Distributed Computing with Open-Source Software

Reza Zadeh

databricks

ICME
INSTITUTE for COMPUTATIONAL & MATHEMATICAL ENGINEERING
at STANFORD UNIVERSITY

Spark

Presented at Infosys OSSmosis

Problem

Data growing faster than processing speeds

Only solution is to parallelize on large clusters

» Wide use in both enterprises and web industry

How do we program these things?

Outline

Data flow vs. traditional network programming

Limitations of MapReduce

Spark computing engine

Machine Learning Example

Current State of Spark Ecosystem

Data flow vs.

Traditional network programming

Traditional Network Programming

Message-passing between nodes (e.g. MPI)

Very difficult to do at scale:

» How to split problem across nodes?

- Must consider network & data locality

» How to deal with failures? (inevitable at scale)

» Even worse: stragglers

» Ethernet networking not fast

» Have to write programs per machine

Rarely used in commodity datacenters

Data Flow Models

Restrict the programming interface so that the system can do more automatically

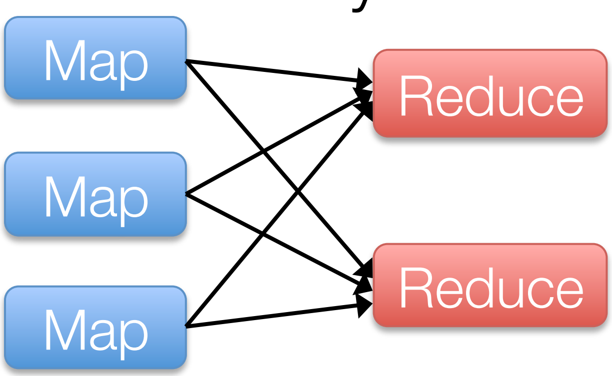
Express jobs as graphs of high-level operators

» System picks how to split each operator into tasks and where to run each task

» Run parts twice fault recovery

Biggest example:

MapReduce



Example MapReduce Algorithms

Matrix-vector multiplication

Power iteration (e.g. PageRank)

Gradient descent methods

Stochastic SVD

Tall skinny QR

Many others!

Why Use a Data Flow Engine?

Ease of programming

- » High-level functions instead of message passing

Wide deployment

- » More common than MPI, especially “near” data

Scalability to very largest clusters

Examples:

Pig, Hive,Scalding, Storm

Limitations of MapReduce

Limitations of MapReduce

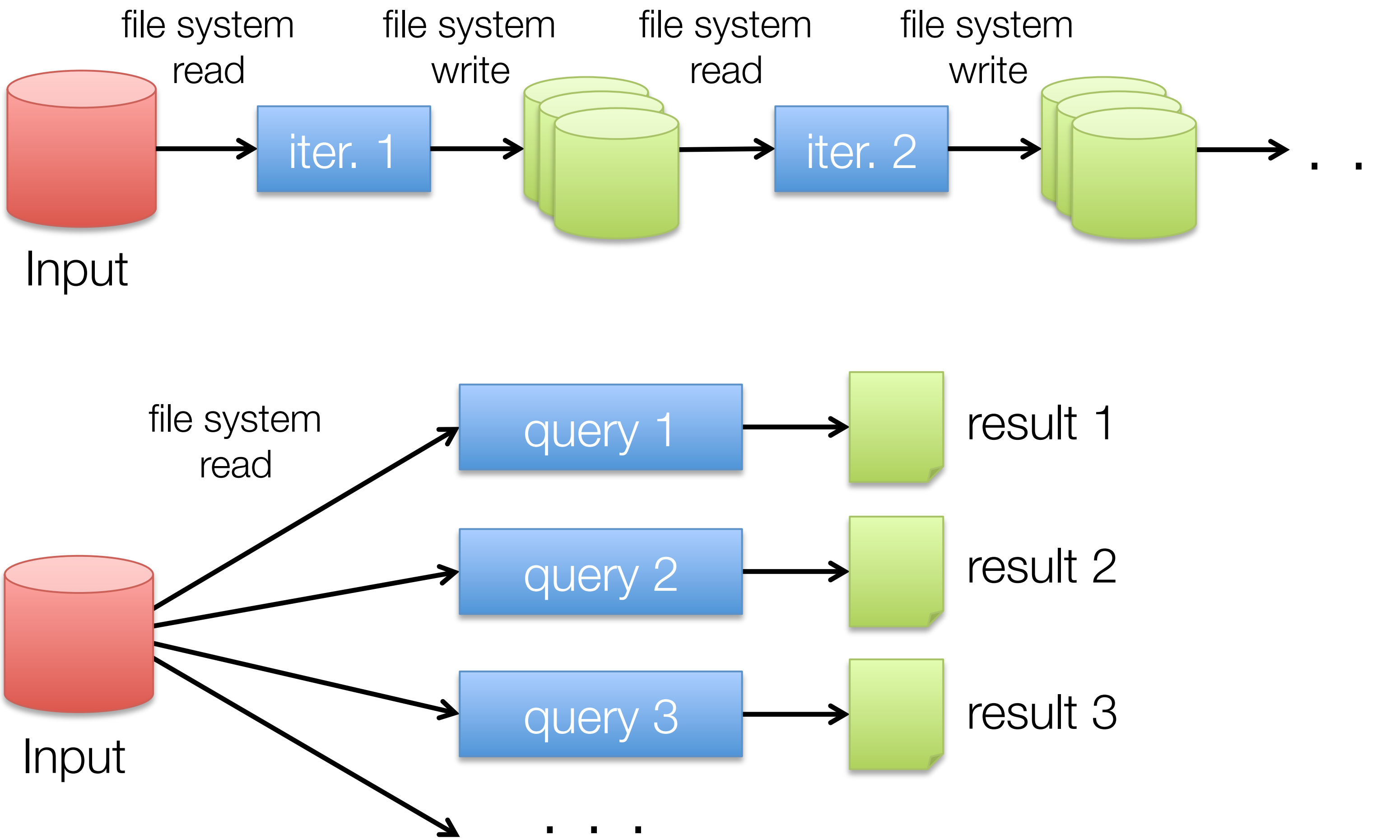
MapReduce is great at one-pass computation, but inefficient for *multi-pass* algorithms

