Introduction to Apache Spark

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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

The Spark Community

amplab UC BERKELEY
databricks
YAHOO!
amazon web services
wanDISCO
intel
cloudera
Alibaba.com
Hortonworks
CLOUD PHYSICS
guavus Go Decisively
AdMobius
ClearStory DATA
IBM
TAGGED
43
CONVIVA
Adobe
bizo
webtrends
stratio
ADATAO BIG DATA INTELLIGENCE
sharethrough
HHMI janelia farm research campus
OOYALA
quantiFind
tuplejump
MAPR TECHNOLOGIES

+You!

Today's Talk

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

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)

Example: Log Mining

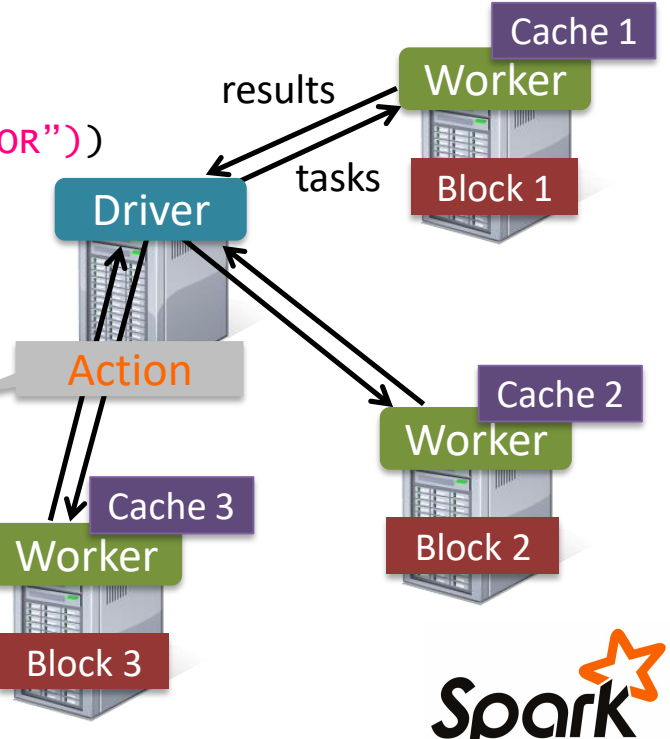
Load error messages from a log into memory, then interactively search for various patterns

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()
. . .
```

Action



Full-text search of Wikipedia

- 60GB on 20 EC2 machine
- 0.5 sec vs. 20s for on-disk

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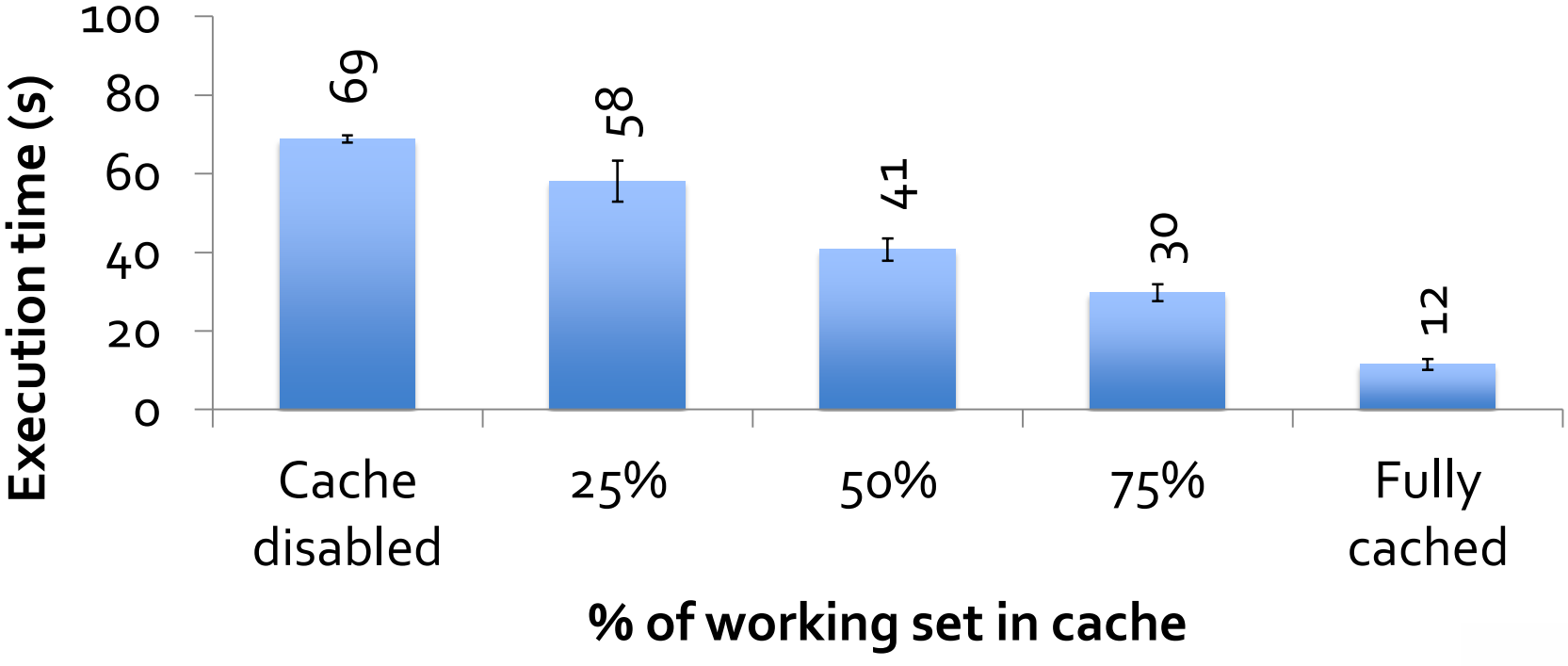
Scaling Down



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])
```

