Apache Spark

INF 551 & 553

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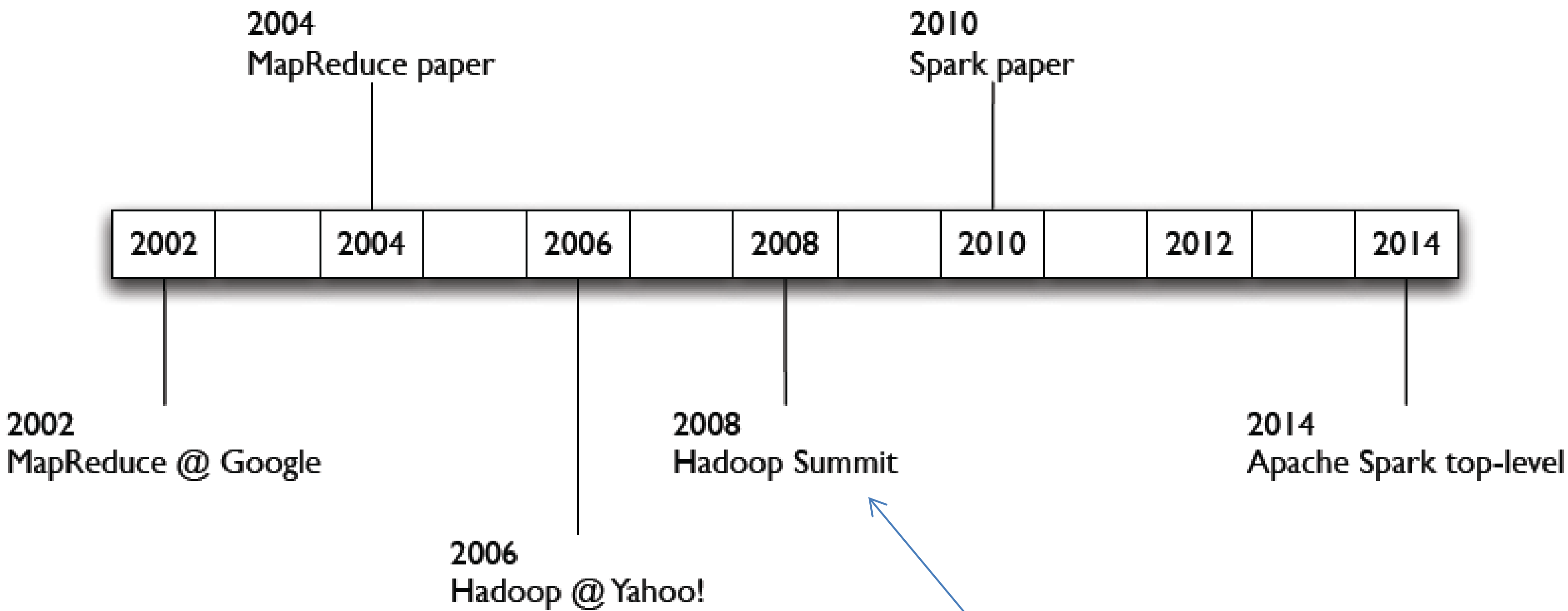
Roadmap

- Spark
  - History, features, RDD, and installation
- RDD operations
  - Creating initial RDDs
  - Actions
  - Transformations
- Examples
- Shuffling in Spark
- Persistence in Spark

History



Apache took over Hadoop

Characteristics of Hadoop

- Acyclic data flow model
  - Data loaded from stable storage (e.g., HDFS)
  - Processed through a sequence of steps
  - Results written to disk

- Batch processing
  - No interactions permitted during processing

Problems

- Ill-suited for iterative algorithms that requires repeated reuse of data
  – E.g., machine learning and data mining algorithms such as k-means, PageRank, logistic regression

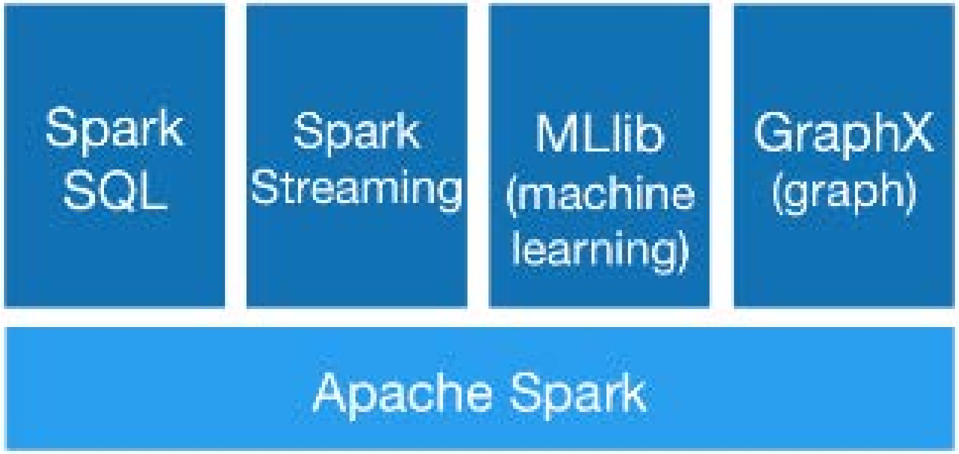
- Ill-suited for interactive exploration of data
  – E.g., OLAP on big data

Spark

- Support working sets (of data) through RDD
  – Enabling reuse & fault-tolerance
- 10x faster than Hadoop in iterative jobs
- Interactively explore 39GB (Wikipedia dump) with sub-second response time
  – Data were distributed over 15 EC2 instances

Spark

- Provides libraries to support
  - embedded use of SQL
  - stream data processing
  - machine learning algorithms
  - processing of graph data



Spark

- Support diverse data sources including HDFS, Cassandra, HBase, and Amazon S3

RDD: Resilient Distributed Dataset

- RDD
  - Read-only, partitioned collection of records
  - Operations performed on partitions in parallel
  - Maintain lineage for efficient fault-tolerance

provenance

- Methods of creating an RDD
  - from an existing collection (e.g., Python list/tuple)
  - from an external file

