Spark

In-Memory Cluster Computing for Iterative and Interactive Applications

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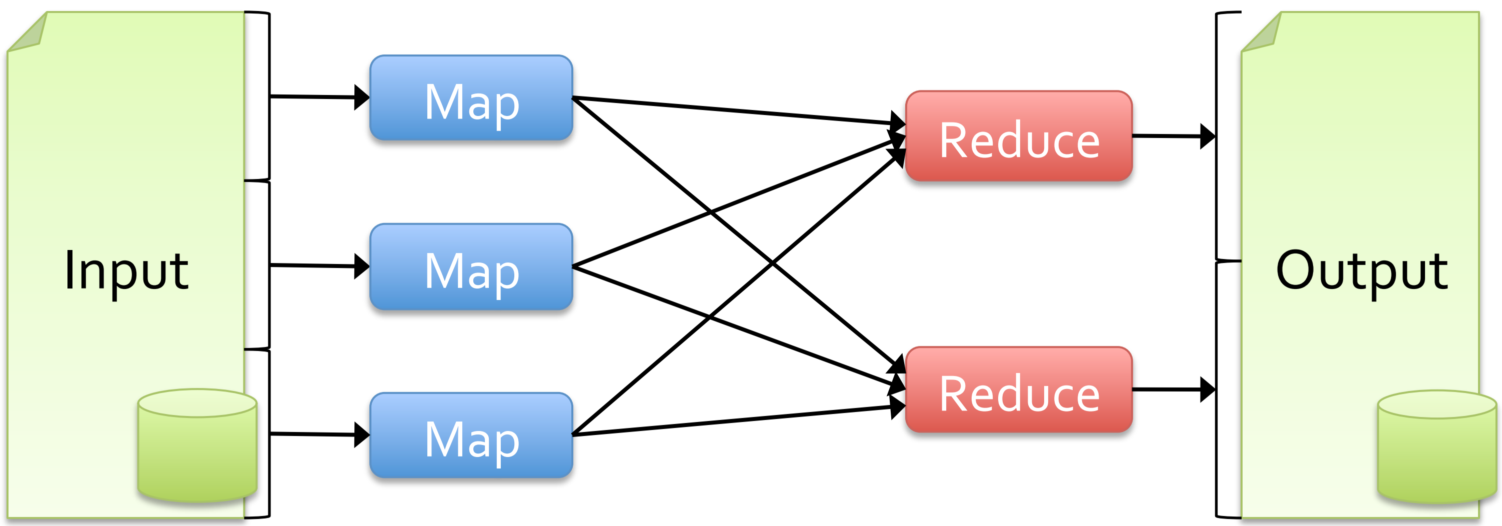
amplab
UC BERKELEY

Environment

amazon
web services™

Motivation

Most current cluster programming models are based on *acyclic data flow* from stable storage to stable storage



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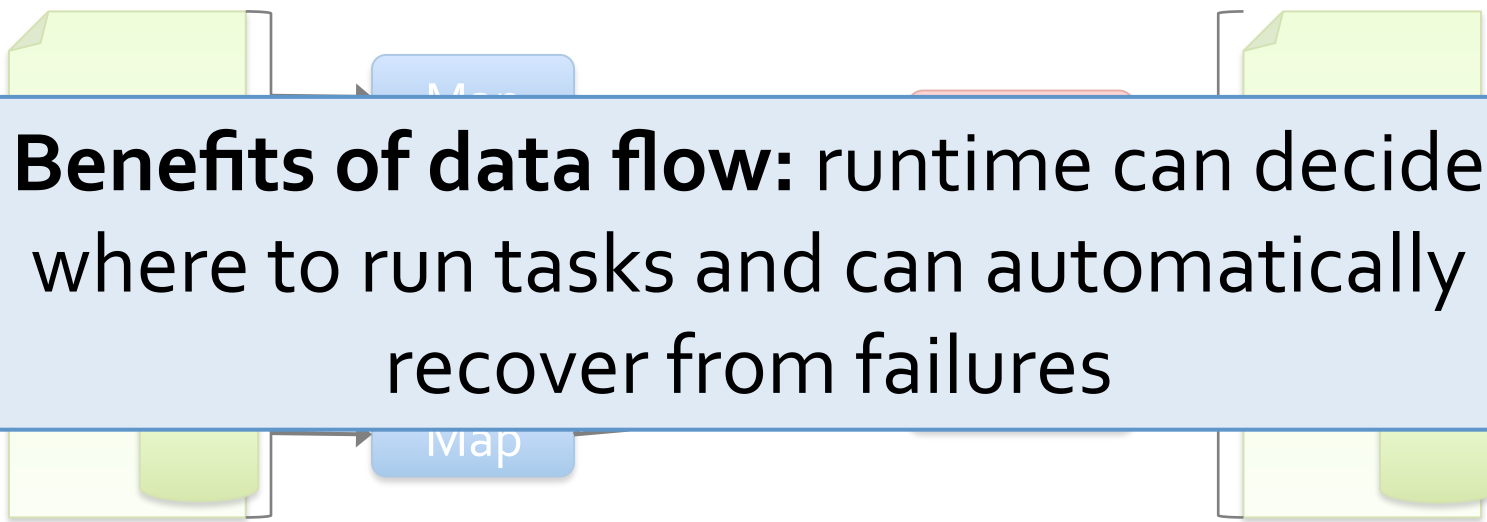


Benefits of data flow: runtime can decide where to run tasks and can automatically recover from failures

