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Making Data Work

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Spark Streaming

Large-scale near-real-time stream processing

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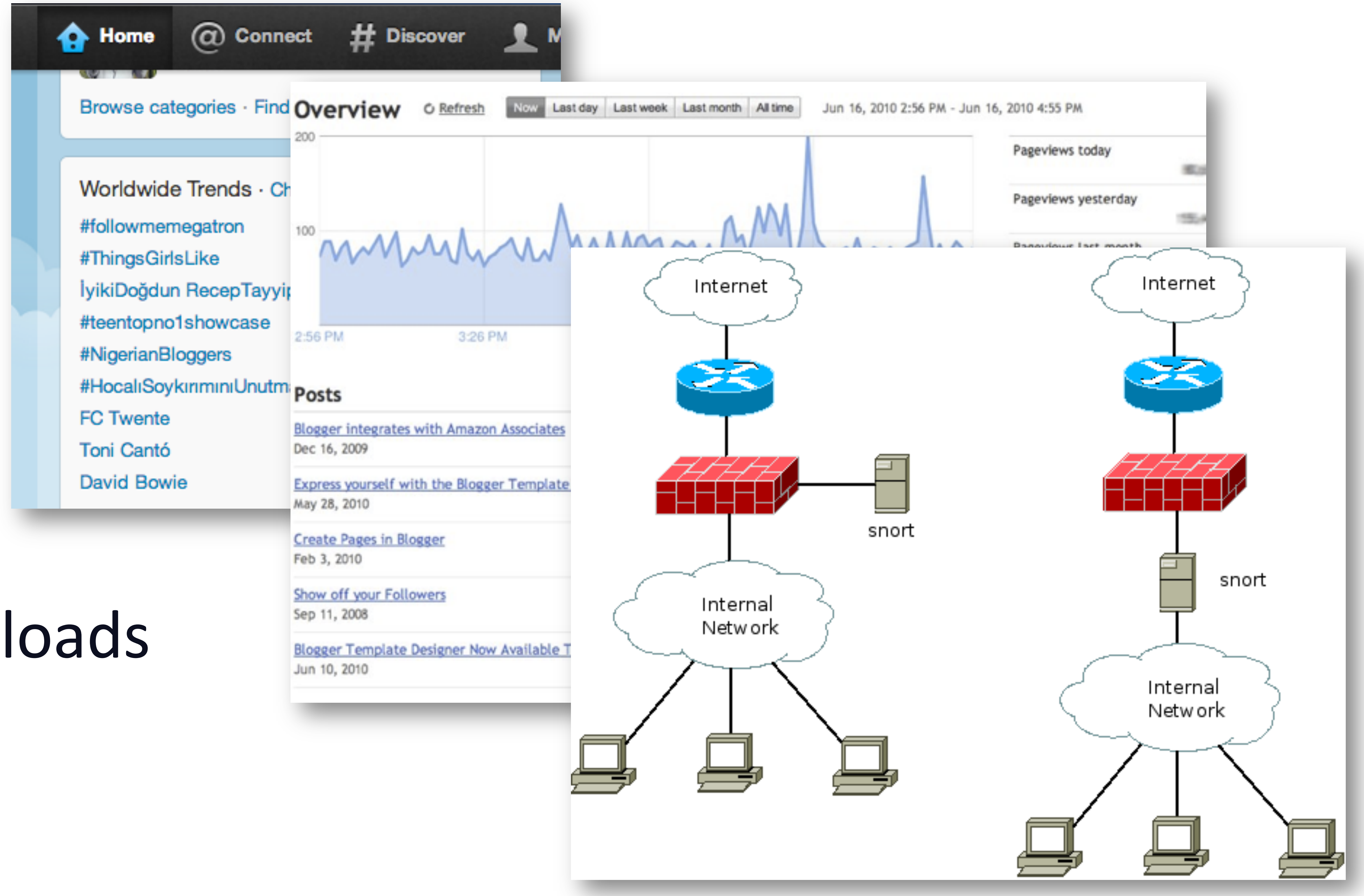
What is Spark Streaming?

- Framework for large scale stream processing
  - Scales to 100s of nodes
  - Can achieve second scale latencies
  - Integrates with Spark's batch and interactive processing
  - Provides a simple batch-like API for implementing complex algorithm
  - Can absorb live data streams from Kafka, Flume, ZeroMQ, etc.

Motivation

- Many important applications must process large streams of live data and provide results in near-real-time
  - Social network trends
  - Website statistics
  - Intrustion detection systems
  - etc.



- Require large clusters to handle workloads

- Require latencies of few seconds

Need for a framework …

… for building such complex stream processing applications

But what are the requirements
from such a framework?

Requirements

- **Scalable** to large clusters
- **Second-scale** latencies
- **Simple** programming model

Case study: Conviva, Inc.

- Real-time monitoring of online video metadata
  - HBO, ESPN, ABC, SyFy, …
- Two processing stacks

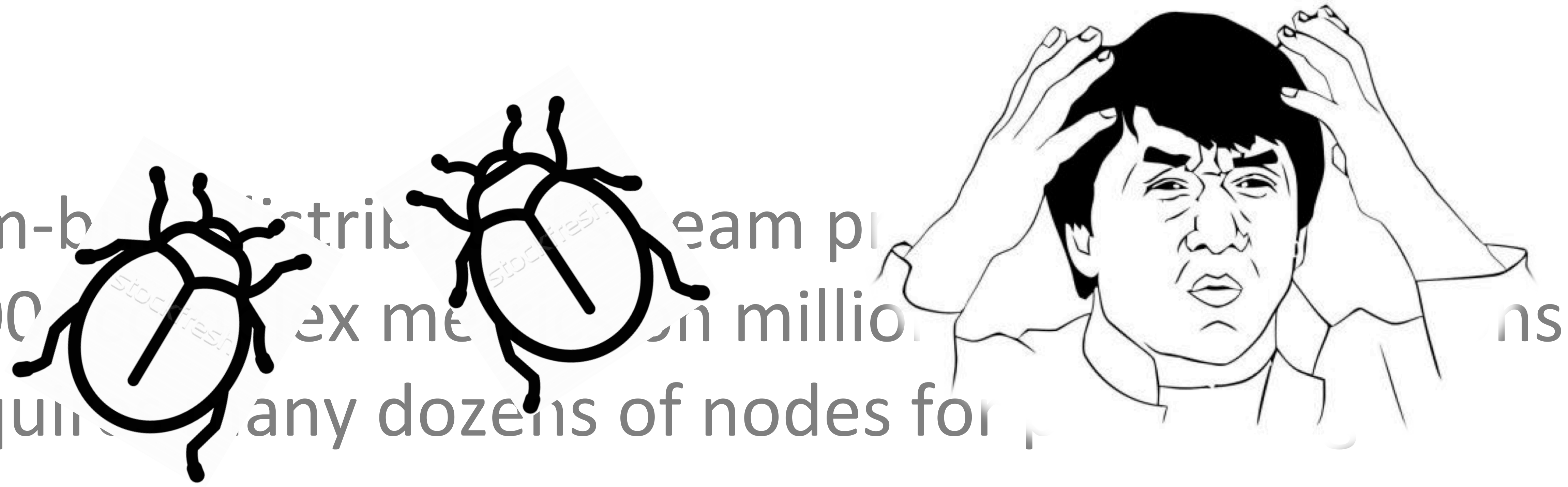
Custom-built distributed stream processing system
- 1000s complex metrics on millions of video sessions
- Requires many dozens of nodes for processing

Hadoop backend for offline analysis
- Generating daily and monthly reports
- **Similar computation as the streaming system**

Case study: XYZ, Inc.

- Any company who wants to process live streaming data has this problem
- Twice the effort to implement any new function
- Twice the number of bugs to solve
- Twice the headache
- Two processing stacks

Custom-b … trib … eam p…
- 1000 … ex me … n millio … ns
- Requi … any dozens of nodes for …



