

Spark with Key/Value Pairs

Lab 4

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Index

■ Working with Key/Value Pairs

- Creating Pair RDDs
- Transformations on Pair RDDs
 - Aggregation/Grouping Data/Join/Sorting Data
- Actions on Pair RDDs
 - countByKey/collectAsMap

■ Shuffle Operation

■ RDD Persistence

■ Exercises

Before we start...

■ Exercise 1 answer

```
1 >>> text_file = sc.textFile("hdfs://localhost:9000/input")
2 >>> filters = text_file.flatMap(lambda line: line.split(" ")) \
3 ...     .map(lambda word: (word, 1)) \
4 ...     .reduceByKey(lambda a, b: a + b) \
5 ...     .filter(lambda a: a[0] == 'cracking' or a[0] == 'bucket')
6 >>> wordcounts.saveAsTextFile("hdfs://localhost:9000/exercise3_1")
```

Before we start...

■ Exercise 2 answer

```
1 >>> text_file = sc.textFile("hdfs://localhost:9000/input")
2 >>> uniques = text_file.flatMap(lambda line: line.split(" ")) \
3 ...           .map(lambda word: (word, 1)) \
4 ...           .reduceByKey(lambda a, b: a)
5 >>> uniques.saveAsTextFile("hdfs://localhost:9000/exercise3_2")
```

Before we start...

■ Please connect your VM using SSH

```
1 # Please your public IP address in xxx.xxx.xxx.xxx
2 student@computer:~$ ssh -X -i bde3.pem ubuntu@xxx.xxx.xxx.xxx
3 Welcome to Ubuntu 14.04.5 LTS (GNU/Linux 3.13.0-125-generic x86_64)
4 [...snipp...]
5 ubuntu@ip-x-x-x:~$
```

Associative Array

■ Associative array

- Abstract data type composed of a collection of (key, value) pairs
- Key: field name, identifier
- Value: data

■ Associative arrays as primitive data types in many programming languages

- Java, C++ STL, Python, Ruby, Go, Lua, ...
- HashMap, map container, dictionaries, hash tables, ...

■ Key/value store

- Data storage designed for storing, retrieving, and managing associative array
- Redis, Memcached, Ignite, NoSQL, Cassandra, ...

Key/Value Pairs in Spark

- **Key/value RDDs are used to perform aggregations**
 - count up reviews for each product
 - group together data with the same key
 - group together two different RDDs

- **Pair RDDs**
 - Spark provides special operations on RDDs containing key/value pairs
 - Operations that act on each key in parallel or regroup data across the network
 - In Python, operations work on RDDs containing built-in Python tuples

Creating Pair RDDs

■ Create RDD from text

- run a flatMap() function that returns key/value pairs

```
1 >>> lines = sc.textFile("data.txt")
2 >>> rdd = lines.flatMap(lambda s: s.split(" "))
3 >>> pairs = rdd.map(lambda s: (s, 1))
4 >>> pairs.collect()
5 (u'Sed', 1), (u'tempor', 1), (u'tincidunt', 1), ..., (u'lorem.', 1)]
```

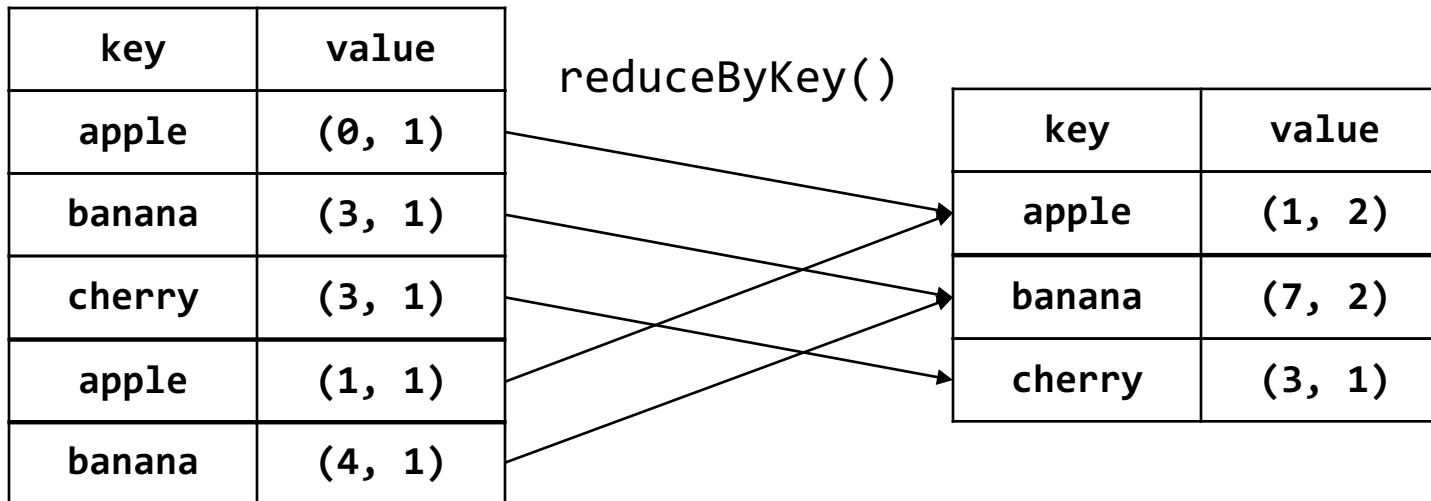

Transformations on Pair RDDs (1)