Motivation

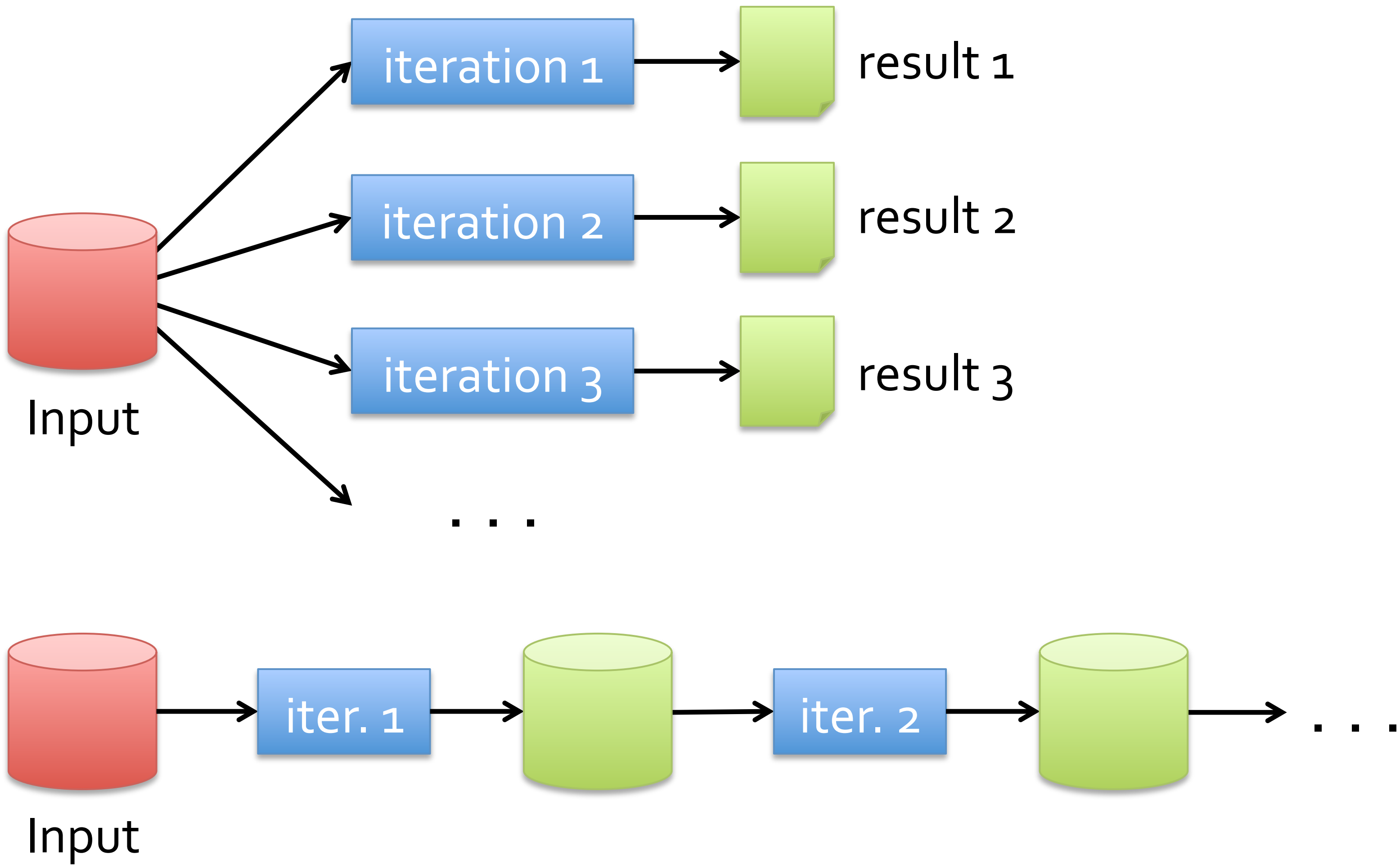
Acyclic data flow is inefficient for applications that repeatedly *reuse* a working set of data:

» **Iterative** algorithms (machine learning, graphs)

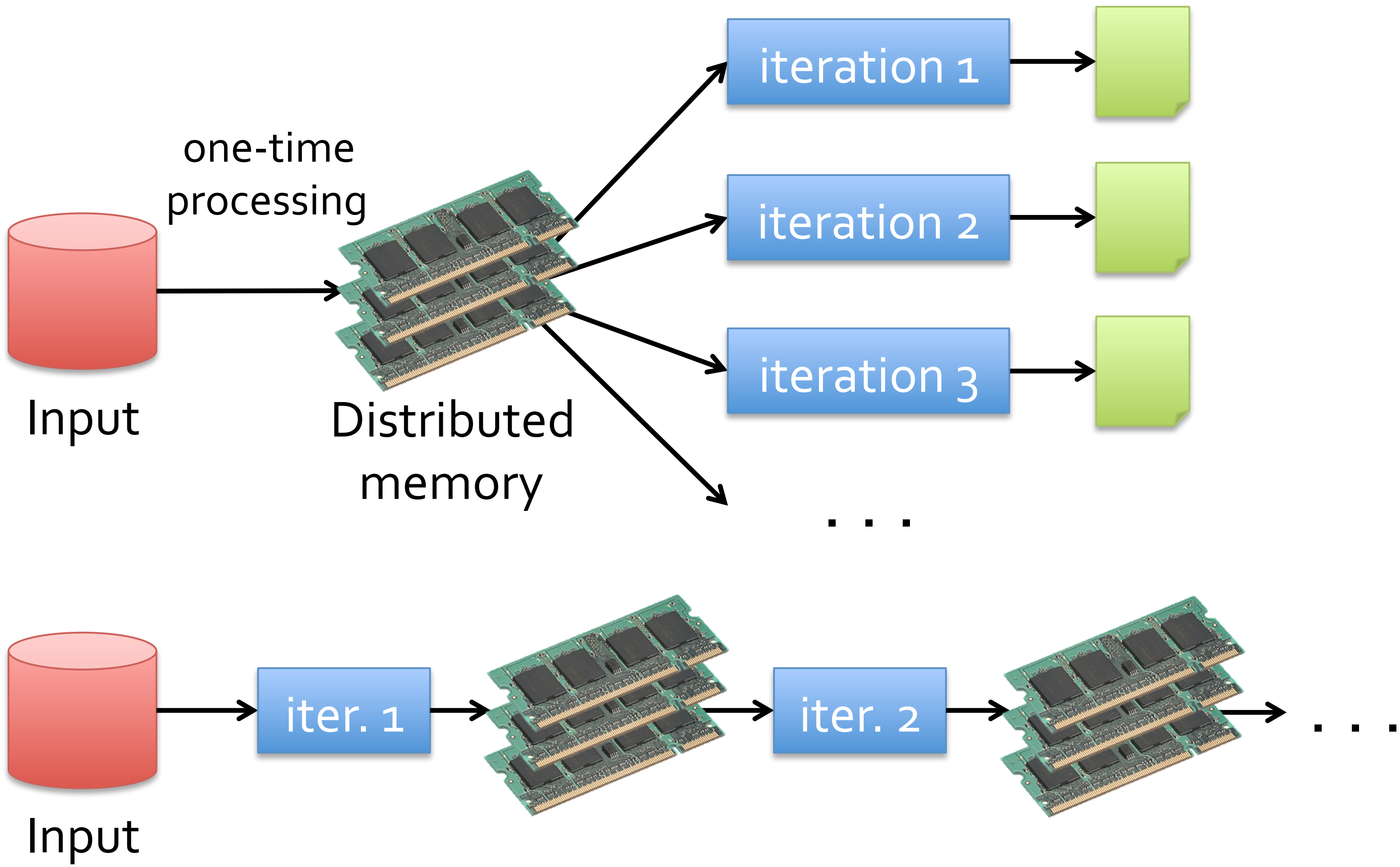
» **Interactive** data mining tools (R, Excel, Python)

With current frameworks, apps reload data from stable storage on each query

Example: Iterative Apps



Goal: Keep Working Set in RAM



Challenge

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

Challenge

Existing distributed storage abstractions have interfaces based on *fine-grained* updates

» Reads and writes to cells in a table

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

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

Solution: Resilient Distributed Datasets (RDDs)