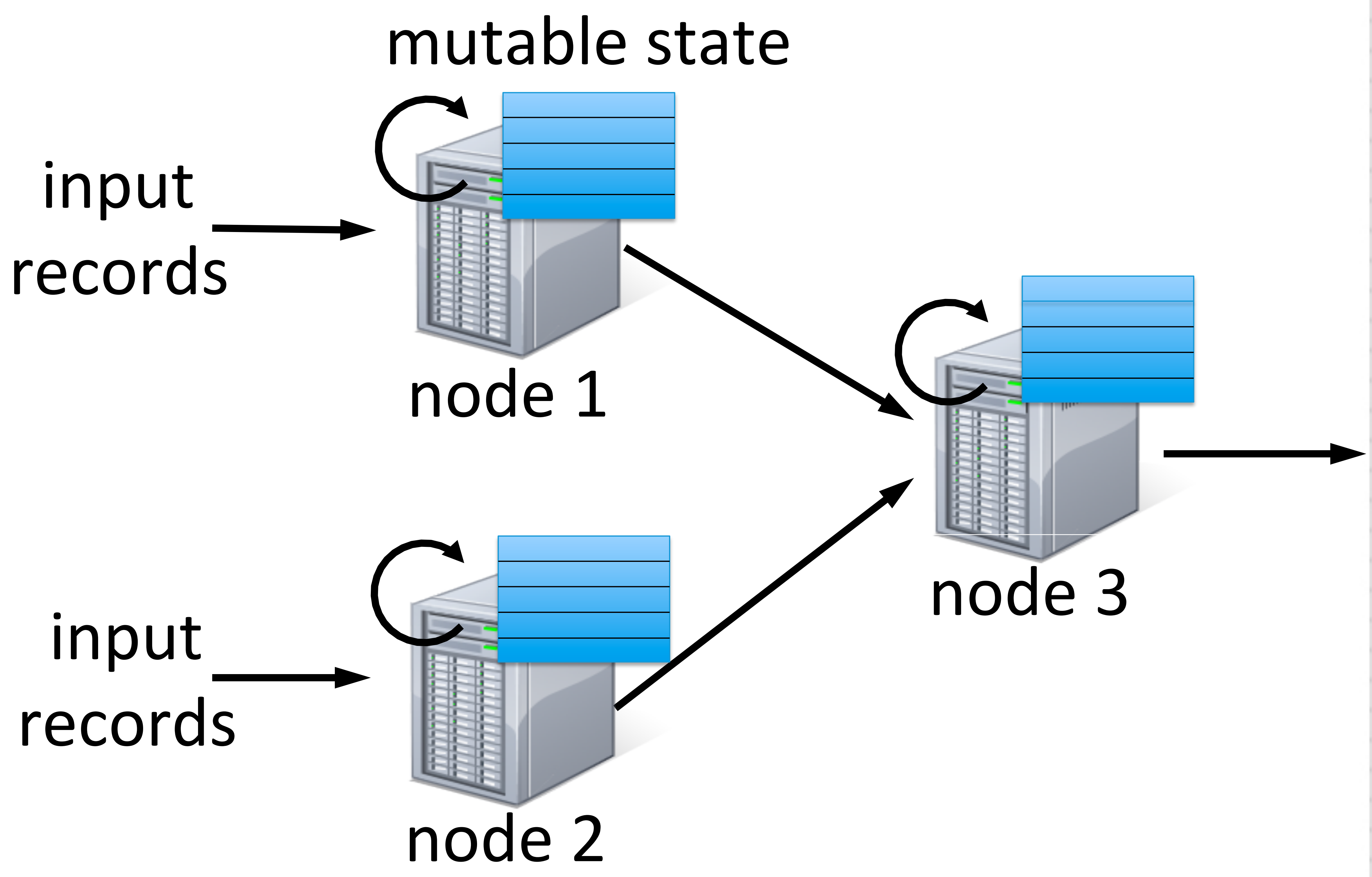
Hadoop b … d fo … analys…
- Gene … aily a … thly re…
- **Simila … putation as the strea…**

Requirements

- **Scalable** to large clusters
- **Second-scale** latencies
- **Simple** programming model
- **Integrated** with batch & interactive processing

Stateful Stream Processing

- Traditional streaming systems have a event-driven **record-at-a-time** processing model
  - Each node has mutable state
  - For each record, update state & send new records
- State is lost if node dies!
- Making stateful stream processing be fault-tolerant is challenging



Existing Streaming Systems

- Storm
  - Replays record if not processed by a node
  - Processes each record *at least once*
  - May update mutable state twice!
  - Mutable state can be lost due to failure!

- Trident – Use transactions to update state
  - Processes each record *exactly once*
  - Per state transaction updates slow

Requirements

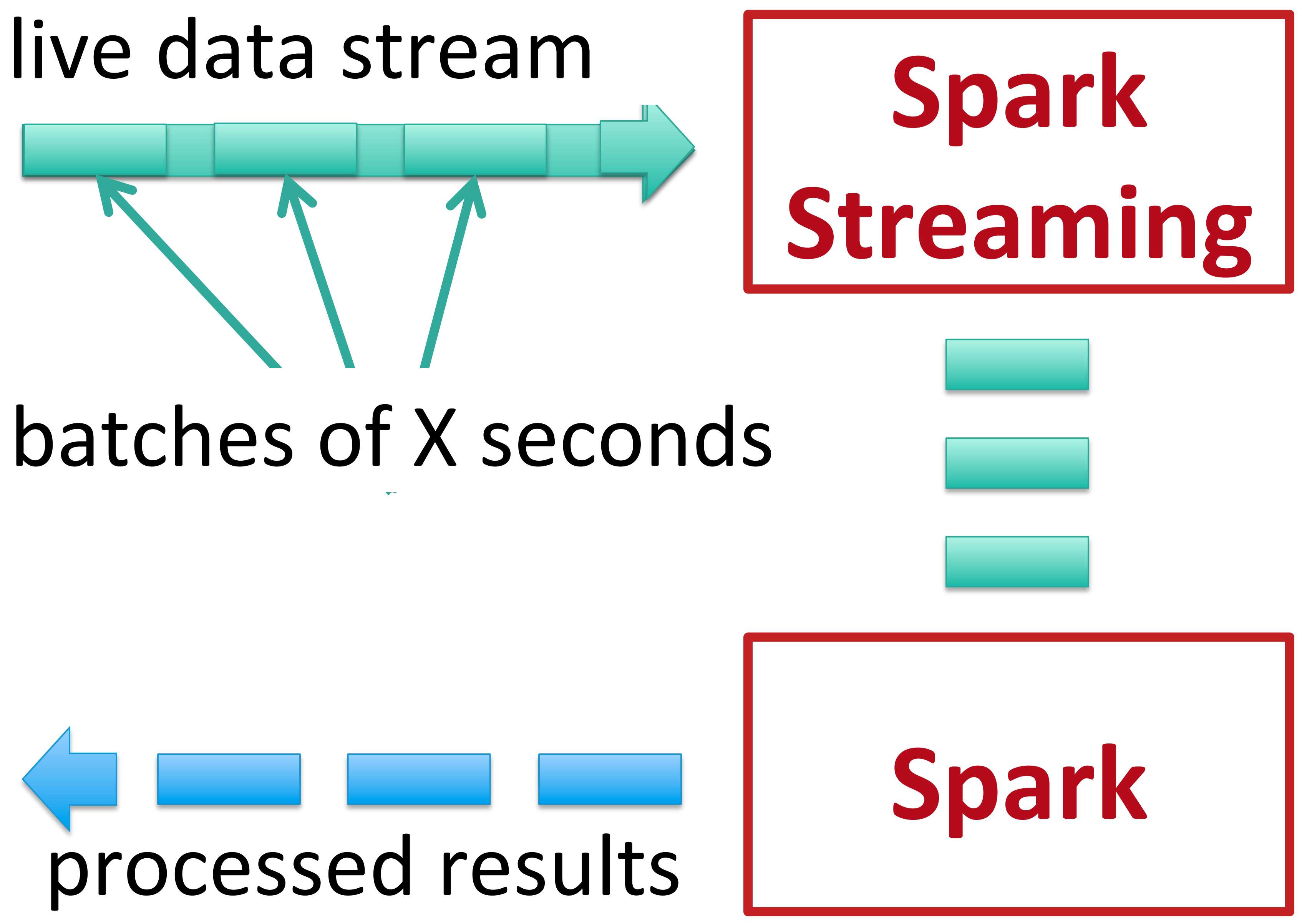
- **Scalable** to large clusters
- **Second-scale** latencies
- **Simple** programming model
- **Integrated** with batch & interactive processing
- **Efficient fault-tolerance** in stateful computations

Spark Streaming

Discretized Stream Processing

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

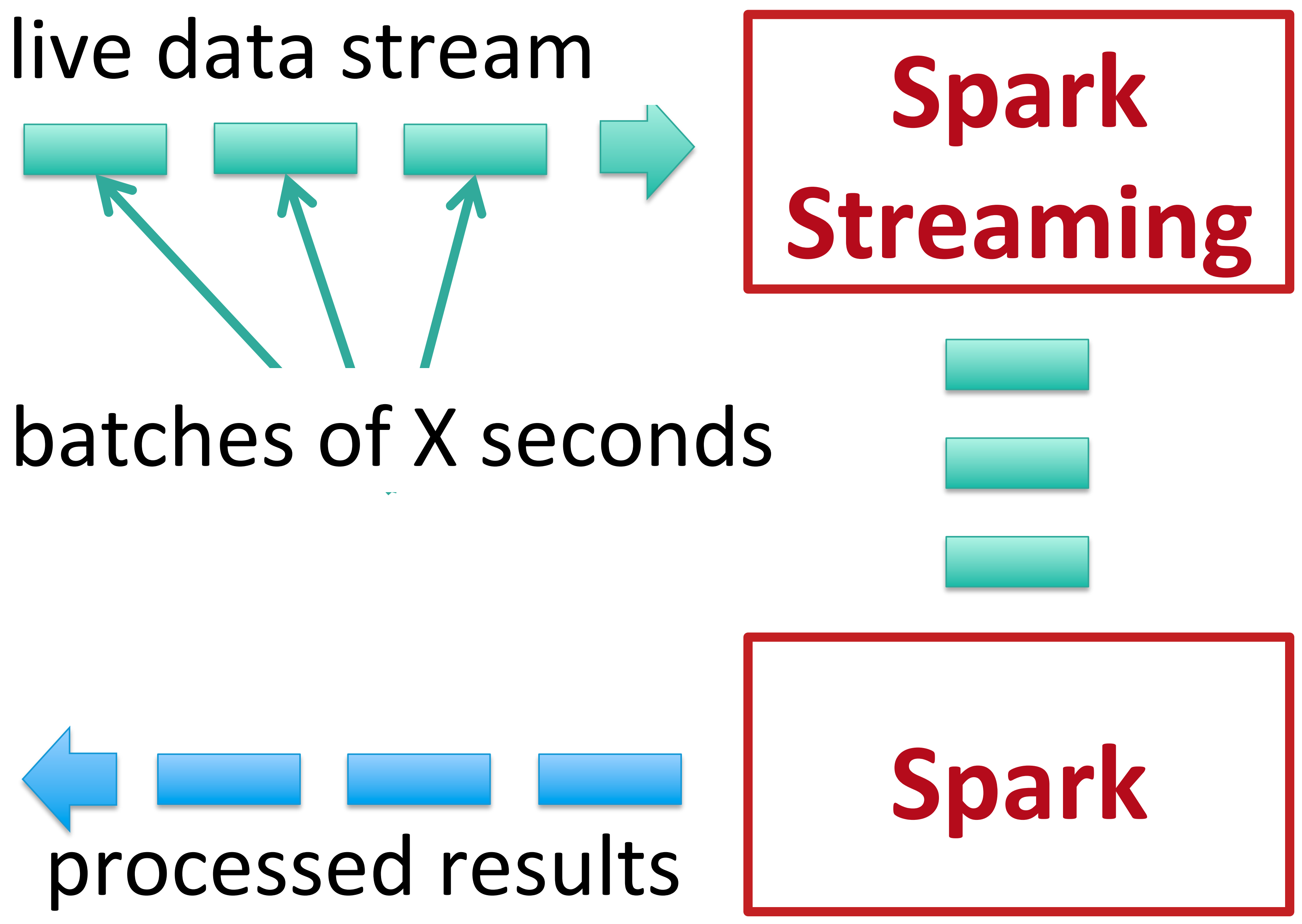
- Chop up the live stream into batches of X seconds
- Spark treats each batch of data as RDDs and processes them using RDD operations
- Finally, the processed results of the RDD operations are returned in batches



