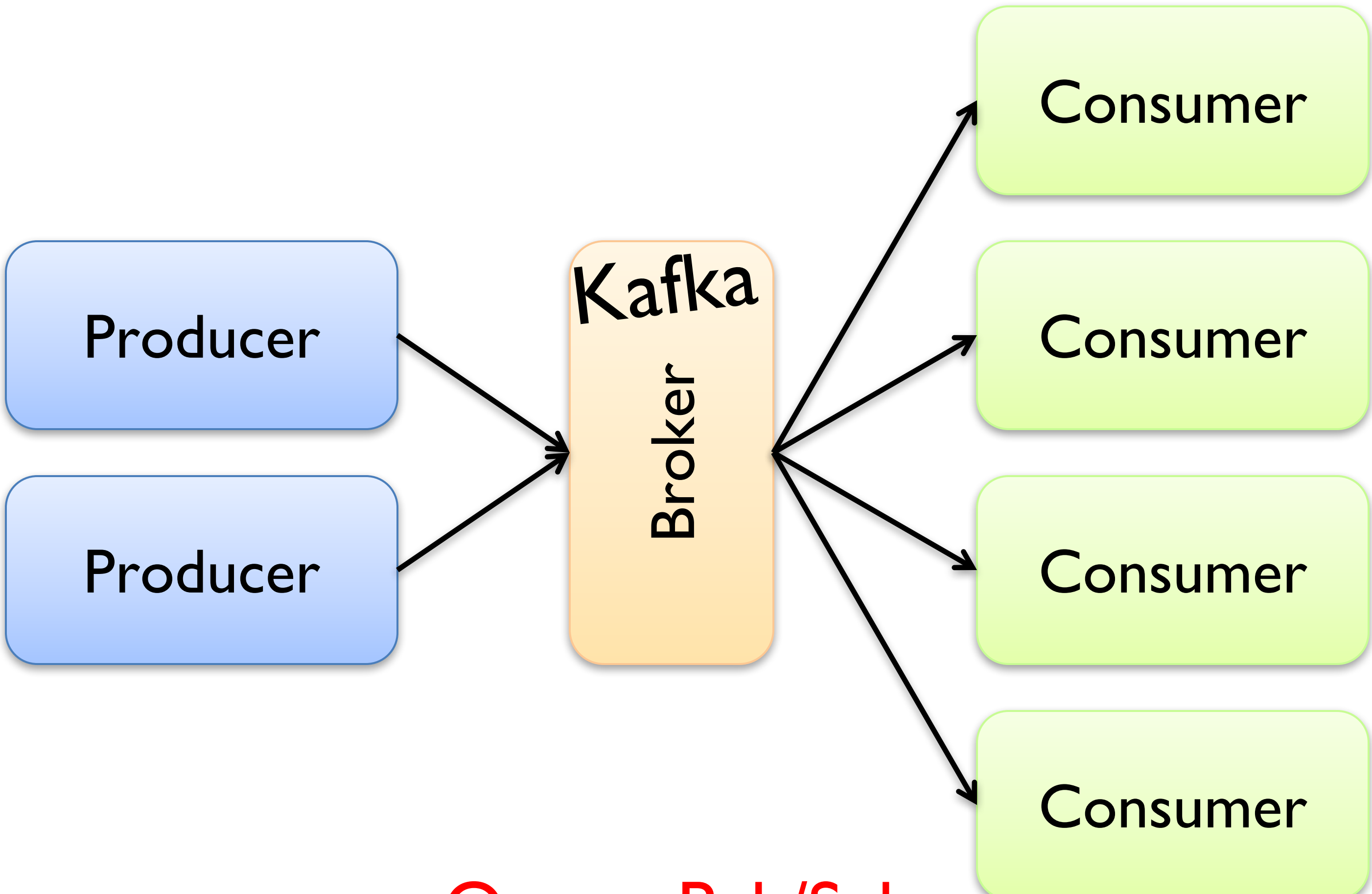


Consumer pulls
e.g., poll, tail

Producer/Consumers

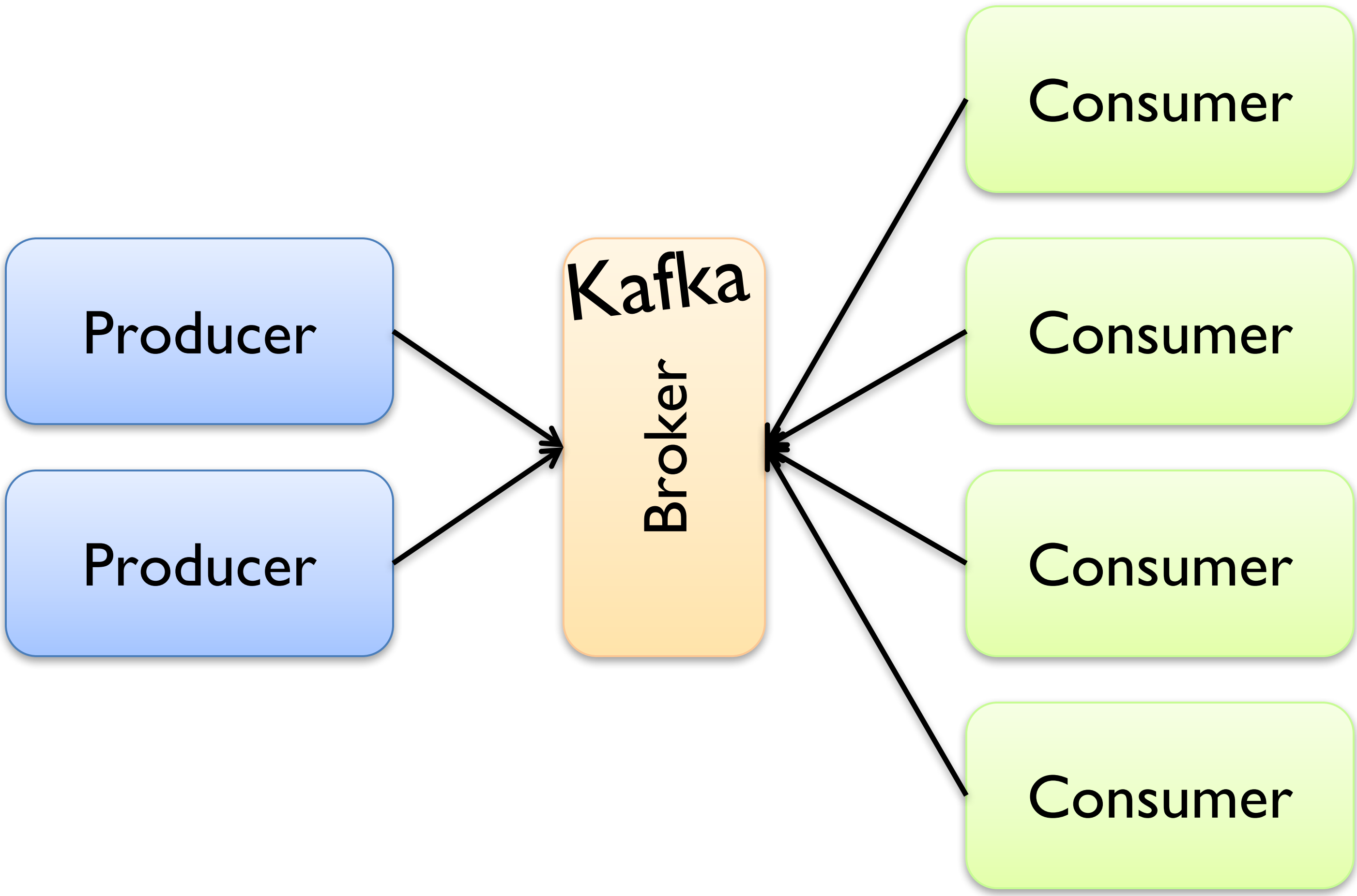


Producer/Consumers



Queue, Pub/Sub

Producer/Consumers



Source: Wikipedia (River)

Storm/Heron

Storm: real-time distributed stream processing system

Started at BackType

BackType acquired by Twitter in 2011

Now an Apache project

Heron: API compatible re-implementation of Storm

Introduced by Twitter in 2015

Open-sourced in 2016

Want real-time stream processing?
I got your back.