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

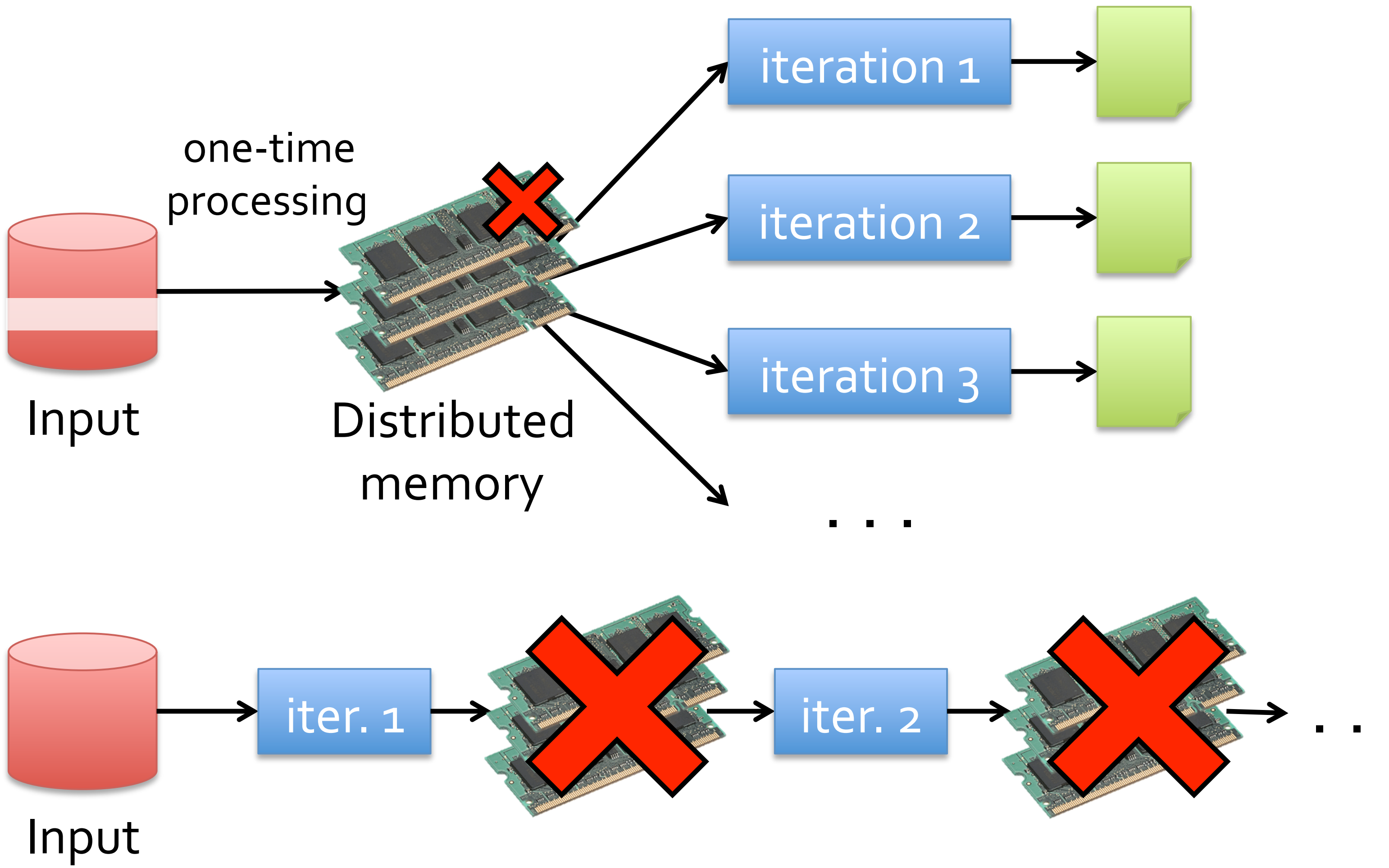
Efficient fault recovery using *lineage*

» Log one operation to apply to many elements

» Recompute lost partitions on failure

» No cost if nothing fails

RDD Recovery



Generality of RDDs

Despite coarse-grained interface, RDDs can express surprisingly many parallel algorithms

» These naturally *apply the same operation to many items*

Capture many current programming models

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

» **Specialized models** for iterative apps: BSP (Pregel), iterative MapReduce, bulk incremental

» Also support new apps that these models don’t

Outline

Programming interface

Applications

Implementation

Demo

Spark Programming Interface

Language-integrated API in Scala

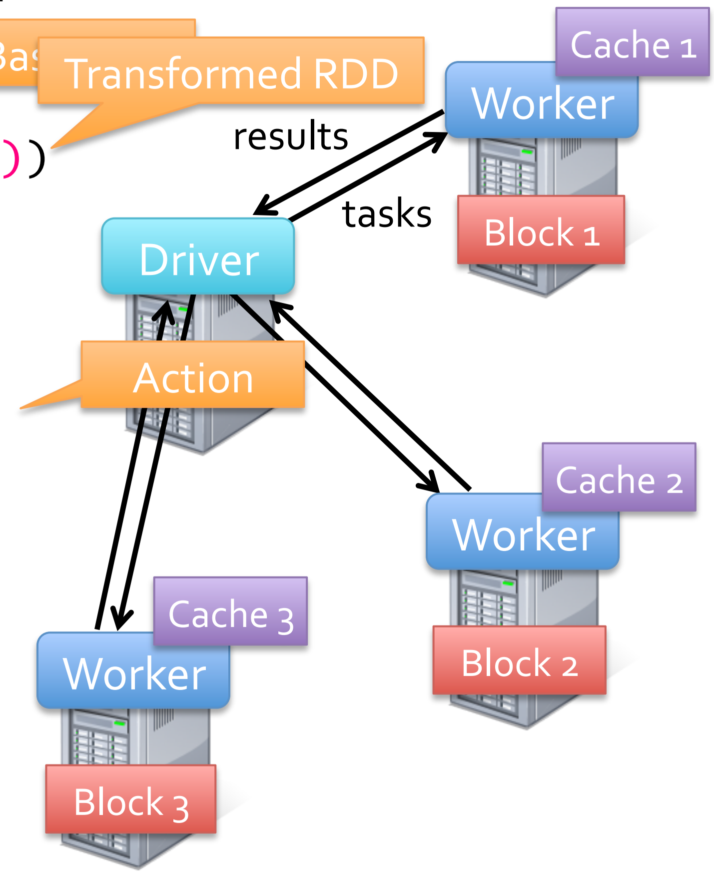
Provides:

- » Resilient distributed datasets (RDDs)
  - Partitioned collections with controllable caching
- » Operations on RDDs
  - Transformations (define RDDs), actions (compute results)
- » Restricted shared variables (broadcast, accumulators)

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.cache()

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

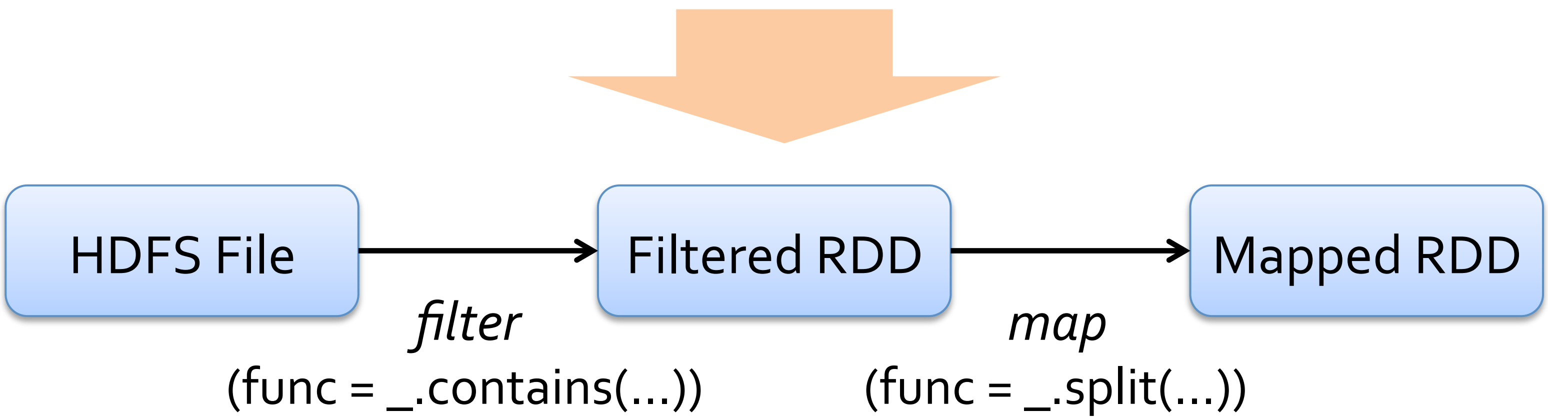


Result: scaled to 1 TB data in 5-7 sec (vs 170 sec for on-disk data)