No efficient primitives for data sharing

» State between steps goes to distributed file system

» Slow due to replication & disk storage

Example: Iterative Apps



Commonly spend 90% of time doing I/O

Result

While MapReduce is simple, it can require *asymptotically* more communication or I/O

Spark computing engine

Spark Computing Engine

Extends a programming language with a distributed collection data-structure

- » "Resilient distributed datasets" (RDD)

Open source at Apache

- » Most active community in big data, with 50+ companies contributing

Clean APIs in Java, Scala, Python

Community: SparkR

Resilient Distributed Datasets (RDDs)

Main idea: Resilient Distributed Datasets

» Immutable collections of objects, spread across cluster

» Statically typed: RDD[T] has objects of type T

```
val sc = new SparkContext()
val lines = sc.textFile("log.txt")   // RDD[String]

// Transform using standard collection operations
val errors = lines.filter(_.startsWith("ERROR"))
val messages = errors.map(_.split('\t')(2))
```

➡ lazily evaluated

```
messages.saveAsTextFile("errors.txt")
```

➡ kicks off a computation

Key Idea

Resilient Distributed Datasets (RDDs)

» Collections of objects across a cluster with user controlled partitioning & storage (memory, disk, ...)

» Built via parallel transformations (map, filter, …)

» The world only lets you make make RDDs such that they can be:

Automatically rebuilt on failure

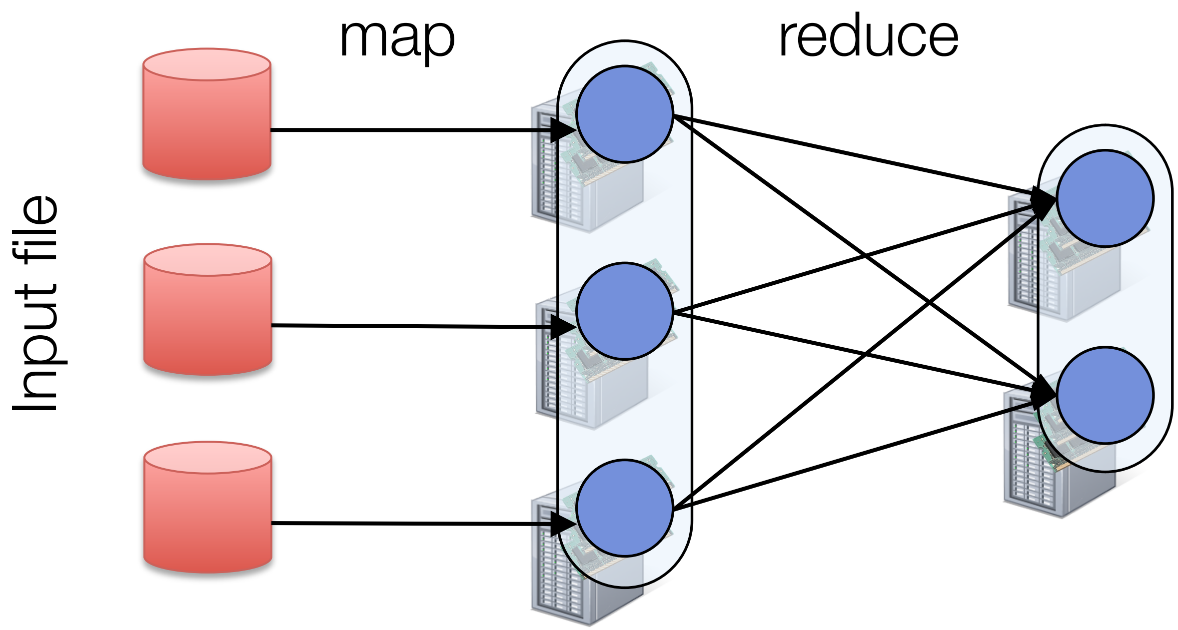
Python, Java, Scala, R

```
// Scala:

val lines = sc.textFile(...)
lines.filter(x => x.contains("ERROR")).count()


// Java (better in java8!):

JavaRDD<String> lines = sc.textFile(...);
lines.filter(new Function<String, Boolean>() {
  Boolean call(String s) {
    return s.contains("error");
  }
}).count();
```

Fault Tolerance

RDDs track *lineage* info to rebuild lost data

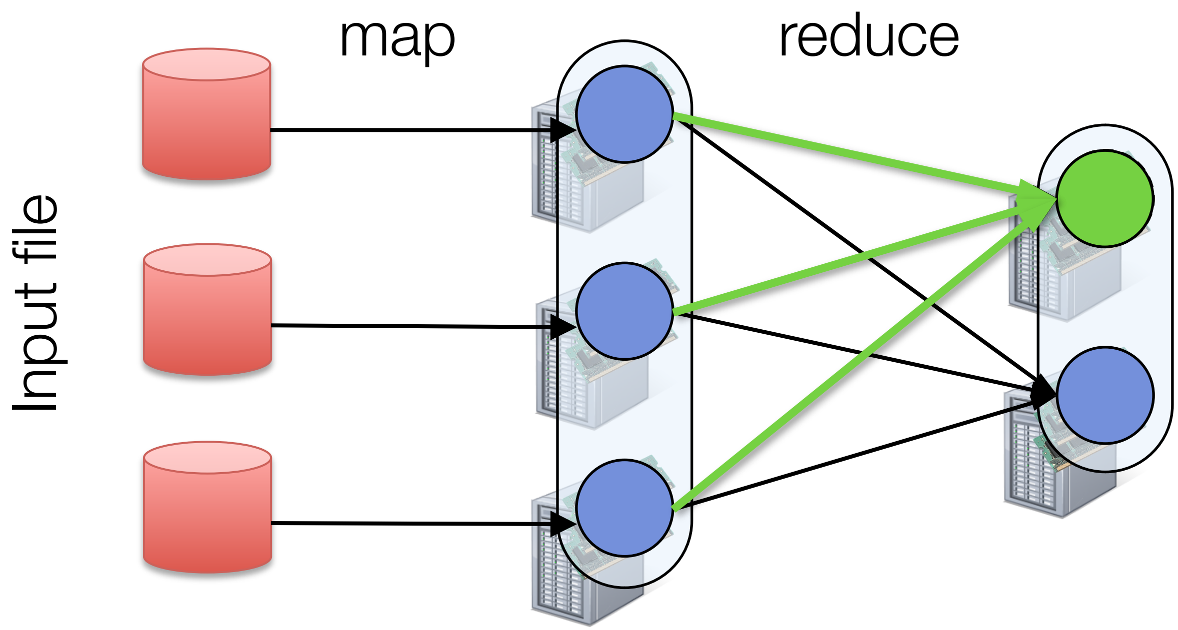
```
file.map(lambda rec: (rec.type, 1))
    .reduceByKey(lambda x, y: x + y)
    .filter(lambda (type, count): count > 10)
```



