Distributed Computing with Spark

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DATABRICKS

Spark

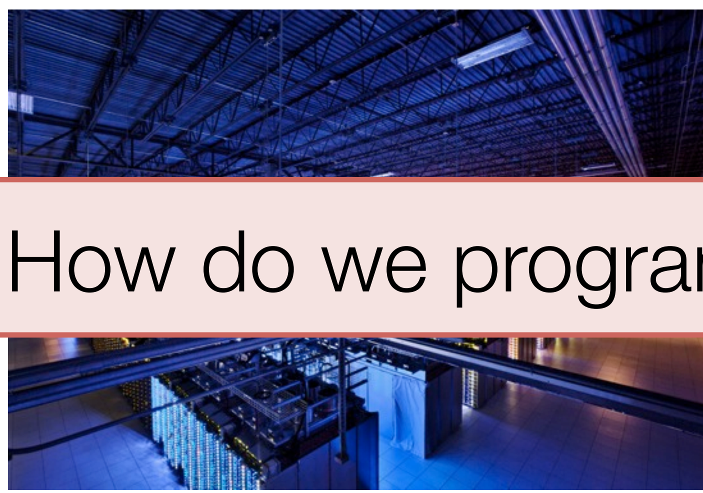
Thanks to Matei Zaharia

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

Built-in Libraries

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 (node not failed, but slow)
- » Ethernet networking not fast
- » Have to write programs for each machine