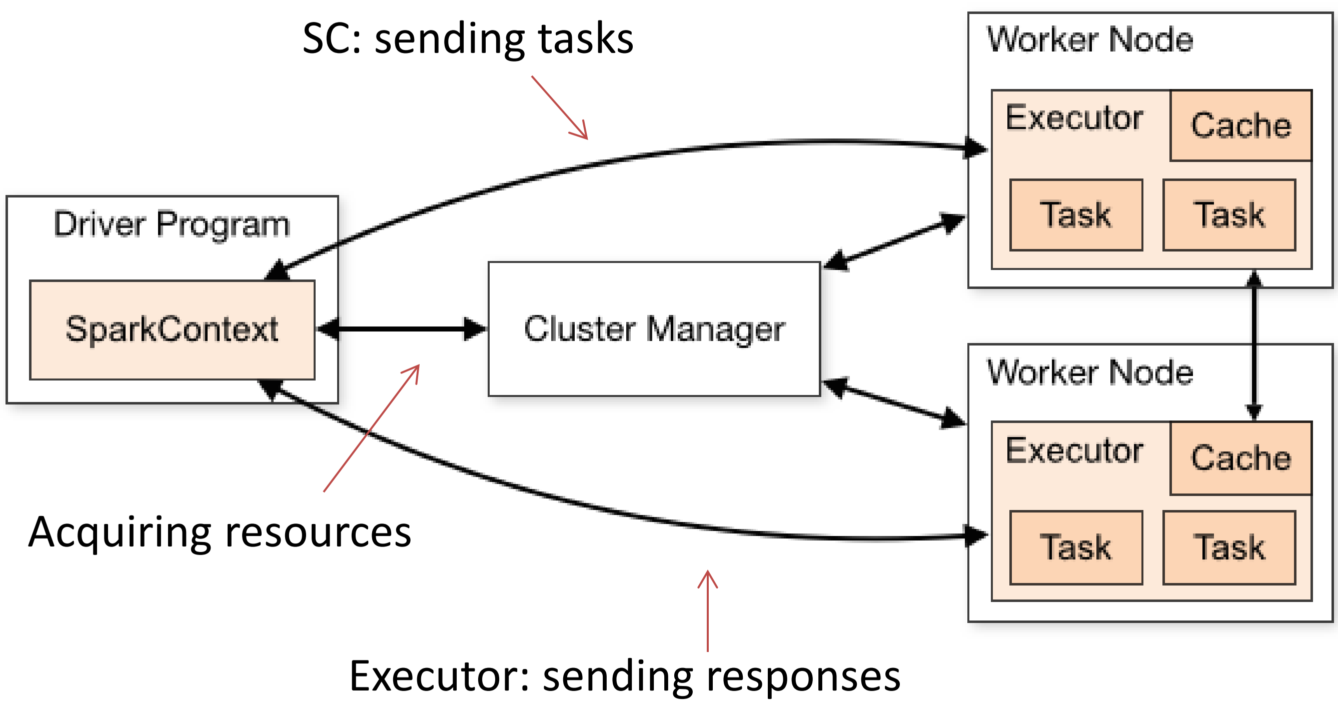
RDD: Resilient Distributed Dataset

- Distributed
  - Data are divided into a number of partitions
  - & distributed across nodes of a cluster to be processed in parallel

- Resilient
  - Spark keeps track of transformations to dataset
  - Enable efficient recovery on failure (no need to replicate large amount of data across network)

Architecture

- SparkContext (SC) object coordinates the execution of application in multiple nodes
  - Similar to Job Tracker in Hadoop MapReduce



Components

- Cluster manager
  – Allocate resources across applications
  – Can run Spark's own cluster manager or
  – Apache YARN (Yet Another Resource Negotiator)

- Executors
  – Run tasks & store data

Spark installation

- http://spark.apache.org/downloads.html
  - Choose "pre-built for Hadoop 2.7 and later"

- Direct link (choose version 2.3.1):
  - http://mirror.cogentco.com/pub/apache/spark/spark-2.3.1/spark-2.3.1-bin-hadoop2.7.tgz

Spark installation

- tar xvf spark-2.3.1-bin-hadoop2.7.tgz
  - This produces "spark-2.3.1-bin-hadoop2.7" folder
  - Containing all Spark stuffs (scripts, programs, libraries, examples, data)

Prerequisites

- Make sure Java is installed & JAVA_HOME is set

Accessing Spark from Python

- Interactive shell:
  - bin/pyspark
  - A SparkContext object sc will be automatically created

- bin/pyspark --master local[4]
  - This starts Spark on local host with 4 threads
  - "--master" specifies the location of Spark master node

Accessing Spark from Python

- Standalone program
  - Executed using spark-submit script
  - E.g., bin/spark-submit wc.py
- You may find many Python Spark examples under
  - examples/src/main/python

wc.py

```
from pyspark import SparkContext
from operator import add

sc = SparkContext(appName="inf551")

lines = sc.textFile('hello.txt')

counts = lines.flatMap(lambda x: x.split(' ')) \
         .map(lambda x: (x, 1)) \
         .reduceByKey(add)

output = counts.collect()

for v in output:
   print '%s, %s' % (v[0], v[1])
```

Make sure you have this file under the same directory where wc.py is located

hello.txt

hello world

hello this world

Suppress verbose log messages

- cd conf
- cp log4j.properties.template log4j.properties

- edit log4j.properties
  - change first line to:
    - log4j.rootCategory=ERROR, console
  - Or to:
    - log4j.rootCategory=WARN, console

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  - Creating initial RDDs
  - Actions
  - Transformations
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- Persistence in Spark

Creating an initial RDD

- From an external file
  - textFile(<path-to-file>, [# of partitions])
  - lines = sc.textFile("hello.txt", 2)

- From an existing Python collection (e.g., list, tuple, and dictionary)
  - data = sc.parallelize([1, 2, 3, 4, 5], 2)
  - create two partitions from given list

Creating RDD from an external file

- lines = sc.textFile("hello.txt") # lines is an RDD
  - Return a collection of lines
  - Spark does not check if file exists right away
  - Nor does it read from the file now

Action

- Perform a computation on an RDD
  – Return a final value (not an RDD) to client
- Usually the last operation on an RDD
- E.g., reduce(func)
  – aggregates all elements in the RDD using func
  – returns aggregated value to client

Actions

- getNumPartitions()
- foreachPartition(func)
- collect()
- take(n)
- count(), sum(), max(), min(), mean()
- reduce(func)
- aggregate(zeroVal, seqOp, combOp)
- takeSample(withReplacement, num, [seed])
- countByKey()

getNumPartitions()

- How many partitions does an RDD have?

- E.g., lines.getNumPartitions()
  => 1

- E.g., data.getNumPartitions()
  => 2

foreachPartition(func)

- What are in each partition?

