STAT606 Computing for Data Science and Statistics

Lecture 21: PySpark

Some slides adapted from C. Budak (U. Michigan) and R. Burns (JHU)

Parallel Computing with Apache Spark

Apache Spark is a computing framework for large-scale parallel processing
- Developed by UC Berkeley AMPLab (Now RISELab)
- Now maintained by Apache Foundation

Implementations are available in Java, Scala and Python (and R, sort of)
- and these can be run interactively!

Easily communicates with several other “big data” Apache tools
- e.g., Hadoop, Mesos, HBase
- Can also be run locally or in the cloud (e.g., GCP and Amazon EC2)

https://spark.apache.org/docs/latest/

Why use Spark?

vs

"Wait, doesn't Hadoop/mrjob already do all this stuff?"

Short answer: yes!

Less short answer: Spark is faster and more flexible than Hadoop

and since Spark is eclipsing Hadoop in industry, it is my responsibility to teach it to you

Spark still follows the MapReduce framework, but is better suited to:

- Interactive sessions
- Caching (i.e., data is stored in RAM on the nodes where it is to be processed, not on disk)
- Repeatedly updating computations (e.g., updates as new data arrive)
- Fault tolerance and recovery

Apache Spark: Overview

Implemented in Scala

- Popular functional programming (sort of…) language
- Runs atop Java Virtual Machine (JVM)
- https://www.scala-lang.org/

But Spark can be called from Scala, Java and Python

- and from R using SparkR: https://spark.apache.org/docs/latest/sparkr.html

We'll do all our coding in Python

- PySpark: https://spark.apache.org/docs/latest/api/python/getting_started/index.html
- but everything you learn can be applied with minimal changes in other supported languages

Running Spark

Option 1: Run in interactive mode

Type `pyspark` on the command line

PySpark provides an interface similar to the Python interpreter

Scala, Java and R also provide their own interactive modes

Option 2: Run on a cluster: write your code, then launch it via a scheduler

`spark-submit`

https://spark.apache.org/docs/latest/submitting-applications.html#launching-applications-with-spark-submit

Similar functionality on Google Cloud Platform

https://cloud.google.com/sdk/gcloud/reference/dataproc/jobs/submit/pyspark

Similar to running Python `mrjob` scripts with the `-r dataproc` flag

Two Basic Concepts

SparkContext

- Object corresponding to a connection to a Spark cluster
  - Automatically created in interactive mode
  - Must be created explicitly when run via scheduler (We'll see an example soon)
- Maintains information about where data is stored
- Allows configuration by supplying a `SparkConf` object

Resilient Distributed Dataset (RDD)

- Represents a collection of data
- Distributed across nodes in a fault-tolerant way (much like HDFS)

More about RDDs

RDDs are the basic unit of Spark

“a collection of elements partitioned across the nodes of the cluster that can be operated on in parallel.” (https://spark.apache.org/docs/latest/rdd-programming-guide.html)

Elements of an RDD are analogous to <key,value> pairs in MapReduce

RDD is roughly analogous to a dataframe in R

RDD elements are somewhat like rows in a table

Spark can also keep (**persist**, in Spark’s terminology) an RDD in memory

Allows reuse or additional processing later

RDDs are **immutable**, like Python tuples and strings.

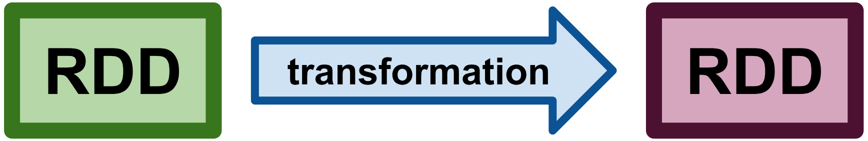
RDD operations

Think of RDD as representing a data set

Two basic operations:

Transformation: results in another RDD

(e.g., `map` takes an RDD and applies some function to every element of the RDD)



Action: computes a value and reports it to driver program

(e.g., `reduce` takes all elements and computes some summary statistic)

RDD operations are lazy!

Transformations are only carried out once an **action** needs to be computed.