Rarely used in commodity datacenters

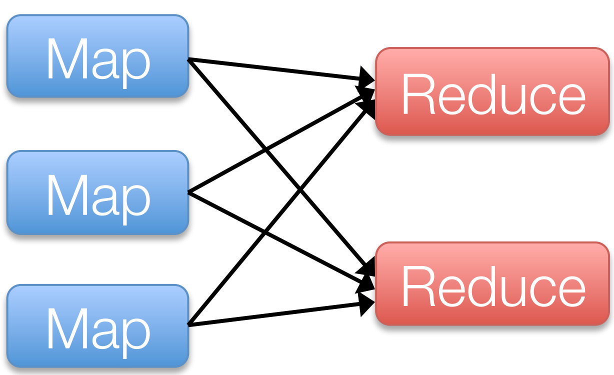
Data Flow Models

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

» Even HPC world is now concerned about resilience

Examples: Pig, Hive, Scalding, Storm

Limitations of MapReduce

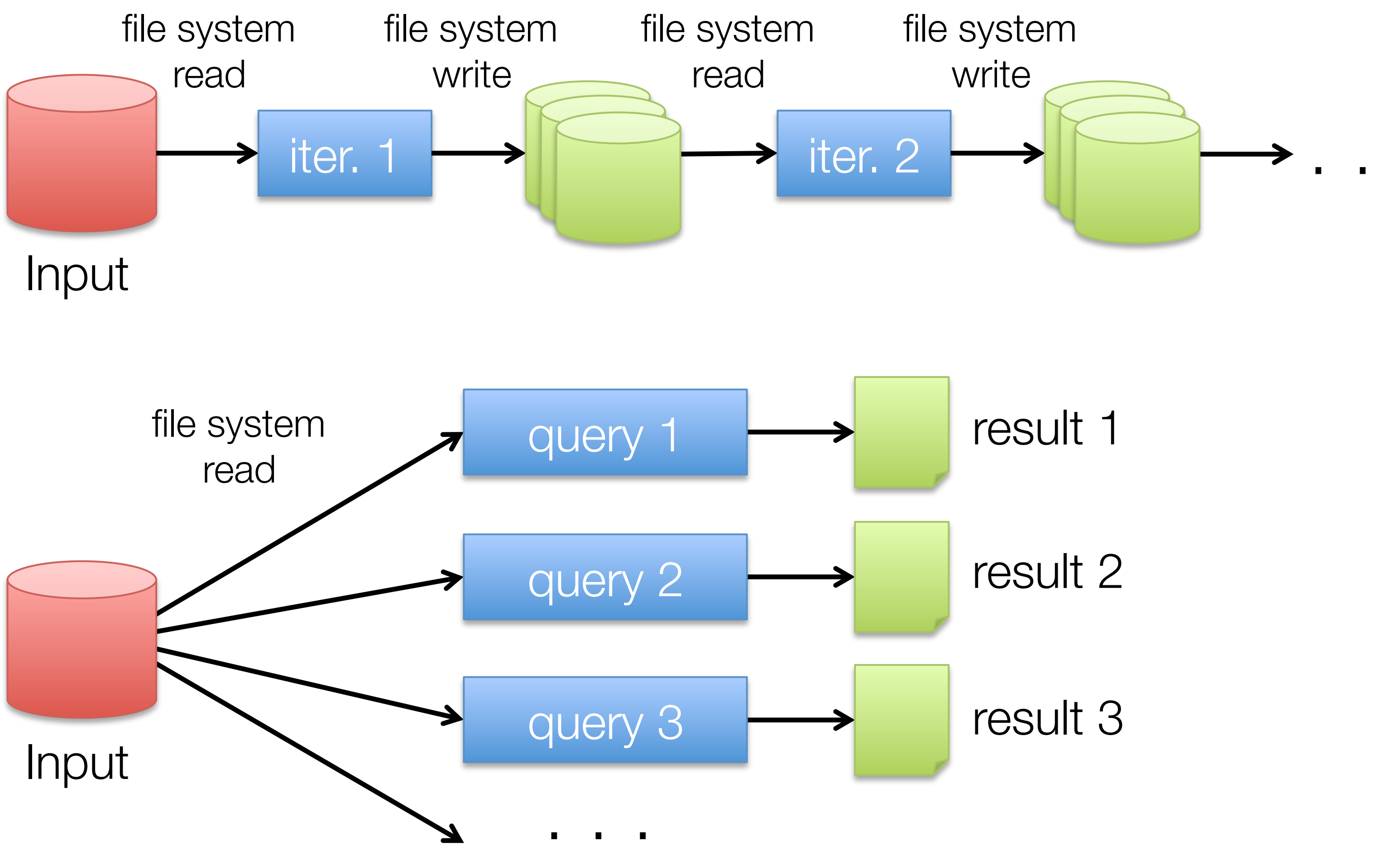
Limitations of MapReduce

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

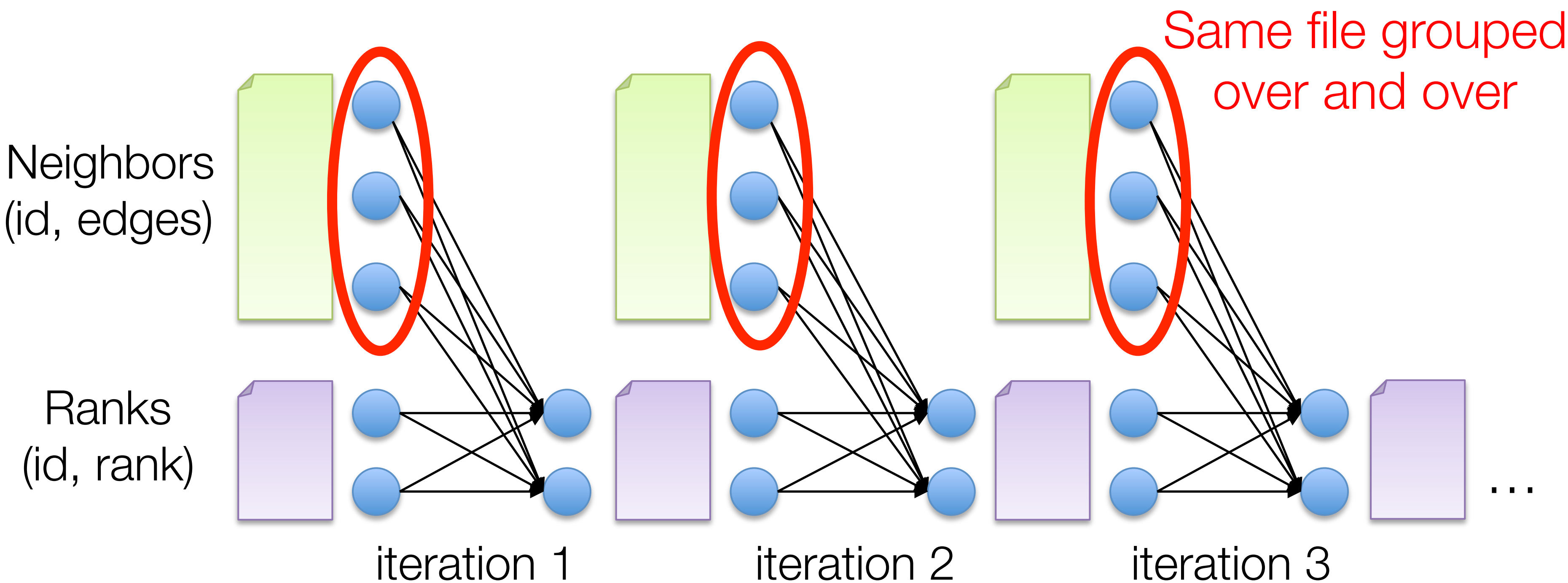


Commonly spend 90% of time doing I/O

Example: PageRank

Repeatedly multiply sparse matrix and vector

Requires repeatedly hashing together page adjacency lists and rank vector



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, R

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))

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

→ lazily evaluated

→ 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

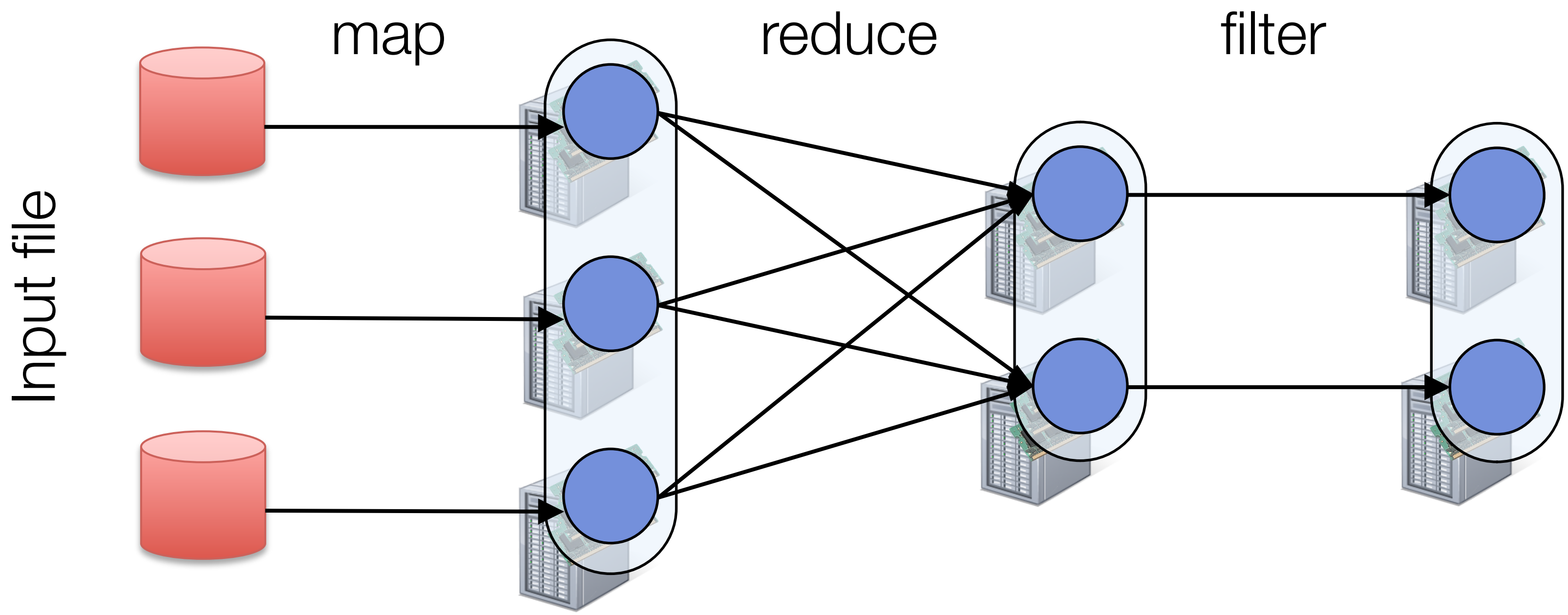
Python, Java, Scala, R

```
// Scala:

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


// Java:

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)
```