Fault Tolerance

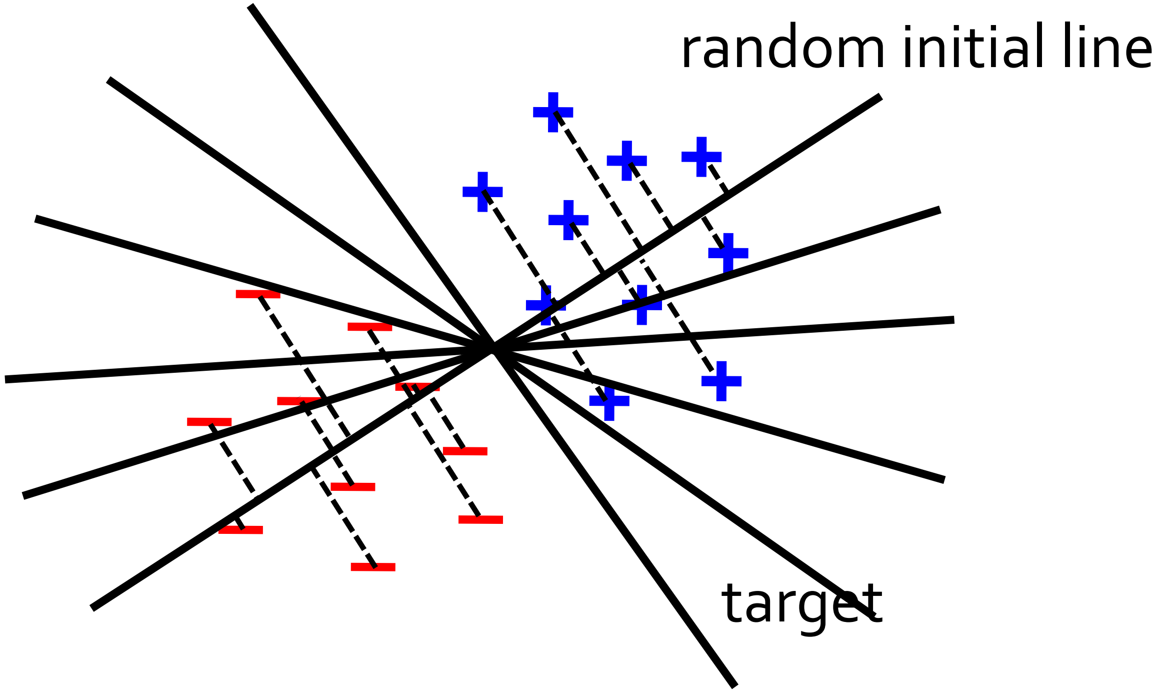
RDDs track *lineage* information that can be used to efficiently reconstruct lost partitions

Ex:
```
messages = textFile(...).filter(_.startsWith("ERROR"))
                        .map(_.split('\t')(2))
```



Example: Logistic Regression

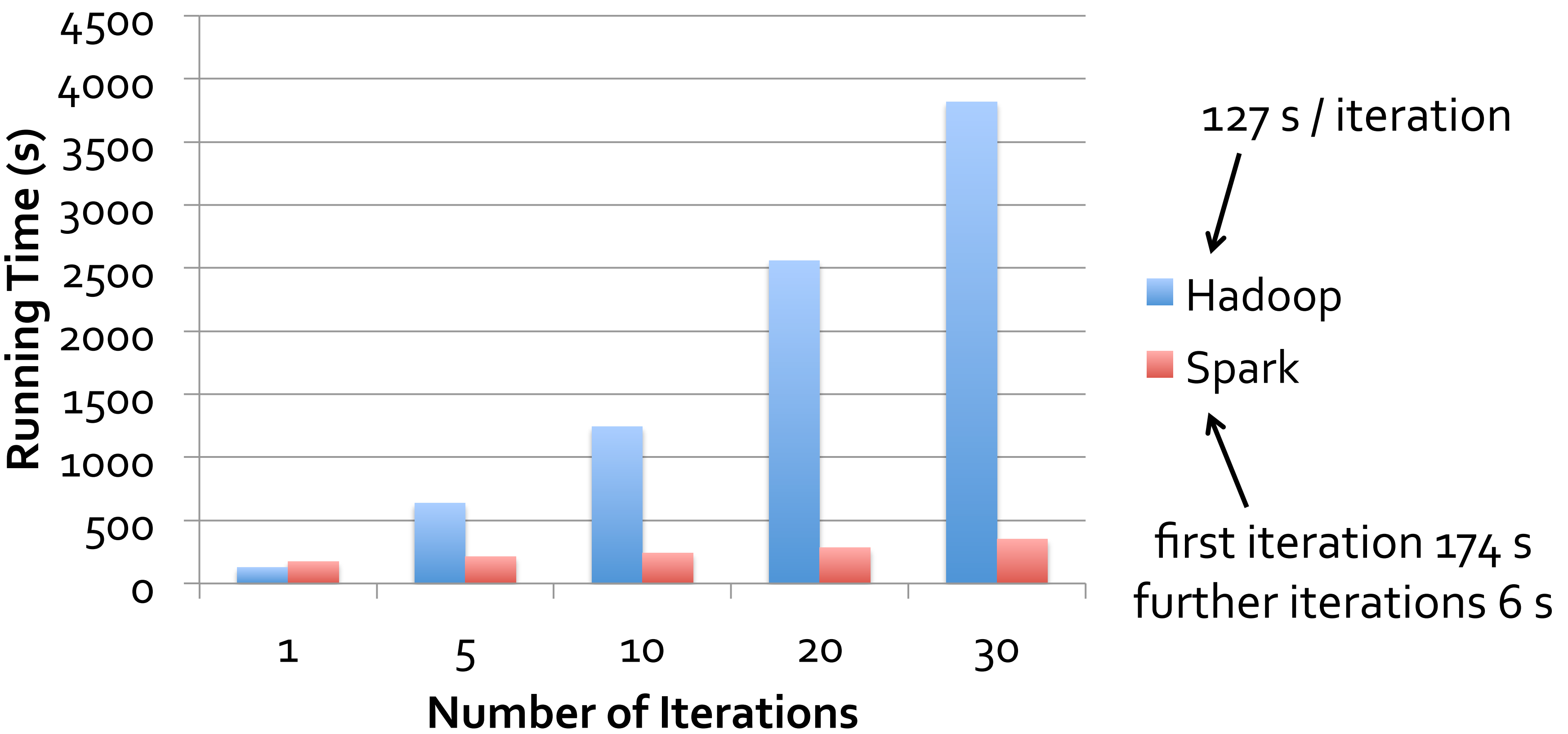
Goal: find best line separating two sets of points