I've got the most intuitive
implementation: a computation graph!

APACHE STORM™

Distributed • Resilient • Real-time

Topologies

Storm topologies = “job”

Once started, runs continuously until killed

A topology is a computation graph

Graph contains vertices and edges

Vertices hold processing logic

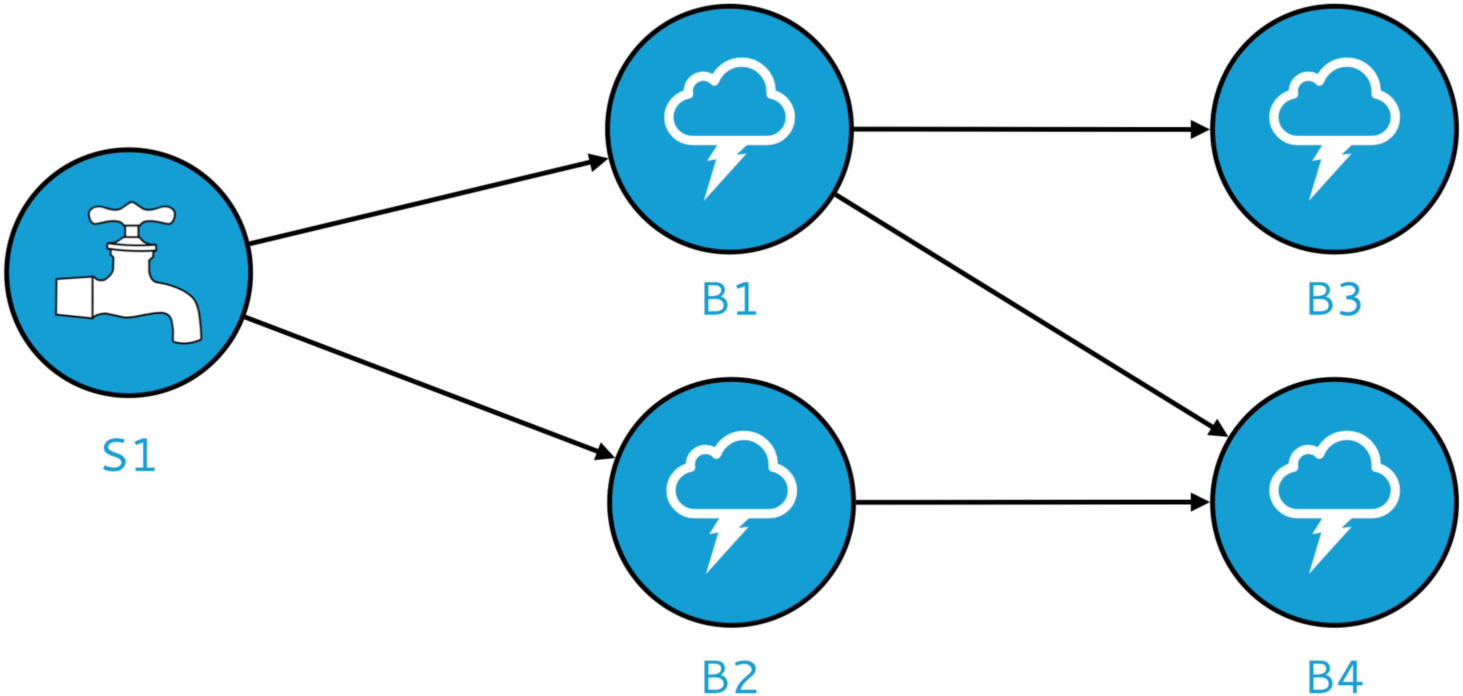
Directed edges indicate communication between vertices

Processing semantics

At most once: without acknowledgments

At least once: with acknowledgements

Spouts and Bolts: Logical Plan



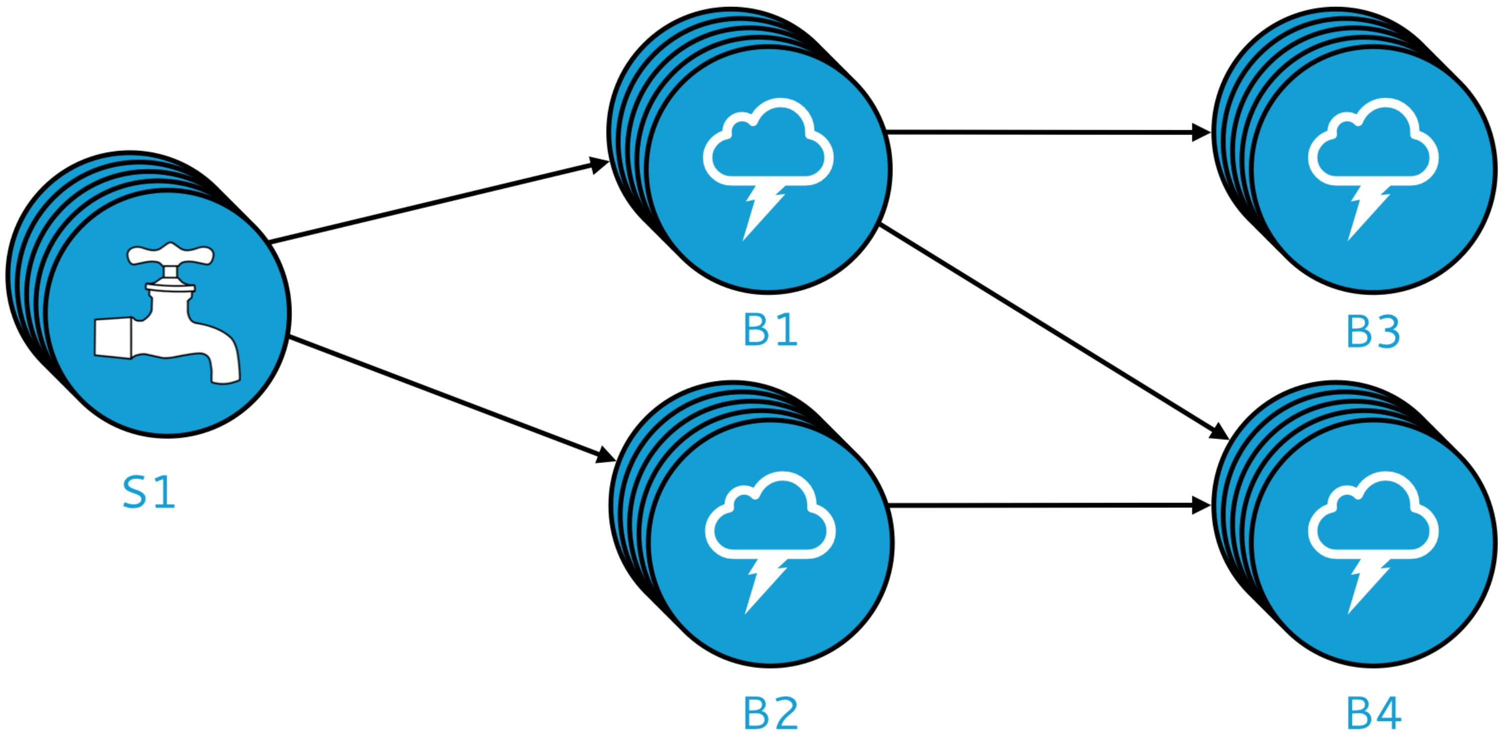
Components

Tuples: data that flow through the topology

Spouts: responsible for emitting tuples

Bolts: responsible for processing tuples

Spouts and Bolts: Physical Plan



Physical plan specifies execution details

Parallelism: how many instances of bolts and spouts to run

Placement of bolts/spouts on machines

...

