Spark

Cluster Computing with Working Sets

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

RAD Lab
UC Berkeley

Background

MapReduce and Dryad raised level of abstraction in cluster programming by hiding scaling & faults

However, these systems provide a limited programming model: acyclic data flow

Can we design similarly powerful abstractions for a broader class of applications?

Spark Goals

Support applications with *working sets* (datasets reused across parallel operations)

» Iterative jobs (common in machine learning)

» Interactive data mining

Retain MapReduce's fault tolerance & scalability

Experiment with programmability

» Integrate into Scala programming language

» Support interactive use from Scala interpreter

Programming Model

Resilient distributed datasets (RDDs)

» Created from HDFS files or “parallelized” arrays

» Can be transformed with map and filter

» *Can be cached across parallel operations*

Parallel operations on RDDs

» Reduce, collect, foreach

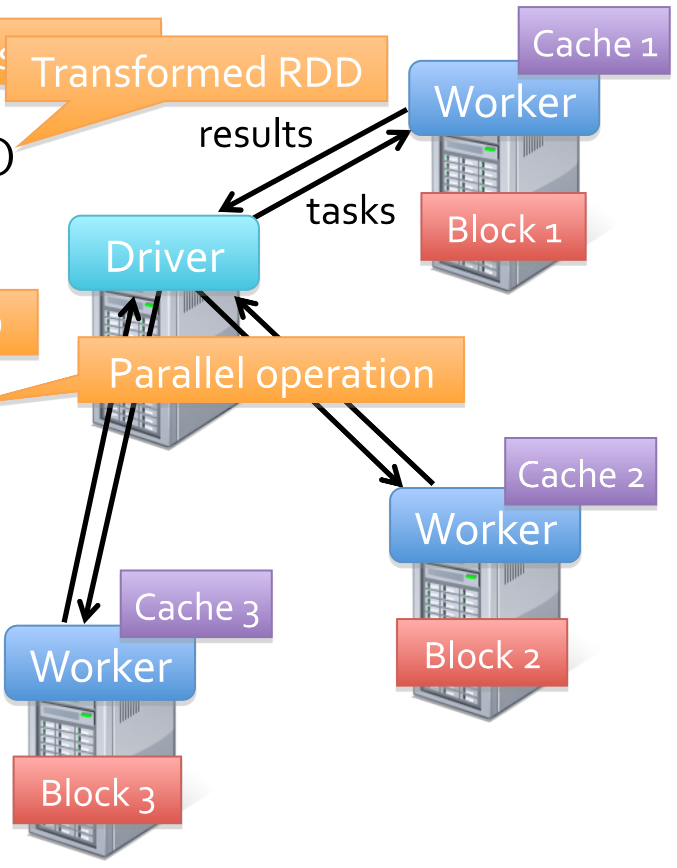
