Big Data - Analytics with Spark

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Outline

- Why Spark
- The Spark programming model
- Language and deployment choices
- Example algorithm (PageRank)

Introduction

What is Spark?

Fast and **Expressive** Cluster Computing
Engine Compatible with Apache Hadoop

Up to **10×** faster on disk,
100× in memory

2-5× less code

Efficient

- General execution graphs
- In-memory storage

Usable

- Rich APIs in Java, Scala, Python
- Interactive shell

Background

- Hadoop introduced a radical new approach based on two key concepts
  - Distribute data when the data is stored
  - Move computation to data
- Spark takes this new approach to the next level
  - Data is distributed in memory
- Apache Spark is a fast, general engine for large scale data processing on a cluster
  - Originally developed at AMPLab at UC Berkeley
  - Started as a research project in 2009
  - The creators founded Databricks to commercialize Spark

The Spark Community

March 27th 2010 - November 30th 2013
Commits to master, excluding merge commits

Contribution Type: **Commits**

amplab UC BERKELEY
databricks™
YAHOO!
amazon web services™
WANdisco
intel
cloudera
阿里巴巴 Alibaba.com
Hortonworks
CLOUD PHYSICS
guavus Go Decisively
CONVIVA
Adobe
AdMobius
ClearStory DATA Now You See It
IBM
TAGGED
stratio
bizo
webtrends
ADATAO BIG DATA INTELLIGENCE
sharethrough
HHMI janelia farm research campus
OOYALA
quantiFind
tuplejump
MAPR TECHNOLOGIES

Get Started

Up and Running in a Few Steps

- Download
- Unzip
- Shell

Project Resources

- Examples on the Project Site
- Examples in the Distribution
- Documentation

http://spark.apache.org

Spark Programming Model

Key Concept: RDD’s

Write programs in terms of **operations** on **distributed datasets**

Resilient Distributed Datasets

- Collections of objects spread across a cluster, stored in RAM or on Disk
- Built through parallel transformations
- Automatically rebuilt on failure

Operations

- Transformations (e.g. map, filter, groupBy)
- Actions (e.g. count, collect, save)

RDD

- RDD (Resilient Distributed Dataset)
  - Resilient – if data in memory is lost, it can be recreated
  - Distributed – stored in memory across the cluster
  - Dataset – initial data can come from a file or be created programmatically
- RDDs are the fundamental unit of data in Spark
- Most Spark programming consists of performing operations on RDDs

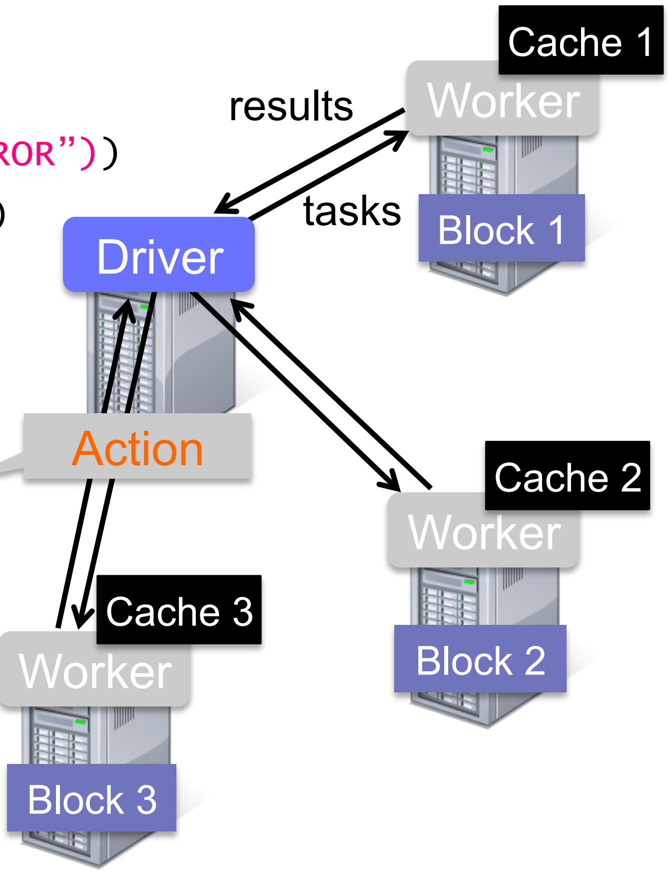
Example: Log Mining

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

Base RDD
Transformed RDD

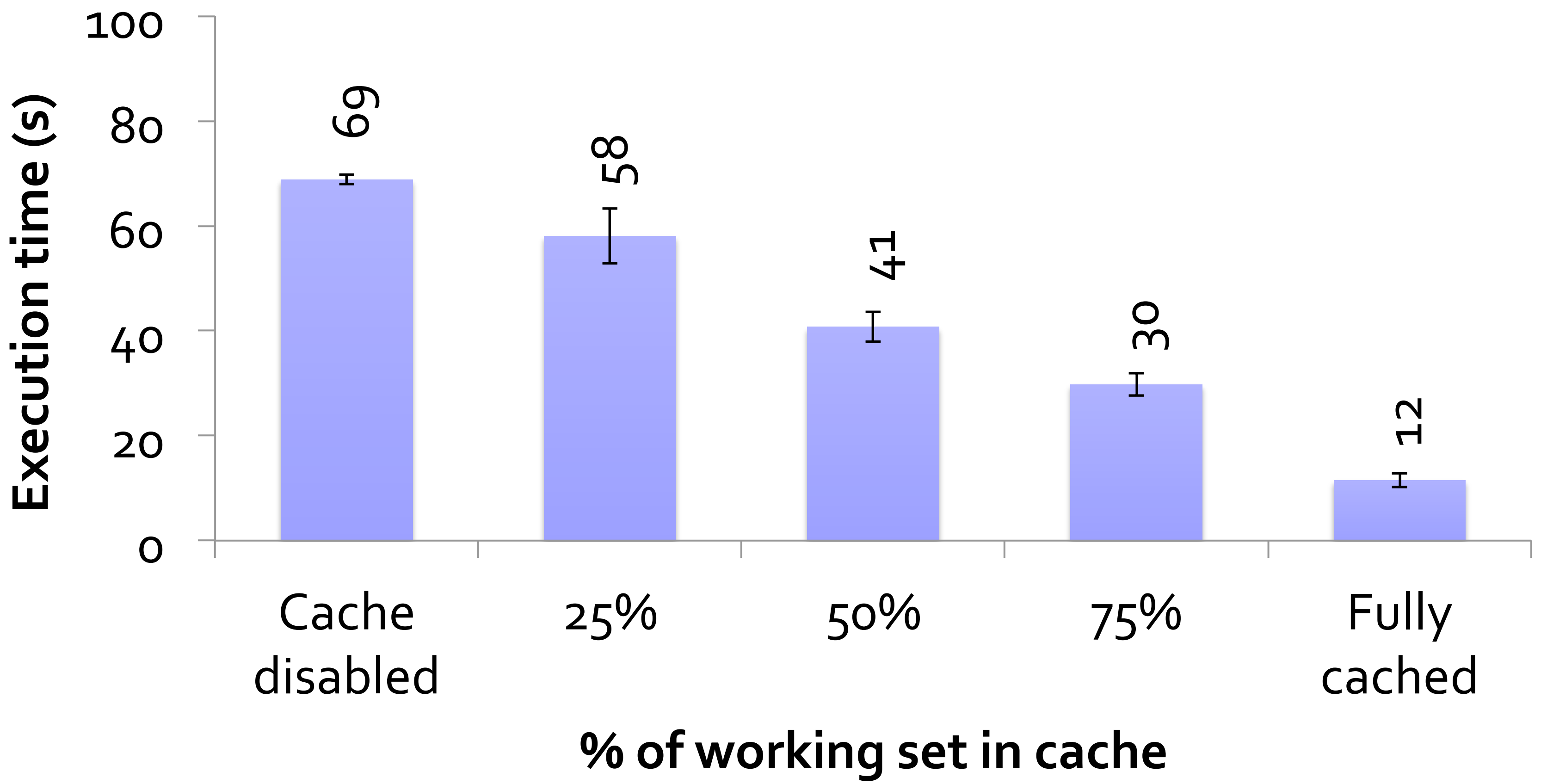
```
lines = spark.textFile(“hdfs://...”)
errors = lines.filter(lambda s: s.startswith(“ERROR”))
messages = errors.map(lambda s: s.split(“\t”)[2])
messages.cache()


messages.filter(lambda s: “mysql” in s).count()
messages.filter(lambda s: “php” in s).count()
. . .
```



