Spark

Fast, Interactive, Language-Integrated Cluster Computing

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www.spark-project.org

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Project Goals

Extend the MapReduce model to better support two common classes of analytics apps:

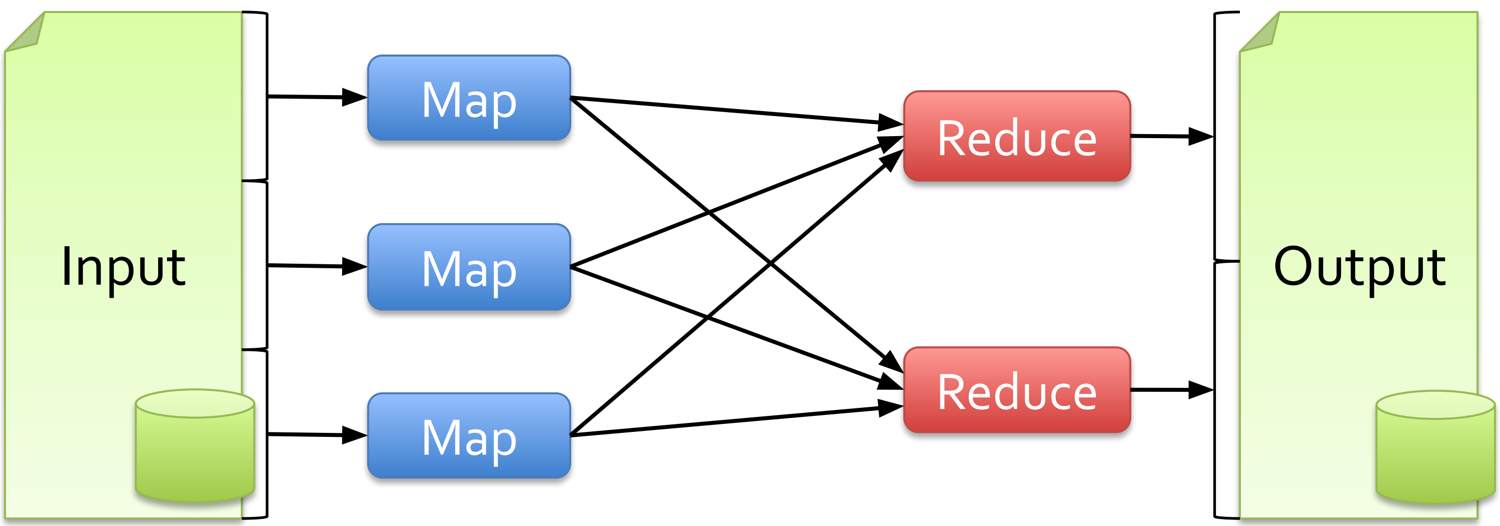
- » **Iterative** algorithms (machine learning, graphs)
- » **Interactive** data mining

Enhance programmability:

- » Integrate into Scala programming language
- » Allow interactive use from Scala interpreter