Stream Groupings

Bolts are executed by multiple instances in parallel

User-specified as part of the topology

When a bolt emits a tuple, where should it go?

Answer: Grouping strategy

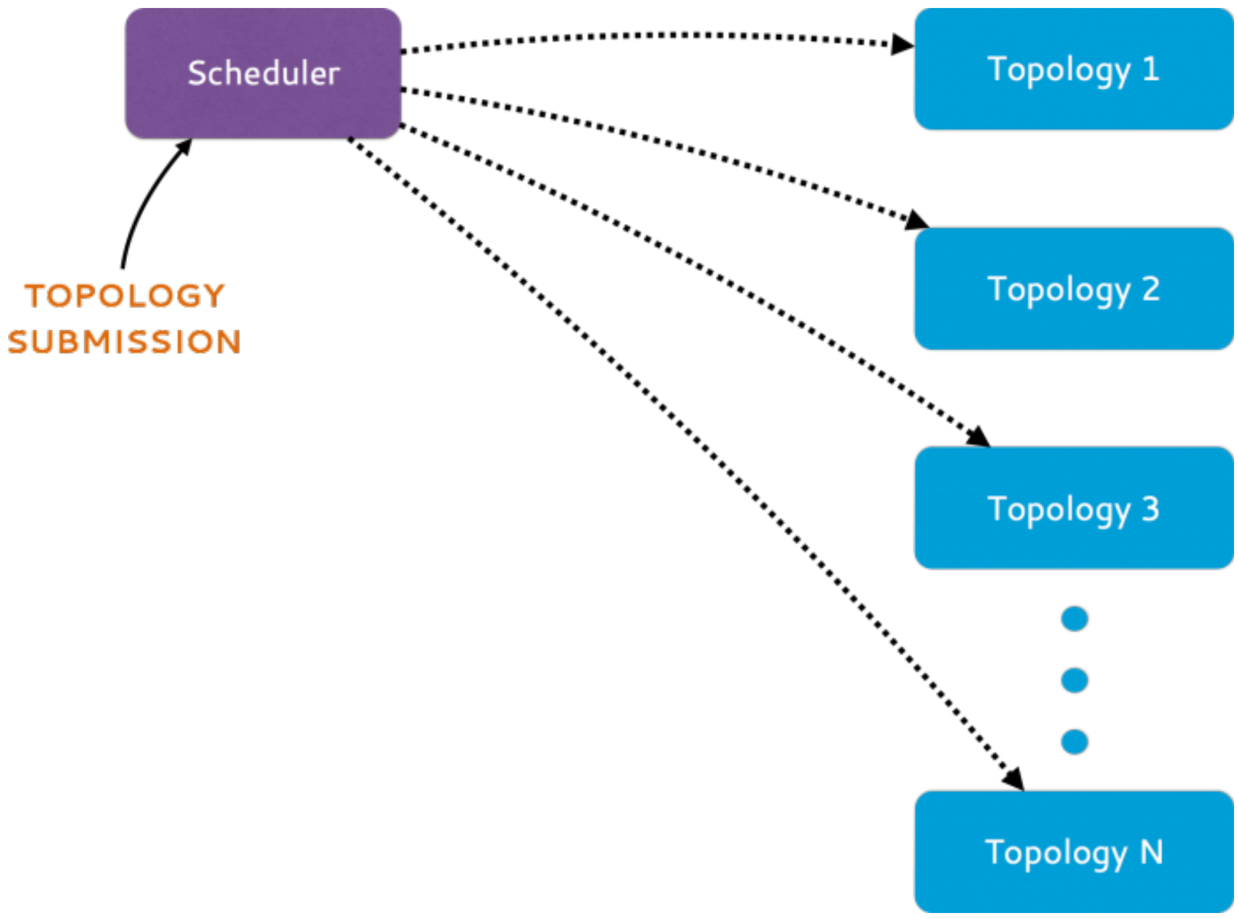
Shuffle grouping: randomly to different instances