Full-text search of Wikipedia
- 60GB on 20 EC2 machine
- 0.5 sec vs. 20s for on-disk

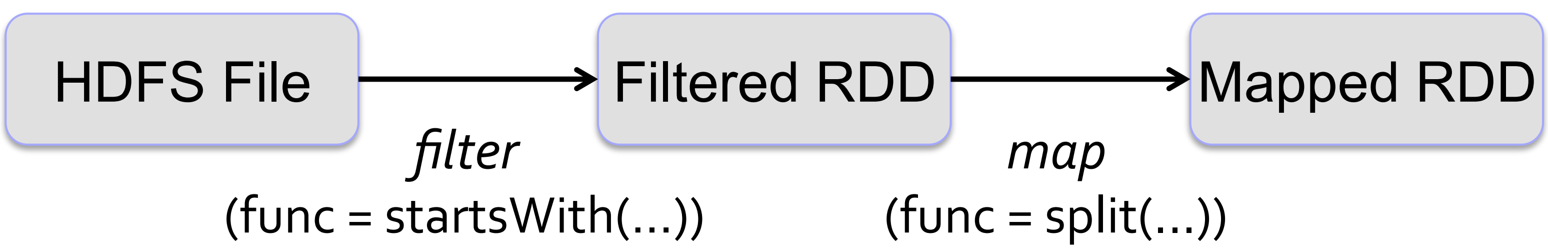
Scaling Down



Fault Recovery

RDDs track *lineage* information that can be used to efficiently recompute lost data

```
msgs = textFile.filter(lambda s: s.startsWith("ERROR"))
               .map(lambda s: s.split("\t")[2])
```



Programming with RDD’s

SparkContext

- Main entry point to Spark functionality
- Available in shell as variable `sc`
- In standalone programs, you'd make your own (see later for details)

Creating RDDs

- Three ways to create an RDD
  - From a file or set of files
  - From data in memory
  - From another RDD

Creating RDDs

```
# Turn a Python collection into an RDD
> sc.parallelize([1, 2, 3])
```

> The elements of the collection are copied to form a distributed dataset that can be operated on in parallel.

```
# Load text file from local FS, HDFS, or S3
> sc.textFile("file.txt")
> sc.textFile("directory/*.txt")
> sc.textFile("hdfs://namenode:9000/path/file")

# Use existing Hadoop InputFormat (Java/Scala only)
> sc.hadoopFile(keyClass, valClass, inputFmt, conf)
```

RDD Operations

- Two types of RDD operations
  - Actions: return values
  - Transformations: define a new RDD based on the current one

Basic Actions

```
> nums = sc.parallelize([1, 2, 3])

# Retrieve RDD contents as a local collection
> nums.collect() # => [1, 2, 3]

# Return first K elements
> nums.take(2)   # => [1, 2]

# Count number of elements
> nums.count()   # => 3

# Merge elements with an associative function
> nums.reduce(lambda x, y: x + y)  # => 6

# Write elements to a text file
> nums.saveAsTextFile("hdfs://file.txt")
```

Transformations

- Transformations create a new RDD from an existing one
- RDDs are immutable
  - Data in an RDD is never changed
  - Transform in sequence to modify the data as needed
- Some common transformations
  - *map(func)* – creates a new RDD by performing a function on each record in the base RDD
  - *filter(function)* – creates a new RDD by including or excluding each record in the base RDD according to a boolean function

Basic Transformations

```
> nums = sc.parallelize([1, 2, 3])

# Pass each element through a function
> squares = nums.map(lambda x: x*x)   // {1, 4, 9}

# Keep elements passing a predicate
> even = squares.filter(lambda x: x % 2 == 0) // {4}

# Map each element to zero or more others
> nums.flatMap(lambda x: => range(x))
  > # => {0, 0, 1, 0, 1, 2}
```

Range object (sequence of numbers 0, 1, …, x-1)

Working with Key-Value Pairs

Spark's "distributed reduce" transformations operate on RDDs of key-value pairs

Python:

```python
pair = (a, b)
pair[0] # => a
pair[1] # => b
```

Scala:

```scala
val pair = (a, b)
pair._1 // => a
pair._2 // => b
```

Java:

```java
Tuple2 pair = new Tuple2(a, b);
pair._1 // => a
pair._2 // => b
```