Motivation

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



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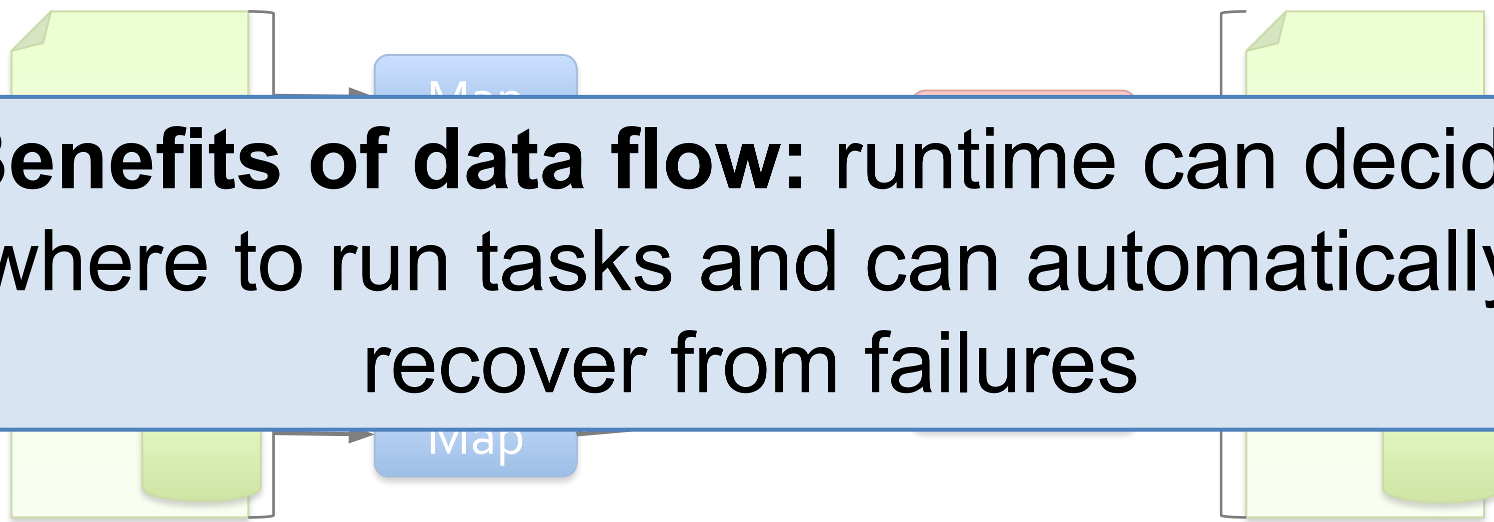


Benefits of data flow: runtime can decide where to run tasks and can automatically recover from failures

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

Solution: Resilient Distributed Datasets (RDDs)

Allow apps to keep working sets in memory for efficient reuse

Retain the attractive properties of MapReduce

- Fault tolerance, data locality, scalability

Support a wide range of applications

Outline

Spark programming model

Implementation

Demo

User applications

Programming Model

Resilient distributed datasets (RDDs)

- Immutable, partitioned collections of objects
- Created through parallel *transformations* (map, filter, groupBy, join, …) on data in stable storage
- Can be *cached* for efficient reuse

