Apache Spark

CS240A

Winter 2016. T Yang

Some of them are based on P. Wendell's Spark slides

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Parallel Processing using Spark+Hadoop

- **Hadoop: Distributed file system that connects machines.**
- **Mapreduce: parallel programming style built on a Hadoop cluster**
- **Spark: Berkeley design of Mapreduce programming**
- **Given a file treated as a big list**
  - A file may be divided into multiple parts (splits).
- **Each record (line) is processed by a Map function,**
  - produces a set of intermediate key/value pairs.
- **Reduce: combine a set of values for the same key**

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>>> words = "The quick brown fox jumps over the lazy dog".split()

Python Examples and List Comprehension

```
>>> lst = [3, 1, 4, 1, 5]
>>> lst.append(2)
>>> len(lst)
5
>>> lst.sort()
>>> lst.insert(4,"Hello")
>>> [1]+ [2]       → [1,2]
>>> lst[0] ->3
```

Python tuples

```
>>> num=(1, 2, 3, 4)
>>> num +(5)   →
   (1,2,3,4, 5)
```

```
for i in [5, 4, 3, 2, 1] :
    print i
print 'Blastoff!'
```

```
>>>M = [x for x in S if x % 2 == 0]
>>>  S = [x**2 for x in range(10)]
[0,1,4,9,16,…,81]
```

```
>>> words ='hello  lazy dog'.split()
>>> stuff = [(w.upper(),  len(w)] for w in words]
→ [ ('HELLO', 5) ('LAZY', 4) , ('DOG', 4)]
```

>>>numset=set([1, 2, 3, 2])
Duplicated entries are deleted
>>>numset=frozenset([1, 2,3])
Such a set cannot be modified

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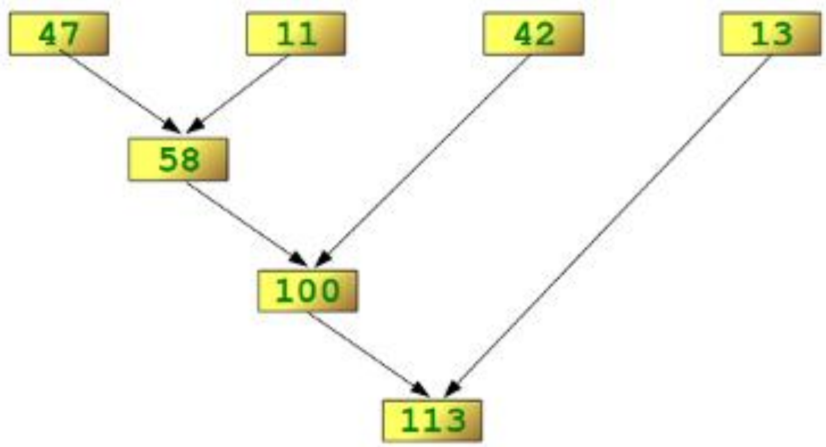
Python map/reduce

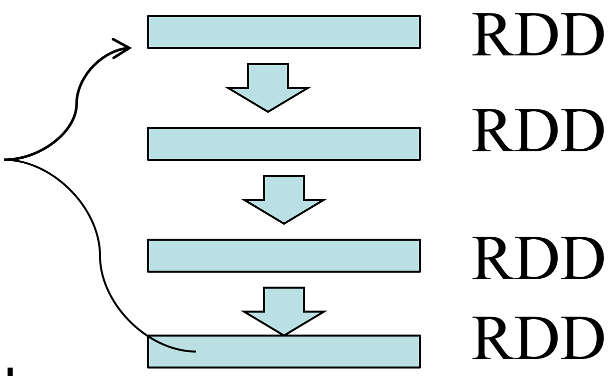
```
a = [1, 2, 3]
b = [4, 5, 6, 7]
c = [8, 9, 1, 2, 3]
f= lambda x:   len(x)
L = map(f, [a, b, c])
[3, 4, 5]
```

```
g=lambda x,y:    x+y
reduce(g, [47,11,42,13])
113
```



Mapreduce programming with SPAK: key concept

Write programs in terms of **operations** on implicitly distributed **datasets (RDD)**



RDD: Resilient Distributed Datasets

- **Like a big list:**
  - 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)**
- **Make sure input/output match**

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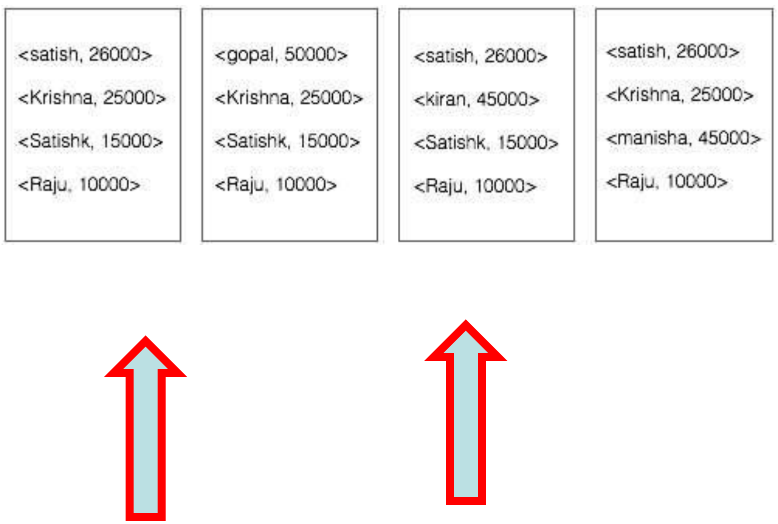
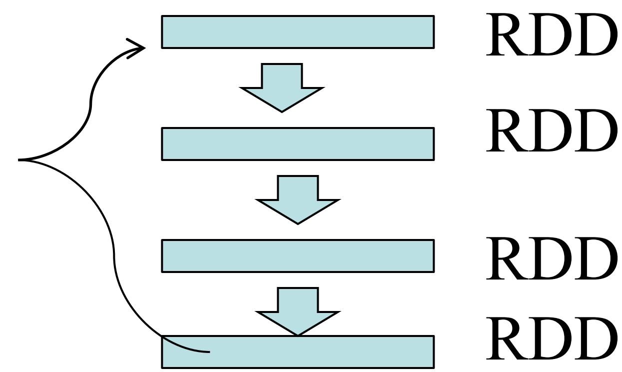
MapReduce vs Spark