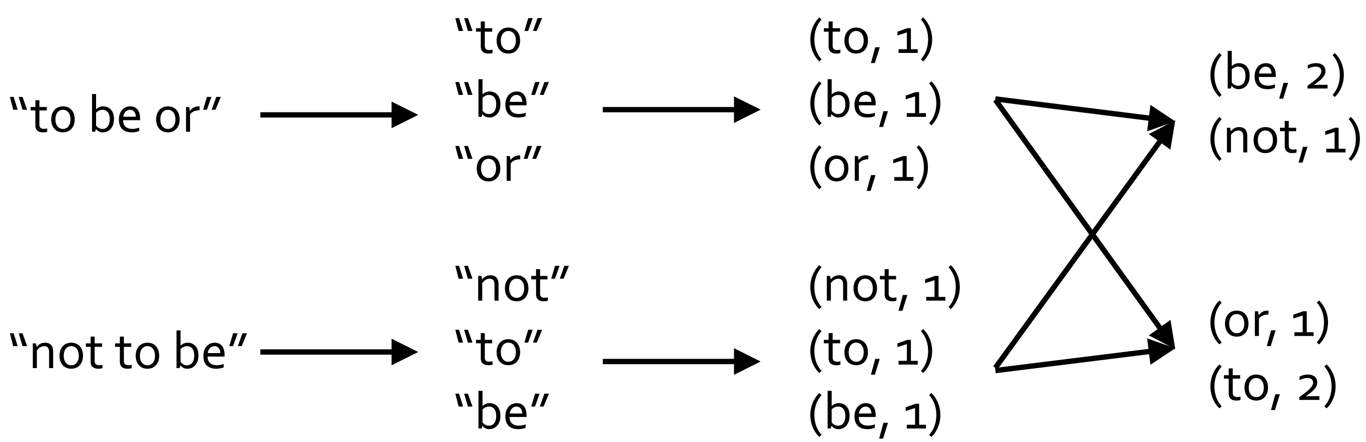
Some Key-Value Operations

```
> pets = sc.parallelize(
    [("cat", 1), ("dog", 1), ("cat", 2)])
> pets.reduceByKey(lambda x, y: x + y)
                        # => {(cat, 3), (dog, 1)}
> pets.groupByKey() # => {(cat, [1, 2]), (dog, [1])}
> pets.sortByKey()  # => {(cat, 1), (cat, 2), (dog, 1)}
```

`reduceByKey` also automatically implements combiners on the map side

Example: Word Count

```
> lines = sc.textFile("hamlet.txt")
> counts = lines.flatMap(lambda line: line.split(" "))
                .map(lambda word => (word, 1))
                .reduceByKey(lambda x, y: x + y)
```



Other Key-Value Operations

```
> visits = sc.parallelize([ (“index.html”, “1.2.3.4”),
                            (“about.html”, “3.4.5.6”),
                            (“index.html”, “1.3.3.1”) ])

> pageNames = sc.parallelize([ (“index.html”, “Home”),
                               (“about.html”, “About”) ])

> visits.join(pageNames)
  # (“index.html”, (“1.2.3.4”, “Home”))
  # (“index.html”, (“1.3.3.1”, “Home”))
  # (“about.html”, (“3.4.5.6”, “About”))

> visits.cogroup(pageNames)
  # (“index.html”, ([“1.2.3.4”, “1.3.3.1”], [“Home”]))
  # (“about.html”, ([“3.4.5.6”], [“About”]))
```

Setting the Level of Parallelism

All the pair RDD operations take an optional second parameter for number of tasks

```
> words.reduceByKey(lambda x, y: x + y, 5)
> words.groupByKey(5)
> visits.join(pageViews, 5)
```

Using Local Variables

Any external variables you use in a closure will automatically be shipped to the cluster:

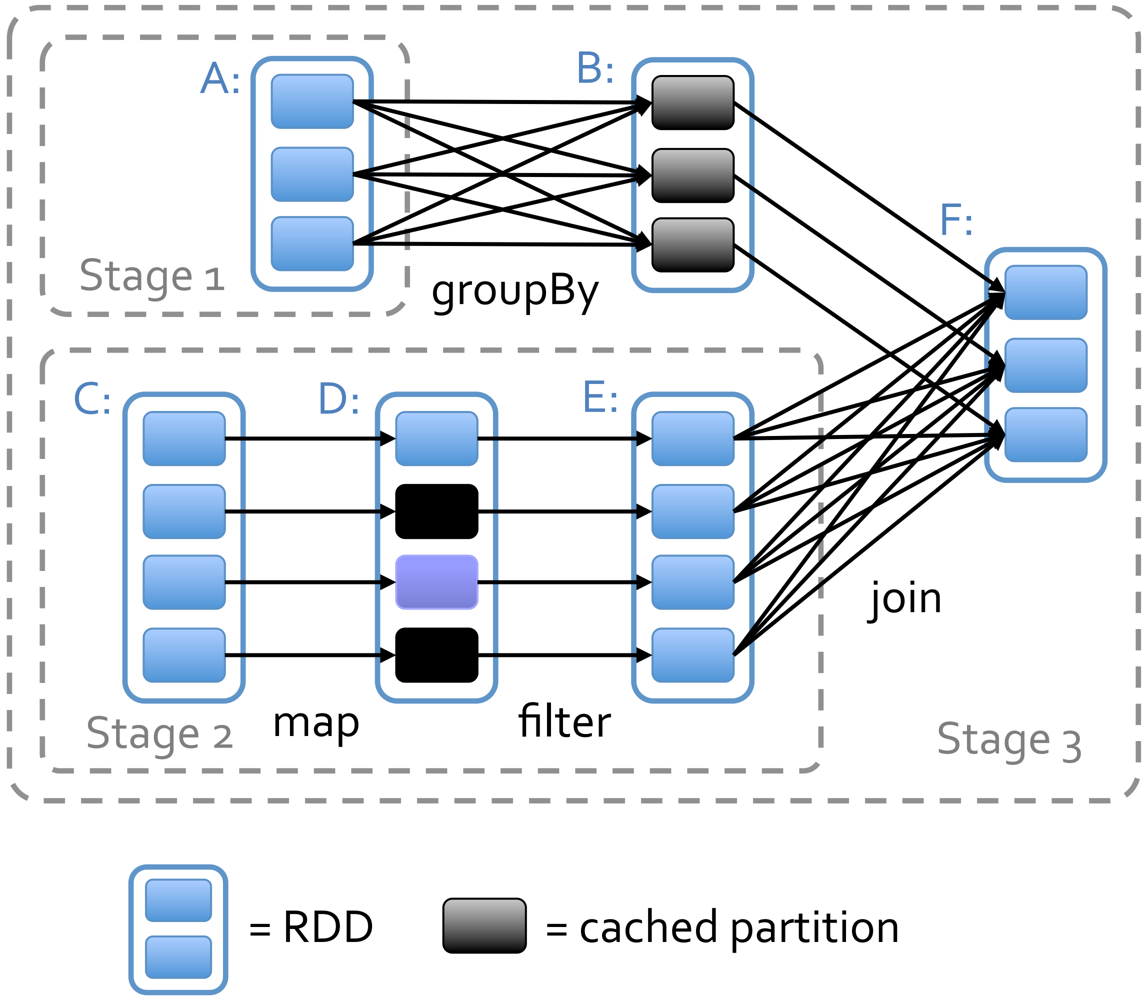
```
> query = sys.stdin.readline()
> pages.filter(lambda x: query in x).count()
```

Some caveats:

- Each task gets a new copy (updates aren't sent back)
- Variable must be Serializable / Pickle-able
- Don't use fields of an outer object (ships all of it!)