- We need to pass transformations that operate on tuples
- Transformations on one pair RDD
 - reduceByKey, groupByKey, combineByKey, mapValues, flatMapValues, sortByKey, ...
- Transformations on two pair RDDs
 - subtractByKey, join, cogroup, ...
- Families of pair RDD functions
 - Aggregations / Grouping / Joins / Sorting

* <https://spark.apache.org/docs/2.1.0/api/python/pyspark.html#pyspark.RDD>

Aggregating Data: reduceByKey() (1)

- Aggregate statistics across all elements with the same key
- `reduceByKey(func)`
 - Merge the values for each key using an associative and commutative reduce function



* <https://spark.apache.org/docs/2.1.0/api/python/pyspark.html#pyspark.RDD>

Aggregating Data: reduceByKey() (2)

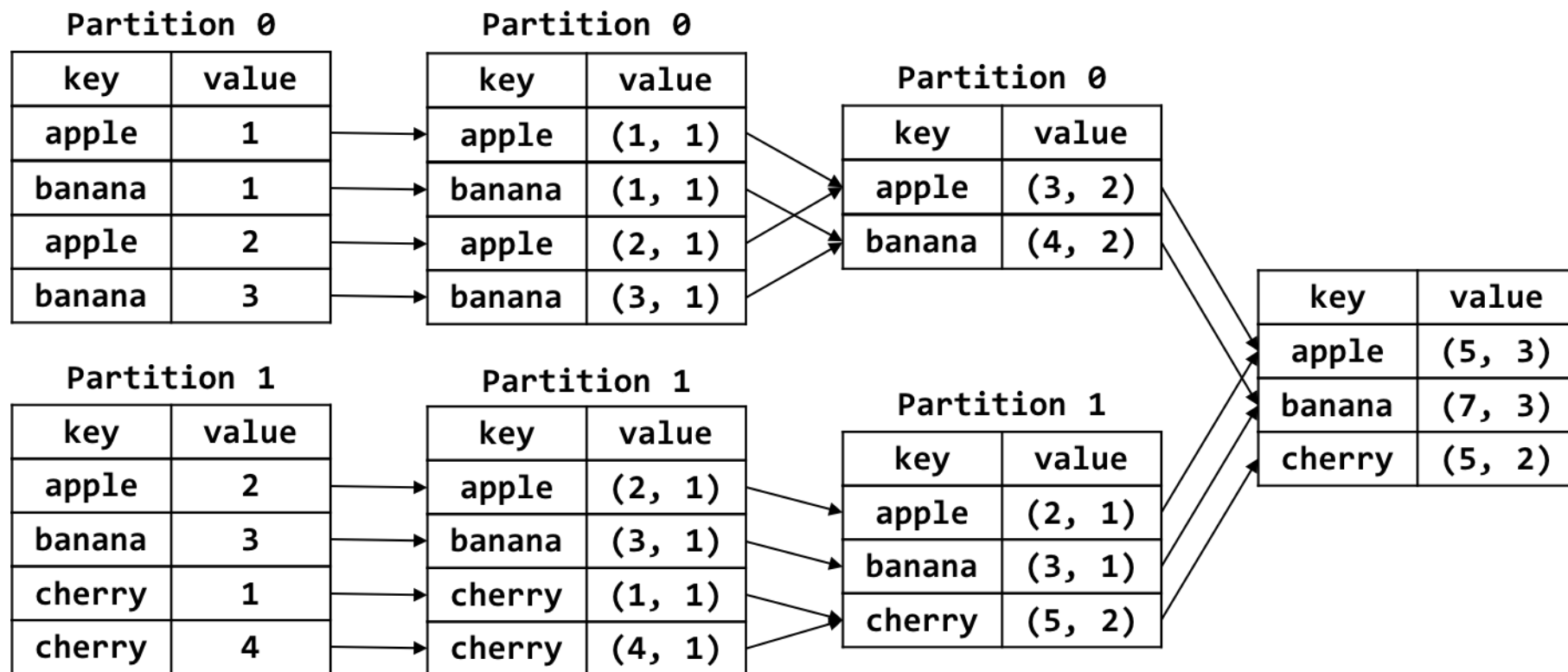
■ Code & output

```
1 >>> data = [("a", 0), ("b", 3), ("c", 3), ("a", 1), ("b", 4)]
2 >>> rdd = sc.parallelize(data)
3 >>> pairs = rdd.mapValues(lambda x: (x, 1)) \
4 >>>     .reduceByKey(lambda x, y: (x[0] + y[0], x[1] + y[1]))
5 >>> pairs.collect()
6 [('a', (1, 2)), ('c', (3, 1)), ('b', (7, 2))]
```

