Spark

Making Big Data Analytics Interactive and Real-Time

Matei Zaharia, in collaboration with
Mosharaf Chowdhury, Tathagata Das, Timothy Hunter,
Ankur Dave, Haoyuan Li, Justin Ma, Murphy McCauley,
Michael Franklin, Scott Shenker, Ion Stoica

spark-project.org

amplab
UC BERKELEY

Overview

Spark is a parallel framework that provides:

» Efficient primitives for in-memory data sharing
» Simple APIs in Scala, Java, SQL
» High generality (applicable to many emerging problems)

This talk will cover:

» What it does
» How people are using it (including some surprises)
» Current research

Motivation

MapReduce simplified data analysis on large, unreliable clusters

But as soon as it got popular, users wanted more:

» More **complex**, multi-pass applications (e.g. machine learning, graph algorithms)

» More **interactive** ad-hoc queries

» More **real-time** stream processing

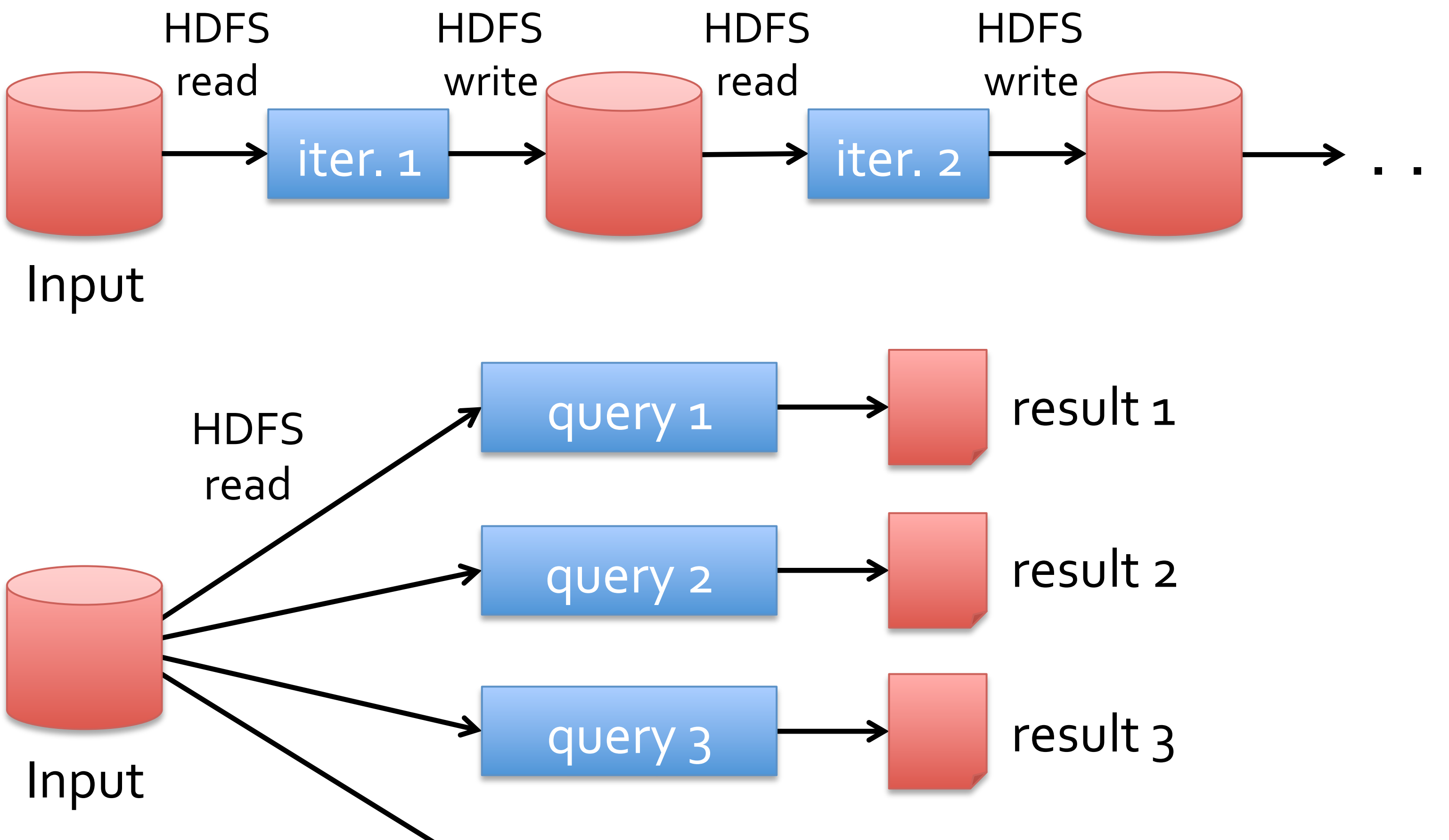
One reaction: specialized models for some of these apps (e.g. Pregel, Storm)

Motivation

Complex apps, streaming, and interactive queries all need one thing that MapReduce lacks:

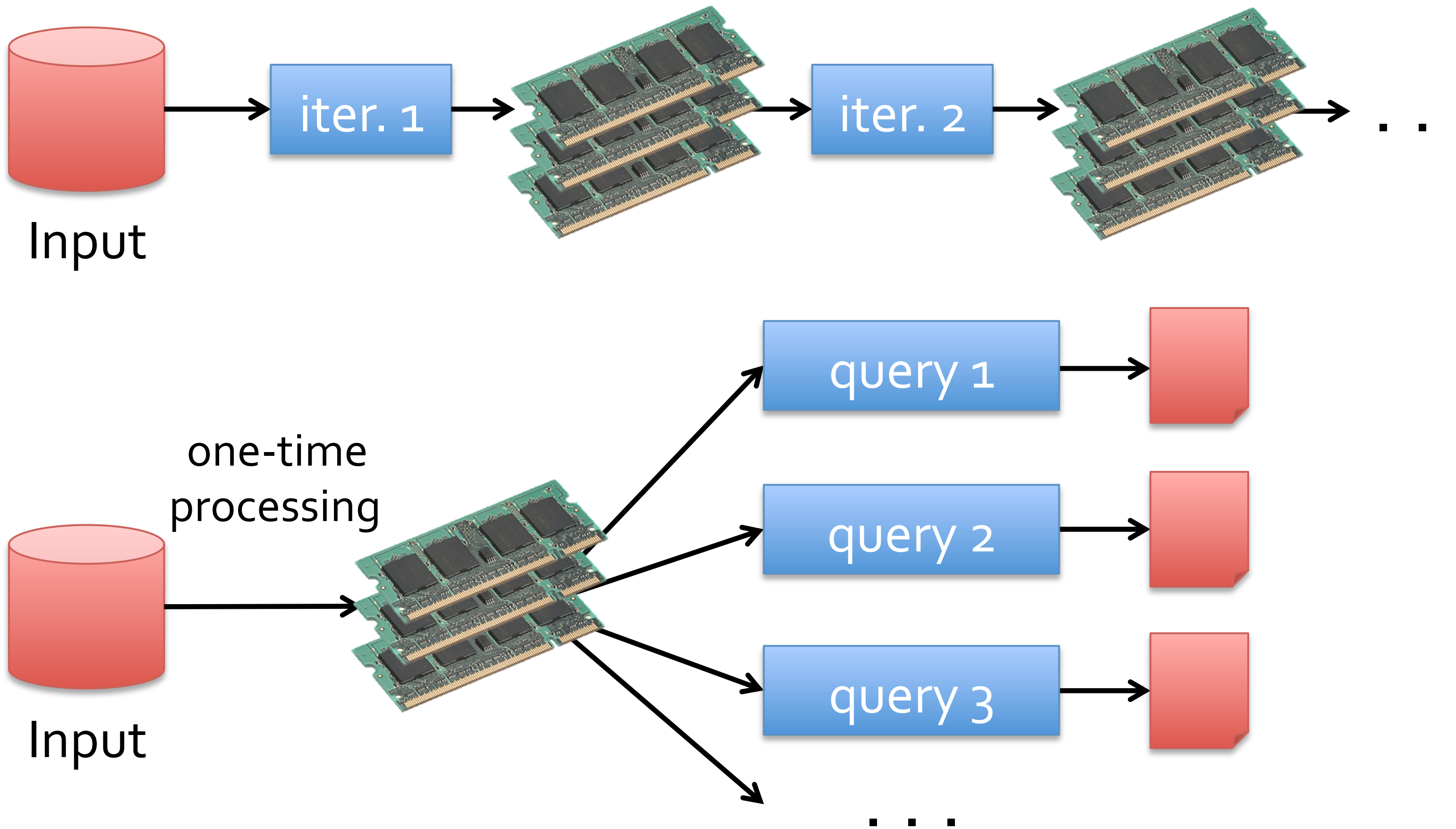
Efficient primitives for **data sharing**

Examples



Slow due to replication and disk I/O,
but necessary for fault tolerance

Goal: Sharing at Memory Speed



10-100× faster than network/disk, but how to get FT?

Challenge

How to design a distributed memory abstraction that is both **fault-tolerant** and **efficient**?

Existing Systems

Existing in-memory storage systems have interfaces based on *fine-grained* updates

» Reads and writes to cells in a table

» E.g. databases, key-value stores, distributed memory

Requires replicating *data* or *logs* across nodes for fault tolerance ➔ expensive!

» 10-100x slower than memory write…

Solution: Resilient Distributed Datasets (RDDs)

Provide an interface based on *coarse-grained* operations (map, group-by, join, …)

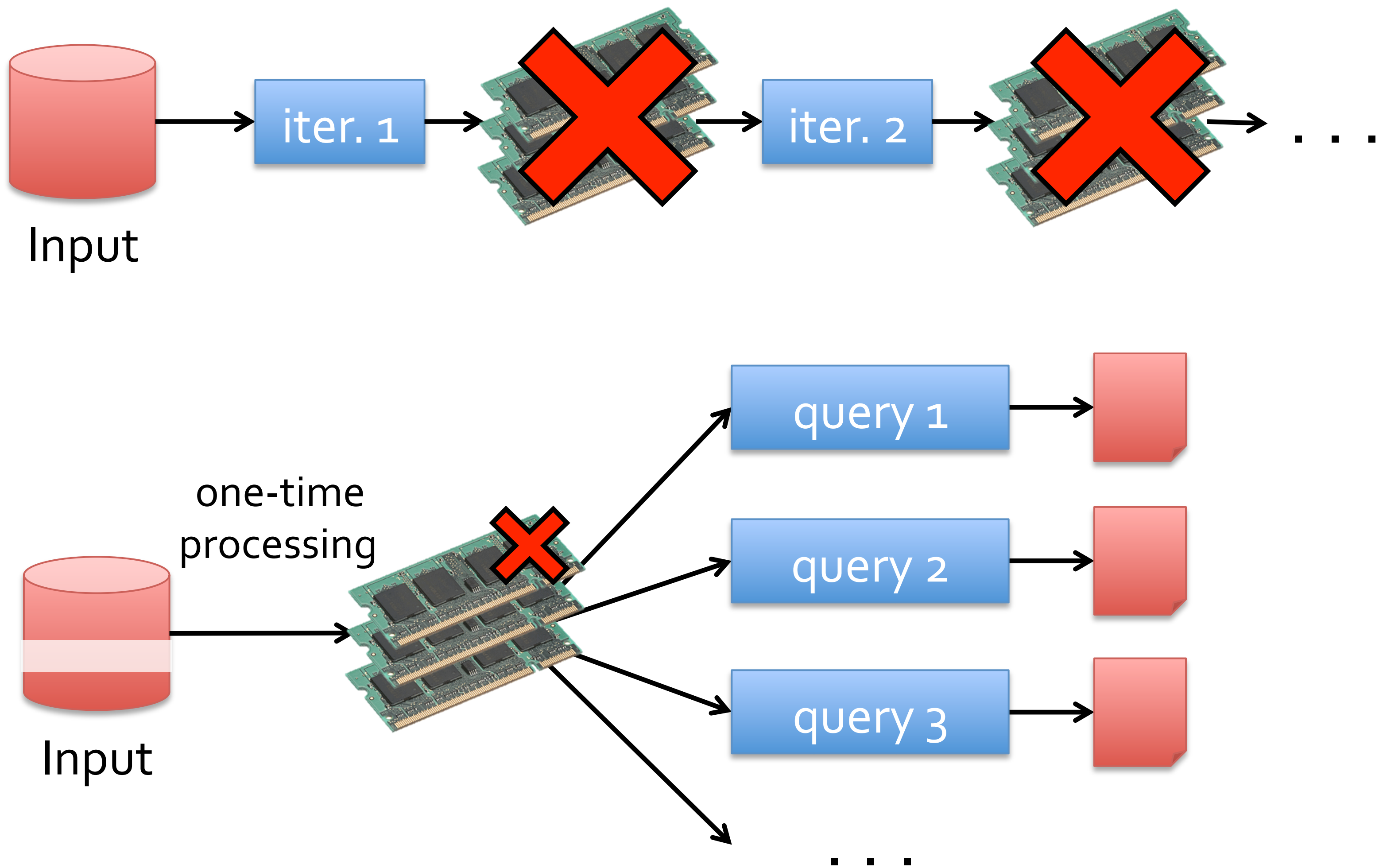
Efficient fault recovery using *lineage*