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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

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

# 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)
```

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)

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")
```

Working with Key-Value Pairs

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

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

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

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

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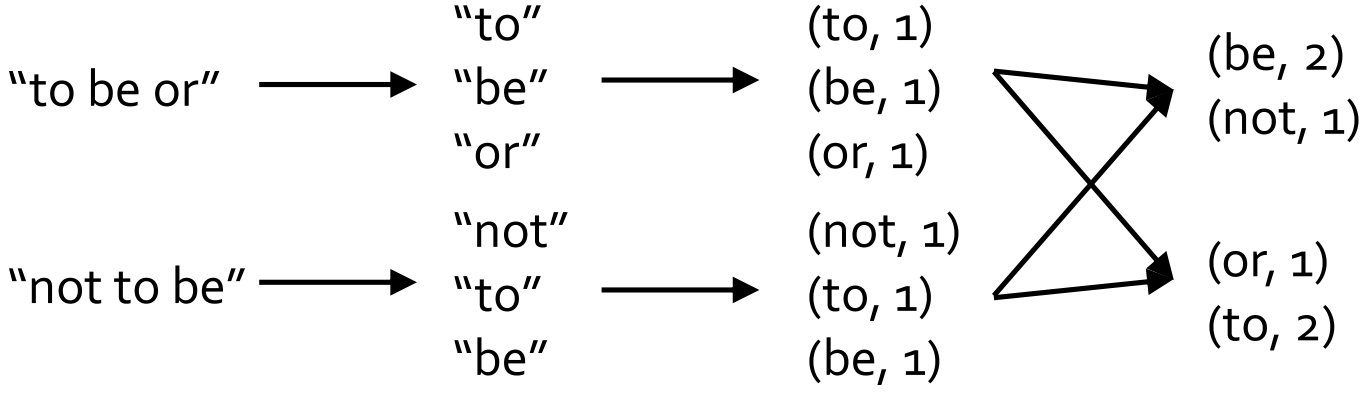
Example: Word Count

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



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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:

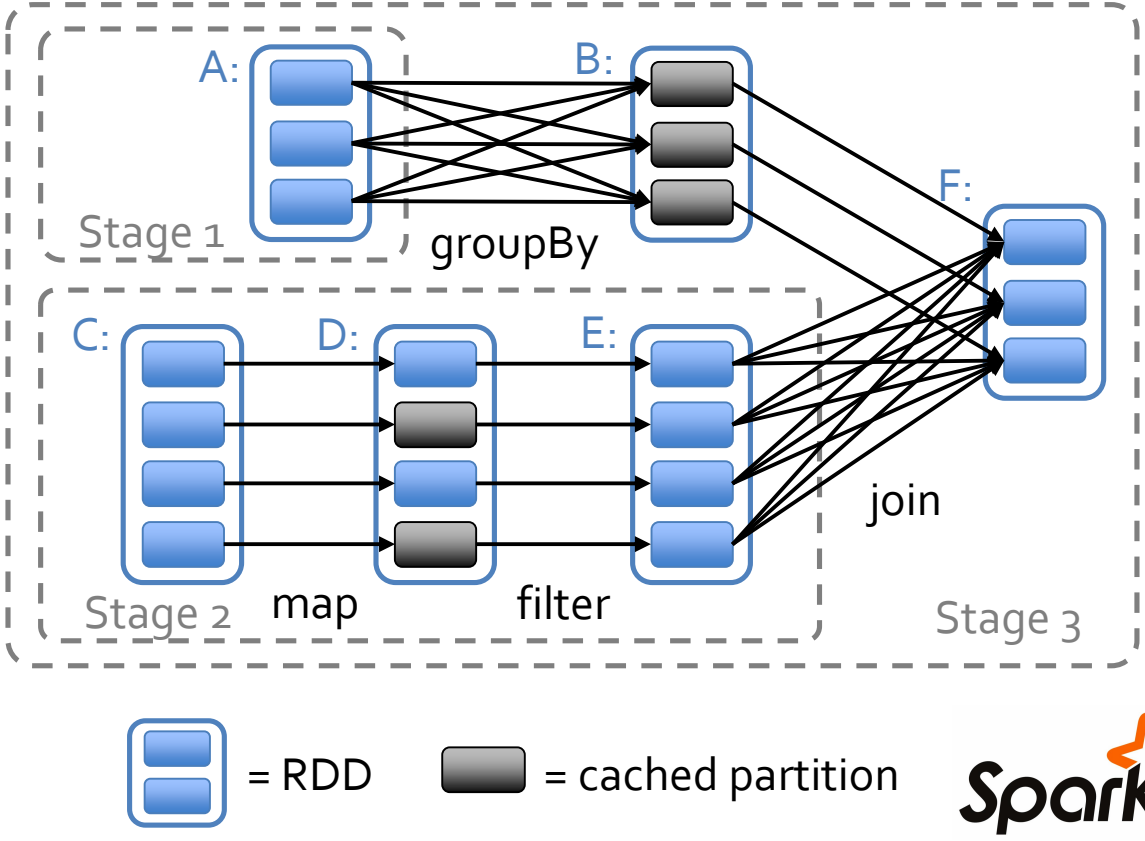
```
> query = sys.stdin.readline()
> pages.filter(lambda x: query in x).count()
```