Discretized Stream Processing

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

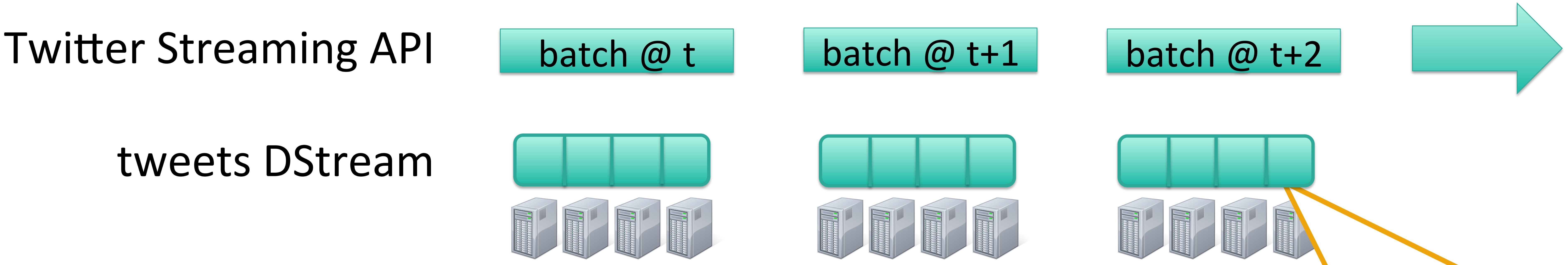
- Batch sizes as low as ½ second, latency ~ 1 second
- Potential for combining batch processing and streaming processing in the same system



Example 1 – Get hashtags from Twitter

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

DStream: a sequence of RDD representing a stream of data



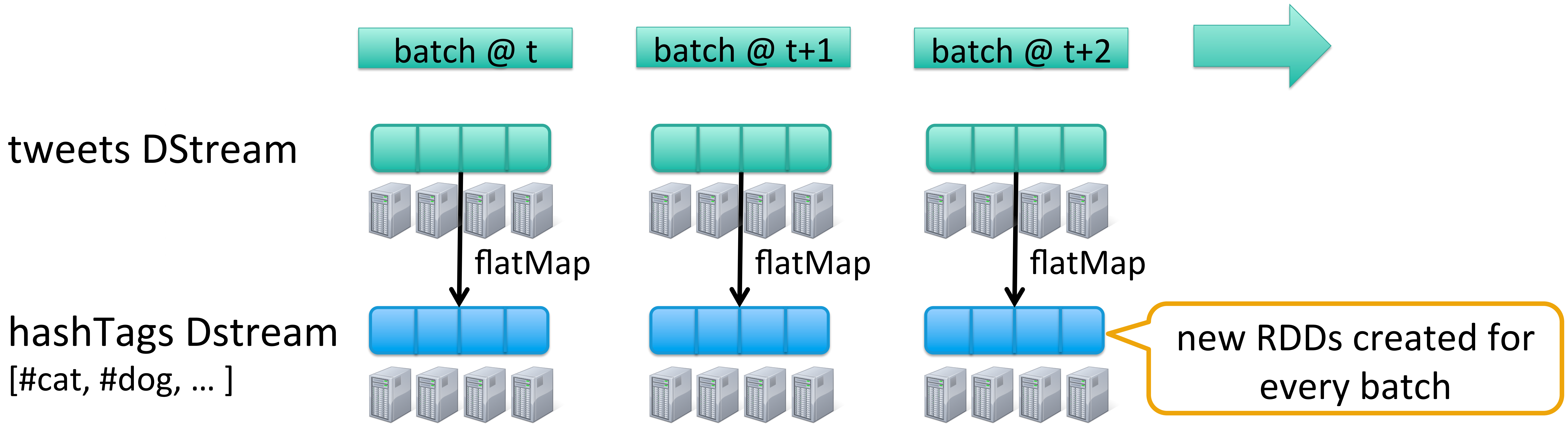
stored in memory as an RDD
(immutable, distributed)

Example 1 – Get hashtags from Twitter

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

new DStream

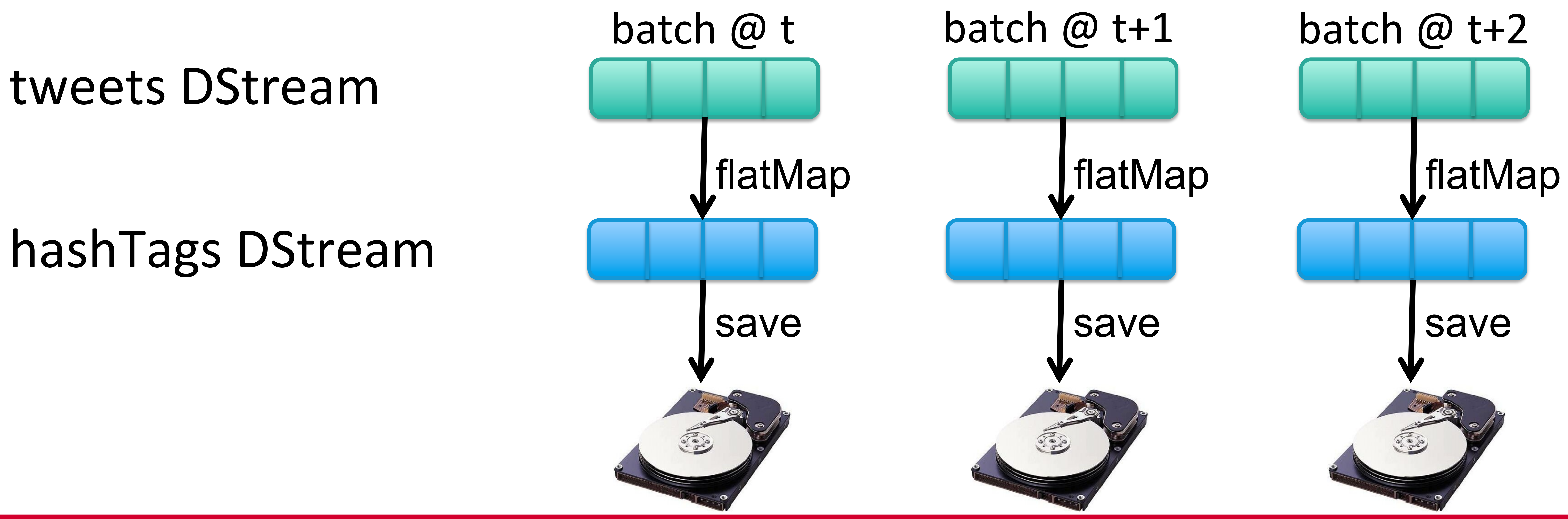
transformation: modify data in one Dstream to create another DStream



