INTRO TO DATA SCIENCE LECTURE 21: DISTRIBUTED SYSTEMS - SPARK

Using Apache Spark

Pat McDonough - Databricks

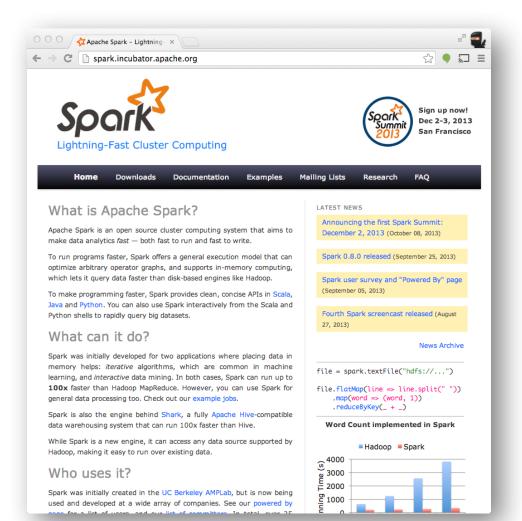


Apache Spark

spark.apache.org

github.com/apache/spark

user@spark.apache.org

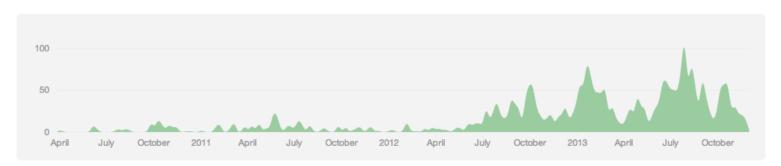


The Spark Community

March 27th 2010 - November 30th 2013

Commits to master, excluding merge commits

















































bizo







INTRODUCTION TO APACHE SPARK



What is Spark?

Fast and Expressive Cluster Computing System Compatible with Apache Hadoop



- General execution graphs
- In-memory storage

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



Key Concepts

Write programs in terms of transformations on distributed datasets

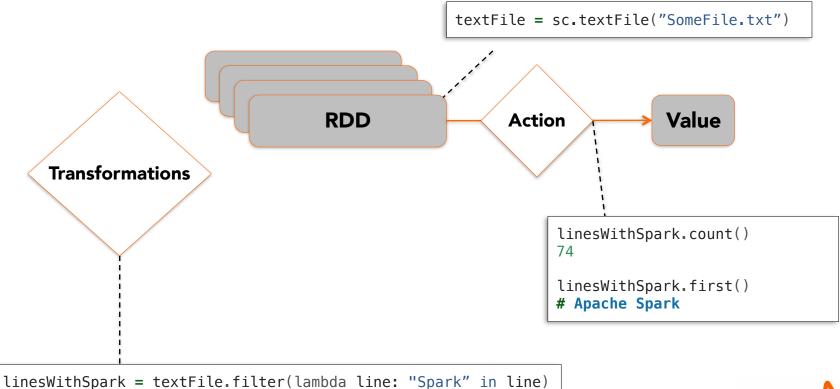
Resilient Distributed Datasets

- 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)

Working With RDDs





Example: Log Mining

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

B Transformed RDD

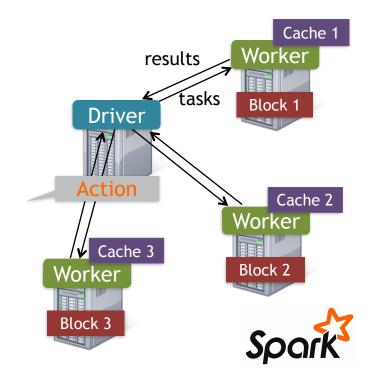
```
lines = spark.ter.... ne("hdfs://...")
errors = lines.filter(lambda s: s.startswith("ERROR"))
messages = errors.map(lambda s: s.split("\t")[2])
messages.cache()
```