Map and reduce tasks operate on key-value pairs



Spark operates on **RDD**

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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

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Spark Context and Creating RDDs

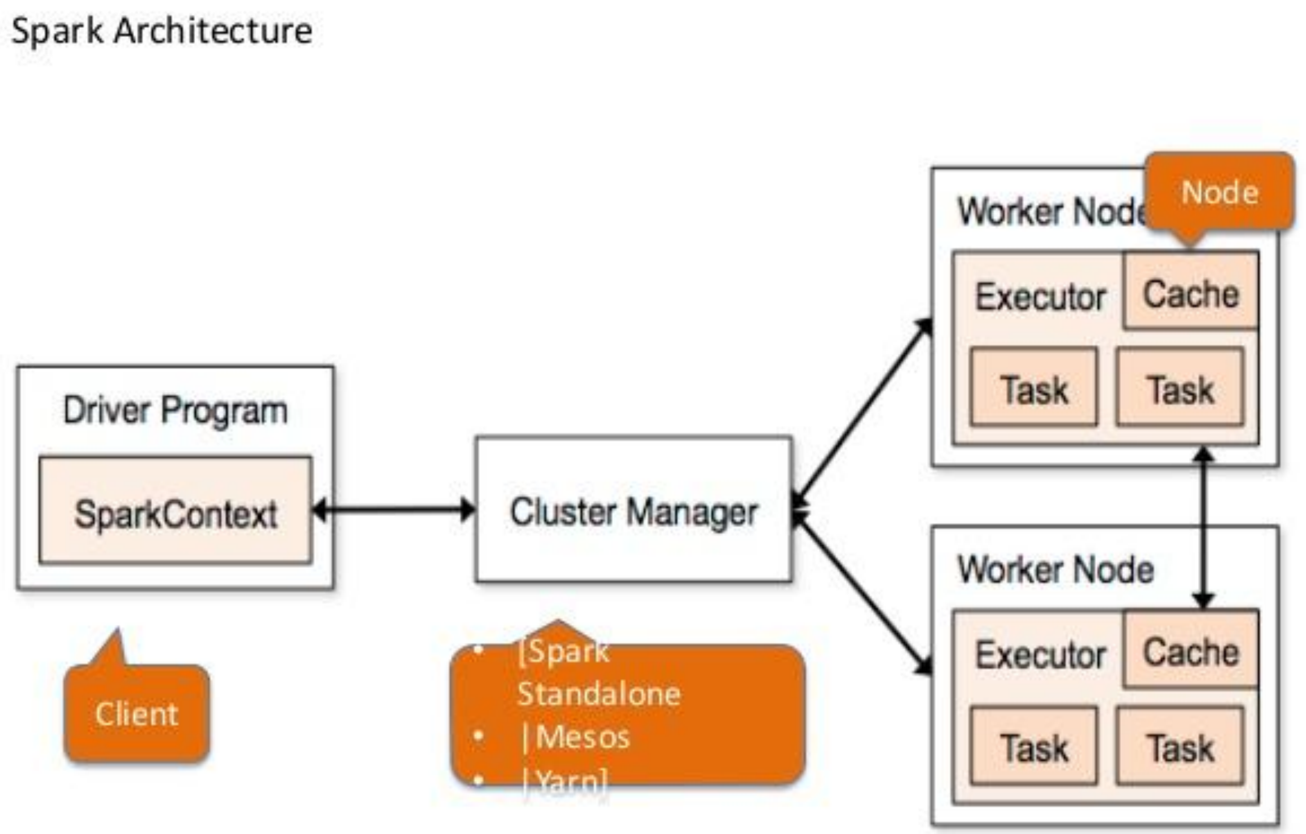
```
#Start with sc – SparkContext as
```