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

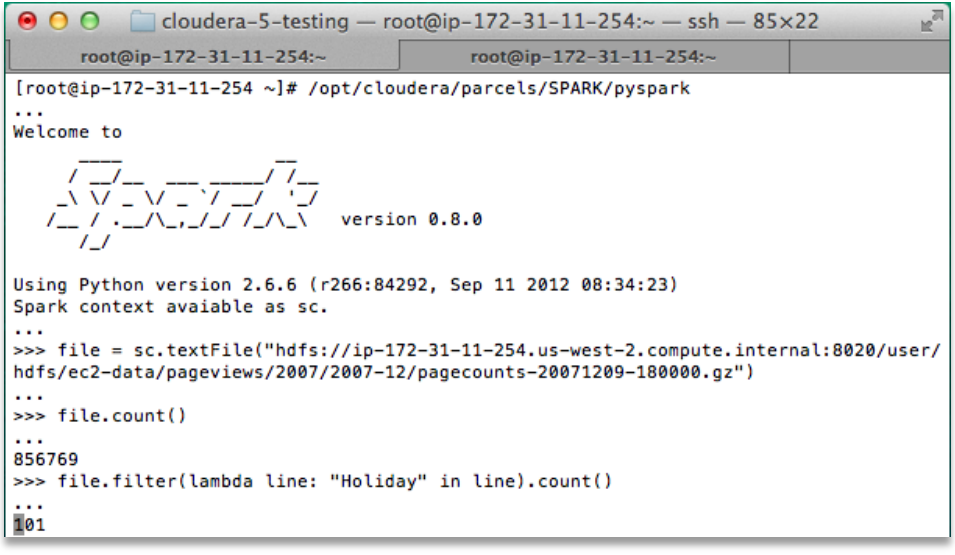
- Python & Scala

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"))
```

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"]))
```

Cluster URL, or local / local[N]

App name

Spark install path on cluster

List of JARs with app code (to ship)

Spark

Add Spark to Your Project

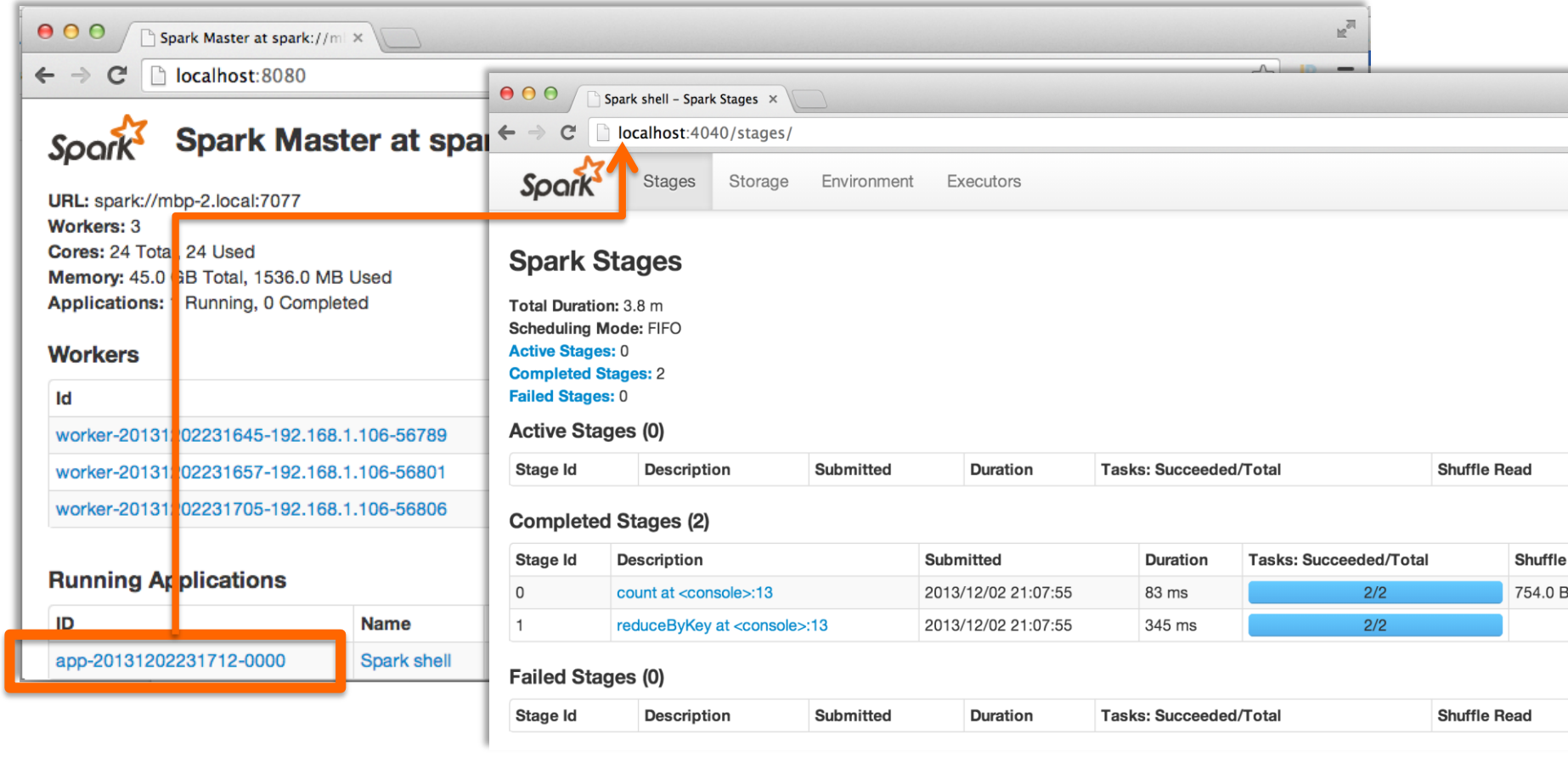
- Scala / Java: add a Maven dependency on