Aggregating Data: combineByKey() (1)

■ combineByKey(func1, func2, func3)

- combine the elements for each key using a custom set of aggregation functions
- createCombiner, mergeValue, mergeCombiners



Aggregating Data: combineByKey() (3)

■ Code & output

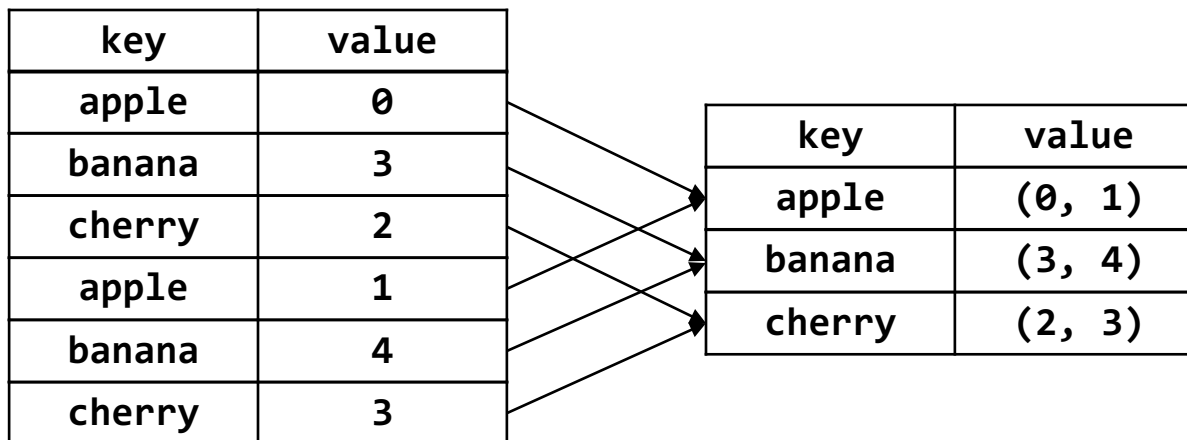
```
1 >>> data = [("a", 1), ("b", 1), ("a", 2), ("b", 3), ("a", 2), ("b", 3), \
2         ("c", 1), ("c", 4)]
3 >>> rdd = sc.parallelize(data, 2)
4 >>> pairs = rdd.combineByKey((lambda x: (x,1)), \
5         (lambda x, y: (x[0] + y, x[1] + 1)), \
6         (lambda x, y: (x[0] + y[0], x[1] + y[1])))
7 >>> pairs.collect()
8 [('a', (5, 3)), ('c', (5, 2)), ('b', (7, 3))]
```

Grouping Data: groupByKey() (1)

■ Grouping data by key

■ groupByKey()

- Group the values for each key in the RDD into a single sequence.
- Hash-partitions the resulting RDD with numPartitions partitions



Grouping Data: groupByKey() (2)

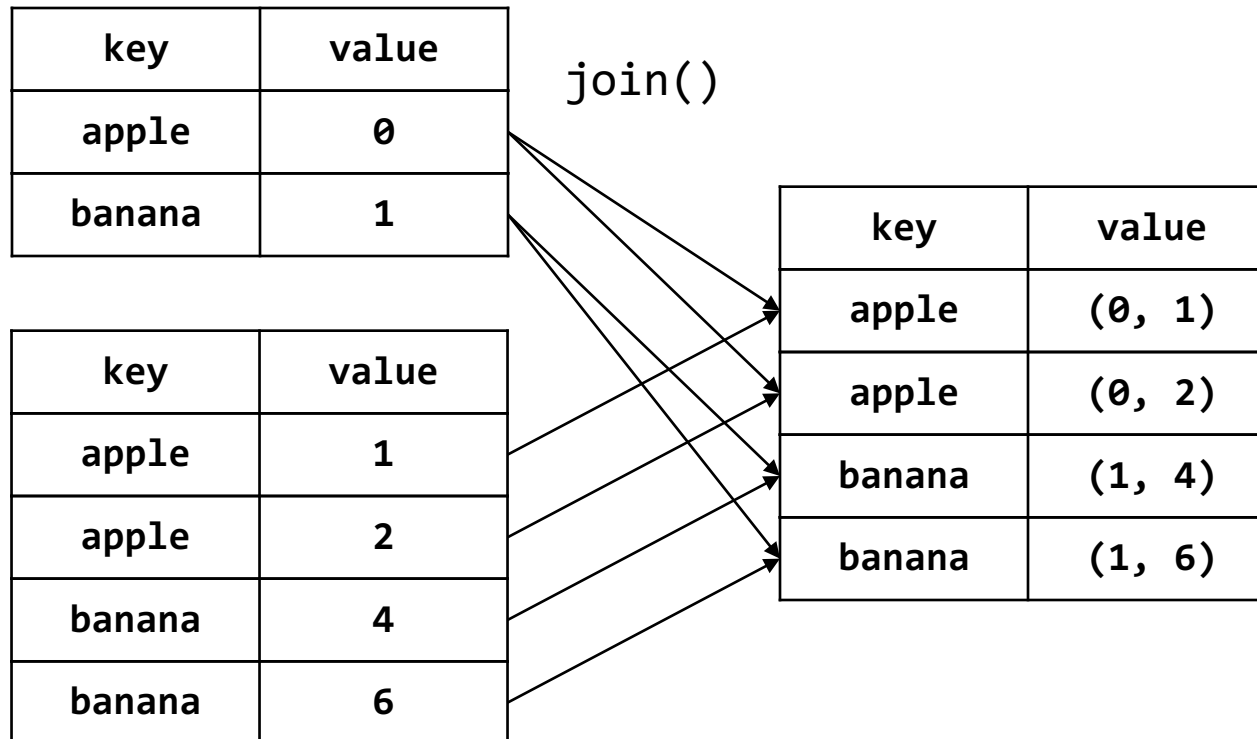
■ Code & output

```
1 >>> data = [("a", 0), ("b", 3), ("a", 2), ("a", 1), ("b", 4), ("c", 3)]
2 >>> rdd = sc.parallelize(data)
3 >>> pairs = rdd.groupByKey().mapValues(list)
6 >>> pairs.collect()
7 [('a', [0, 2, 1]), ('c', [3]), ('b', [3, 4])]
```

