Spark

Cluster Computing with Working Sets

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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

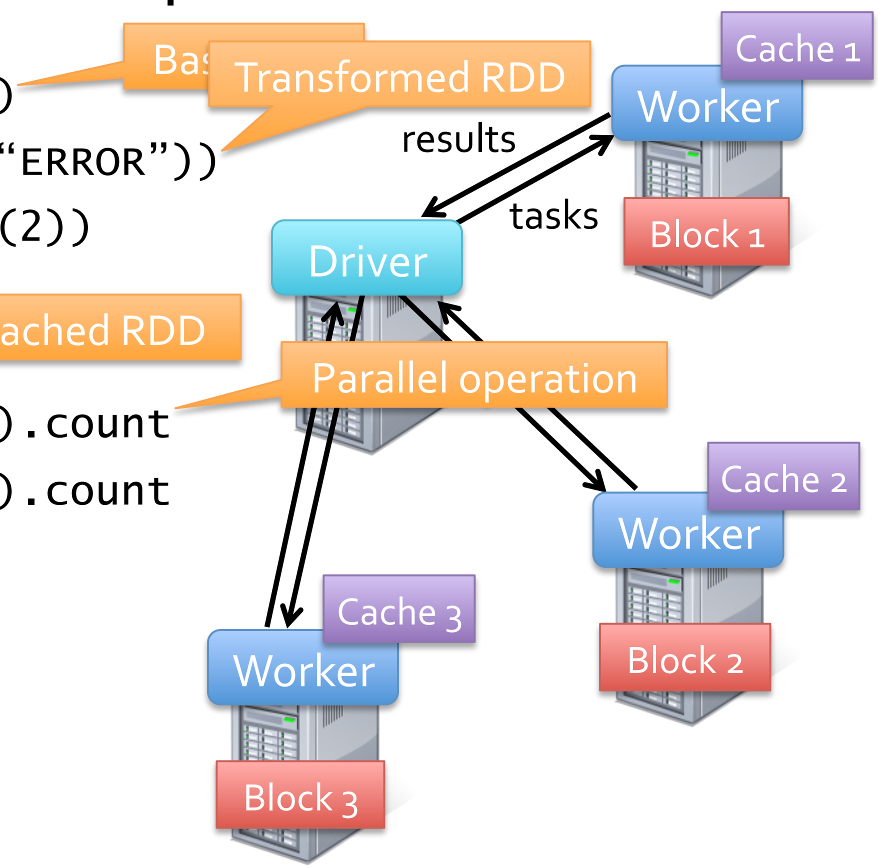
Shared variables

» Accumulators (add-only), broadcast variables

Example: Log Mining

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

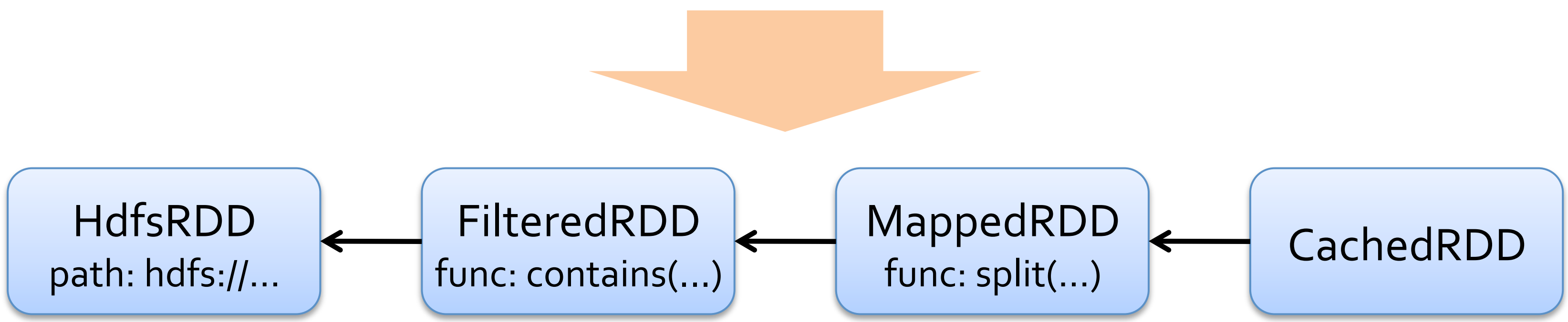
```
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
messages = errors.map(_.split('\t')(2))
cachedMsgs = messages.cache()

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



RDD Representation