Example 1 – 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



every batch saved to HDFS

Java Example

Scala

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

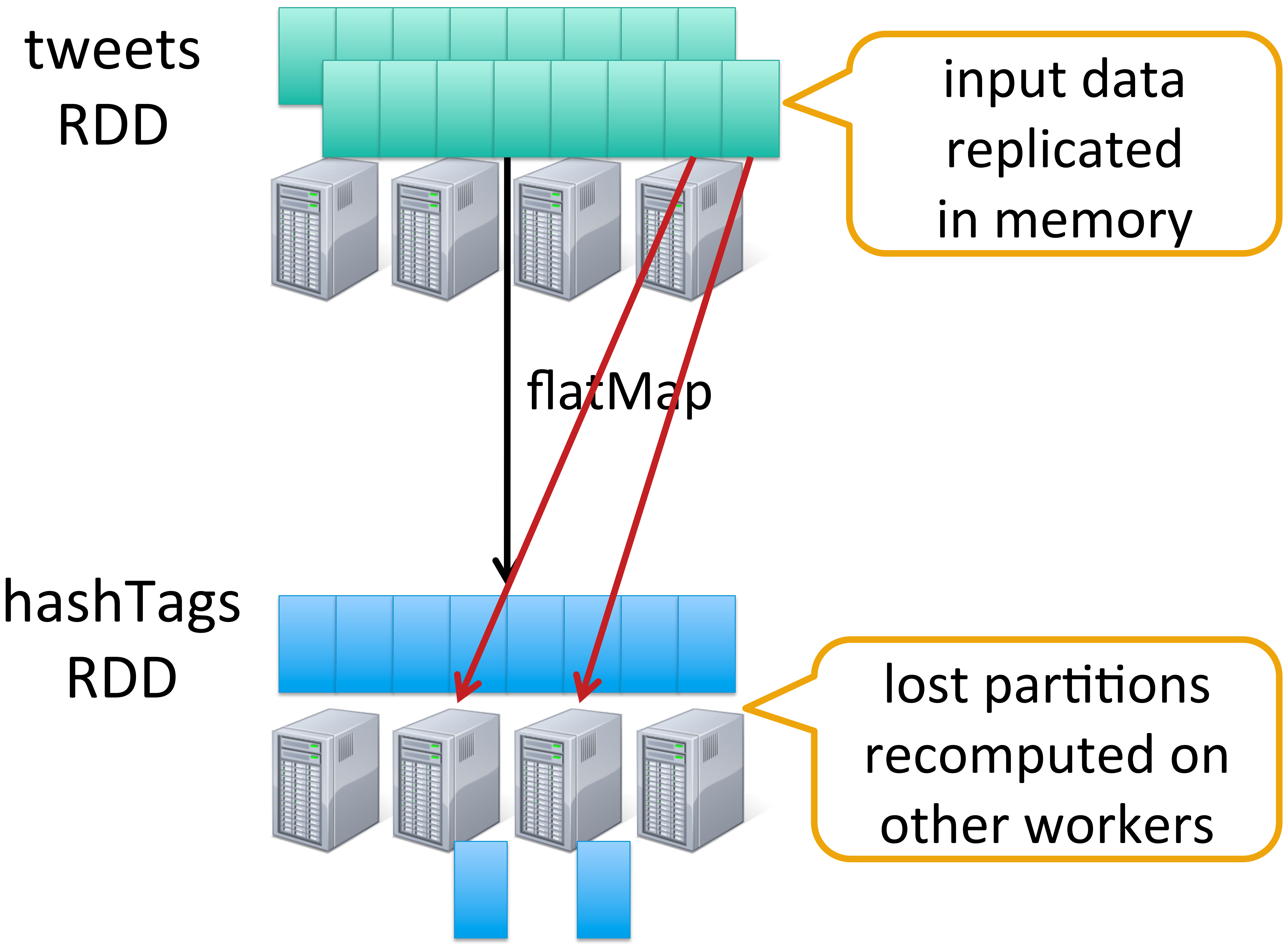
Java

```
JavaDStream<Status> tweets = ssc.twitterStream(<Twitter username>, <Twitter password>)
JavaDstream<String> hashTags = tweets.flatMap(new Function<...> {  })
hashTags.saveAsHadoopFiles("hdfs://...")
```

Function object to define the transformation

Fault-tolerance

- RDDs are remember the sequence of operations that created it from the original fault-tolerant input data
- Batches of input data are replicated in memory of multiple worker nodes, therefore fault-tolerant
- Data lost due to worker failure, can be recomputed from input data



Key concepts

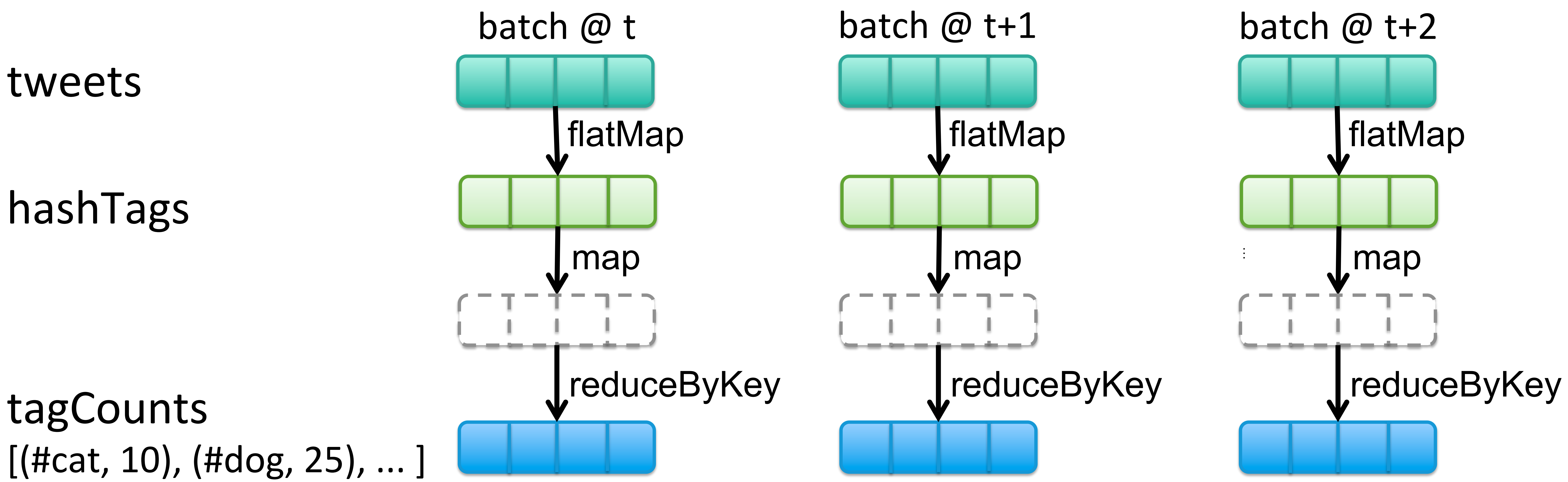
- **DStream** – sequence of RDDs representing a stream of data
  - Twitter, HDFS, Kafka, Flume, ZeroMQ, Akka Actor, TCP sockets

- **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 2 – Count the hashtags

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



Example 3 – 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()
```

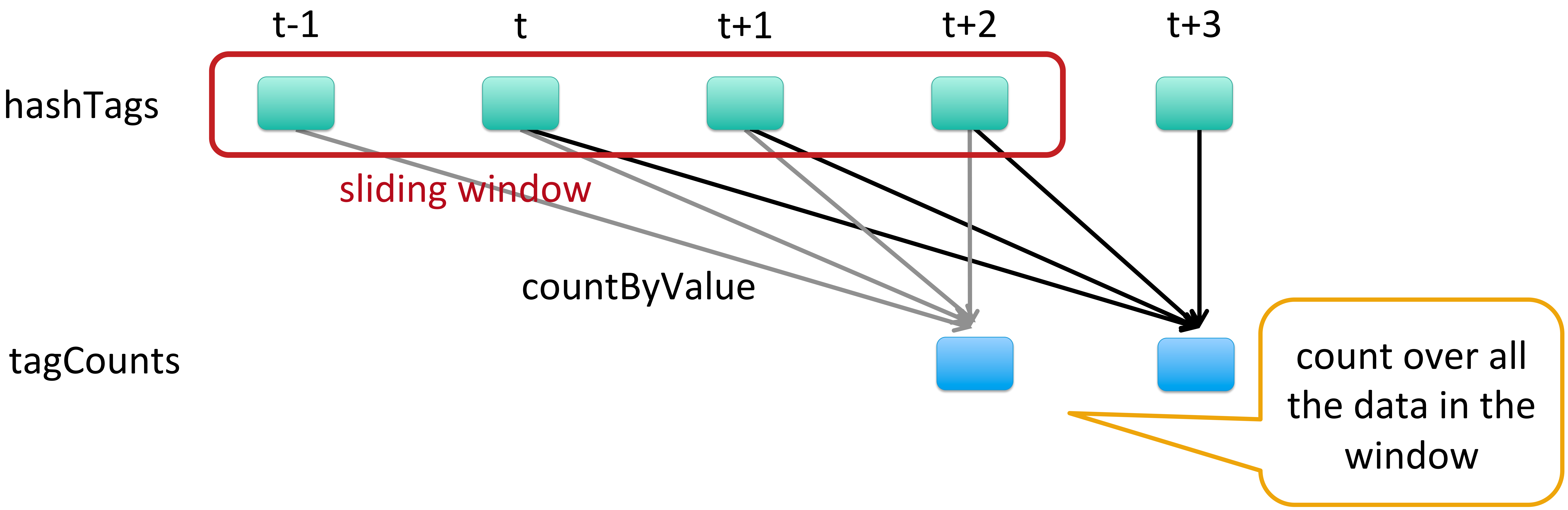
sliding window operation

window length

sliding interval

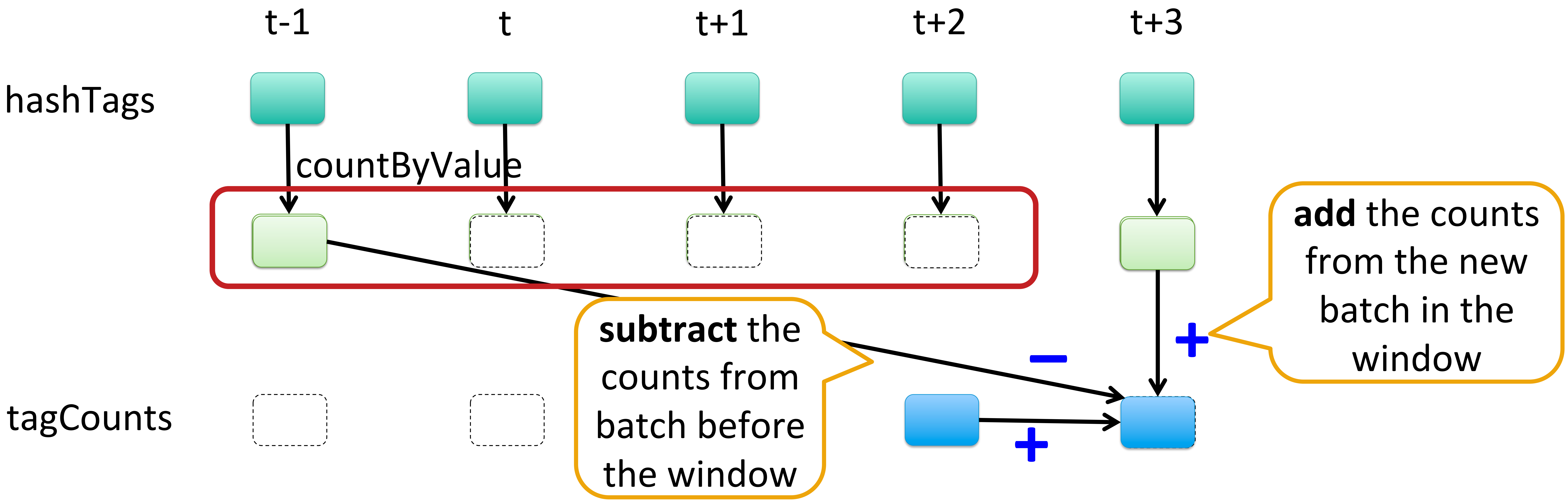
Example 3 – Counting the hashtags over last 10 mins