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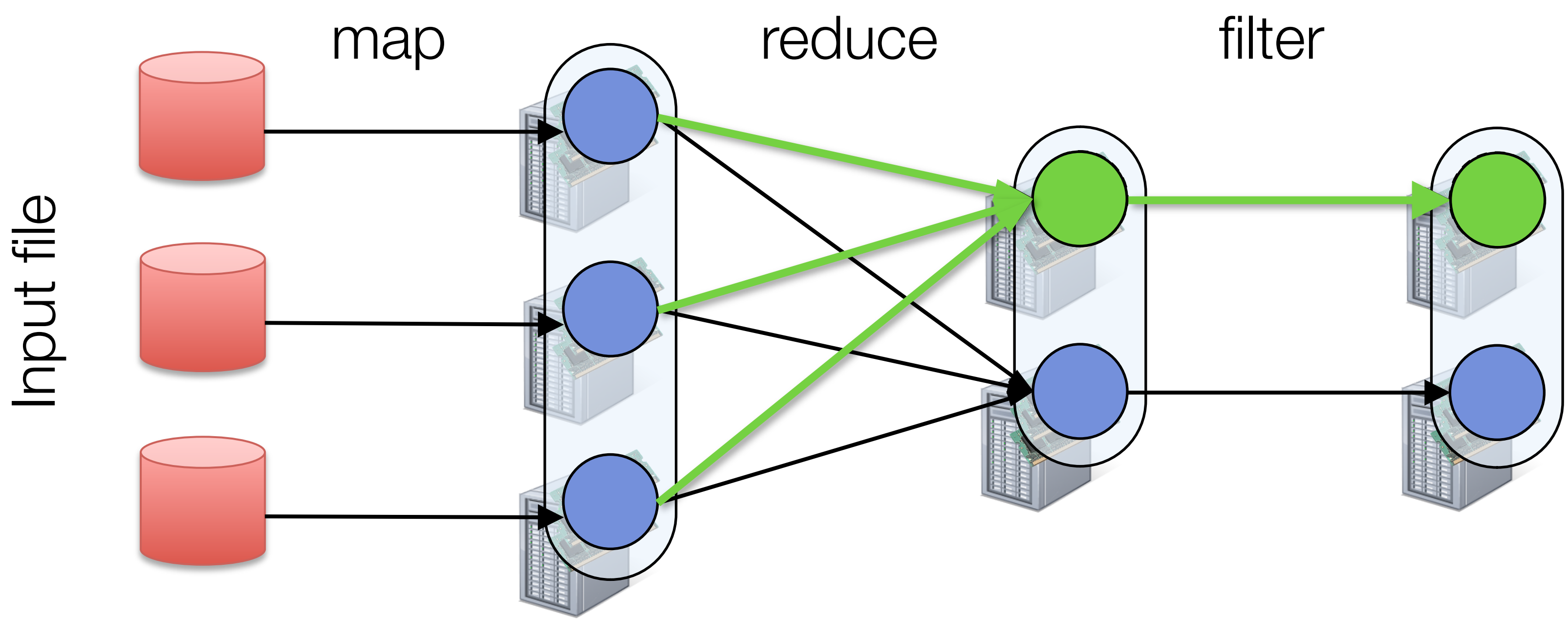