Main entry point to Spark functionality

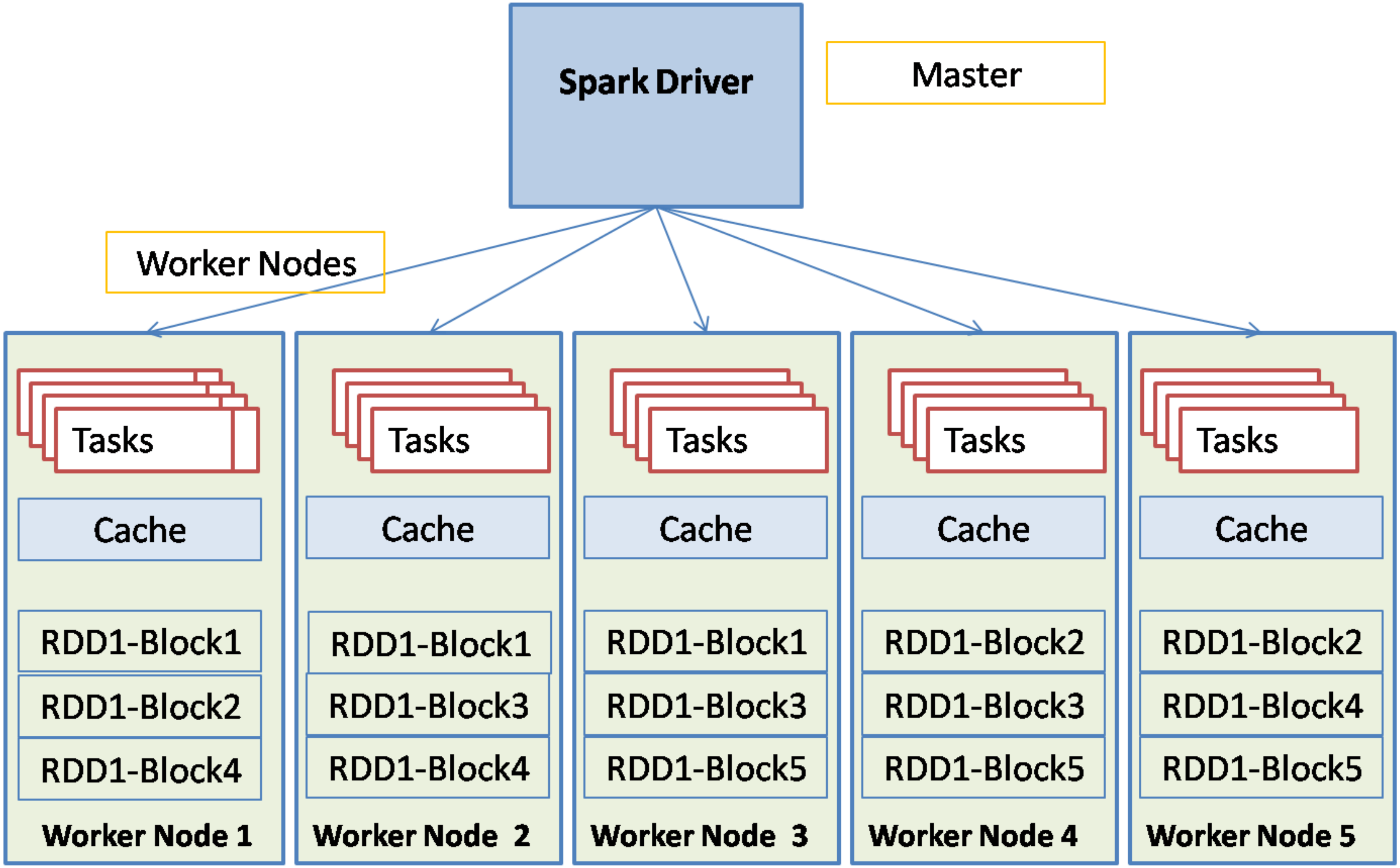
```
# Turn a Python collection into an RDD
>sc.parallelize([1, 2, 3])

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

Spark Architecture



Spark Components



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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}
```

```
#read a text file and count number of lines
containing error

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

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")
```

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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
```

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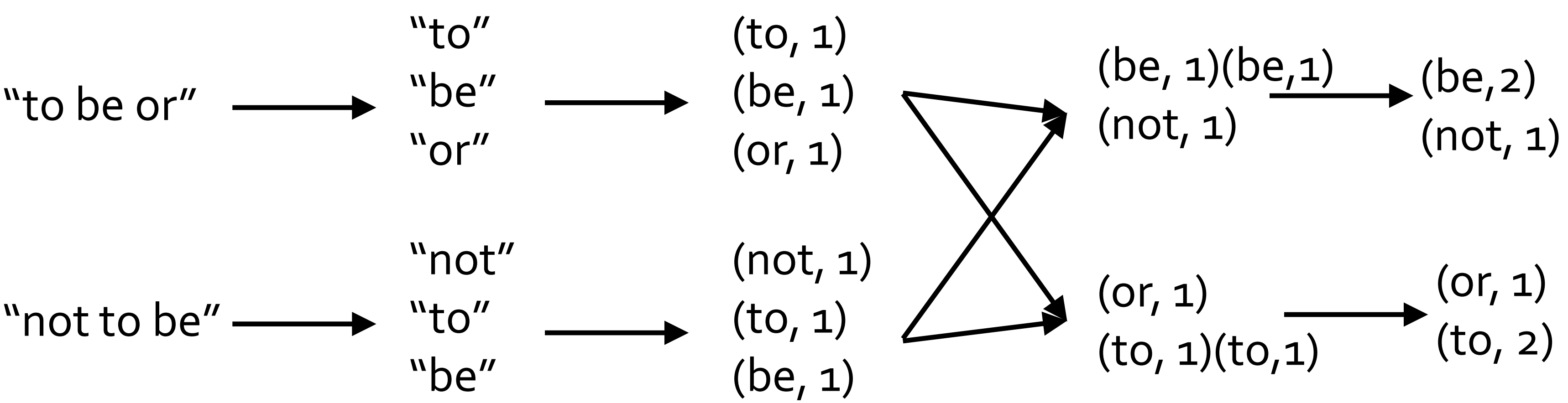
Some Key-Value Operations