Under The Hood: DAG Scheduler

- General task graphs
- Automatically pipelines functions
- Data locality aware
- Partitioning aware to avoid shuffles



More RDD Operators

- map
- filter
- groupBy
- sort
- union
- join
- leftOuterJoin
- rightOuterJoin

- reduce
- count
- fold
- reduceByKey
- groupByKey
- cogroup
- cross
- zip

sample
take
first
partitionBy
mapWith
pipe
save ...

How to Run Spark

Language Support

Python

```
lines = sc.textFile(...)
lines.filter(lambda s: "ERROR" in s).count()
```

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();
```

Standalone Programs

- Python, Scala, & Java

Interactive Shells

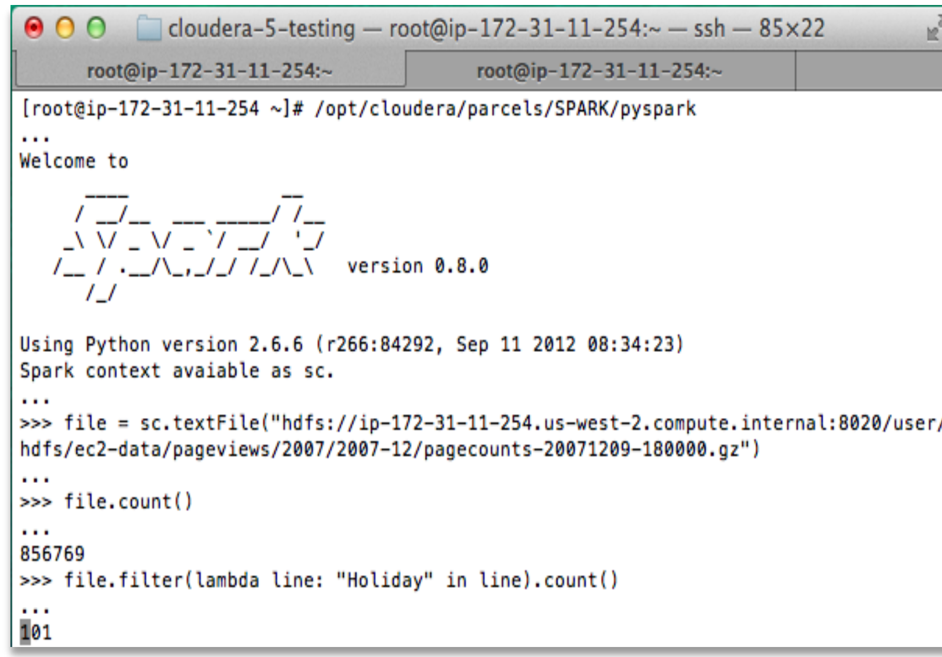
- Python & Scala

Performance

- Java & Scala are faster due to static typing
- …but Python is often fine

Interactive Shell

- The Fastest Way to Learn Spark
- Available in Python and Scala
- Runs as an application on an existing Spark Cluster…
- OR Can run locally



… or a Standalone Application

```
import sys
from pyspark import SparkContext

if __name__ == "__main__":
    sc = SparkContext( “local”, “WordCount”,
                     sys.argv[0], None)
    lines = sc.textFile(sys.argv[1])

    counts = lines.flatMap(lambda s: s.split(“ ”)) \
                  .map(lambda word: (word, 1)) \
                  .reduceByKey(lambda x, y: x + y)

    counts.saveAsTextFile(sys.argv[2])
```

Create a SparkContext

Scala

```
import org.apache.spark.SparkContext
import org.apache.spark.SparkContext._

val sc = new SparkContext("url", "name", "sparkHome", Seq("app.jar"))
```

Cluster URL, or local / local[N]

App name

Spark install path on cluster

List of JARs with app code (to ship)

Java

```
import org.apache.spark.api.java.JavaSparkContext;

JavaSparkContext sc = new JavaSparkContext(
    "masterUrl", "name", "sparkHome", new String[] {"app.jar"}));
```

Python

