Lightning-fast cluster computing

An Analogy

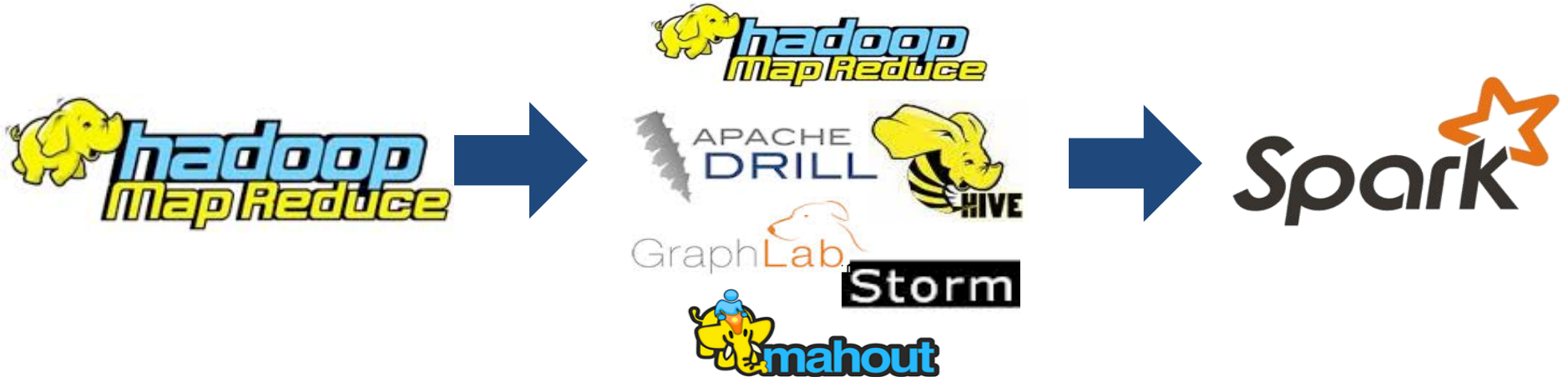
First cellular phones

Specialized devices

Unified device (smartphone)