Spark remembers the sequence of transformations to run...
    ...but doesn't execute them until it has to
    e.g., to produce the result of a reduce operation for the user.

This allows for gains in efficiency in some contexts
    mainly because it avoids expensive intermediate computations

Okay, let's dive in!

In the slides that follow, I am assuming that we are logged on to a cluster that has a Spark server running. Your homework will walk you through how to set up a cluster like this on Google Cloud Platform.

```
[keith@m ~]$ pyspark
Python 3.8.8 | packaged by conda-forge | (default, Feb 20 2021, 16:22:27)
[GCC 9.3.0] on linux
Type "help", "copyright", "credits" or "license" for more information.
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use
setLogLevel(newLevel).
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 3.1.1
      /_/
Using Python version 3.8.8 (default, Feb 20 2021 16:22:27)
Spark context Web UI available at
http://stat606-test-server-m.c.stat606-s24-trial.internal:35879
Spark context available as 'sc' (master = yarn, app id = application_1617664534064_0001).
SparkSession available as 'spark'.
>>>
```

Okay, let’s dive in!

```
[keith@m ~]$ pyspark
Python 3.8.8 | packaged by conda-forge | (default, Fe
[GCC 9.3.0] on linux
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      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 3.1.1
      /_/

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Spark context available as 'sc' (master = yarn, app id = application_1617664534064_0001).
SparkSession available as 'spark'.
>>>
```

There will be information here (sometimes multiple screens’ worth) about establishing a Spark session. You can safely ignore this information, for now, but if you’re running your own Spark cluster this is where you’ll need to look when it comes time to troubleshoot.

Spark finishes setting up our interactive session and gives us a prompt like the Python interpreter.

Creating an RDD from a file

```
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 3.1.1
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Spark context available as 'sc' (master = yarn, app id = application_1617664534064_0001).
SparkSession available as 'spark'.
>>> sc
<SparkContext master=yarn appName=PySparkShell>
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/ps_demo_file.txt')
>>> data.collect()
['This is just a demo file.', 'Normally, a file this small would have no
need for Hadoop.']
>>>
```

Creating an RDD from a file

```
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 3.1.1
      /_/
Using Python version 3.8.8 (default, Feb 20 2021 16:22:2
Spark context Web UI available at
http://stat606-test-server-m.c.stat606-s24-trial.internal:35879
Spark context available as 'sc' (master = yarn, app id = application_1617664534064_0001).
SparkSession available as 'spark'.
>>> sc
<SparkContext master=yarn appName=PySparkShell>
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/ps_demo_file.txt')
>>> data.collect()
['This is just a demo file.', 'Normally, a file this small would have no
need for Hadoop.']
>>>
```

SparkContext is automatically created by the PySpark interpreter, and saved in the variable `sc`. When we write a job to be run on the cluster, we will have to define `sc` ourselves.

This creates an RDD from the given file. Note that PySpark had no trouble finding our file in our GCP storage bucket.

Our first RDD action. `collect()` gathers the elements of the RDD into a list.

Creating an RDD from a file

```
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 3.1.1
      /_/
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>>> sc
<SparkContext master=yarn appName=PySparkShell>
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/ps_demo_file.txt')
>>> data.collect()
['This is just a demo file.', 'Normally, a file this small would have no
need for Hadoop.']
>>>
```

All demo files for this lecture are available on Google Cloud storage and on the course webpage.

PySpark keeps track of RDDs

```
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 3.1.1
      /_/
[...]
>>> sc
<SparkContext master=yarn appName=PySparkShell>
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/ps_demo_file.txt')
>>> data
gs://uw-stat606s24-pyspark/ps_demo_file.txt MapPartitionsRDD[5] at textFile
at NativeMethodAccessorImpl.java:0
>>>
```

PySpark keeps track of RDDs

PySpark keeps track of where the original data resides. `MapPartitionsRDD` is like an array of all the RDDs that we've created (though it's not a variable you can access).

```
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 3.1.1
      /_/
[...]
>>> sc
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gs://uw-stat606s24-pyspark/ps_demo_file.txt MapPartitionsRDD[5] at textFile
at NativeMethodAccessorImpl.java:0
>>>
```

Simple MapReduce task: Summations

```
[keith@m ~]$ gsutil cat gs://uw-stat606s24-pyspark/numbers.txt
10
23
16
7
12
0
1
1
2
3
5
8
-1
42
64
101
-101
3
[keith@m ~]$
```

I have a file containing some numbers.
Let’s add them up using PySpark.