Join (1)

■ Join(other)

- Return an RDD containing all pairs of elements with matching keys in self and other.



Join (2)

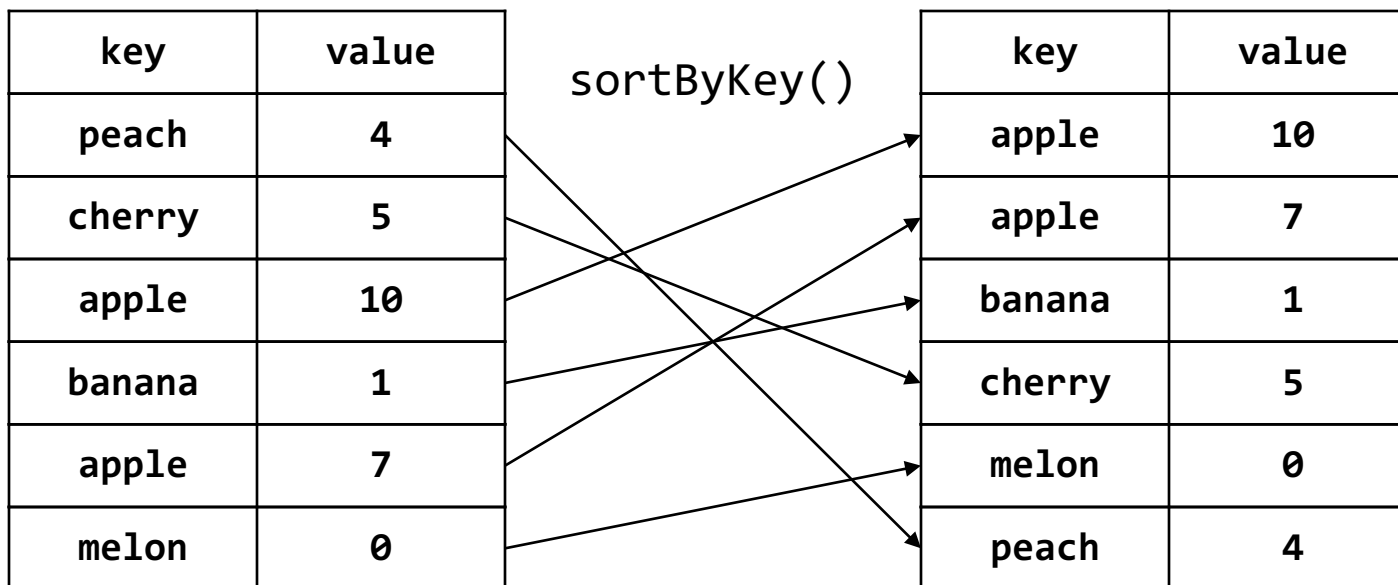
■ Code & output

```
1 >>> x = [("a", 0), ("b", 1)]
2 >>> y = [("a", 1), ("a", 2), ("b", 4), ("b", 6), ("c", 5)]
3 >>> x1 = sc.parallelize(x)
4 >>> y1 = sc.parallelize(y)
5 >>> pairs = x1.join(y1)
6 >>> pairs.collect()
7 [('a', (0, 1)), ('a', (0, 2)), ('b', (1, 4)), ('b', (1, 6))]
```

Sorting Data: sortByKey() (1)

■ sortByKey(ascending)

- Sorts this RDD, which is assumed to consist of (key, value) pairs



Sorting Data: sortByKey() (1)