```
> 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”]))
```

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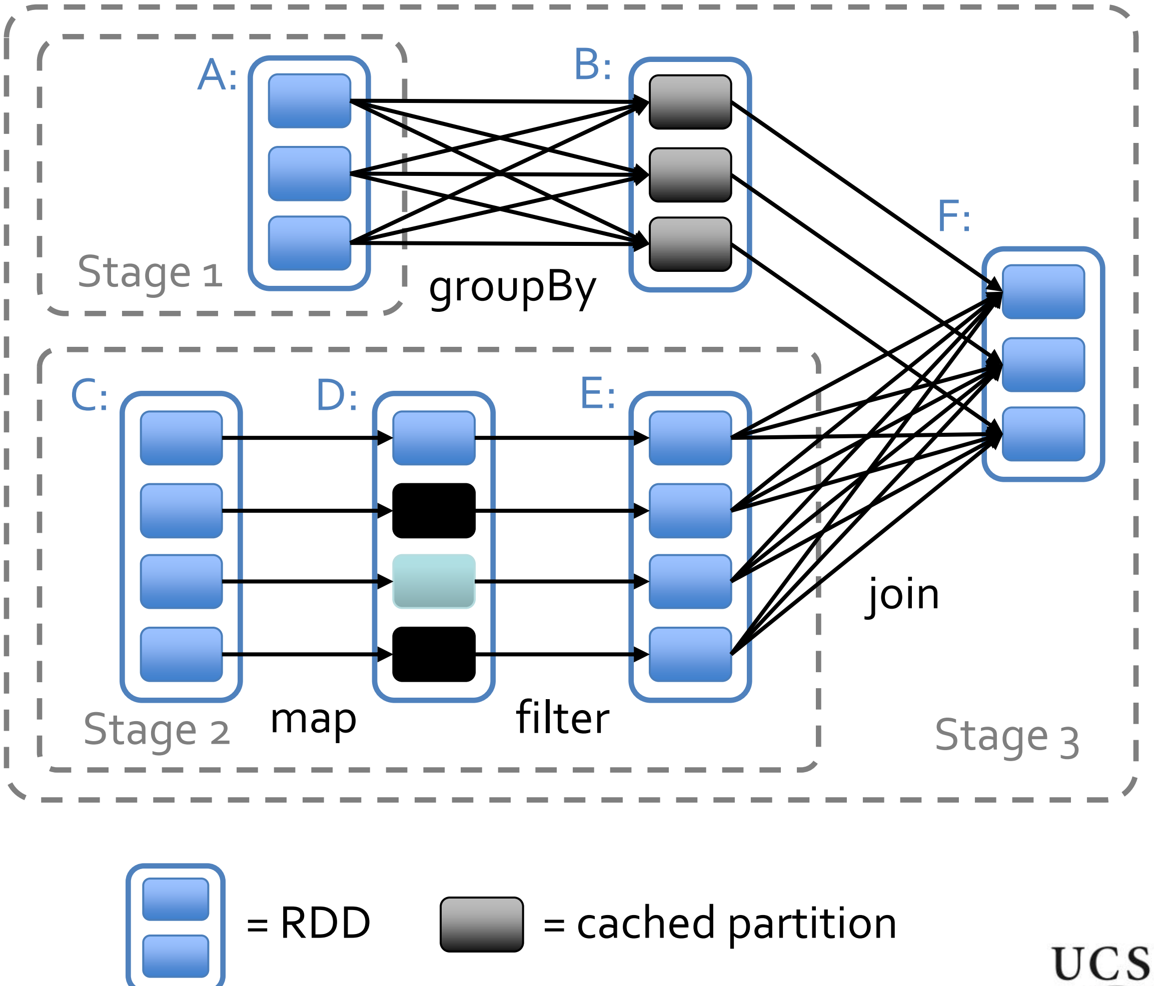
Under The Hood: DAG Scheduler

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



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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)
```

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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 ...

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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**

```
cloudera-5-testing — root@ip-172-31-11-254:~ — ssh — 85×22
root@ip-172-31-11-254:~        root@ip-172-31-11-254:~
[root@ip-172-31-11-254 ~]# /opt/cloudera/parcels/SPARK/pyspark
...
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 0.8.0
      /_/

Using Python version 2.6.6 (r266:84292, Sep 11 2012 08:34:23)
Spark context avaiable as sc.
...
>>> file = sc.textFile("hdfs://ip-172-31-11-254.us-west-2.compute.internal:8020/user/
hdfs/ec2-data/pageviews/2007/2007-12/pagecounts-20071209-180000.gz")
...
>>> file.count()
...
856769
>>> file.filter(lambda line: "Holiday" in line).count()
...
101
```

… 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])
```

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Create a SparkContext

Scala

```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

```java
import org.apache. Ja k

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

Python

```python
from pyspark import SparkContext

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

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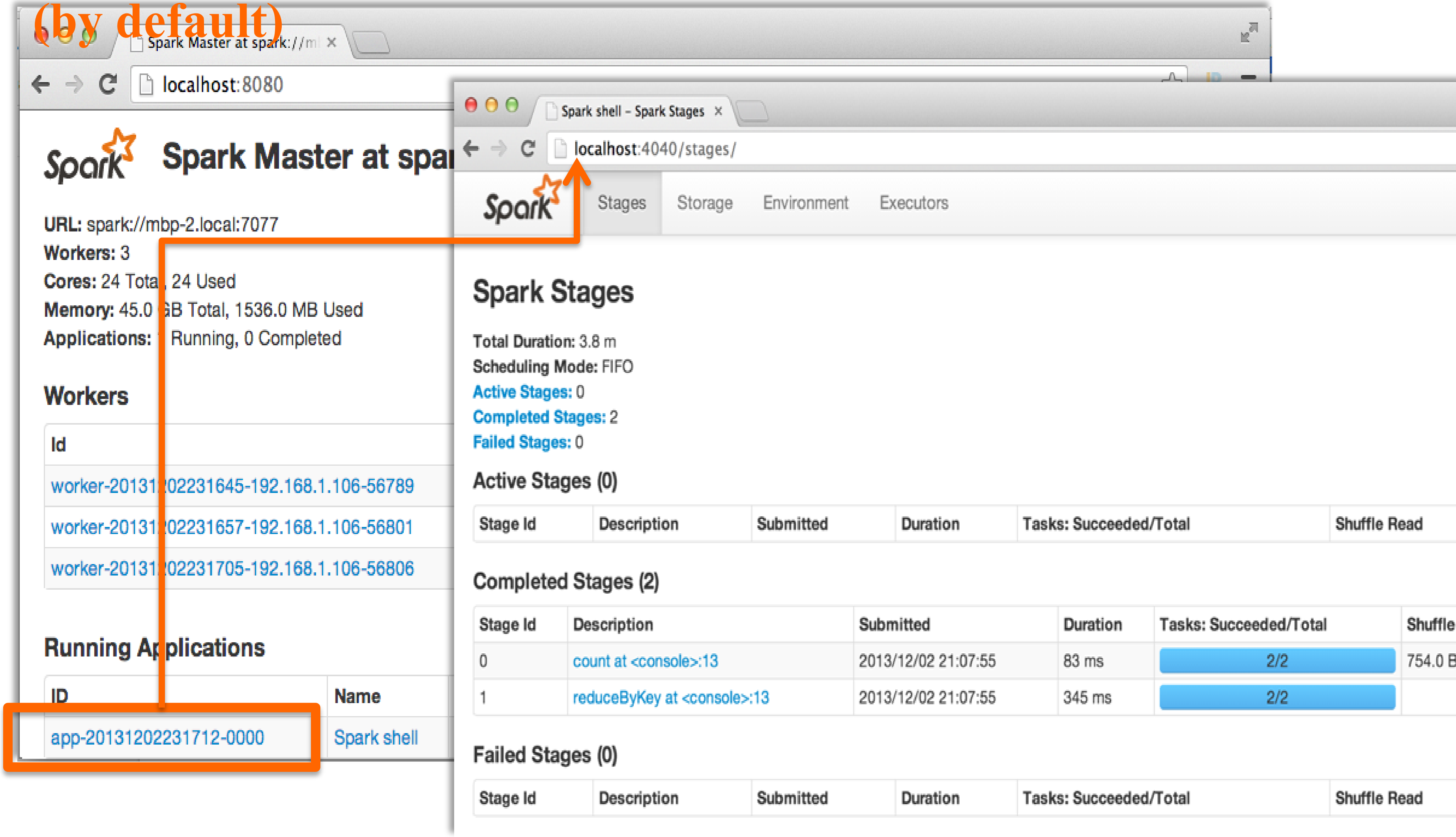
Administrative GUIs