Field grouping: based on a field in the tuple

Global grouping: to only a single instance

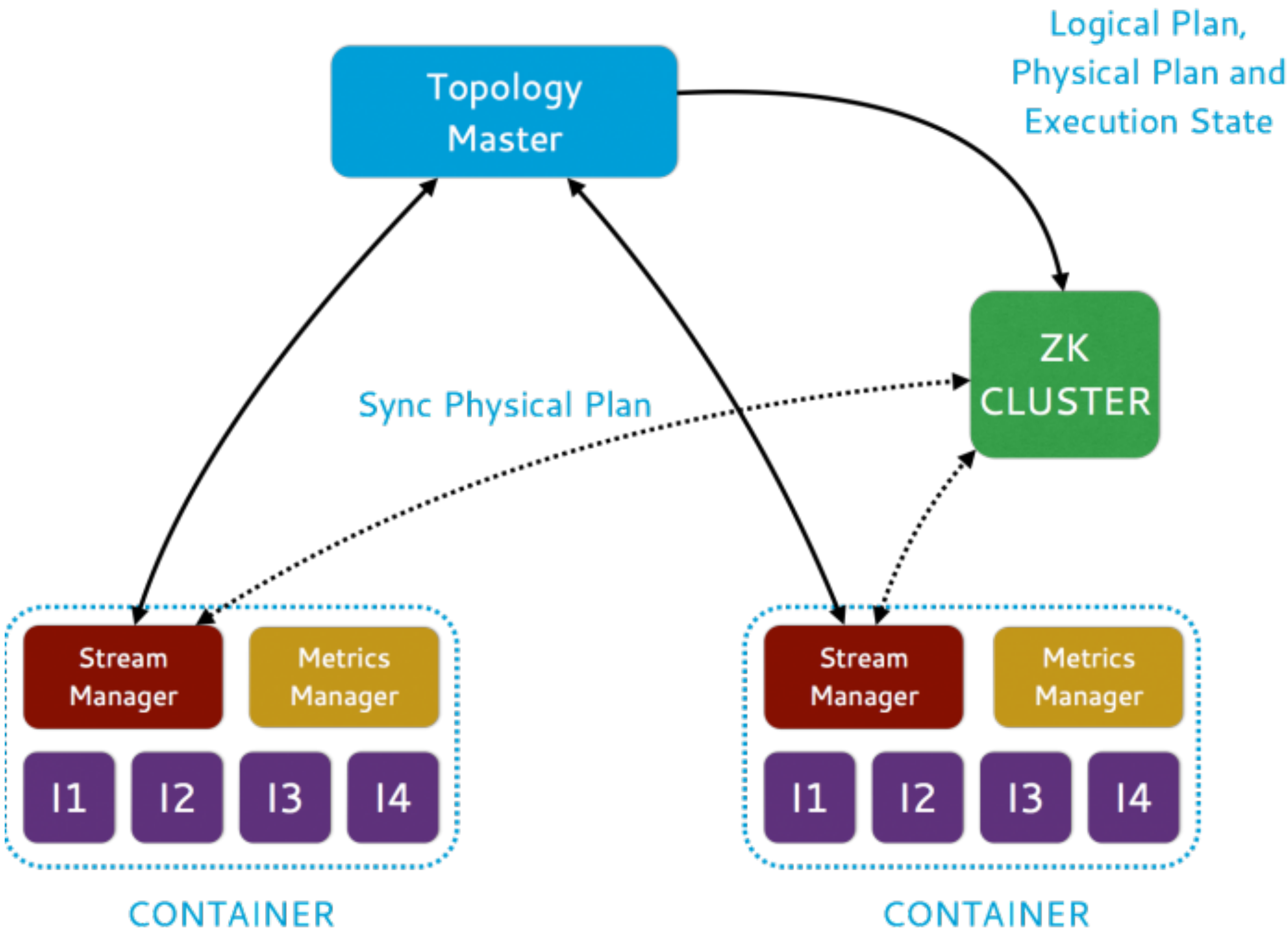
All grouping: to every instance

Heron Architecture



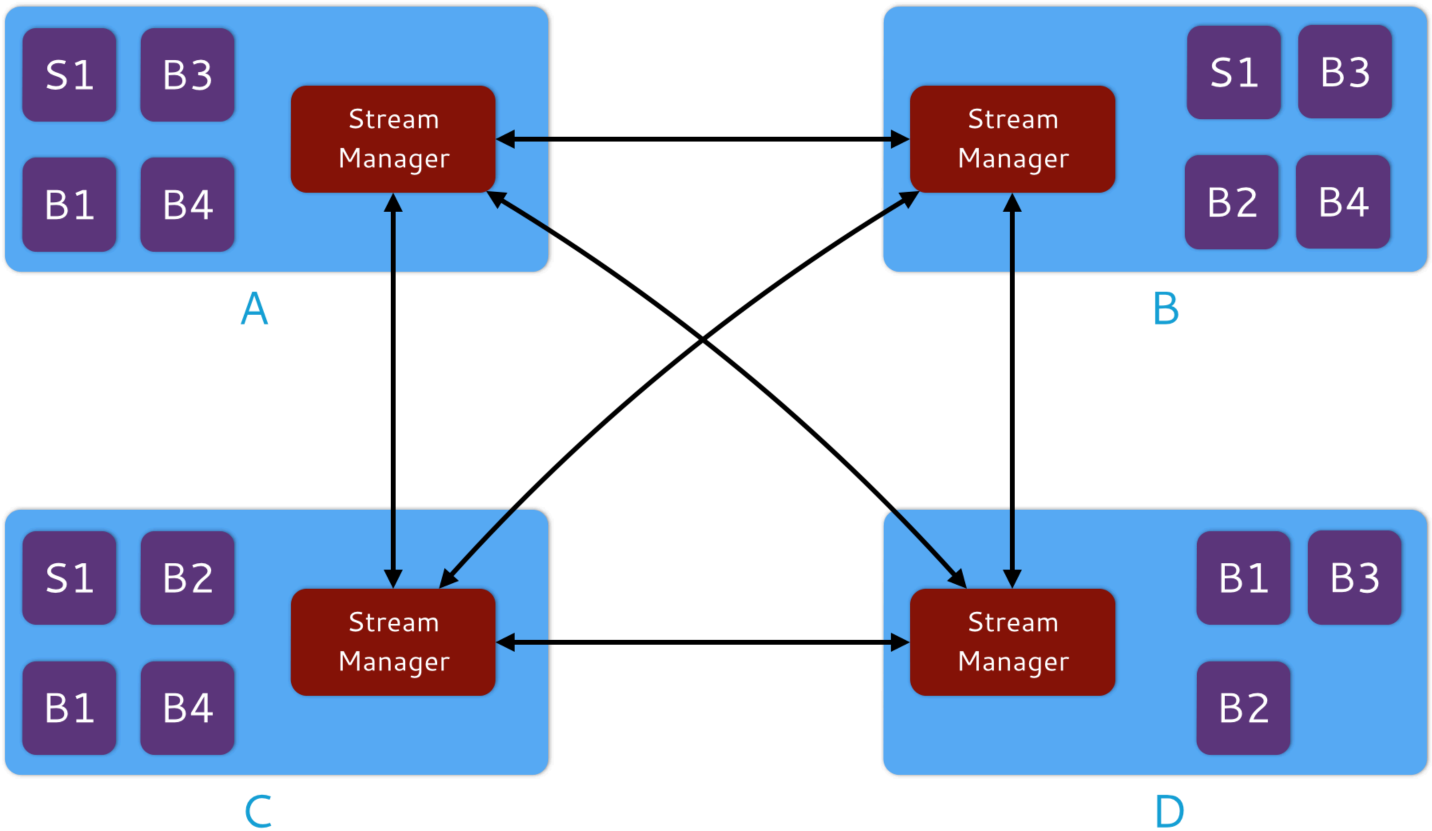
Source: https://blog.twitter.com/2015/flying-faster-with-twitter-heron

Heron Architecture



Source: https://blog.twitter.com/2015/flying-faster-with-twitter-heron

Heron Architecture



Stream Manager

Manages routing tuples between spouts and bolts

Responsible for applying backpressure

Some me some code!

```
TopologyBuilder builder = new TopologyBuilder();
builder.setSpout("word", new WordSpout(), parallelism);
builder.setBolt("consumer", new ConsumerBolt(), parallelism)
    .fieldsGrouping("word", new Fields("word"));

Config conf = new Config();
// Set config here
// ...

StormSubmitter.submitTopology("my topology”, conf,
    builder.createTopology());
```

Some me some code!

```
public static class WordSpout extends BaseRichSpout {
  @Override
  public void declareOutputFields(
      OutputFieldsDeclarer outputFieldsDeclarer) {
    outputFieldsDeclarer.declare(new Fields("word"));
  }

  @Override
  public void nextTuple() {
    // ...
    collector.emit(word);
  }
}
```

Some me some code!

```
public static class ConsumerBolt extends BaseRichBolt {
  private OutputCollector collector;
  private Map<String, Integer> countMap;

  public void prepare(Map map, TopologyContext
      topologyContext, OutputCollector outputCollector) {
    collector = outputCollector;
    countMap = new HashMap<String, Integer>();
  }

  @Override
  public void execute(Tuple tuple) {
    String key = tuple.getString(0);
    if (countMap.get(key) == null) {
      countMap.put(key, 1);
    } else {
      Integer val = countMap.get(key);
      countMap.put(key, ++val);
    }
  }
}
```

What's the issue?

Source: Wikipedia (Plumbing)


Spark Streaming
Stream Processing Frameworks
Source: Wikipedia (River)

Hmm, I gotta get in on this streaming thing…

APACHE Spark™

But I got all this batch processing framework that I gotta lug around.

I know: we'll just chop the stream into little pieces, pretend each is an RDD, and we're on our merry way!

Want real-time stream processing? I got your back.

I've got the most intuitive implementation: a computation graph!