Spark

An Analogy



Batch processing

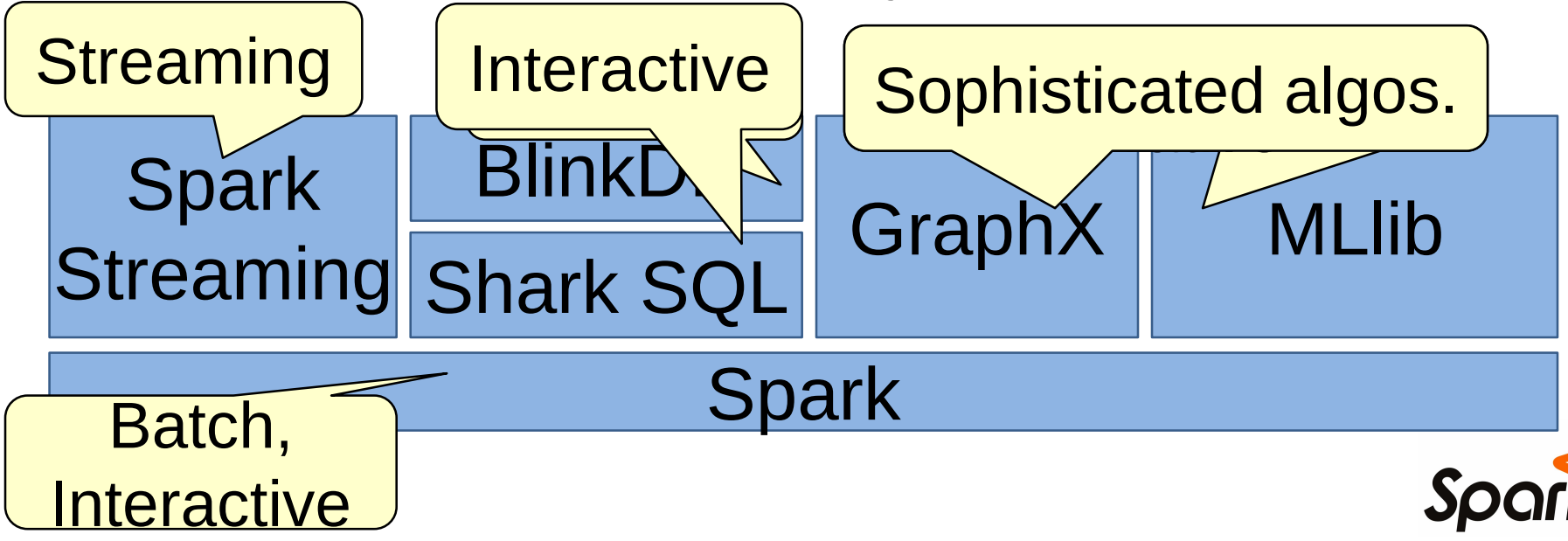
Specialized systems

Unified system

Spark

Spark

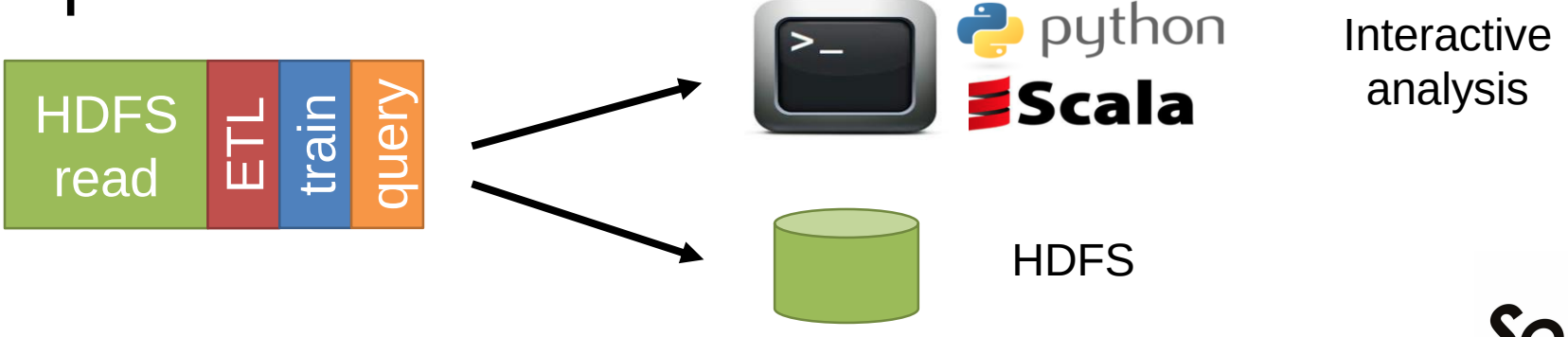
- Unifies ***batch, streaming, interactive*** comp.
- Easy to build sophisticated applications
  - Support iterative, graph-parallel algorithms
  - Powerful APIs in Scala, Python, Java



What it Means for Users

- Separate frameworks:

Spark:



INTRODUCTION TO APACHE SPARK

What is Spark?

Fast and **Expressive** Cluster Computing System 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

