Spark: A framework for iterative and interactive cluster computing

Matei Zaharia
(presented by Anthony D. Joseph)

LASER Summer School
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My Talks at LASER 2013

1. AMP Lab introduction
2. The Datacenter Needs an Operating System
3. Mesos, part one
4. Dominant Resource Fairness
5. Mesos, part two
6. Spark

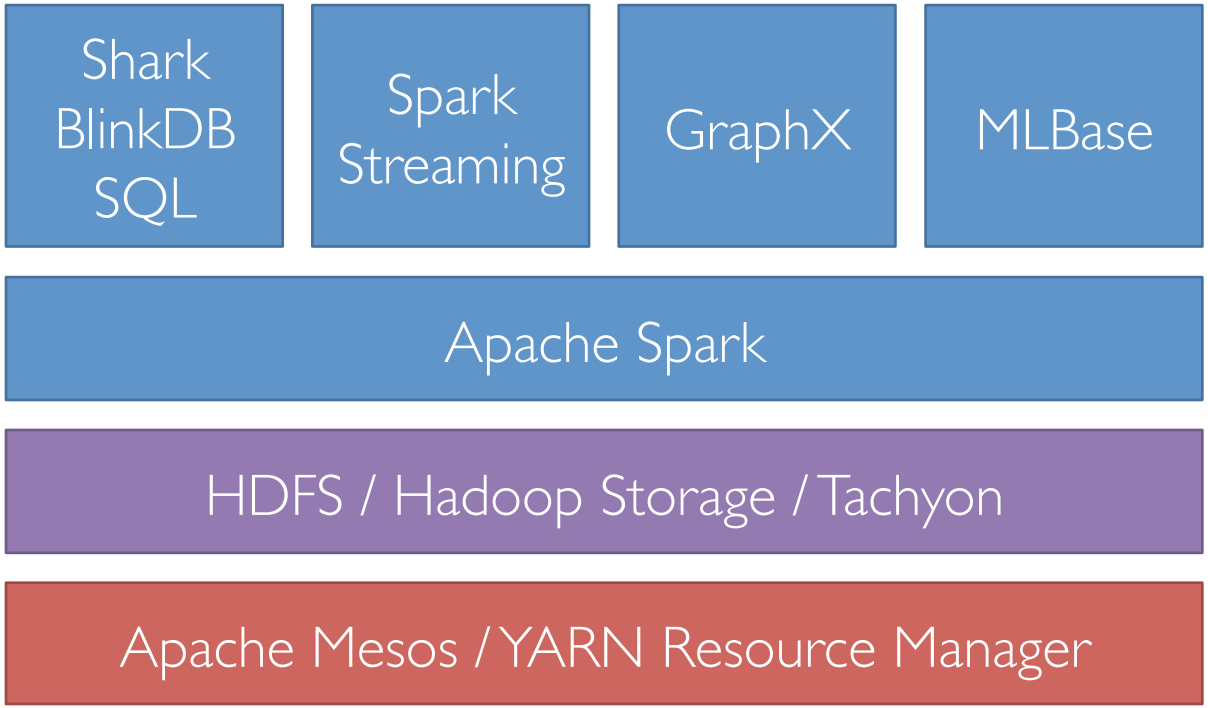
Researchers

- Matei Zaharia
- Mosharaf Chowdhury
- Michael Franklin
- Scott Shenker
- Ion Stoica

http://spark.incubator.apache.org/

Spark: Cluster Computing with Working Sets. Matei Zaharia, Mosharaf Chowdhury, Michael J. Franklin, Scott Shenker, Ion Stoica. HotCloud 2010. June 2010.

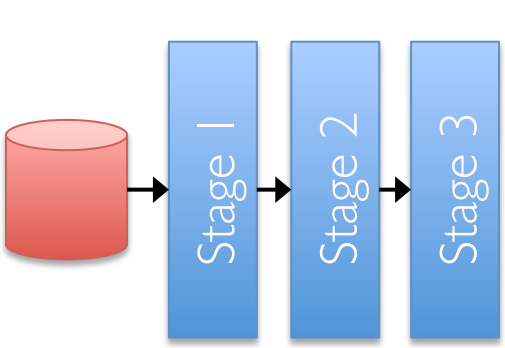
Berkeley Data Analytics Stack



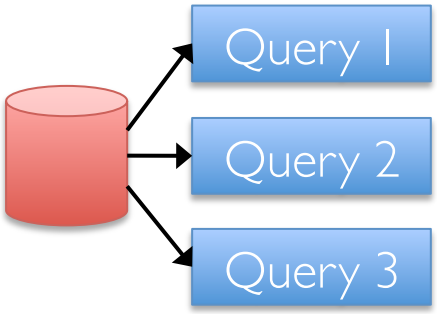
Motivation

Complex jobs, Machine Learning algorithms, interactive queries and online processing all need one thing that Hadoop MR lacks:

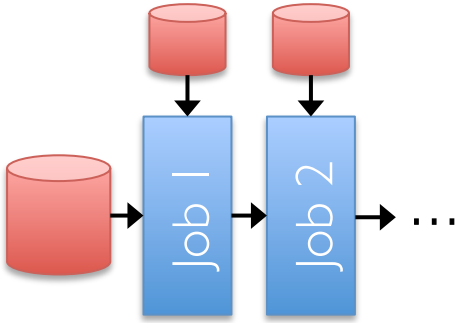
Efficient primitives for **data sharing**