■ Code & output

```
1 >>> data = [("p", 4), ("c", 5), ("a", 10), ("b", 1), ("a", 7), ("m", 0)]
2 >>> rdd = sc.parallelize(data)
3 >>> pairs1 = rdd.sortByKey(1)
4 >>> pairs2 = rdd.sortByKey(0)
5 >>> pairs1.collect()
6 [('a', 10), ('a', 7), ('b', 1), ('c', 5), ('m', 0), ('p', 4)]
7 >>> pairs2.collect()
8 [('p', 4), ('m', 0), ('c', 5), ('b', 1), ('a', 10), ('a', 7)]
```

Actions on Pair RDDs

- All of the traditional actions available on the base RDD are also available on pair RDDs
- Some additional actions are available on pair RDDs to take advantage of the key/value nature of the data
 - `countByKey`, `collectAsMap`, `Lookup`

countByKey()

■ countByKey()

- Count the number of elements for each key, and return the result to the master as a dictionary

■ Code & output

```
1 >>> list = [("p", 4), ("c", 5), ("a", 10), ("b", 1), ("a", 7), ("m", 0)]
2 >>> temp = sc.parallelize(list)
3 >>> temp.countByKey()
4 defaultdict(<type 'int'>, {'a': 2, 'p': 1, 'c': 1, 'b': 1, 'm': 1})
```

collectAsMap()

■ collectAsMap()

- Return the key-value pairs in this RDD to the master as a dictionary

■ Code & output

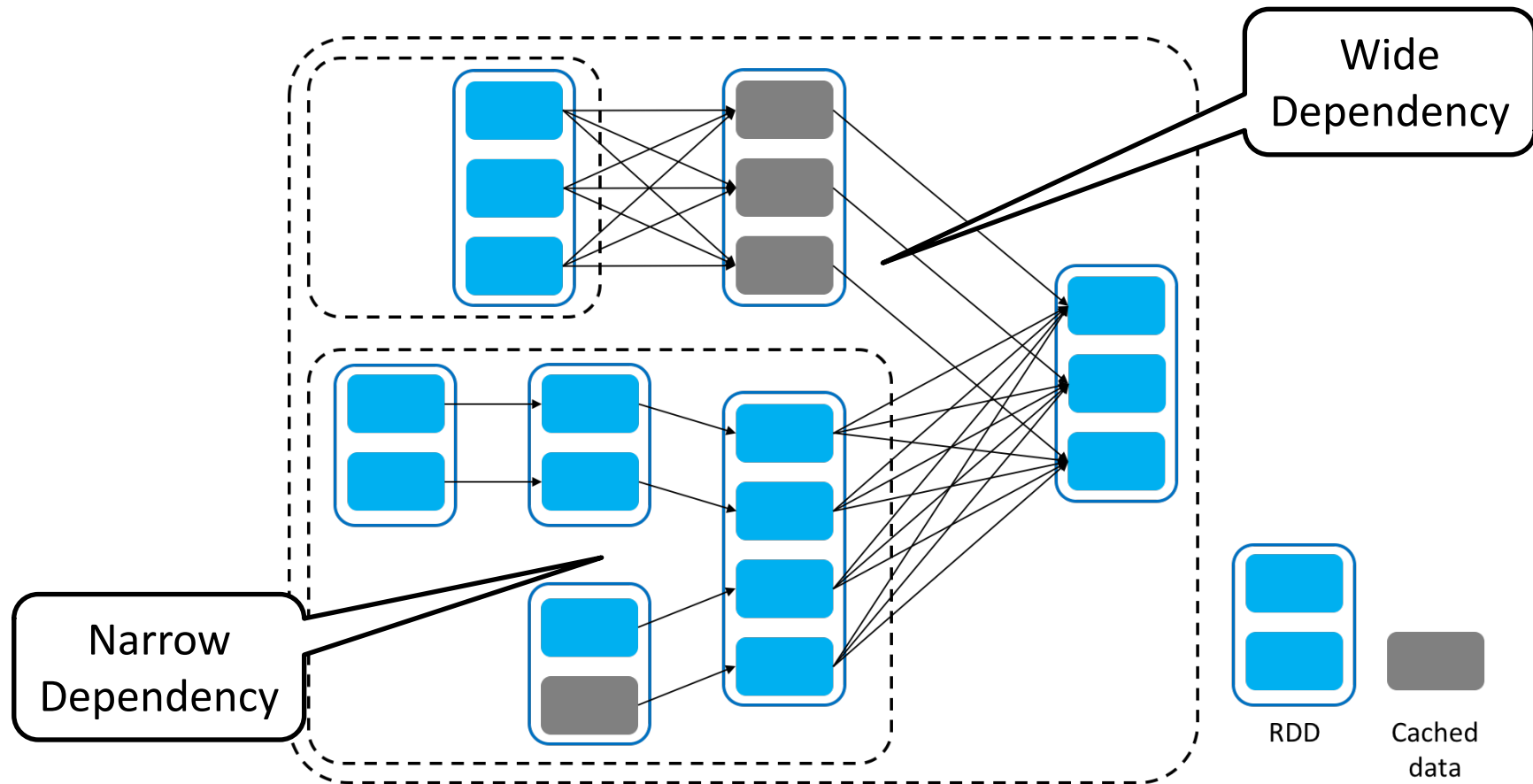
```
1 >>> data = [("p", 4), ("c", 5), ("a", 10), ("b", 1), ("a", 7), ("m", 0)]
2 >>> rdd = sc.parallelize(data)
3 >>> rdd.collectAsMap()
4 {'a': 7, 'p': 4, 'c': 5, 'b': 1, 'm': 0}
```