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

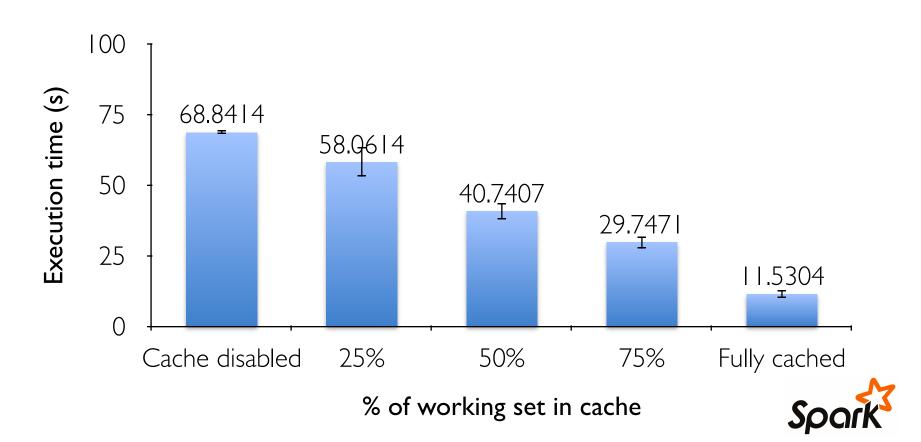
. . .

Full-text search of Wikipedia

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

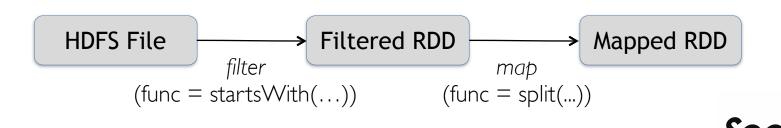


Scaling Down



Fault Recovery

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



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

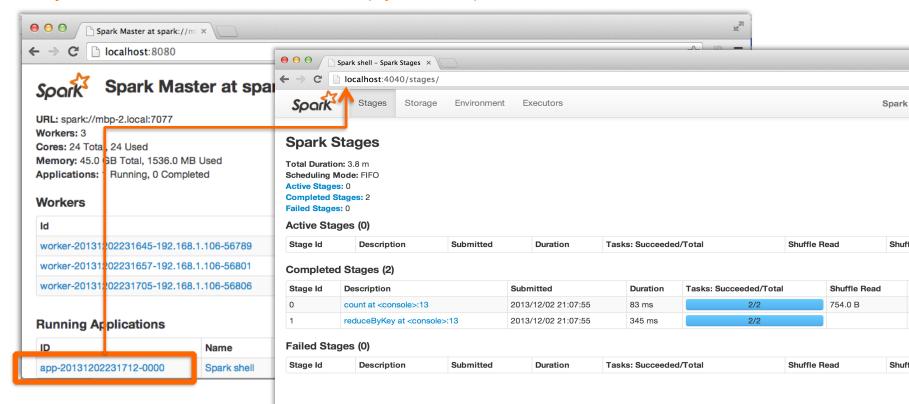
- The Fastest Way to Learn Spark
- Available in Python and Scala
- Runs as an application on an existing Spark Cluster...
- OR Can run locally

```
| Coloudera-5-testing - root@ip-172-31-11-254:~ - ssh - 85×22 | root@ip-172-31-11-254:~ | root@i
```



Administrative GUIs

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

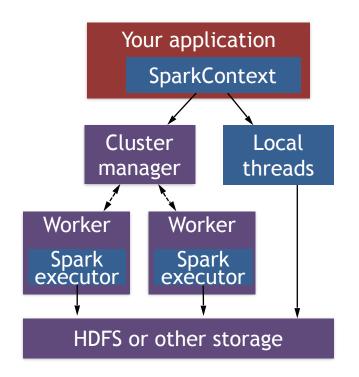


JOB EXECUTION



Software Components

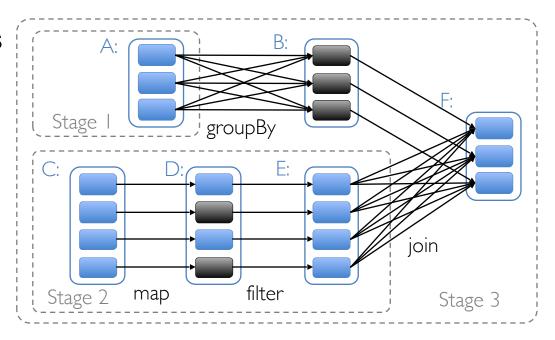
- Spark runs as a library in your program (1 instance per app)
- Runs tasks locally or on cluster
 - Mesos, YARN or standalone mode
- Accesses storage systems via Hadoop InputFormat API
 - Can use HBase, HDFS, S3, ...