```
from pyspark import SparkContext

sc = SparkContext("masterUrl", "name", "sparkHome", ["library.py"]))
```

Add Spark to Your Project

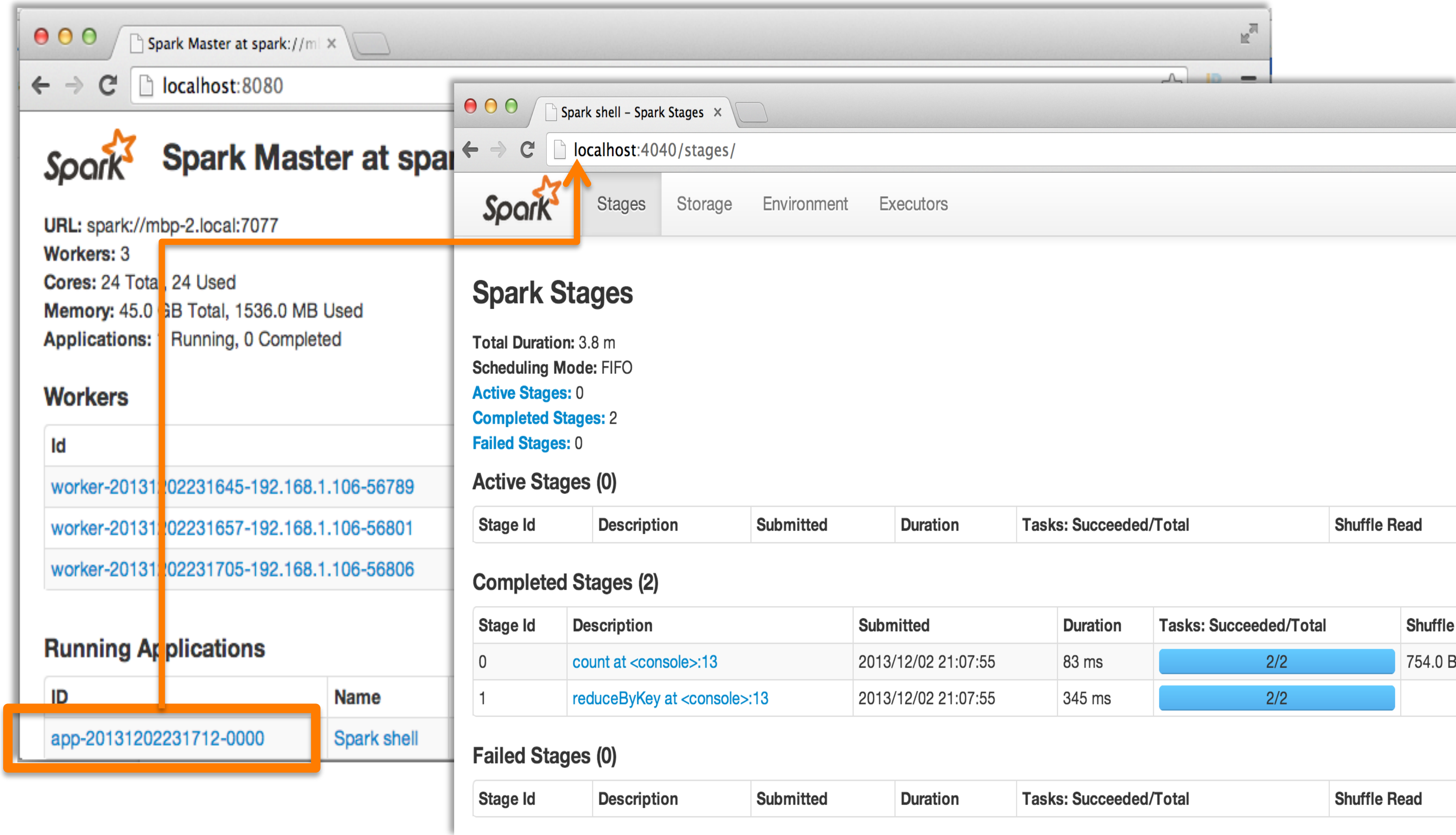
- Scala / Java: add a Maven dependency on

groupId:	org.spark-project
artifactId:	spark-core_2.10
version:	0.9.0

- Python: run program with our pyspark script

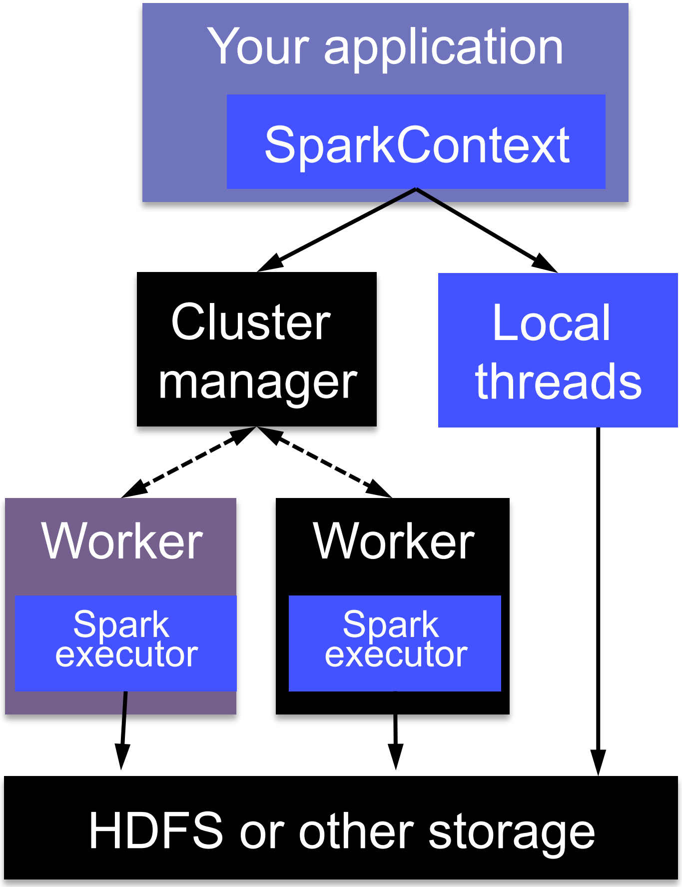
Administrative GUIs

http://<Standalone Master>:8080 (by default)



Software Components

- Spark runs as a library in your program (1 instance per app)
- Runs tasks locally or on cluster
  - Mesos, YARN or standalone mode
- Accesses storage systems via Hadoop InputFormat API
  - Can use HBase, HDFS, S3, …



Local Execution

- Just pass `local` or `local[k]` as master URL
- Debug using local debuggers