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

- Python: run program with our pyspark script

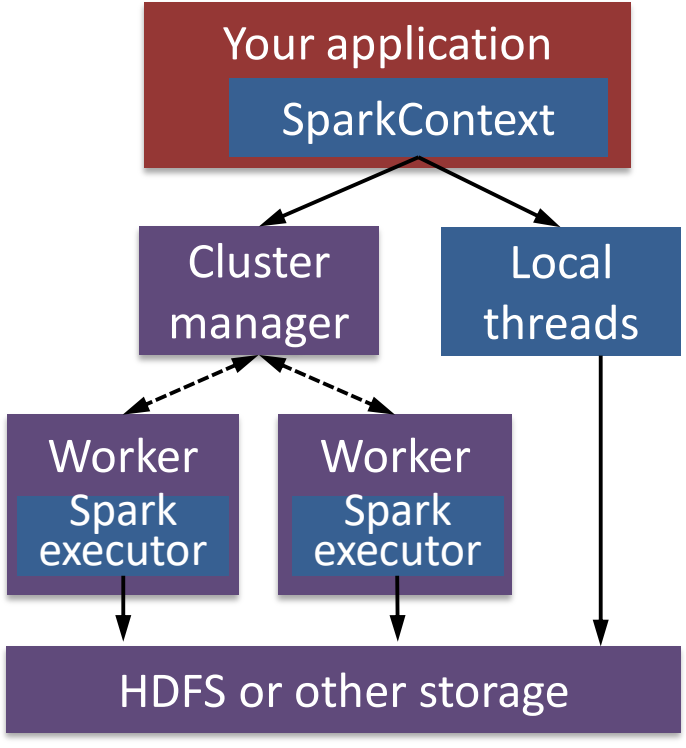
Administrative GUIs

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, …



Spark

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

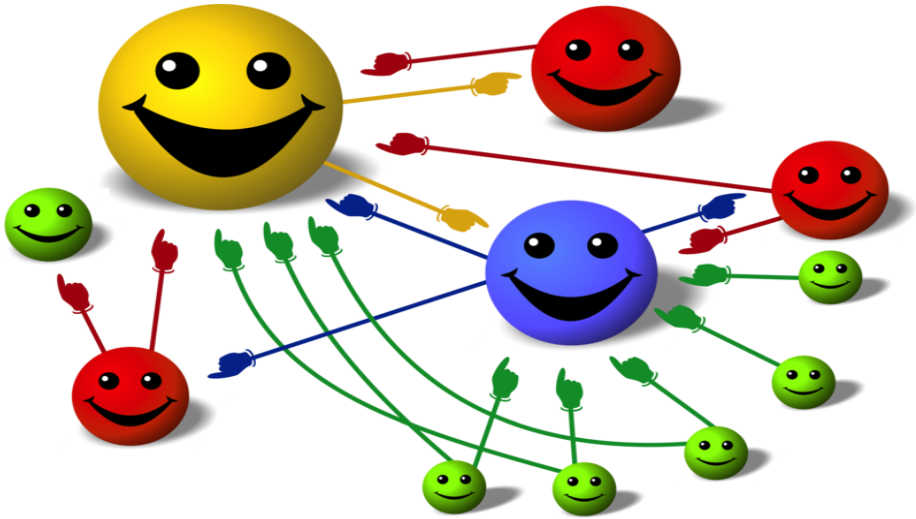
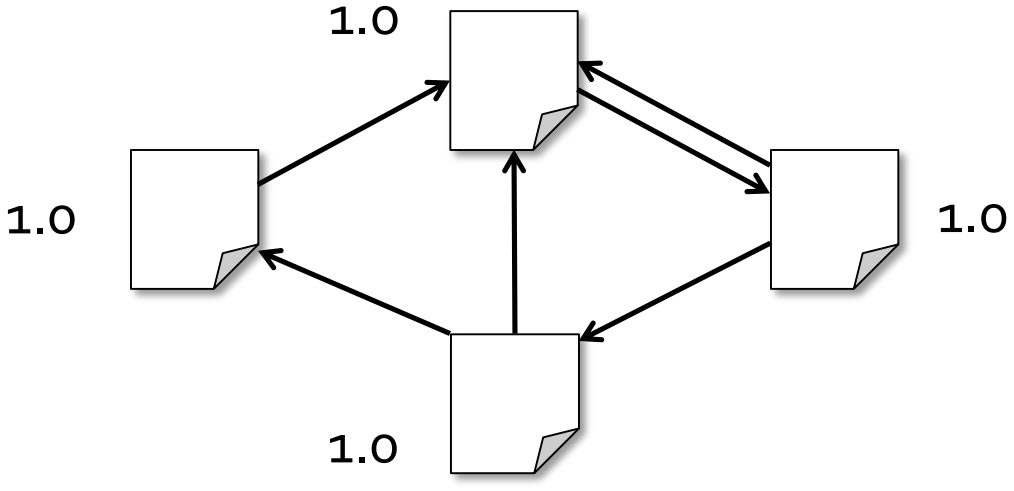