Iterative job

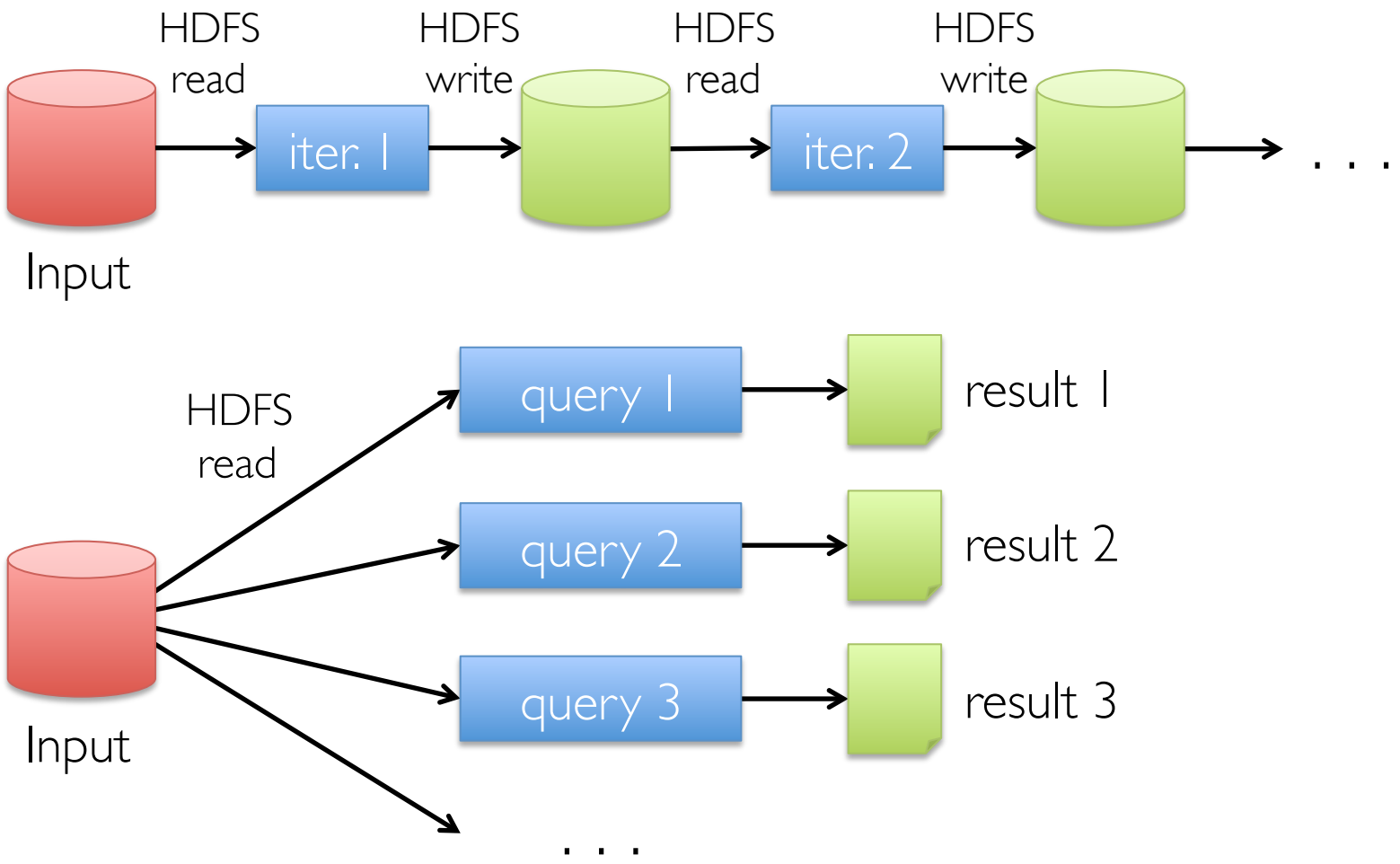


Interactive mining

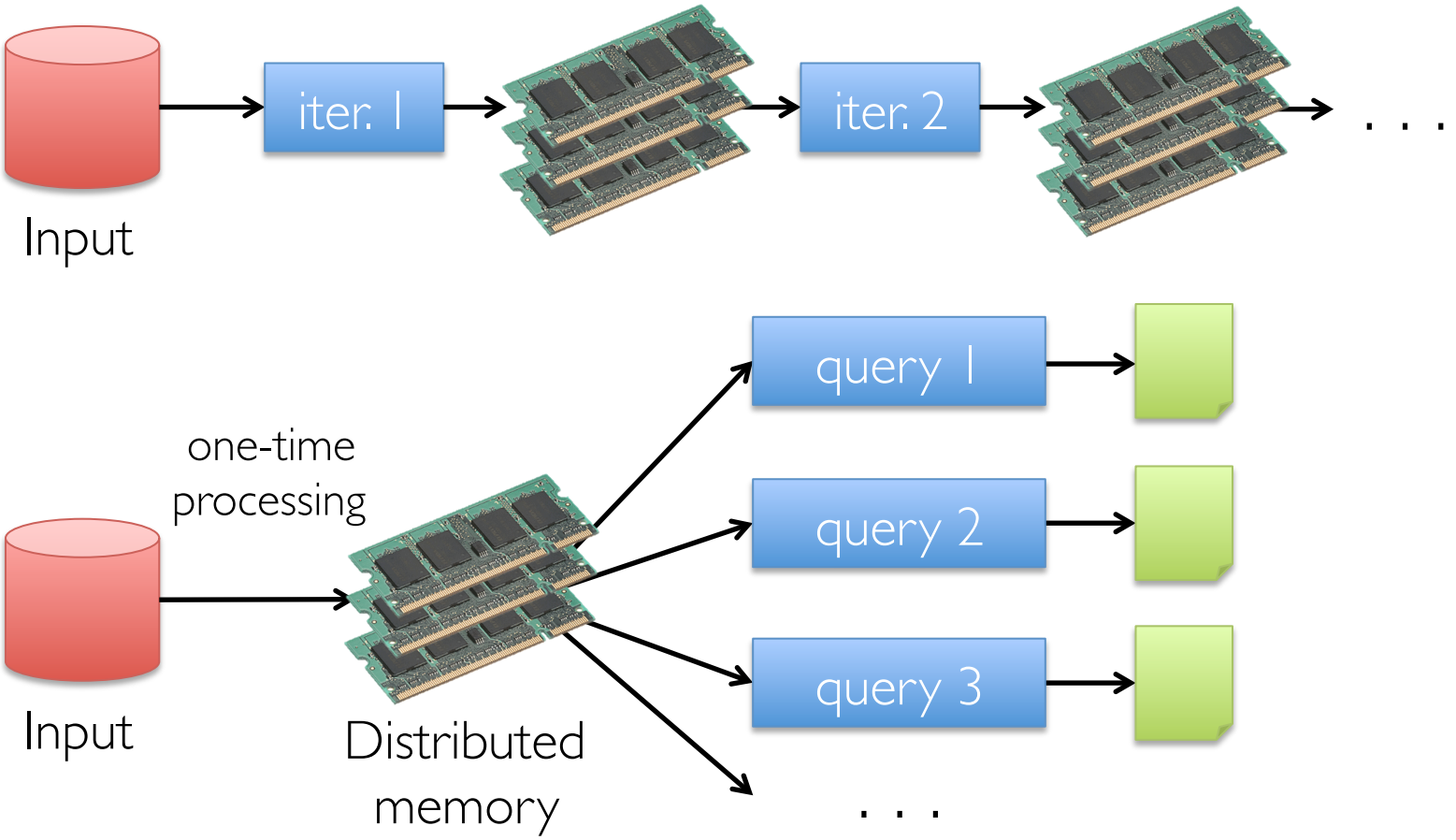


Stream processing

Transfer and Sharing in Hadoop



In-Memory Data Sharing



Spark Goals

Support iterative and stream jobs

Experiment with programmability

- » Leverage Scala to integrate cleanly into programs
- » Support interactive use from Scala interpreter

Retain MapReduce's fine-grained fault-tolerance

Programming Model

Driver program
- » Implements high-level control flow of an application
- » Launches various operations in parallel

Distributed datasets
- » HDFS files, "parallelized" Scala collections
- » Can be transformed with map and filter
- » *Can be cached across parallel operations*

Parallel operations
- » Foreach, reduce, collect

Shared variables
- » Accumulators (add-only), Broadcast variables (read-only)

Distributed Datasets

Represented by a Scala object and constructed:

- From a file in a shared filesystem (e.g., HDFS)
- By "*parallelizing*" a Scala collection (e.g., an array) in the driver program – dividing it into a number of slices
- By "*transforming*" an existing Distributed Dataset (e.g., using a user-provided function *A* ➔ *List[B]*, or *flatMap*)

Parallel Operations

reduce – Combines dataset elements using an associative function to produce a result at the driver program

collect – Sends all elements of the dataset to the driver program (e.g., update an array in parallel with *parallelize*, *map*, and *collect*)

foreach – Passes each element through a user provided function

No grouped *reduce* operation

Shared Variables

Broadcast variables

» Used for large read-only data (e.g., lookup table) in multiple parallel operations – distributed once instead of packaging with every closure

Accumulators

» Variables that works can only "add" to using an associative operation, and only the driver program can read