  - For Java / Scala, just run your program in a debugger
  - For Python, use an attachable debugger (e.g. PyDev)
- Great for development & unit tests

Cluster Execution

- Easiest way to launch is EC2:
  ./spark-ec2 -k keypair –i id_rsa.pem –s slaves \
  [launch|stop|start|destroy] clusterName
- Several options for private clusters:
  - Standalone mode (similar to Hadoop's deploy scripts)
  - Mesos
  - Hadoop YARN
- Amazon EMR: tinyurl.com/spark-emr

Example Application: PageRank

Example: PageRank

- Good example of a more complex algorithm
  - Multiple stages of map & reduce
- Benefits from Spark's in-memory caching
  - Multiple iterations over the same data

Basic Idea

Give pages ranks (scores) based on links to them

- Links from many pages ➔ high rank
- Link from a high-rank page ➔ high rank

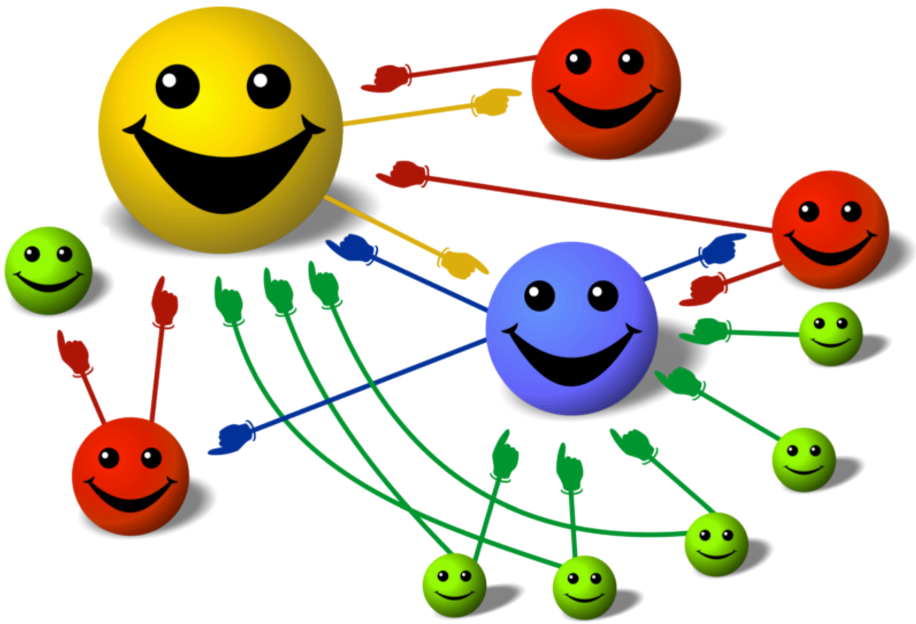
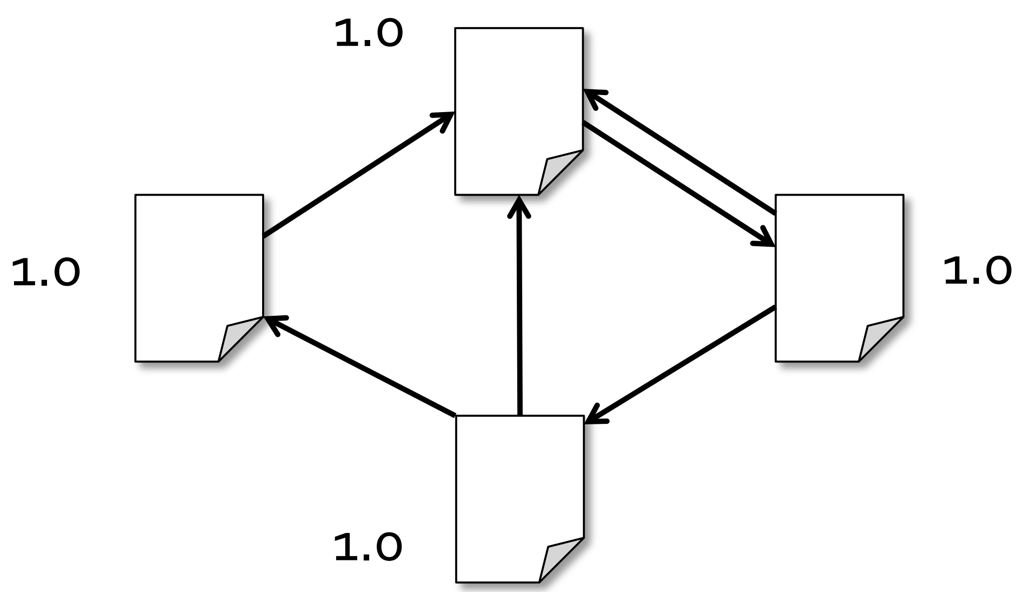


Image: en.wikipedia.org/wiki/File:PageRank-hi-res-2.png

Algorithm

1. Start each page at a rank of 1
2. On each iteration, have page p contribute $rank_p$ / $|neighbors_p|$ to its neighbors
3. Set each page's rank to $0.15 + 0.85 \times contribs$



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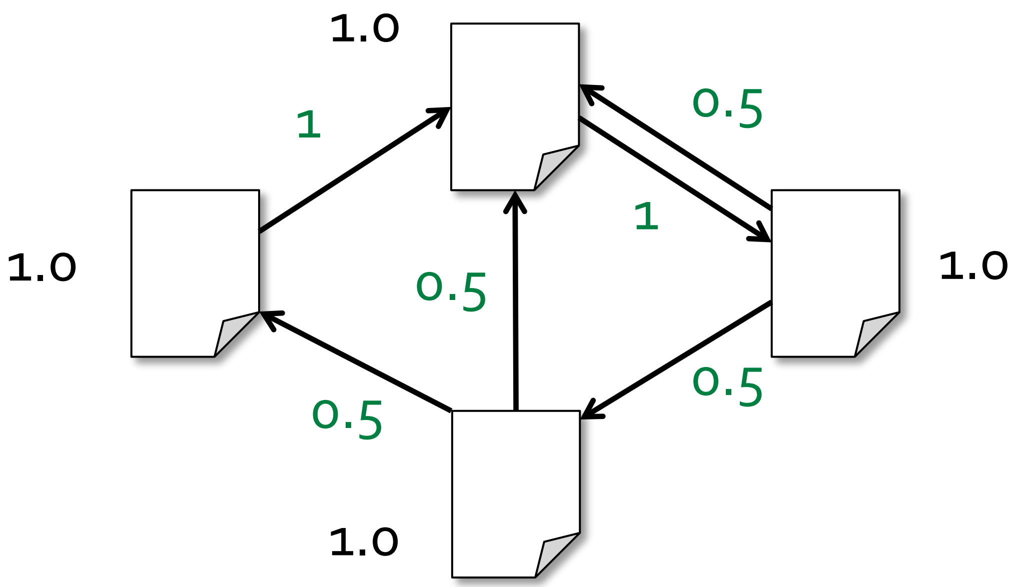

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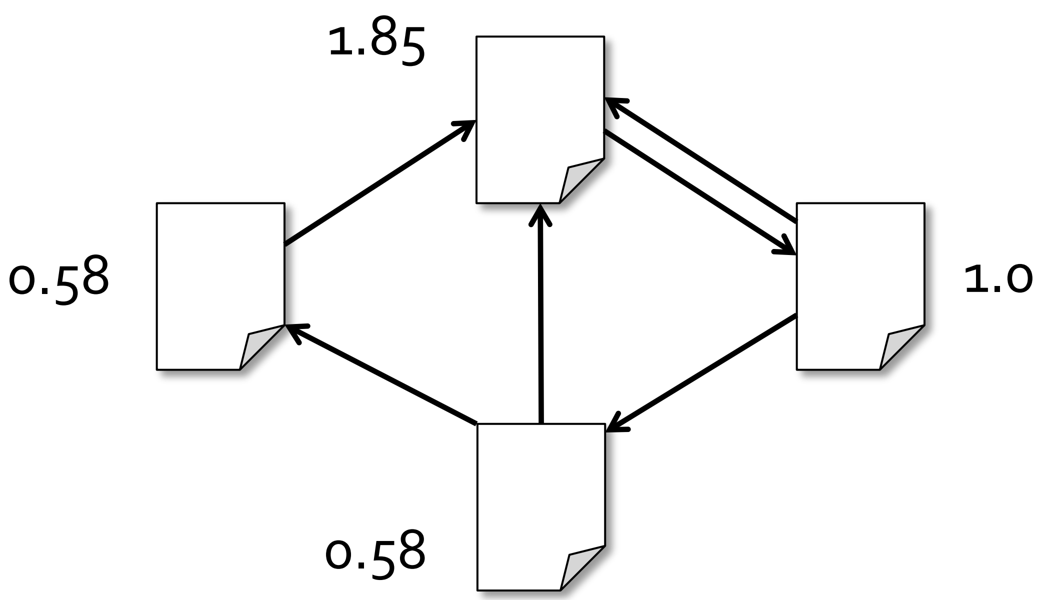

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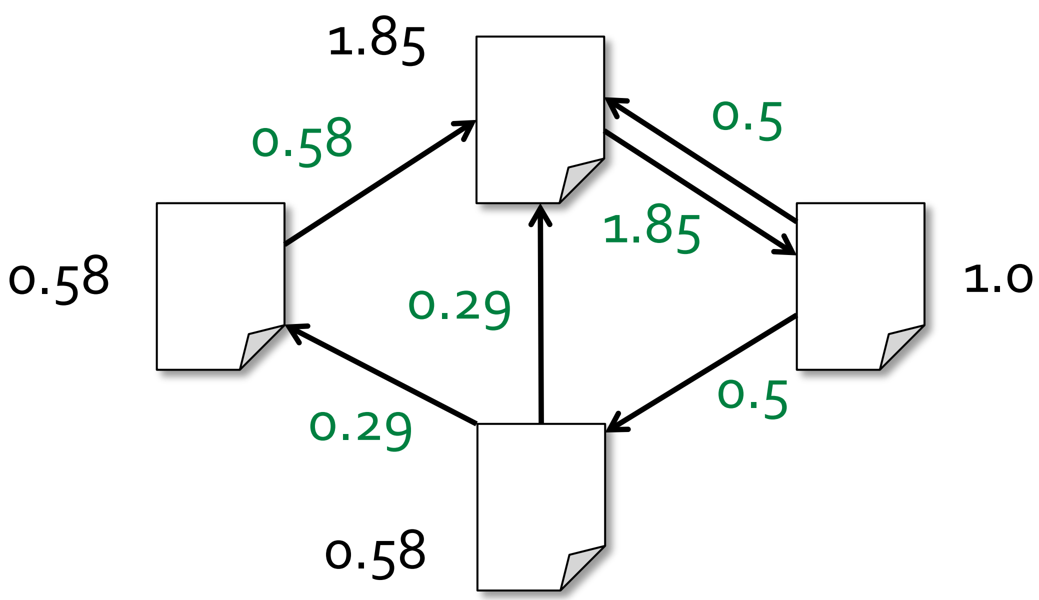

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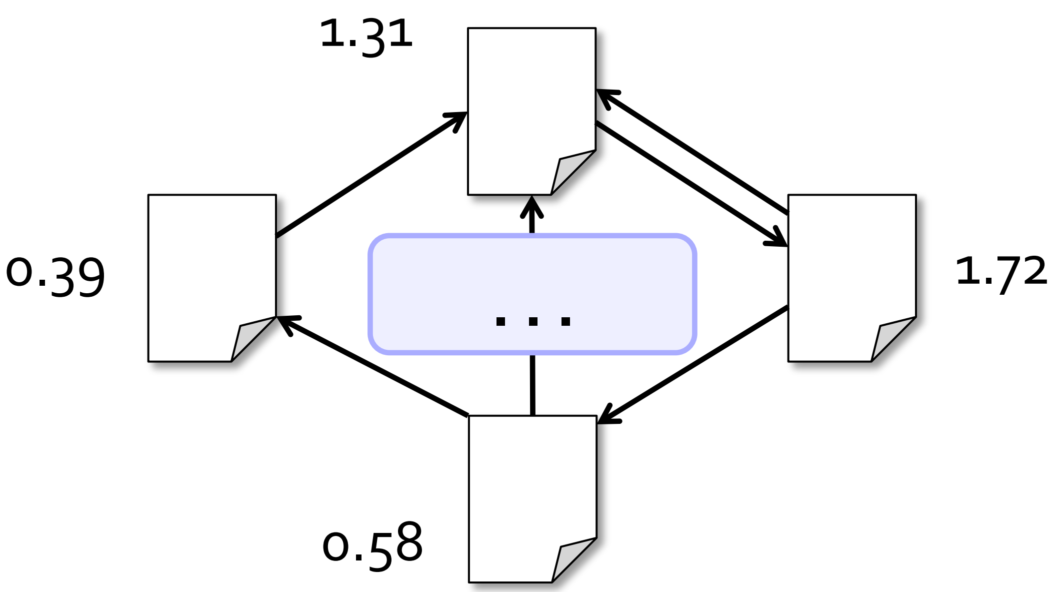

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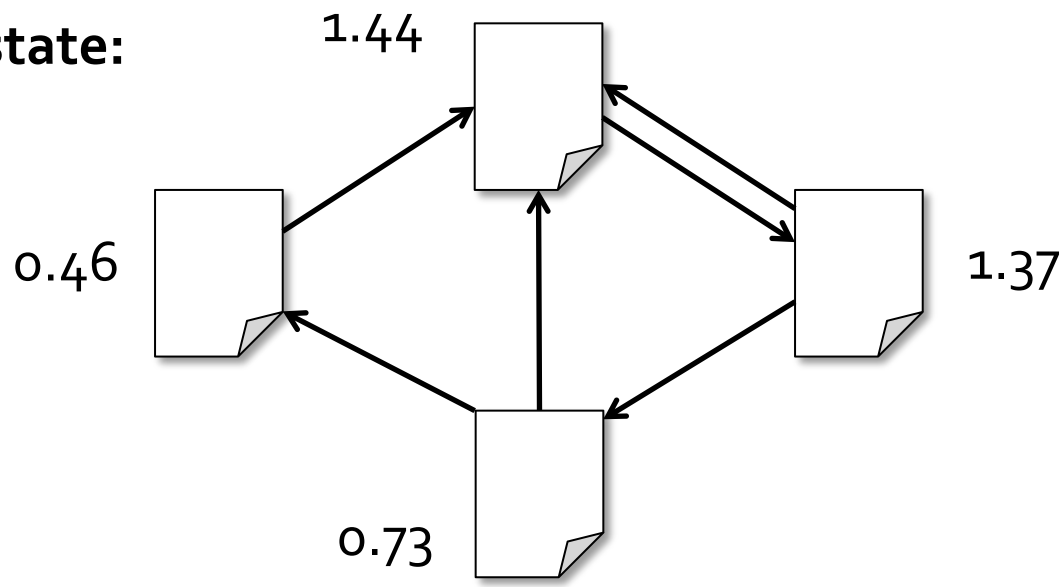