Iterator for the list of elements in the partition

- def printf(iterator):

  par = list(iterator)

  print 'partition:', par

- sc.parallelize([1, 2, 3, 4, 5], 2).foreachPartition(printf)

=> partition: [3, 4, 5]

partition: [1, 2]

collect()

- Show the entire content of an RDD

- sc.parallelize([1, 2, 3, 4, 5], 2).collect()

- collect()
  - Fetch the entire RDD as a Python list
  - RDD may be partitioned among multiple nodes
  - collect() brings all partitions to the client's node

- Problem:
  - may run out of memory when the data set is large

take(n)

- take(n): collect first n elements from an RDD

- l = [1,2,3,4,5]
- rdd = sc.parallelize(l, 2)
- rdd.take(3)

=>

[1,2,3]

count()

- Return the number of elements in the dataset
  - It first counts in each partition
  - Then sum them up in the client

- l = [1,2,3,4,5]
- rdd = sc.parallelize(l, 2)
- rdd.count()

=> 5

sum()

- Add up the elements in the dataset

- l = [1,2,3,4,5]
- rdd = sc.parallelize(l)
- rdd.sum()

=> 15

reduce(func)

- Use func to aggregate the elements in RDD

- func(a,b):
  - Takes two input arguments, e.g., a and b
  - Outputs a value, e.g., a + b

- func should be commutative and associative
  - Applied to each partition (like a combiner)

reduce(func)

- func is continually applied to elements in RDD
  - [1, 2, 3]
  - First, compute func(1, 2) => x
  - Then, compute func(x, 3)
- If RDD has only one element x, it outputs x
- Similar to reduce() in Python

Recall Python example

- def add(a, b): return a + b

- reduce(add, [1, 2, 3])

  $\Rightarrow$ 6

Or simply reduce(lambda a, b: a + b, [1, 2, 3])

Spark example

- def add(a, b): return a + b
- data = sc.parallelize([1, 2, 3], 2)
- data.reduce(add)

  $\Rightarrow$ 6

Or simply: data.reduce(lambda a, b: a + b)

Implementation of reduce(func)

- Suppose [1, 2, 3, 4, 5] => two partitions:
  - [1, 2] and [3, 4, 5]

- rdd = sc.parallelize([1, 2, 3, 4, 5], 2)

- Consider reduce(add)

Local reduction

- Apply add to reduce each partition locally
  - Using mapPartition(func) (see transformations)

- Func: apply 'add' function to reduce a partition
  - E.g., using Python reduce function
  - reduce(add, [1, 2]) => 3
  - reduce(add, [3, 4, 5]) => 12

Global reduction

- Collect all local results
  - using collect()

  => res = [3, 12]

- Use Python reduce to obtain final result
  - reduce(add, res) => reduce(add, [3, 12]) =15

Example: finding largest integers

- data = [5, 4, 4, 1, 2, 3, 3, 1, 2, 5, 4, 5]
- pdata = sc.parallelize(data)

- pdata.reduce(lambda x, y: max(x, y))

  $\Rightarrow$5

- Or simply: pdata.reduce(max)

aggregate(zeroValue, seqOp, combOp)

But note reduce here is different from that in Python:
zeroValue can have different type than values in p

- For each partition p (values in the partition),
  - "reduce"(seqOp, p, zeroValue)
  - Note if p is empty, it will return zeroValue

- For a list of values, vals, from all partitions, execute:
  - reduce(combOp, vals, zeroValue)

seqOp and combOp

- seqOp(U, v):
  - how to aggregate values v's in the partition into U
  - U: accumulator, initially U = zeroValue
  - Note: U and v may be of different data type

- combOp(U, p):
  - how to combine results from multiple partitions
  - U: accumulator, initially U = zeroValue
  - p: result from a partition

Python reduce() w/o initial value

- reduce(func, list)

- If list is empty => ERROR
- Else if list contains a single element v, return v
- Otherwise, set accumulator x = list[0]
  - for each of remaining element list[i]
    - x = func(x, list[i])
  - Return final value of x

Python reduce() with initial value

- reduce(func, list, initialValue)

- Same as:
  - reduce(func, [initialValue] + list)

- Note: list can be empty now
  - reduce() will return initialValue when list is empty

reduce(f) vs aggregate(z, f1, f2)

- func in reduce(func) needs to be commutative and associative
  - While f1 and f2 in aggregate(z, f1, f2) do not need to be
  - f1: similar to the combiner function in Hadoop

- Need to specify initial value for aggregate()
  - & it can be of different type than values in RDD

Example

- data = sc.parallelize([1], 2)
- data.foreachPartition(printf)
  - P1: []
  - P2: [1]

- data.aggregate(1, add, add)
  - P1 => [1] => after reduction => 1
  - P2 => [1] + [1] = [1, 1] => 2
  - final: [1] + [1, 2] => [1, 1, 2] => 4

Example

- data.aggregate(2, add, lambda U, v: U * v)
  - P1 => 2
  - P2 => 3
  - Final: [2] + [2, 3] => 2 * 2 * 3 = 12

    (where [2] is zeroValue, [2,3] is the list of values from partitions)

Implementing count() using aggregate()

- data = sc.parallelize([1, 2, 3, 4, 5])
- ...

al

Implementing mean() using aggregate()

- data = sc.parallelize([1, 2, 3, 4, 5])
- …

takeSample(withReplacement, num, [seed])

- Take a random sample of elements in rdd

- withReplacement: True if with replacement
- num: sample size
- optional seed: for random number generator

- Useful in many applications, e.g., k-means clustering

Example

- data = sc.parallelize(xrange(10))

- data.takeSample(False, 2, 1)
  - [8, 0]

countByKey()

- Only available on RDDs of type (K, V)
  – i.e., RDD that contains a list of key-value pairs, e.g., ('hello', 3)

- Return a hashmap (dictionary in Python) of (K, Int) pairs with count for each unique key in RDD
  – Count for key k = # of tuples whose key is k

Example

- d = [('hello', 1), ('world', 1), ('hello', 2), ('this', 1), ('world',0)]
- data = sc.parallelize(d)

- data.countByKey()

=> {'this': 1, 'world': 2, 'hello': 2}

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Transformation

- Create a new RDD from an existing one

- E.g., map(func)
  - Applies func to each element of an RDD
  - Returns a new RDD representing mapped result

Lazy transformations

- Spark does not apply them to RDD right away
  - Just remember what needs to be done
  - Perform transformations until an action is applied

- Advantage
  - Results of transformations pipelined to the action
  - No need to return intermediate results to clients

  => more efficient

Avoid re-computation

- However, this means that the same RDD may be recomputed multiple times if it is used in multiple actions

  => All transformations need to be redone

  => Consequence: costly

- Solution: allow caching of RDDs in memory
  - May also persist them on disk

Transformations

- map(func)
- filter(func)
- flatMap(func)
- reduceByKey(func, [numTasks])
- groupByKey([numTasks])
- sortByKey([asc], [numTasks])
- distinct([numTasks])
- mapPartitions(func)

Specify # of reduce tasks

Transformations

- join(rdd, [numTasks])
  - leftOuterJoin
  - rightOuterJoin
  - fullOuterJoin
- aggregateByKey(zeroValue, seqOp, combOp, [numTasks])
- mapValues(func)
- flatMapValues(func)
- union/intersection/subtract
- subtractByKey

map(func)

- map(func): Apply a function func to each element in input RDD
  - func returns a value (could be a list)

- Output the new RDD containing the transformed values produced by func

Example

- lines = sc.textFile("hello.txt")

- lineSplit = lines.map(lambda s: s.split())

  => [['hello', 'world'], ['hello', 'this', 'world']]

- lineLengths = lines.map(lambda s: len(s))

  => [11, 16]

filter(func)

- filter(func): return a new RDD with elements of existing RDD for which func returns true

- func should be a boolean function

- lines1 = lines.filter(lambda line: "this" in line)
  $\Rightarrow$ ['hello this world']

- What about: lines.filter(lambda s: len(s) > 11)?