```
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*

- Technique to incrementally compute count generalizes to many reduce operations
  - Need a function to "inverse reduce" ("subtract" for counting)

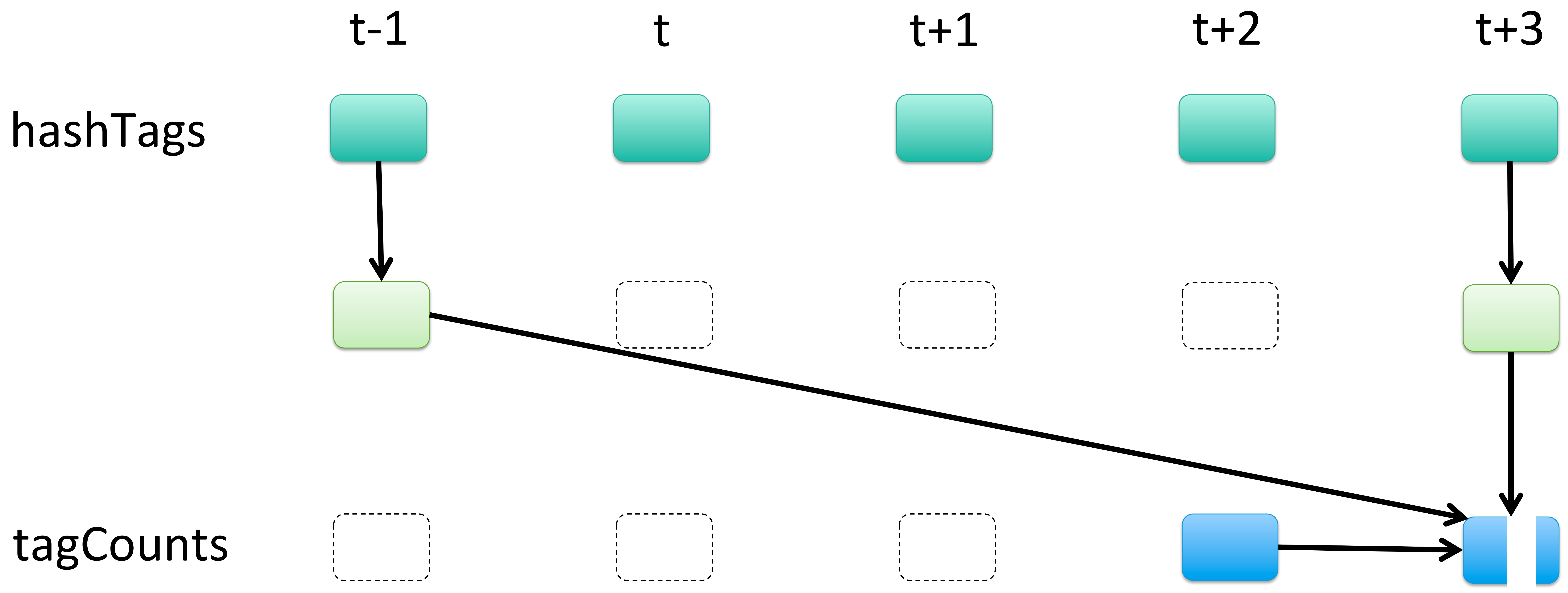
- Could have implemented counting as:

```
hashTags.reduceByKeyAndWindow(_ + _, _ - _, Minutes(1), …)
```

Demo

Fault-tolerant Stateful Processing

All intermediate data are RDDs, hence can be recomputed if lost



Fault-tolerant Stateful Processing

- State data not lost even if a worker node dies
  - Does not change the value of your result
- *Exactly once* semantics to all transformations
  - No double counting!

Other Interesting Operations

- Maintaining arbitrary state, track sessions
  - Maintain per-user mood as state, and update it with his/her tweets

```
tweets.updateStateByKey(tweet => updateMood(tweet))
```

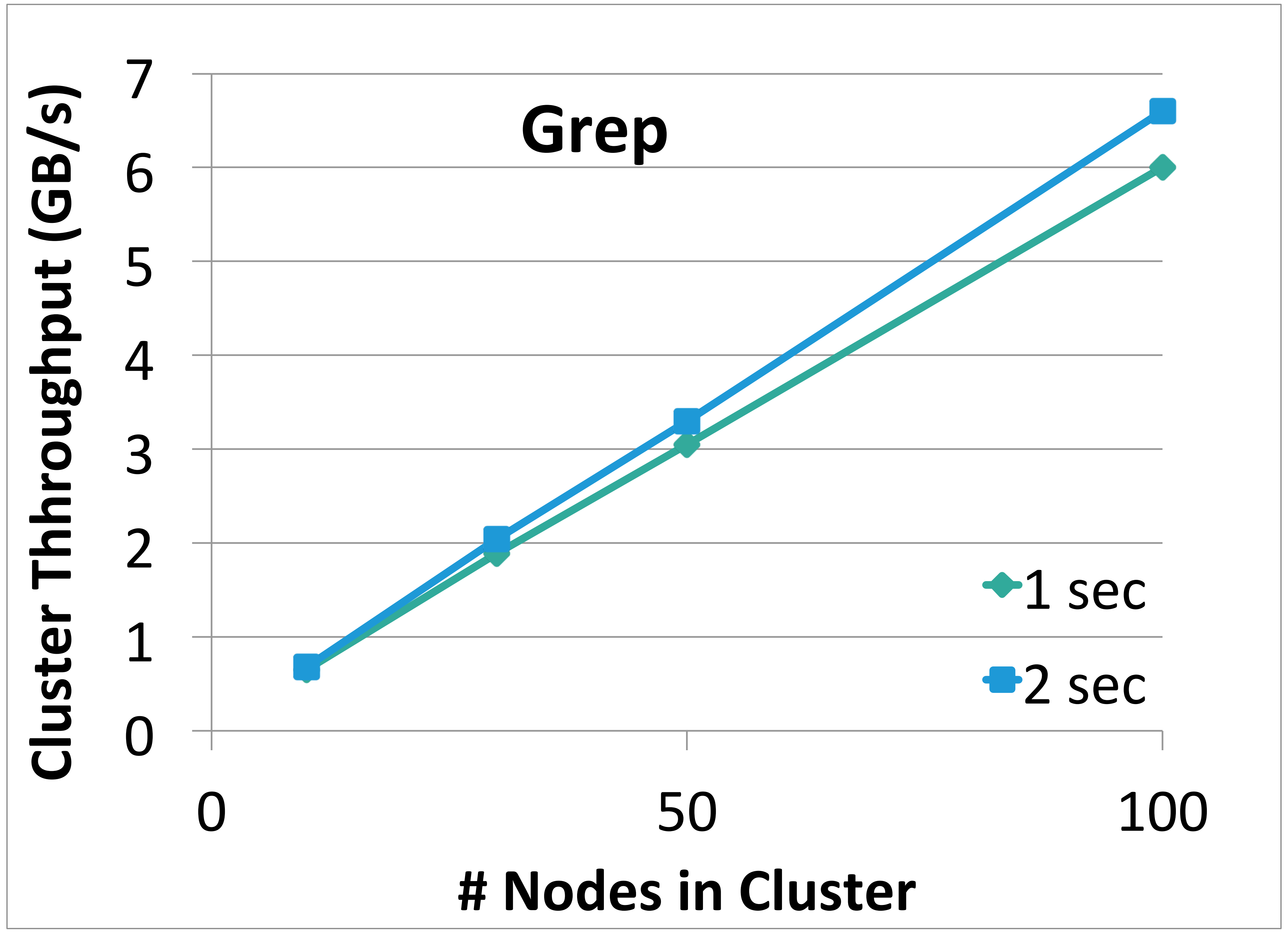
- Do arbitrary Spark RDD computation within DStream
  - Join incoming tweets with a spam file to filter out bad tweets

