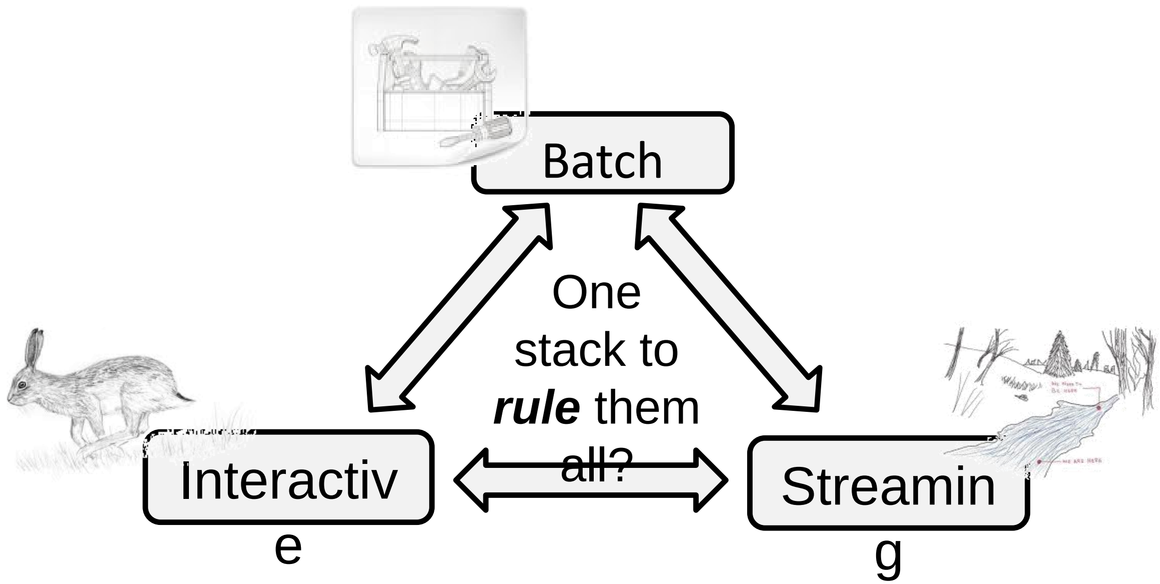
Advanced Big Data Systems

Guido Salvaneschi

Different data processing goals

- Low latency (**interactive**) queries on historical data: enable faster decisions
  - E.g., identify why a site is slow and fix it
- Low latency queries on live data (**streaming**): enable decisions on real-time data
  - E.g., detect & block worms in real-time (a worm may infect 1mil hosts in 1.3sec)
- **Sophisticated** data processing: enable “better” decisions
  - E.g., anomaly detection, trend analysis

Goals

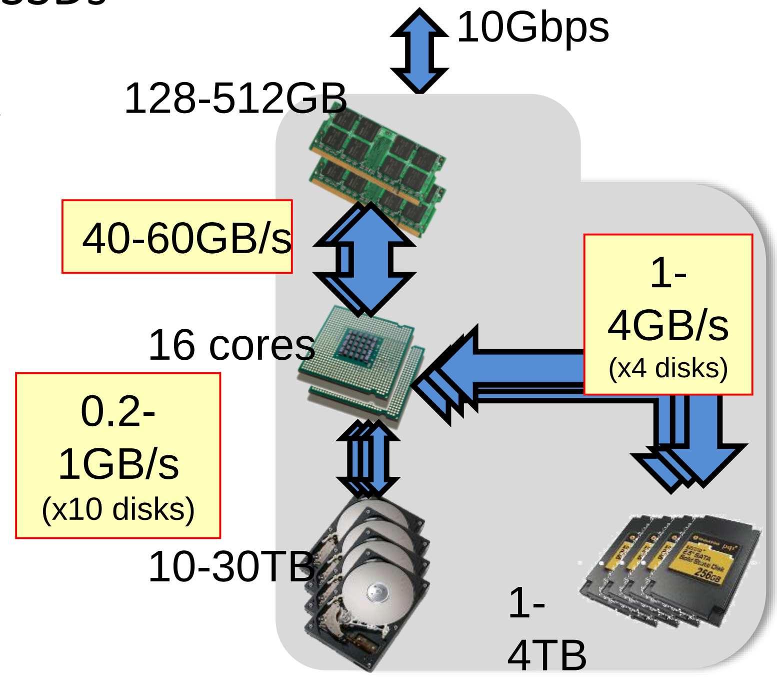


- ***Easy*** to combine ***batch***, ***streaming***, and ***interactiv***e computations
- ***Easy*** to develop ***sophisticated*** algorithms
- ***Compatible*** with existing open source ecosystem (Hadoop/HDFS)

Memory use

- Aggressive use of memory can be a solution

- Memory transfer rates >> disk or even SSDs
  - Gap is growing especially w.r.t. disk
- Many datasets already fit into memory
  - The inputs of over 90% of jobs in Facebook, Yahoo!, and Bing clusters fit into memory
  - E.g., 1TB = 1 billion records @ 1 KB each
- Memory density (still) grows with Moore's law
  - RAM/SSD hybrid memories at horizon



High end datacenter node

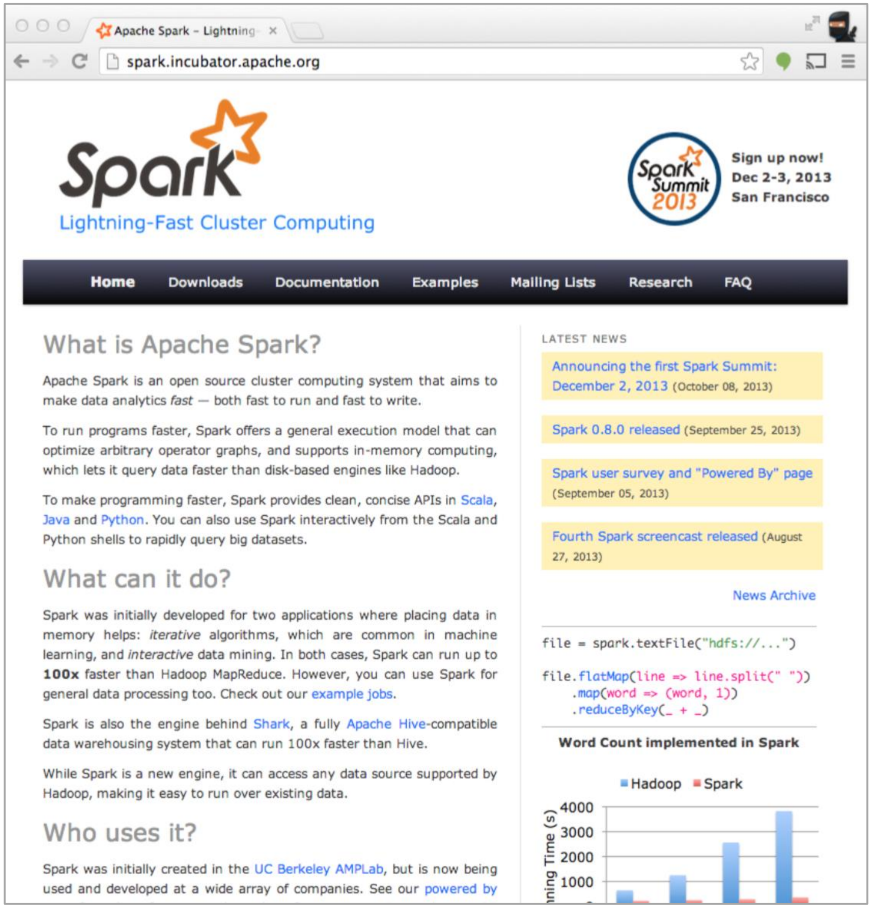
Spark

- Project start - UC Berkeley, 2009
  - Matei Zaharia et al. Spark: Cluster Computing with Working Sets,. HotCloud 2010.
  - Matei Zaharia et al. Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing. NSDI 2012.