Fault Tolerance

RDDs track *lineage* info to rebuild lost data

```
file.map(lambda rec: (rec.type, 1))
    .reduceByKey(lambda x, y: x + y)
    .filter(lambda (type, count): count > 10)
```



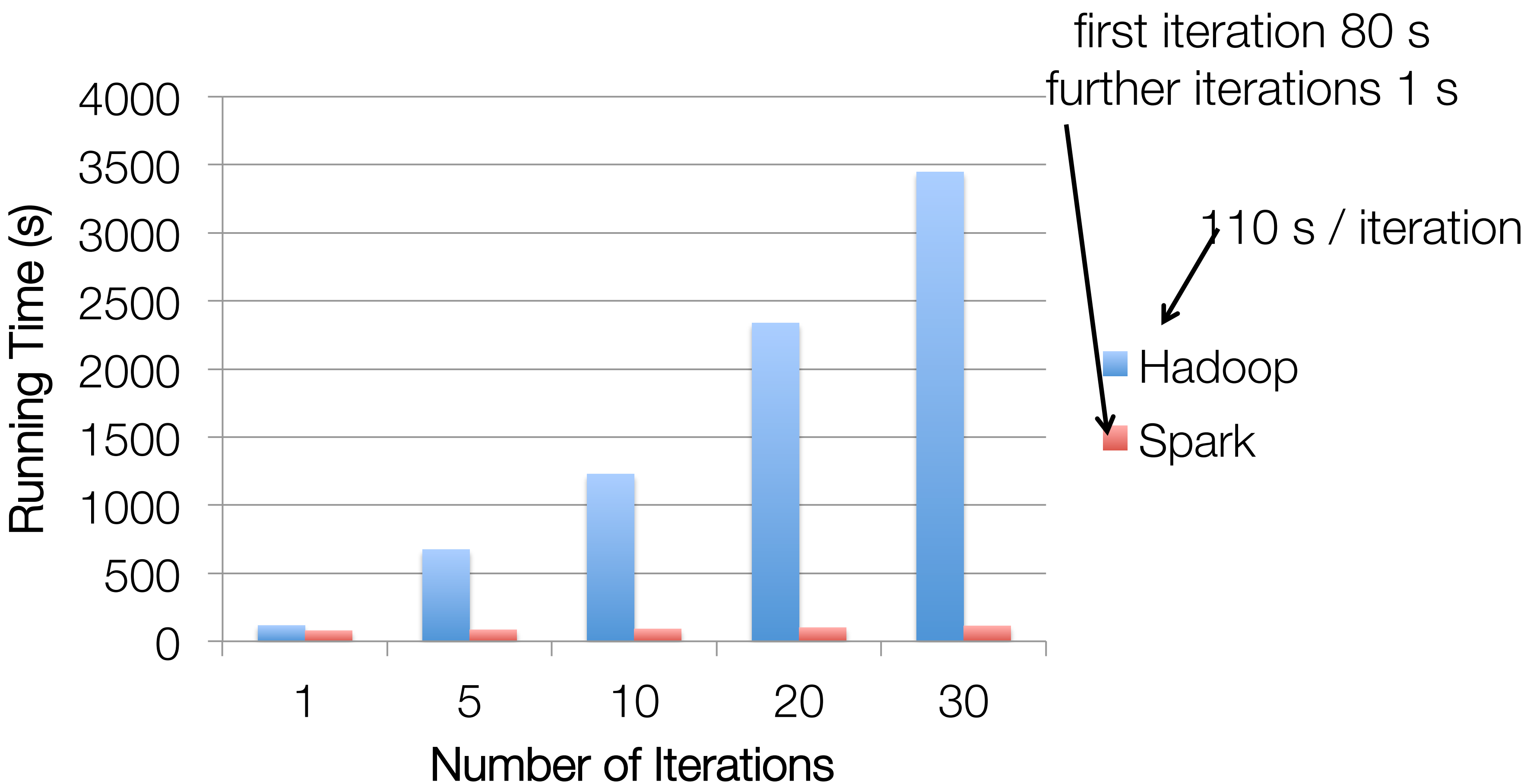
Machine Learning example

Logistic Regression

$$w \leftarrow w - \alpha \cdot \sum_{i=1}^{n} g(w; x_i, y_i)$$