» Log one operation to apply to many elements

» Recompute lost partitions on failure

» No cost if nothing fails

RDD Recovery



Generality of RDDs

RDDs can express surprisingly many parallel algorithms

» These naturally *apply same operation to many items*

Capture many current programming models

» **Data flow models**: MapReduce, Dryad, SQL, …

» **Specialized models** for iterative apps: Pregel, iterative MapReduce, PowerGraph, …

Allow these models to be **composed**

Outline

Programming interface

Examples

User applications

Implementation

Demo

Current research: Spark Streaming

Spark Programming Interface

Language-integrated API in Scala*

Provides:

» Resilient distributed datasets (RDDs)
  - Partitioned collections with controllable caching

» Operations on RDDs
  - Transformations (define RDDs), actions (compute results)

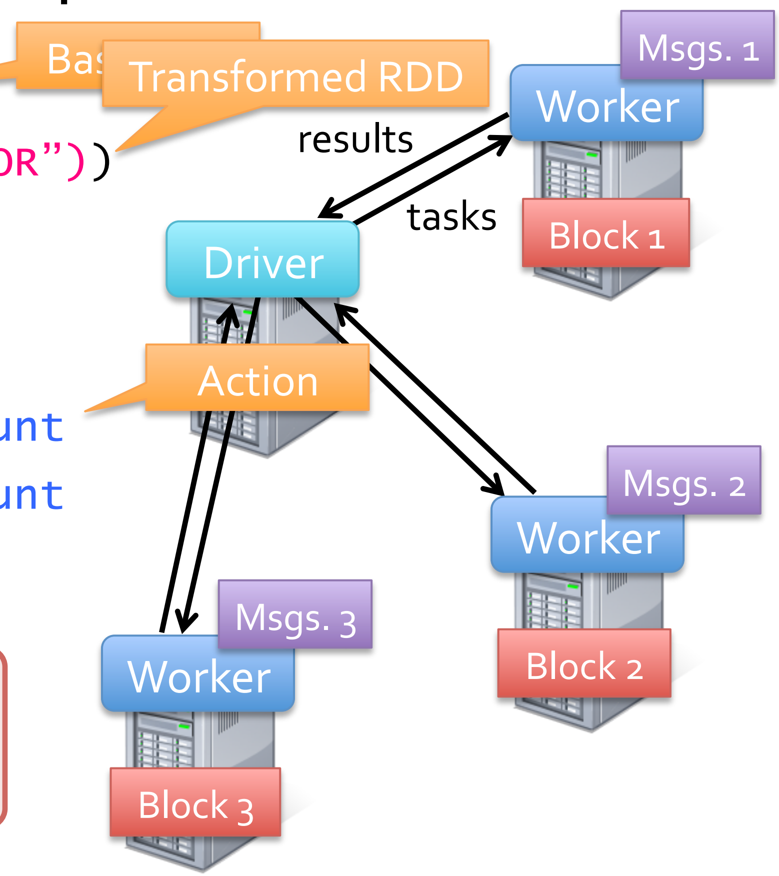
» Restricted shared variables (broadcast, accumulators)

*Also Java, SQL and soon Python

Example: Log Mining

Load error messages from a log into memory, then interactively search for various patterns

```
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
messages = errors.map(_.split('\t')(2))
cachedMsgs = messages.persist()

cachedMsgs.filter(_.contains("foo")).count
cachedMsgs.filter(_.contains("bar")).count
. . .
```

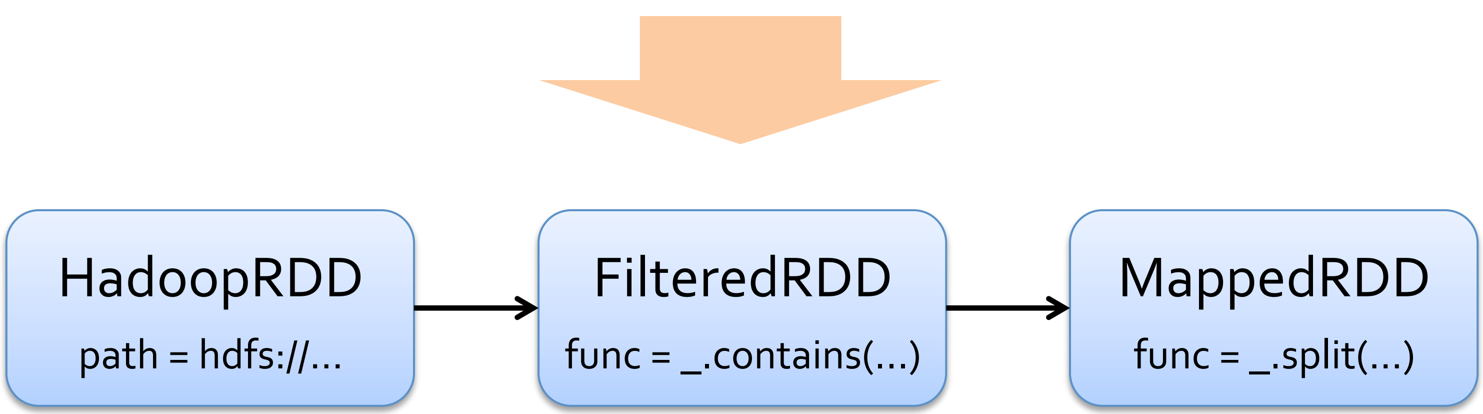


Result: scaled to 1 TB data in 5-7 sec (vs 170 sec for on-disk data)

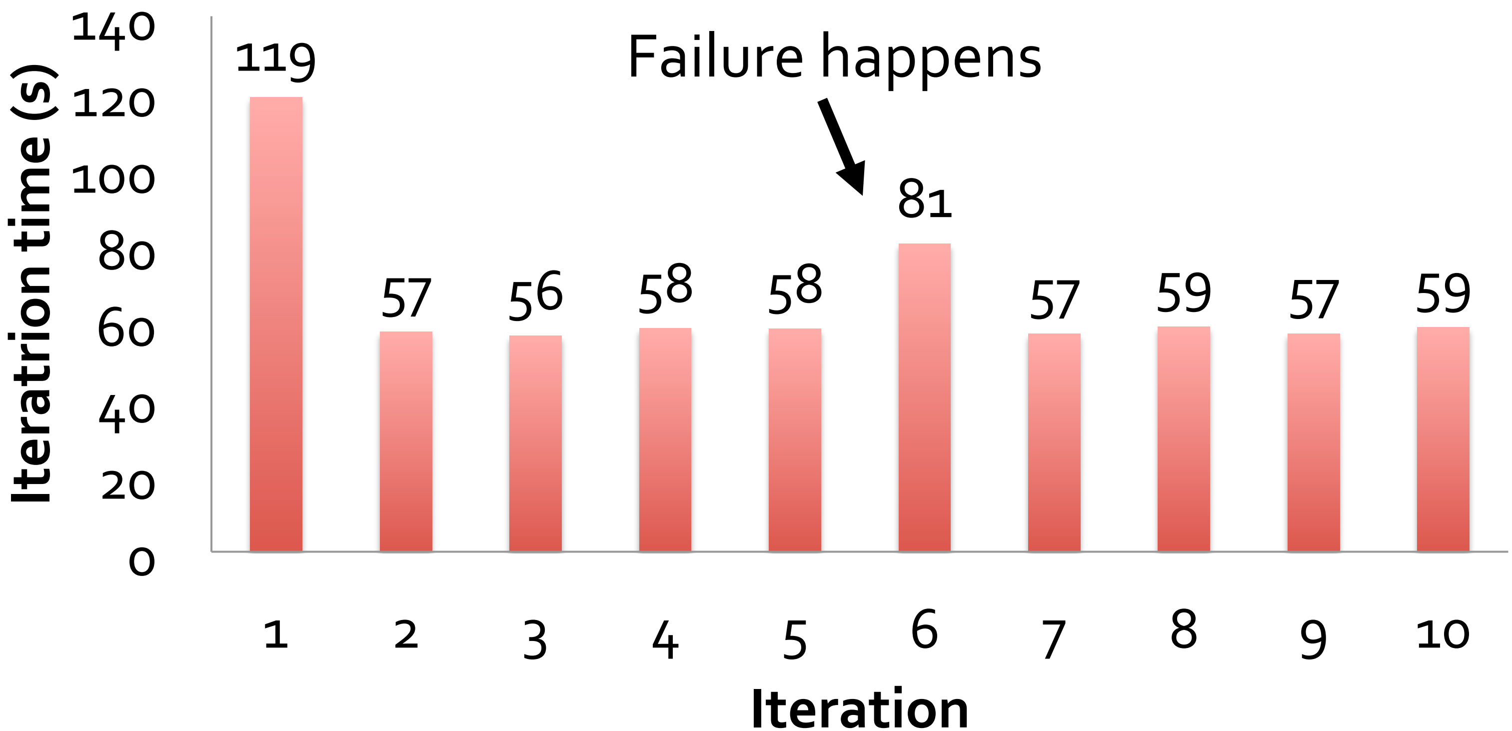
Fault Recovery

RDDs track the graph of transformations that built them (their *lineage*) to rebuild lost data

E.g.:
```
messages = textFile(...).filter(_.contains(“error”))
                        .map(_.split(‘\t’)(2))
```