- In February 2014, Spark became a Top-Level Apache Project

- Open source (mostly Scala code)

- http://spark.apache.org/



Pros and Cons of MapReduce

Greatly simplifies "big data" analysis on large, unreliable clusters

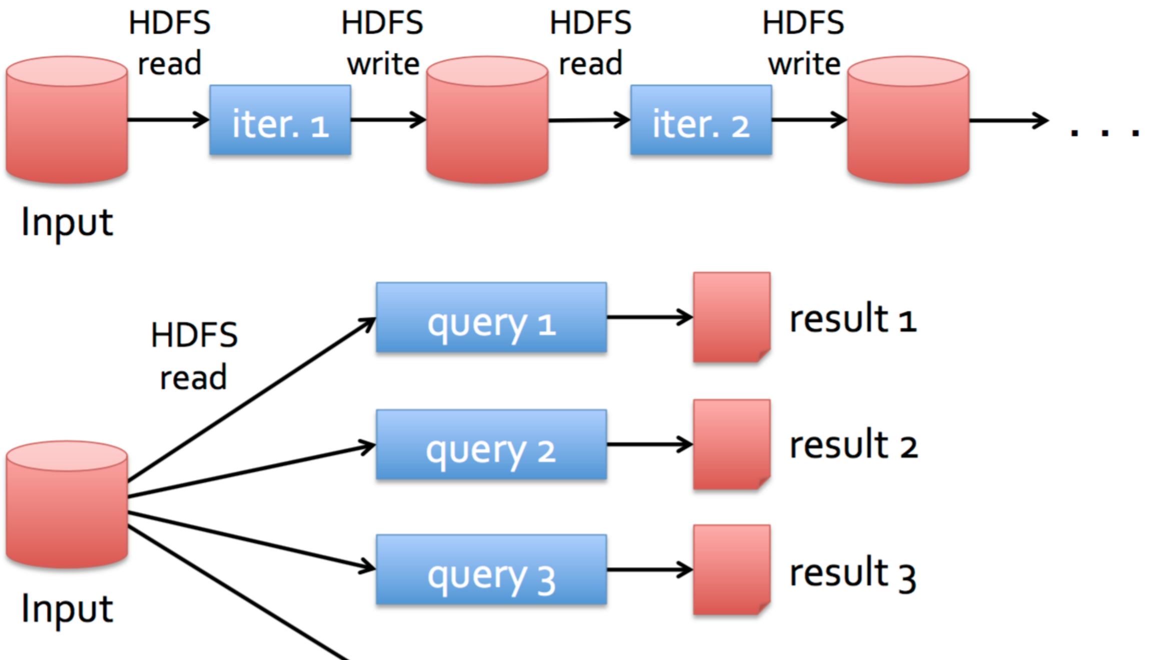
- Simple interface: map and reduce
- Hides details of parallelism, data partition, fault-tolerance, load-balancing...

- Problems
  - cannot support **complex** (iterative) applications efficiently
  - cannot support **interactive** applications efficiently
- Root cause
  - Inefficient data sharing

- Hardware had advanced since Hadoop started.
  - Very large RAMs, Faster networks (10Gb+).
  - Bandwidth to disk not keeping up

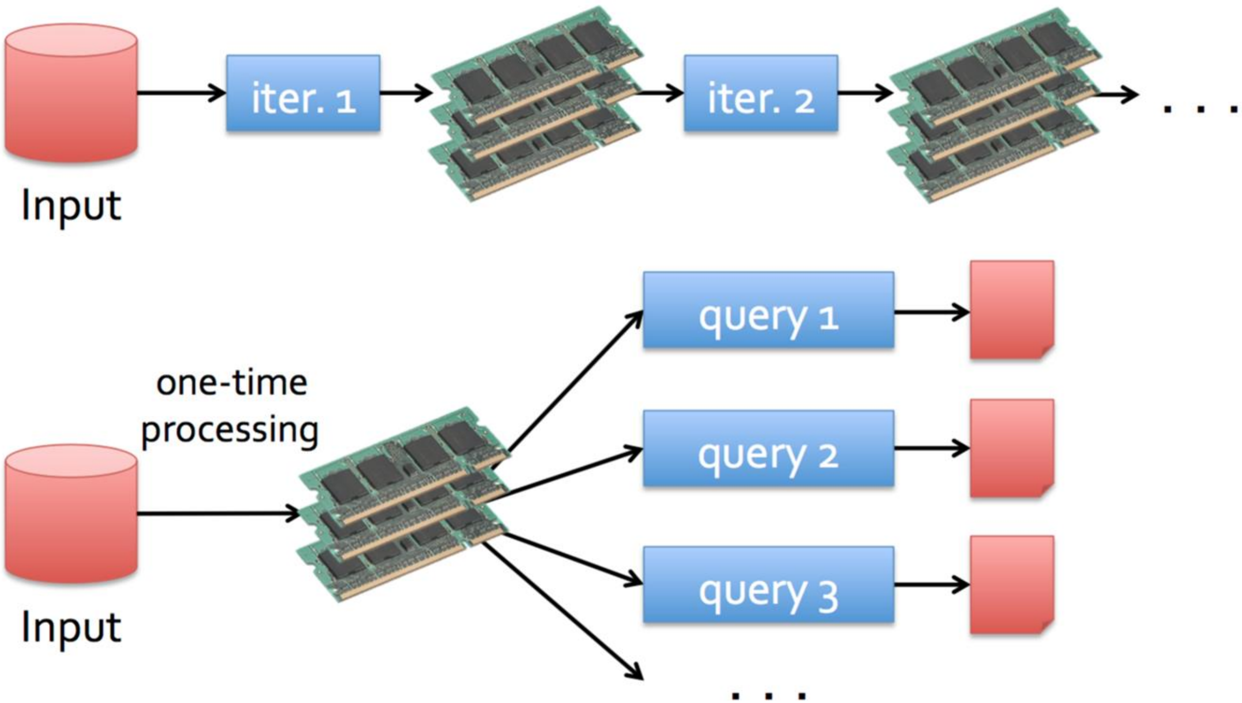
In MapReduce, the only way to share data across jobs is stable storage -> **slow**!

Limitations of MapReduce



Slow due to replication and disk I/O,
but necessary for fault tolerance

Goal: In-Memory Data Sharing



Challenges

10-100x faster than network/disk, but how to achieve fault-tolerance **efficiently**?

- Data replication?
- Log fine-grained updates to mutable states?

- Network bandwidth is scarce resource
- Disk I/O is slow
- Costly for data-intensive apps

Observation

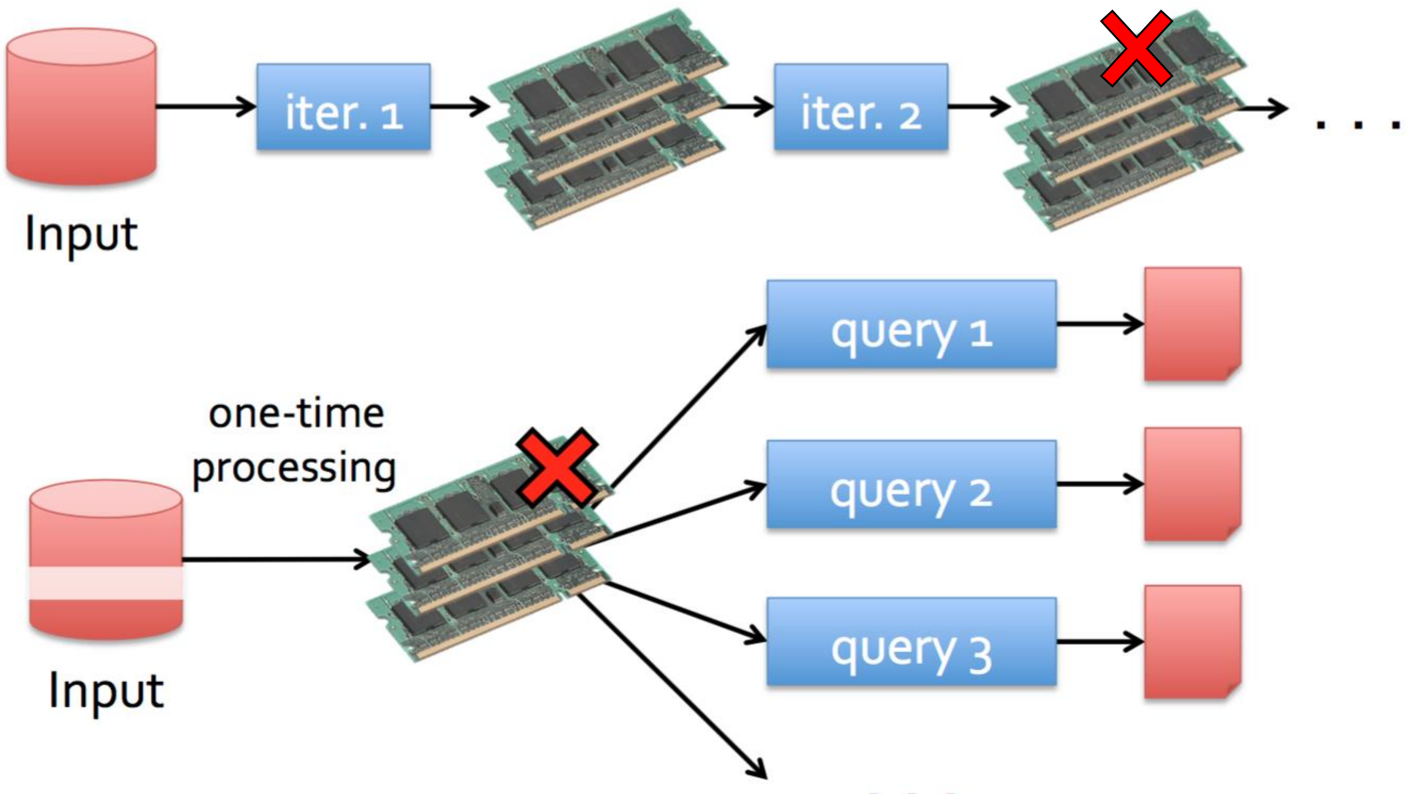
Coarse-grained operation:
In many distributed computing, **same** operation is applied to multiple data items in parallel

RDD (Resilient Distributed Datasets)

- Restricted form of distributed shared memory
  - immutable, partitioned collection of records
  - can only be built through coarse-grained deterministic transformations (map, filter, join...)