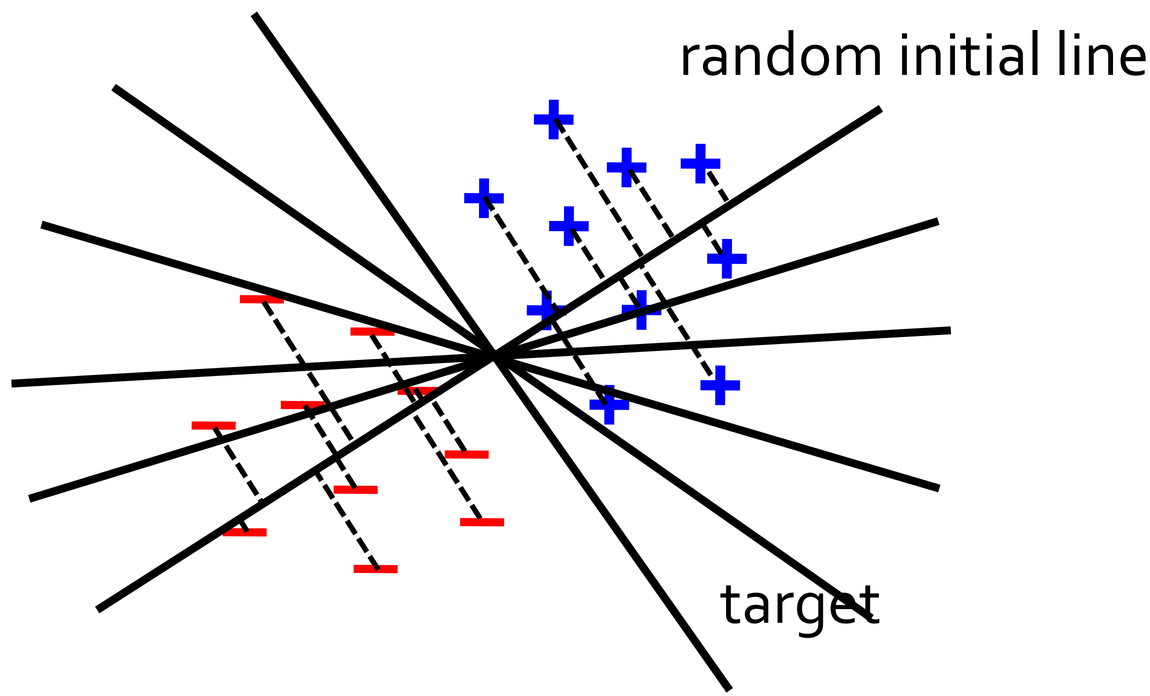
Each RDD object maintains *lineage* information that can be used to reconstruct lost partitions

Ex:
```
cachedMsgs = textFile(...).filter(_.contains("error"))
                          .map(_.split('\t')(2))
                          .cache()
```



Example: Logistic Regression

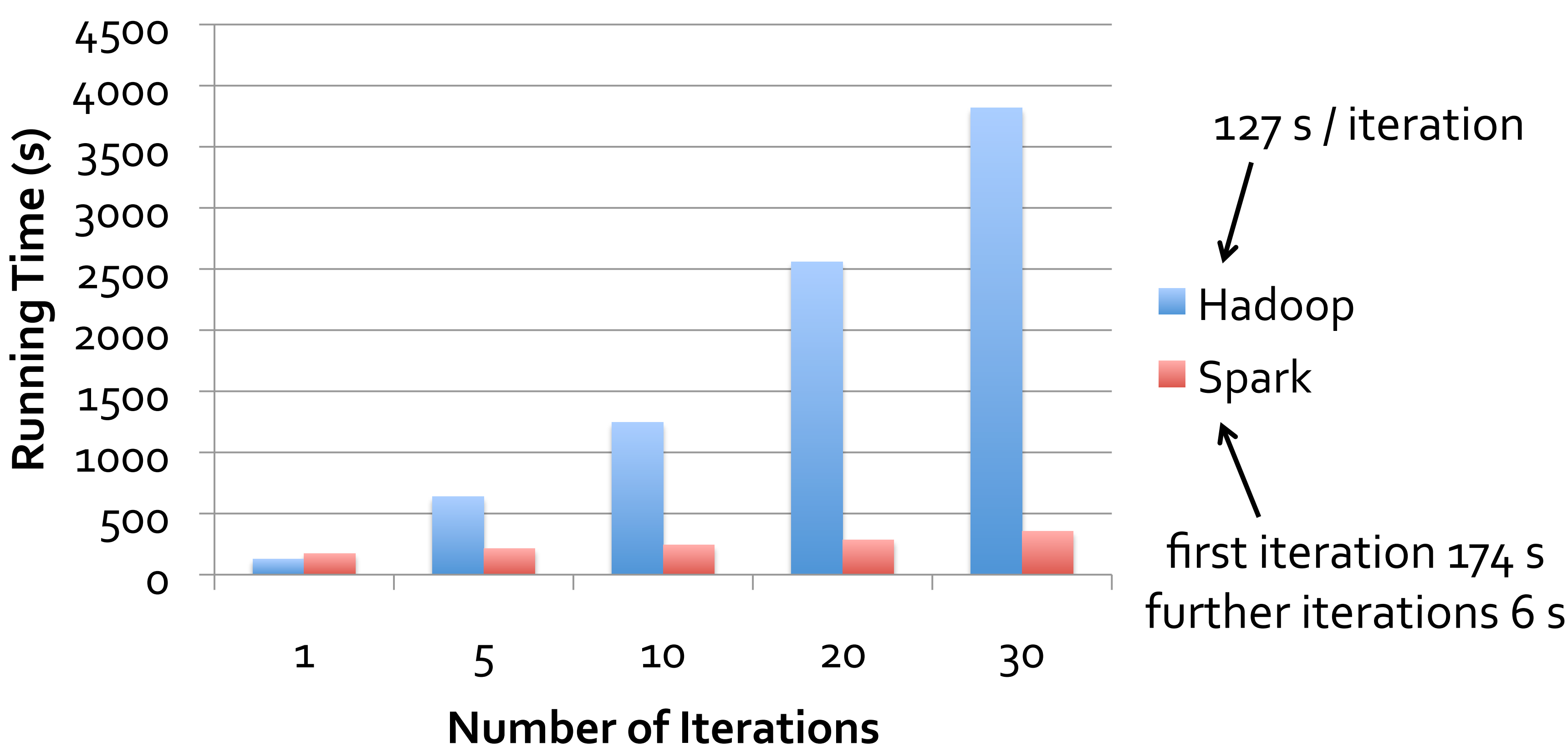
Goal: find best line separating two sets of points



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
- » Cannot define multiple distributed datasets, run multiple map & reduce pairs on them, or decide which operations to run next interactively