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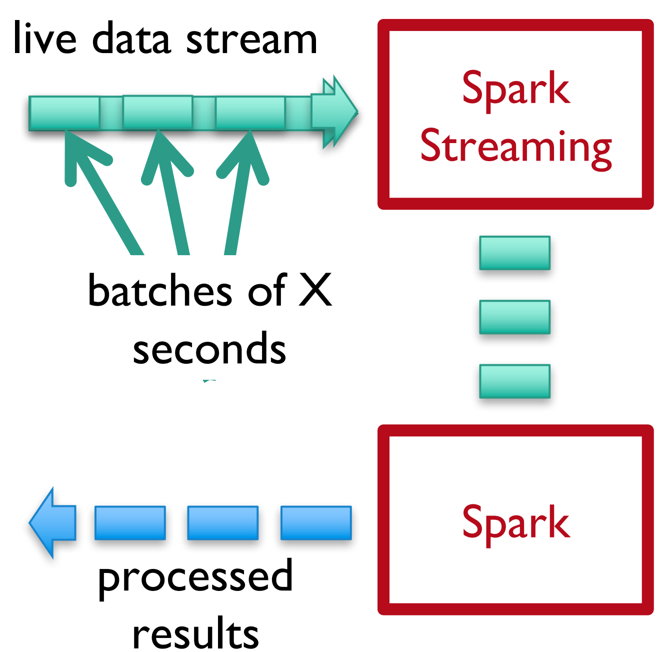
Spark Streaming: Discretized Streams

Run a streaming computation as a series of very small, deterministic batch jobs

Chop up the stream into batches of X seconds

Process as RDDs!

Return results in batches



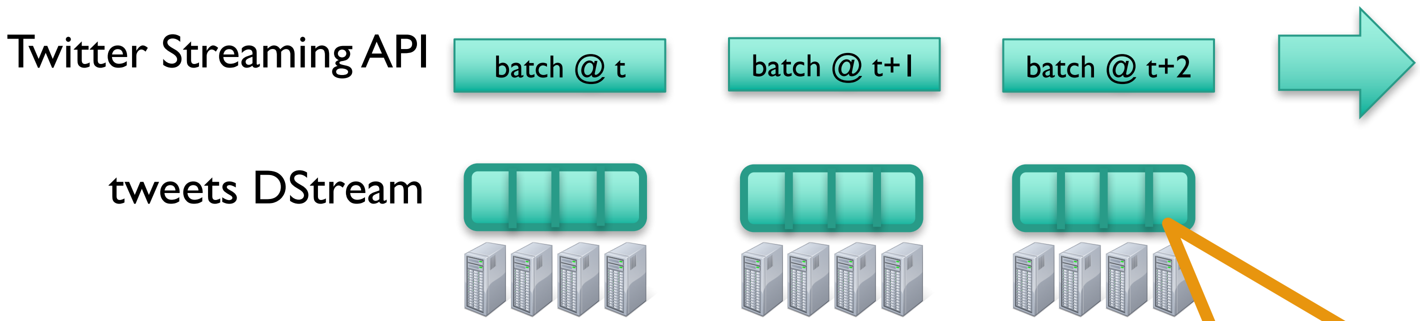
Typical batch window ~1s

Source: All following Spark Streaming slides by Tathagata Das

Example: Get hashtags from Twitter

```
val tweets = ssc.twitterStream(<Twitter username>, <Twitter password>)
```

DStream: a sequence of RDD representing a stream of data



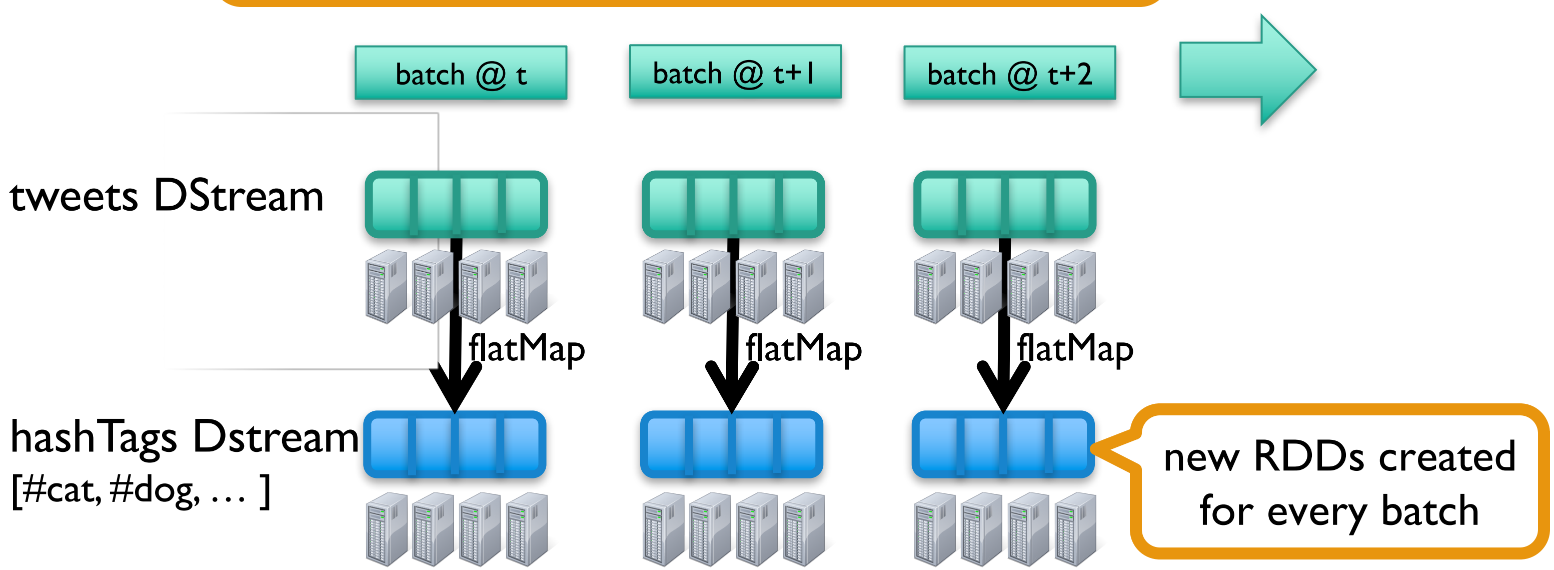
stored in memory as an RDD
(immutable, distributed)

Example: Get hashtags from Twitter

```
val tweets = ssc.twitterStream(<Twitter username>, <Twitter password>)
val hashTags = tweets.flatMap (status => getTags(status))
```