- Efficient fault-tolerance using lineage
  - Log coarse-grained operations instead of fine-grained data updates
  - An RDD has enough information about how it's derived from other dataset
  - Recompute lost partitions on failure

Fault-tolerance



Spark and RDDs

- Implements Resilient Distributed Datasets (RDDs)

- Operations on RDDs
  - **Transformations**: defines new dataset based on previous ones
  - **Actions**: starts a job to execute on cluster

- Well-designed interface to represent RDDs
  - Makes it very easy to implement transformations
  - Most Spark transformation implementation < 20 LoC

Operation	Meaning
partitions()	Return a list of Partition objects
preferredLocations(*p*)	List nodes where partition *p* can be accessed faster due to data locality
dependencies()	Return a list of dependencies
iterator(*p, parentIters*)	Compute the elements of partition *p* given iterators for its parent partitions
partitioner()	Return metadata specifying whether the RDD is hash/range partitioned

Table 3: Interface used to represent RDDs in Spark.

Simple Yet Powerful

WordCount Implementation: Hadoop vs. Spark

```java
public class WordCount {

  public static class TokenizerMapper
       extends Mapper<Object, Text, Text, IntWritable>{

    private final static IntWritable one = new IntWritable(1);
    private Text word = new Text();

    public void map(Object key, Text value, Context context
                    ) throws IOException, InterruptedException {
      StringTokenizer itr = new StringTokenizer(value.toString());
      while (itr.hasMoreTokens()) {
        word.set(itr.nextToken());
        context.write(word, one);
      }
    }
  }

  public static class IntSumReducer
       extends Reducer<Text,IntWritable,Text,IntWritable> {
    private IntWritable result = new IntWritable();

    public void reduce(Text key, Iterable<IntWritable> values,
                       Context context
                       ) throws IOException, InterruptedException {
      int sum = 0;
      for (IntWritable val : values) {
        sum += val.get();
      }
      result.set(sum);
      context.write(key, result);
    }
  }

  public static void main(String[] args) throws Exception {
    Configuration conf = new Configuration();
    Job job = Job.getInstance(conf, "word count");
    job.setJarByClass(WordCount.class);
    job.setMapperClass(TokenizerMapper.class);
    job.setCombinerClass(IntSumReducer.class);
    job.setReducerClass(IntSumReducer.class);
    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);
    FileInputFormat.addInputPath(job, new Path(args[0]));
    FileOutputFormat.setOutputPath(job, new Path(args[1]));
    System.exit(job.waitForCompletion(true) ? 0 : 1);
  }
}
```

```scala
val textFile = sc.textFile("hdfs://...")
val counts = textFile.flatMap(line => line.split(" ")).map(word => (word, 1)).reduceByKey(_ + _)
counts.saveAsTextFile("hdfs://...")
```

Pregel: iterative graph processing, 200 LoC using Spark

HaLoop: iterative MapReduce, 200 LoC using Spark

Spark

- Fast, expressive cluster computing system compatible with Apache Hadoop
  - Works with any Hadoop-supported storage system (HDFS, S3, Avro, …)

- Improves **efficiency** through:
  - In-memory computing primitives
  - General computation graphs

→ Up to 100× faster

- Improves **usability** through:
  - Rich APIs in Java, **Scala**, Python
  - Interactive shell

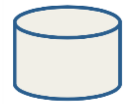
→ Often 2-10× less code

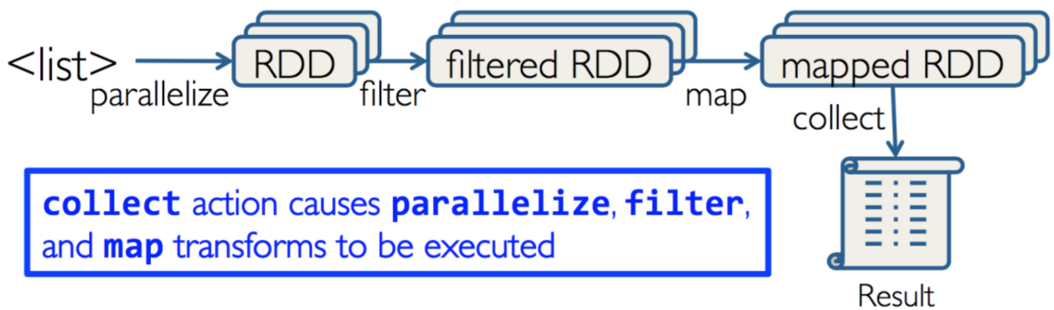
More on RDDs

Work with distributed collections as you would with local ones

- Resilient distributed datasets (RDDs)
  - Immutable collections of objects spread across a cluster
  - Built through parallel transformations (map, filter, etc)
  - Automatically rebuilt on failure
  - Controllable persistence (e.g., caching in RAM)
    - Different storage levels available, fallback to disk possible
- Operations
  - **Transformations** (e.g. map, filter, groupBy, join)
    - Lazy operations to build RDDs from other RDDs
  - **Actions** (e.g. count, collect, save)
    - Return a result or write it to storage

Workflow with RDDs

- Create an RDD from a data source: <list> 
- Apply transformations to an RDD: map filter
- Apply actions to an RDD: collect count




```
distFile = sc.textFile("...", 4)
```

- RDD distributed in 4 partitions
- Elements are lines of input
- *Lazy evaluation* means no execution happens now