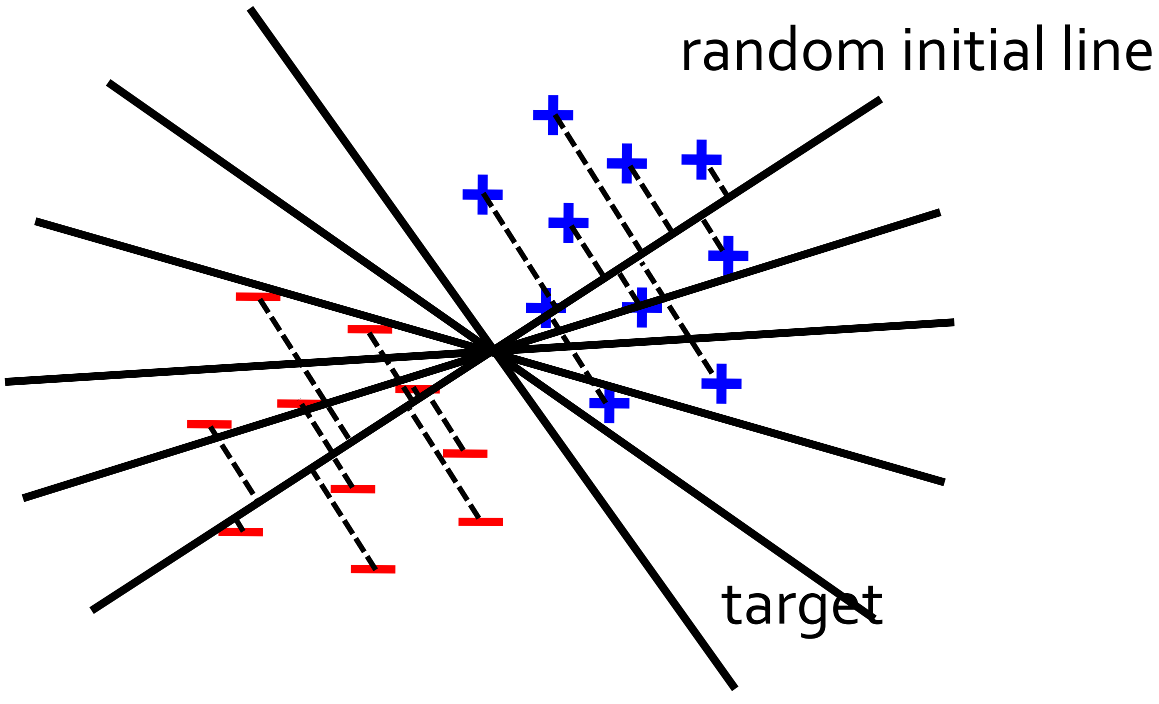


Fault Recovery Results



Example: Logistic Regression

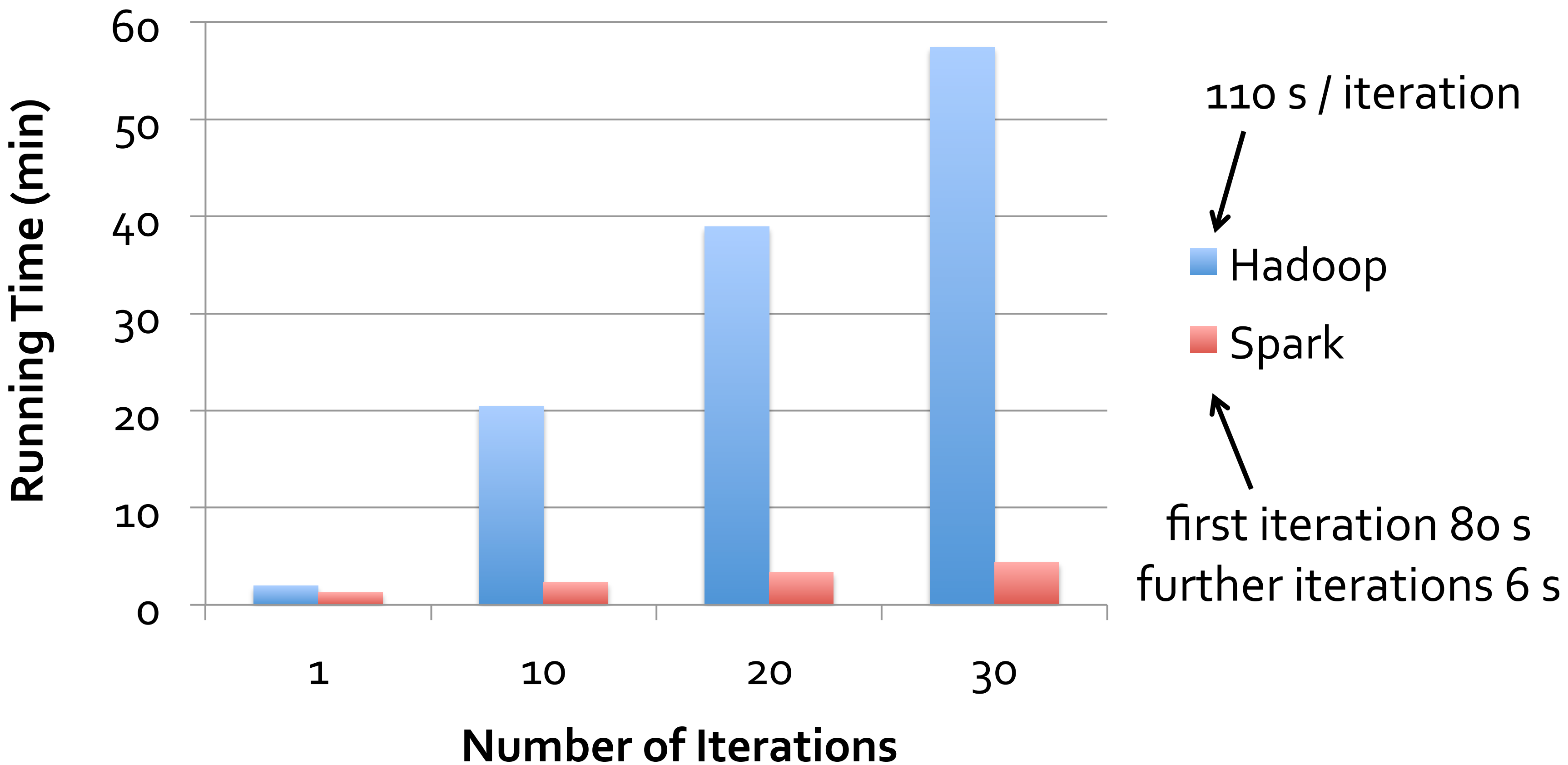
Goal: find best line separating two sets of points



Example: Logistic Regression

```
val data = spark.textFile(...).map(readPoint).persist()

var w = Vector.random(D)

for (i <- 1 to ITERATIONS) {
  val gradient = data.map(p =>
    (1 / (1 + exp(-p.y*(w dot p.x))) - 1) * p.y * p.x
  ).reduce(_ + _)
  w -= gradient
}

println("Final w: " + w)
```

Logistic Regression Performance



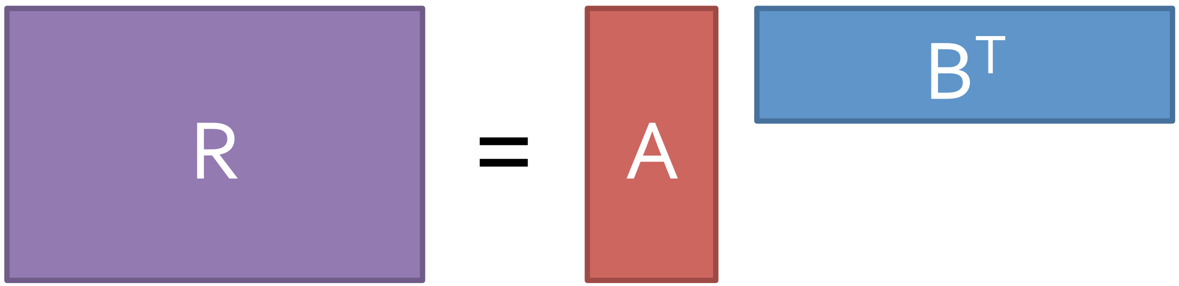
Example: Collaborative Filtering

Goal: predict users' movie ratings based on past ratings of other movies

$$R = \begin{array}{cc} \begin{pmatrix} 1 & ? & ? & 4 & 5 & ? & 3 \\ ? & ? & 3 & 5 & ? & ? & 3 \\ 5 & ? & 5 & ? & ? & ? & 1 \\ 4 & ? & ? & ? & ? & 2 & ? \end{pmatrix} & \text{Users} \\ \text{Movies} & \end{array}$$

Model and Algorithm

Model R as product of user and movie feature matrices A and B of size U×K and M×K



Alternating Least Squares (ALS)

» Start with random A & B

» Optimize user vectors (A) based on movies

» Optimize movie vectors (B) based on users

» Repeat until converged

Serial ALS

```
var R = readRatingsMatrix(...)

var A = // array of U random vectors
var B = // array of M random vectors

for (i <- 1 to ITERATIONS) {
  A = (0 until U).map(i => updateUser(i, B, R))
  B = (0 until M).map(i => updateMovie(i, A, R))
}
```

Range objects

Naïve Spark ALS

```
var R = readRatingsMatrix(...)

var A = // array of U random vectors
var B = // array of M random vectors

for (i <- 1 to ITERATIONS) {
  A = spark.parallelize(0 until U, numSlices)
           .map(i => updateUser(i, B, R))
           .collect()
  B = spark.parallelize(0 until M, numSlices)
           .map(i => updateMovie(i, A, R))
           .collect()
}
```

Problem:
R re-sent
to all nodes
in each
iteration

Efficient Spark ALS

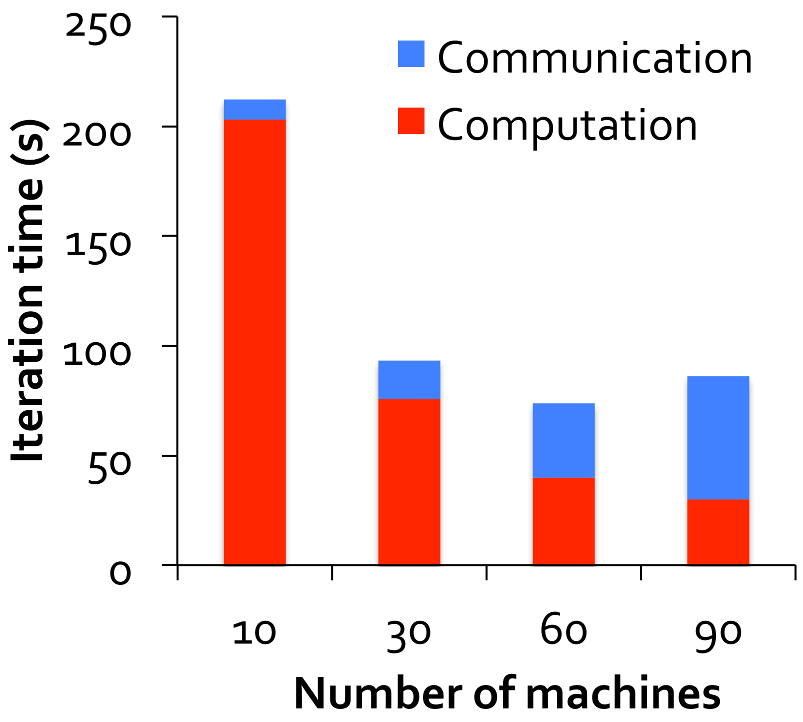
```
var R = spark.broadcast(readRatingsMatrix(...))

var A = // array of U random vectors
var B = // array of M random vectors

for (i <- 1 to ITERATIONS) {
  A = spark.parallelize(0 until U, numSlices)
           .map(i => updateUser(i, B, R.value))
           .collect()
  B = spark.parallelize(0 until M, numSlices)
           .map(i => updateMovie(i, A, R.value))
           .collect()
}
```

Solution: mark R as broadcast variable

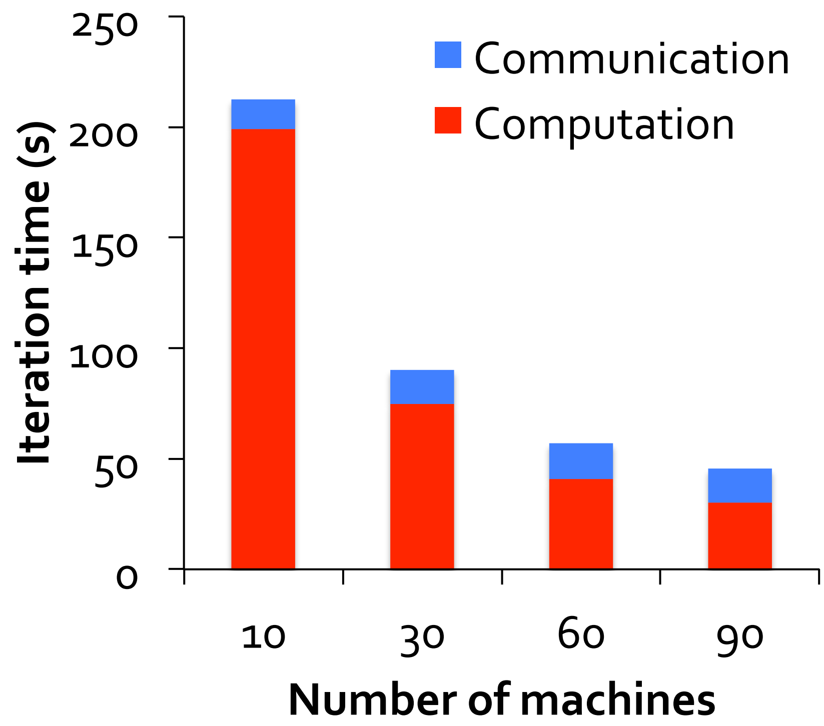
Result: 3× performance improvement

Scaling Up Broadcast

Initial version (HDFS)



Cornet P2P broadcast



[Chowdhury et al, SIGCOMM 2011]

Other RDD Operations

Transformations (define a new RDD)	map filter sample groupByKey reduceByKey sortByKey	flatMap union join cogroup cross …
Actions (return a result to driver program)	collect reduce count save …	

Spark in Java

```
lines.filter(_.contains("error")).count()
```

```
JavaRDD<String> lines = sc.textFile(...);

lines.filter(new Function<String, Boolean>() {
  Boolean call(String s) {
    return s.contains("error");
  }
}).count();
```

Spark in Python (Coming Soon!)

```
lines = sc.textFile(sys.argv[1])

counts = lines.flatMap(lambda x: x.split(' ')) \
              .map(lambda x: (x, 1)) \
              .reduceByKey(lambda x, y: x + y)
```

Outline

Programming interface

Examples

User applications

Implementation

Demo

Current research: Spark Streaming

Spark Users

CONVIVA foursquare

quantiFind airbnb YAHOO!

KLOUT PRINCETON UNIVERSITY Carnegie Mellon University

University of California Berkeley UCSF

400+ user meetup, 20+ contributors

User Applications

Crowdsourced traffic estimation (Mobile Millennium)

Video analytics & anomaly detection (Conviva)

Ad-hoc queries from web app (Quantifind)

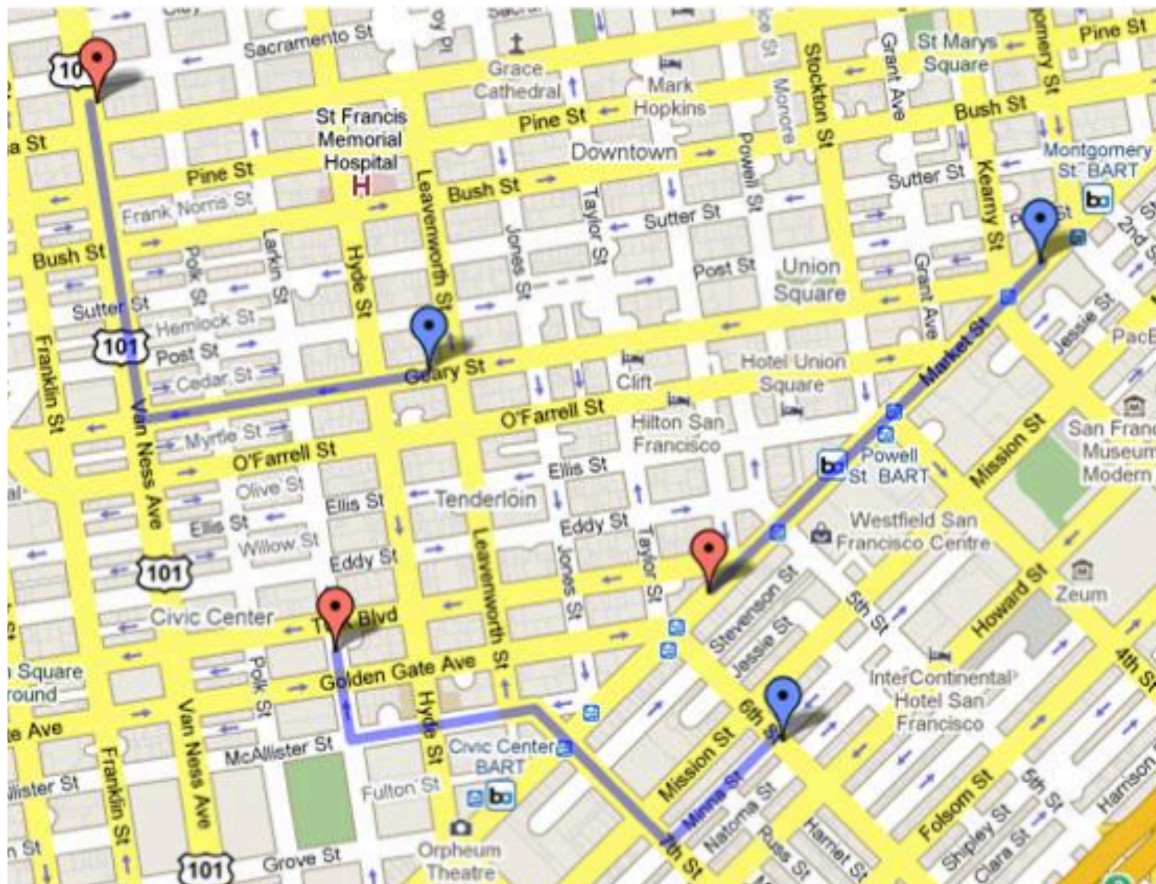
Twitter spam classification (Monarch)