Image: en.wikipedia.org/wiki/File:PageRank-hi-res-2.png

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 × contribs



Spark

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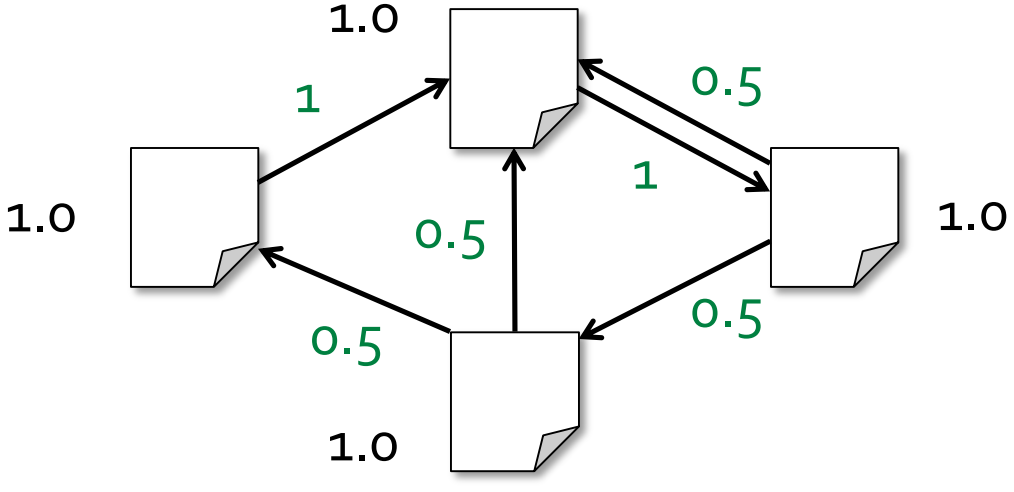

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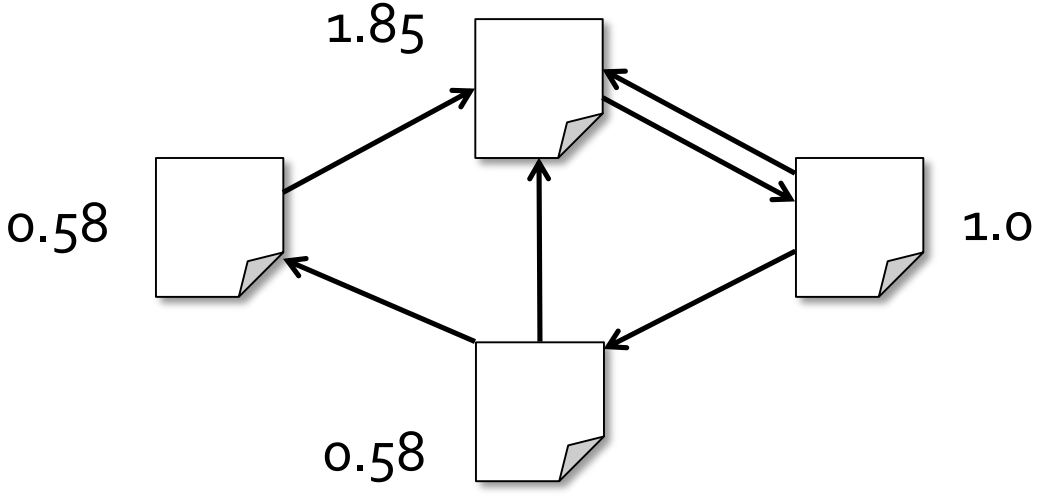

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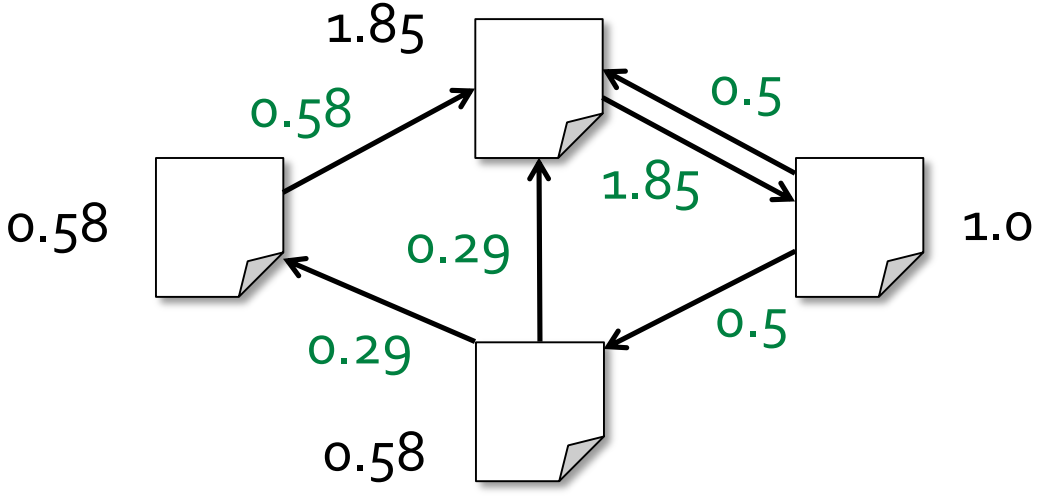