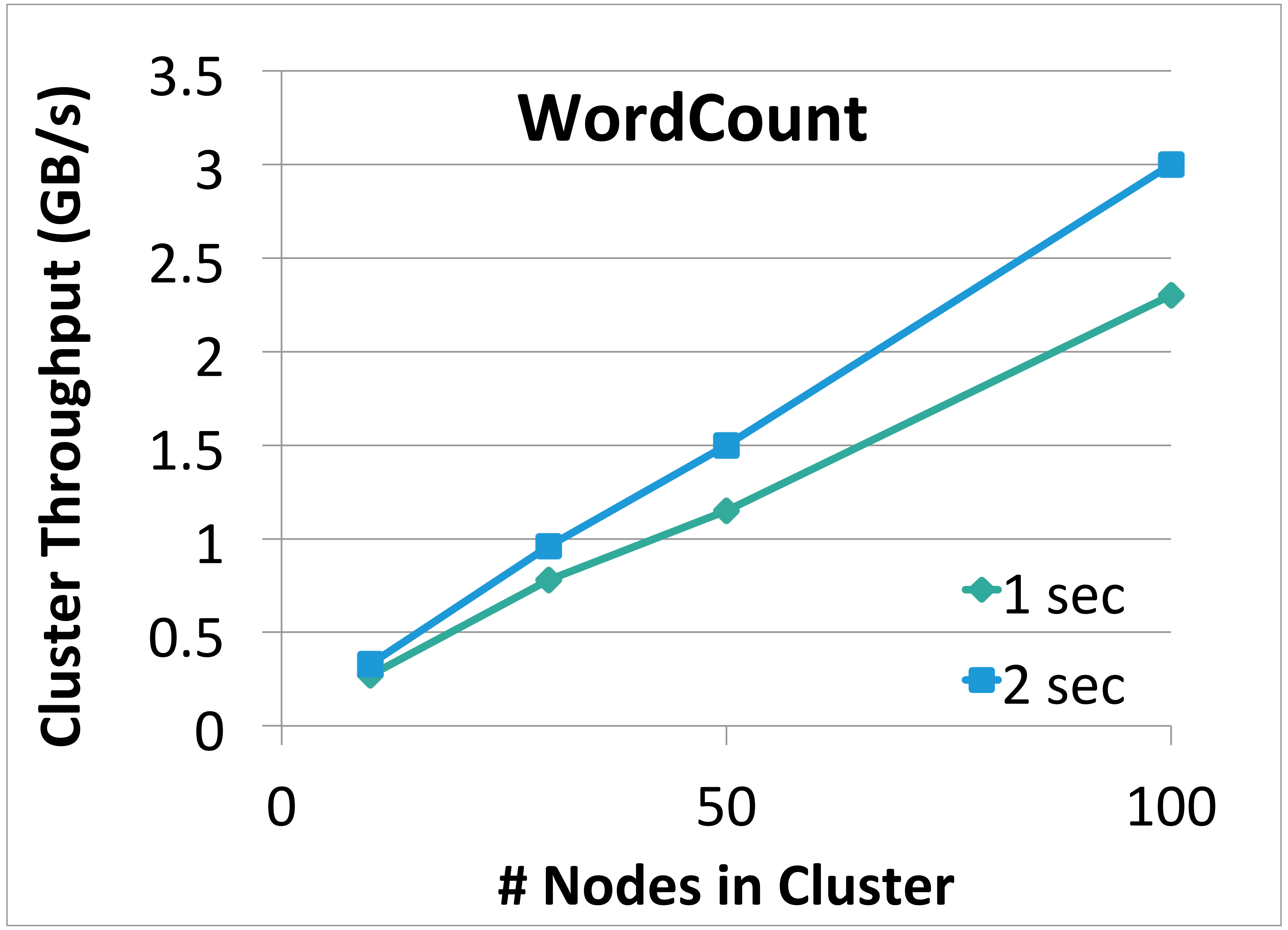
```
tweets.transform(tweetsRDD => {
    tweetsRDD.join(spamHDFSFile).filter(...)
})
```

Performance

Can process **6 GB/sec (60M records/sec)** of data on 100 nodes at **sub-second** latency

- Tested with 100 streams of data on 100 EC2 instances with 4 cores each





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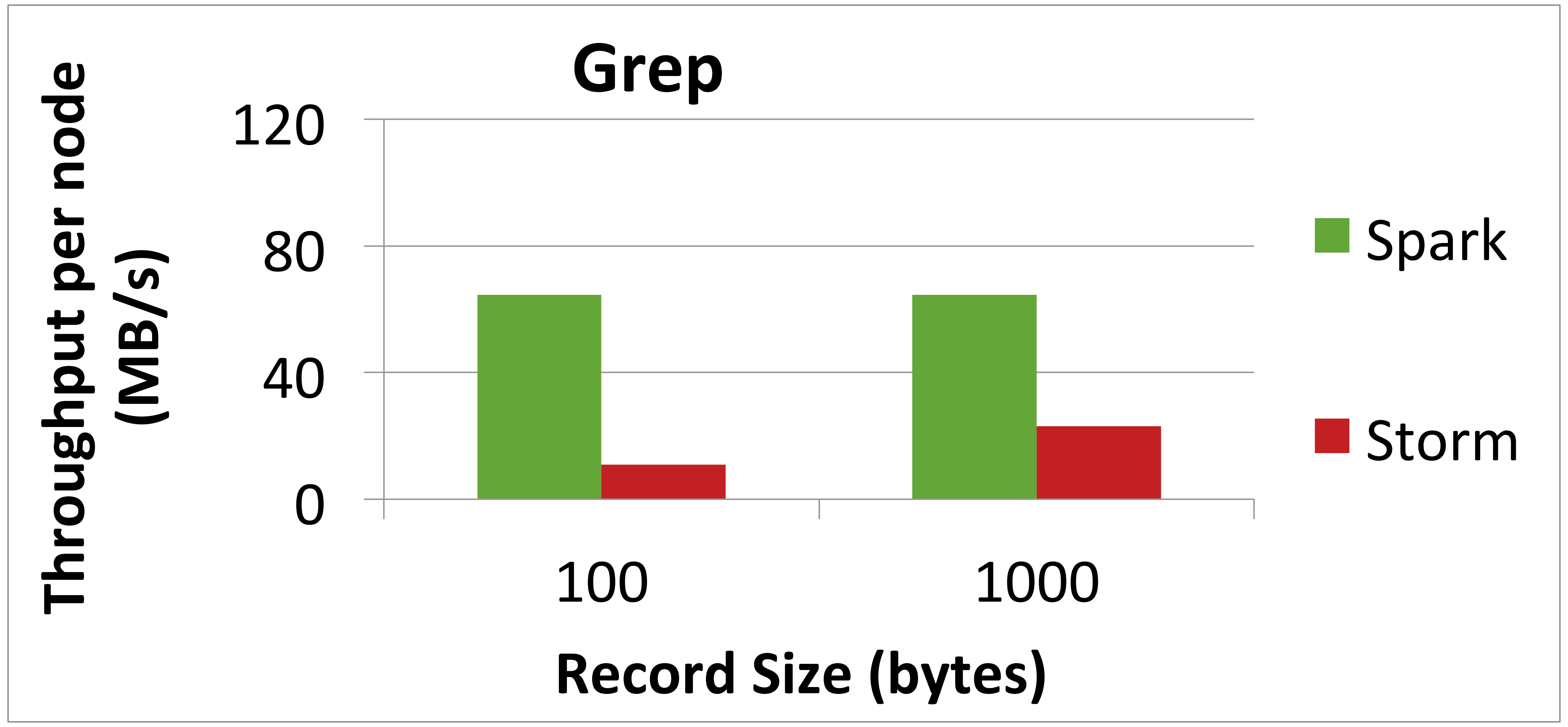
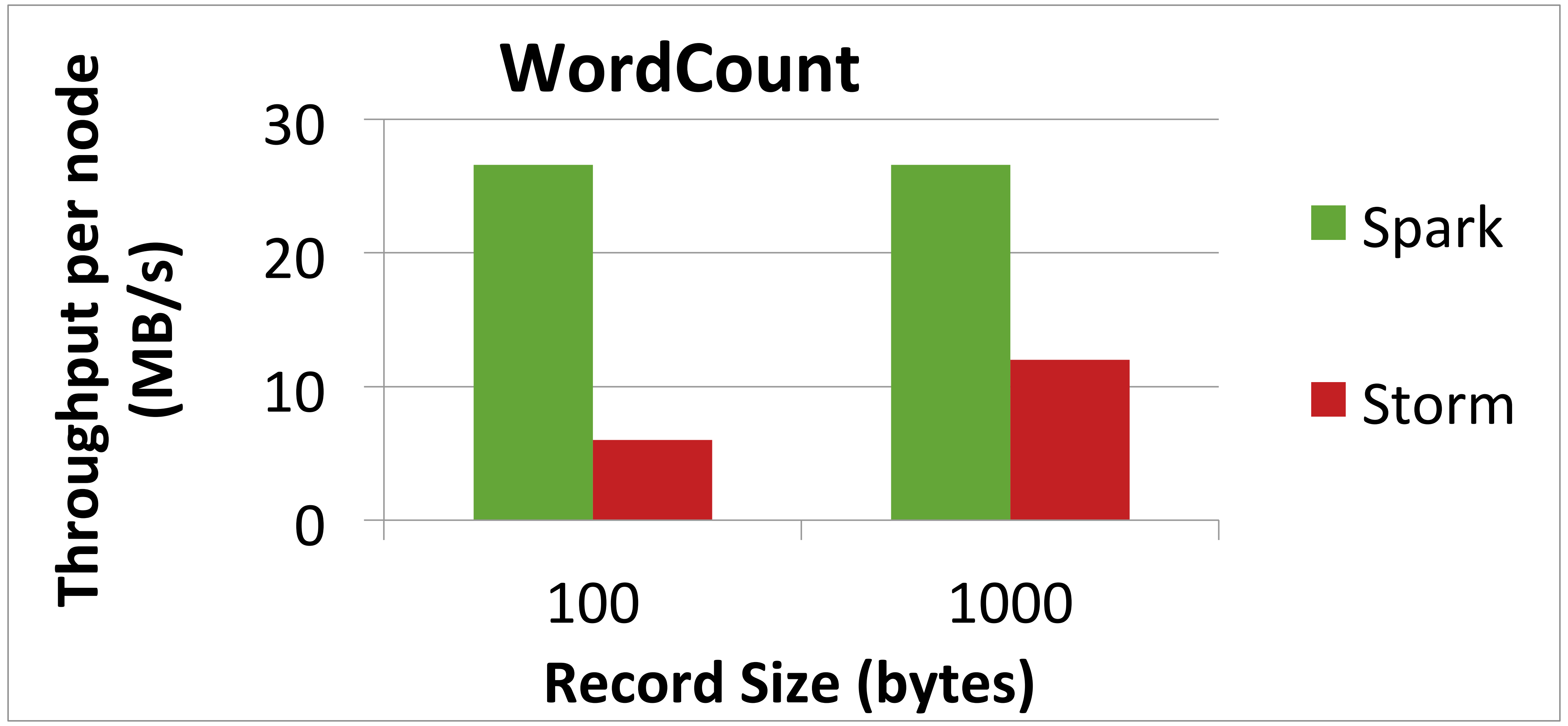
Comparison with Storm and S4