Final state:

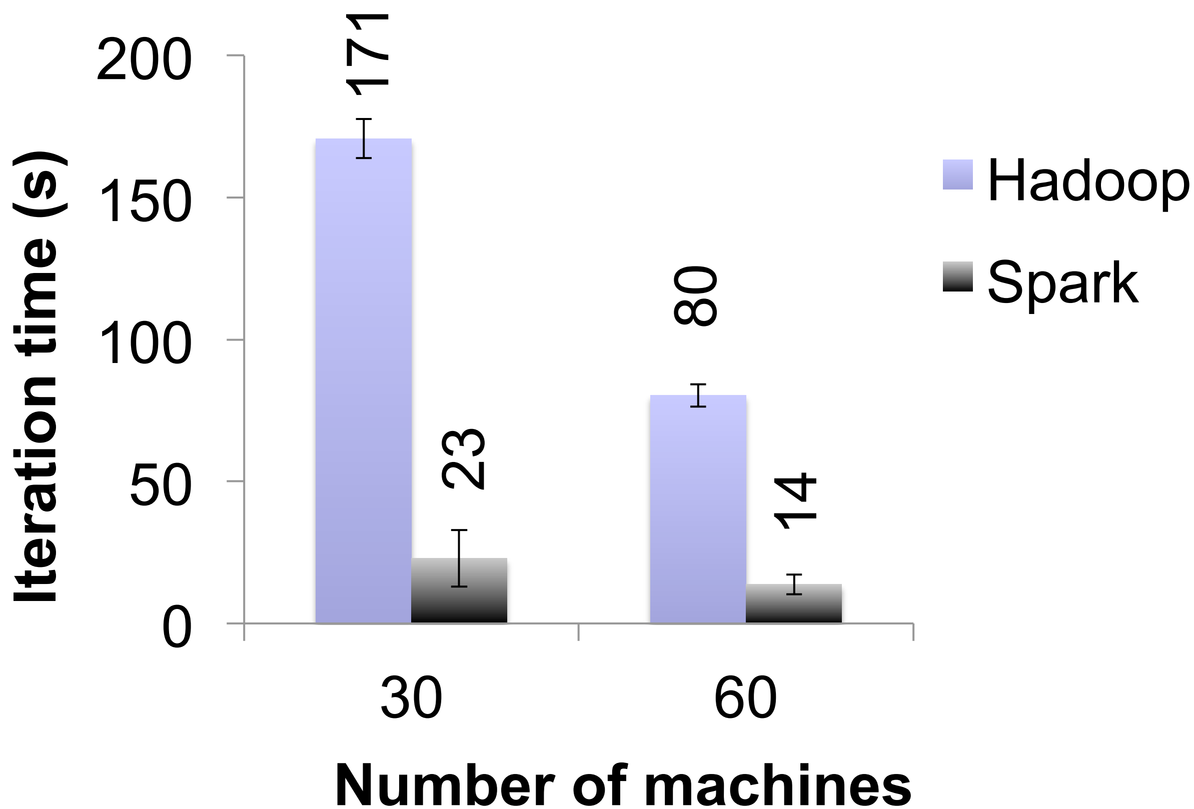


Scala Implementation

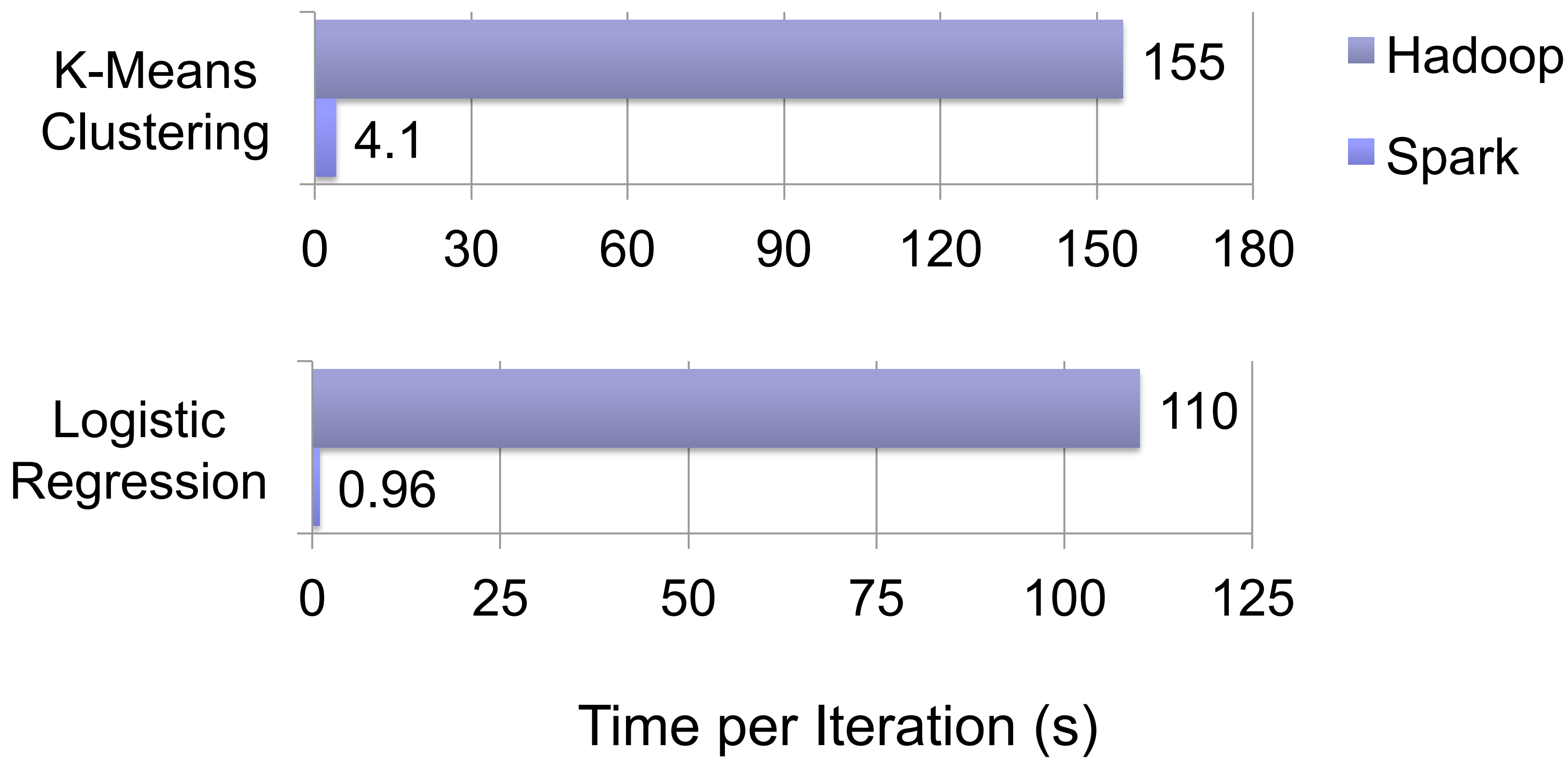
```
val links = // load RDD of (url, neighbors) pairs
var ranks = // load RDD of (url, rank) pairs

for (i <- 1 to ITERATIONS) {
  val contribs = links.join(ranks).flatMap {
    case (url, (links, rank)) =>
      links.map(dest => (dest, rank/links.size))
  }
  ranks = contribs.reduceByKey(_ + _)
                  .mapValues(0.15 + 0.85 * _)
}
ranks.saveAsTextFile(...)
```

PageRank Performance



Other Iterative Algorithms



Summary

Summary

- Spark offers a rich API to make data analytics *fast*: both fast to write and fast to run
- Achieves 100x speedups in real applications
- Growing community with 25+ companies contributing

END