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



EXAMPLE APPLICATION: PAGERANK

Google PageRank

Give pages ranks (scores) based on links to them

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

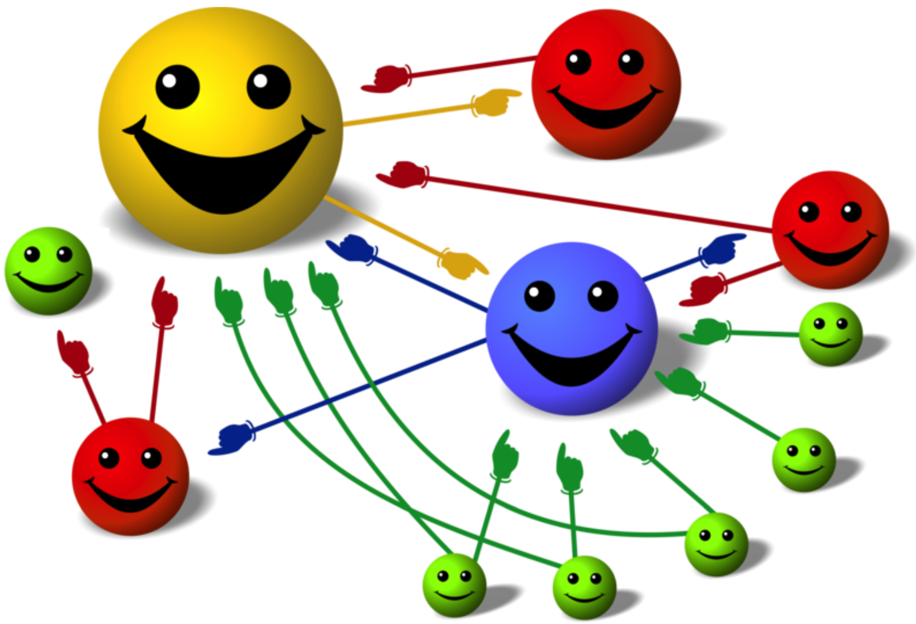


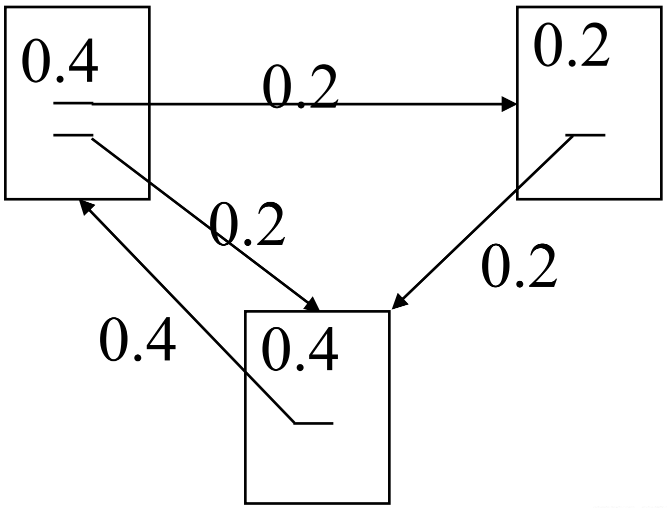
Image: en.wikipedia.org/wiki/File:PageRank-hi-res-2.png

PageRank (one definition)

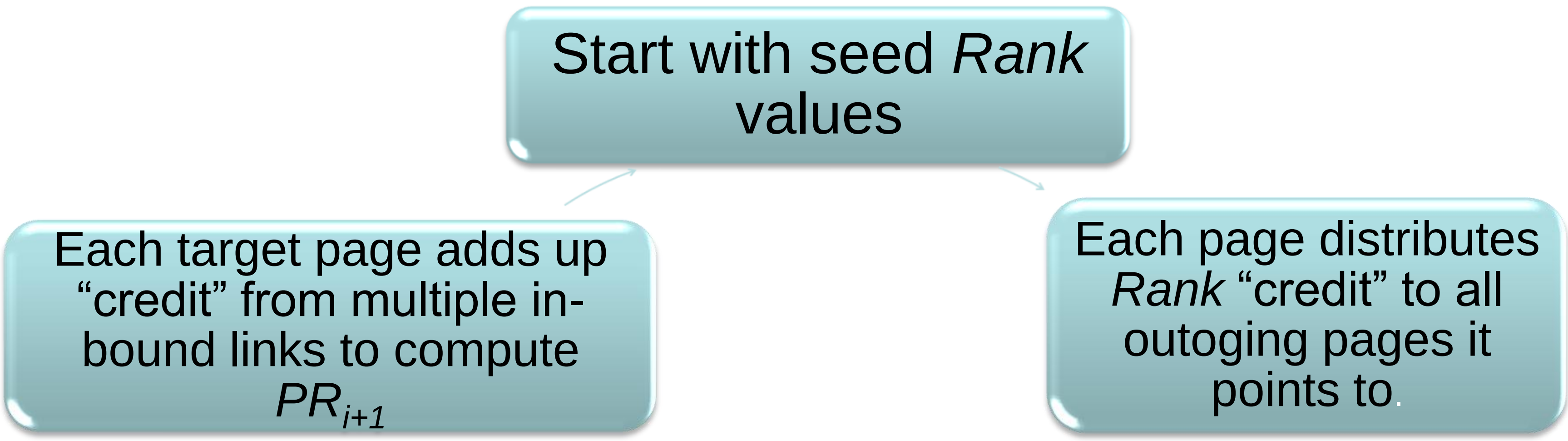
- Model page reputation on the web

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

- i=1,n lists all parents of page x.
- PR(x) is the page rank of each page.
- C(t) is the out-degree of t.
- d is a damping factor .