Notes

- data = sc.parallelize([1, 2, 3, 4, 5, 1, 3, 5], 2)

- data.map(lambda x: x if x % 2 == 0 else None).collect()

Result

[None, 2, None, 4, None, None, None, None]

- def f(x):

```
def f(x):
    if x % 2 == 0:
        return x
    else:
        pass
```

Same as "return None"

- data.map(f).collect()

Produce the same result as above

Python filter

- l = [1, 2, 3, 4, 5, 1, 3, 5]

- filter(lambda x: x % 2 == 0, l)
  - [2, 4]

Spark implementation of filter

- def even(x): return x % 2 == 0
- data.filter(even)

Implemented as follows:

- def processPartition(iterator):

  return filter(even, iterator)
- data.mapPartitions(processPartition)

mapPartitions(func)

- Apply transformation to a partition
  - input to func is an iterator (over the elements in the partition)
  - func must return an iterable (a list or use yield to return a generator)

- Different from map(func)
  - func in map(func) applies to an element

Example: implementing aggregate()

- rdd = sc.parallelize([1, 2, 3, 4, 5], 2)
- def sumf(iterator):

```
    sum, count = 0, 0
    for v in iterator:
        sum += v
        count += 1
    yield (sum, count)
```

- yield returns a generator
- may also return [(sum, count)]

- rdd.mapPartitions(sumf)

=> rdd: [(3, 2), (12, 3)]

Example: implementing aggregate()

- def aggr(x, y):

  return (x[0] + y[0], x[1] + y[1])

- rdd.mapPartitions(sumf).reduce(aggr)

$\Rightarrow$(15, 5)

- The above shows how we can implement:
  - rdd.aggregate((0,0), lambda U, v: (U[0] + v, U[1] + 1), lambda U, V: (U[0] + V[0], U[1] + V[1]))

Another way

- def seqFunc(U, x): return (U[0] + x, U[1] + 1)
- def combFunc(U, V): return (U[0] + V[0], U[1] + V[1])

- def sumf(iterator):

  return [reduce(seqFunc, iterator, (0, 0))]

- rdd.mapPartitions(sumf).reduce(combFunc)

In general

- data.aggregate(initVal, combFunc, reduFunc)

=>

1. res = data.mapPartitions(lambda p: [reduce(combFunc, p, initVal)]).collect()

2. reduce(reduFunc, res, initVal)

Exercise

- Implement count() using mapPartitions() and reduce() only
  - rdd = sc.parallelize([1, 1, 2, 3, 3, 3], 2)
  - rdd.count() => 6

flatMap(func)

- flatMap(func):
  - similar to map
  - But func here **must** return a list (or generator) of elements
  - & flatMap merges these lists into a single list

- lines.flatMap(lambda x: x.split())

=>rdd: ['hello', 'world', 'hello', 'this', 'world']

reduceByKey()

- reduceByKey(func)
  - Input: a collection of (k, v) pairs
  - Output: a collection of (k, v’) pairs

- v’: aggregated value of v's in all (k, v) pairs with the same key k by applying func

- func is the aggregation function
  - Similar to func in the reduce(func, list) in Python

reduceByKey(func)

- It first performs partition-site reduction & then global reduction
  - By executing the same reduce function

- In other words, func needs to be commutative and associative

- More details:
  - http://spark.apache.org/docs/latest/api/python/pyspark.html

Example

- rddp = sc.parallelize([(1,2), (1,3), (2,2), (1,4), (3,5), (2, 4), (1, 5), (2, 6)], 2)

- def printf(part):

      print list(part)

- rddp.foreachPartition(printf)
  - Partition 1: [(1, 2), (1, 3), (2, 2), (1, 4)]
  - Partition 2: [(3, 5), (2, 4), (1, 5), (2, 6)]

Example

- from operator import add
- rddp.reduceByKey(add)

- It will first execute local reduce:
  - Partition 1: [(1, 2), (1, 3), (2, 2), (1, 4)] => (1, 9), (2,2)
  - Partition 2: [(3, 5), (2, 4), (1, 5), (2, 6)] => (3, 5), (1, 5), (2, 10)

Example

- Final reduce at reducer side
  - (1, 9), (1, 5) => (1, 14)
  - (2, 2), (2, 10) => (2, 12)
  - (3, 5) => (3, 5)

- Note that if there are two reducers, then:
  - Some keys, e.g., 1, may be reduced by one reducer
  - Others, e.g., 2 and 3, by the other

reduceByKey() vs. reduce()

- reduceByKey() returns an RDD
  – Reduce values per key

- reduce() returns a non-RDD value
  – Reduce all values!

Exercise

- Implement countByKey using reduceByKey
  – rddp = sc.parallelize([(1,2), (1,3), (2,2), (1,4), (3,5), (2, 4), (1, 5), (2, 6)], 2)
  – rddp.countByKey() => {1: 4, 2: 3, 3: 1}

aggregateByKey

- aggregateByKey(zeroValue, seqOp, combOp)
  - Input RDD: a list of (k, v) pairs
  - Aggregate values for each key

- Return a value U for each key
  - Note that U may be a tuple
  - zeroValue = initial value for U
  - seqOp(U, v): how to add value v of input RDD into U
  - combOp(U1, U2): how to combine two U's (created by different partitions)

Computing group averages

- rdd1 = rddp.aggregateByKey((0,0), lambda U,v: (U[0] + v, U[1] + 1), lambda U1,U2: (U1[0] + U2[0], U1[1] + U2[1]))
  - [(2, (12, 3)), (1, (14, 4)), (3, (5, 1))]

- rdd1.map(lambda (x, (y, z)): (x, float(y)/z))
  - [(2, 4.0), (1, 3.5), (3, 5.0)]

Example: aggregateByKey

- data = sc.parallelize([(1, 1), (1,2), (1,3)], 2)

- data.foreachPartition(printf)
  - [(1, 1)]
  - [(1, 2), (1, 3)]