Task Scheduler

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









Advanced Features

- Controllable partitioning
 - Speed up joins against a dataset
- Controllable storage formats
 - Keep data serialized for efficiency, replicate to multiple nodes, cache on disk
- Shared variables: broadcasts, accumulators
- See online docs for details!



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



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
```

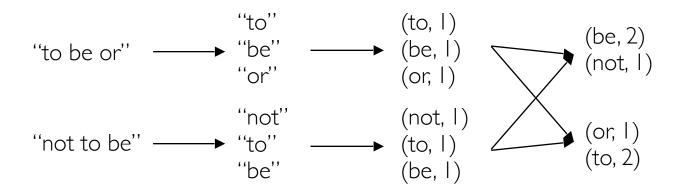


Some Key-Value Operations

reduceByKey also automatically implements combiners on the map side



Example: Word Count





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!)



Closure Mishap Example

This is a problem:

```
class MyCoolRddApp {
  val param = 3.14
  val log = new Log(...)
  ...

def work(rdd: RDD[Int]) {
  rdd.map(x => x + param)
      .reduce(...)
  }
}
```

NotSerializableException: MyCoolRddApp (or Log)

How to get around it:

```
class MyCoolRddApp {
...
...

def work(rdd: RDD[Int]) {
  val param_ = param
  rdd.map(x => x + raram_)
    .reduce(...)
```

References only local variable instead of this.param



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 ..



CREATING SPARK APPLICATIONS



Add Spark to Your Project

Scala / Java: add a Maven dependency on

groupld: org.spark-project

artifactId: spark-core_2.9.3

version: 0.8.0

Python: run program with our pyspark script



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

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