Example: Logistic Regression

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

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

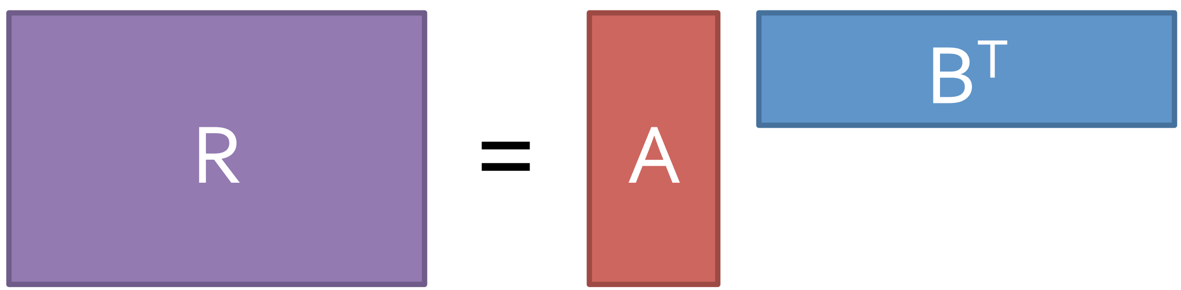
$$R = \begin{pmatrix} 1 & ? & ? & 4 & 5 & ? & 3 \\ ? & ? & 3 & 5 & ? & ? & 3 \\ 5 & ? & 5 & ? & ? & ? & 1 \\ 4 & ? & ? & ? & ? & 2 & ? \end{pmatrix}$$