new DStream

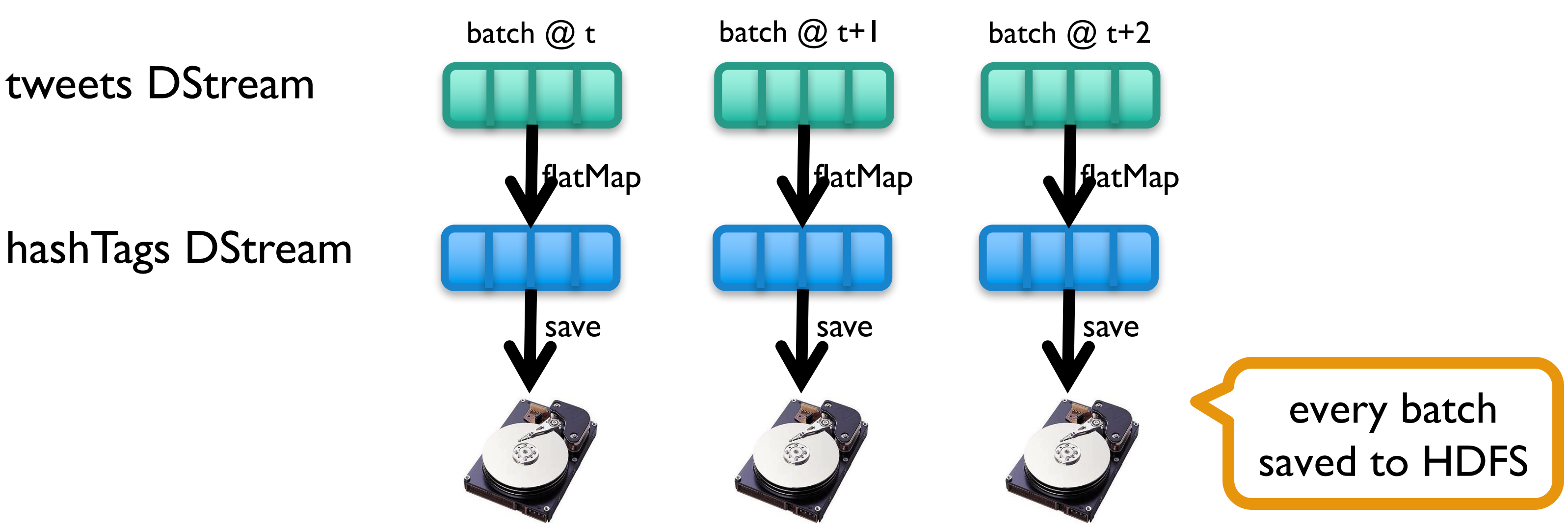
transformation: modify data in one Dstream to create another DStream



Example: Get hashtags from Twitter

```
val tweets = ssc.twitterStream(<Twitter username>, <Twitter password>)
val hashTags = tweets.flatMap (status => getTags(status))
hashTags.saveAsHadoopFiles("hdfs://...")
```

output operation: to push data to external storage

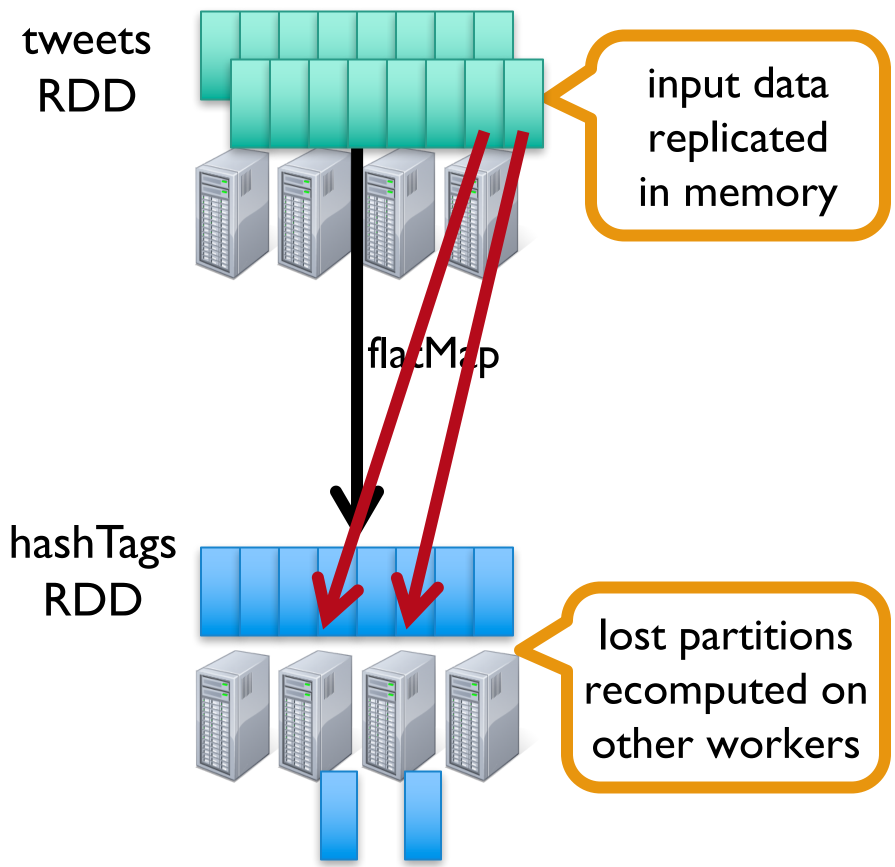


Fault Tolerance

Bottom line: they’re just RDDs!

Fault Tolerance

Bottom line: they're just RDDs!



Key Concepts

DStream – sequence of RDDs representing a stream of data

Twitter, HDFS, Kafka, Flume, ZeroMQ, Akka Actor, TCP sockets

Transformations – modify data from on DStream to another

Standard RDD operations – map, countByValue, reduce, join, …

Stateful operations – window, countByValueAndWindow, …

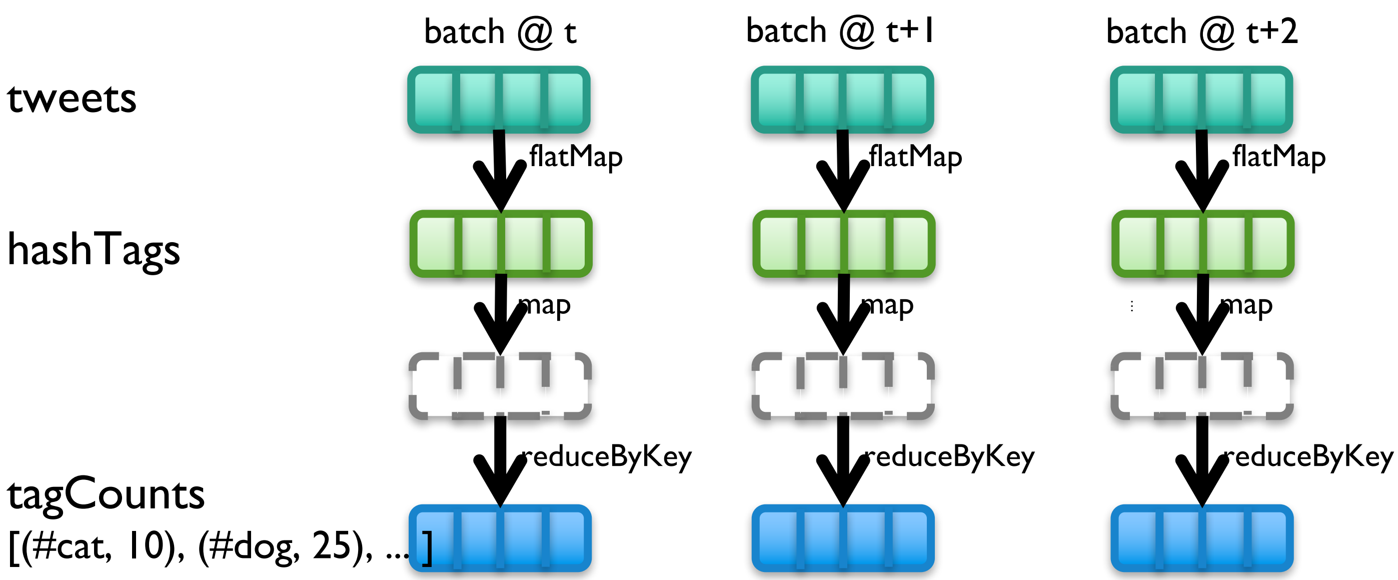
Output Operations – send data to external entity

saveAsHadoopFiles – saves to HDFS

foreach – do anything with each batch of results

Example: Count the hashtags

```
val tweets = ssc.twitterStream(<Twitter username>, <Twitter password>)
val hashTags = tweets.flatMap (status => getTags(status))
val tagCounts = hashTags.countByValue()
```