Shared variables

» Accumulators (add-only), broadcast variables

Example: Log Mining

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

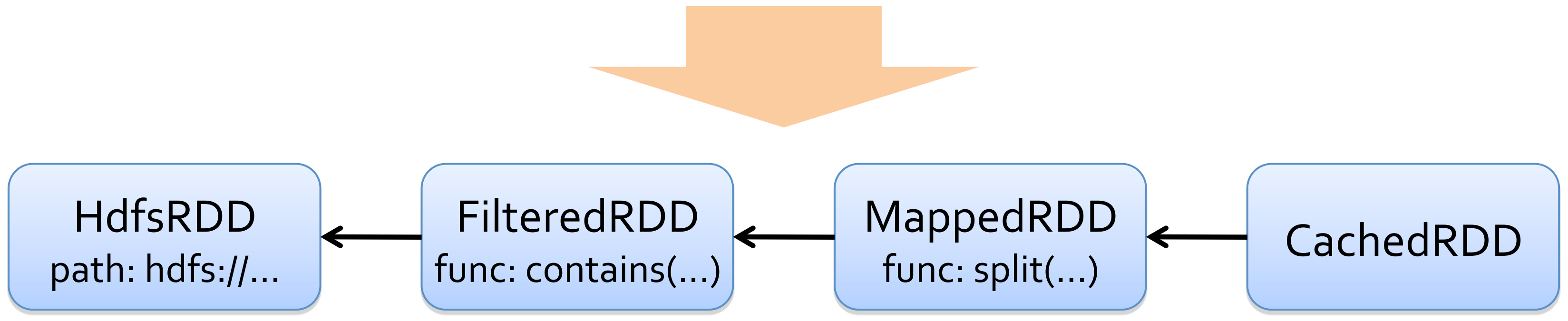
```
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
messages = errors.map(_.split('\t')(2))
cachedMsgs = messages.cache()

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



RDD Representation

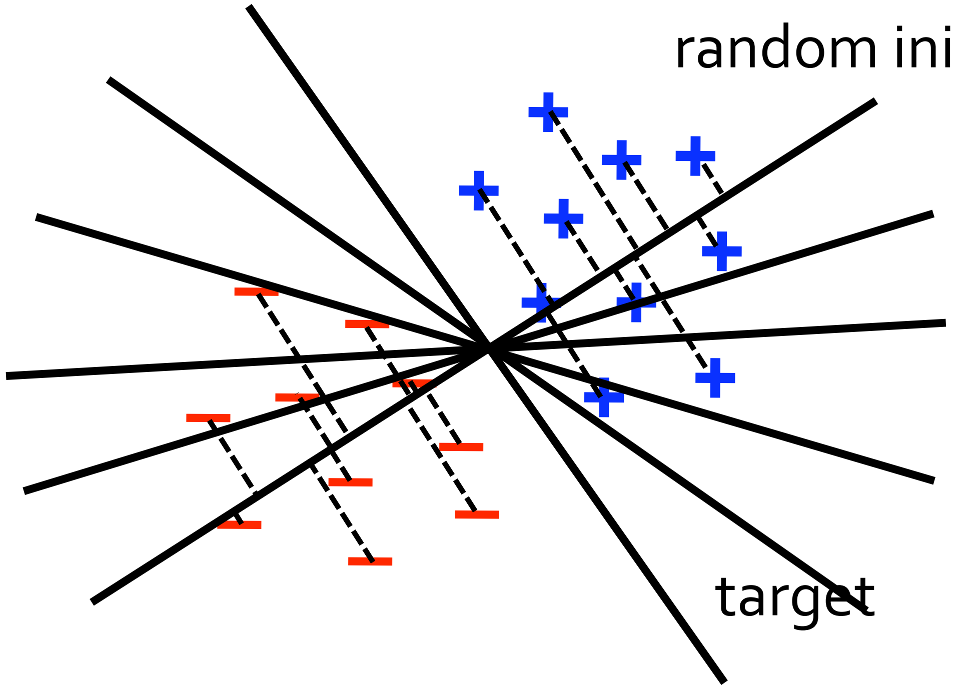
Each RDD object maintains *lineage* information that can be used to reconstruct lost partitions

Ex:
```
cachedMsgs = textFile(...).filter(_.contains(“error”))
                          .map(_.split(‘\t’)(2))
                          .cache()
```



Example: Logistic Regression

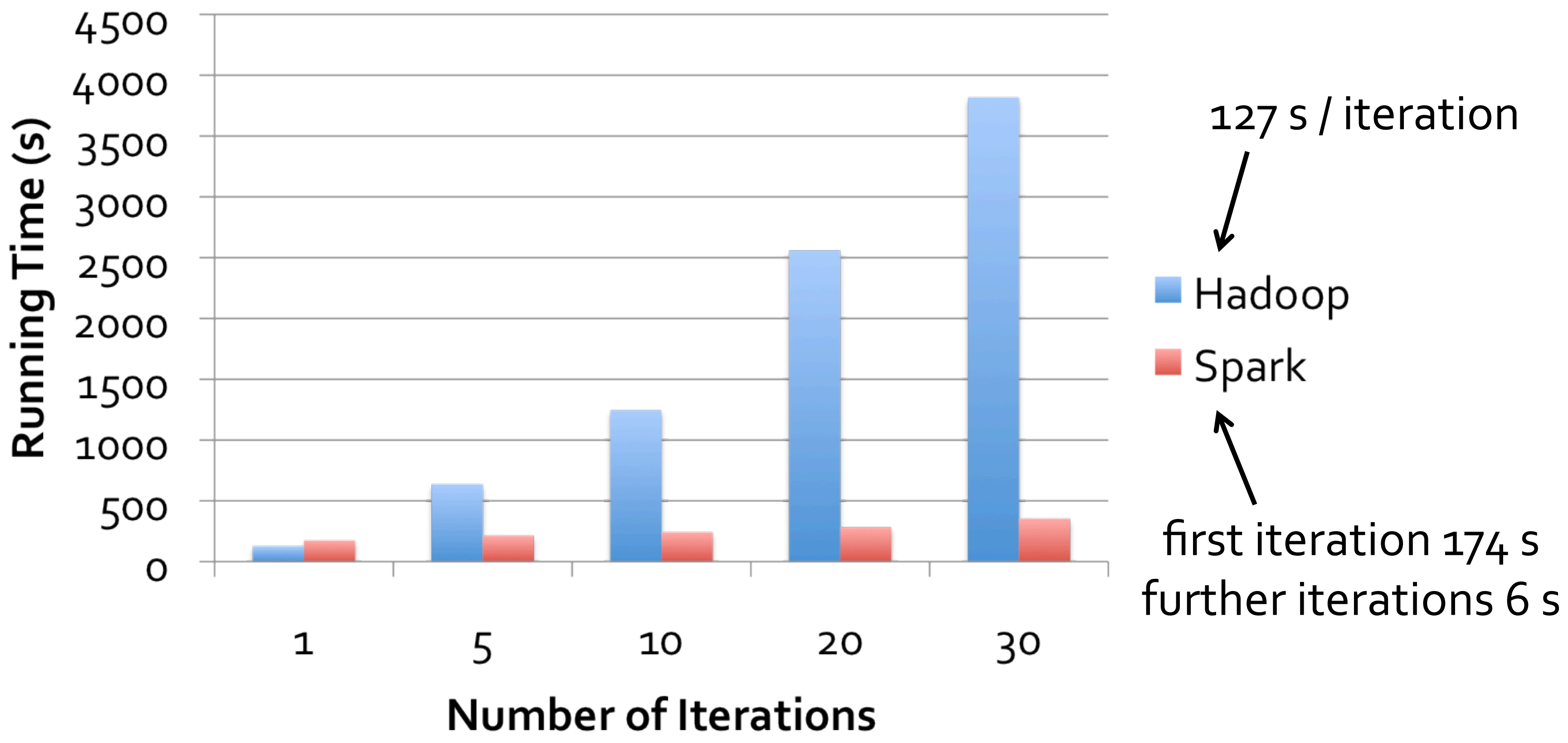
Goal: find best line separating two sets of points



Logistic Regression Code

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

var w = Vector.random(D)

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

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

Logistic Regression Performance



Demo

Conclusions & Future Work

Spark provides a limited but efficient set of fault tolerant distributed memory abstractions

» Resilient distributed datasets (RDDs)
» Restricted shared variables

In future work, plan to further extend this model:

» More RDD transformations (e.g. shuffle)
» More RDD persistence options (e.g. disk + memory)
» Updatable RDDs (for incremental or streaming jobs)
» Data sharing across applications

Related Work

DryadLINQ

- » Build queries through language-integrated SQL operations on lazy datasets
- » Cannot have a dataset persist *across* queries
- » No concept of shared variables for broadcast etc

Pig and Hive

- » Query languages that can call into Java/Python/etc UDFs
- » No support for caching a datasets 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

Twister and Haloop

- » Iterative MapReduce implementations using caching
- » Can't define multiple distributed datasets, run multiple map & reduce pairs on them, or decide which operations to run next interactively