DNA sequence analysis (SNAP)

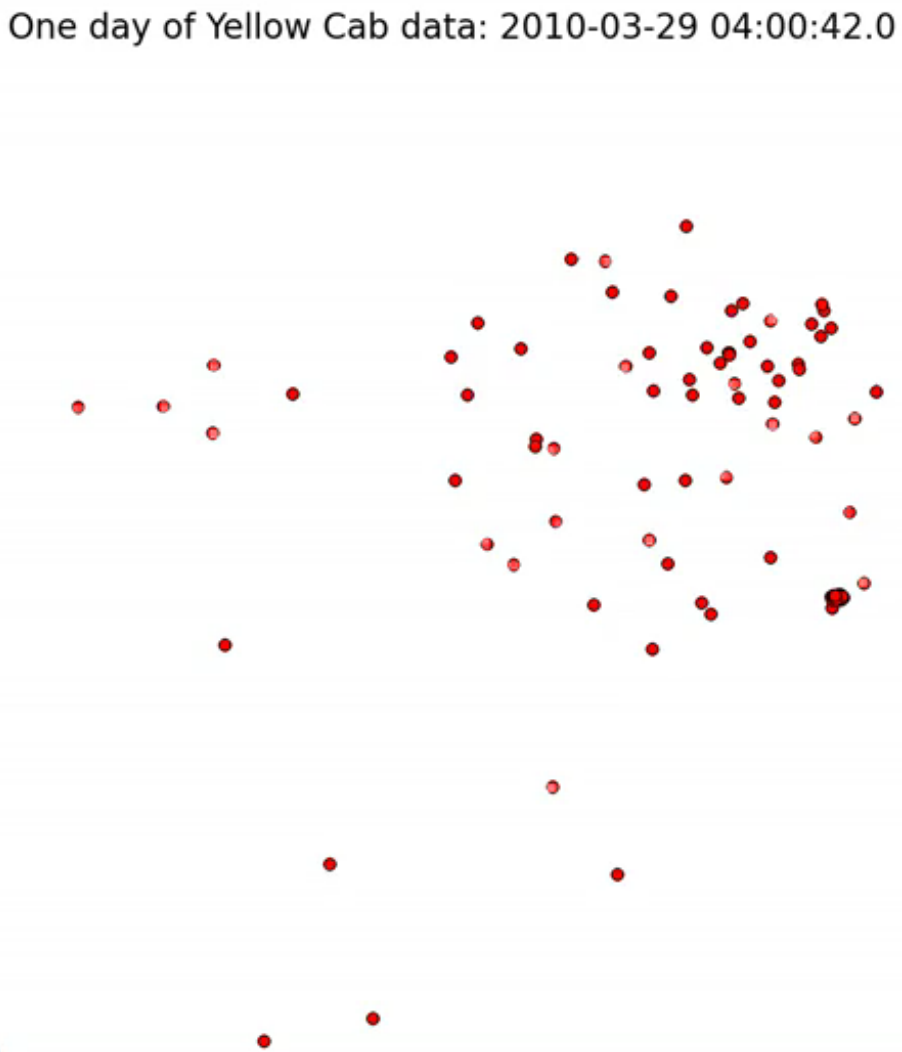
...

Mobile Millennium Project

Estimate city traffic from GPS-equipped vehicles (e.g. SF taxis)



Sample Data

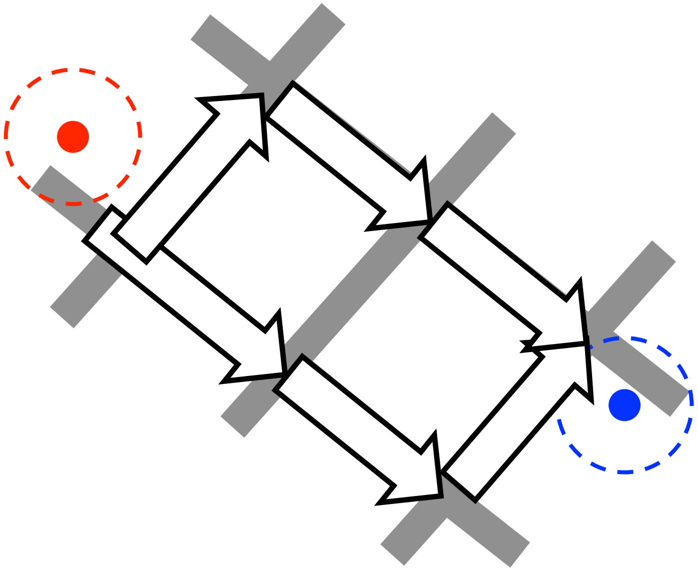


Credit: Tim Hunter, with support of the Mobile Millennium team; P.I. Alex Bayen; traffic.berkeley.edu

Challenge

Data is noisy and sparse (1 sample/minute)

Must infer path taken by each vehicle in addition to travel time distribution on each link



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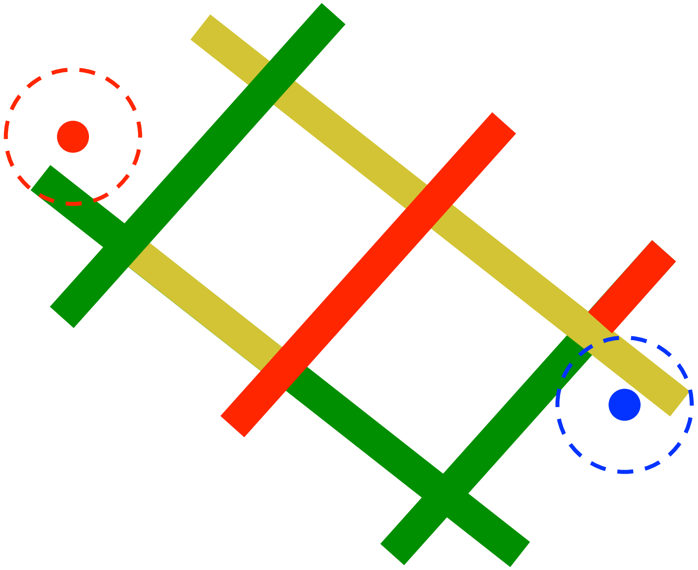
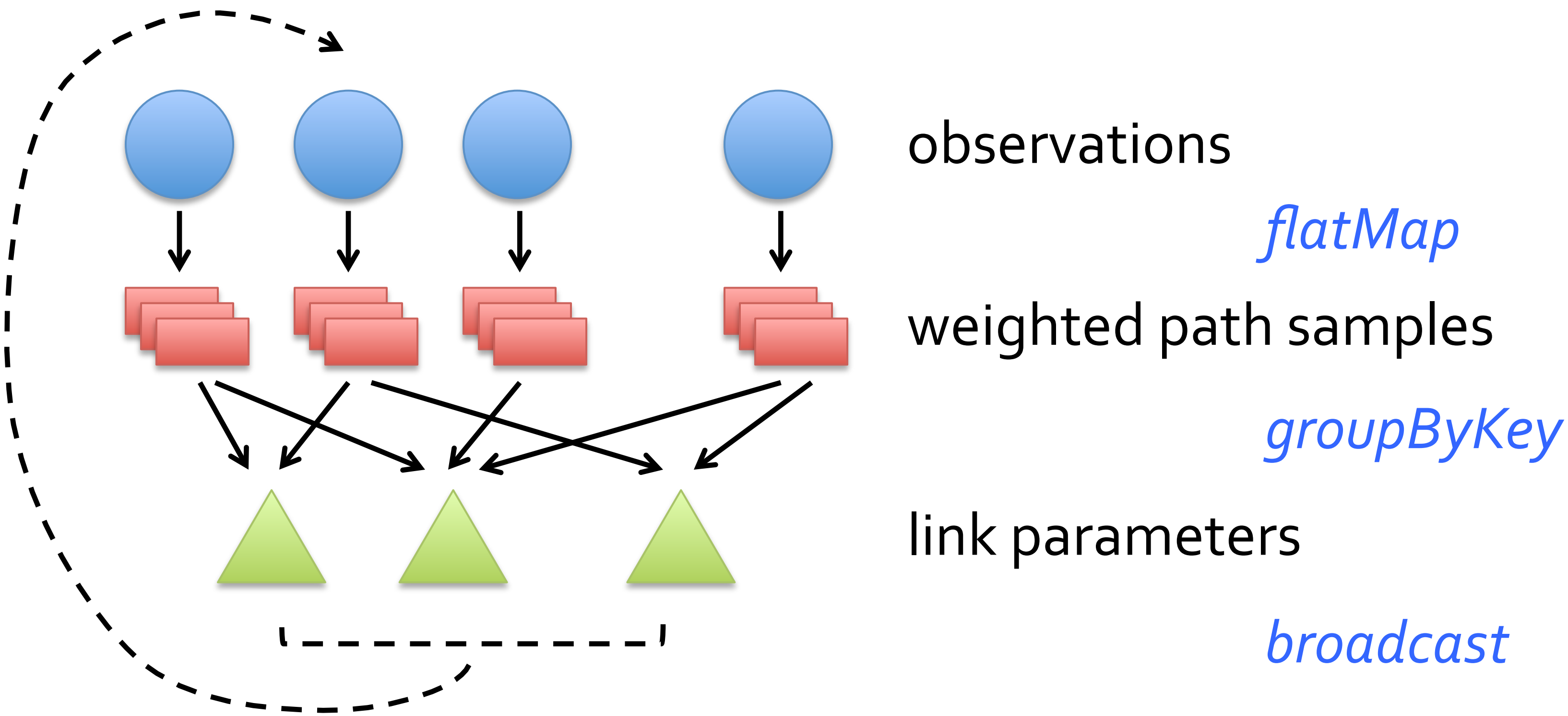