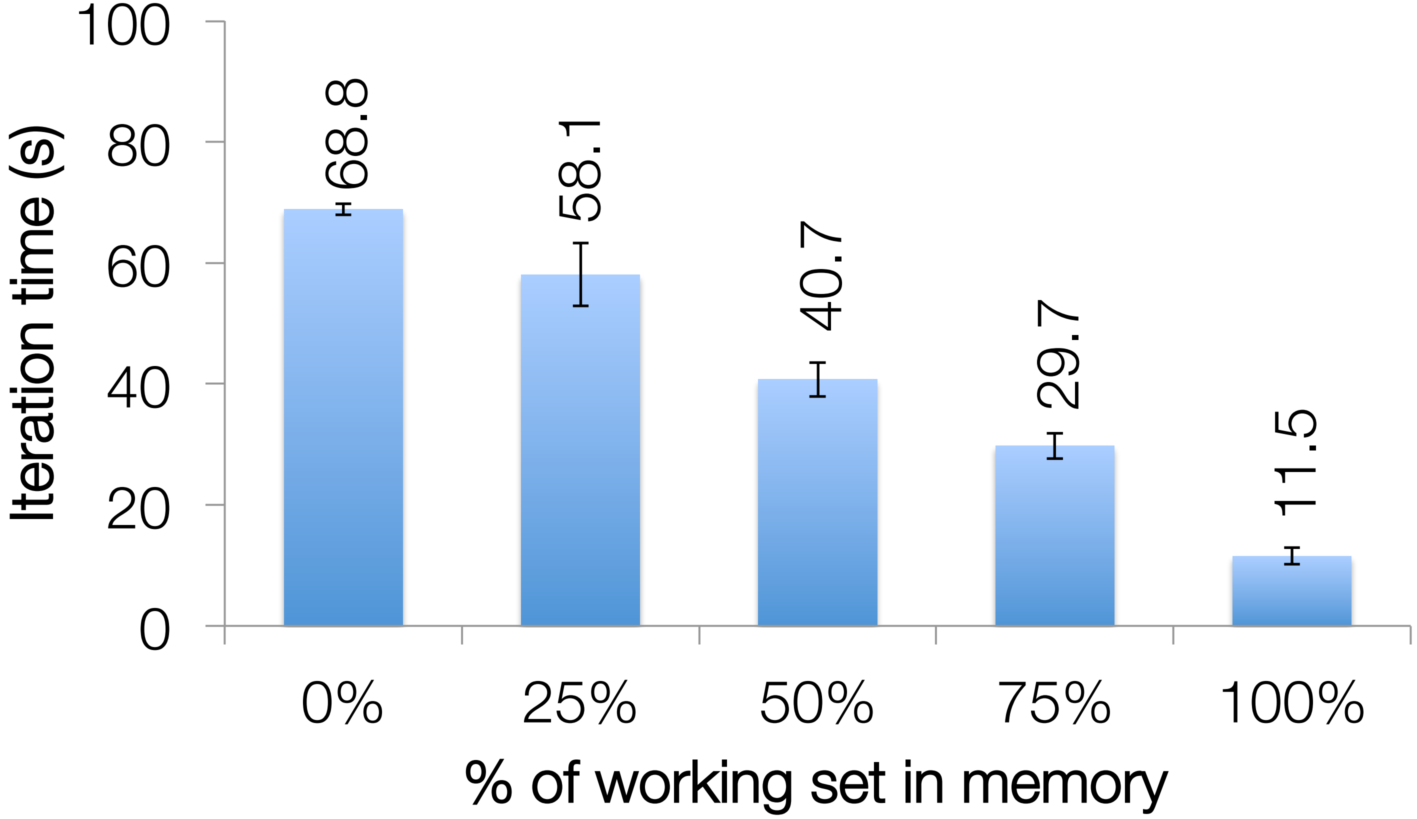
```
val points = spark.textFile(...).map(parsePoint).cache()
var w = Vector.zeros(d)
for (i <- 1 to numIterations) {
  val gradient = points.map { p =>
    (1 / (1 + exp(-p.y * w.dot(p.x)) - 1) * p.y * p.x
  ).reduce(_ + _)
  w -= alpha * gradient
}
```