Example: Mining Console Logs

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

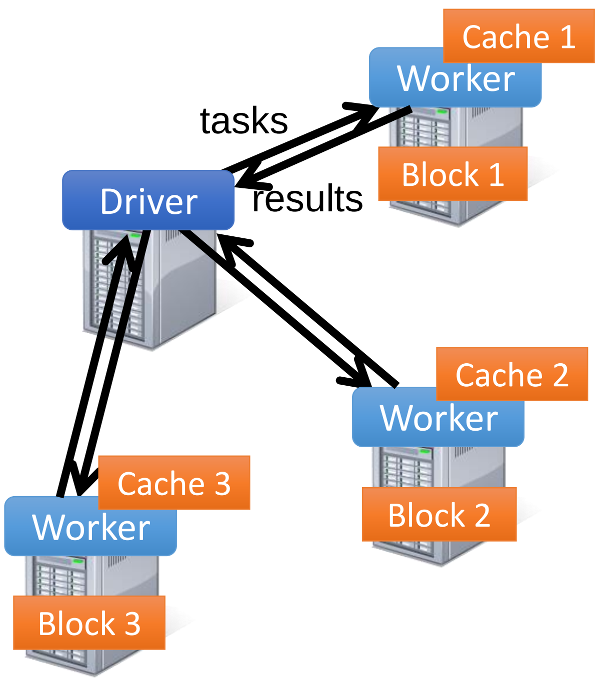
Base RDD

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()
```

Action

```
messages.filter(lambda s: “foo” in s).count()
messages.filter(lambda s: “bar” in s).count()
. . .
```

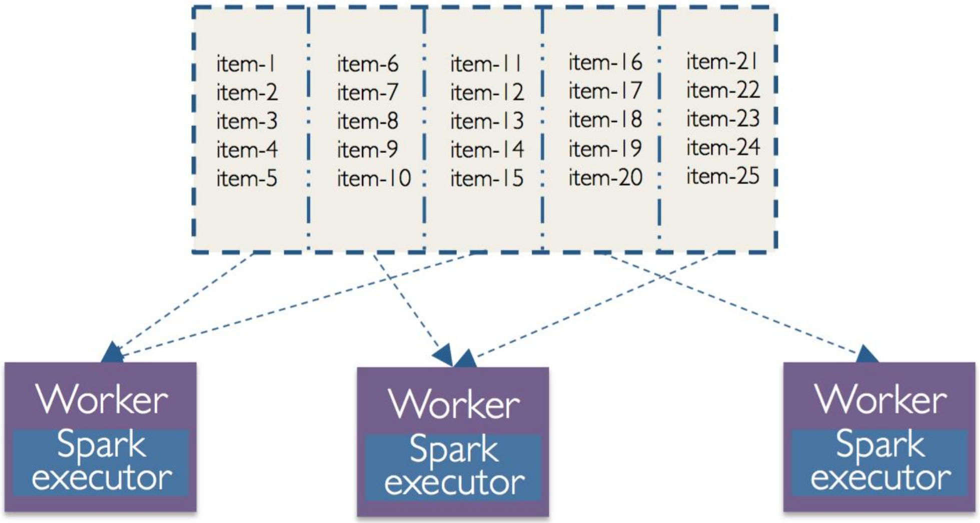


Result: scaled to 1 TB data in 5-7 sec
(vs 170 sec for on-disk data)

Result: full-text search of Wikipedia in <1 sec
(vs 20 sec for on-disk data)

Partitions

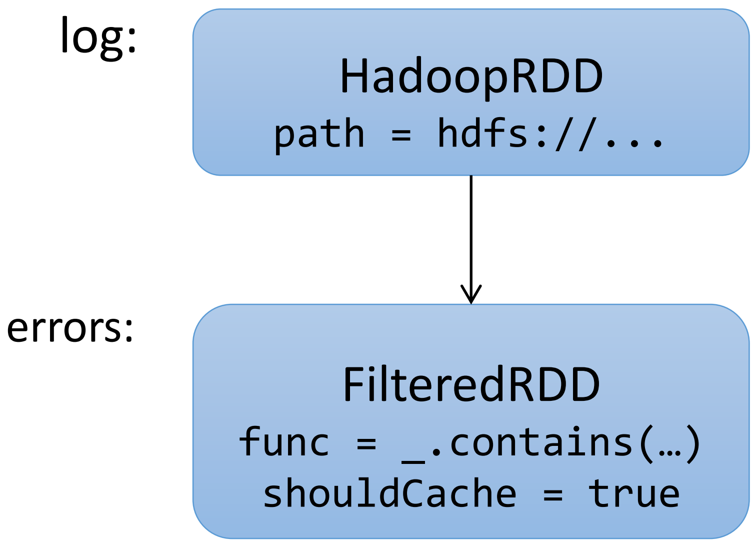
- Programmer specifies number of partitions for an RDD
  - Default value used if unspecified
  - *more partitions = more parallelism* (If workers are available)



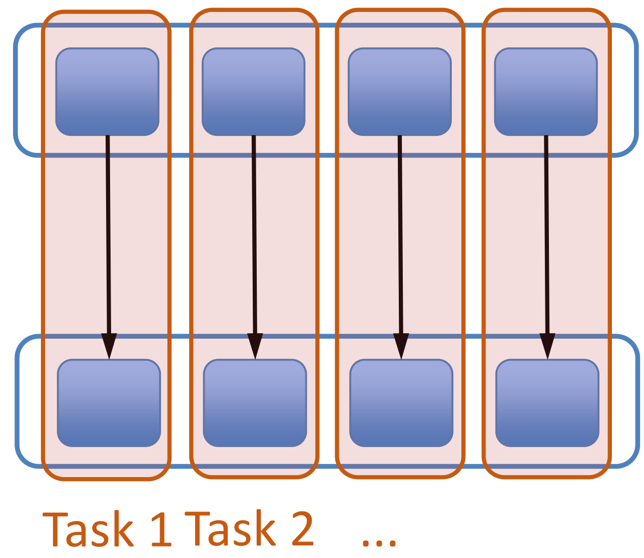
RDD split into
5 partitions

RDD partition-level view

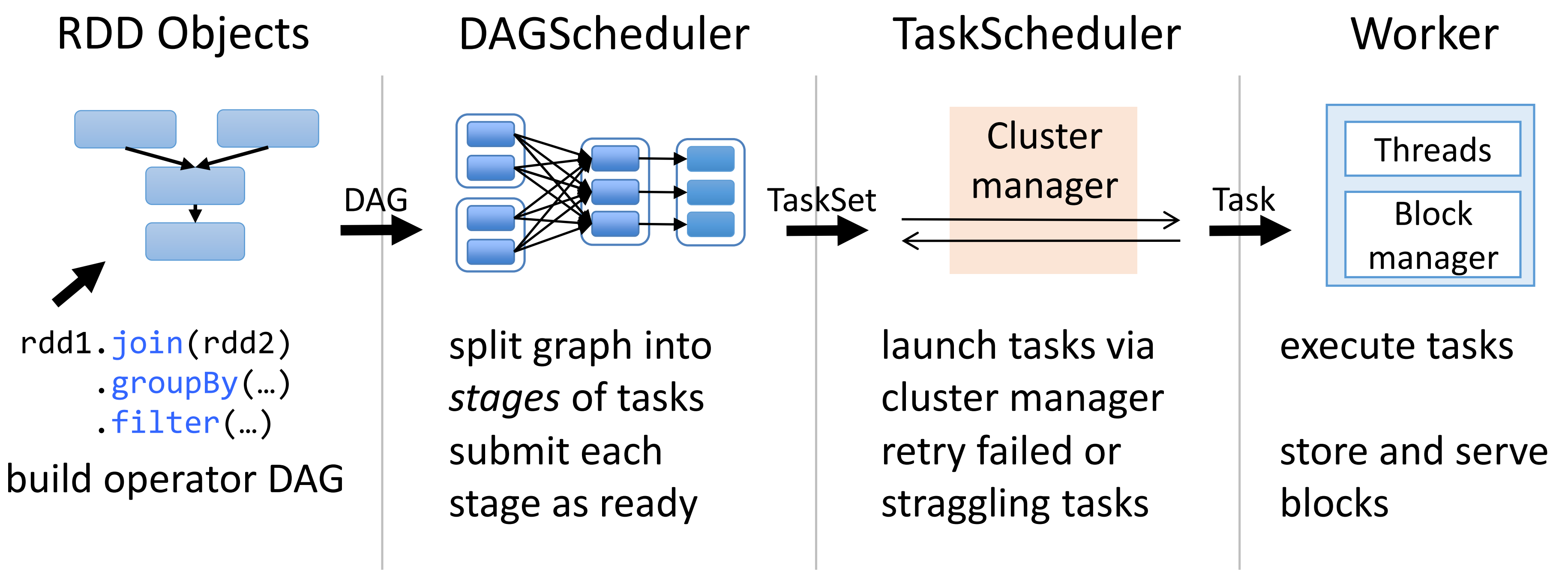
Dataset-level view:



Partition-level view:



Job scheduling



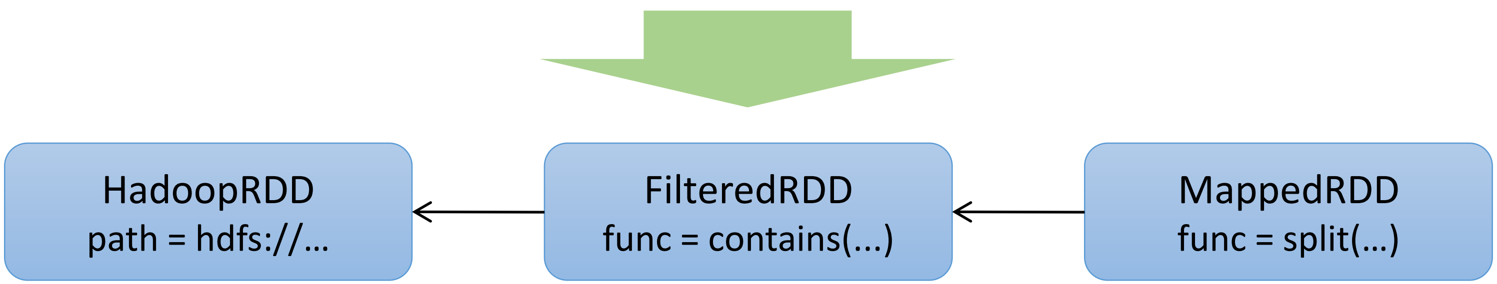
source: https://cwiki.apache.org/confluence/display/SPARK/Spark+Internals

RDD Fault Tolerance

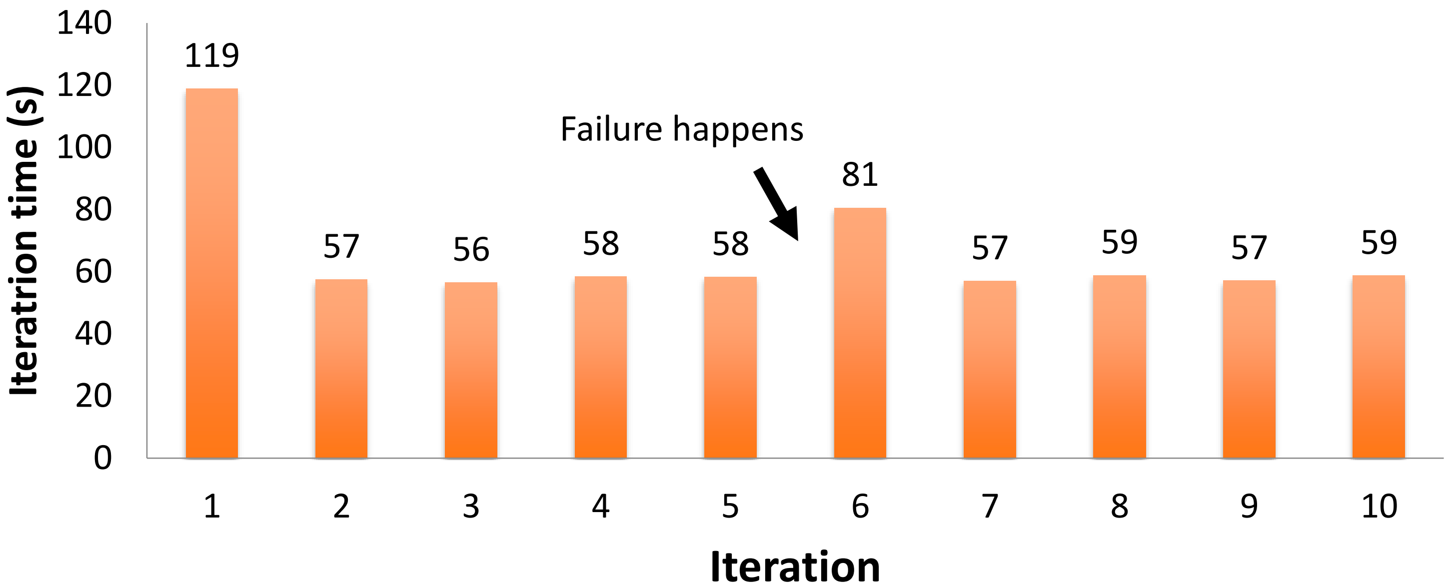
RDDs track the transformations used to build them (their *lineage*) to recompute lost data

E.g:

```
messages = textFile(...).filter(lambda s: s.contains("ERROR"))
                        .map(lambda s: s.split('\t')[2])
```

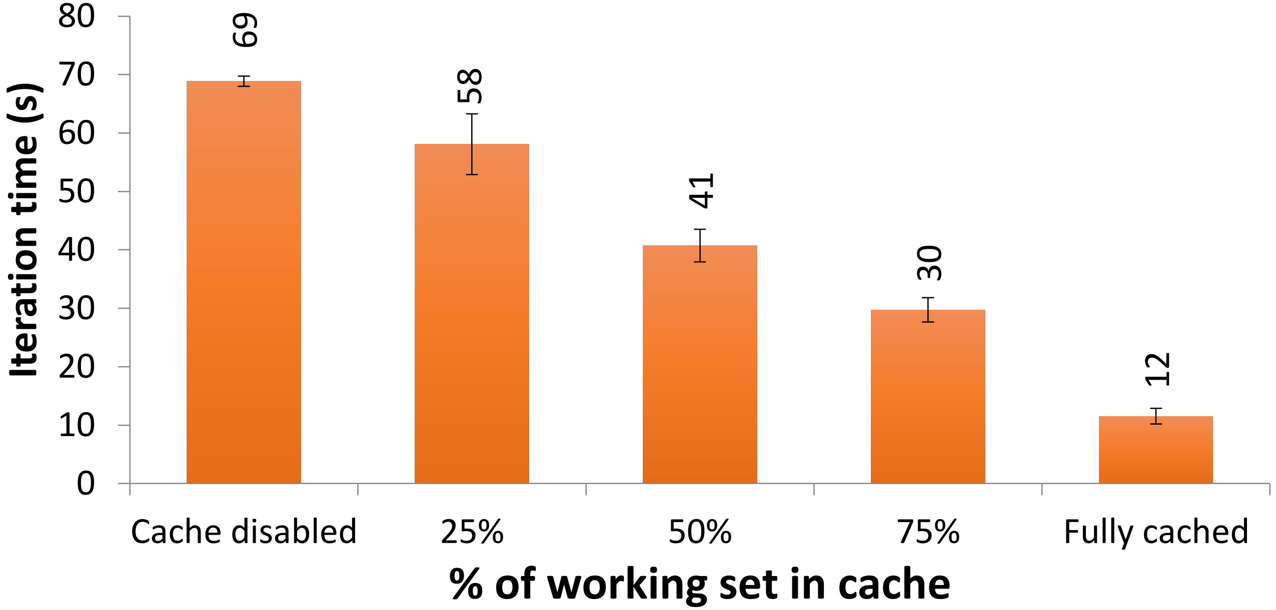


Fault Recovery Test



running time for 10 iterations of k-means on 75 nodes, each iteration contains 400 tasks on 100GB data

Behavior with Less RAM



Spark in Java and Scala

Java API:

```
JavaRDD<String> lines = spark.textFile(…);

errors = lines.filter(
  new Function<String, Boolean>() {
    public Boolean call(String s) {
      return s.contains("ERROR");
    }
});

errors.count()
```

Scala API:

```
val lines = spark.textFile(…)

errors = lines.filter(s => s.contains("ERROR"))
// can also write filter(_.contains("ERROR"))

errors.count
```

Creating RDDs

```
# Turn a local 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 any existing Hadoop InputFormat
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(0, 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 act 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);  // class scala.Tuple2
pair._1 // => a
pair._2 // => b
```

Some Key-Value Operations

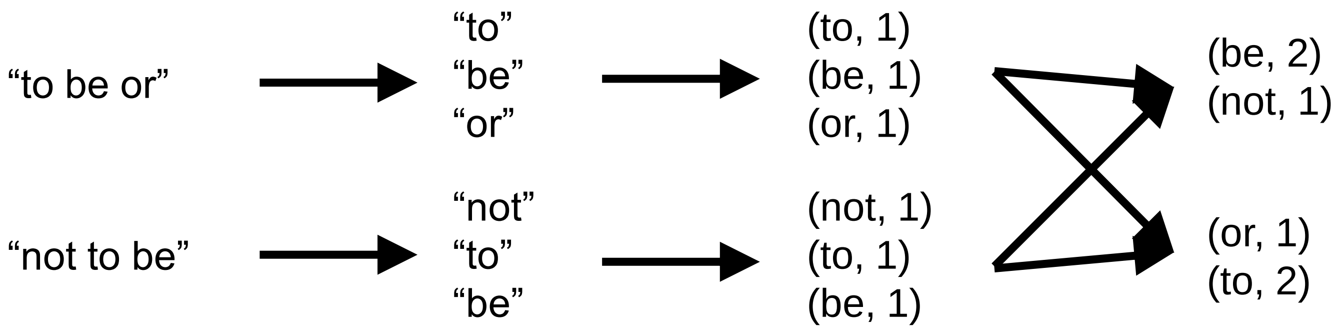
```
pets = sc.parallelize([(“cat”, 1), (“dog”, 1), (“cat”, 2)])

pets.reduceByKey(lambda x, y: x + y)
# => {(cat, 3), (dog, 1)}

pets.groupByKey()
# => {(cat, Seq(1, 2)), (dog, Seq(1)}

pets.sortByKey()
# => {(cat, 1), (cat, 2), (dog, 1)}
```

`reduceByKey` also automatically implements combiners on the map side

Example: Word Count

```
val lines = sc.textFile(“hamlet.txt”)
val counts = lines.flatMap(_.split(“ ”))
                 .map((_, 1))
                 .reduceByKey(x + y)
```

[Scala]




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

[Python]

Multiple Datasets

```
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”, (Seq(“1.2.3.4”, “1.3.3.1”), Seq(“Home”)))
# (“about.html”, (Seq(“3.4.5.6”), Seq(“About”)))
```

Controlling the Level of Parallelism

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

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

Using Local Variables

- External variables you use in a closure will automatically be shipped to the cluster:

```
query = raw_input(“Enter a query:”)
pages.filter(lambda x: x.startswith(query)).count()
```

- Some caveats:
  - Each task gets a new copy (updates aren’t sent back)
  - Variable must be Serializable (Java/Scala) or Pickle-able (Python)
  - Don’t use fields of an outer object (ships all of it!)

Closure Mishap Example

```
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)

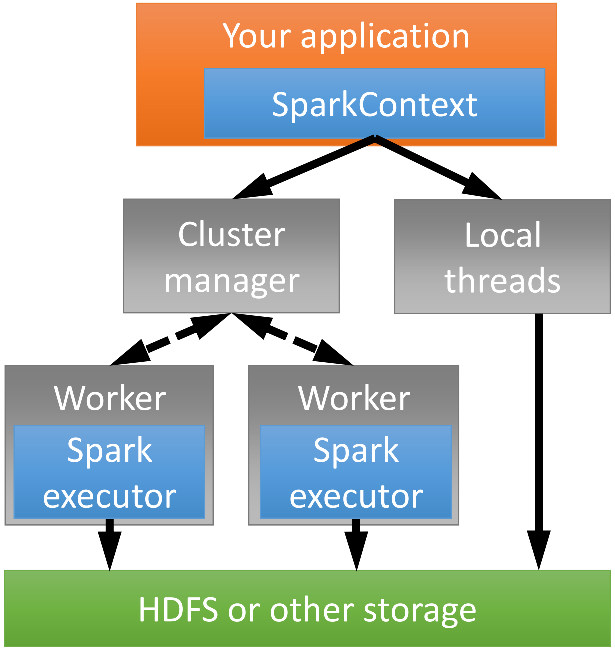
How to get around it:

```
class MyCoolRddApp {
  ...

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

References only local variable
instead of `this.param`

Software Components

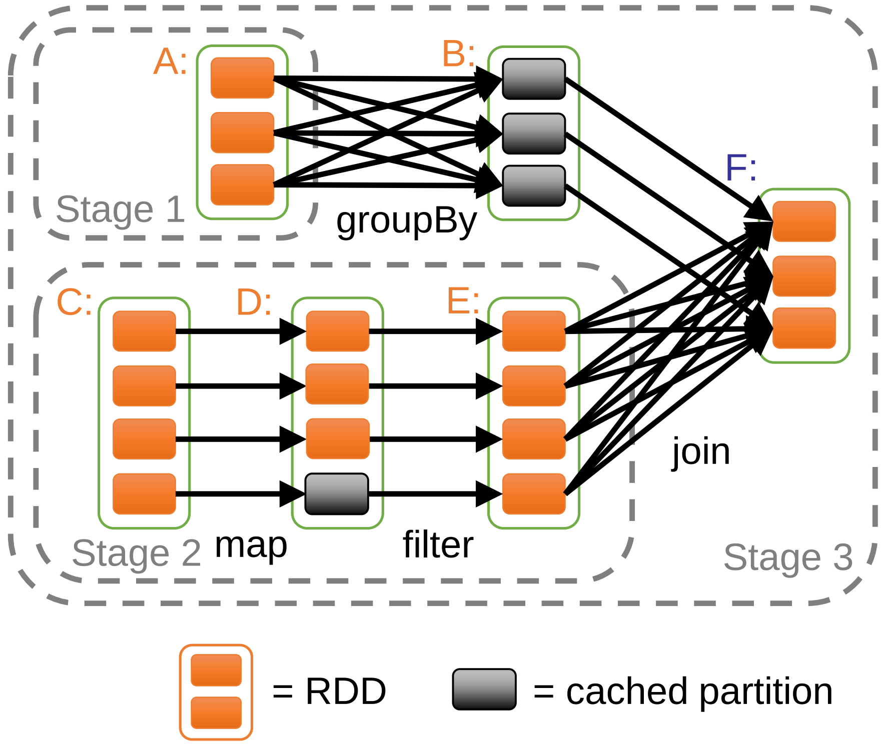
- Spark runs as a library in your program (one instance per app)
- Runs tasks locally or on a cluster
  - Standalone deploy cluster, Mesos or YARN
- Accesses storage via Hadoop InputFormat API
  - Can use HBase, HDFS, S3, …



- A Spark program is two programs:
  A driver program and a workers program
- Worker programs run on cluster nodes or in local threads
- RDDs are distributed across workers

Task Scheduler

- Supports general task graphs
- Pipelines functions where possible
- Cache-aware data reuse & locality
- Partitioning-aware to avoid shuffles



Hadoop Compatibility

- Spark can read/write to any storage system/format that has a plugin for Hadoop!
  - Examples: HDFS, S3, HBase, Cassandra, Avro, SequenceFile
  - Reuses Hadoop's InputFormat and OutputFormat APIs

- APIs like `SparkContext.textFile` support filesystems, while `SparkContext.hadoopRDD` allows passing any Hadoop JobConf to configure an input source

Complete App: Scala