Example: Count the hashtags over last 10 mins

```
val tweets = ssc.twitterStream(<Twitter username>, <Twitter password>)
val hashTags = tweets.flatMap (status => getTags(status))
val tagCounts = hashTags.window(Minutes(10), Seconds(1)).countByValue()
```

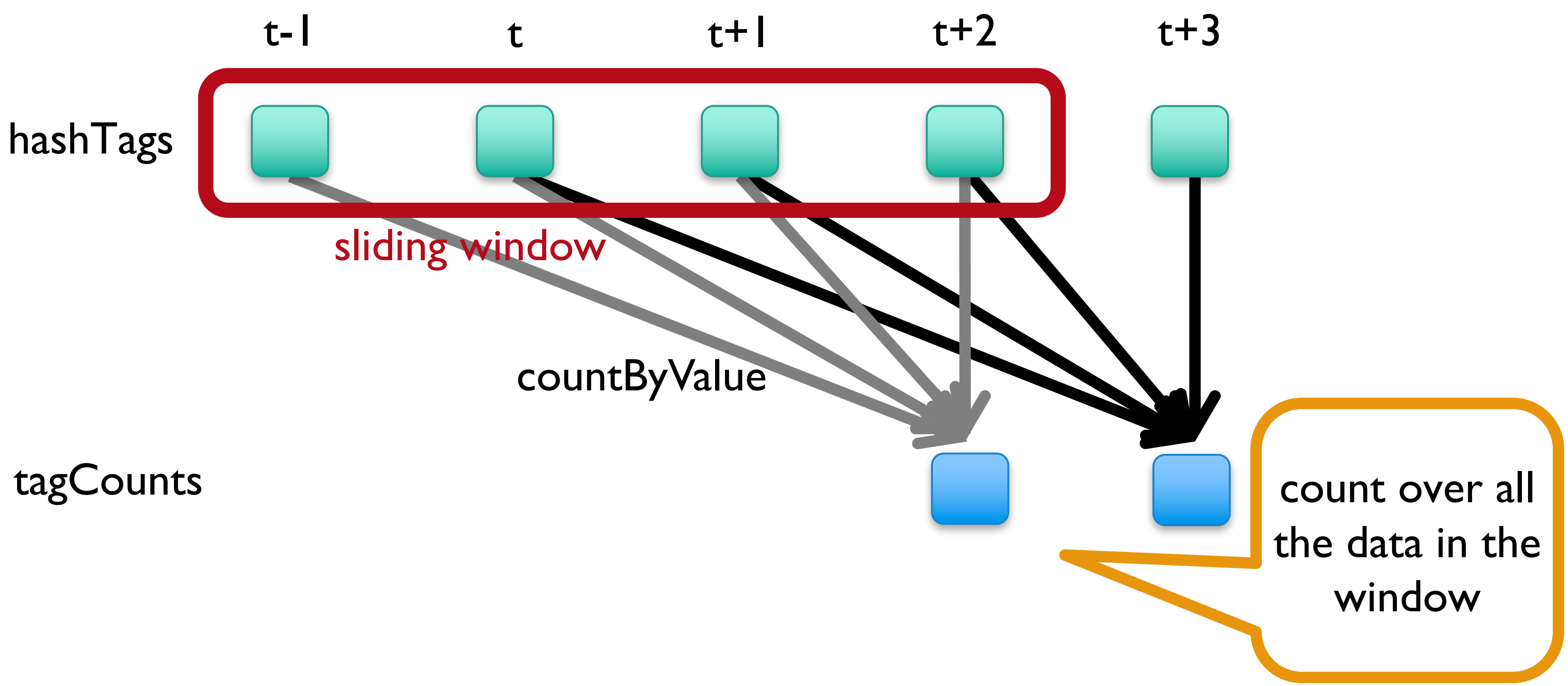
sliding window operation

window length

sliding interval

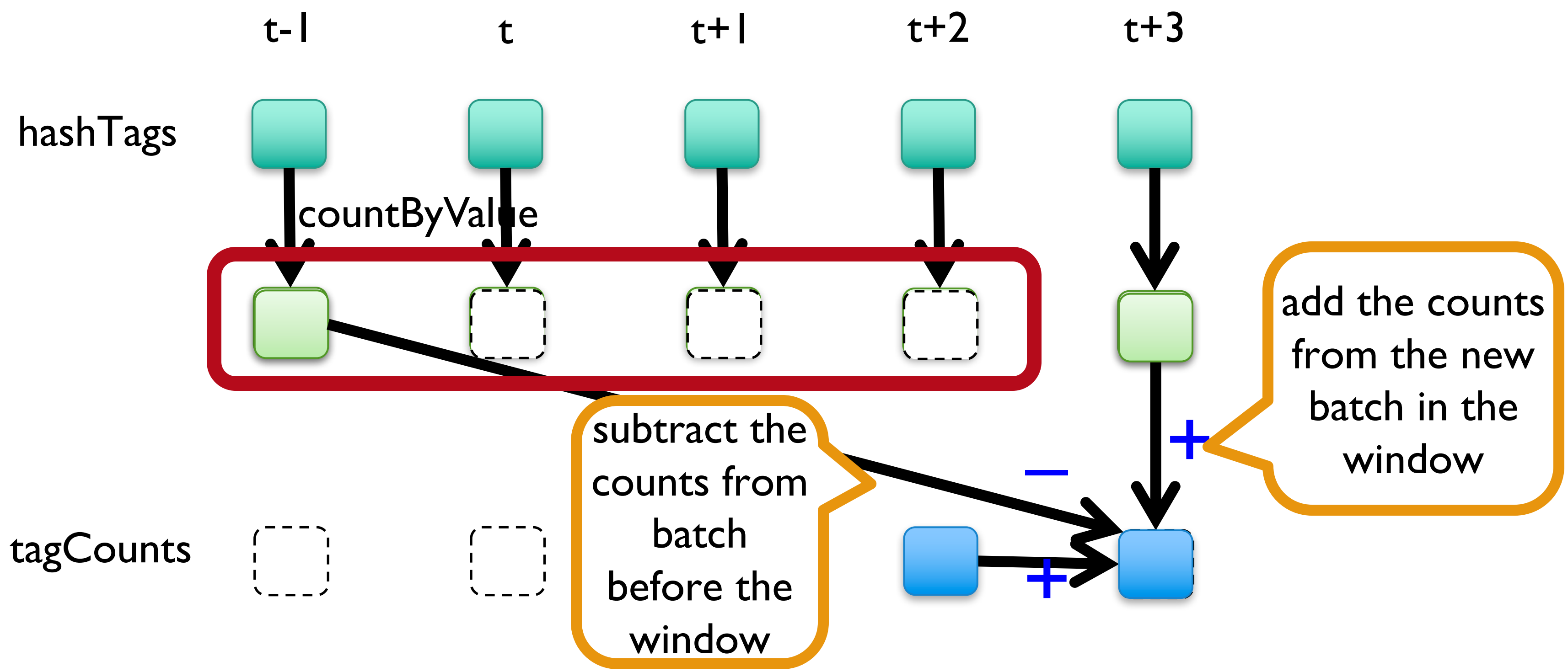
Example: Count the hashtags over last 10 mins

```
val tagCounts = hashTags.window(Minutes(10), Seconds(1)).countByValue()
```



Smart window-based countByValue

```
val tagCounts = hashtags.countByValueAndWindow(Minutes(10), Seconds(1))
```