Key Concepts

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

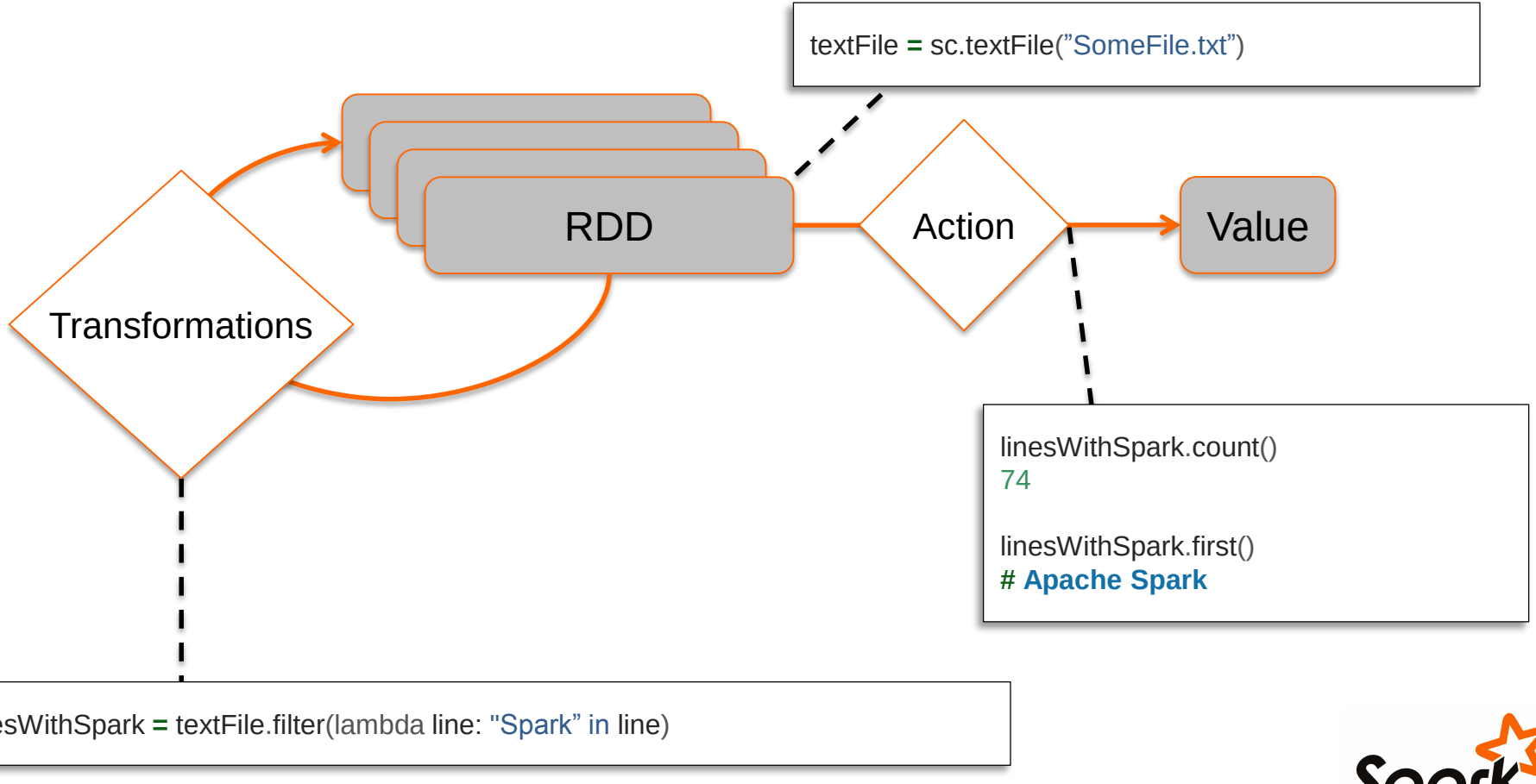
Resilient Distributed Datasets

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

Operations

- Transformations (e.g. map, filter, groupBy)
  - Lazy operations to build RDDs from other RDD
- Actions (e.g. count, collect, save)
  - Return a result or write it to storage