Higher throughput than Storm

- Spark Streaming: **670k** records/second/node
- Storm: **115k** records/second/node
- Apache S4: 7.5k records/second/node





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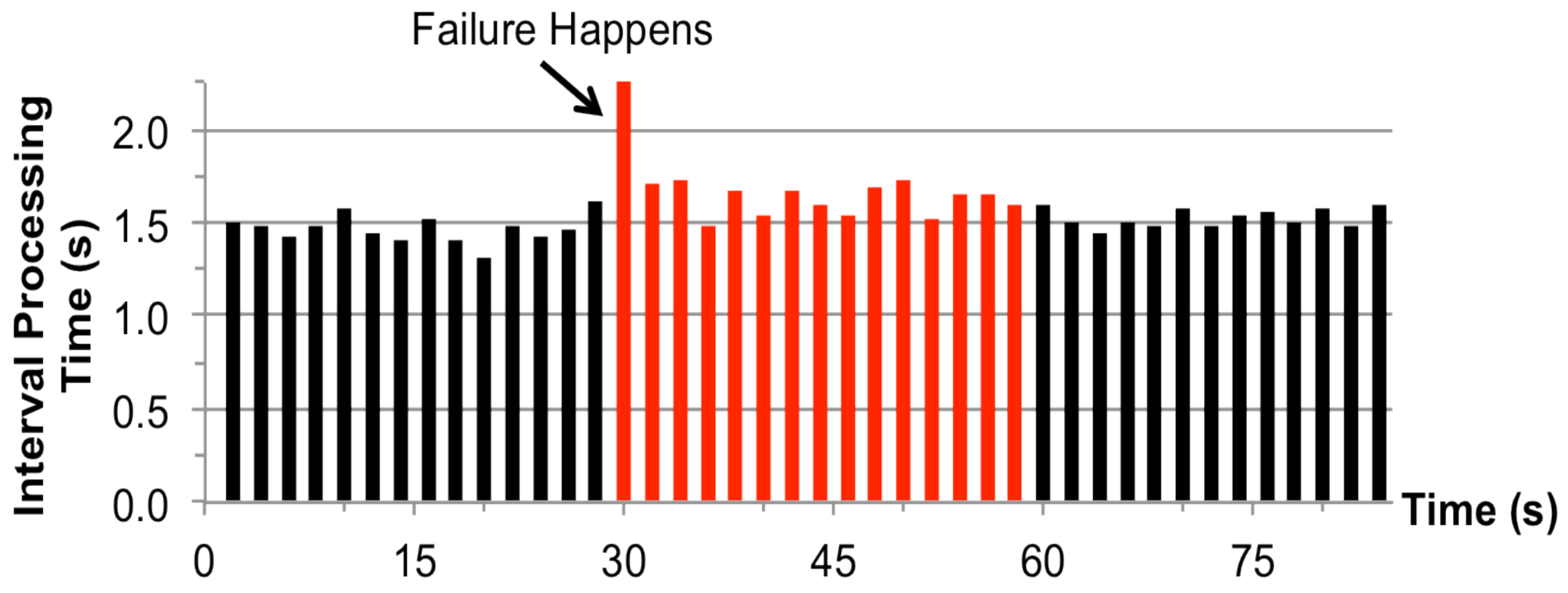
Fast Fault Recovery