- data.aggregateByKey(1, add, add).collect()
  - [(1, 8)]

Compared with aggregate()

- data = sc.parallelize([1, 2, 3], 2)
- data.foreachPartition(printf)
  - [1]
  - [2, 3]
- data.aggregate(1, add, add)
  - 9

aggregateByKey vs. aggregate

- zeroValue in aggregateByKey
  - Used only seqOp (i.e., reduction within a partition)
- zeroValue in aggregate
  - Used in both seqOp and combOp
  - E.g., data.aggregate(2, add, add) => 9

aggregateByKey vs. reduceByKey

- aggregateByKey more general than reduceKey
  - can specify initial value for U, the accumulator
  - aggregated value may have different type than that of value v of input RDD

- E.g., in previous example:
  - v is an integer, while U is a tuple (sum, count)

Exercise

- Implement reduceByKey(add) using aggregateByKey()

- rddp = sc.parallelize([(1,2), (1,3), (2,2), (1,4), (3,5), (2, 4), (1, 5), (2, 6)], 2)
  – rddp.reduceByKey(add) => [(2, 12), (1, 14), (3, 5)]

groupByKey()

- groupByKey()
  - Similar to reduceByKey(func)
  - But without func & returning (k, Iterable(v)) instead

- rddp.groupByKey()

$\Rightarrow$[(2, <iterable>), (1, …), (3, …)]

Example

- rddp.groupByKey().map(lambda x: (x[0], list(x[1]))).collect()
  - map converts iterable into a list

=> [(2, [2, 4, 6]), (1, [2, 3, 4, 5]), (3, [5])]

sortByKey(True/False)

- sortByKey([asc])
  - Sort input RDD with (k, v) pairs by key
  - Ascending if asc (a boolean value) is True

- rddp.sortByKey(False).collect()

=> [(3, 5), (2, 2), (2, 4), (2, 6), (1, 2), (1, 3), (1, 4), (1, 5)]

distinct()

- Return an RDD with distinct elements of source RDD

- data = [5, 4, 4, 1, 2, 3, 3, 1, 2, 5, 4, 5]
- pdata = sc.parallelize(data, 2)

- pdata.distinct().collect()

=> [2, 4, 1, 3, 5]

Exercise

- Implement distinct() using reduceByKey()

- rdd = sc.parallelize([3, 1, 2, 3, 1, 3, 3, 2])
- rdd.distinct()

  => [1, 2, 3]

rdd.map((la da x : (x,1)).groupByKey

ma m a k) .k)

k (:)

join(rdd)

- rdd1.join(rdd2)
  - Joining tuples of two RDDs on the key
  - rdd1: an RDD containing a list of (k, v)'s
  - rdd2: another RDD containing a list of (k, w)'s

- Output an RDD containing (k, (v, w))'s
  - That is, (k, v) joins with (k, w) => (k, (v, w))

Example

- ds1 = sc.parallelize([(1,2), (2,3)])
- ds2 = sc.parallelize([(2,4), (3,5)])

- ds1.join(ds2)
  - [(2, (3, 4))]

Outer joins

- Also retain dangling tuples

- ds1.leftOuterJoin(ds2)
  - [(1, (2, None)), (2, (3, 4))]

- ds1.rightOuterJoin(ds2)
  - [(2, (3, 4)), (3, (None, 5))]

- ds1.fullOuterJoin(ds2)
  - [(1, (2, None)), (2, (3, 4)), (3, (None, 5))]

mapValues

- mapValues(func)
  - For each key, apply func to each value of the key

- x = sc.parallelize([("a", ["apple", "banana", "lemon"]), ("b", ["grapes"])])
- x.mapValues(lambda l: len(l)).collect()
  - [('a', 3), ('b', 1)]

flatMapValues(func)

- mapValues part
  - For each key k, apply func to its value, return a list [i1, i2, …]
- flatMap part
  - flatten the lists into a single list but retain the key

  => [(k, i1), (k, i2), …, (k', i1'), (k', i2'), …]

Example

- rdd = sc.parallelize([(1, "hello world"), (2, "hello this world")])
  - For example, 1 and 2 may be document id's

- rdd2 = rdd.flatMapValues(lambda s: s.split())
  - [(1, 'hello'), (1, 'world'), (2, 'hello'), (2, 'this'), (2, 'world')]

Exercise

- Use mapValues() and flatMap() implement flatMapValues() in the previous slide

union(rdd)

- rdd1.union(rdd2)
  - Returns all elements in rdd1 and rdd2
  - Does not remove duplicates (so bag union)

- rdd1 = sc.parallelize([1, 1, 2, 3, 3, 3], 2) → 2 partitions
- rdd2 = sc.parallelize([1, 2, 2, 5], 2) → 2 partitions
- rdd1.union(rdd2) → 4 partitions
  - [1, 1, 2, 3, 3, 3, 1, 2, 2, 5]

intersection(rdd)

- rdd1.intersection(rdd2)
  – Returns elements in both rdd1 and rdd2
  – Duplicates will be removed! (so set-semantics)

- rdd1 = sc.parallelize([1, 1, 2, 3, 3, 3])
- rdd2 = sc.parallelize([1, 2, 2, 5])
- rdd1.intersection(rdd2)
  – [2, 1]

subtract(rdd)

- rdd1.subtract(rdd2)
  - Return values in rdd1 that do not appear in rdd2
  - Note: neither set nor bag semantics!

- rdd1 = sc.parallelize([1, 1, 2, 3, 3, 3])
- rdd2 = sc.parallelize([1, 2, 2, 5])
- rdd1.subtract(rdd2)
  - [3, 3, 3]
  - Note: 1 **not** included in result (unlike bag difference)

subtractByKey(rdd)

- rdd1.subtractByKey(rdd2)
  - Return each (key, value) pair in rdd1 that has no pair with matching key in rdd2

- rdd1 = sc.parallelize([1, 1, 2, 3, 3, 3]).map(lambda x: (x, 1))
- rdd2 = sc.parallelize([1, 2, 2, 5]).map(lambda x: (x, 1))
- rdd1.subtractByKey(rdd2)
  - [(3, 1), (3, 1), (3, 1)]

Roadmap

- Spark
  - History, features, RDD, and installation
- RDD operations
  - Creating initial RDDs
  - Actions
  - Transformations
- Examples
- Shuffling in Spark

WordCount

- from operator import add
- lines = sc.textFile("hello.txt")
- counts = lines.flatMap(lambda x: x.split(' ')) \
                    .map(lambda x: (x, 1)) \
                    .reduceByKey(add)
- counts.collect()

=> [(u'this', 1), (u'world', 2), (u'hello', 2)]