Partitioning

RDDs know their partitioning functions

```
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```
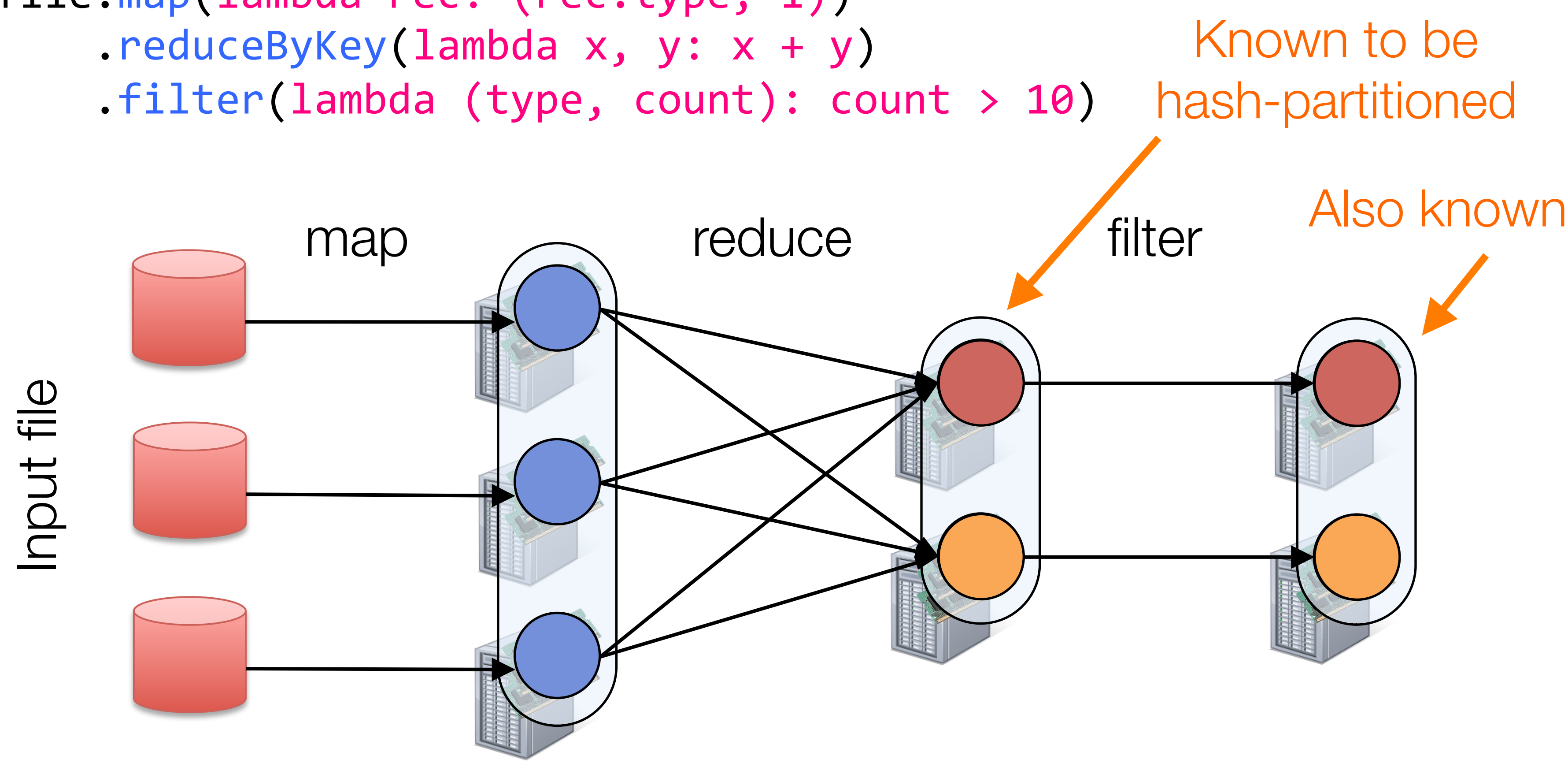



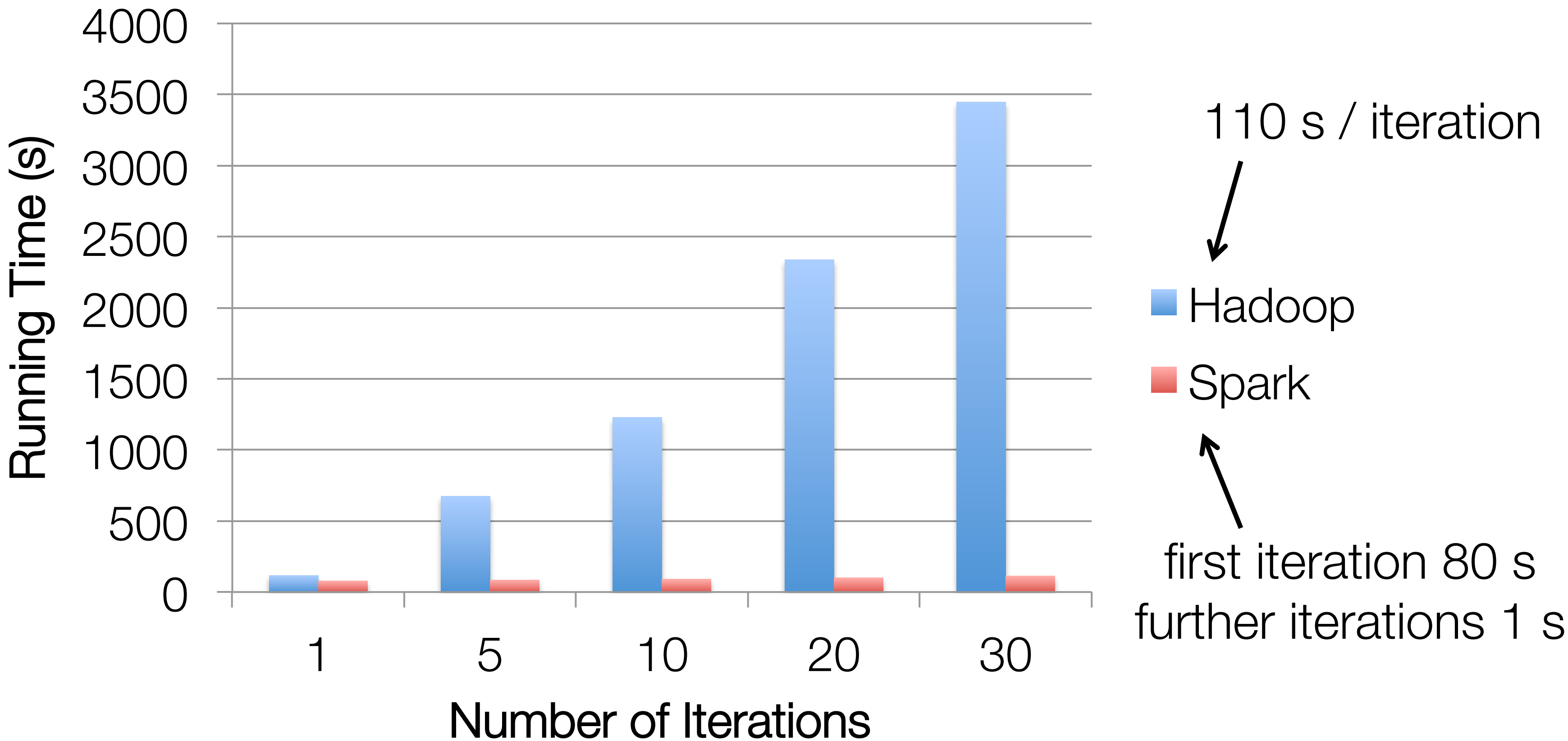
Machine Learning example

Logistic Regression

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

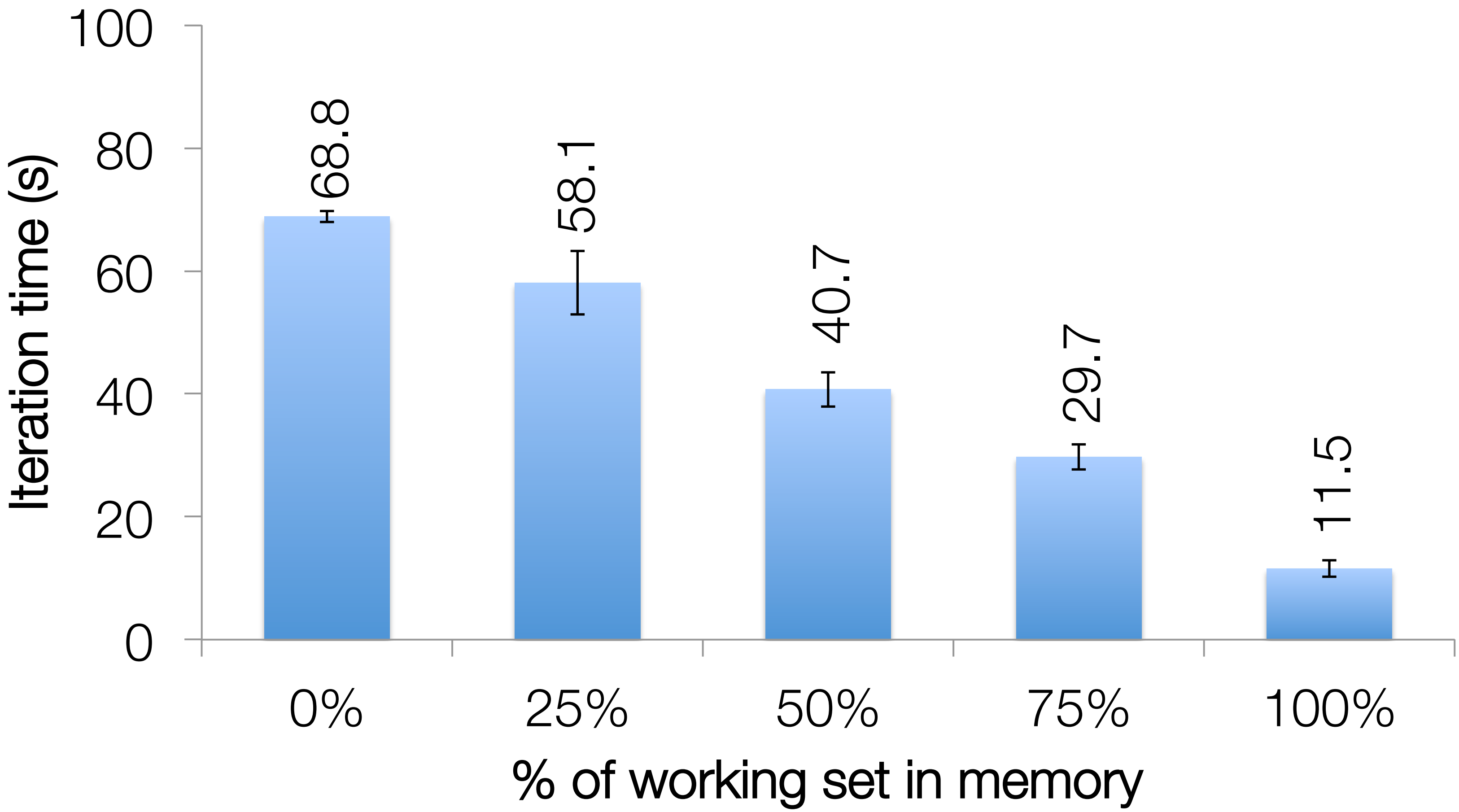
```
val points = spark.textFile(...).map(parsePoint).cache()