Actions on RDDs

- Count, reduce, collect, save, …

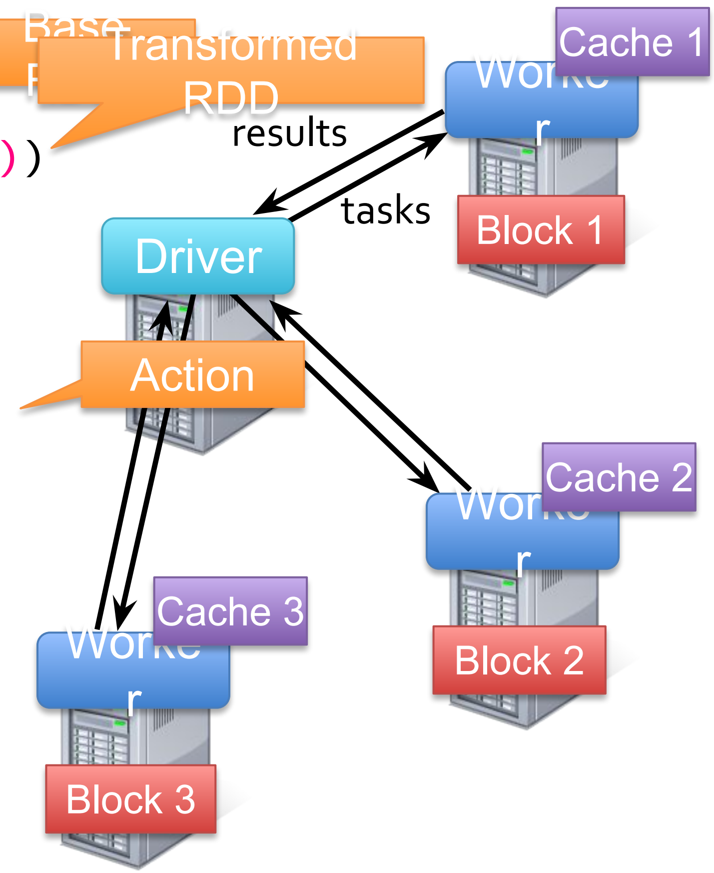
Spark Operations

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	

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
. . .
```

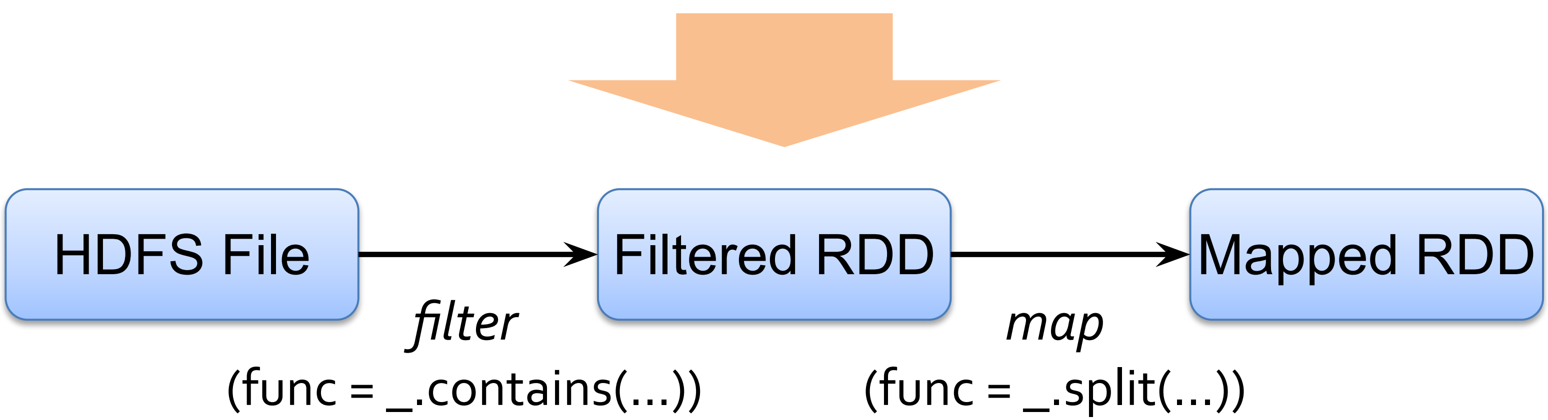


Result: scaled to 1 TB data in 5-7 sec
(vs 170 sec for on-disk data)

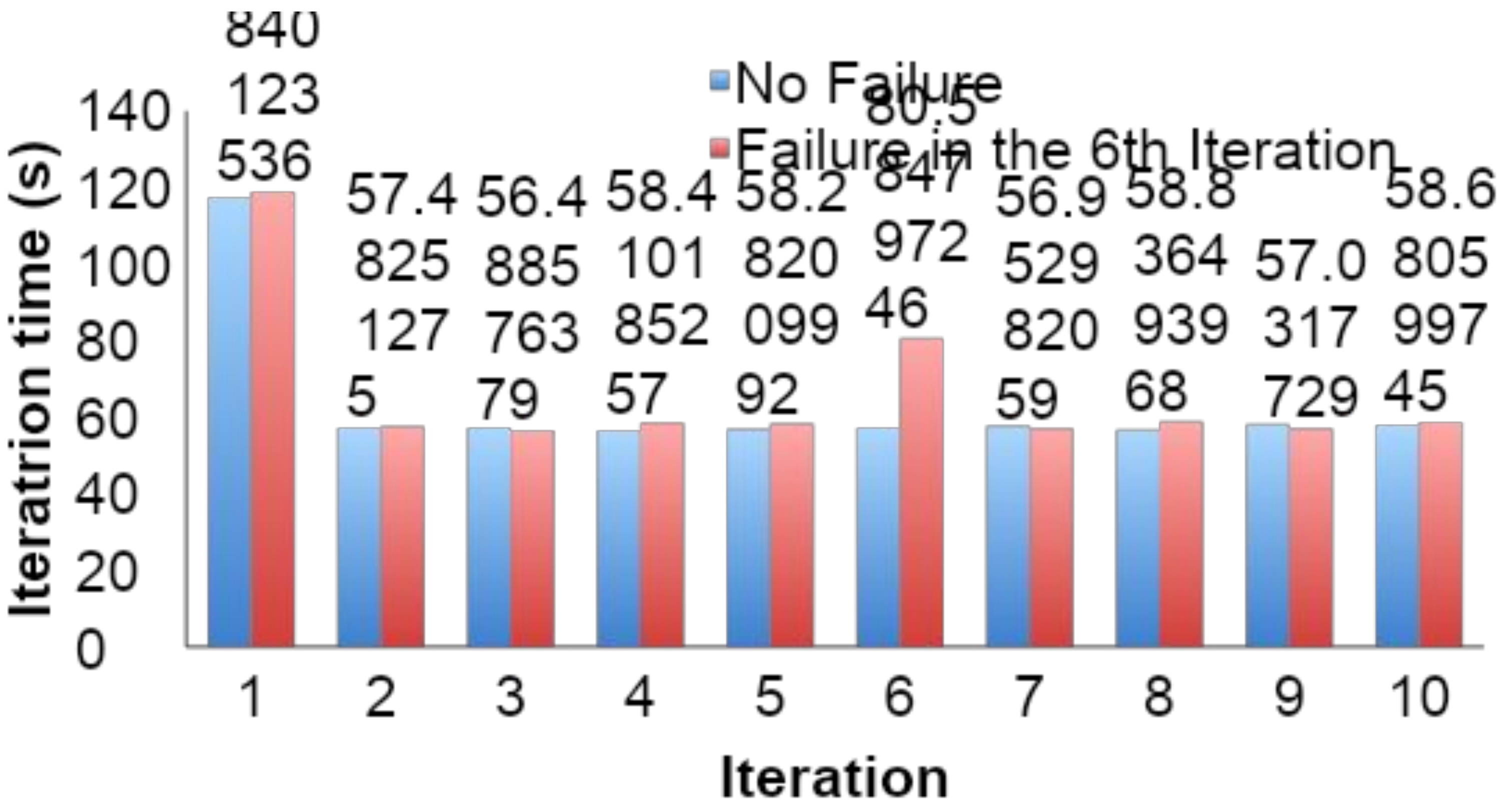
RDD Fault Tolerance

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