```
import spark.SparkContext
import spark.SparkContext._

object WordCount {
  def main(args: Array[String]) {
    val sc = new SparkContext("local", "WordCount", args(0), Seq(args(1)))
    val lines = sc.textFile(args(2))
    lines.flatMap(_.split(" "))
         .map(word => (word, 1))
         .reduceByKey(_ + _)
         .saveAsTextFile(args(3))
  }
}
```

Complete App: Python

```
import sys
from pyspark import SparkContext

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

    lines.flatMap(lambda s: s.split(“ ”)) \
         .map(lambda word: (word, 1)) \
         .reduceByKey(lambda x, y: x + y) \
         .saveAsTextFile(sys.argv[2])
```

Page Rank

- Give pages ranks (scores) based on links to them
  - Links from many pages ➔ high rank
  - Link from a high-rank page ➔ high rank
- 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

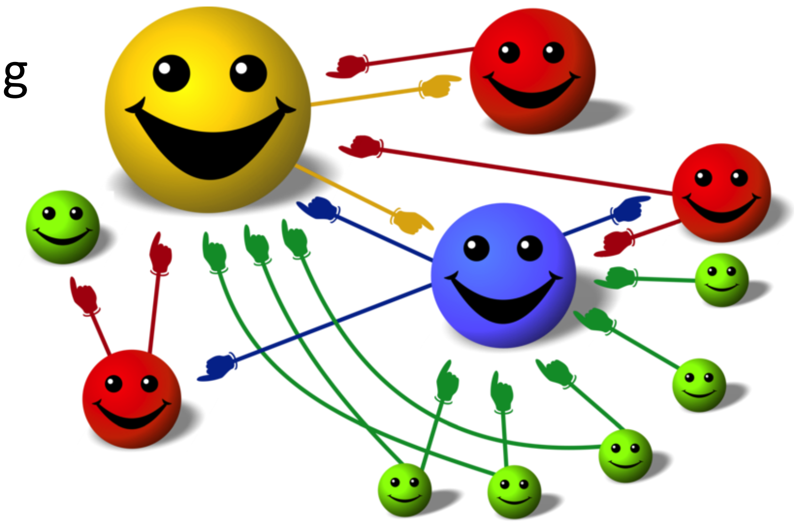


Image: en.wikipedia.org/wiki/File:PageRank-hi-res-2.png

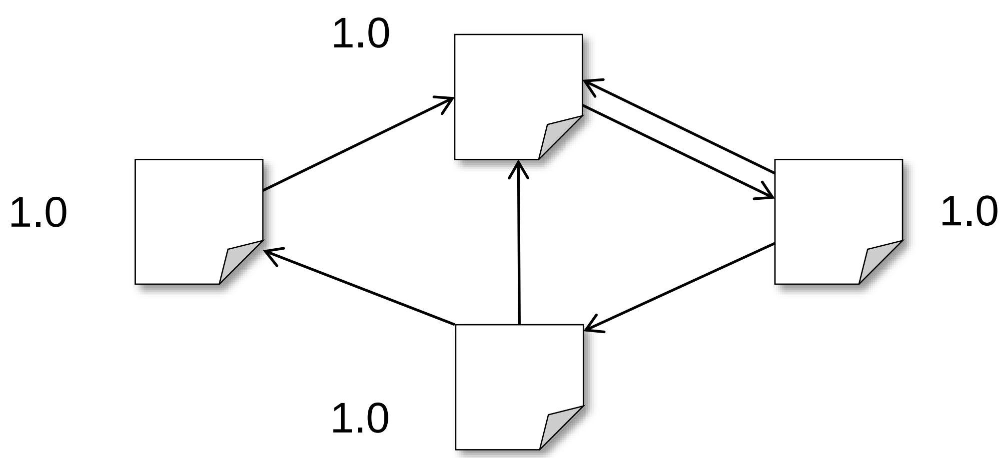
Page Rank

$$PR(x) = (1-d) + d\sum_{i=1}^{n}\frac{PR(t_i)}{C(t_i)}$$

- Sketch of algorithm:
- Start with seed *PRi* values