var w = Vector.zeros(d)
for (i <- 1 to numIterations) {
  val gradient = points.map { p =>
    (1 / (1 + exp(-p.y * w.dot(p.x)) - 1) * p.y * p.x
  ).reduce(_ + _)
  w -= alpha * gradient
}
```

Logistic Regression Results



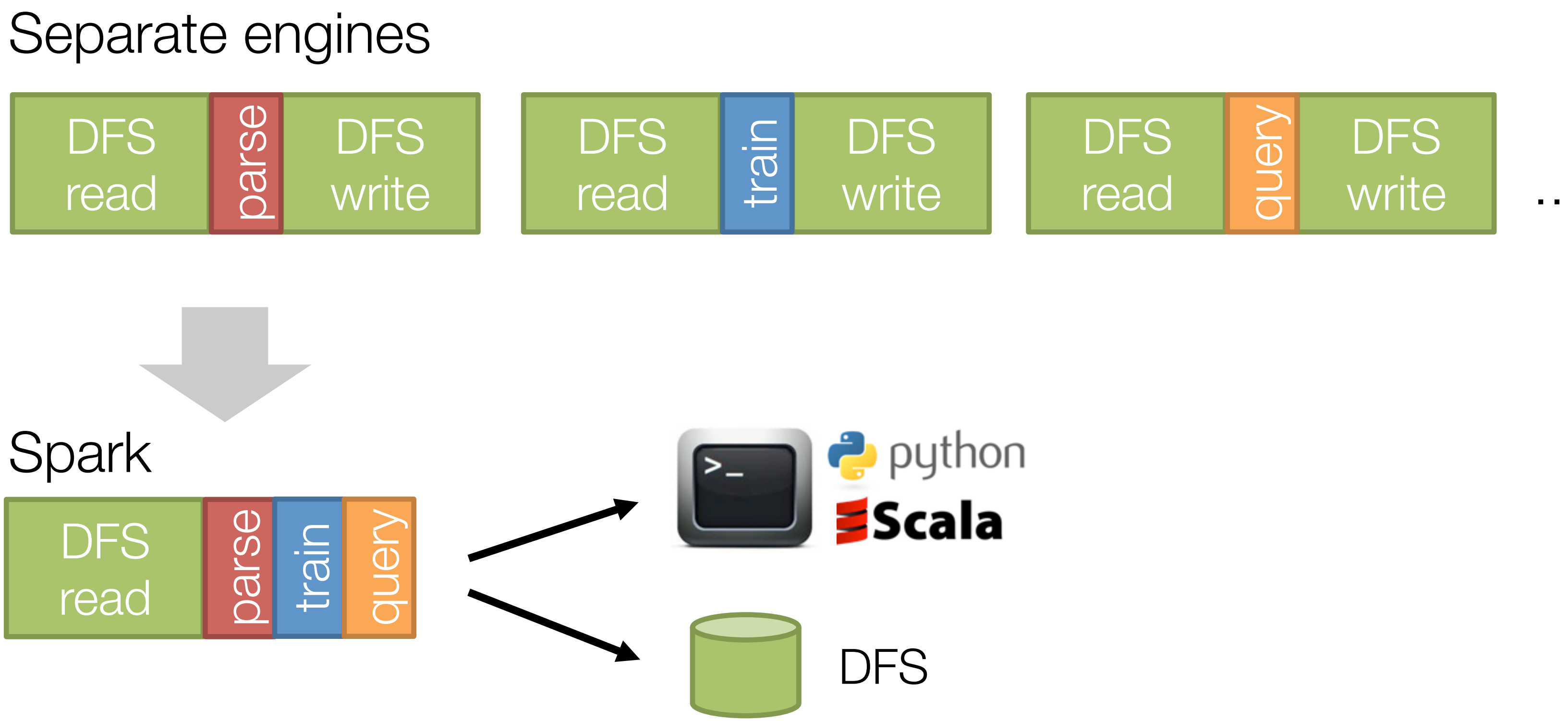
100 GB of data on 50 m1.xlarge EC2 machines

Behavior with Less RAM



Benefit for Users

Same engine performs data extraction, model training and interactive queries