RDD Dependencies (1)

- **The shuffle is mechanism for re-distributing data so that it's grouped differently across partitions**
- **Narrow vs. wide dependencies**
 - Narrow: each partition of the parent RDD is used by at most one partition of child RDD
 - map, mapValues, flatMap, filter, mapPartitions, mapPartitionsWithIndex, ...
 - Wide: each partition of the parent RDD is used by multiple child RDDs
 - join, groupByKey, reduceByKey, combineByKey, distinct, cogroup, ...

RDD Dependencies (2)

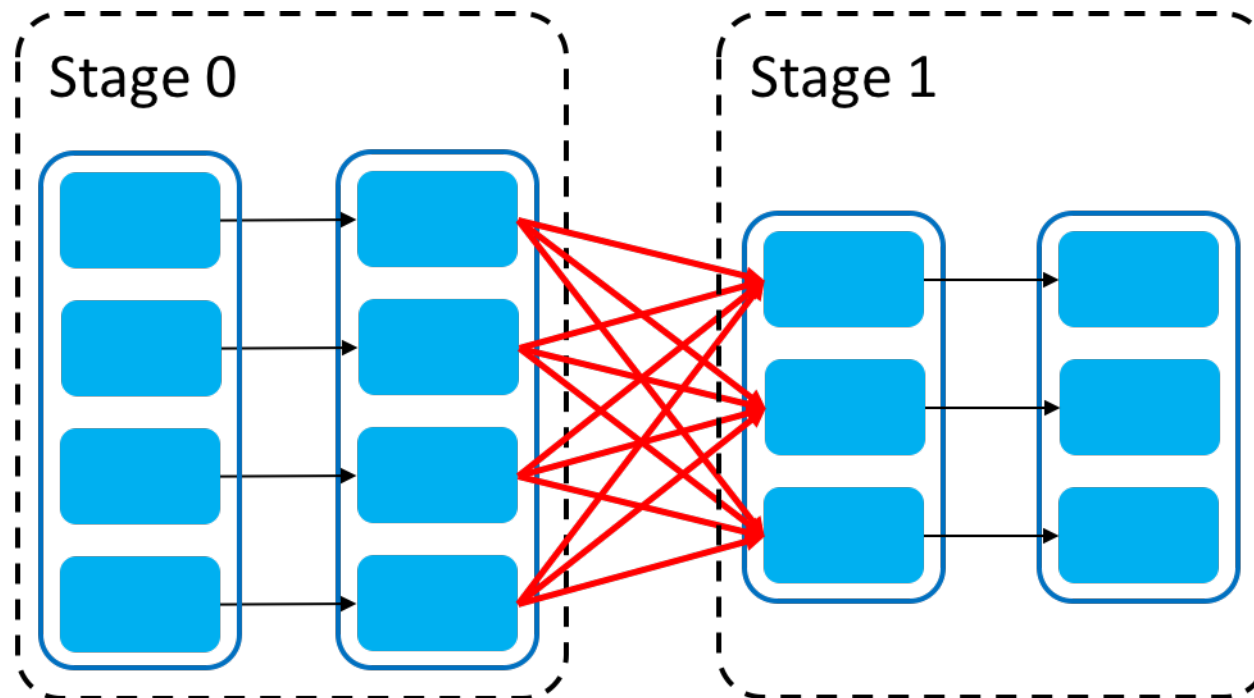
■ Narrow vs. wide dependencies



Shuffle Operations (1)

■ What is the shuffle?

- Spark's mechanism for re-distributing data so that it's grouped differently across partitions
- Copy data across executors and machines



Shuffle Operations (2)

■ Example: `reduceByKey()`

- To organize all the data for a single `reduceByKey` reduce task to execute, Spark needs to perform an all-to-all operation
- read from all partitions to find all the values for all keys
- bring together values across partitions to compute the final result for each key

■ Operations which can cause a shuffle

- repartition operations like `repartition` and `coalesce`
- *ByKey operations like `groupByKey` and `reduceByKey`
- join operations like `cogroup` and `join`

RDD persistence

■ `persist()` or `cache()`

- Each node stores any partitions of it that it computes **in memory** and reuses them in other actions on that dataset
- Caching is a key tool for **iterative algorithms** and fast interactive use
- Spark recommends users call `persist` on the resulting RDD if they plan to reuse it