Recovers from faults/stragglers within **1 sec**

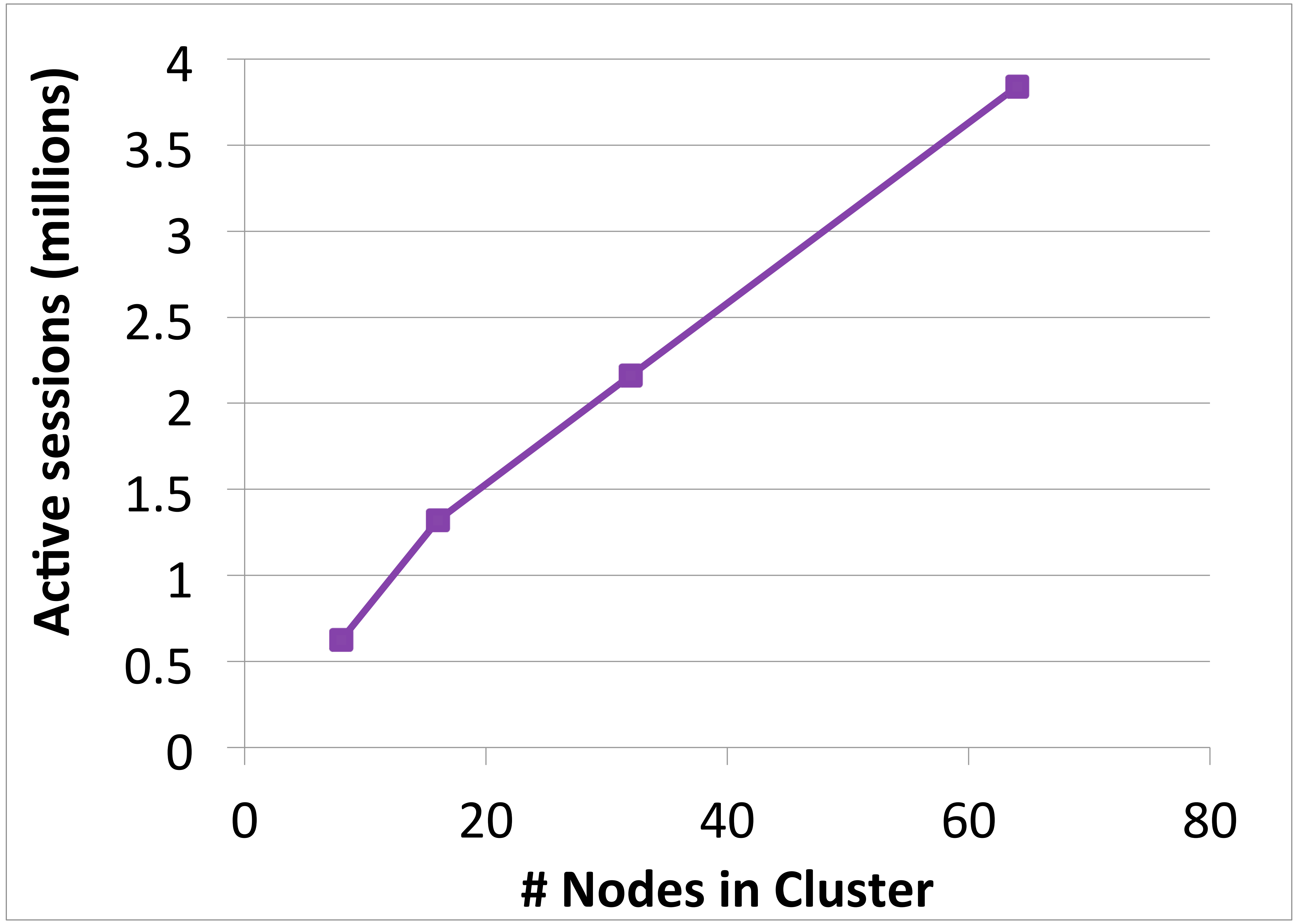


Sliding WordCount on 10 nodes with 30s checkpoint interval

Real Applications: Conviva

Real-time monitoring of video metadata

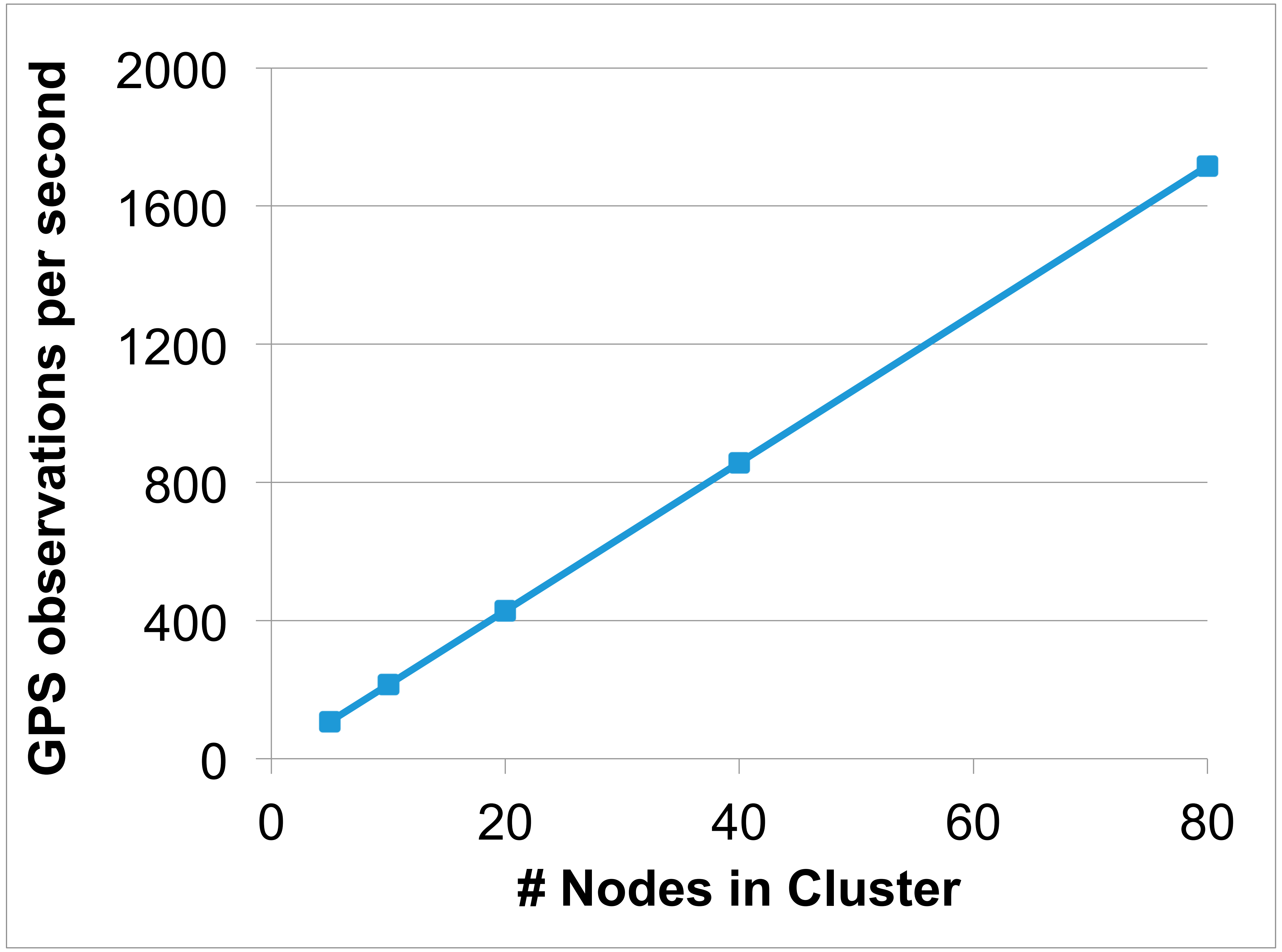
- Achieved 1-2 second latency
- Millions of video sessions processed
- Scales linearly with cluster size



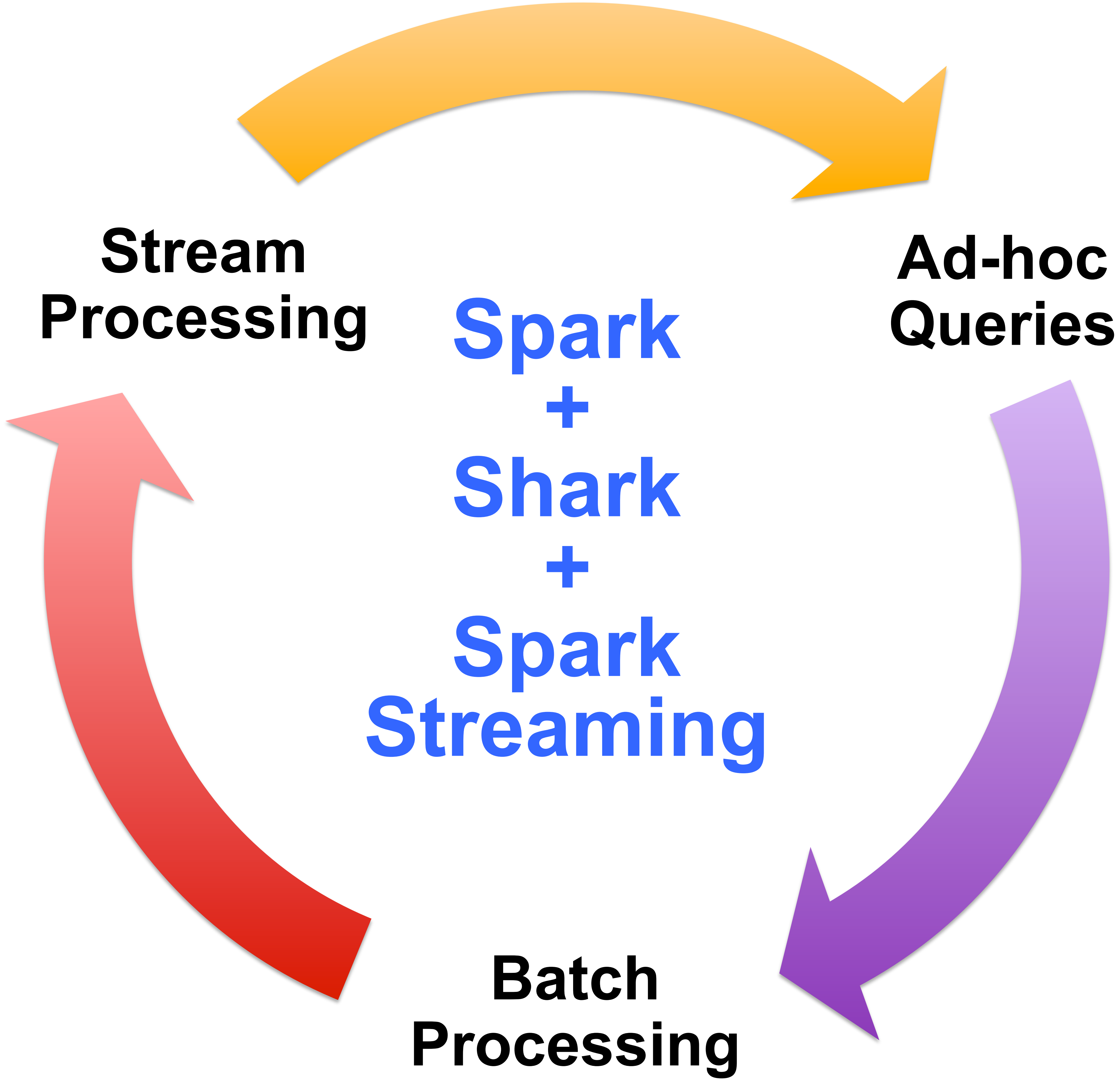
Real Applications: Mobile Millennium Project

Traffic transit time estimation using online machine learning on GPS observations

- Markov chain Monte Carlo simulations on GPS observations
- Very CPU intensive, requires dozens of machines for useful computation
- Scales linearly with cluster size



Vision - *one stack to rule them all*



Spark program vs Spark Streaming program

Spark Streaming program on Twitter stream

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

Spark program on Twitter log file

```
val tweets = sc.hadoopFile("hdfs://...")
val hashTags = tweets.flatMap (status => getTags(status))
hashTags.saveAsHadoopFile("hdfs://...")
```

Vision - *one stack to rule them all*

- Explore data interactively using Spark Shell / PySpark to identify problems
- Use same code in Spark stand-alone programs to identify problems in production logs
- Use similar code in Spark Streaming to identify problems in live log streams

```
$ ./spark-shell
scala> val file = sc.hadoopFile(“smallLogs”)
...
scala> val filtered = file.filter(_.contains(“ERROR”))
...
sc
..
```

```
object ProcessProductionData {
  def main(args: Array[String]) {
    val sc = new SparkContext(...)
    val file = sc.hadoopFile(“productionLogs”)
    val filtered = file.filter(_.contains(“ERROR”))
    val mapped = file.map(...)

}
```

```
object ProcessLiveStream {
  def main(args: Array[String]) {
    val sc = new StreamingContext(...)
    val stream = sc.kafkaStream(...)
    val filtered = file.filter(_.contains(“ERROR”))
    val mapped = file.map(...)
    ...
  }
}
```

Vision - *one stack to rule them all*

- Explore data interactively using Spark Shell / PySpark to identify problems
- Use same code in Spark stand-alone programs to identify problems in production logs
- Use similar code in Spark Streaming to identify problems in live log streams

```
scala> val file = sc.hadoopFile("smallLogs")
...
scala> val filtered = file.filter(_.contains("ERROR"))
...
```

```
object ProcessProductionData {
  def main(args: Array[String]) {
    val sc = new SparkContext(...)
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```

```
object ProcessLiveStream {
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    val sc = new StreamingContext(...)
    val stream = sc.kafkaStream(...)
    val filtered = file.filter(_.contains("ERROR"))
    val mapped = file.map(...)
    ...
  }
}
```

Stream Processing

Ad-hoc Queries

Spark
+
Shark
+
Spark Streaming

Batch Processing

Alpha Release with Spark 0.7

- Integrated with Spark 0.7
  - Import **spark.streaming** to get all the functionality
- Both Java and Scala API
- Give it a spin!
  - Run locally or in a cluster
- Try it out in the hands-on tutorial later today

Summary

- Stream processing framework that is ...
  - Scalable to large clusters
  - Achieves second-scale latencies
  - Has simple programming model
  - Integrates with batch & interactive workloads
  - Ensures efficient fault-tolerance in stateful computations
- For more information, checkout our paper: http://tinyurl.com/dstreams