Logistic Regression Results



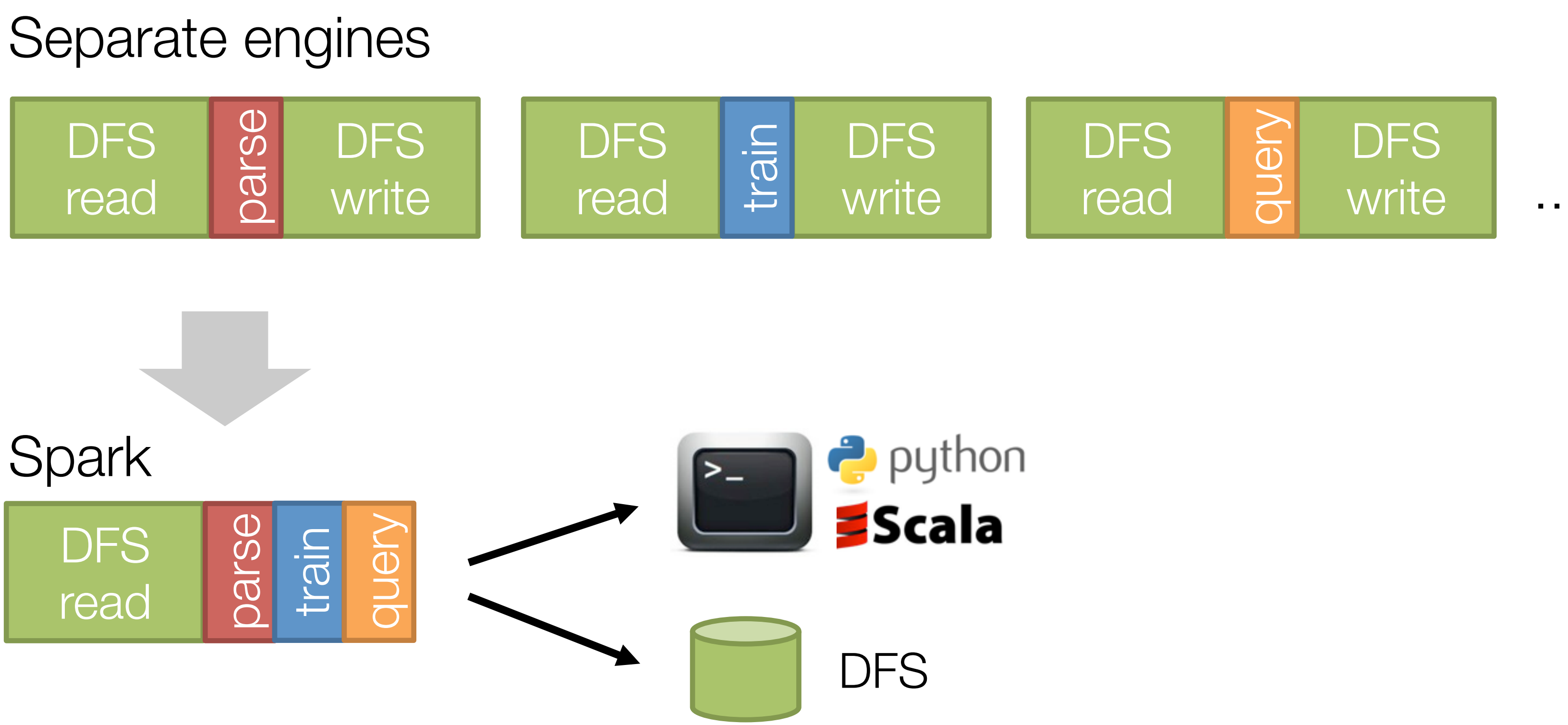
100 GB of data on 50 m1.xlarge EC2 machines