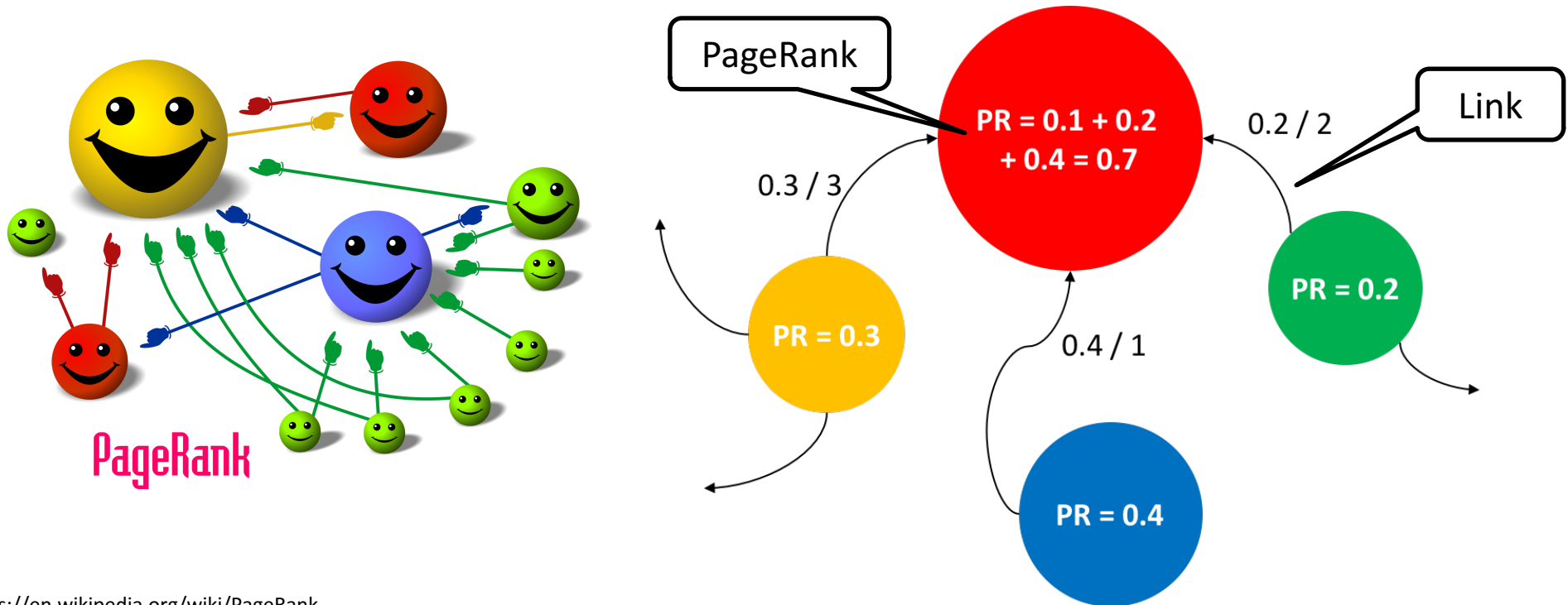
■ Storage Level

- `MEMORY_ONLY`, `MEMORY_AND_DISK`, `DISK_ONLY`
- `persist` it in memory as deserialized/serialized Java objects
- `persist` the dataset on disk
- In Python, stored objects will always be serialized with the Pickle library

Example: PageRank (1)

■ What is PageRank?

- Algorithm used by **Google Search** to rank websites in search engine
- PageRank works by counting the number and quality of links to a page
 - Determine a rough estimate of how important the website is



Example: PageRank (2)

■ spark-2.1.0/examples/src/main/python/pagerank.py

```
1 lines = spark.read.text(sys.argv[1]).rdd.map(lambda r: r[0])
2 links = lines.map(lambda urls: parseNeighbors(urls)).distinct() \
3     .groupByKey().cache()
4 ranks = links.map(lambda url_neighbors: (url_neighbors[0], 1.0))
5 for iteration in range(int(sys.argv[2])):
6     contribs = links.join(ranks).flatMap(
7         lambda url_urls_rank: computeContribs(url_urls_rank[1][0],url_urls_rank[1][1]))
8     ranks = contribs.reduceByKey(add).mapValues(lambda rank: rank * 0.85 + 0.15)
```

Example: PageRank (3)


■ Run pagerank.py

```
1 ubuntu@ip-x-x-x:~/spark-2.1.0$ bin/spark-submit/examples/src/main/python/  
2 pagerank.py data/mllib/pagerank_data.txt 100  
3 WARN ...  
4 [Stage 1: =====> (5 + 1) / 4]
```

Example: PageRank (4)

■ Check the effect of RDD cache()



 **Spark Master at spark://172.31.1.25:7077**

URL: spark://172.31.1.25:7077

REST URL: spark://172.31.1.25:6066 (cluster mode)