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

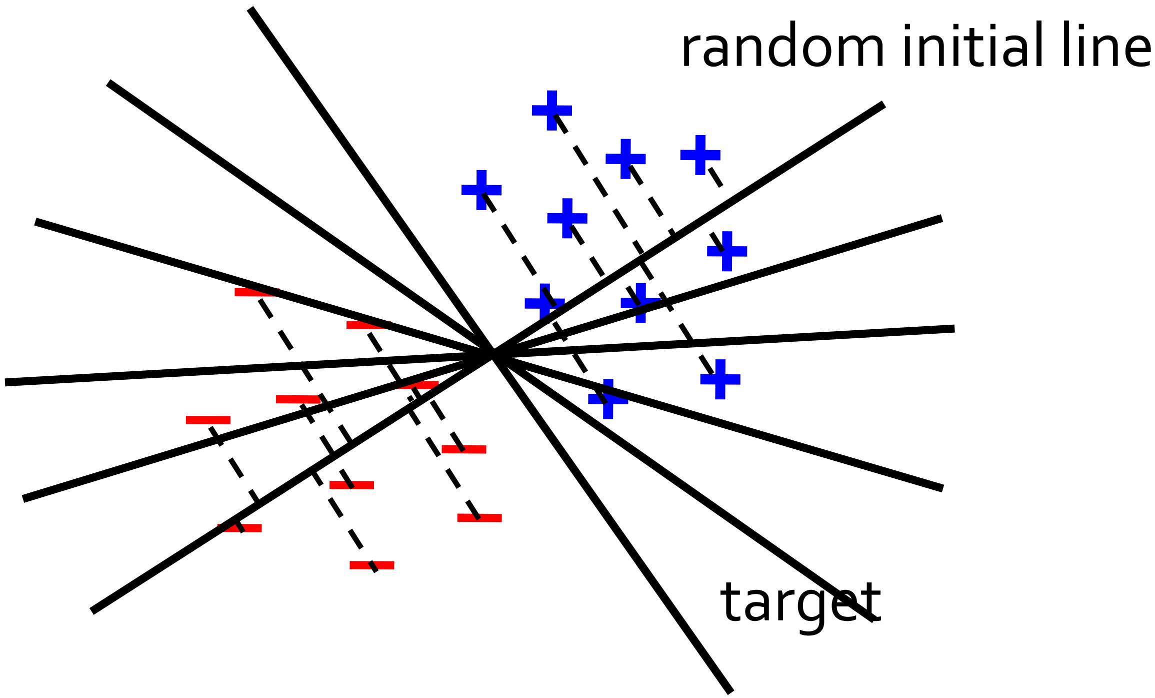


Fault Recovery Results



Example: Logistic Regression

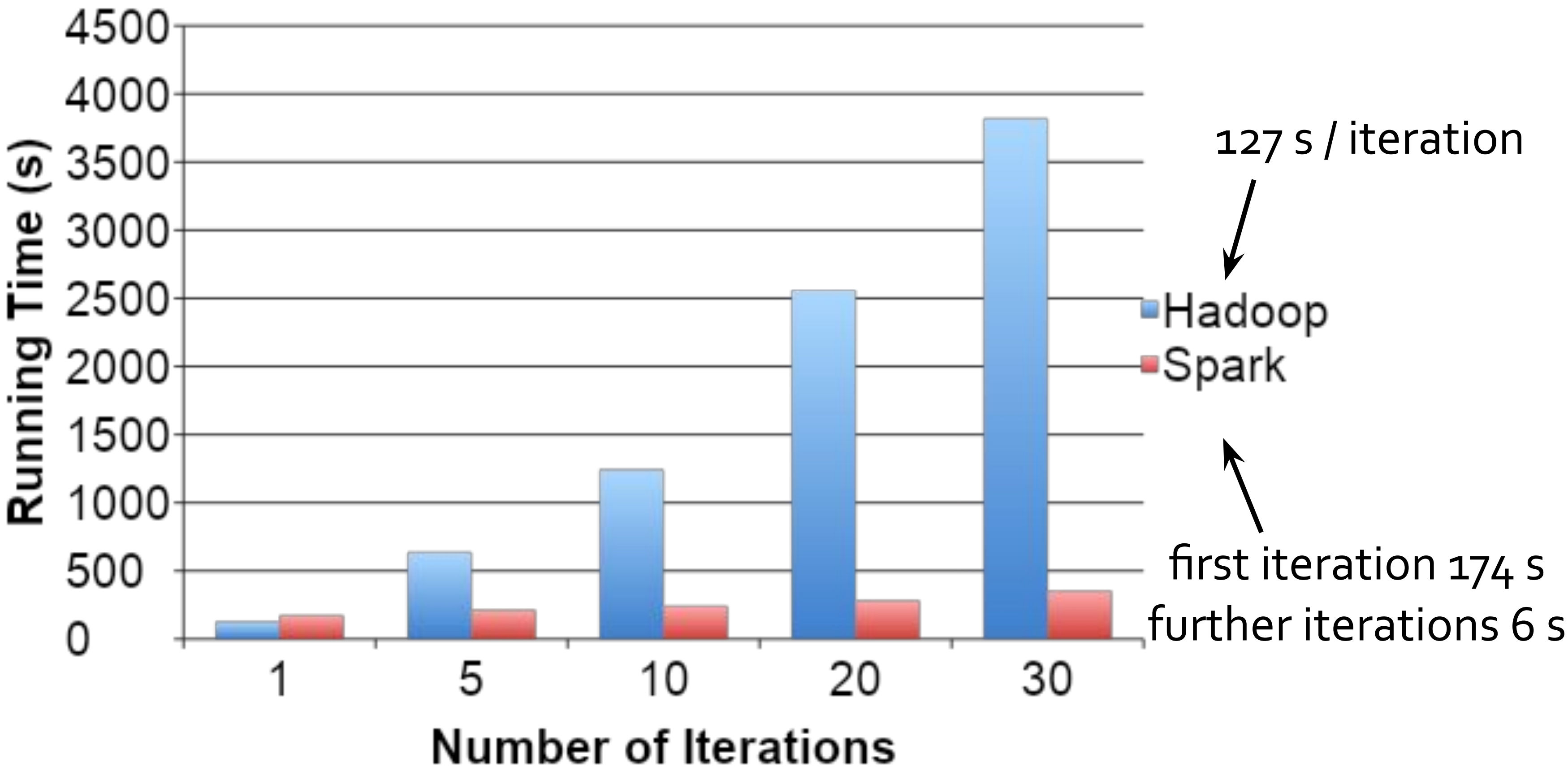
Goal: find best line separating two sets of points



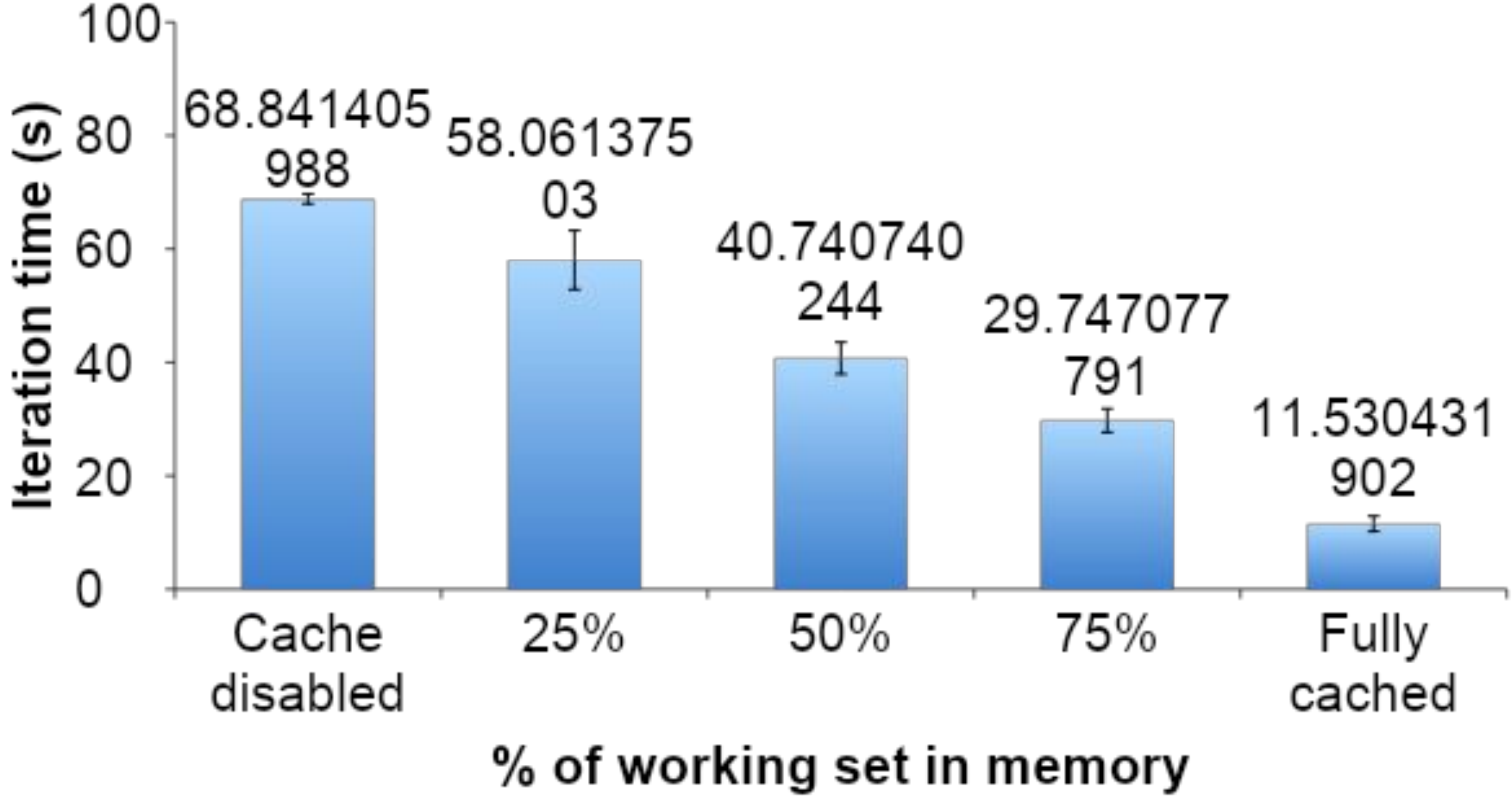
Example: Logistic Regression

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



Behavior with Not Enough RAM



Spark Applications

In-memory data mining on Hive data (Conviva)