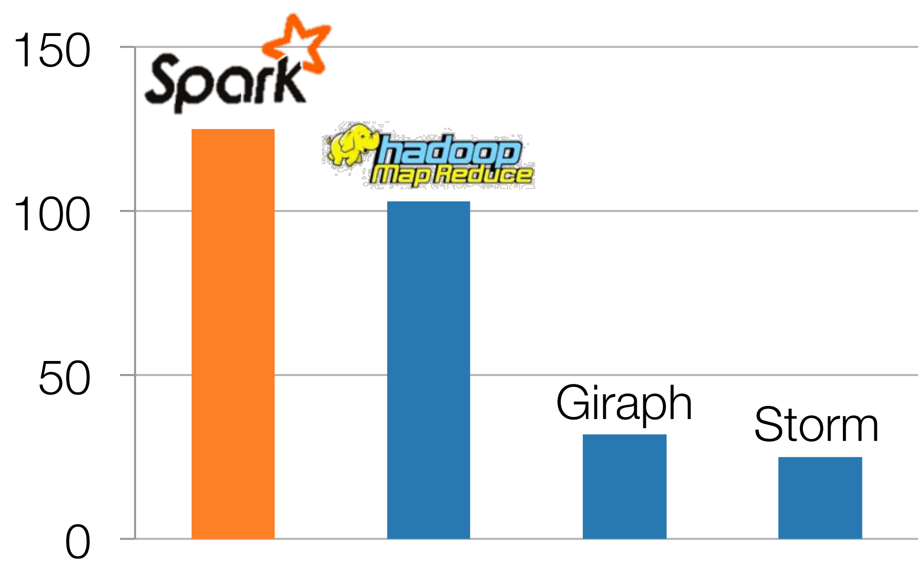
State of the Spark ecosystem

Spark Community

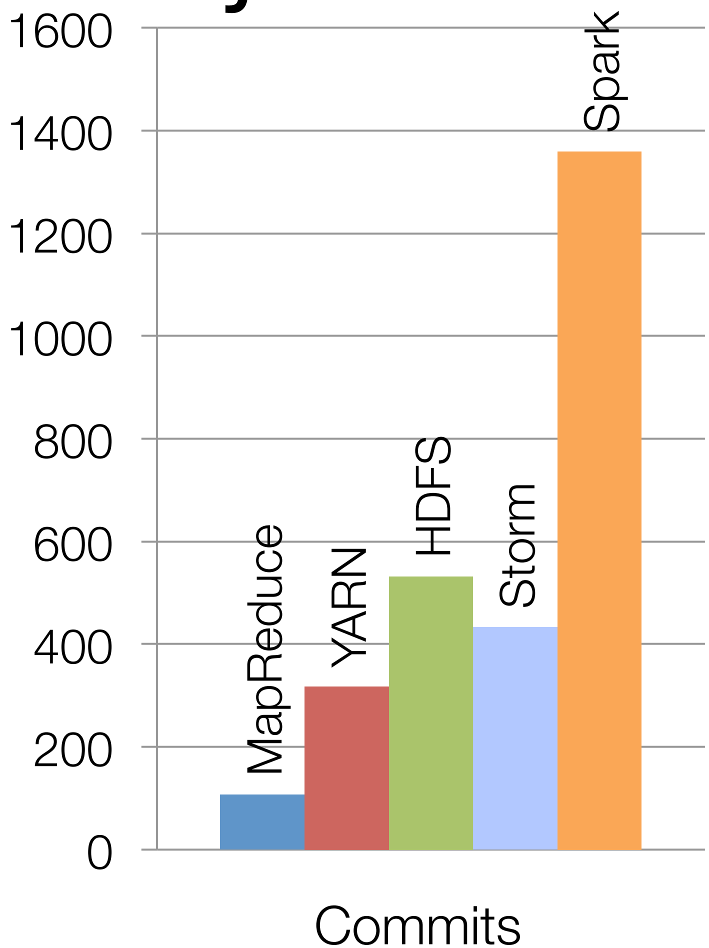
Most active open source community in big data

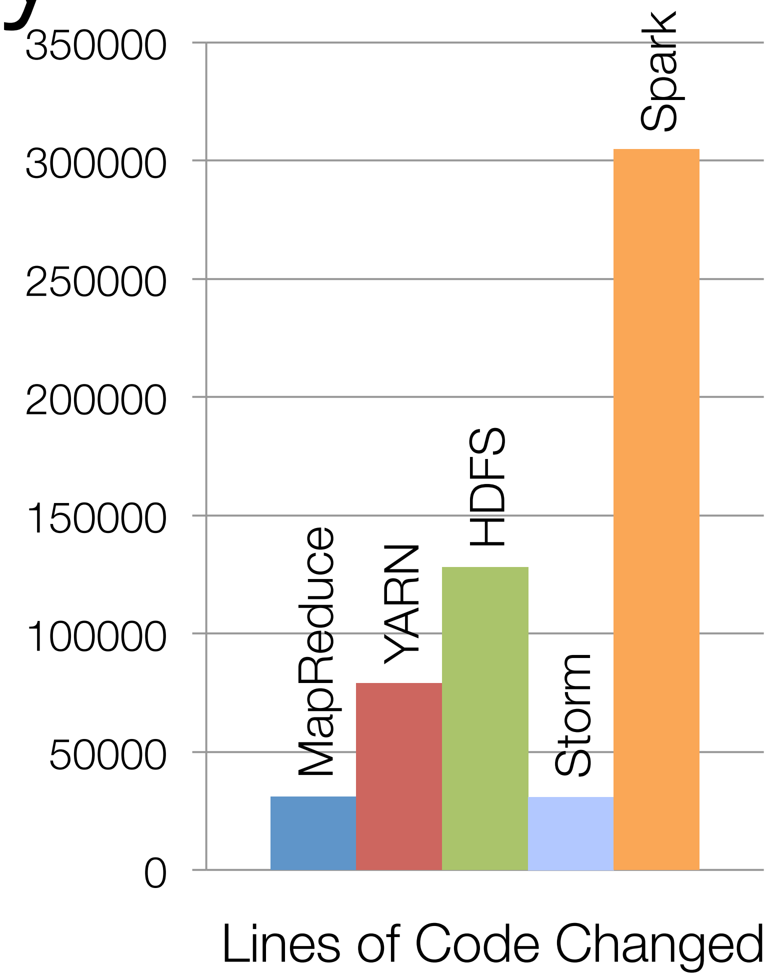
200+ developers, 50+ companies contributing

Contributors in past year



Project Activity





Activity in past 6 months

Continuing Growth

Contributors per month to Spark