Alive Workers: 1

Cores in use: 1 Total, 1 Used

Memory in use: 10.0 GB Total, 10.0 GB Used

Applications: 1 [Running](#), 1 [Completed](#)

Drivers: 0 Running, 0 Completed

Status: ALIVE

Workers

Worker Id	Address	State	Cores	Memory
worker-20171030101445-172.31.1.25-57806	172.31.1.25:57806	ALIVE	1 (1 Used)	10.0 GB (10.0 GB Used)

Running Applications

Application ID	Name	Cores	Memory per Node	Submitted Time	User	State	Duration
app-20171030101702-0001	(kill) pagerank.py	1	10.0 GB	2017/10/30 10:17:02	ubuntu	RUNNING	3.4 min

Completed Applications

Example: PageRank (5)

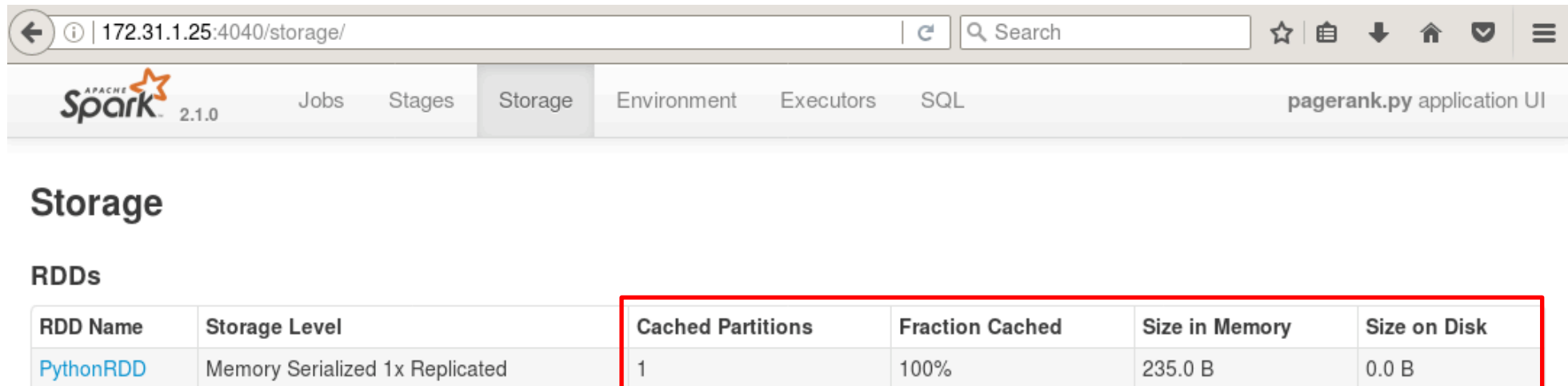
■ Check the effect of RDD cache()

The screenshot shows the Apache Spark UI at the address 172.31.1.25:4040/jobs/. The 'Storage' tab is highlighted with a red box. Below the navigation bar, the 'Spark Jobs (?)' section shows the user 'ubuntu', total uptime of 3.7 min, and scheduling mode of FIFO. There is 1 active job. A link to the 'Event Timeline' is provided. The 'Active Jobs (1)' section contains a table with the following data:

Job Id	Description	Submitted	Duration	Stages: Succeeded/Total	Tasks (for all stages): Succeeded/Total
0	collect at /home/ubuntu/spark-2.1.0/examples/src/main/python/pagera... (kill)	2017/10/30 10:17:09	3.6 min	114/203	3315/10403

Example: PageRank (6)

■ Check the effect of RDD cache()



Storage

RDDs

RDD Name	Storage Level	Cached Partitions	Fraction Cached	Size in Memory	Size on Disk
PythonRDD	Memory Serialized 1x Replicated	1	100%	235.0 B	0.0 B

Exercise (1)

- Find words with 7 words and store them both in hdfs and txt (6 point)

- Save alphabetical order from z to a

- Hint

- <https://spark.apache.org/docs/2.1.0/api/python/pyspark.html#pyspark.RDD>

Exercise (2)

■ In the following code, find where to apply `cache()` (4 point)

```
1 lines = spark.read.text(sys.argv[1]).rdd.map(lambda r: r[0])    // 1
2 data = lines.map(parseVector)    // 2
3 kPoints = data.takeSample(False, K, 1)    // 3
4 while tempDist > convergeDist:
5     closest = data.map(lambda p: (closestPoint(p, kPoints), (p, 1)))    // 4
6     pointStats = closest.reduceByKey(
7         lambda p1_c1, p2_c2: (p1_c1[0] + p2_c2[0], p1_c1[1] + p2_c2[1]))    // 5
8     newPoints = pointStats.map(lambda st: (st[0], st[1][0] / st[1][1])).collect()    // 6
9     tempDist = sum(np.sum((kPoints[iK] - p) ** 2) for (iK, p) in newPoints)
10    for (iK, p) in newPoints:
11        kPoints[iK] = p
```

■ Appendix