Spark Version of Word Count

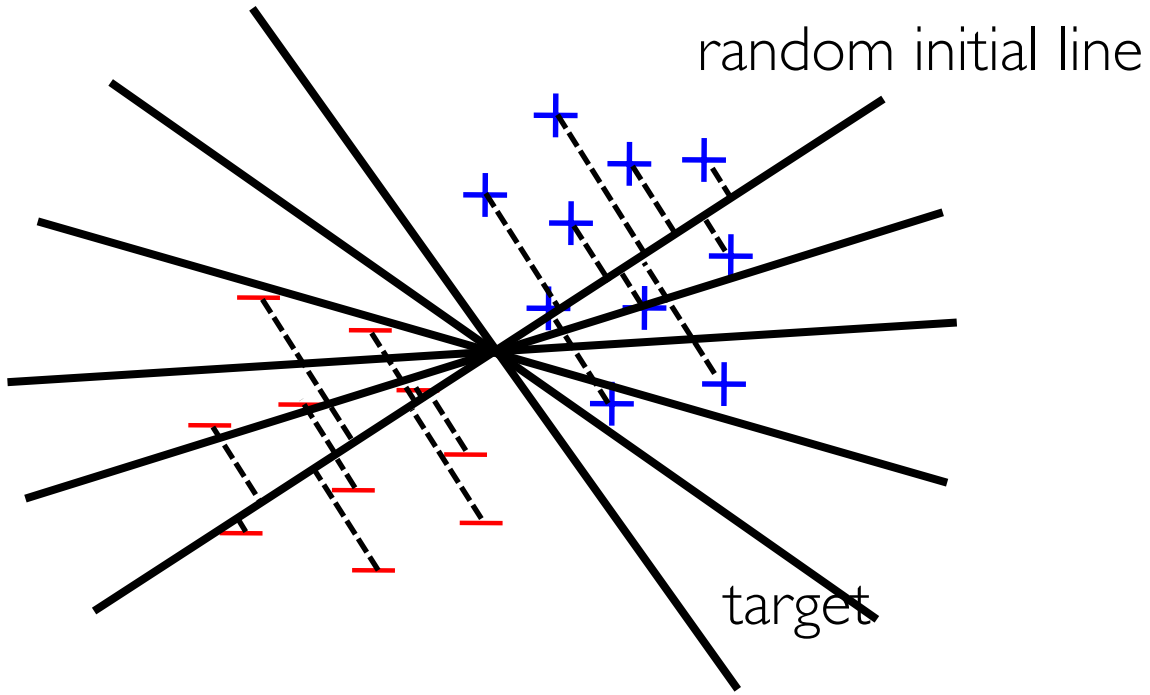
```
file = spark.textFile("hdfs://...")


file.flatMap(line => line.split(" "))
    .map(word => (word, 1))
    .reduceByKey(_ + _)
```

Example 1:
Logistic Regression

Logistic Regression

Goal: find best line separating two sets of points



Logistic Regression Implementations

Serial Version

```
val data = readData(...)

var w = Vector.random(D)

for (i <- 1 to ITERATIONS) {
  var gradient = Vector.zeros(D)
  for (p <- data) {
    val s = (1/(1+exp(-p.y*
      (w dot p.x)))-1) * p.y
    gradient += s * p.x
  }
  w -= gradient
}

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

Spark Version

```
val data = spark.hdfsTextFile(...)
  .map(readPoint _).cache()

var w = Vector.random(D)

for (i <- 1 to ITERATIONS) {
  var gradient = spark.accumulator(
    Vector.zeros(D))
  for (p <- data) {
    val s = (1/(1+exp(-p.y*
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  data.foreach(p => {
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Spark Version

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for (i <- 1 to ITERATIONS) {
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  data.foreach(p => {
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    gradient += scale * p.x
  })
  w -= gradient.value
}

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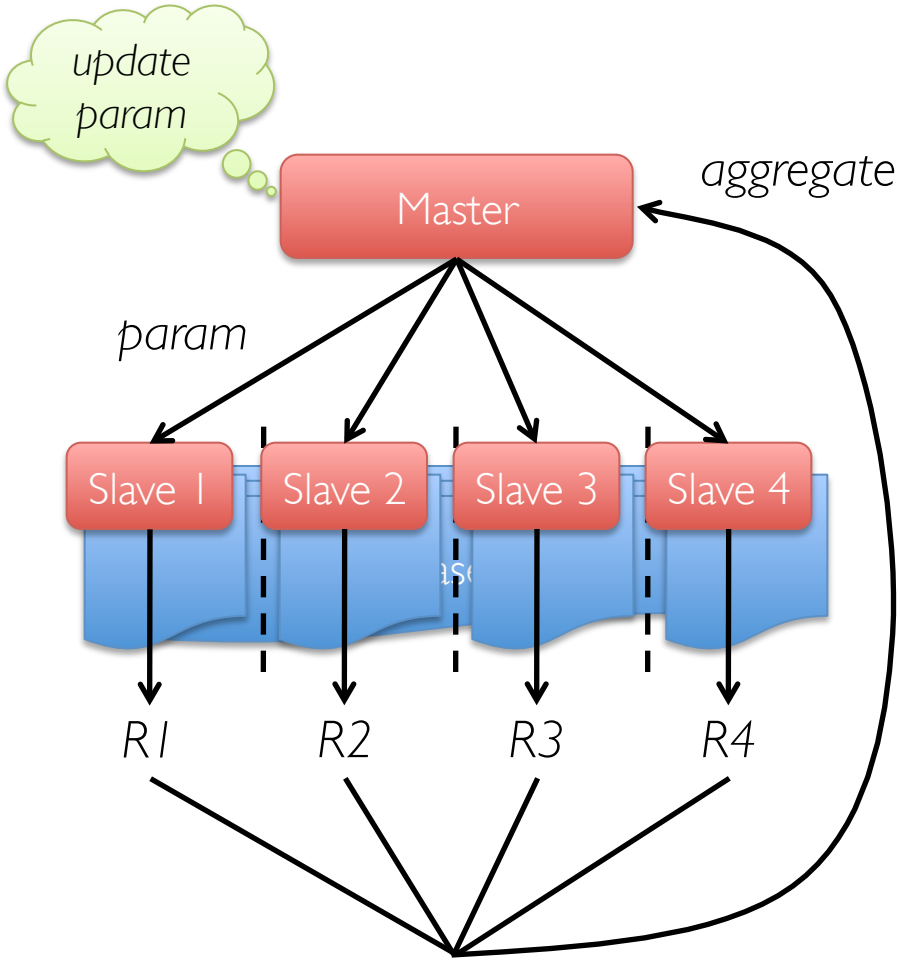