Smart window-based reduce

Incremental counting generalizes to many reduce operations

Need a function to "inverse reduce" ("subtract" for counting)

```
val tagCounts = hashtags
    .countByValueAndWindow(Minutes(10), Seconds(1))
```

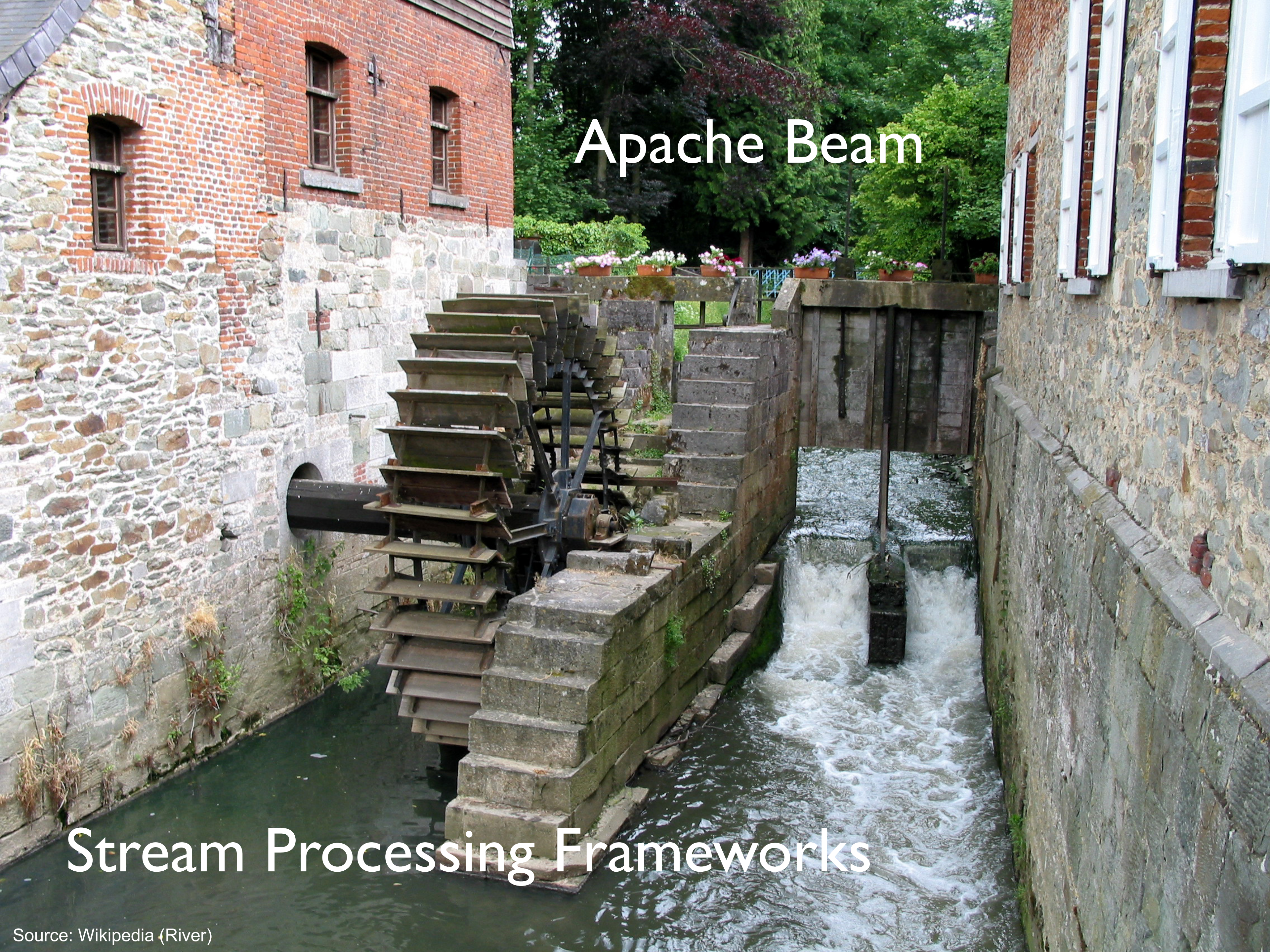
```
val tagCounts = hashtags
    .reduceByKeyAndWindow(_ + _, _ - _, Minutes(10), Seconds(1))
```

What's the problem?

event time

vs.

processing time


Apache Beam
Stream Processing Frameworks
Source: Wikipedia (River)

Apache Beam

2013: Google publishes paper about MillWheel

2015: Google releases Cloud Dataflow

2016: Google donates API and SDK to Apache
to become Apache Beam

Programming Model

Core Concepts

Pipeline: a data processing task
PCollection: a distributed dataset that a pipeline operates on
Transform: a data processing operation
Source: for reading data
Sink: for writing data

Processing semantics: exactly once

Looks a lot like Spark!

```
Pipeline p = Pipeline.create(options);

p.apply(TextIO.Read.from("gs://your/input/"))







 .apply(FlatMapElements.via((String word) ->
     Arrays.asList(word.split("[^a-zA-Z']+"))))
 .apply(Filter.by((String word) -> !word.isEmpty()))
 .apply(Count.perElement())
 .apply(MapElements.via((KV<String, Long> wordCount) ->
    wordCount.getKey() + ": " + wordCount.getValue()))
 .apply(TextIO.Write.to("gs://your/output/"));
```

The Beam Model

What results are computed?

Where in event time are the results computed?

When in processing time are the results materialized?

How do refinements of results relate?

Event Time vs. Processing Time

What's the distinction?

Watermark: System's notion when all data in a window is expected to arrive

Where in event time are the results computed?

When in processing time are the results materialized?

How do refinements of results relate?

Trigger: a mechanism for declaring when output of a window should be materialized

Default trigger "fires" at watermark

Late and early firings: multiple "panes" per window

Event Time vs. Processing Time

What's the distinction?

Watermark: System's notion when all data in a window is expected to arrive

Where in event time are the results computed?

When in processing time are the results materialized?

How do refinements of results relate?

How do multiple "firings" of a window (i.e., multiple "panes") relate?

Options: Discarding, Accumulating, Accumulating & retracting

Word Count

```
Pipeline p = Pipeline.create(options);

p.apply(TextIO.Read.from("gs://your/input/"))








 .apply(FlatMapElements.via((String word) ->
     Arrays.asList(word.split("[^a-zA-Z']+"))))
 .apply(Filter.by((String word) -> !word.isEmpty()))
 .apply(Count.perElement())
 .apply(MapElements.via((KV<String, Long> wordCount) ->
    wordCount.getKey() + ": " + wordCount.getValue()))
 .apply(TextIO.Write.to("gs://your/output/"));
```

Word Count

With windowing...

```
Pipeline p = Pipeline.create(options);

p.apply(KafkaIO.read("tweets")
    .withTimestampFn(new TweetTimestampFunction())
    .withWatermarkFn(kv ->
        Instant.now().minus(Duration.standardMinutes(2))))
 .apply(Window.into(FixedWindows.of(Duration.standardMinutes(2)))
    .triggering(AtWatermark()
        .withEarlyFirings(AtPeriod(Duration.standardMinutes(1)))
        .withLateFirings(AtCount(1)))
    .accumulatingAndRetractingFiredPanes())
 .apply(FlatMapElements.via((String word) ->
     Arrays.asList(word.split("[^a-zA-Z']+"))))
 .apply(Filter.by((String word) -> !word.isEmpty()))
 .apply(Count.perElement())
 .apply(KafkaIO.write("counts"))
```

Where in event time?

When in processing time?

How do refines relate?

Source: Wikipedia (Japanese rock garden)