Predictive analytics (Quantifind)

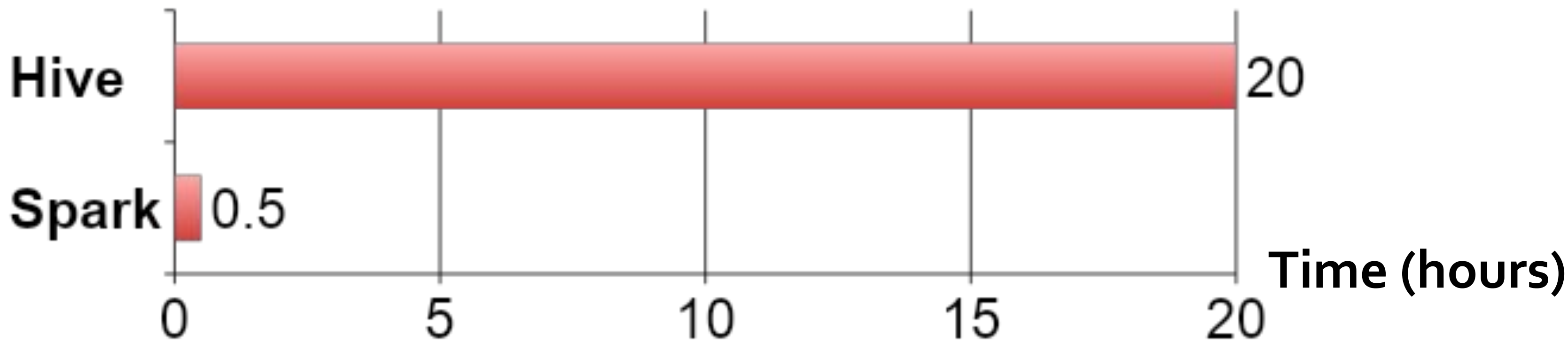
City traffic prediction (Mobile Millennium)

Twitter spam classification (Monarch)

Collaborative filtering via matrix factorization

…

Conviva GeoReport



Aggregations on many keys w/ same WHERE clause

40× gain comes from:

- Not re-reading unused columns or filtered records
- Avoiding repeated decompression
- In-memory storage of deserialized objects