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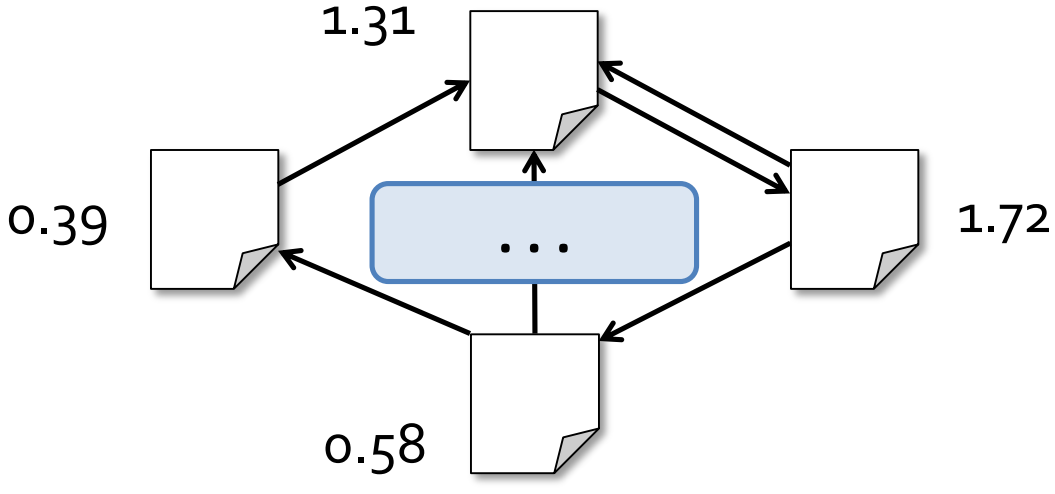

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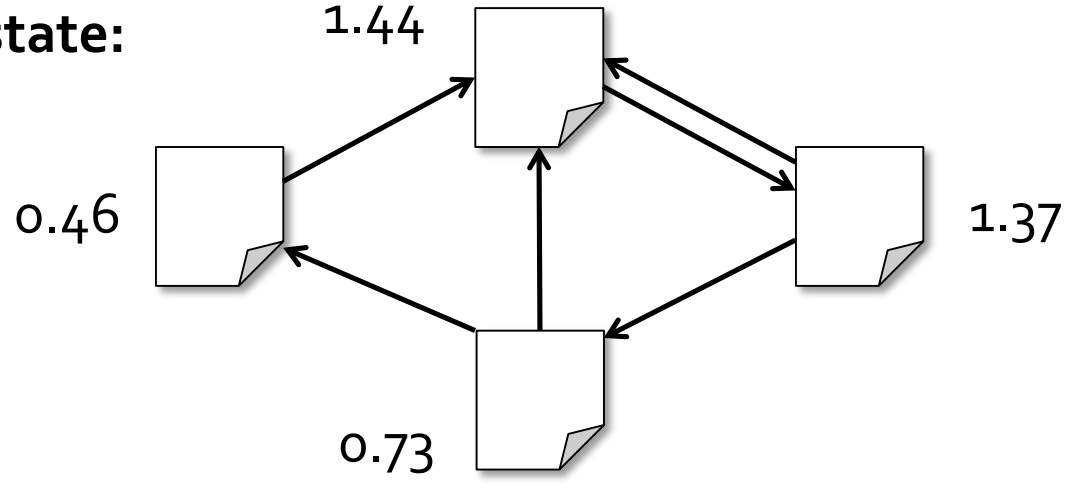
Final state:



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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(...)
```

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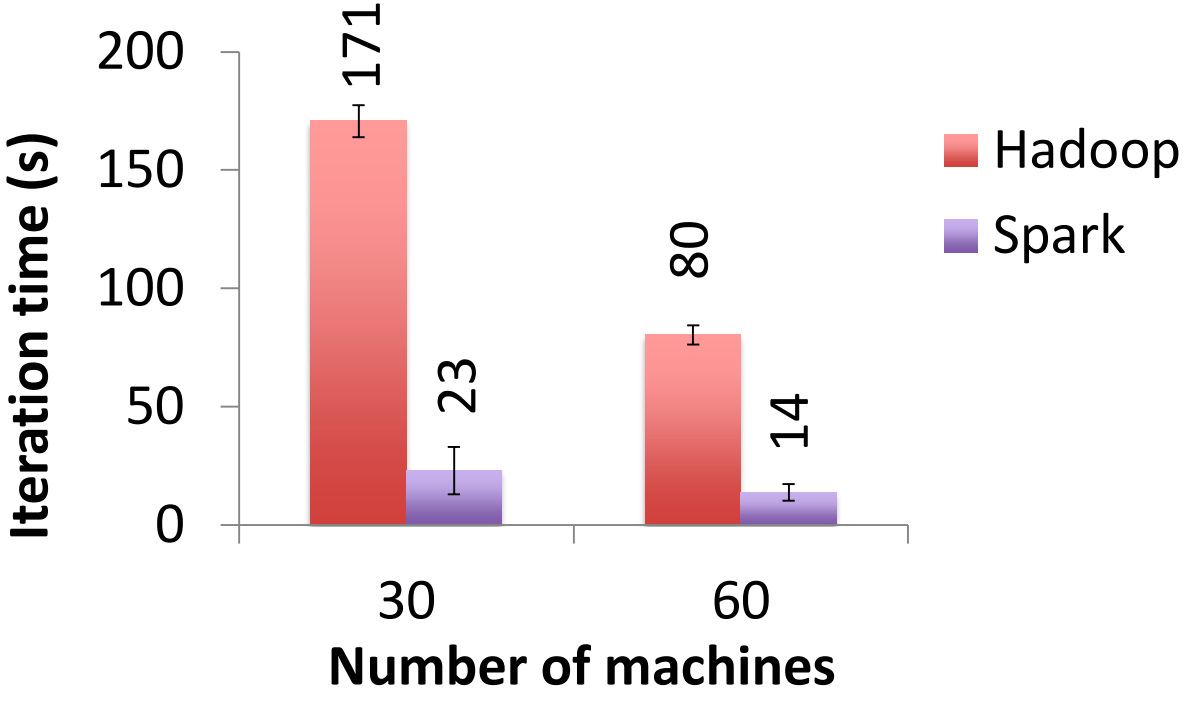
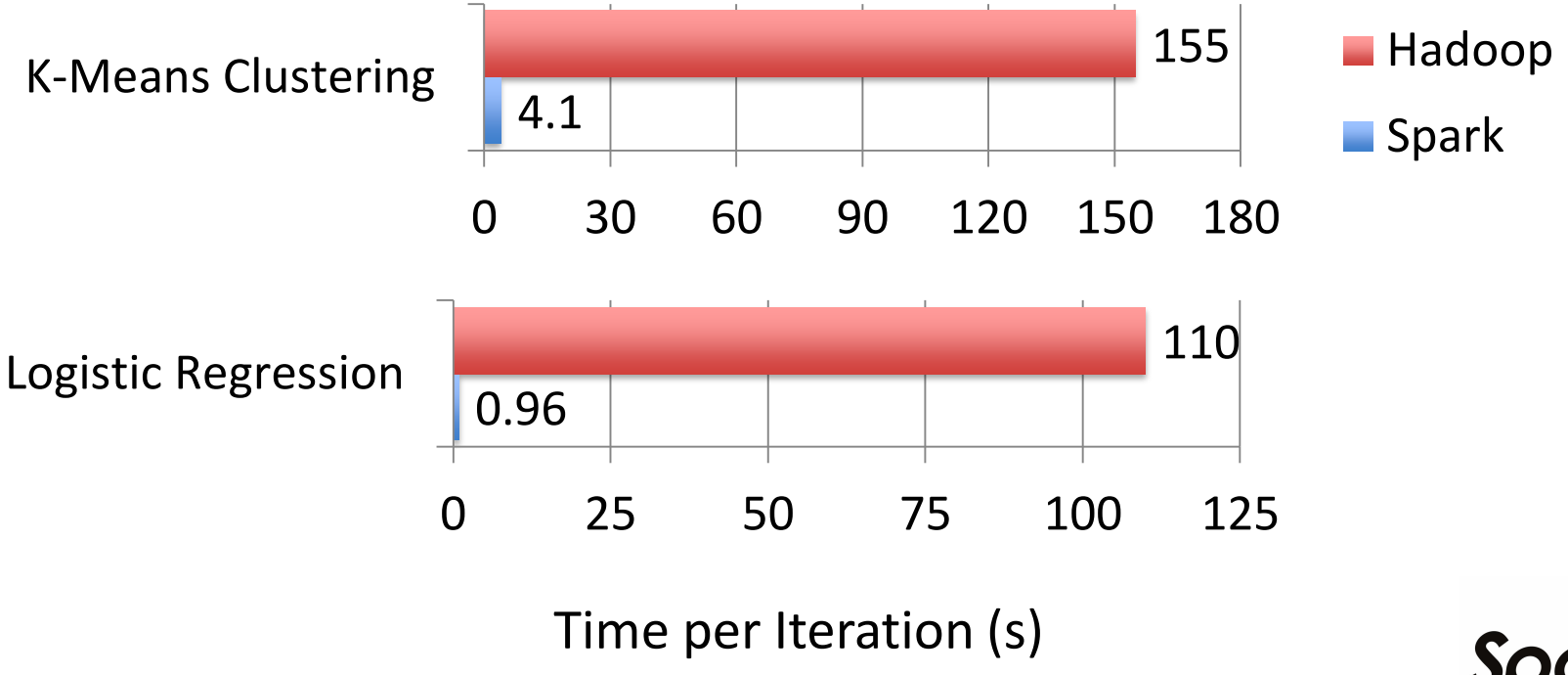
PageRank Performance



Other Iterative Algorithms



CONCLUSION

Conclusion

- 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

Get Started

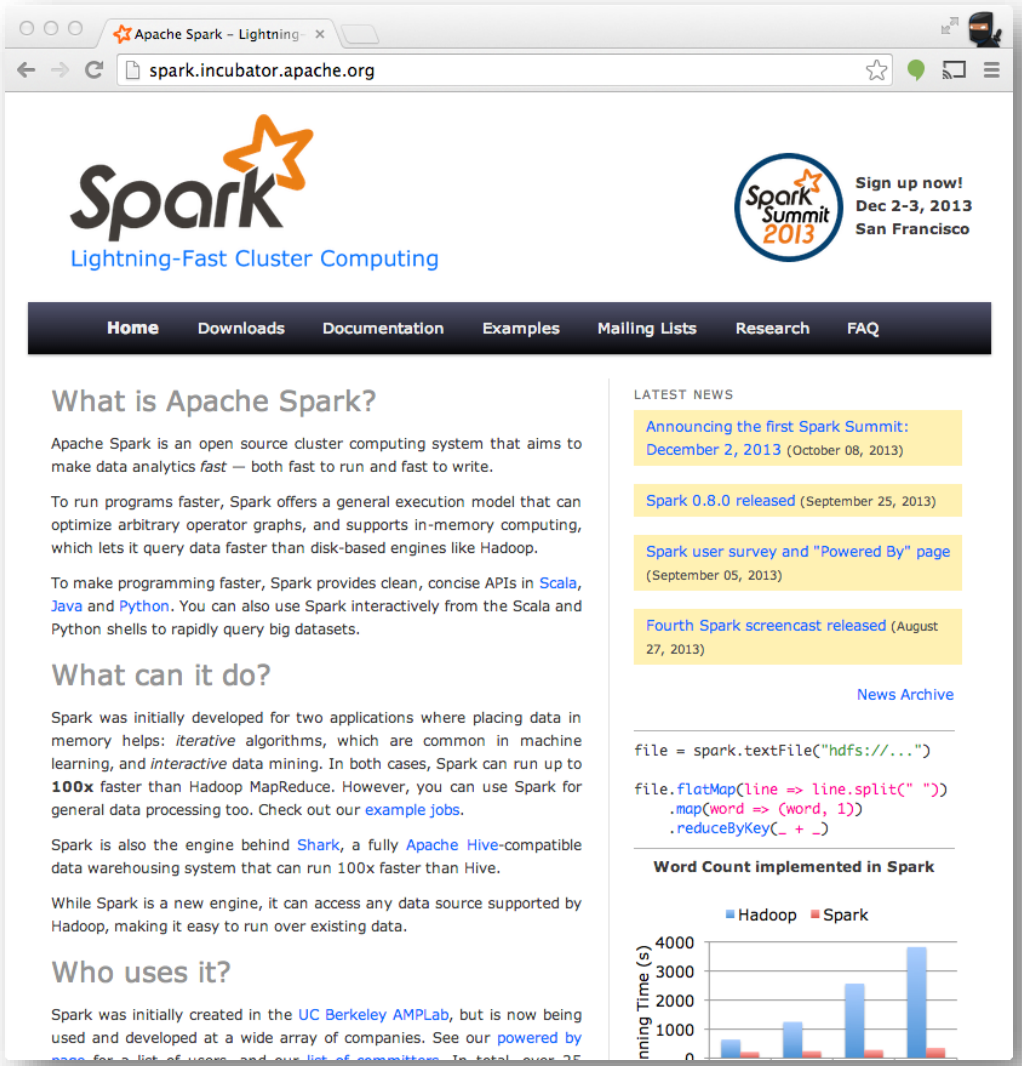
Up and Running in a Few Steps

- Download
- Unzip
- Shell

Project Resources

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

http://spark.incubator.apache.org



Datasets And Dataframes

- https://spark.apache.org/docs/latest/sql-programming-guide.html

Dataset

- A *Dataset* is a distributed collection of data.
  - Like RDDs: Strong typing, ability to use powerful lambda functions
  - Plus the benefits of Spark SQL's optimized execution engine.
  - A Dataset can be constructed from JVM objects and then manipulated using functional transformations (map, flatMap, filter, etc.).
  - The Dataset API is available in Scala and Java.
  - Python does not have the support for the Dataset API. But due to Python's dynamic nature, many of the benefits of the Dataset API are already available
    - i.e. you can access the field of a row by name naturallyrow.columnName).
  - The case for R is similar to Python

DataSets

- Datasets are similar to RDDs, however, instead of using Java serialization or Kryo **they use a specialized Encoder to serialize the objects for processing or transmitting over the network.**

- While both encoders and standard serialization are responsible for turning an object into bytes, encoders are code generated dynamically and use a format that **allows Spark to perform many operations like filtering, sorting and hashing without deserializing the bytes back into an object**