Working With RDDs



Example: Log Mining

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

Transformed RDD

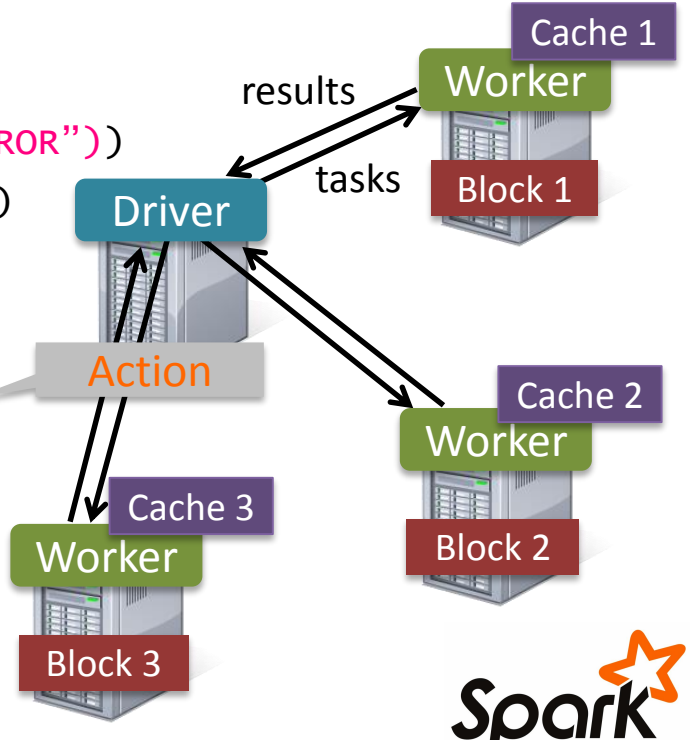
```
lines = spark.textFile("hdfs://...")
errors = lines.filter(lambda s: s.startswith("ERROR"))
messages = errors.map(lambda s: s.split("\t")[2])
messages.cache()

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

Action

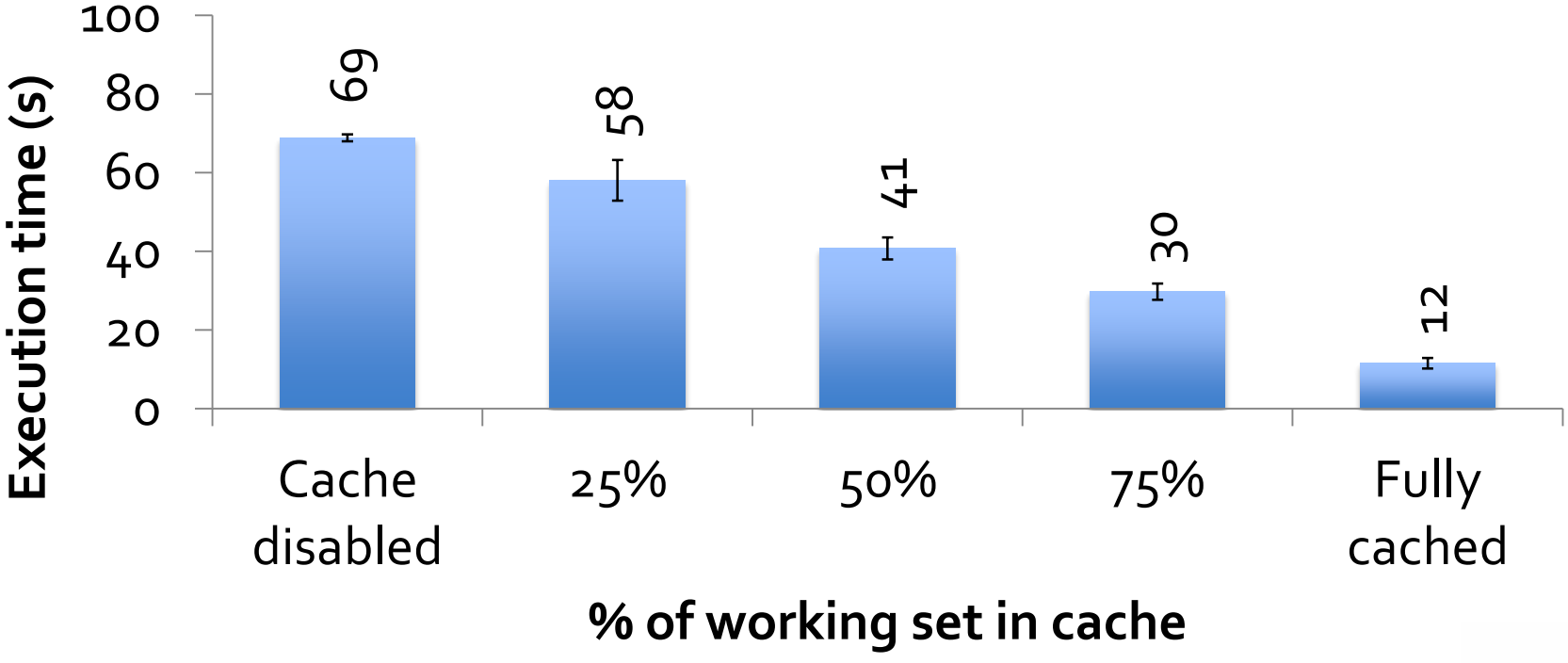
Full-text search of Wikipedia

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



Spark

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])
```