Users

Movies

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

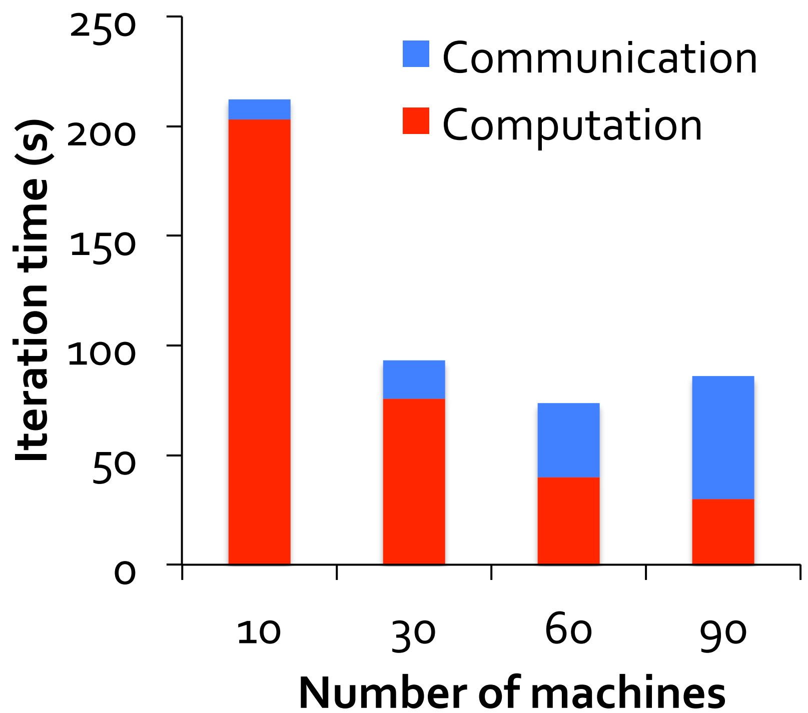
```
var R = spark.broadcast(readRatingsMatrix(...))

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

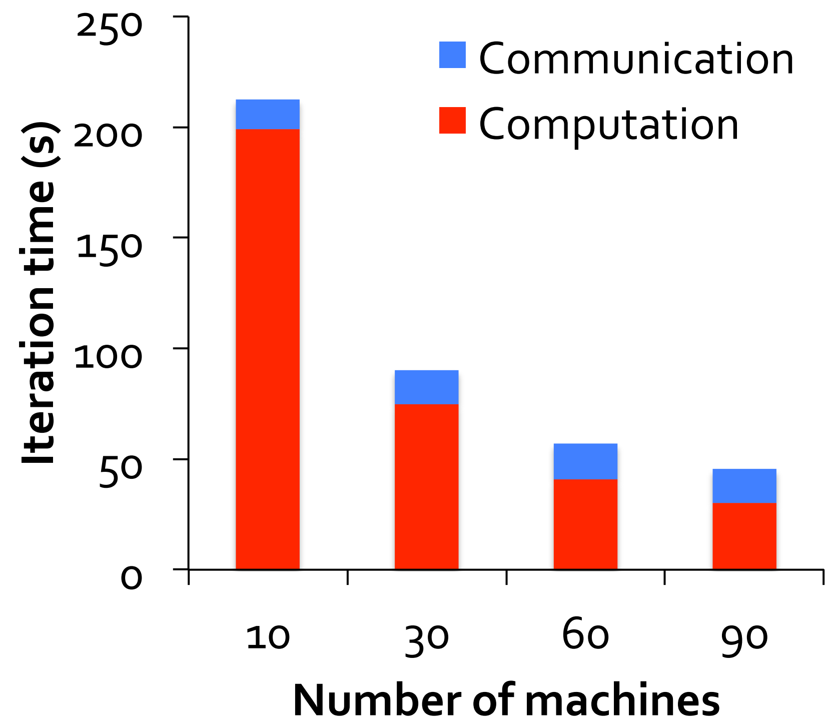
Result: 3× performance improvement

Scaling Up Broadcast

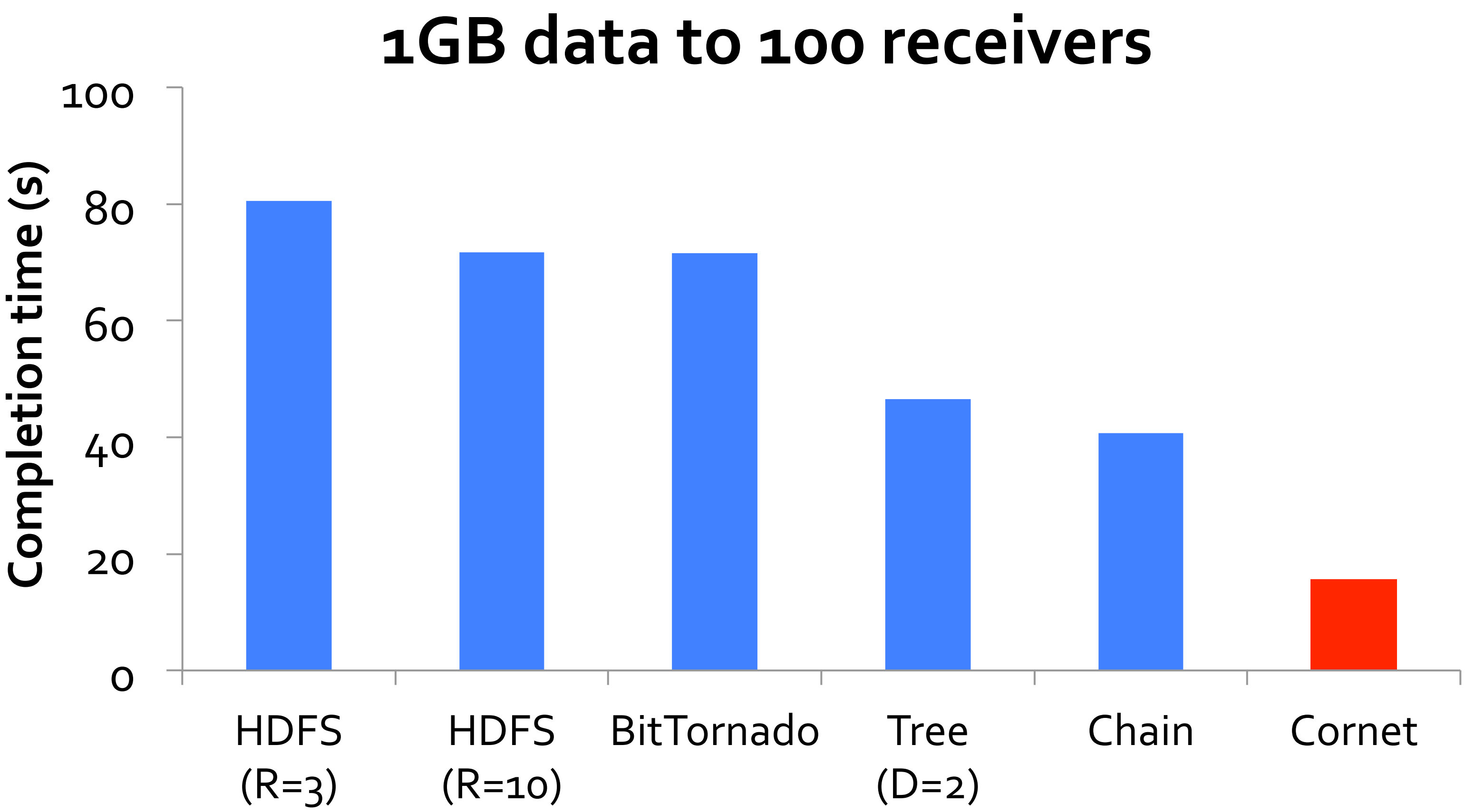
Initial version (HDFS)



Cornet broadcast



Cornet Performance



[Chowdhury et al, SIGCOMM 2011]

Spark Applications

EM alg. for traffic prediction (Mobile Millennium)

Twitter spam classification (Monarch)

In-memory OLAP & anomaly detection (Conviva)

Time series analysis

Network simulation

…

Mobile Millennium Project

Estimate city traffic using GPS observations from probe vehicles
(e.g. SF taxis)

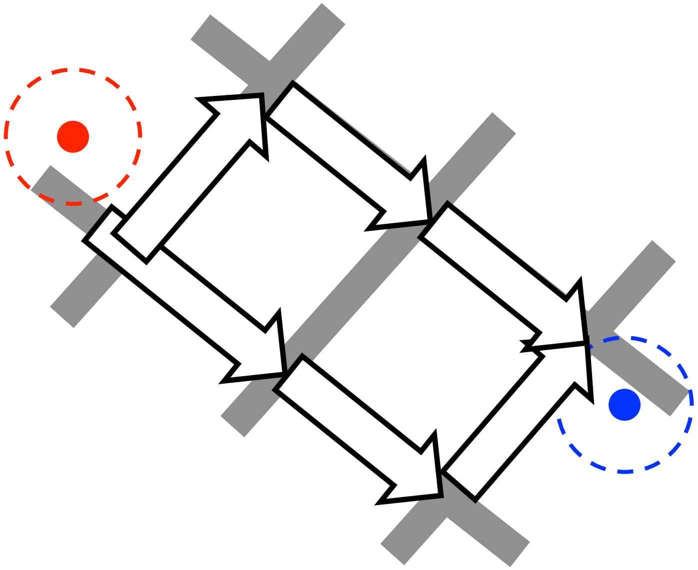
Sample Data