- Data sets also expose more internals to query planning (expressions, fields, etc)

https://spark.apache.org/docs/latest/sql-getting-started.html#creating-datasets

Creating Datasets

- See code here:
  - https://spark.apache.org/docs/latest/sql-getting-started.html#creating-datasets

Dataframes

- A *DataFrame* is a *Dataset* organized into named columns.
  - It is conceptually equivalent to a table in a relational database or a data frame in R/Python, but with richer optimizations under the hood.
- DataFrames can be constructed from a wide array of sources such as: structured data files, tables in Hive, external databases, or existing RDDs.
- The DataFrame API is available in Scala, Java, Python, and R.
  - In Scala and Java, a DataFrame is represented by a Dataset of Rows.
  - In the Scala API, DataFrameis simply a type alias of Dataset[Row].
  - While, in Java API, users need to use Dataset<Row> to represent a DataFrame.

Creating Dataframes

```
import org.apache.spark.sql.Dataset;
import org.apache.spark.sql.Row;

Dataset<Row> df = spark.read().json("examples/src/main/resources/people.json");

// Displays the content of the DataFrame to stdout
df.show();
// +----+-------+
// | age|   name|
// +----+-------+
// |null|Michael|
// |  30|   Andy|
// |  19| Justin|
// +----+-------+
```

https://spark.apache.org/docs/latest/sql-getting-started.html#creating-dataframes

Creating Dataframes

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```

https://spark.apache.org/docs/latest/sql-getting-started.html#creating-dataframes

RDDs or Datasets and Dataframes?

- Probably Datasets and Dataframes
- Finer grained expressiveness allows more fully decoupled DAG for scheduler
  - This means more opportunities for parallelism.