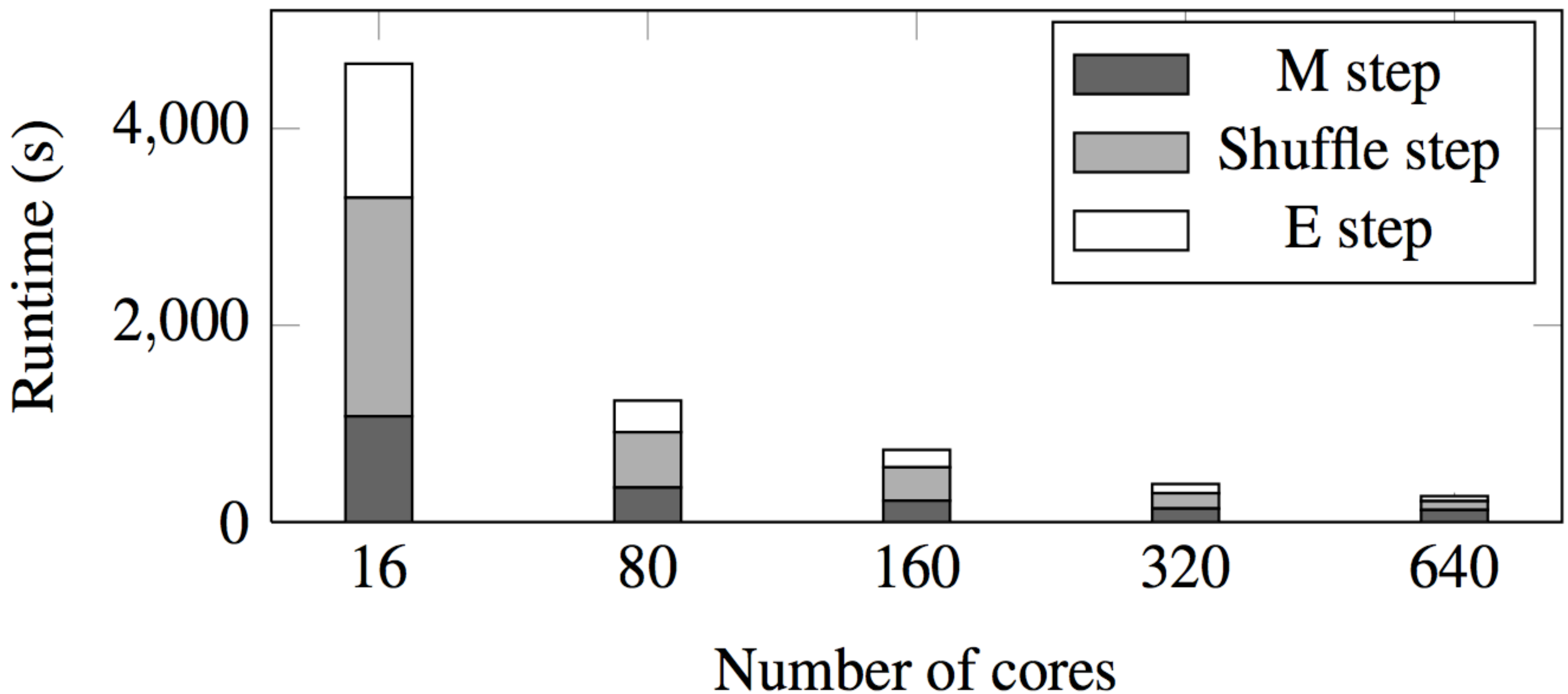
Solution

EM algorithm to estimate paths and travel time distributions simultaneously



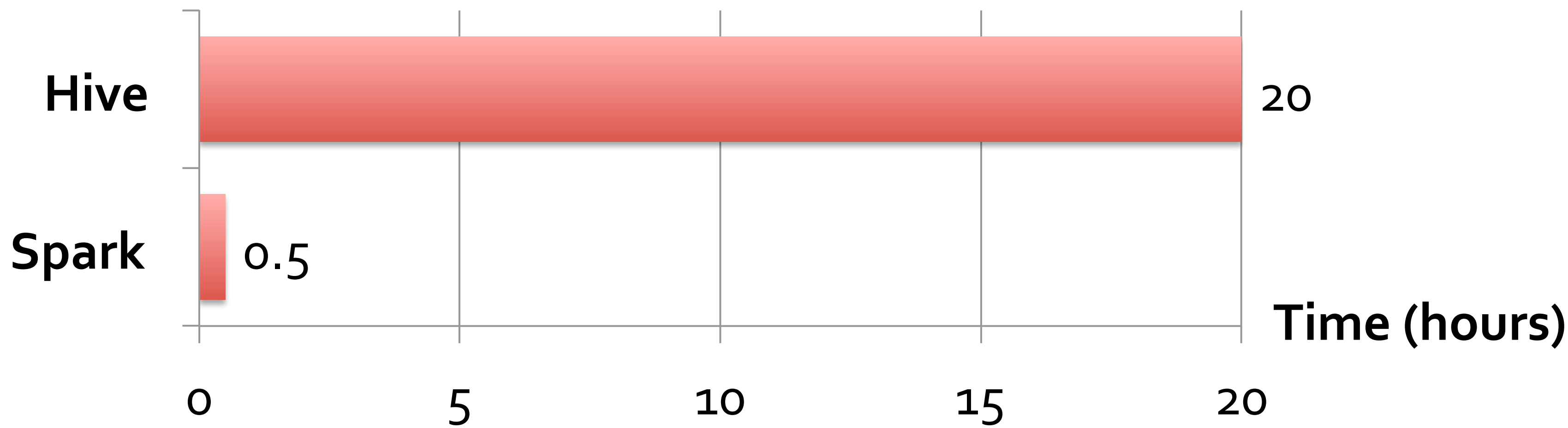
Results

[Hunter et al, SOCC 2011]



3× speedup from caching, 4.5x from broadcast

Conviva GeoReport



SQL aggregations on many keys w/ same filter

40× gain over Hive from avoiding repeated I/O, deserialization and filtering

Other Programming Models

Pregel on Spark (Bagel)

» 200 lines of code

Iterative MapReduce

» 200 lines of code

Hive on Spark (Shark)

» 5000 lines of code

» Compatible with Apache Hive

» Machine learning ops. in Scala

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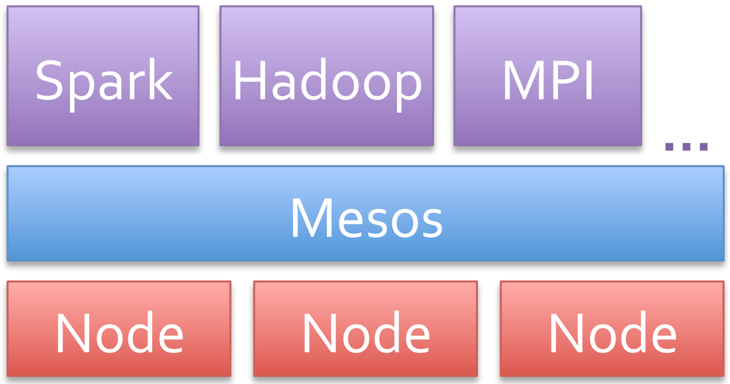
Current research: Spark Streaming

Implementation

Runs on Apache Mesos cluster manager to coexist w/ Hadoop



Supports any Hadoop storage system (HDFS, HBase, ...)

Easy local mode and EC2 launch scripts

No changes to Scala

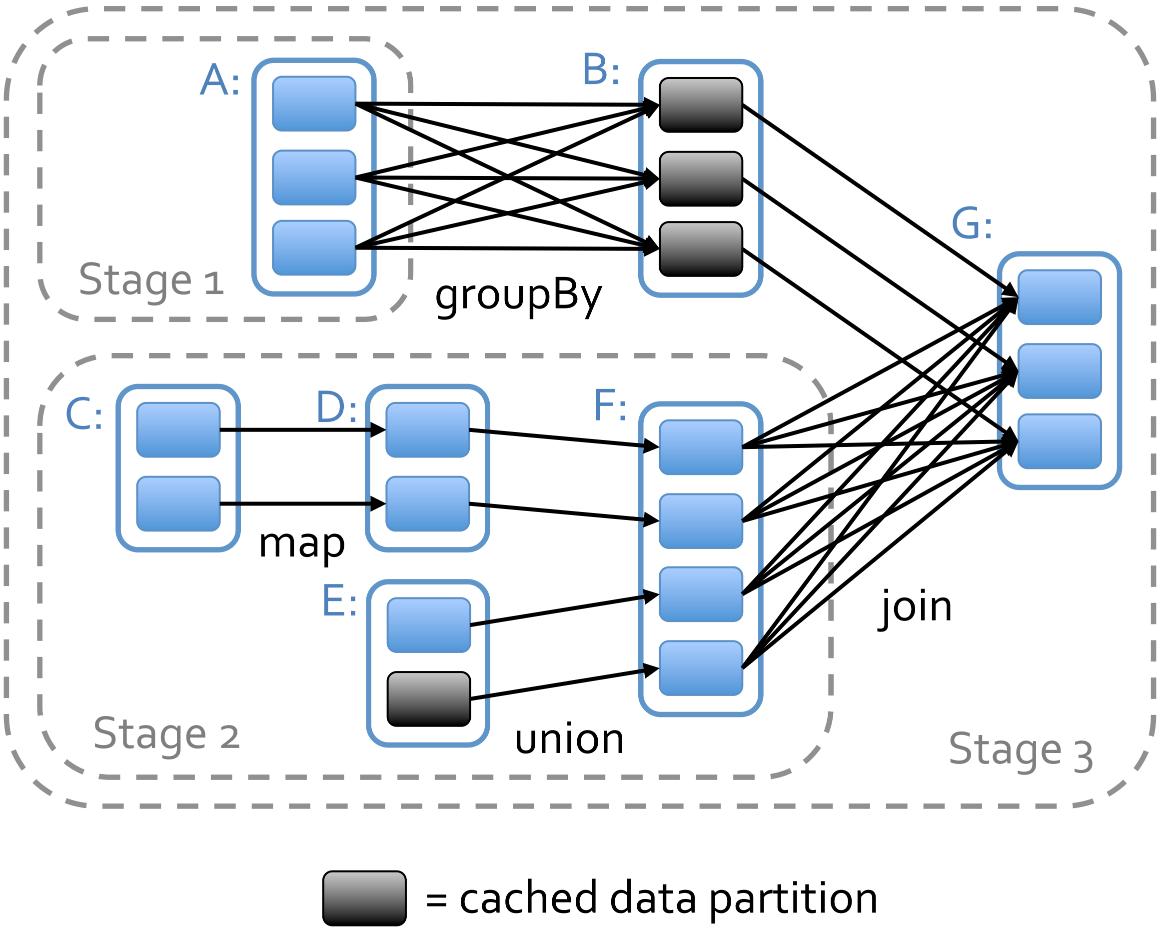
Task Scheduler

Runs general DAGs

Pipelines functions within a stage

Cache-aware data reuse & locality

Partitioning-aware to avoid shuffles



Language Integration

Scala closures are Serializable Java objects

» Serialize on master, load & run on workers

Not quite enough

» Nested closures may reference entire outer scope, pulling in non-Serializable variables not used inside

» Solution: bytecode analysis + reflection

Interactive Spark

Modified Scala interpreter to allow Spark to be used interactively from the command line

- » Track variables that each line depends on
- » Ship generated classes to workers

Enables in-memory exploration of big data

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Motivation

Many "big data" apps need to work in real time

- Site statistics, spam filtering, intrusion detection, ...

To scale to 100s of nodes, need:

- **Fault-tolerance:** for both crashes and stragglers
- **Efficiency:** don't consume many resources beyond base processing

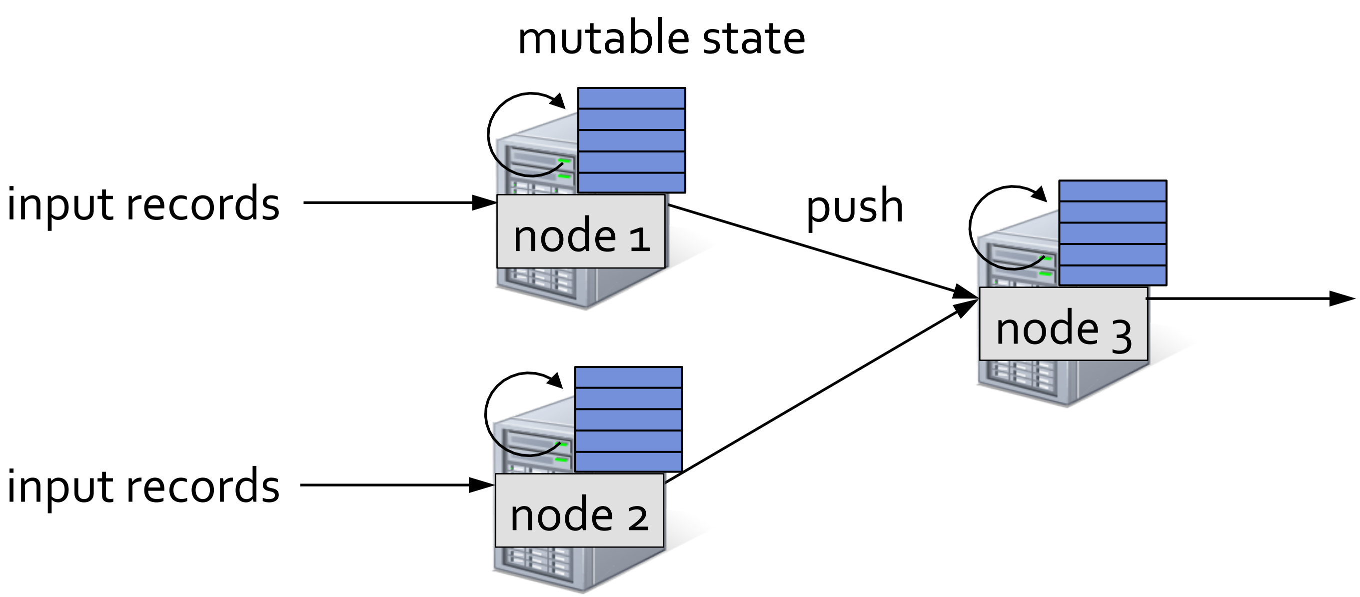
Challenging in existing streaming systems