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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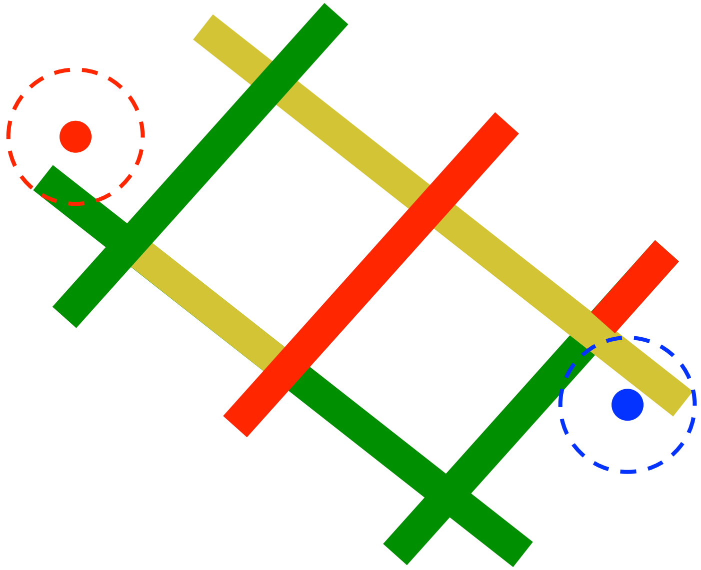
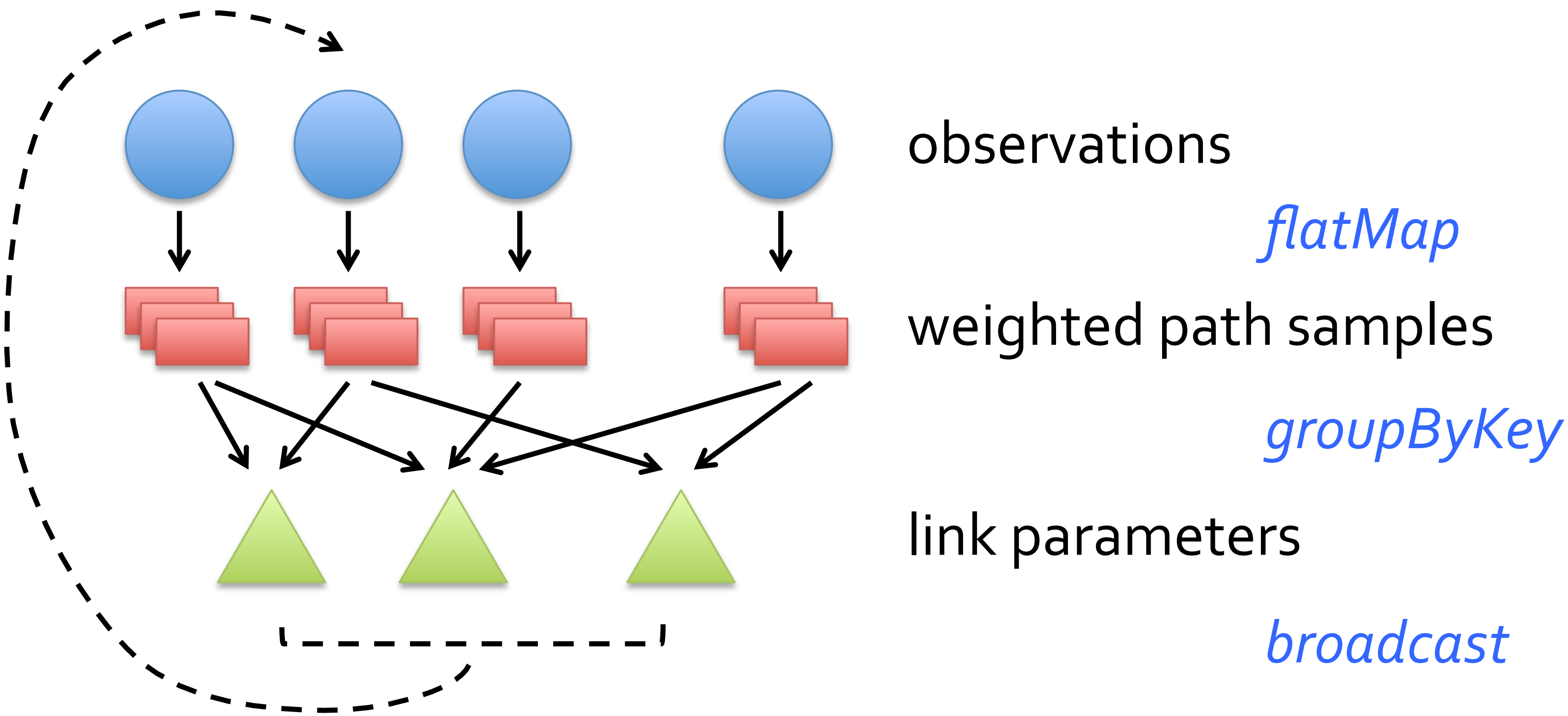


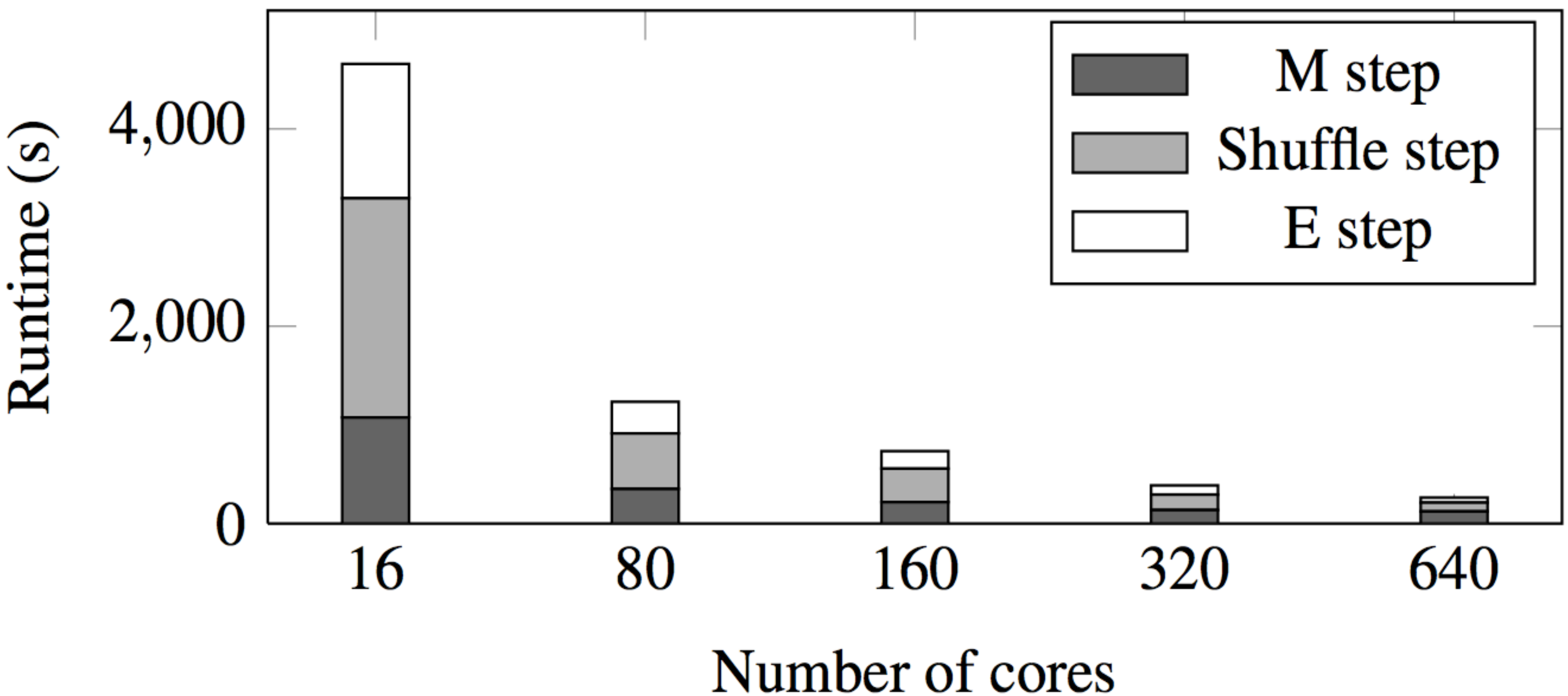
Solution

EM algorithm to estimate paths and travel time distributions simultaneously



Results

[Hunter et al, SOCC 2011]



3× speedup from caching, 4.5x from broadcast

Cluster Programming Models

RDDs can express many proposed data-parallel programming models

- » **MapReduce, DryadLINQ**
- » **Bulk incremental processing**
- » **Pregel** graph processing
- » **Iterative MapReduce** (e.g. Haloop)
- » **SQL**

Allow apps to efficiently *intermix* these models

Models We Have Built

Pregel on Spark (Bagel)

» 200 lines of code

Haloop on Spark

» 200 lines of code

Hive on Spark (Shark)

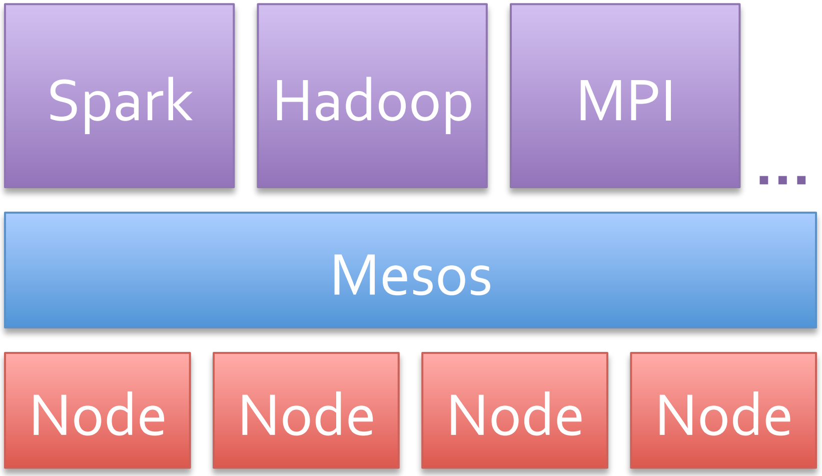
» 3000 lines of code

» Compatible with Apache Hive