Computing PageRank Iteratively



- Effects at each iteration is local. i+1th iteration depends only on ith iteration
- At iteration i, PageRank for individual nodes can be computed independently

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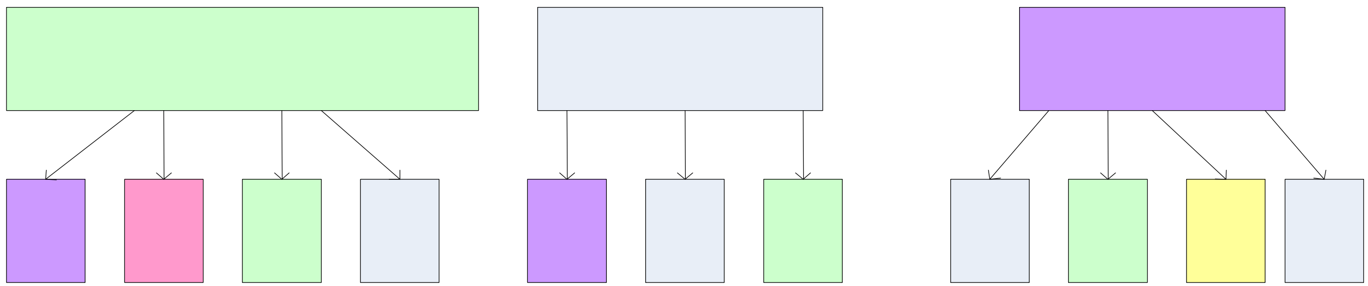
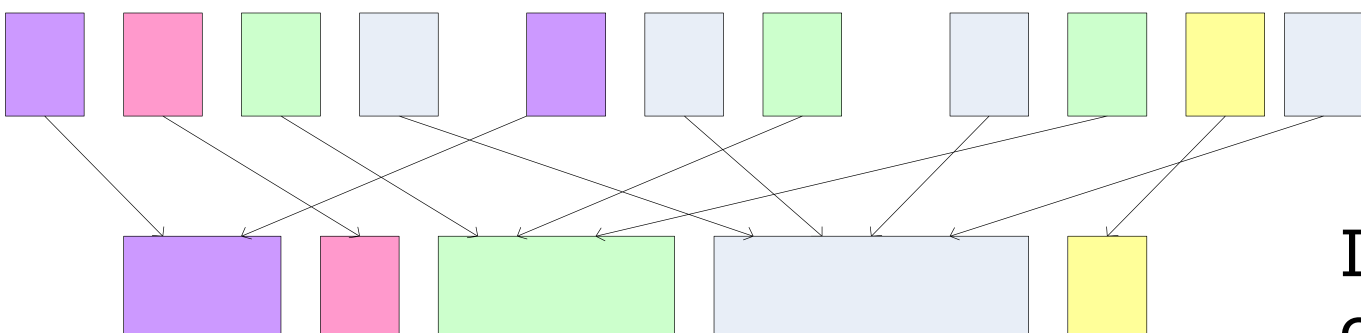
PageRank using MapReduce

Map: distribute PageRank "credit" to link targets



Reduce: gather up PageRank "credit" from multiple sources to compute new PageRank value



Iterate until convergence

Source of Image: Lin 2008

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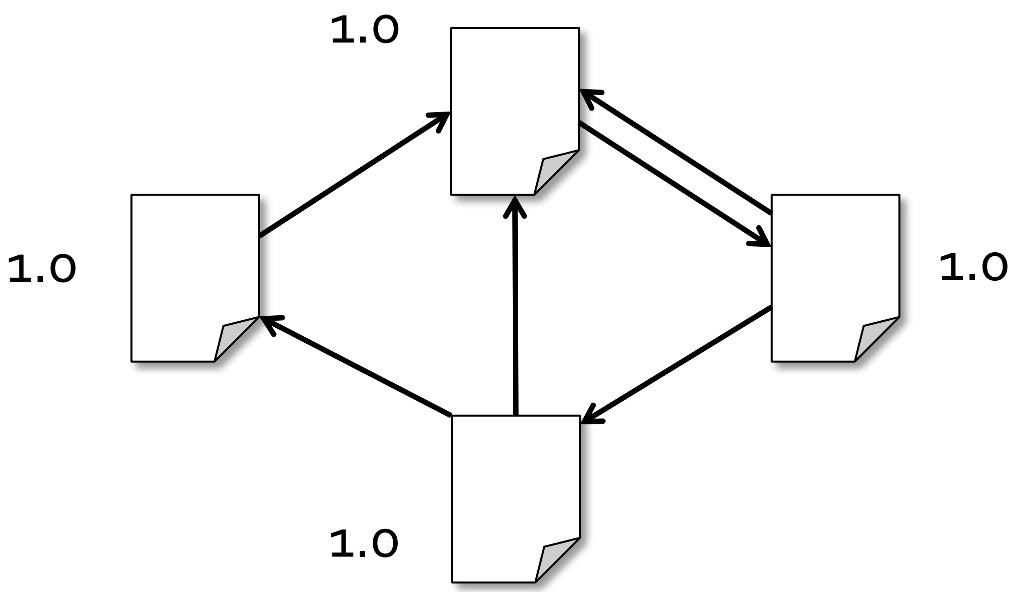
Algorithm demo

