Spark

Fast, Interactive, Language-Integrated Cluster Computing

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www.spark-project.org

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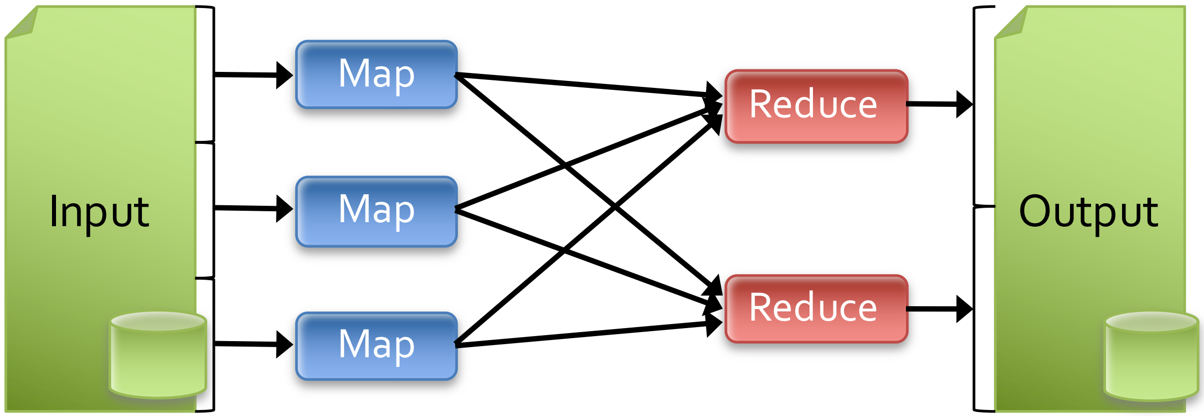
Project Goals

- 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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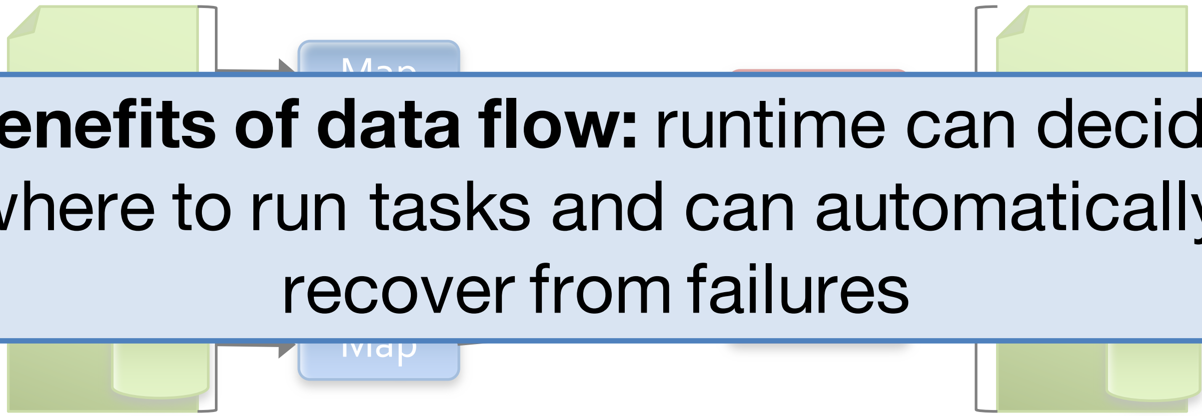


Benefits of data flow: runtime can decide where to run tasks and can automatically recover from failures

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

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	

Outline

- Spark programming model
- Implementation
- 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