» ML operators in Scala

Implementation

Spark runs on the Mesos cluster manager [NSDI 11], letting it share resources with Hadoop & other apps



Can read from any Hadoop input source (HDFS, S3, …)

No changes to Scala language & compiler

Outline

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Conclusion

Spark's RDDs offer a simple and efficient programming model for a broad range of apps

Solid foundation for higher-level abstractions

Join our open source community:

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

Spark Operations

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

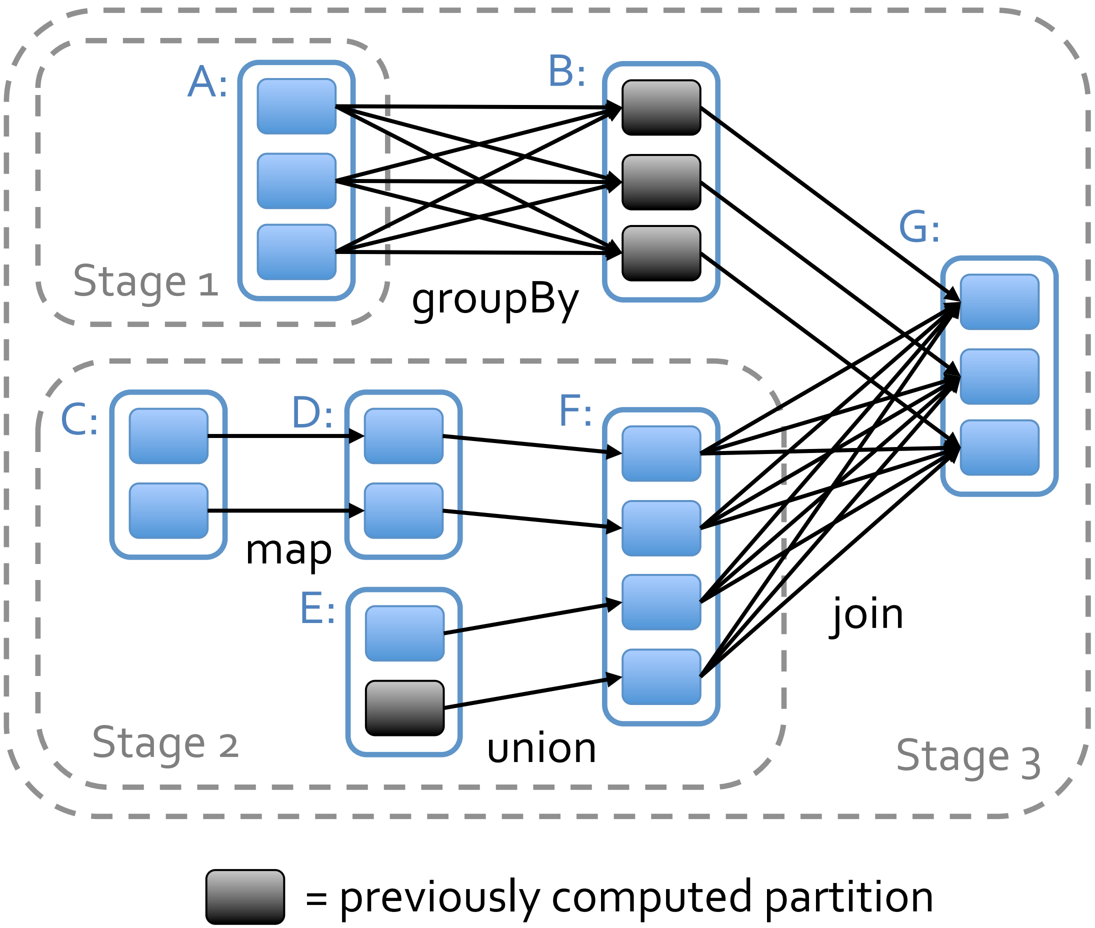
Job Scheduler

Dryad-like task DAG

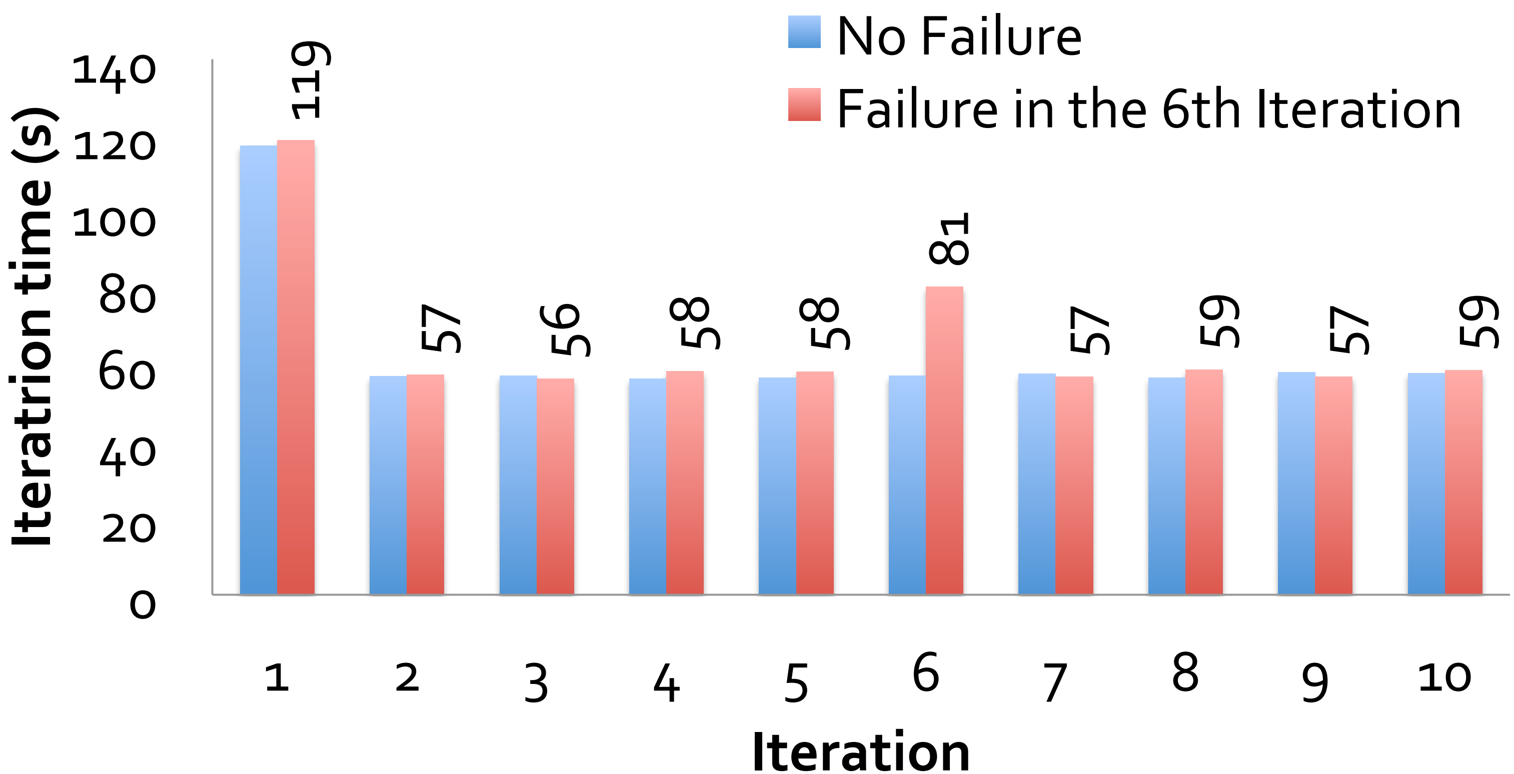
Reuses previously computed data

Partitioning-aware to avoid shuffles

Automatic pipelining



Fault Recovery Results



Behavior with Not Enough RAM