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

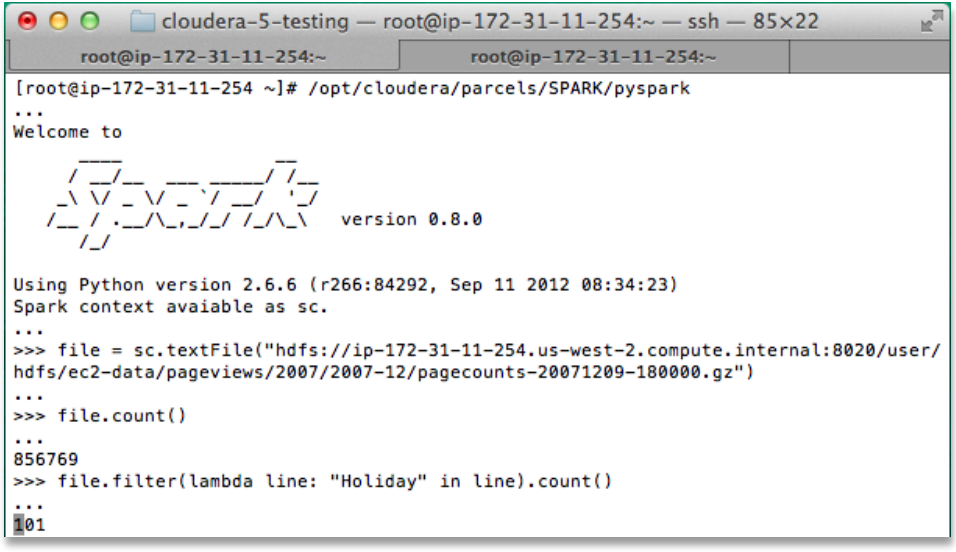
- Python & Scala

Performance

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

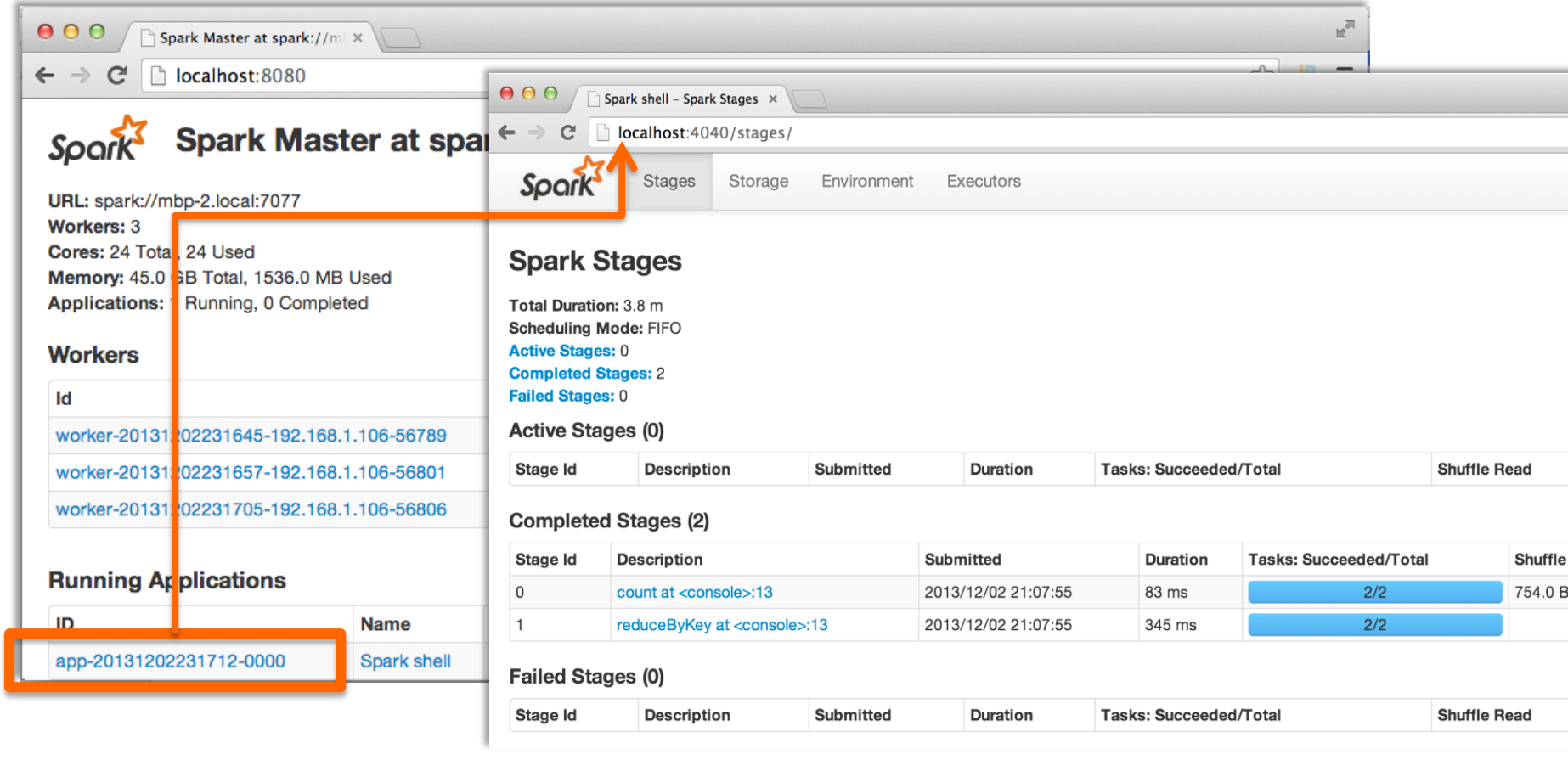
Interactive Shell

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



Administrative GUIs

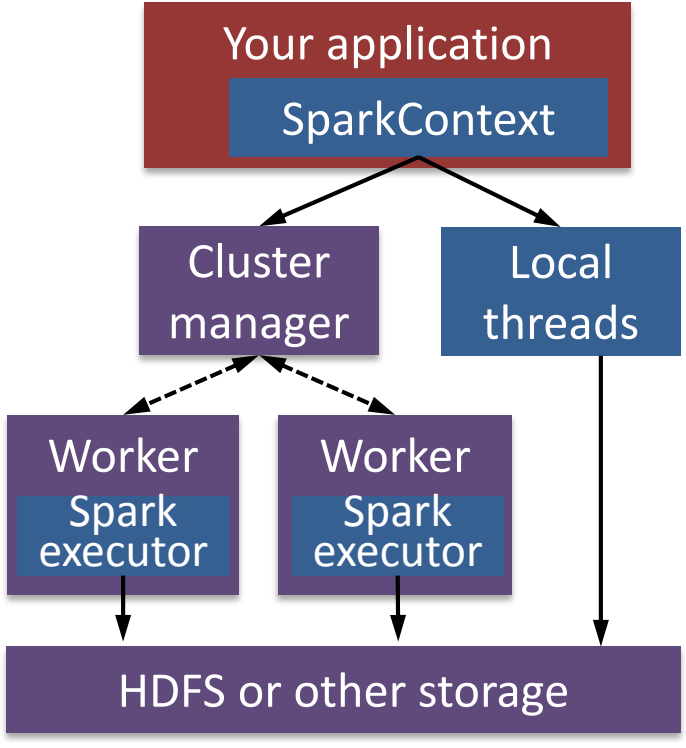
http://<Standalone Master>:8080 (by default)