Word length histogram

- long: if > 4 letters
- short: otherwise

- def myFunc(x):

```
def myFunc(x):
    if len(x) > 4:
        return ('long', 1)
    else:
        return ('short', 1)
```

Word length histogram

- sc.textFile("hello.txt") \
  .flatMap(lambda x: x.split(" ")) \
  .map(myFunc) \
  .reduceByKey(add) \
  .collect()

  => [('short', 1), ('long', 4)]

Adding ratings for each person

Ratings.txt

(patrick, 4)
(matei, 3)
(patrick, 1)
(aaron, 2)
(aaron, 2)
(reynold, 1)
(aaron, 5)

(aaron, 9)
(patrick, 5)
…

Adding ratings for each person

- sc.textFile("ratings.txt") \

  .map(lambda s: s[1:-1].split(",")) \

  .collect()

Strip off ()

=>

[[u'patrick', u'4'], [u'matei', u'3'], [u'patrick', u'1'], [u'aaron', u'2)'], [u'aaron', u'2'], [u'reynold', u'1'], [u'aaron', u'5']]

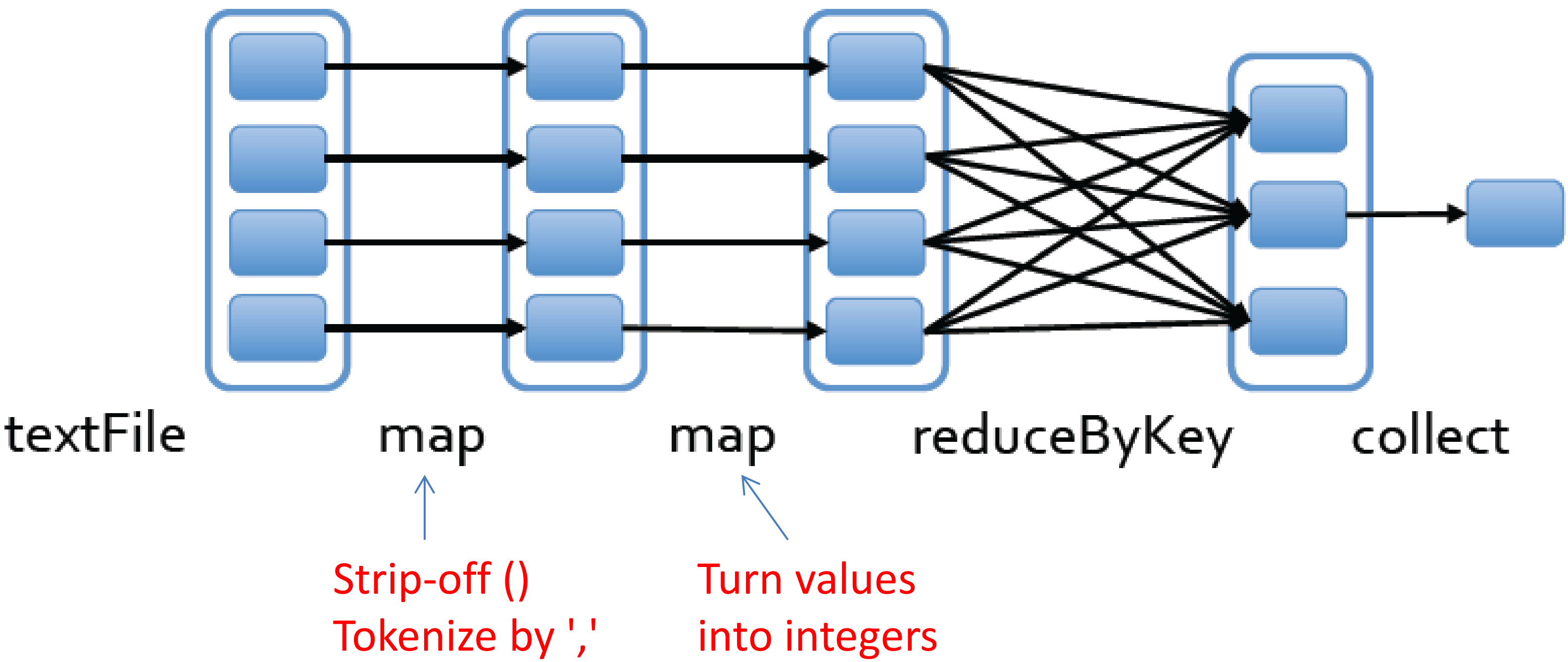
Adding ratings for each person

-
```
sc.textFile("ratings.txt") \
    .map(lambda s: s[1:-1].split(",")) \
    .map(lambda p: (p[0], int(p[1]))) \
    .reduceByKey(lambda a, b: a + b) \
    .collect()
```

=> [(u'patrick', 5), (u'aaron', 9), (u'reynold', 1), (u'matei', 3)]

Execution steps

- Note that reduceByKey requires shuffling



Roadmap

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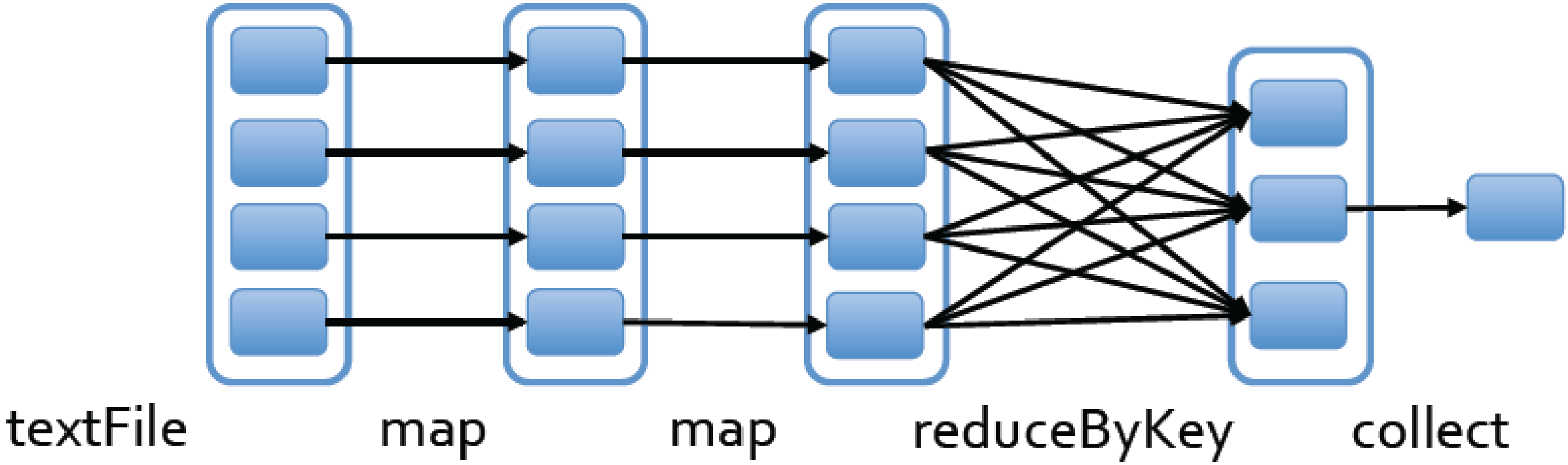
- Persistence in Spark