Frameworks Built on Spark

Pregel on Spark (Bagel)

- Google message passing model for graph computation
- 200 lines of code

Hive on Spark (Shark)

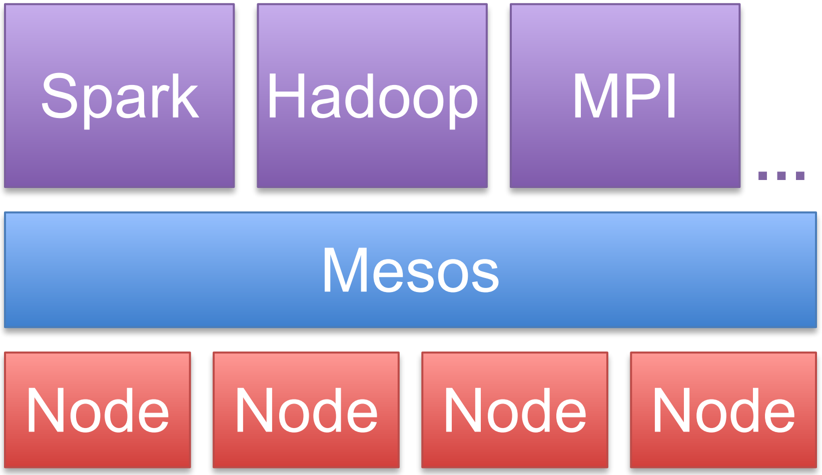
- 3000 lines of code
- Compatible with Apache Hive
- ML operators in Scala

Implementation

Runs on Apache Mesos to share resources with Hadoop & other apps

Can read from any Hadoop input source (e.g. HDFS)

No changes to Scala compiler



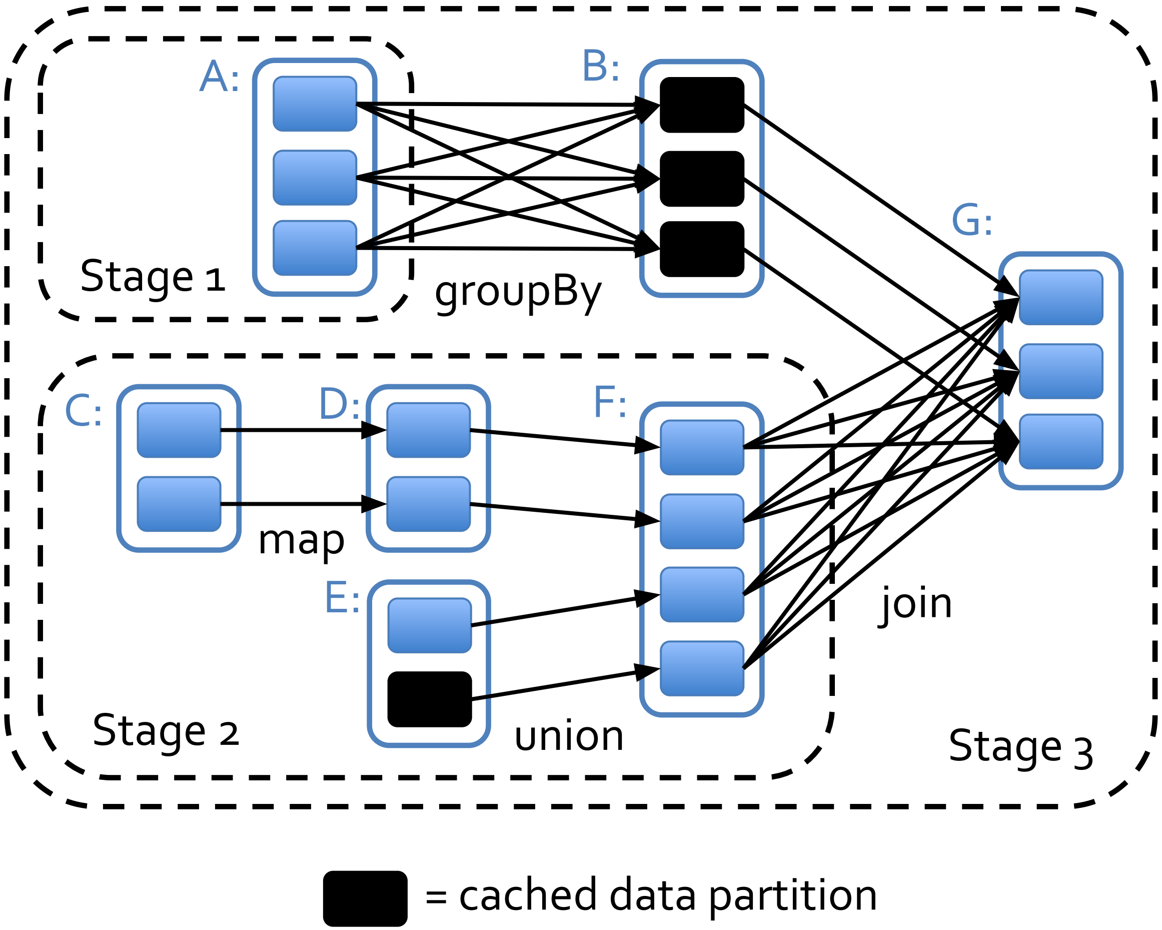
Spark Scheduler

Dryad-like DAGs

Pipelines functions within a stage

Cache-aware work reuse & locality

Partitioning-aware to avoid shuffles



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
- Distribute generated classes over the network

Conclusion

Spark provides a simple, efficient, and powerful programming model for a wide range of apps

Download our open source release:

www.spark-project.org

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Related Work

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

Relational databases
- Lineage/provenance, logical logging, materialized views

GraphLab, Piccolo, BigTable, RAMCloud
- Fine-grained writes similar to distributed shared memory

Iterative MapReduce (e.g. Twister, HaLoop)
- Implicit data sharing for a fixed computation pattern

Caching systems (e.g. Nectar)
- Store data in files, no explicit control over what is cached