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



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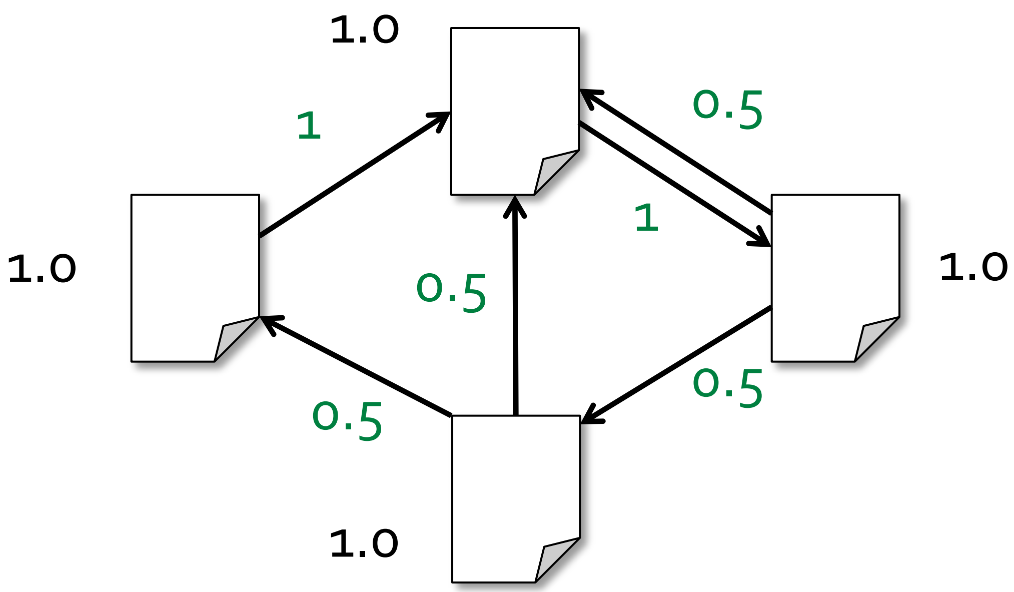

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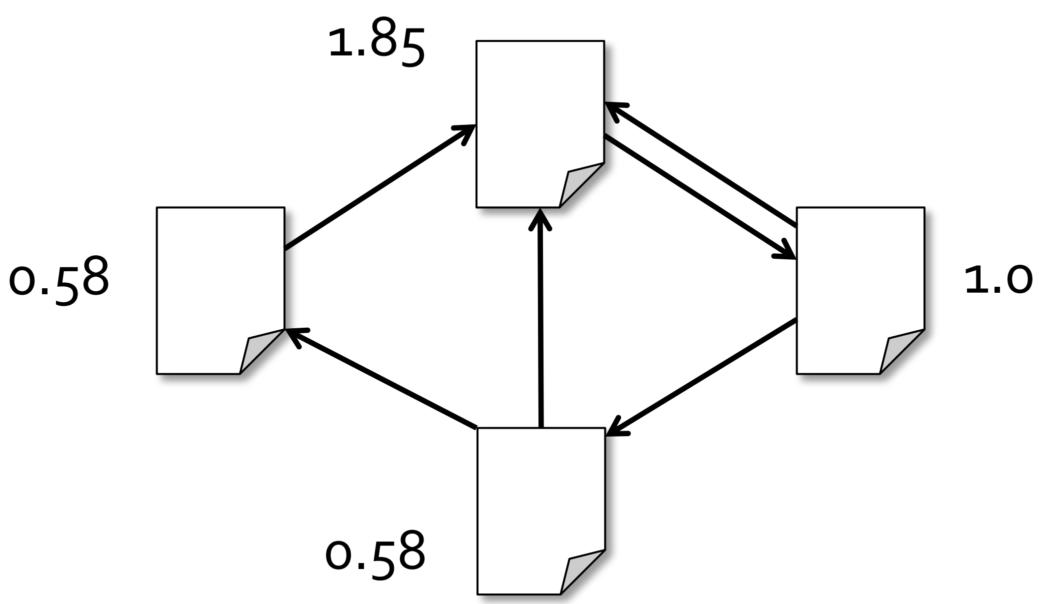

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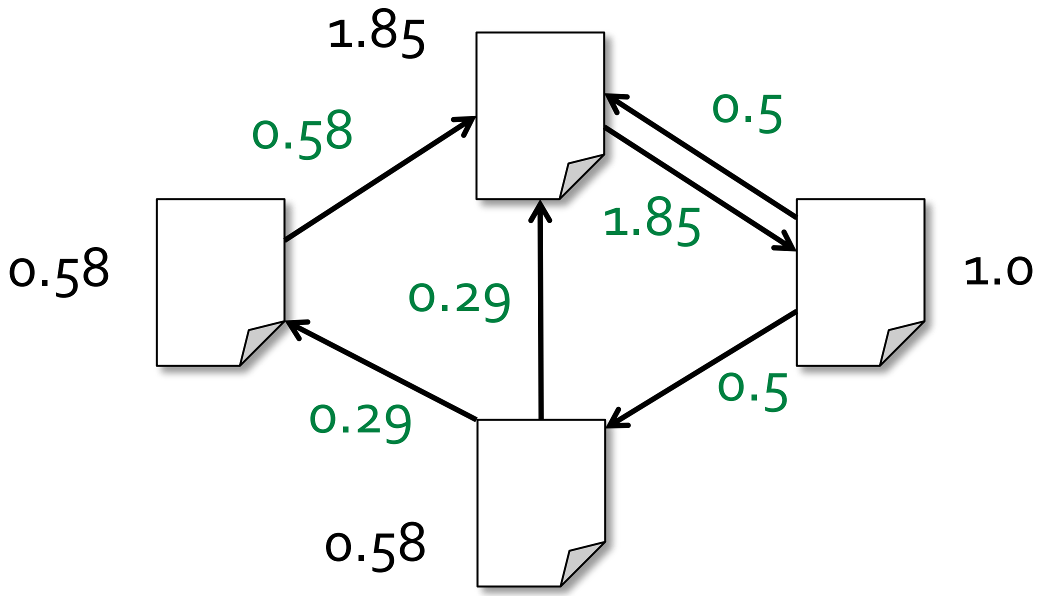