Shuffling

- Data are essentially repartitioned
  - E.g., reduceByKey repartitions the data by key
- A costly operation: a lot of local & network I/O's



Another example: sortByKey

- Sampling stage:
  - Sample data to create a range-partitioner
  - Ensure even partitioning
- "Map" stage:
  - Write (sorted) data to destined partition for reduce stage

Data are shuffled between Map and Reduce stage

- "Reduce" stage:
  - get map output for specific partition
  - Merge the sorted data

Transformations that require shuffling

- reduceByKey(func)
- groupByKey()
- sortByKey([asc])
- distinct()

Transformations that require shuffling

- join(rdd):
  - leftOuterJoin
  - rightOuterJoin
  - fullOuterJoin
- aggregateByKey(zeroValue, seqOp, combOp)
- intersection/subtract
- subtractByKey

Transformations that do not need shuffling

- map(func)
- filter(func)
- flatMap(func)
- mapValues(func)
- union
- mapPartitions(func)

Roadmap

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RDD persistence

- rdd.persist(<storageLevel>)

- Store the content of RDD for later reuse
  - storageLevel specifies where content is stored
  - E.g., in memory (default) or on disk

- rdd.persist() or rdd.cache()
  - Content stored in main memory

RDD persistence

- Executed at nodes having partitions of RDD

- Avoid re-computation of RDD in reuse

Example

- ratings = sc.textFile("ratings.txt") \
  .map(lambda s: s[1:-1].split(",")) \
  .map(lambda p: (p[0], int(p[1]))) \
  .cache()

- ratings.reduceByKey(lambda a, b: a + b).collect()
  - ratings RDD will be computed for the first time & result cached

Example

- ratings.countByKey()
  - It will use cached content of "ratings" rdd

Automatic persistence

- Spark automatically persists intermediate data in shuffling operations (e.g., reduceByKey)

- This avoids re-computation when node fails

K-means clustering

- Find k clusters in a data set
  - k is pre-determined
- Iterative process
  - Start with initial guess of centers of clusters
  - Repeatedly refine the guess until stable (e.g., centers do not change much)
- Need to use data set at each iteration

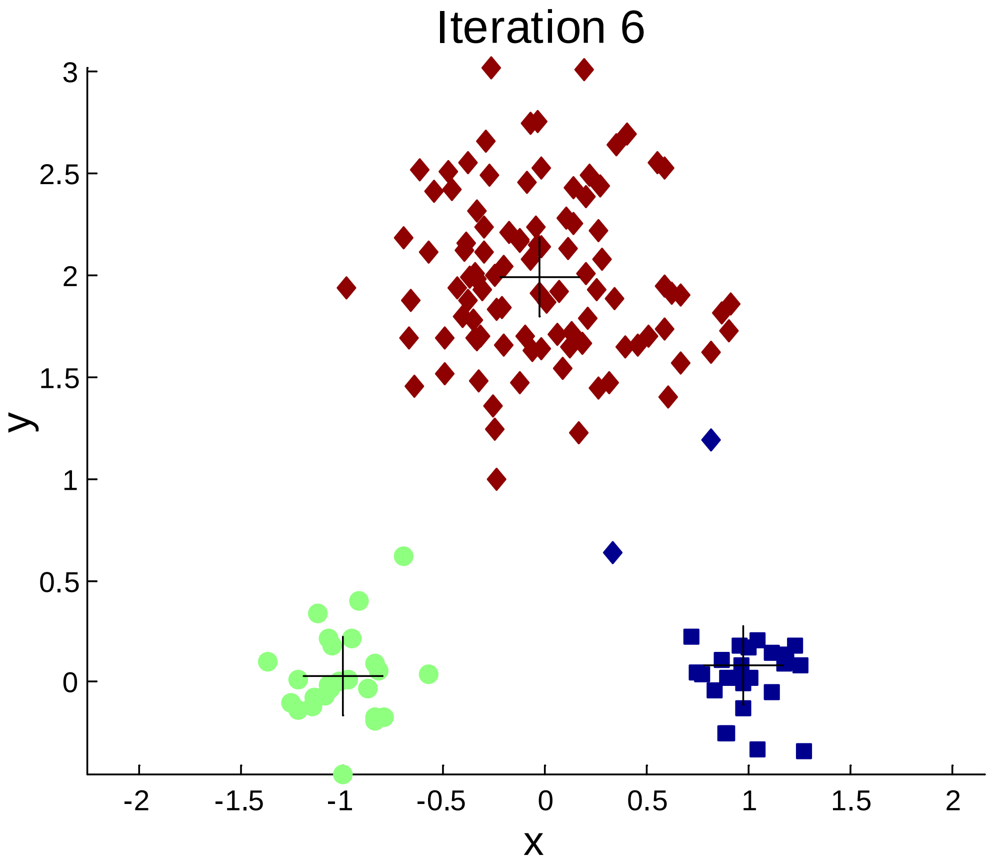
K-means clustering

- Assign point p to the closest center c
  - Distance = Euclidean distance between p and c

- Re-compute the centers based on assignments

- Coordinates of center of a cluster =
  - Average coordinate of all points in the cluster
  - E.g., (1, 1, 1) (3, 3, 3) => center: (2, 2, 2)

K-means clustering



```
sc = SparkContext(appName="PythonKMeans")
lines = sc.textFile(sys.argv[1])
data = lines.map(parseVector).cache()
K = int(sys.argv[2])
convergeDist = float(sys.argv[3])

kPoints = data.takeSample(False, K, 1)
tempDist = 1.0

while tempDist > convergeDist:
    closest = data.map(
        lambda p: (closestPoint(p, kPoints), (p, 1)))
    pointStats = closest.reduceByKey(
        lambda p1_c1, p2_c2: (p1_c1[0] + p2_c2[0], p1_c1[1] + p2_c2[1]))
    newPoints = pointStats.map(
        lambda st: (st[0], st[1][0] / st[1][1])).collect()

    tempDist = sum(np.sum((kPoints[iK] - p) ** 2) for (iK, p) in newPoints)

    for (iK, p) in newPoints:
        kPoints[iK] = p

print("Final centers: " + str(kPoints))

sc.stop()
```