Behavior with Less RAM



Benefit for Users

Same engine performs data extraction, model training and interactive queries



State of the Spark ecosystem

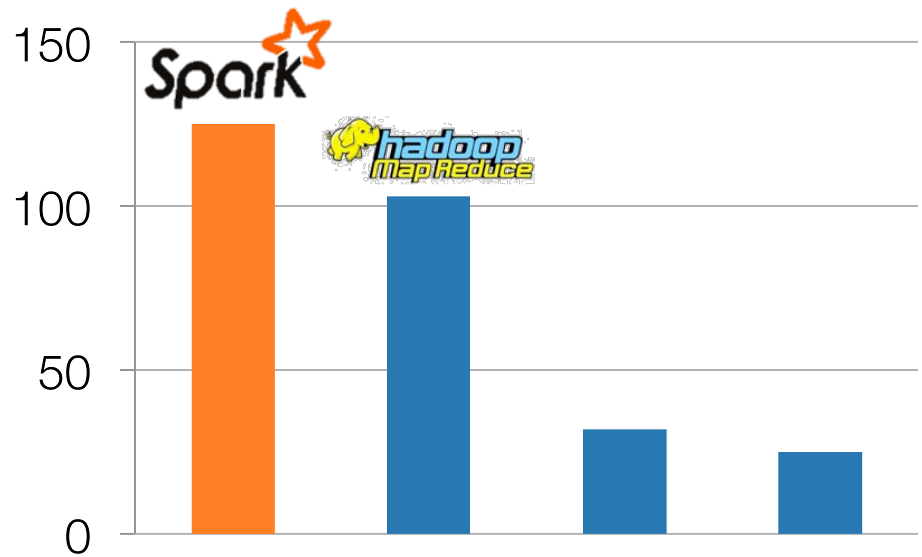
Spark Community

Most active open source community in big data

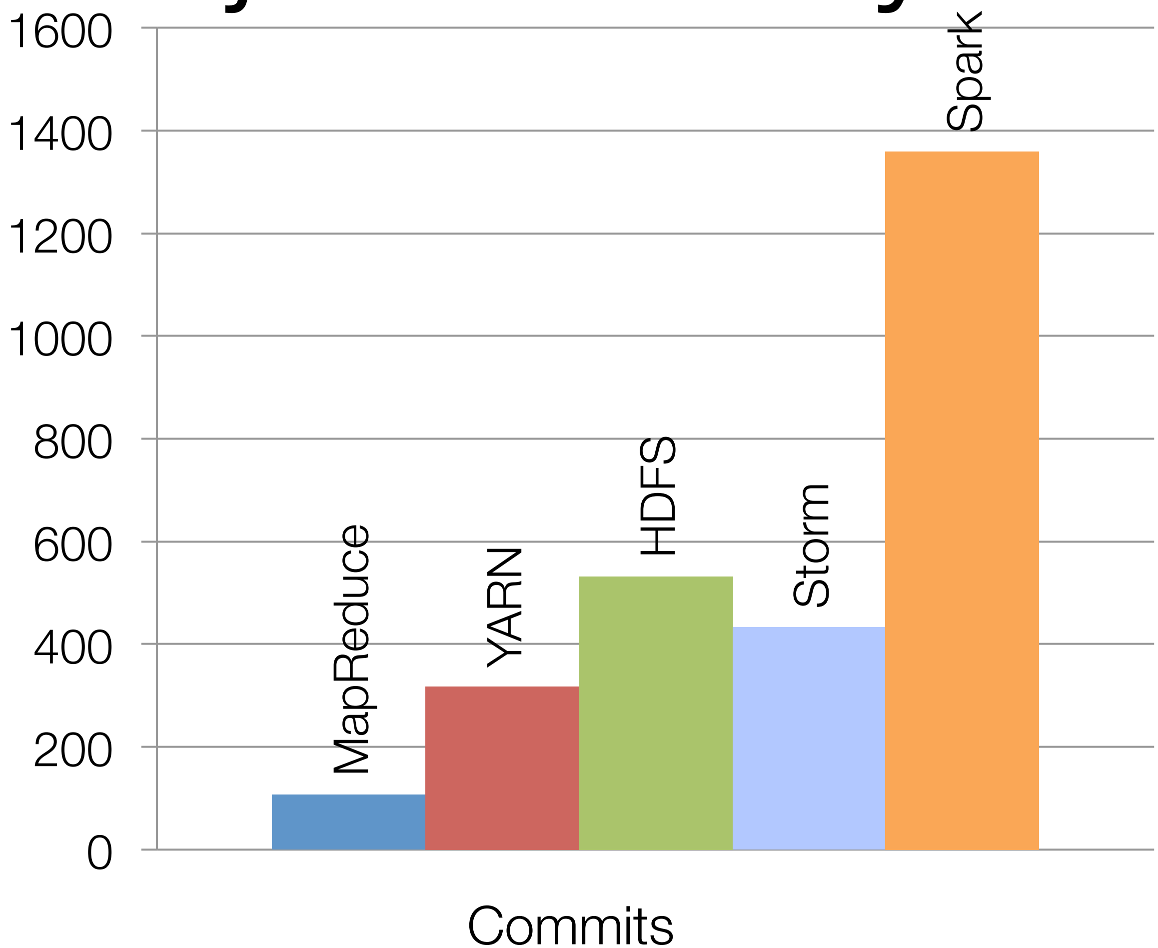
200+ developers,
50+ companies contributing