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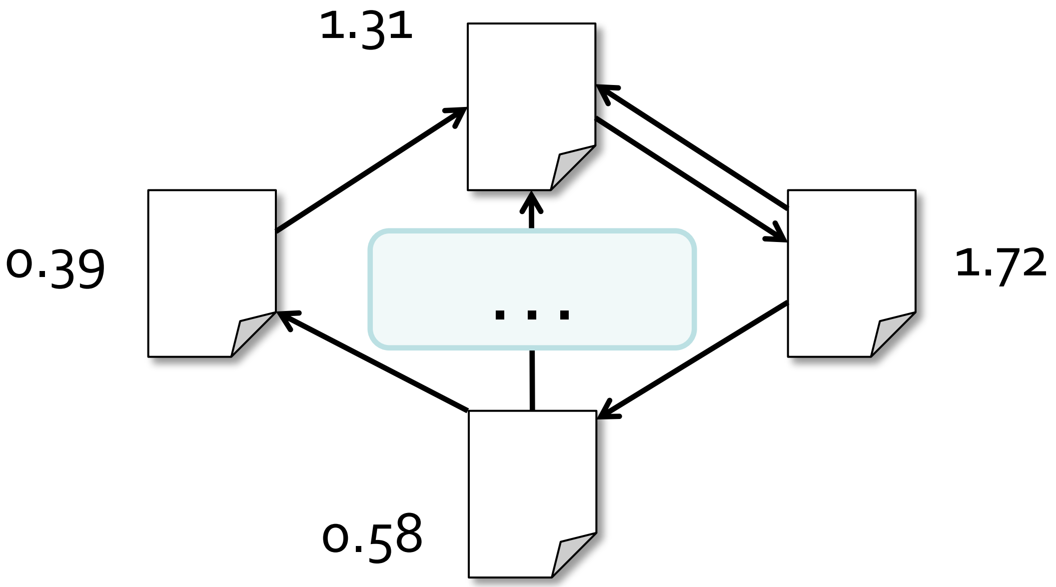

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Algorithm

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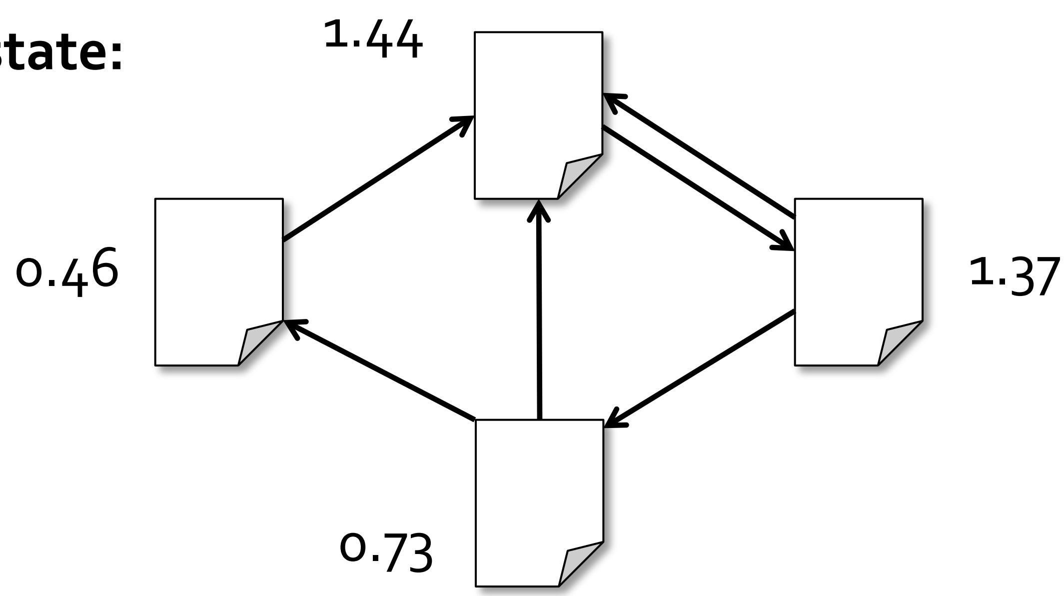
Final state:



HW: SimplePageRank

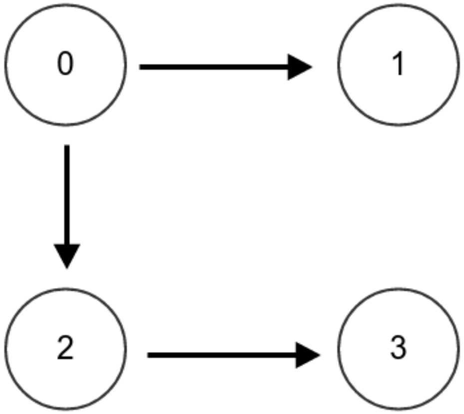
Random surfer model to describe the algorithm

- Stay on the page: 0.05 *weight
- Randomly follow a link: 0.85/out-going-Degree to each child
  - If no children, give that portion to other nodes evenly.
- Randomly go to another page: 0.10
  - Meaning: contribute 10% of its weight to others. Others will evenly get that weight. Repeat for everybody. Since the sum of all weights is num-nodes, 10%*num-nodes divided by num-nodes is 0.1

$$R(x) = 0.1 + 0.05\, R(x) + \text{incoming-contributions}$$

Initial weight 1 for everybody

To/From	0	1	2	3	Random Factor	New Weight
0	0.05	0.283	0.0	0.283	0.10	0.716
1	0.425	0.05	0.0	0.283	0.10	0.858
2	0.425	0.283	0.05	0.283	0.10	1.141
3	0.00	0.283	0.85	0.05	0.10	1.283



Data structure in SimplePageRank