Functional Programming Version

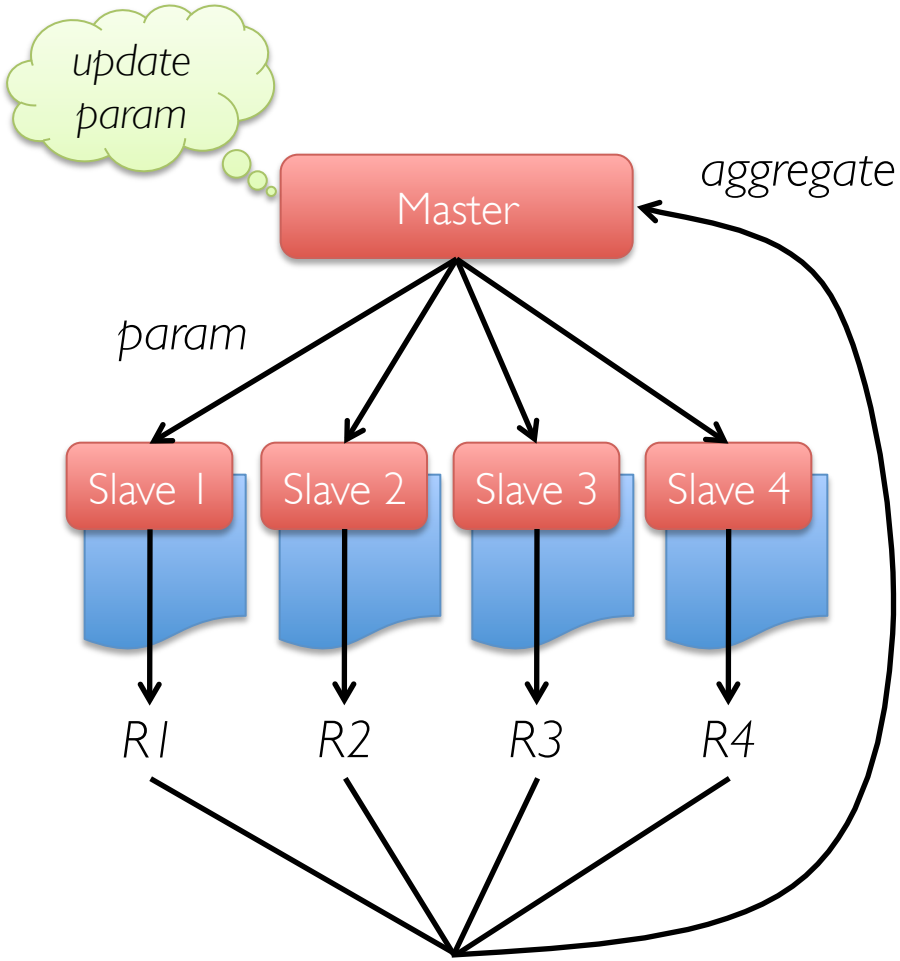
```
val data = spark.hdfsTextFile(...).map(readPoint).cache()

var w = Vector.random(D)

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

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

Job Execution

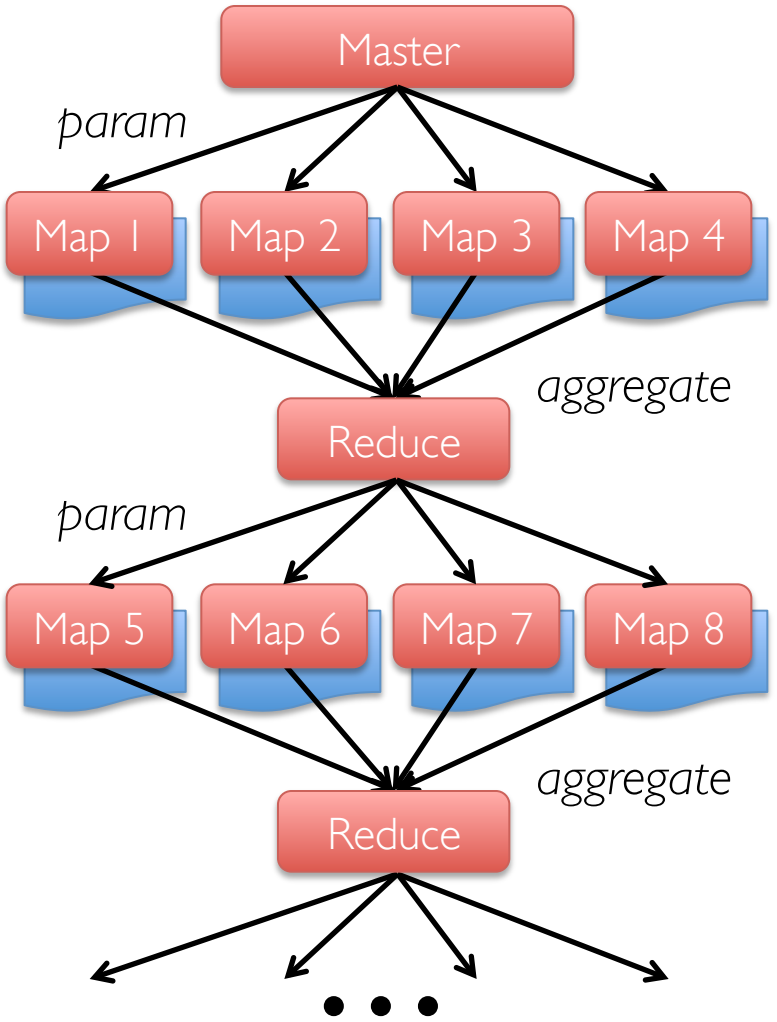


Spark

Job Execution

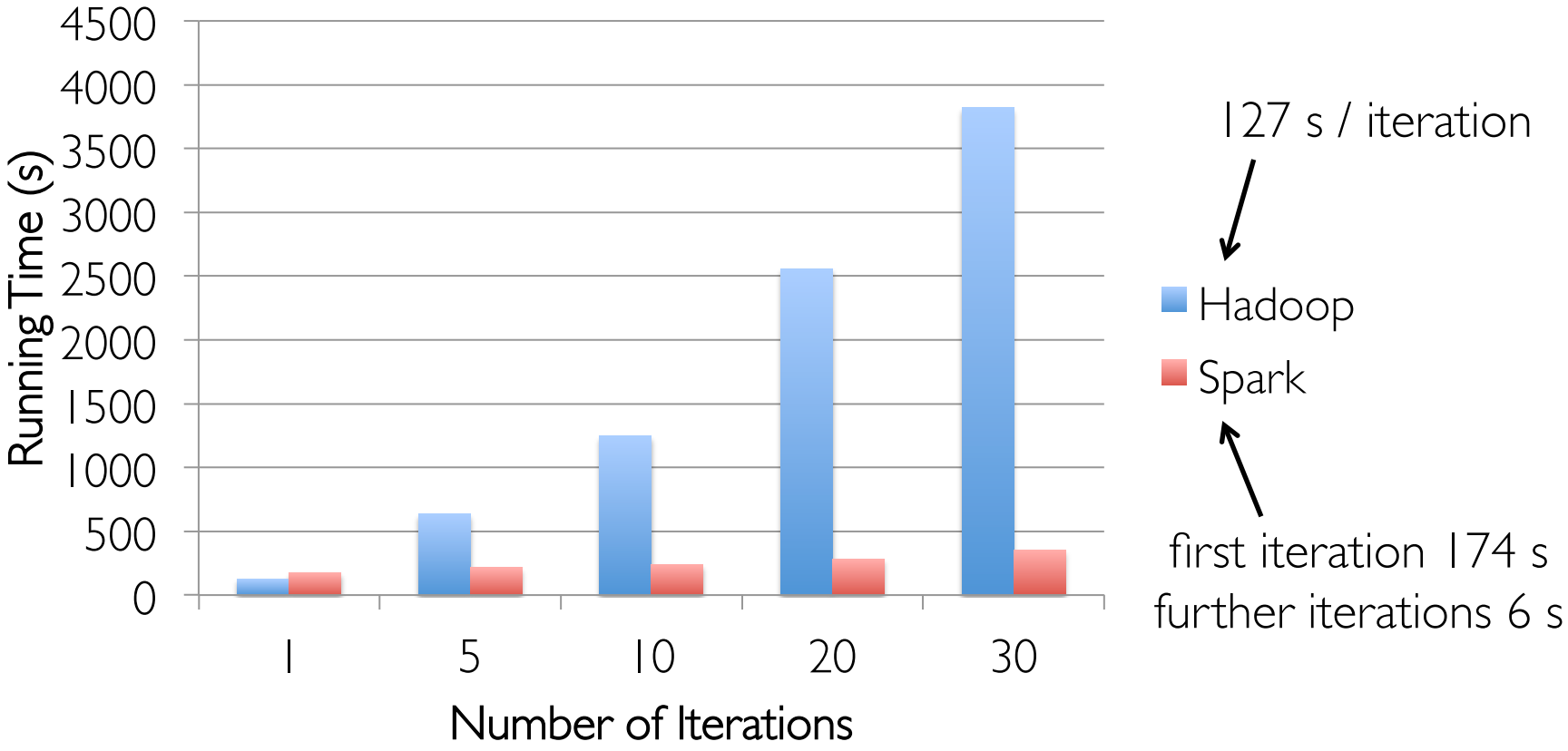


Spark



Hadoop / Dryad

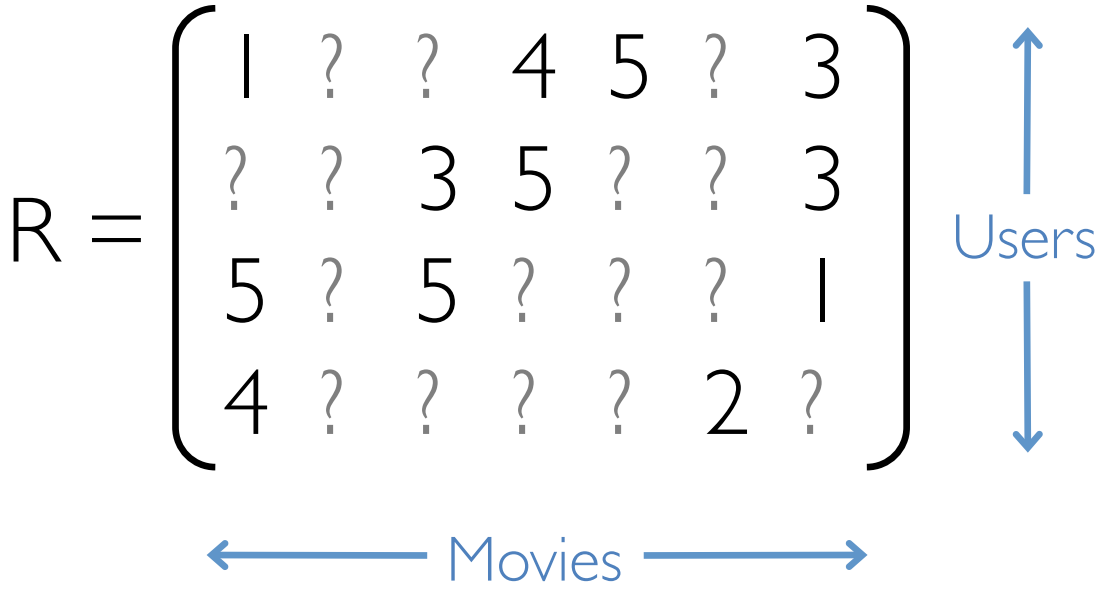
Performance



Example 2:
Alternating Least Squares

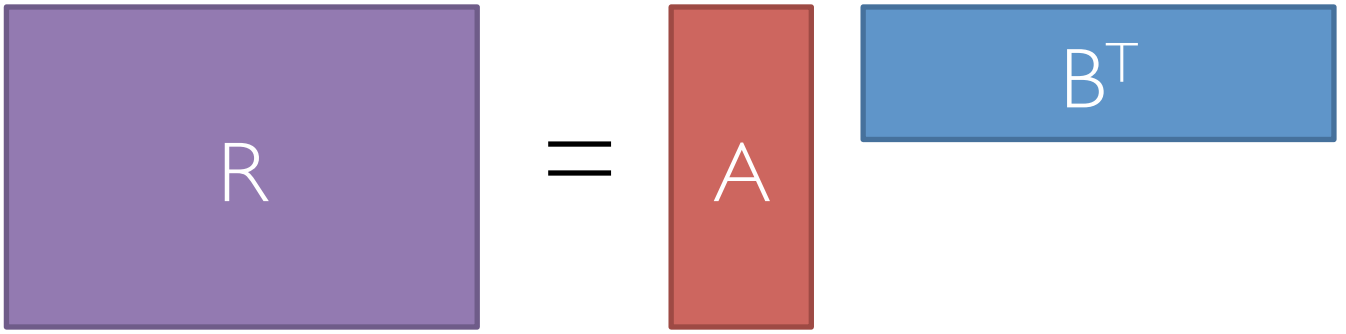
Collaborative Filtering

Predict movie ratings for a set of users based on their past ratings



Matrix Factorization

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



Problem: given subset of R, optimize A and B

Alternating Least Squares Algorithm

Start with random A and B

Repeat:

1. Fixing B, optimize A to minimize error on scores in R
2. Fixing A, optimize B to minimize error on scores in R

Serial ALS