- Each page distributes *PRi* “credit” to all pages it links to
- Each target page adds up “credit” from multiple in-bound links to compute *PRi+1*
- Iterate until values converge

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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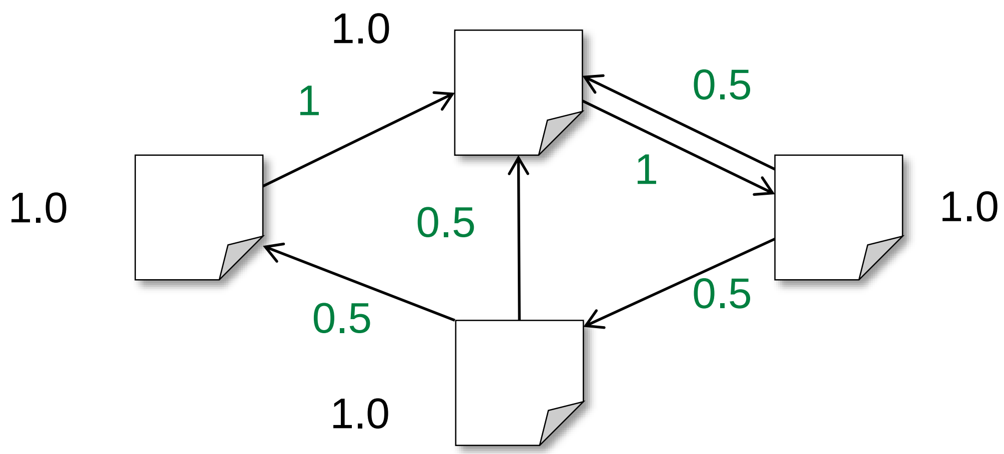

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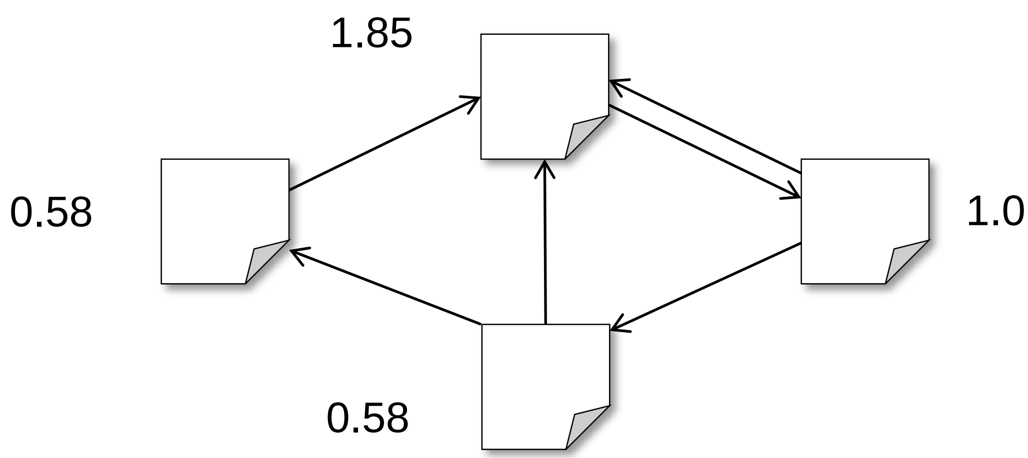

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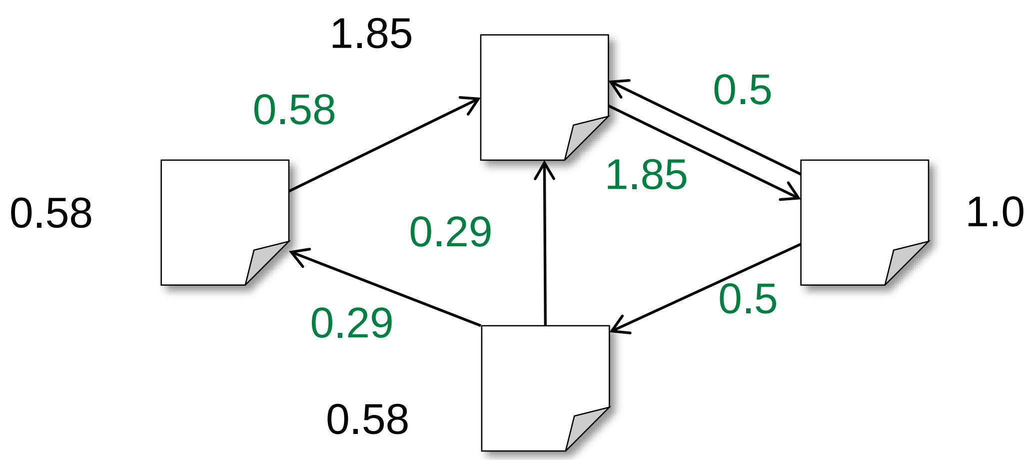

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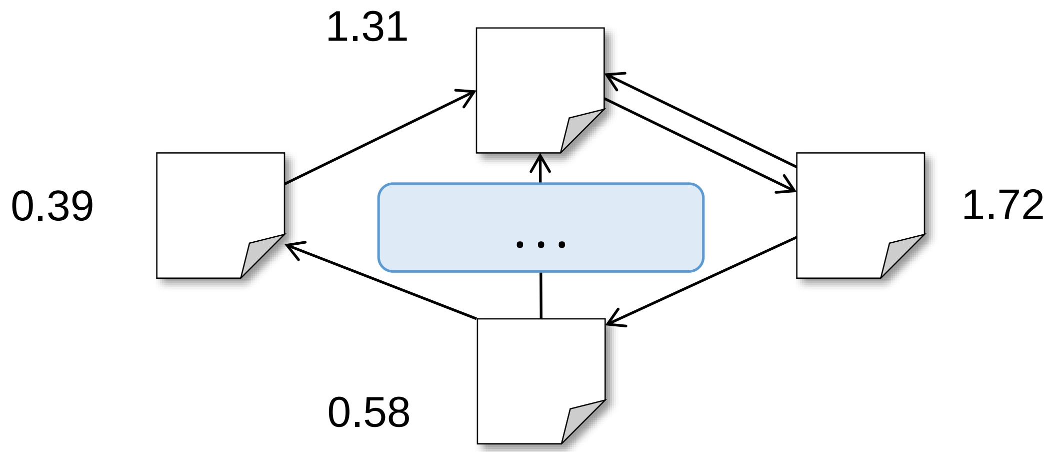

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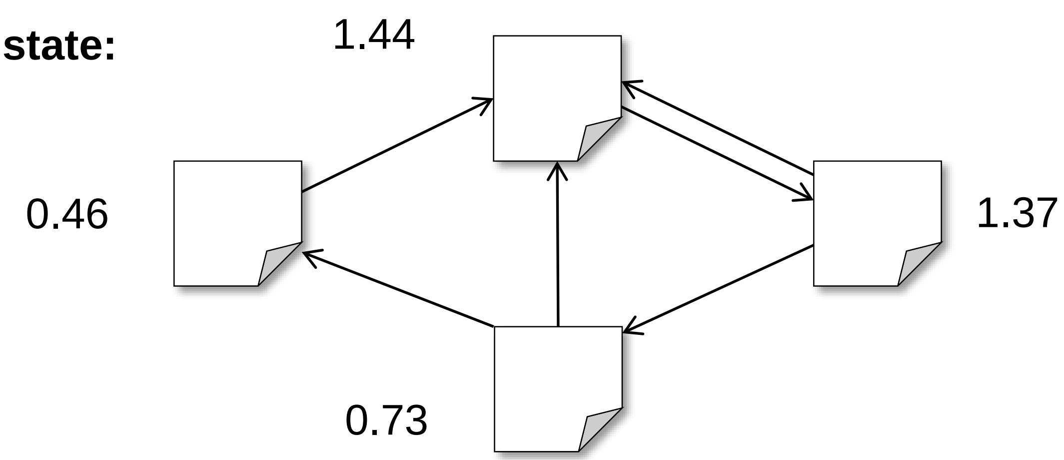
Final state:



Page Rank: MapReduce (Just an intuition)

One PageRank iteration:

- Input:
  (id_1, [$score_1^{(t)}$, out_{11}, out_{12}, ..]), (id_2, [$score_2^{(t)}$, out_{21}, out_{22}, ..]) ..
- Output:
  (id_1, [$score_1^{(t+1)}$, out_{11}, out_{12}, ..]), (id_2, [$score_2^{(t+1)}$, out_{21}, out_{22}, ..]) ..

Input format must match the output format

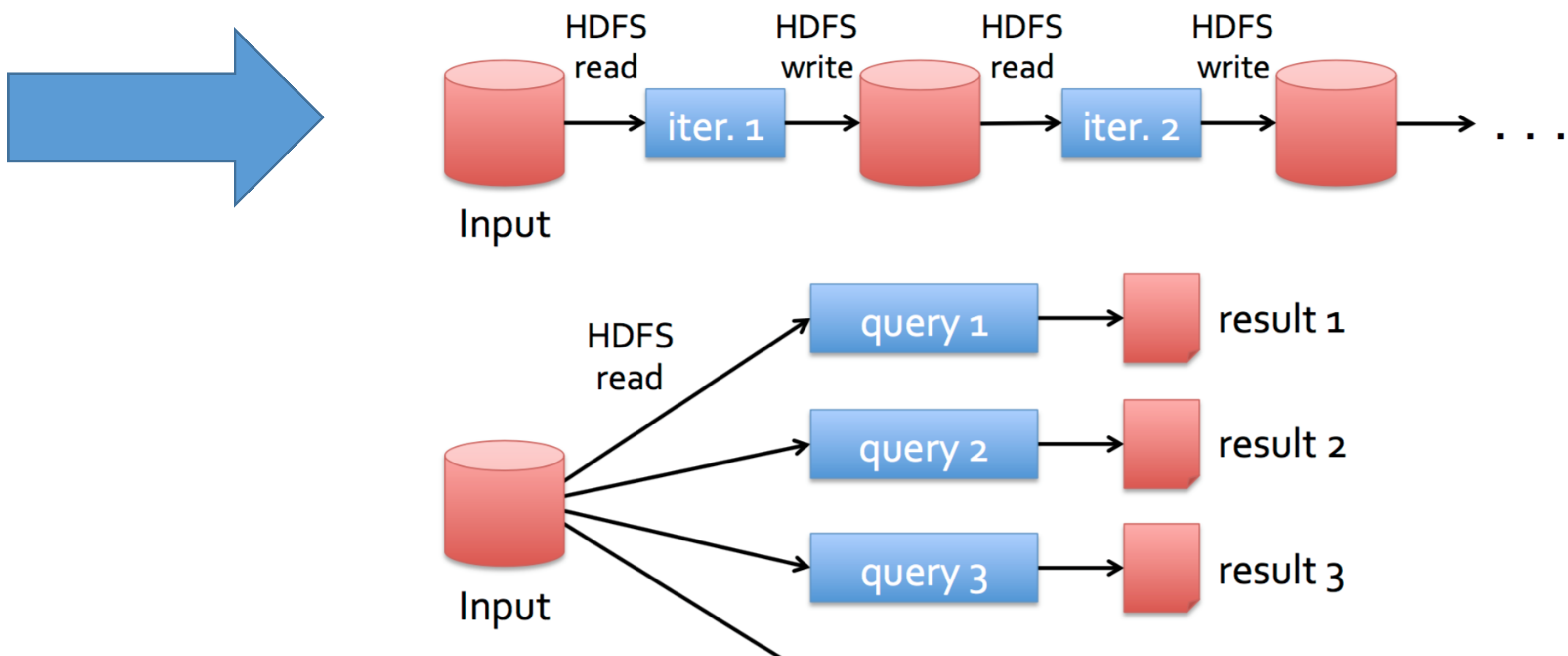
Pseudocode