Traditional Streaming Systems

Continuous processing model

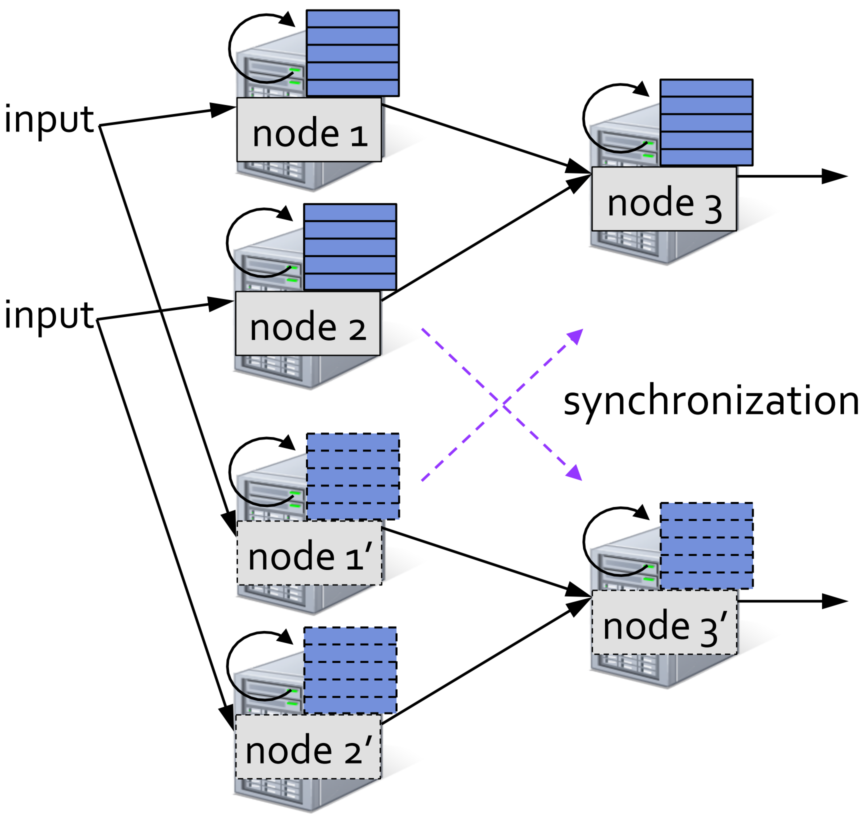
» Each node has long-lived state

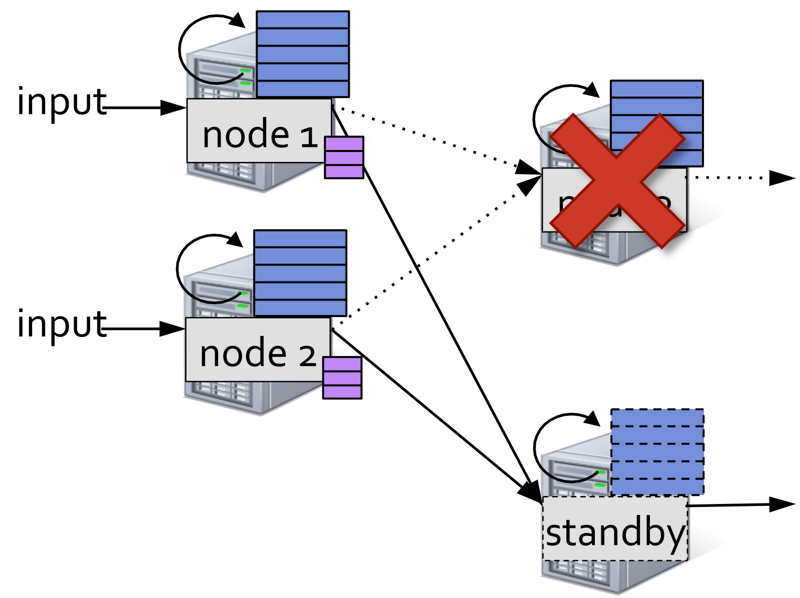
» For each record, update state & send new records



Traditional Streaming Systems

Fault tolerance via *replication* or *upstream backup*:





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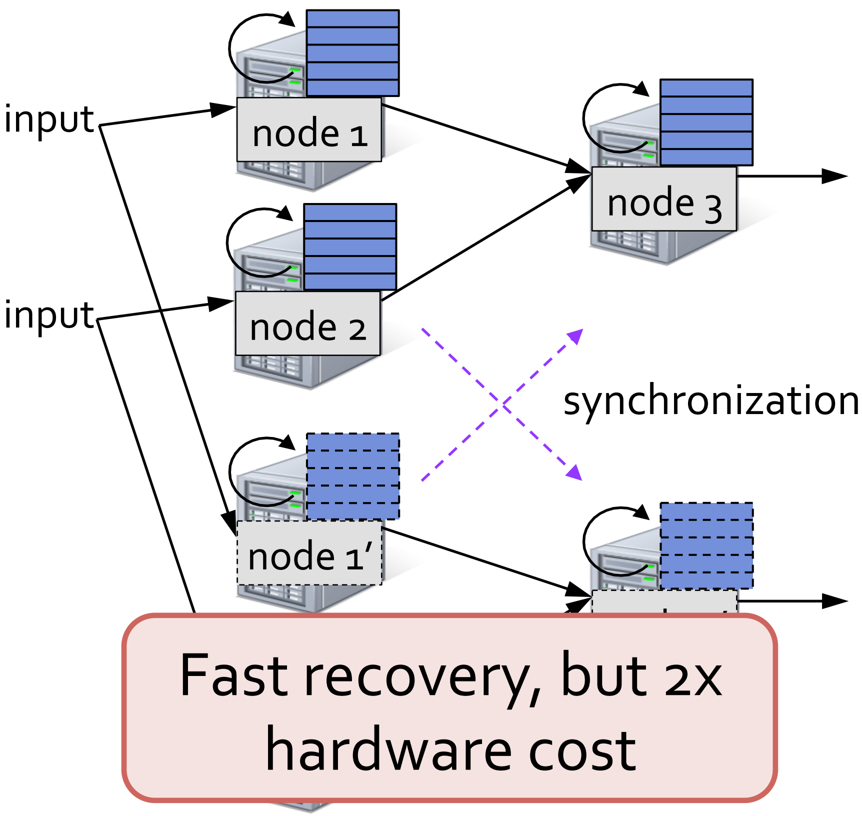
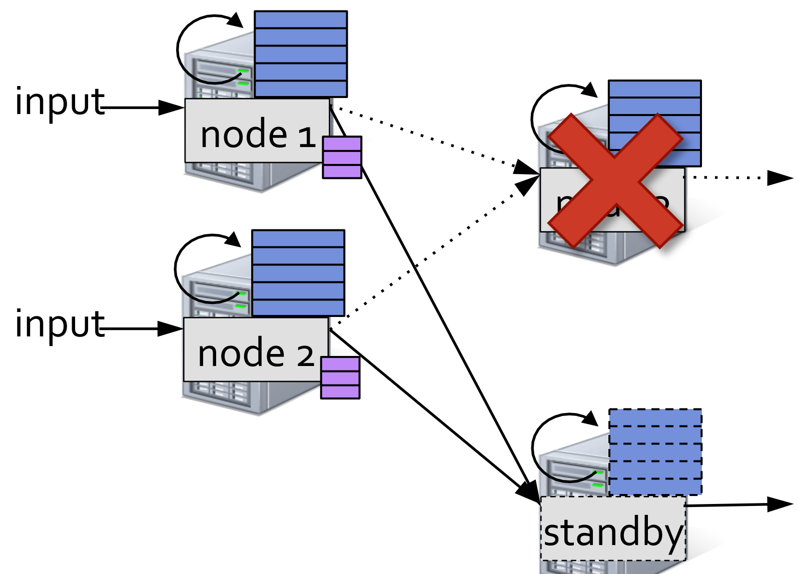


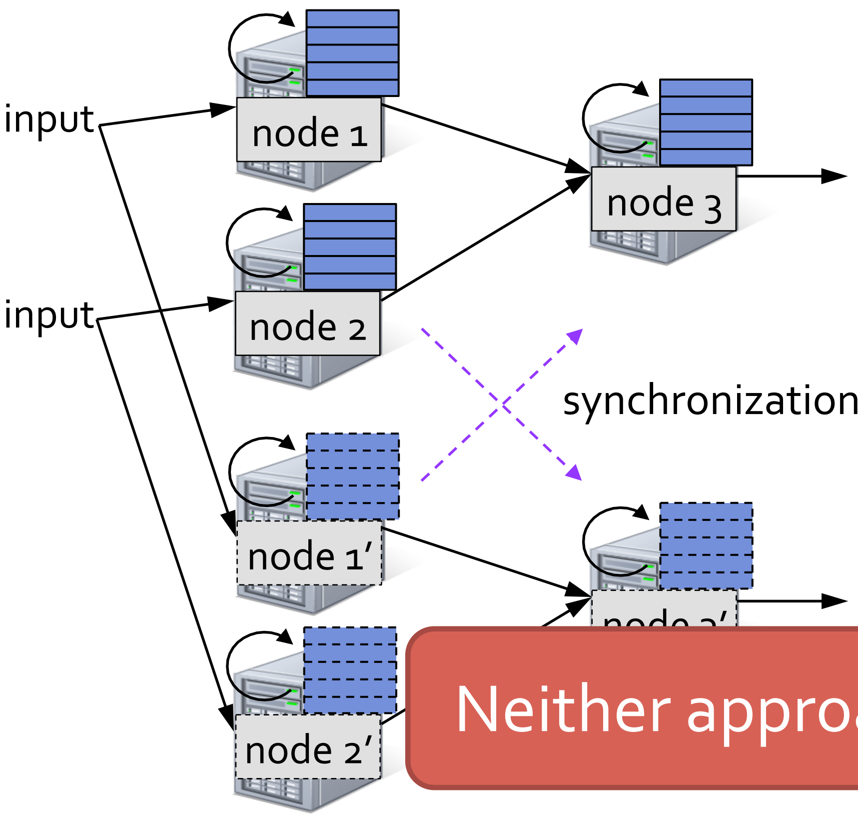
Fast recovery, but 2x hardware cost



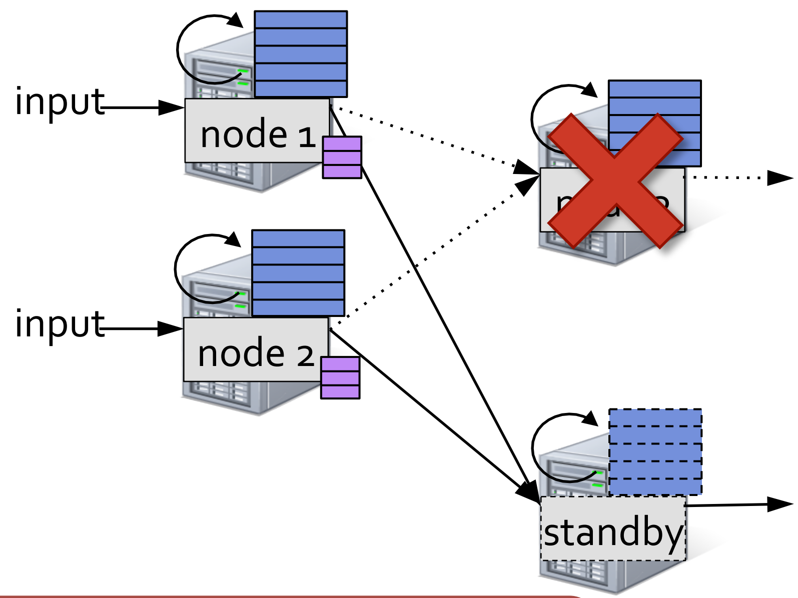
Only need 1 standby, but slow to recover

Traditional Streaming Systems

Fault tolerance via *replication* or *upstream backup*:



[Borealis, Flux]



[Hwang et al, 2005]

Neither approach can handle stragglers

Observation

Batch processing models, such as MapReduce, do provide fault tolerance efficiently

» Divide job into deterministic tasks

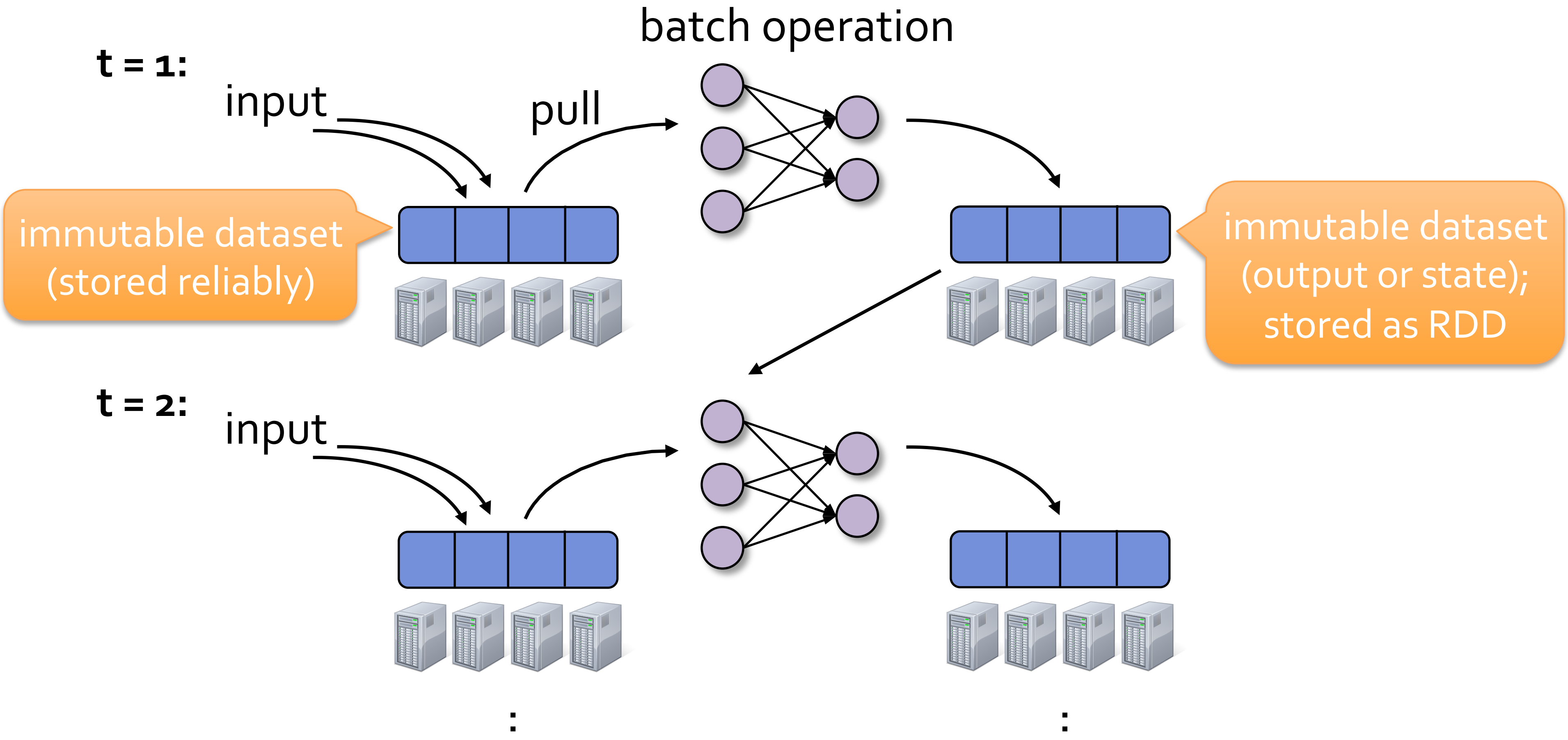
» Rerun failed/slow tasks in parallel on other nodes