JOB EXECUTION

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, …



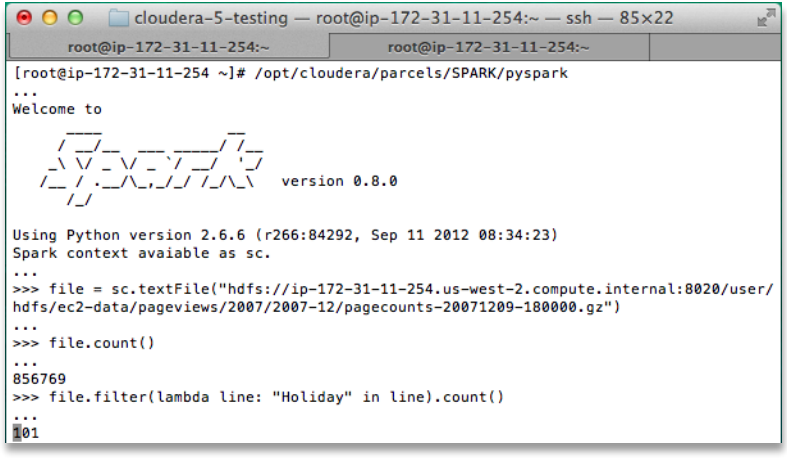
Spark

WORKING WITH SPARK

Using the Shell

Launching:

```
spark-shell
pyspark (IPYTHON=1)
```



Modes:

```
MASTER=local     ./spark-shell   # local, 1 thread
MASTER=local[2] ./spark-shell   # local, 2 threads
MASTER=spark://host:port ./spark-shell  # cluster
```