```
val R = readRatingsMatrix(...)

var A = (0 until U).map(i => Vector.random(K))
var B = (0 until M).map(i => Vector.random(K))

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))
}
```

Naïve Spark ALS

```
val R = readRatingsMatrix(...)

var A = (0 until U).map(i => Vector.random(K))
var B = (0 until M).map(i => Vector.random(K))

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()
}
```

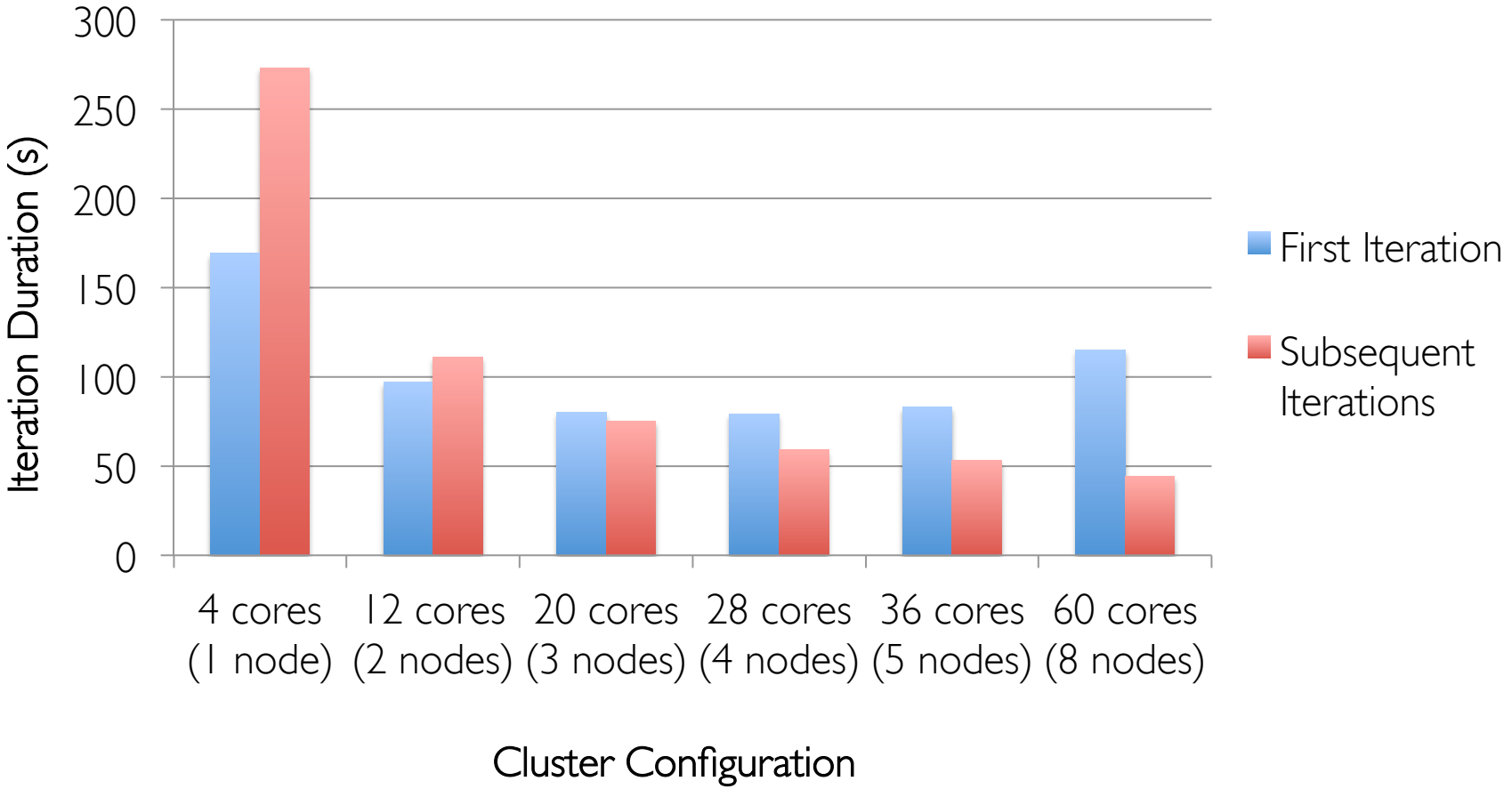
Problem:
R re-sent to all nodes in each parallel operation

Efficient Spark ALS

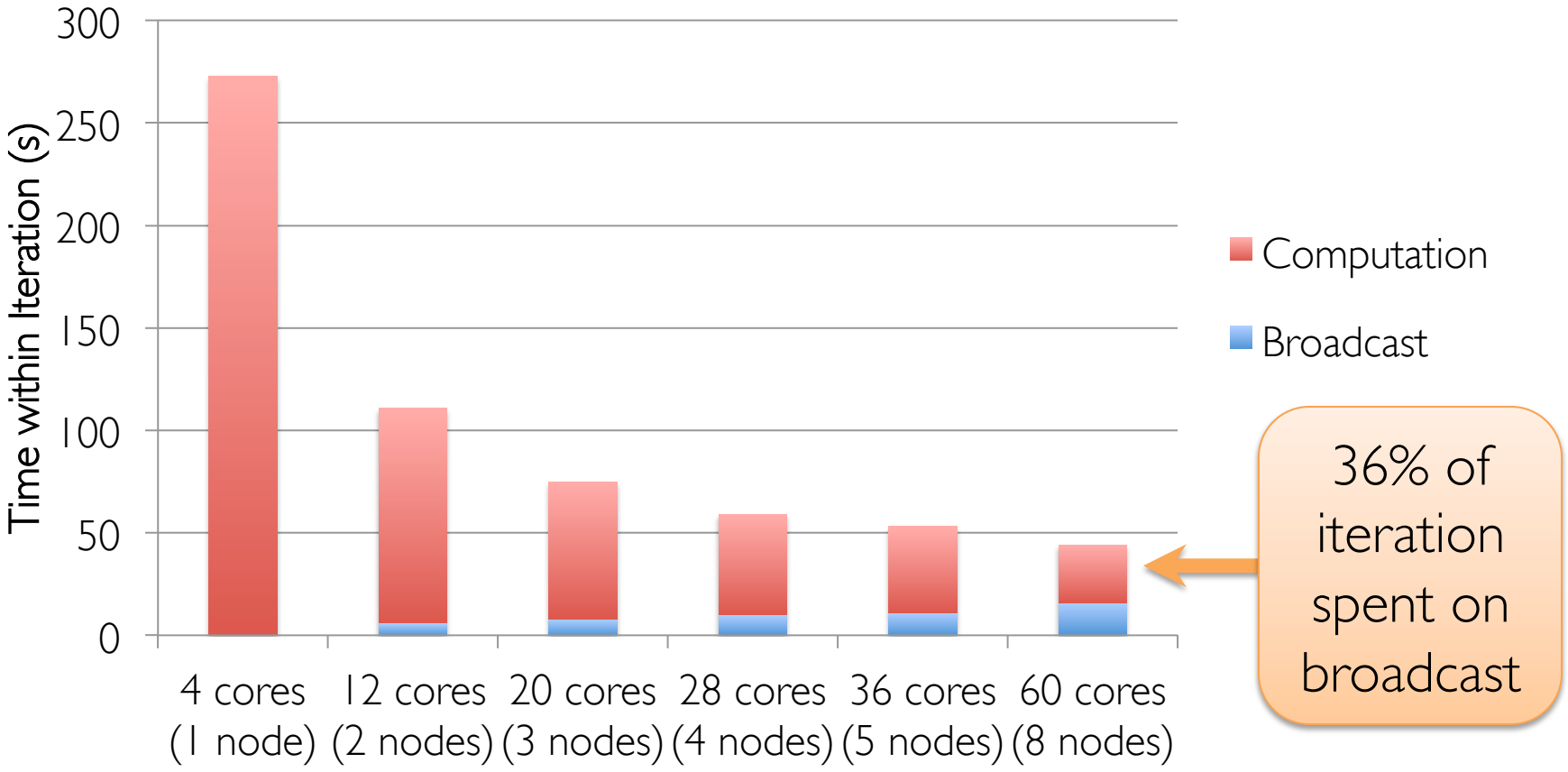
```
val R = spark.broadcast(readRatingsMatrix(...))