Idea: run streaming computations as a series of *small, deterministic batch jobs*

» Same recovery schemes at much smaller timescale

» To make latency low, store state in RDDs

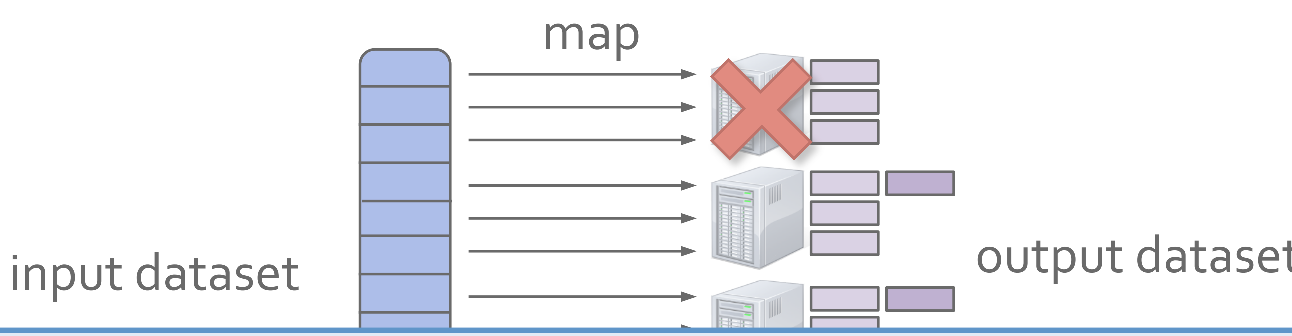
Discretized Stream Processing



Fault Recovery

Checkpoint state RDDs periodically

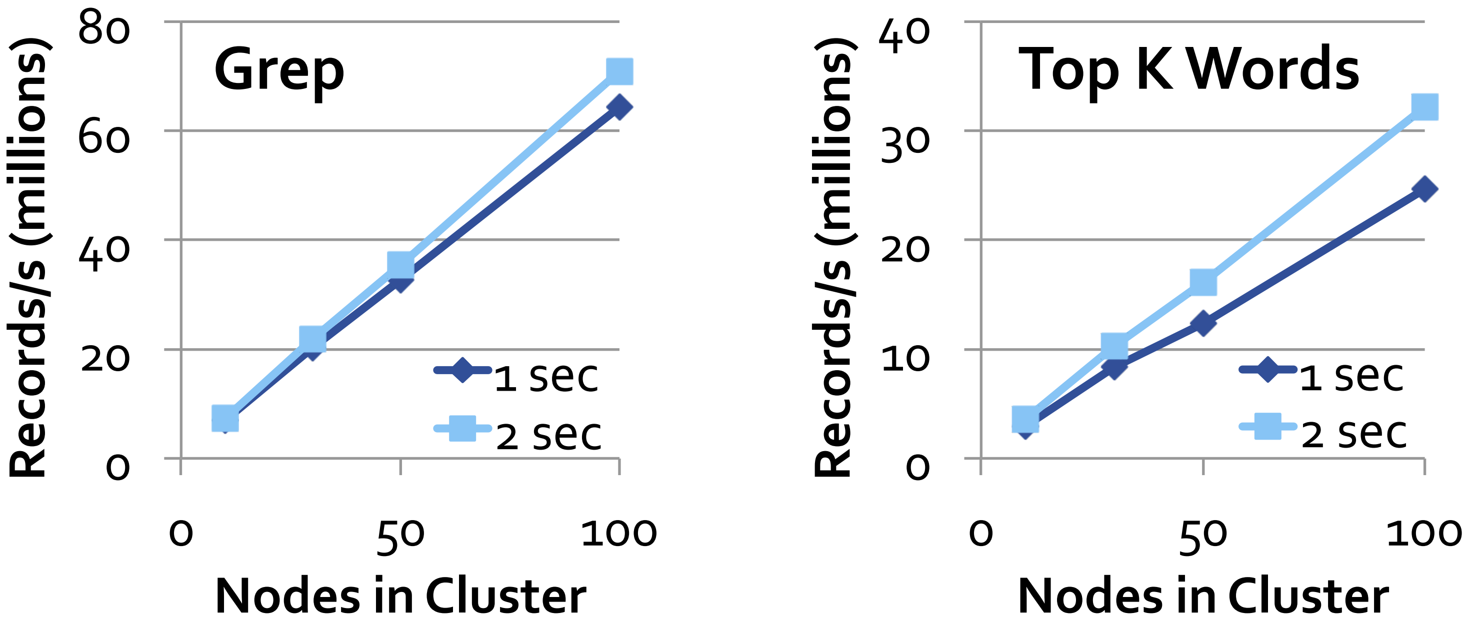
If a node fails/straggles, rebuild lost RDD partitions **in parallel** on other nodes



Faster recovery than upstream backup, without the cost of replication

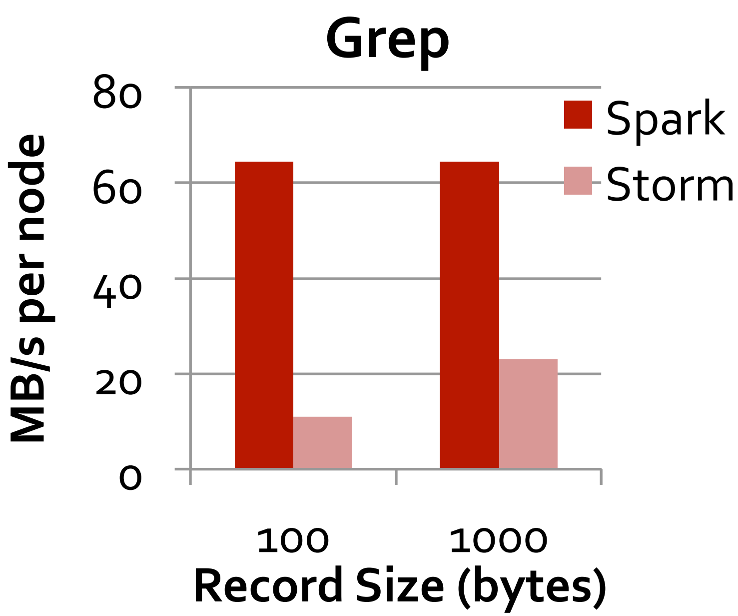
How Fast Can It Go?

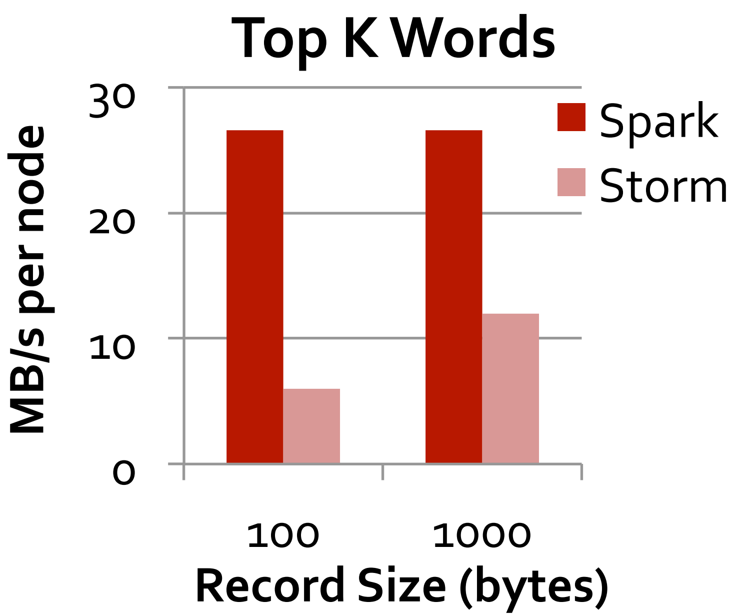
Can process over **60M records/s** (**6 GB/s**) on 100 nodes at **sub-second** latency



Max throughput under a given latency (1 or 2s)

Comparison with Storm





Storm limited to 100K records/s/node

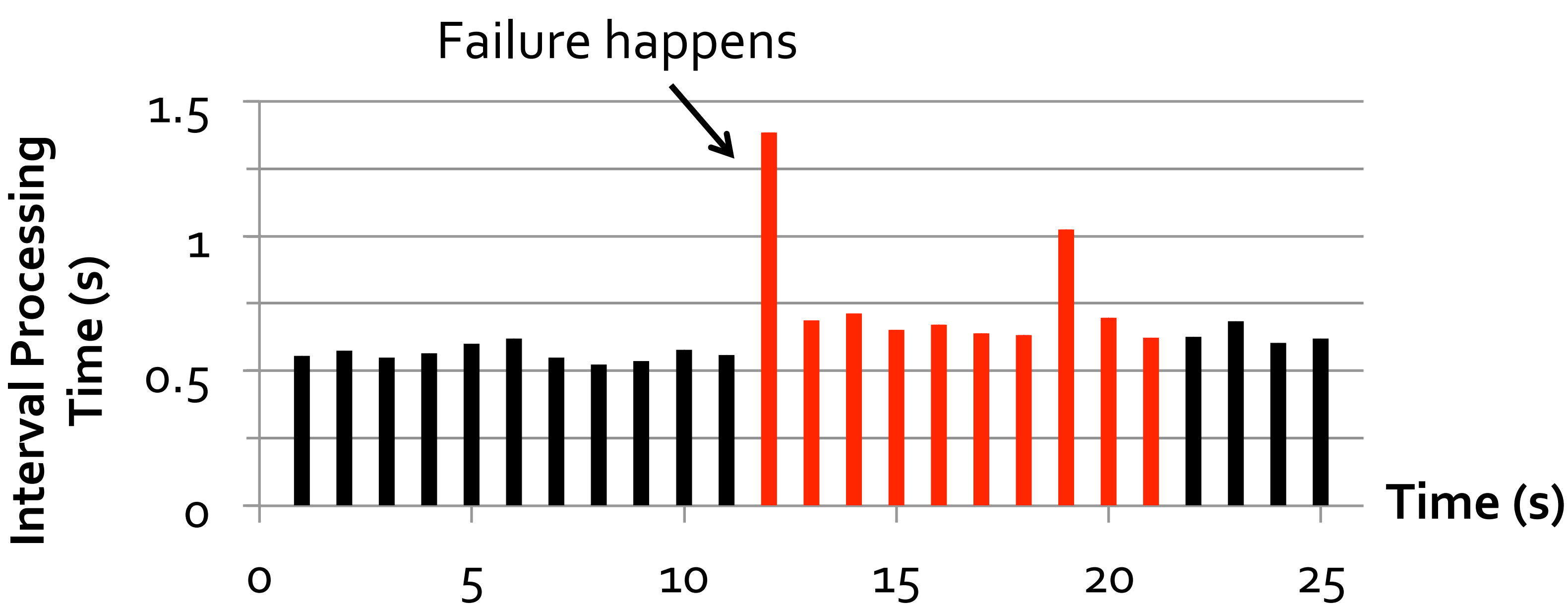
Also tried S4: 10K records/s/node

Commercial systems: O(500K) total

Lack Spark's FT guarantees

How Fast Can It Recover?