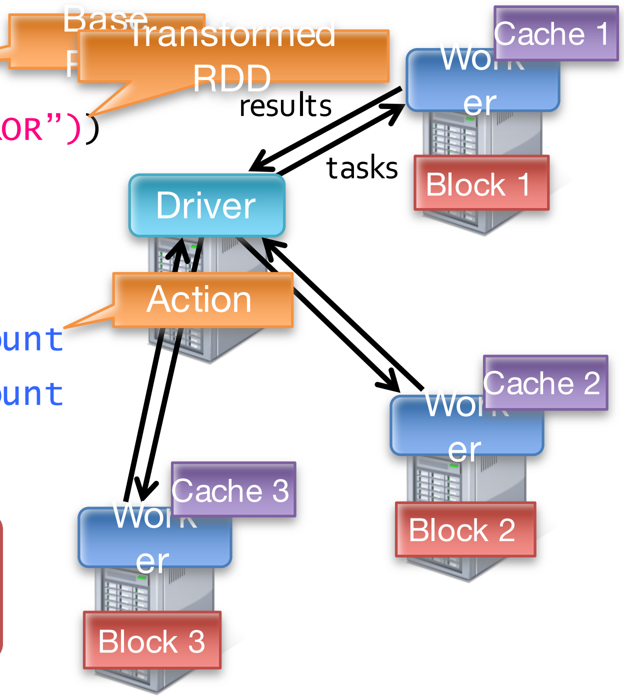
- Count, reduce, collect, save, …

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
. . .
```



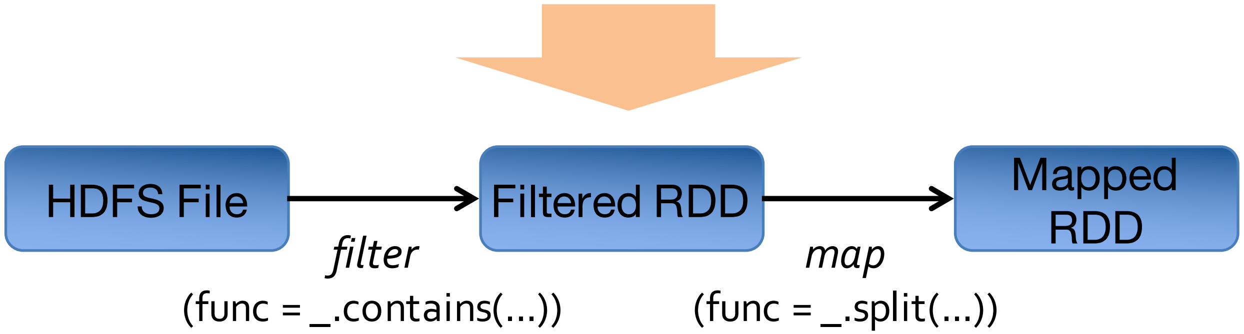
Result: scaled to 1 TB data in 5-7 sec
(vs 170 sec for on-disk data)

RDD Fault Tolerance

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

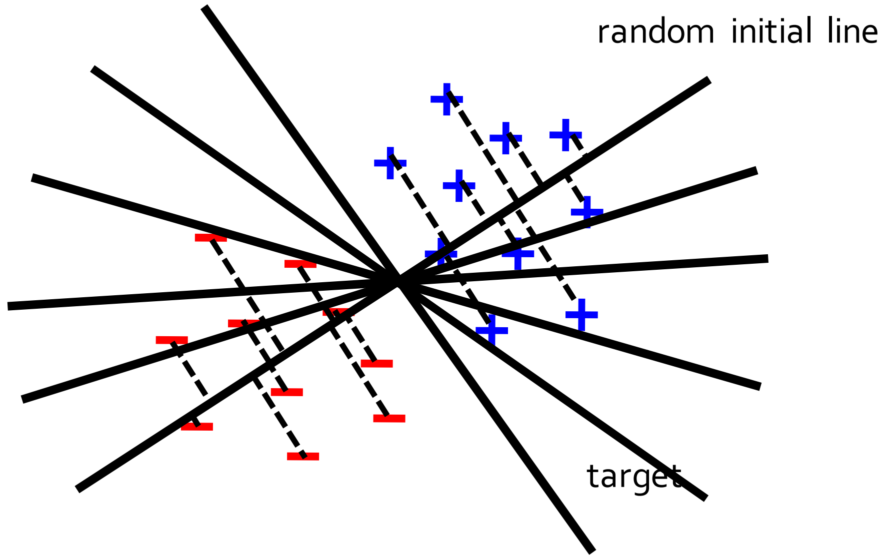
Ex:

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



Example: Logistic Regression

Goal: find best line separating two sets of points



Example: Logistic Regression

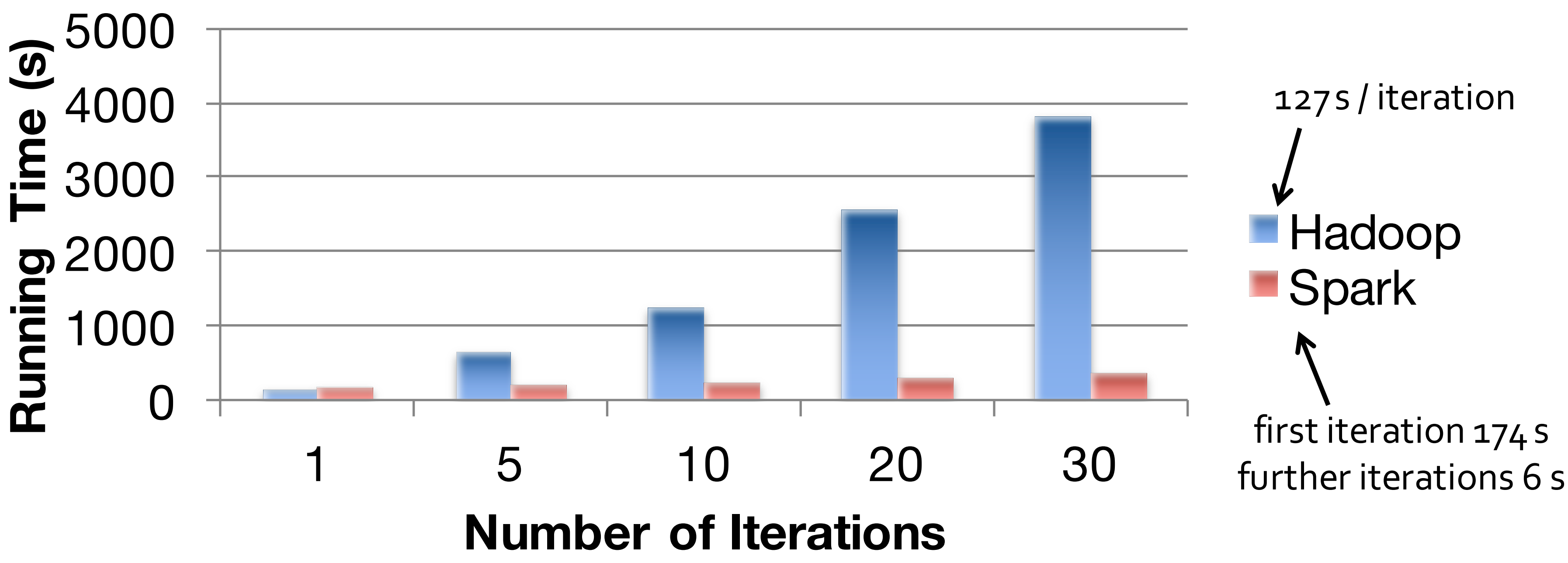