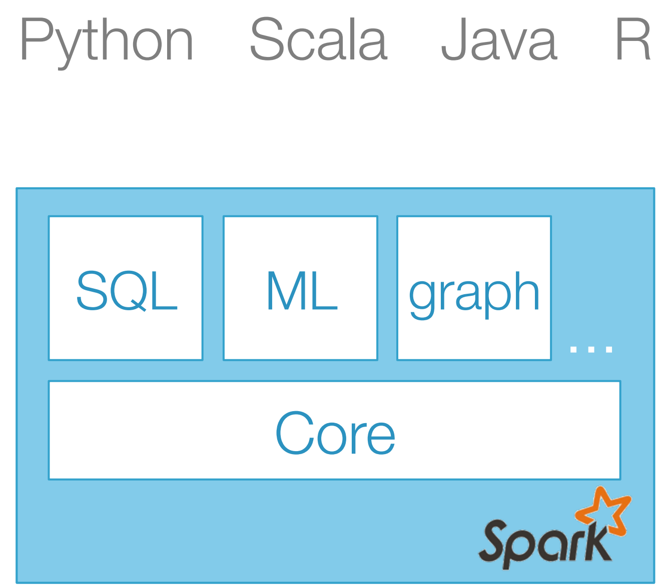
source: ohloh.net

Built-in libraries

Standard Library for Big Data

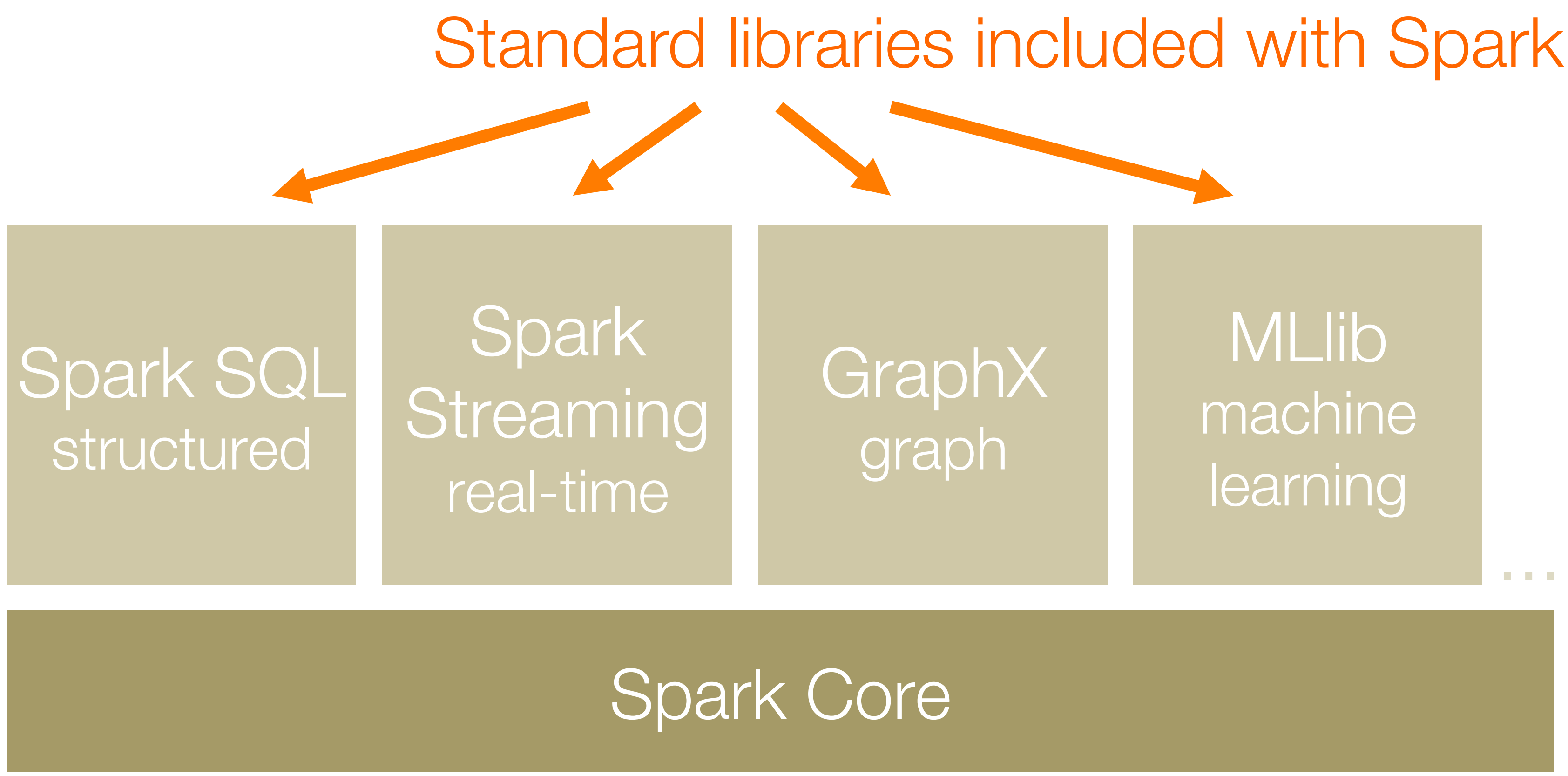
Big data apps lack libraries of common algorithms

Spark's generality + support for multiple languages make suitable to offer this



Much of future activity will be in these libraries

A General Platform



Machine Learning Library (MLlib)