var A = (0 until U).map(i => Vector.random(K))
var B = (0 until M).map(i => Vector.random(K))

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

ALS Performance



Subsequent Iteration Breakdown



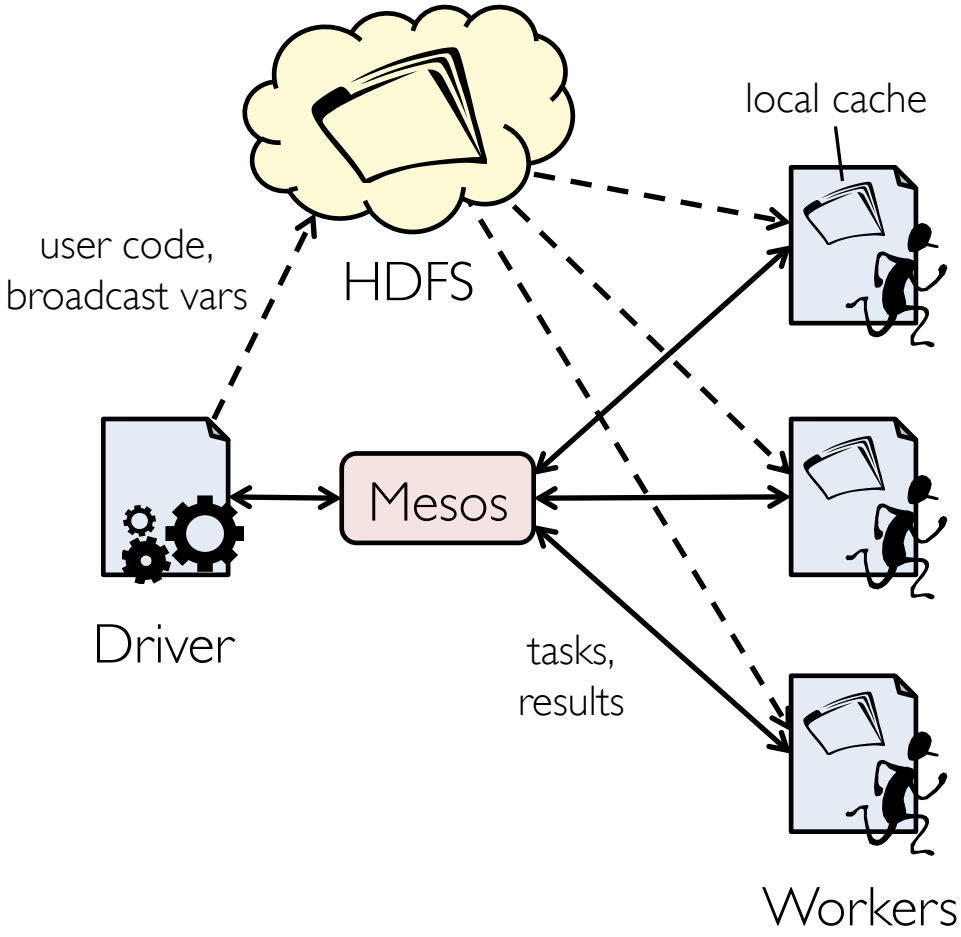
Architecture

Driver program connects to Mesos and schedules tasks

Workers run tasks, report results and variable updates

Data shared with HDFS/NFS

No communication between workers for now



Challenge

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

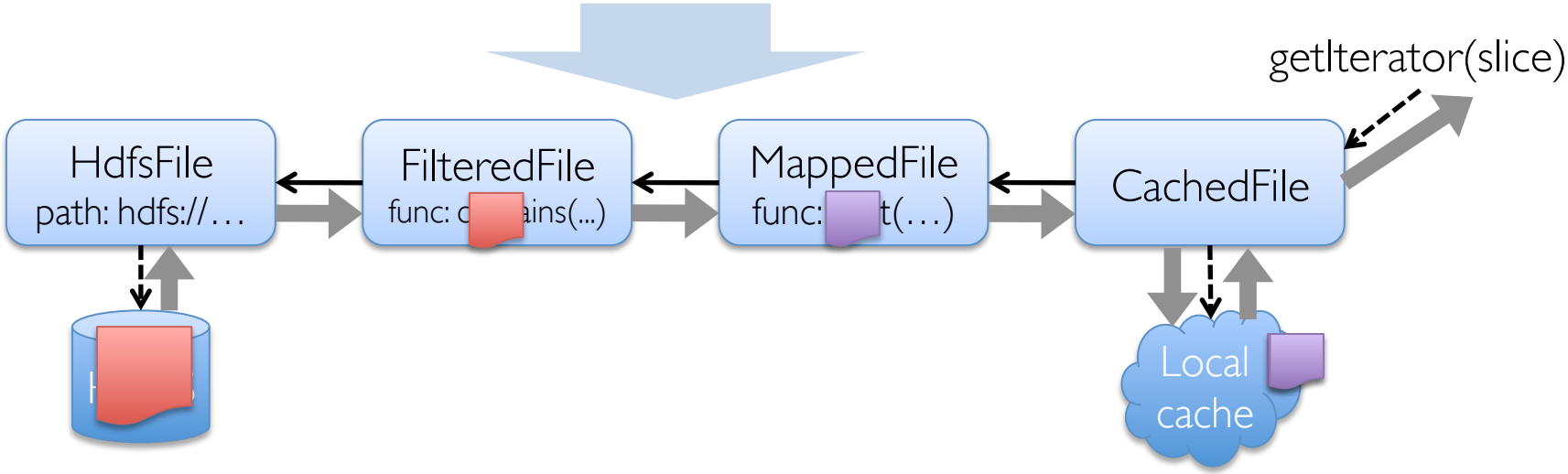
Traditional in-memory storage systems replicate data or update logs across nodes ➔ slow!

» Network write is 10-100× slower than memory

Resilient Distributed Datasets

Each distributed dataset object maintains a *lineage* that is used to rebuild slices that are lost / fall out of cache

Ex:
```
errors = textFile("log").filter(_.contains("error"))
                        .map(_.split('\t')(1))
                        .cache()
```



Resilient Distributed Datasets

RDDs provide an interface for coarse-grained *transformations* (map, group-by, join, …)

Efficient fault recovery using *lineage*
- » Log one operation to apply to many elements
- » Recompute lost partitions of RDD on failure
- » No cost if nothing fails

Rich enough to capture many models:
- » **Data flow models**: MapReduce, Dryad, SQL, …
- » **Specialized models** for iterative apps: Pregel, Hama, …

M. Zaharia, et al, Resilient Distributed Datasets: A fault-tolerant abstraction for in-memory cluster computing, NSDI 2012.

Interactive Spark

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

Required two changes:

- Modified wrapper code generation so that each "line" typed has references to objects for its dependencies
- Place generated classes in distributed filesystem

Enables in-memory exploration of big data

Milestones

2010: Spark open sourced

Feb 2013: Spark Streaming alpha open sourced

Jun 2013: Spark entered Apache Incubator

Aug 2013: Machine Learning library for Spark

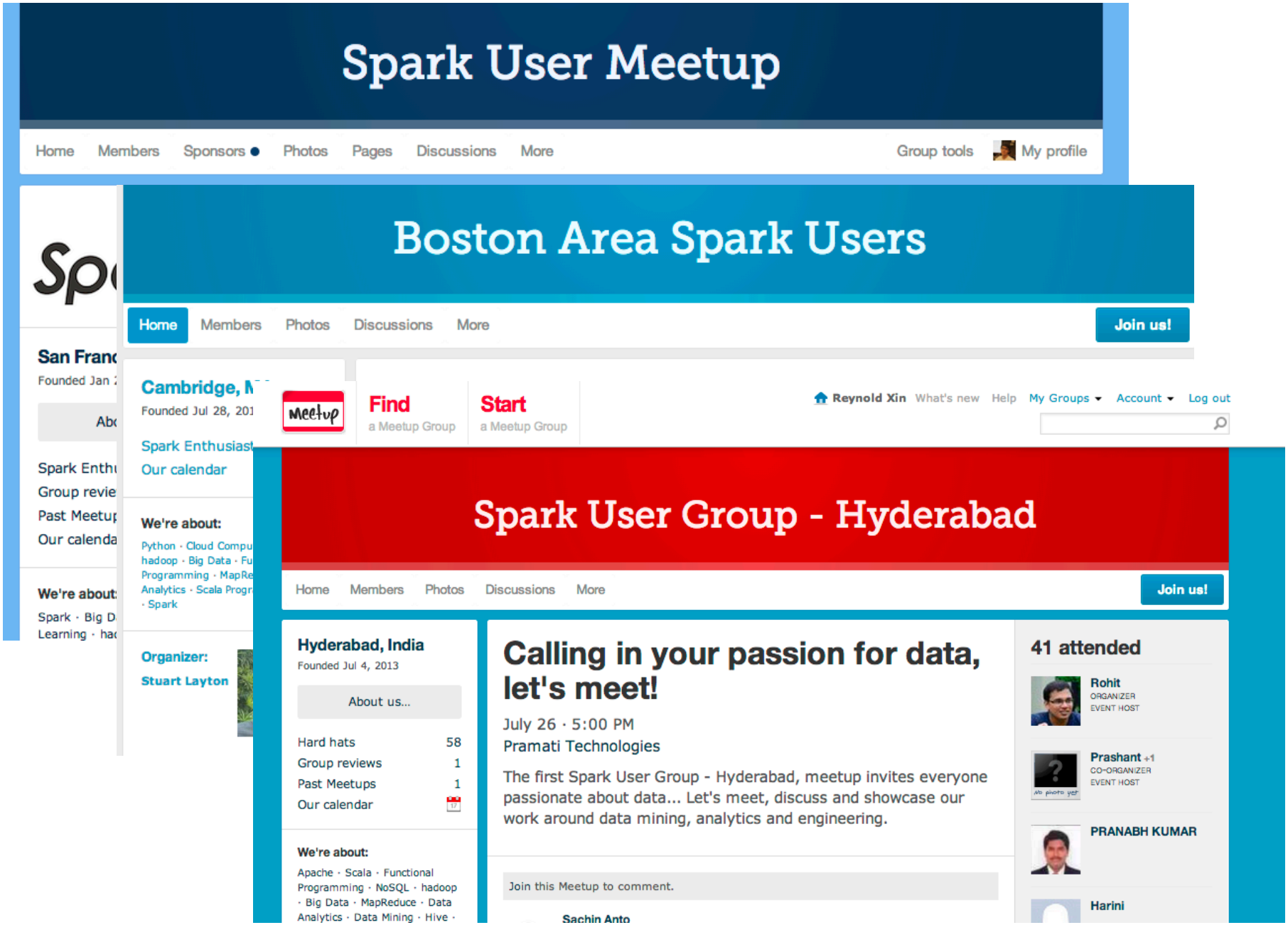
Frameworks Built on Spark

MapReduce

HaLoop
- » Iterative MapReduce from UC Irvine / U Washington

Pregel on Spark (Bagel)
- » Graph processing framework from Google based on BSP message-passing model

Hive on Spark (Shark)
- » In progress


Spark User Meetup
Home Members Sponsors Photos Pages Discussions More
Group tools
My profile
Boston Area Spark Users
Home Members Photos Discussions More
Join us!
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Spark Enthusiast
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We're about:
Python · Cloud Compu
hadoop · Big Data · Fu
Programming · MapRe
Analytics · Scala Progr
· Spark
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Stuart Layton
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a Meetup Group
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Group reviews 1
Past Meetups 1
Our calendar
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Calling in your passion for data, let's meet!
July 26 · 5:00 PM
Pramati Technologies
The first Spark User Group - Hyderabad, meetup invites everyone passionate about data... Let's meet, discuss and showcase our work around data mining, analytics and engineering.
Join this Meetup to comment.
Sachin Anto
41 attended
Rohit
ORGANIZER
EVENT HOST
Prashant +1
CO-ORGANIZER
EVENT HOST
PRANABH KUMAR
Harini

Related Work

Daytona
- » Supports iteration and ML workloads
- » Azure-specific integration

DryadLINQ
- » SQL-like queries integrated in C# programs
- » Build queries through operations on lazy datasets
- » Cannot have a dataset persist *across* queries
- » No concept of shared variables for broadcast etc