```
val data = spark.textFile(...).map(readPoint).cache()

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



This is for a 29 GB dataset on 20 EC2 m1.xlarge machines (4 cores each)

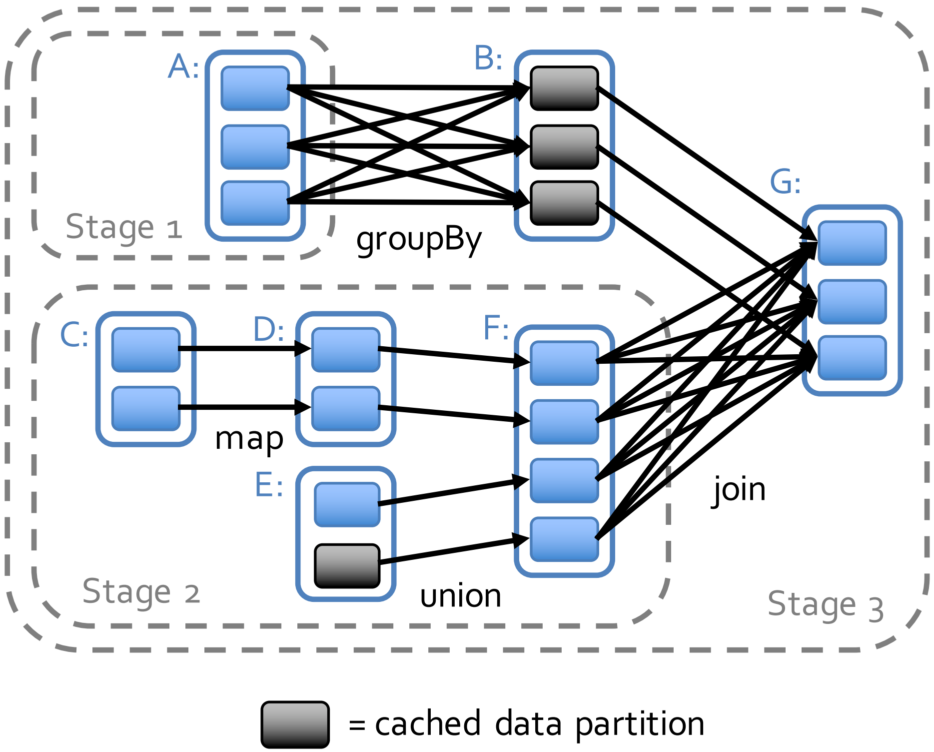
Spark Scheduler

Dryad-like DAGs

Pipelines functions within a stage

Cache-aware work reuse & locality

Partitioning-aware to avoid shuffles



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

Let’s dive on Spark for executing and analyzing K-Means

https://databricks.com/blog/2015/01/28/introducing-streaming-k-means-in-spark-1-2.html