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



Sliding WordCount on 20 nodes with 10s checkpoint interval

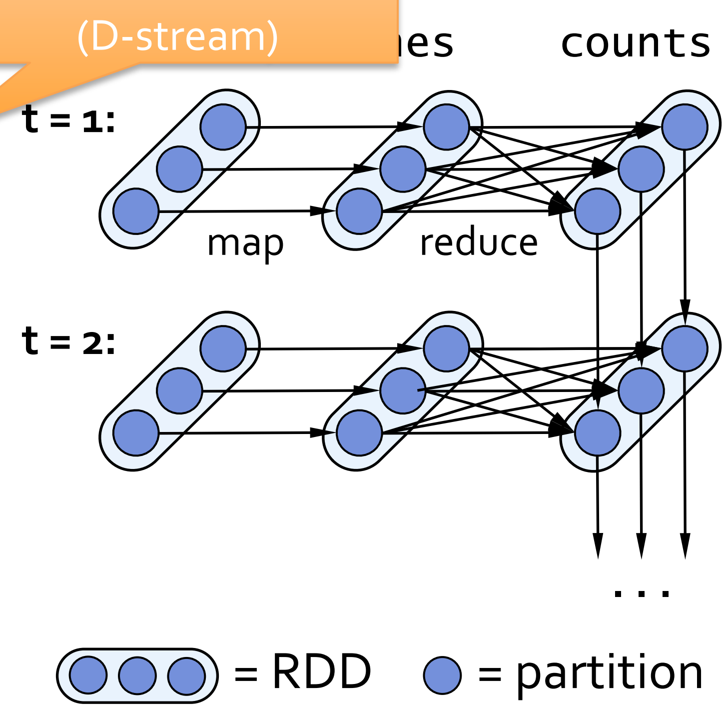
Programming Interface

Extension to Spark: Spark Streaming

» All Spark operators plus new "stateful" ones

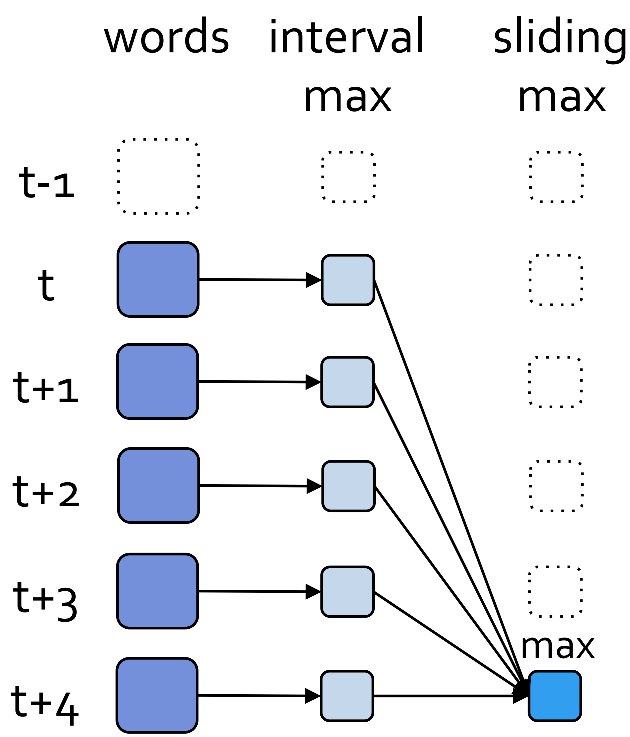
```
// Running count of pageviews by URL

views = readStream("http:...", "1s")

ones = views.map(ev => (ev.url, 1))

counts = ones.runningReduce(_ + _)
```

"Discretized stream"
(D-stream)

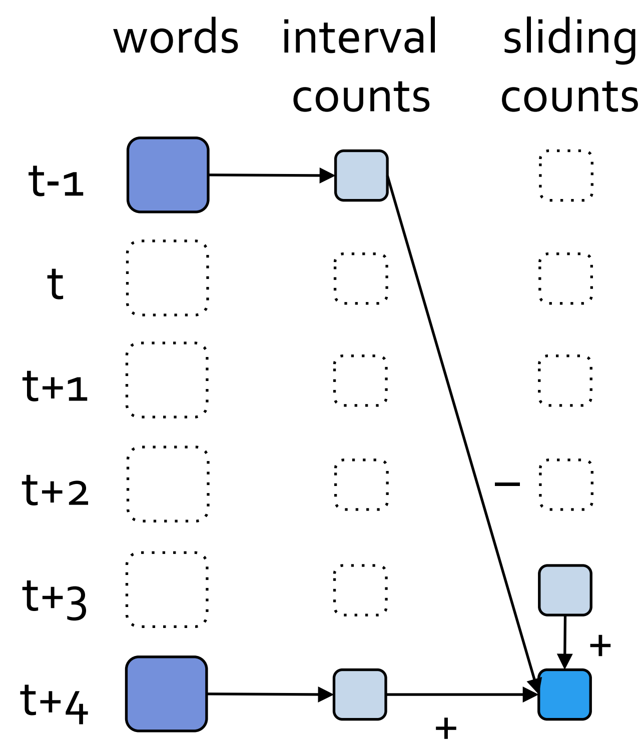


Incremental Operators

```
words.reduceByWindow(“5s”, max)    words.reduceByWindow(“5s”, _+_, _-_)
```



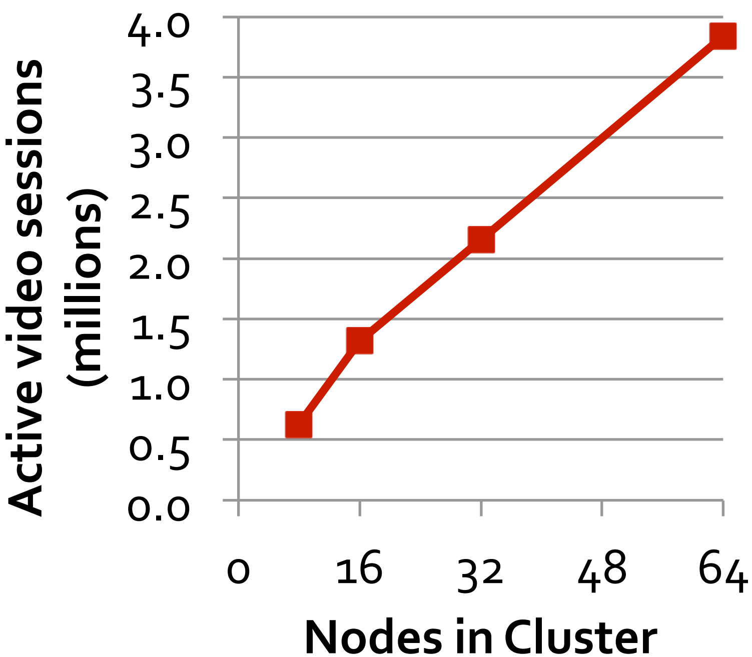
Associative function



Associative & invertible

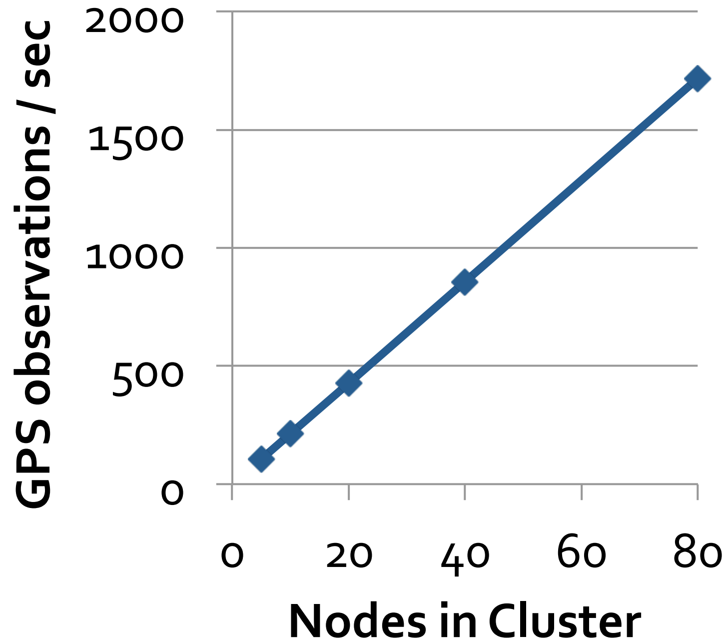
Applications

Conviva video dashboard



(>50 session-level metrics)

Mobile Millennium traffic estimation



(online EM algorithm)

Unifying Streaming and Batch

D-streams and RDDs can seamlessly be combined

» Same execution and fault recovery models

Enables powerful features:

» Combining streams with historical data:

```
pageViews.join(historicCounts).map(...)
```

used in MM application

» Interactive ad-hoc queries on stream state:

```
pageViews.slice("21:00","21:05").topK(10)
```

used in Conviva app

Benefits of a Unified Stack

Write each algorithm only once

Reuse data across streaming & batch jobs

Query stream state instead of waiting for import

Some users were doing this manually!

» Conviva anomaly detection, Quantifind dashboard

Conclusion

"Big data" is moving beyond one-pass batch jobs, to low-latency apps that need data sharing

RDDs offer fault-tolerant sharing at memory speed

Spark uses them to combine streaming, batch & interactive analytics in one system

www.spark-project.org

Related Work

DryadLINQ, FlumeJava

- Similar "distributed collection" API, but cannot reuse datasets efficiently *across* queries

GraphLab, Piccolo, BigTable, RAMCloud

- Fine-grained writes requiring replication or checkpoints

Iterative MapReduce (e.g. Twister, HaLoop)

- Implicit data sharing for a fixed computation pattern

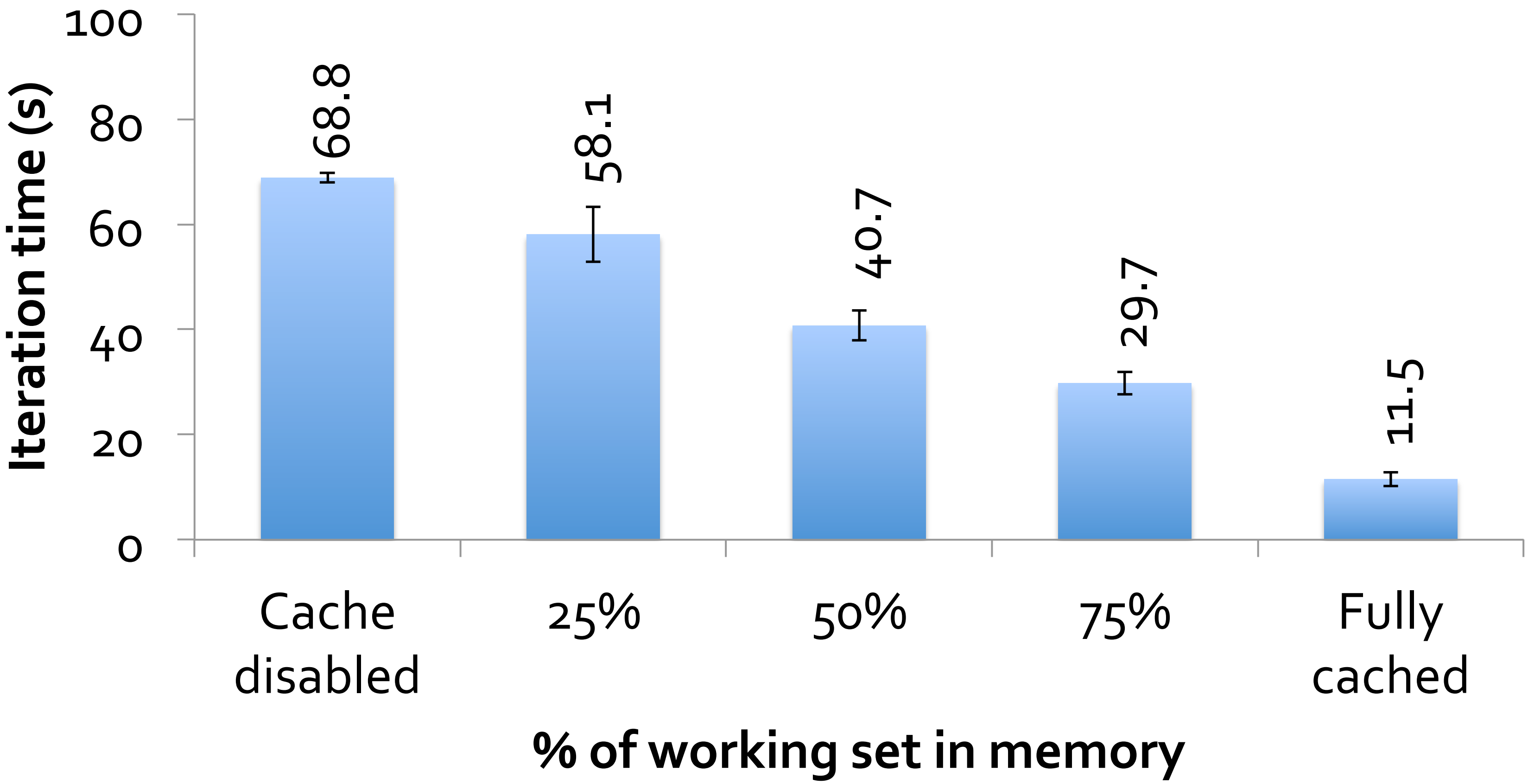
Relational databases

- Lineage/provenance, logical logging, materialized views

Caching systems (e.g. Nectar)

- Store data in files, no explicit control over what is cached

Behavior with Not Enough RAM



RDDs for Debugging

Debugging *general* distributed apps is very hard

However, Spark and other recent frameworks run deterministic tasks for fault tolerance

Leverage this determinism for debugging:

» Log lineage for all RDDs created (small)

» Let user *replay* any task in jdb, *rebuild* any RDD to query it interactively, or check *assertions*