YAHOO! intel Adobe IBM
redhat amazon web services ebay
cloudera DATASTAX MAPR
阿里巴巴 Alibaba.com ClearStory DATA Now You See It webtrends
bizo CONVIVA DATABRICKS

Contributors in past year



Project Activity



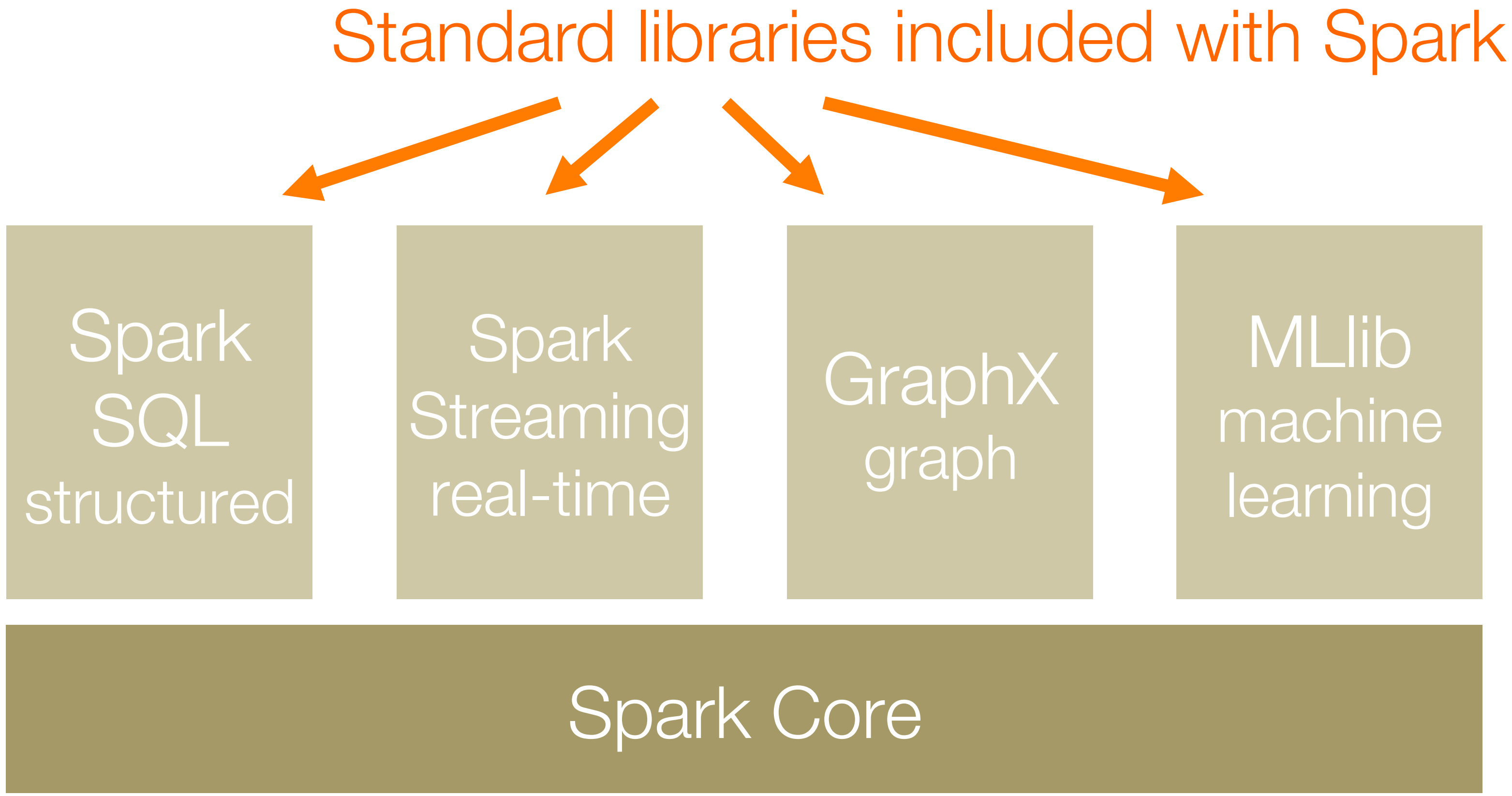
Activity in past 6 months

Continuing Growth

Contributors per month to Spark

source: ohloh.net

A General Platform



Conclusion

Data flow engines are becoming an important platform for numerical algorithms

While early models like MapReduce were inefficient, new ones like Spark close this gap

More info: spark.apache.org