Pig & Hive
- » Query languages that can call into Java/Python/etc UDFs
- » No support for caching a dataset across queries

OpenMP
- » Compiler extension for parallel loops in C++
- » Annotate variables as read-only or accumulator above loop
- » Cluster version exists, but not fault-tolerant

Conclusions

Spark provides two abstractions that enable iterative jobs and interactive use:

1. **Distributed datasets** with controllable persistence, supporting fault-tolerant parallel operations
2. **Shared variables** for efficient broadcast and imperative style programming

Language integration achieved using Scala features + some amount of hacking

All this is surprisingly little code (~1600 lines)

http://spark.incubator.apache.org/

Apache Mesos and Spark

Conceived of by graduate students

Implemented locally first

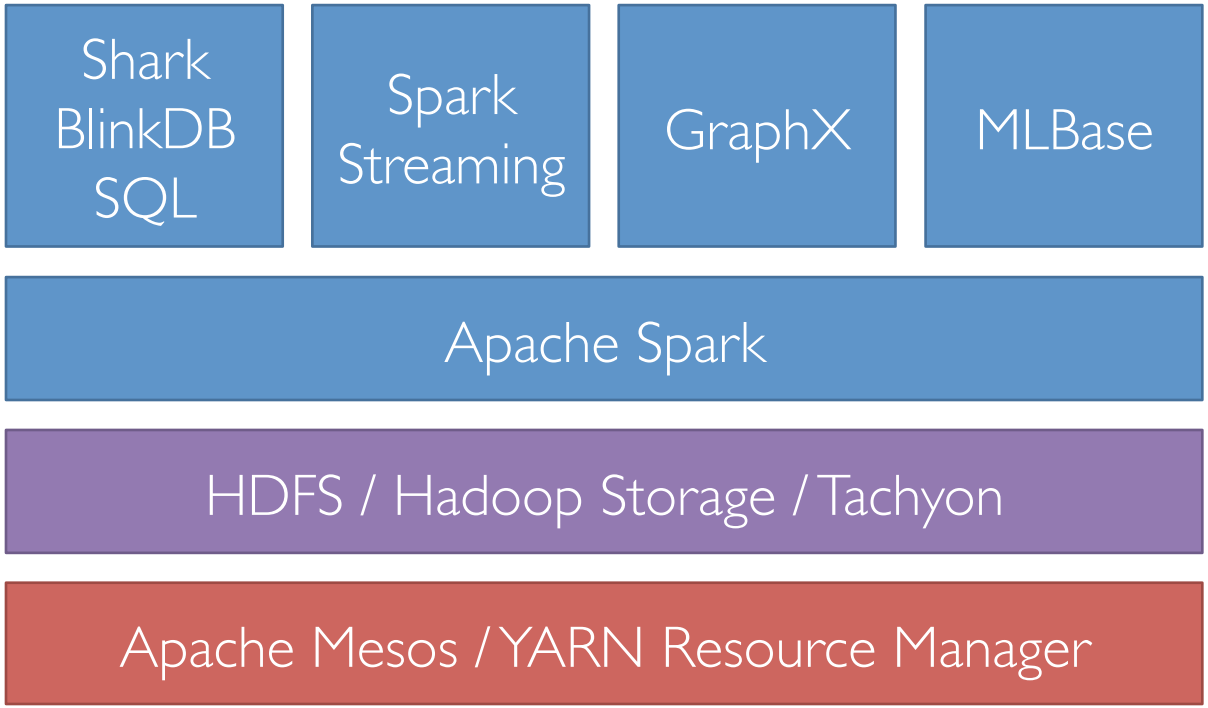
Tested and scaled up using Amazon EC2

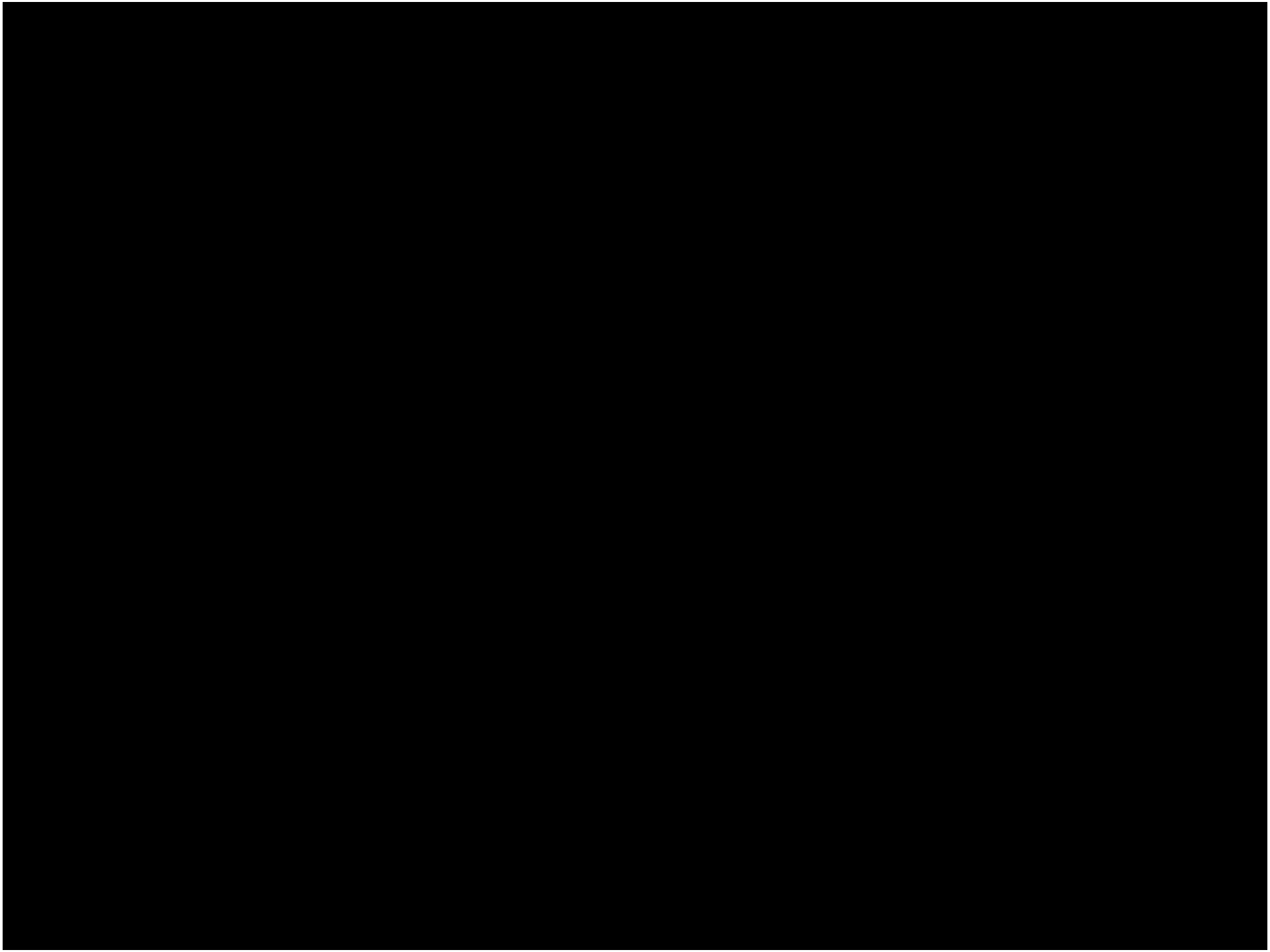
Released and open sourced to community

You can do the same!

Berkeley Data Analytics Stack

http://amplab.cs.berkeley.edu/





Language Integration

Scala closures are Serializable objects

- » Serialize on driver, load & run on workers

Not quite enough

- » Nested closures may reference entire outer scope
- » May pull in non-Serializable variables not used inside
- » Solution: bytecode analysis + reflection

Shared variables

- » Accumulators: serialized form contains ID
- » Broadcast vars: serialized form is path to HDFS file