```
fun map( key: url, value: [pagerank, outlink_list] )
   foreach outlink in outlink_list
      emit( key: outlink, value: pagerank/size(outlink_list) )
   emit( key: url, value: outlink_list )

fun reduce( key: url, value: list_pr_or_urls )
   outlink_list = []
   pagerank = 0
   foreach pr_or_urls in list_pr_or_urls
      if is_list( pr_or_urls )
         outlink_list = pr_or_urls
      else
         pagerank += pr_or_urls
   pagerank = 0.15 + ( 0.85 * pagerank )
   emit( key: url, value: [pagerank, outlink_list] )
```

(1) Each page **distributes** *PRi* "credit" to all pages it links to

(2) Each target page **adds up** "credit" from multiple in-bound links

The result of each iteration is persisted!



Slow due to replication and disk I/O,
but necessary for fault tolerance

Scala Implementation ()

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

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

ranks.saveAsTextFile(...)
```

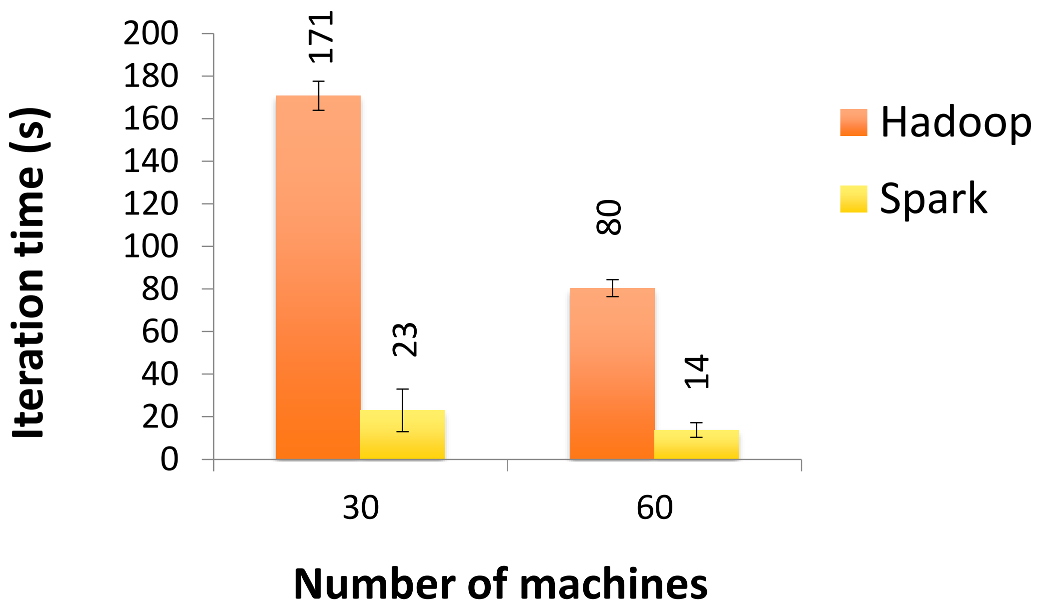
```
// Intermediate values
scala> contributions.collect
Scala> Array[(String, Double)] =
Array((MapR,1.0), (Baidu,0.5), (Blogger,0.5),
(Google,0.5), (Baidu,0.5), (MapR,1.0))
```

```scala
// A possible initialization
val links = sc.parallelize(List(("MapR",List("Baidu","Blogger")),("Baidu",
List("MapR")),("Blogger",List("Google","Baidu")),("Google", List("MapR"))))
.partitionBy(new HashPartitioner(4)).persist()
var ranks = links.mapValues(v => 1.0)
```

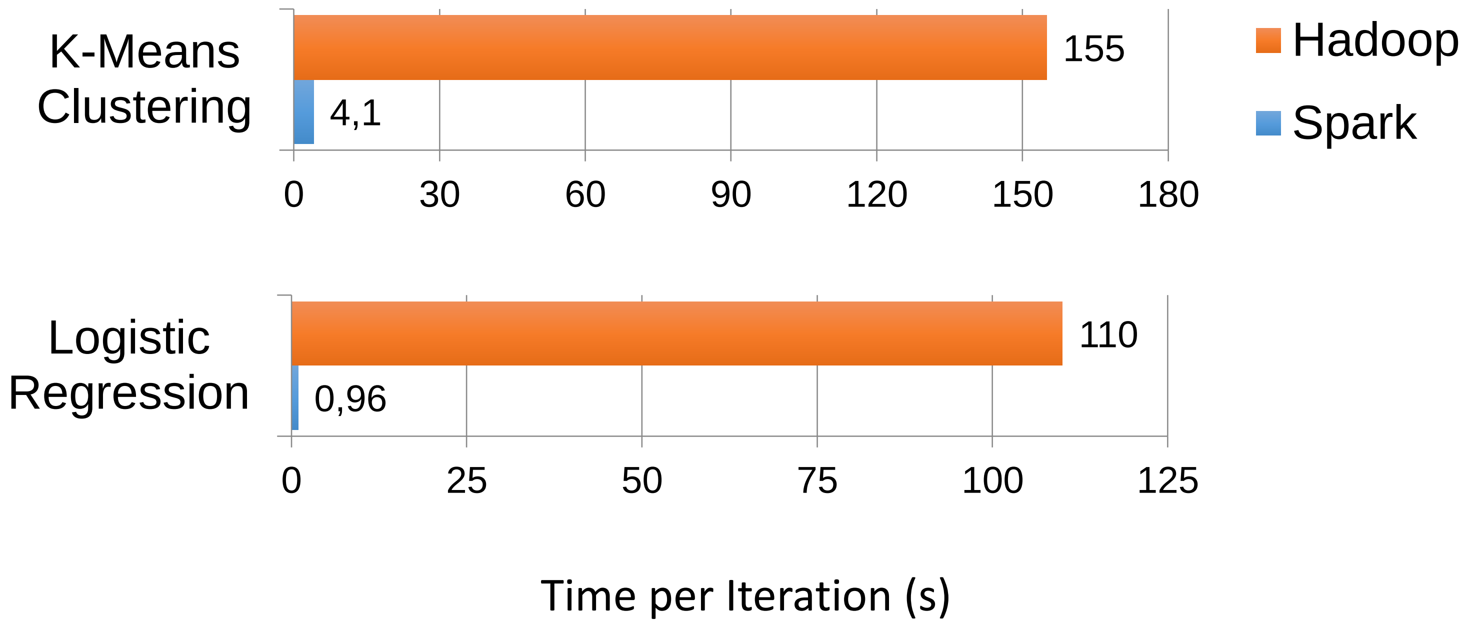
Python Implementation

```
links = # RDD of (url, neighbors) pairs
ranks = # RDD of (url, rank) pairs

for i in range(NUM_ITERATIONS):
    def compute_contribs(pair):
        [url, [links, rank]] = pair  # split key-value pair
        return [(dest, rank/len(links)) for dest in links]

    contribs = links.join(ranks).flatMap(compute_contribs)
    ranks = contribs.reduceByKey(lambda x, y: x + y) \
                    .mapValues(lambda x: 0.15 + 0.85 * x)

ranks.saveAsTextFile(...)
```

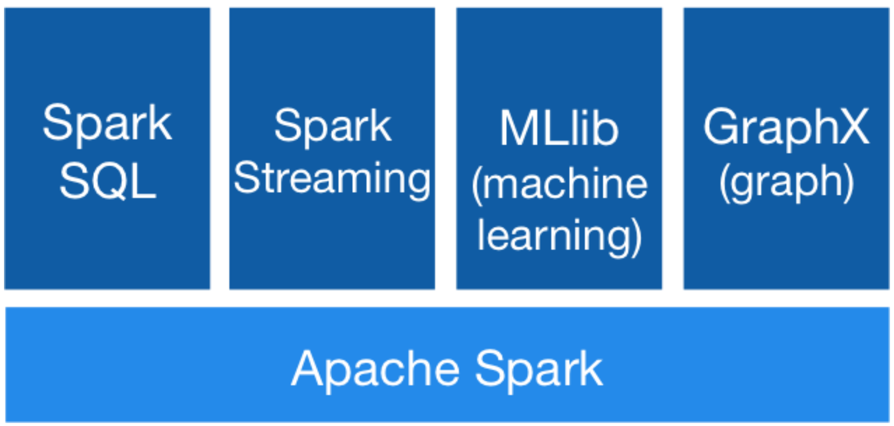
PageRank Performance

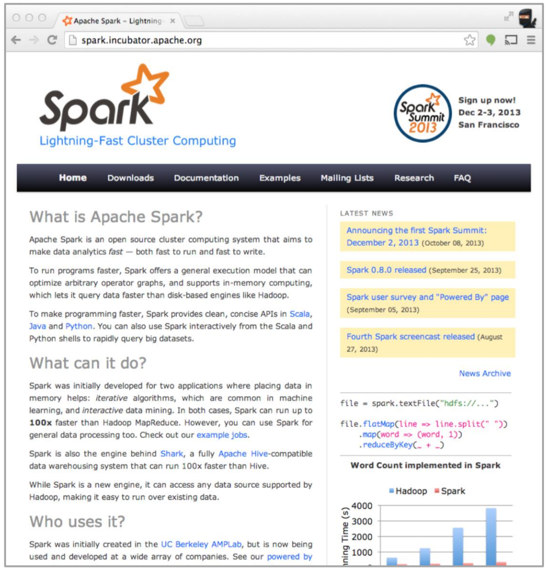


Other Iterative Algorithms



Spark ecosystem





Sources & References

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RDDs

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Spark

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Extra: shark

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