Persist data points in memory

Initial centers

New centers

Sum of distances between new and old centers

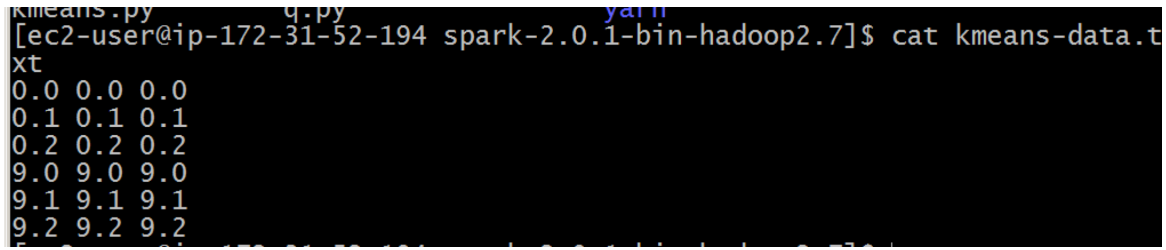
Parse input & find closest center

```python
def parseVector(line):
    return np.array([float(x) for x in line.split(' ')])


def closestPoint(p, centers):
    bestIndex = 0
    closest = float("+inf")
    for i in range(len(centers)):
        tempDist = np.sum((p - centers[i]) ** 2)
        if tempDist < closest:
            closest = tempDist
            bestIndex = i
    return bestIndex
```

kmeans-data.txt

- A text file contains the following lines
  - 0.0 0.0 0.0
  - 0.1 0.1 0.1
  - 0.2 0.2 0.2
  - 9.0 9.0 9.0
  - 9.1 9.1 9.1
  - 9.2 9.2 9.2



- Each line is a 3-dimensional data point

Parse & cache the input dataset

- "data" RDD is now cached in main memory

```
>>> lines = sc.textFile("kmeans-data.txt")
>>> lines.collect()
[u'0.0 0.0 0.0', u'0.1 0.1 0.1', u'0.2 0.2 0.2', u'9.0 9.0 9.0', u'9.1 9
.1 9.1', u'9.2 9.2 9.2']
>>>
>>> def parseVector(line):
...     return np.array([float(x) for x in line.split(' ')])
...
>>> data = lines.map(parseVector).cache()
>>> data.collect()
[array([ 0.,  0.,  0.]), array([ 0.1,  0.1,  0.1]), array([ 0.2,  0.2,
0.2]), array([ 9.,  9.,  9.]), array([ 9.1,  9.1,  9.1]), array([ 9.2,
9.2,  9.2])]
```

Generating initial centers

- Recall takeSample() action
  - False: sample without replacement
  - K = 2

```
>>> kPoints = data.takeSample(False, K, 1)
>>> kPoints
[array([ 0.1,  0.1,  0.1]), array([ 0.2,  0.2,  0.2])]
>>>
```

Assign point to its closest center

- Center 0 has points: (0, 0, 0) and (.1, .1, .1)
- Center 1 has the rest: (.2, .2, .2), (.9, .9, .9), …

```
>>> def closestPoint(p, centers):
...     bestIndex = 0
...     closest = float("+inf")
...     for i in range(len(centers)):
...         tempDist = np.sum((p - centers[i]) ** 2)
...         if tempDist < closest:
...             closest = tempDist
...             bestIndex = i
...     return bestIndex
...
>>> closest = data.map(lambda p: (closestPoint(p, kPoints), (p, 1)))
>>> closest.collect()
[(0, (array([ 0.,  0.,  0.]), 1)), (0, (array([ 0.1,  0.1,  0.1]), 1)),
(1, (array([ 0.2,  0.2,  0.2]), 1)), (1, (array([ 9.,  9.,  9.]), 1)), (
1, (array([ 9.1,  9.1,  9.1]), 1)), (1, (array([ 9.2,  9.2,  9.2]), 1))]
>>>
```

Getting statistics for each center

- pointStats has a key-value pair for each center
- Key is center # (0 or 1 for this example)
- Value is a tuple (sum, count)
  - sum = the sum of coordinates over all points in the cluster
  - Count = # of points in the cluster

```
>>> pointStats = closest.reduceByKey(lambda p1_c1, p2_c2: (p1_c1[0] + p2
_c2[0], p1_c1[1] + p2_c2[1]))
>>> pointStats.collect()
[(0, (array([ 0.1,  0.1,  0.1]), 2)), (1, (array([ 27.5,  27.5,  27.5]),
 4))]
```

Computing coordinates of new centers

- Coordinate = sum of point coordinates/count
  - E.g., center 0: [.1, .1, .1] /2 = [.05, .05, .05]

```
>>> newPoints = pointStats.map(lambda st: (st[0], st[1][0] / st[1][1])).
collect()
>>> newPoints
[(0, array([ 0.05,  0.05,  0.05])), (1, array([ 6.875,  6.875,  6.875]))
]
>>>
```

Can use mapValues here too:

newPoints1 = pointStats.mapValues(lambda stv: stv[0]/stv[1]).collect()

Distance btw new & old centers

- Old center: [.1, .1, .1] and [.2, .2, .2]
- New center: [.05, .05, .05] and [6.875, 6.875, 6.875]

- Distance = $(.1-.05)^2*3 + (6.875-.2)^2*3 \sim 133.67$
  - To be more exact, it is sqrt(133.67) = 11.56

```
>>> tempDist = sum(np.sum((kPoints[iK] - p) ** 2) for (iK, p) in newPoin
ts)
>>> tempDist
133.67437499999994
```

RDD operations

- A complete list:
  - http://spark.apache.org/docs/latest/api/python/pyspark.html

Resources

- Spark programming guide:
  - https://spark.apache.org/docs/latest/
- Lambda, filter, reduce and map:
  - http://www.python-course.eu/lambda.php
- Improving Sort Performance in Apache Spark: It's a Double
  - http://blog.cloudera.com/blog/2015/01/improving-sort-performance-in-apache-spark-its-a-double/

Readings

- Spark: Cluster Computing with Working Sets, 2010.

- Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing, 2012.

References

- [Functional programming in Python](https://docs.python.org/2/howto/functional.html)
  – https://docs.python.org/2/howto/functional.html

- Learning Spark by Matei Zaharia, et. Al. O'Reilly, 2015
  – https://www.safaribooksonline.com/library/view/learning-spark/9781449359034/

References

- Sort-based shuffle implementation
  - https://issues.apache.org/jira/browse/SPARK-2045
- Sort-Based Shuffle in Spark
  - https://issues.apache.org/jira/secure/attachment/12655884/Sort-basedshuffledesign.pdf

References

- Pyspark source code:
  - Path-to-dir\spark-2.1.0-bin-hadoop2.7\python\pyspark\rdd.py (and others)