```
points = context.sql("select latitude, longitude from tweets")
model = KMeans.train(points, 10)
```

40 contributors in past year

MLlib algorithms

classification: logistic regression, linear SVM, naïve Bayes, classification tree

regression: generalized linear models (GLMs), regression tree

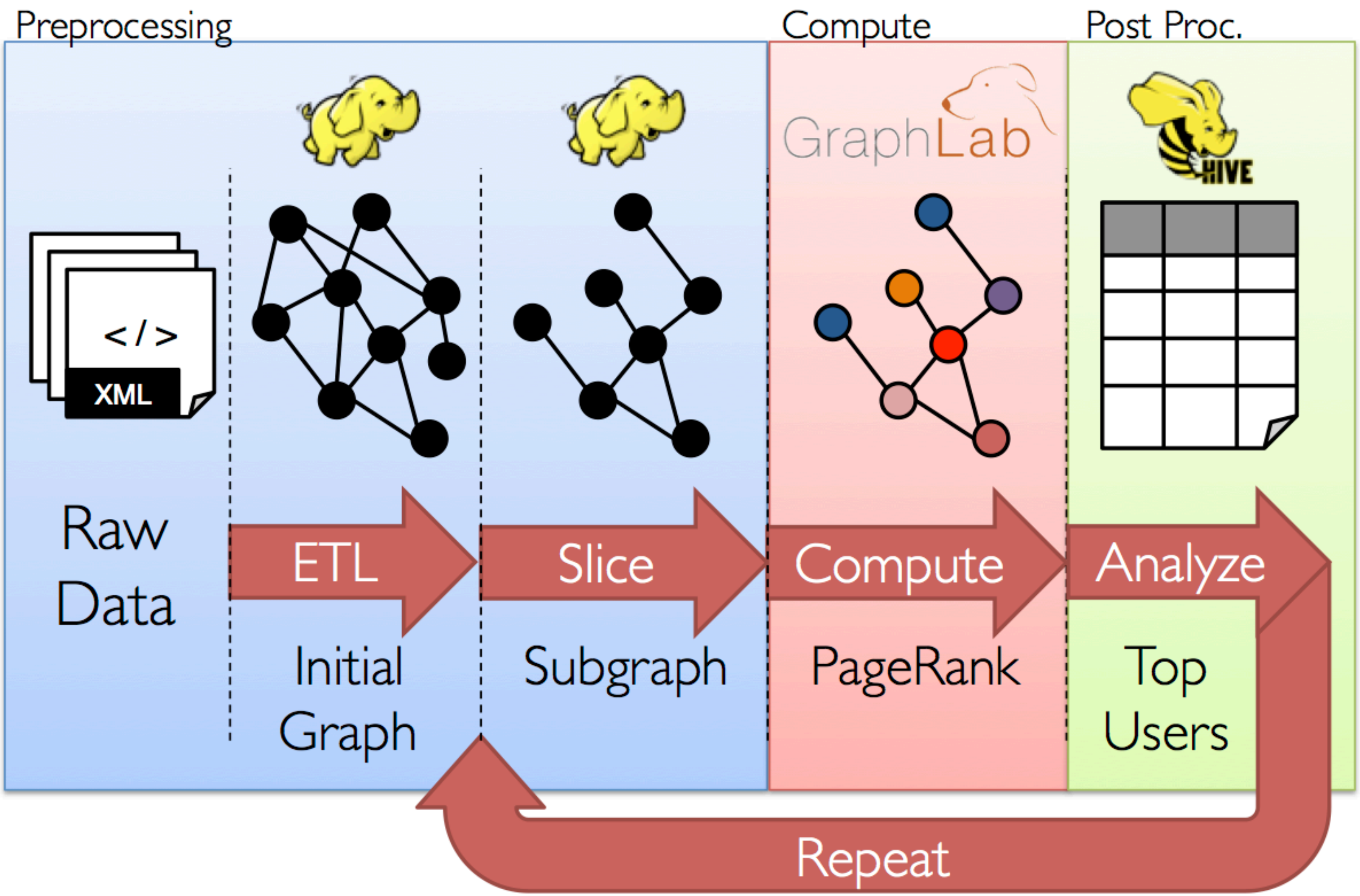
collaborative filtering: alternating least squares (ALS), non-negative matrix factorization (NMF)

clustering: k-means||

decomposition: SVD, PCA

optimization: stochastic gradient descent, L-BFGS

GraphX


Preprocessing
Compute
Post Proc.
GraphLab
HIVE
</>
XML
Raw Data
ETL
Initial Graph
Slice
Subgraph
Compute
PageRank
Analyze
Top Users
Repeat

GraphX

General graph processing library

Build graph using RDDs of nodes and edges

Large library of graph algorithms with composable steps

GraphX Algorithms

Collaborative Filtering

» Alternating Least Squares
» Stochastic Gradient Descent
» Tensor Factorization

Structured Prediction

» Loopy Belief Propagation
» Max-Product Linear Programs
» Gibbs Sampling

Semi-supervised ML

» Graph SSL
» CoEM

Community Detection

» Triangle-Counting
» K-core Decomposition
» K-Truss

Graph Analytics

» PageRank
» Personalized PageRank
» Shortest Path
» Graph Coloring

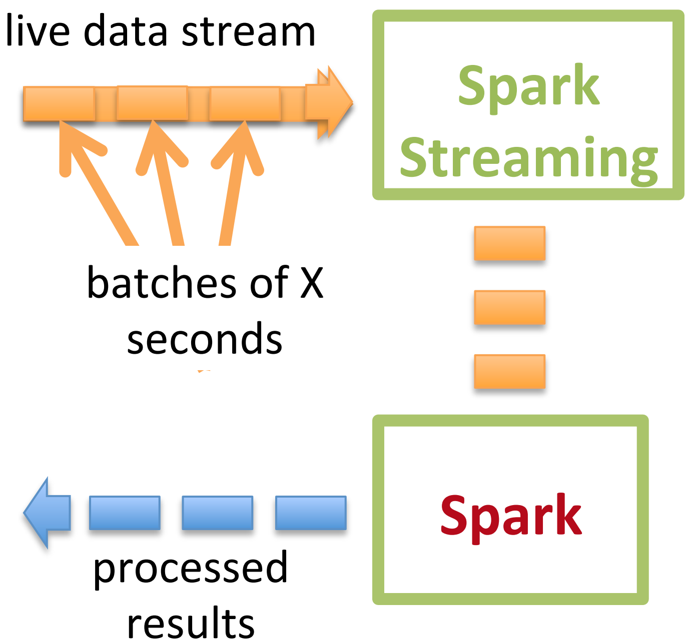
Classification

» Neural Networks

Spark Streaming

Run a streaming computation as a **series of very small, deterministic batch jobs**

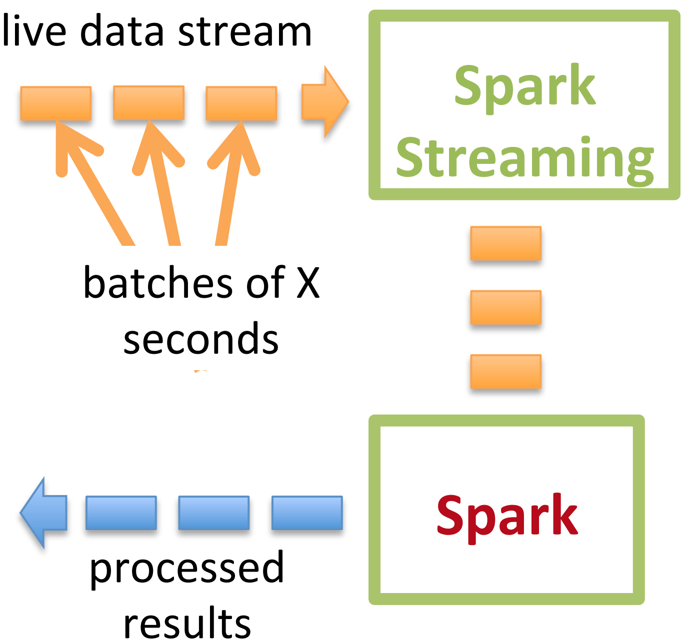
- Chop up the live stream into batches of X seconds
- Spark treats each batch of data as RDDs and processes them using RDD operations
- Finally, the processed results of the RDD operations are returned in batches



Spark Streaming

Run a streaming computation as a **series of very small, deterministic batch jobs**

- Batch sizes as low as ½ second, latency ~ 1 second
- Potential for combining batch processing and streaming processing in the same system



Spark SQL

```
// Run SQL statements
val teenagers = context.sql(
  "SELECT name FROM people WHERE age >= 13 AND age <= 19")


// The results of SQL queries are RDDs of Row objects
val names = teenagers.map(t => "Name: " + t(0)).collect()
```

Spark SQL

Enables loading & querying structured data in Spark

From Hive:

```
c = HiveContext(sc)
rows = c.sql("select text, year from hivetable")
rows.filter(lambda r: r.year > 2013).collect()
```

From JSON:

```
c.jsonFile("tweets.json").registerAsTable("tweets")
c.sql("select text, user.name from tweets")
```

tweets.json


```
{"text": "hi",
 "user": {
  "name": "matei",
  "id": 123
}}
```

Conclusions

Spark and Research

Spark has all its roots in research, so we hope to keep incorporating new ideas!

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

Class Schedule

Schedule

Today and tomorrow

Hands-on exercises, download course materials and slides: http://stanford.edu/~rezab/sparkclass/

Friday

Advanced talks on Spark libraries and uses