Spark

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

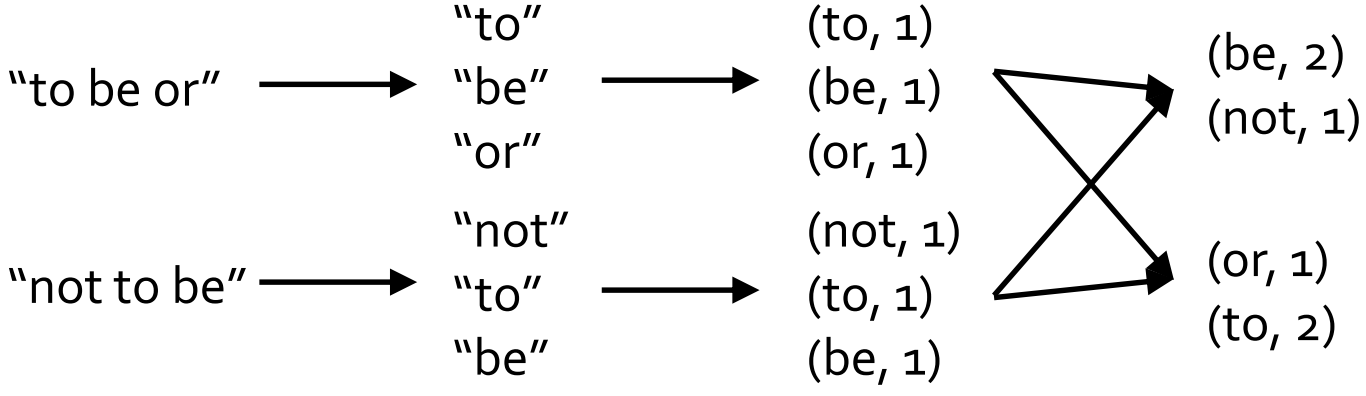
```
> pets = sc.parallelize(
    [("cat", 1), ("dog", 1), ("cat", 2)])
> pets.reduceByKey(lambda x, y: x + y)
                    # => {(cat, 3), (dog, 1)}
> pets.groupByKey() # => {(cat, [1, 2]), (dog, [1])}
> pets.sortByKey()  # => {(cat, 1), (cat, 2), (dog, 1)}
```

`reduceByKey` also automatically implements combiners on the map side

Spark

Example: Word Count

```
> file = spark.textFile("hdfs://...")
> file.flatMap(line => line.split(" "))
        .map(word => (word, 1))
        .reduceByKey(_ + _)
```



Spark

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”]))
```

Spark

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)
```

More RDD Operators

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

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

sample

take

first

partitionBy

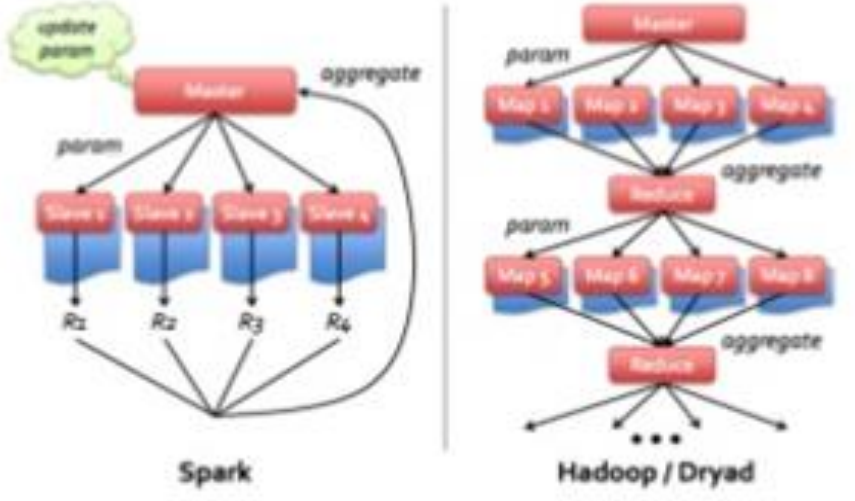
mapWith

pipe

save ...

Spark vs Hadoop MapReduce

- In-memory data flow model optimized for multi-stage jobs
- Novel approach to fault tolerance
- Similar programming style to Scalding/Cascading



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