```
import org.a Cluster URL, or local App Spark install / local[N] name path on cluster
                                                                           List of JARs with
                                                                            app code (to ship)
```

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

from pyspark import SparkContext

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



Complete Spark App in Python



EXAMPLE APPLICATION: PAGERANK



Example: PageRank

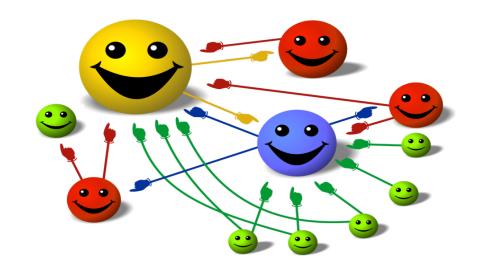
- Good example of a more complex algorithm
 - Multiple stages of map & reduce
- Benefits from Spark's in-memory caching
 - Multiple iterations over the same data



Basic Idea

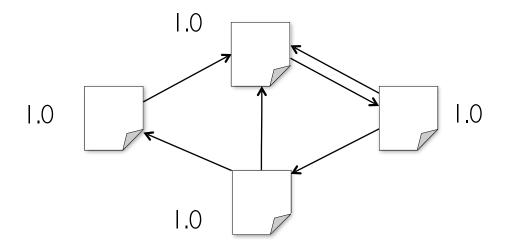
Give pages ranks (scores) based on links to them

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



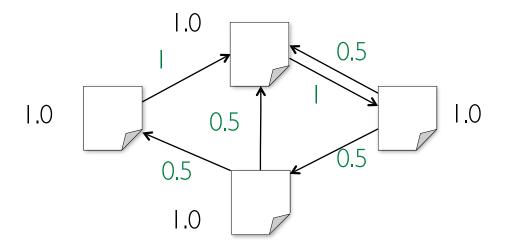


- 1. Start each page at a rank of 1
- 2. On each iteration, have page p contribute $rank_p / |neighbors_p|$ to its neighbors
- 3. Set each page's rank to $0.15 + 0.85 \times \text{contribs}$



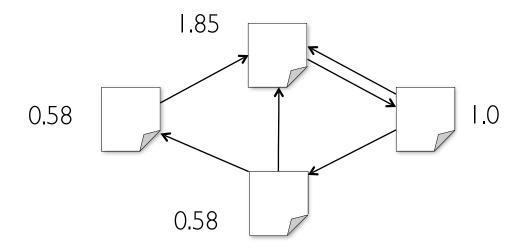


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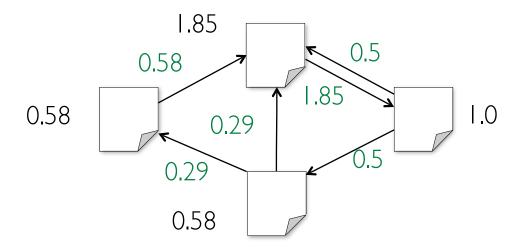


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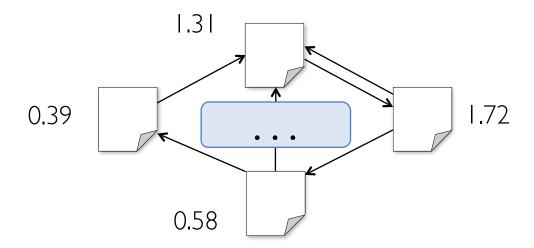


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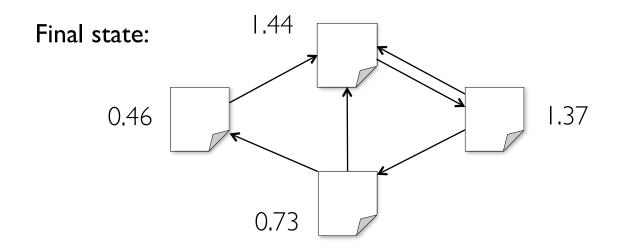


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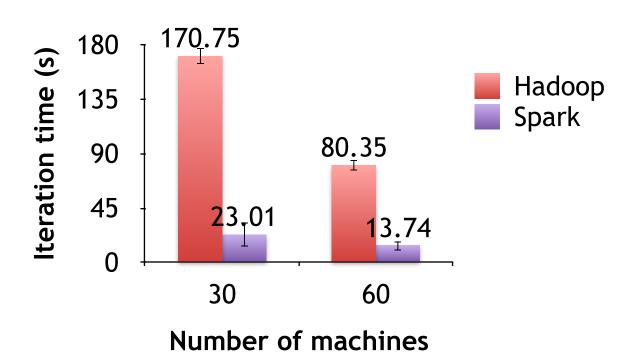


Scala Implementation

```
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(...)
```

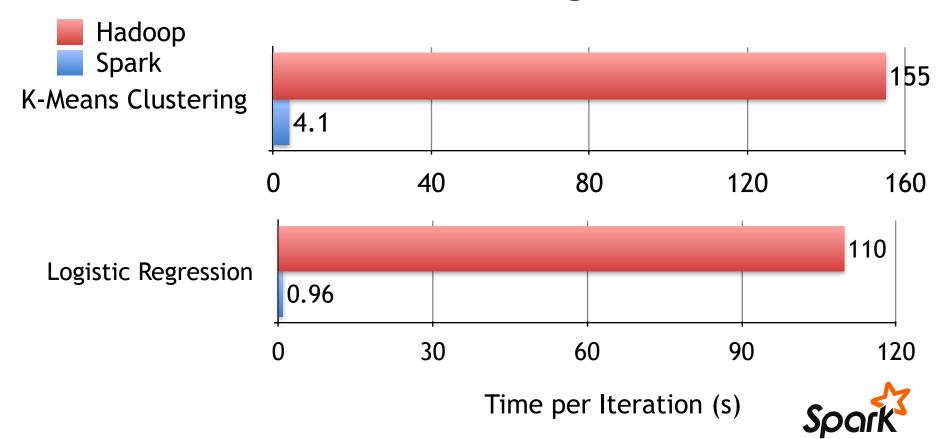


PageRank Performance





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.apache.org