Simple MapReduce task: Summations

```
[pyspark interactive session]
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/numbers.txt')
>>> data.collect()
['10', '23', '16', '7', '12', '0', '1', '1', '2', '3', '5', '8', '-1', '42', '64', '101',
'-101', '3']
>>> stripped = data.map(lambda line: line.strip())
>>> stripped.collect()
['10', '23', '16', '7', '12', '0', '1', '1', '2', '3', '5', '8', '-1', '42', '64', '101',
'-101', '3']
>>>
```

Using `strip()` here is redundant: PySpark automatically splits on whitespace when it reads from a text file. This is again just to show an example.

Reminder: `collect()` is an RDD action that produces a list of the RDD elements.

Simple MapReduce task: Summations

```
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/numbers.txt')
>>> stripped = data.map(lambda line: line.strip())
>>> intdata = stripped.map(lambda n: int(n))
>>> intdata.reduce(lambda x,y: x+y)
196
>>>
```

Simple MapReduce task: Summations

```
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/numbers.txt')
>>> stripped = data.map(lambda line: line.strip())
>>> intdata = stripped.map(lambda n: int(n))
>>> intdata.reduce(lambda x,y: x+y)
190
>>>
```

PySpark doesn’t actually perform any computations on the data until this line.

Test your understanding:
Why is this the case?

Simple MapReduce task: Summations

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>>> data = sc.textFile('gs://uw-stat606s24-pyspark/numbers.txt')
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>>>
```

PySpark doesn’t actually perform any computations on the data until this line.

Test your understanding:
Why is this the case?

Answer: Because PySpark RDD operations are lazy, PySpark doesn’t perform any computations until we actually ask it for something via an **RDD action**.

Simple MapReduce task: Summations

```
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/numbers.txt')
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>>> intdata = stripped.map(lambda n: int(n))
>>> intdata.reduce(lambda x,y: x+y)
190
>>>
```

Warning: RDD laziness also means that if you have an error, you often won't find out about it until you call an RDD action!

PySpark doesn't actually perform any computations on the data until this line.

Test your understanding:
Why is this the case?

Answer: Because PySpark RDD operations are lazy, PySpark doesn't perform any computations until we actually ask it for something via an **RDD action**.

Simple MapReduce task: Summations

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>>> data = sc.textFile('gs://uw-stat606s24-pyspark/numbers.txt')
>>> stripped = data.map(lambda line: line.strip())
>>> intdata = stripped.map(lambda n: int(n))
>>> intdata.reduce(lambda x,y: x+y)
196
>>>
```

The Spark way of doing things also means that we can write all of the above much more succinctly.

```
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/numbers.txt')
>>> data.map( lambda n: int(n)).reduce( lambda x,y:x+y )
196
```

Example RDD Transformations

`map`: apply a function to every element of the RDD

`filter`: retain only the elements satisfying a condition

`flatMap`: apply a map, but “flatten” the structure (details in a few slides)

`sample`: take a random sample from the elements of the RDD

`distinct`: remove duplicate entries of the RDD

`reduceByKey`: on RDD of (K, V) pairs, return RDD of (K, V) pairs

values for each key are aggregated using the given reduce function.

More: https://spark.apache.org/docs/latest/rdd-programming-guide.html#transformations

RDD.map()

```
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/numbers.txt').map(lambda n: int(n))
>>> data.collect()
[10, 23, 16, 7, 12, 0, 1, 1, 2, 3, 5, 8, -1, 42, 64, 101, -101, 3]
>>> doubles = data.map(lambda n: 2*n)
>>> doubles.collect()
[20, 46, 32, 14, 24, 0, 2, 2, 4, 6, 10, 16, -2, 84, 128, 202, -202, 6]
>>> sc.addPyFile('gs://uw-stat606s24-pyspark/poly.py')
>>> from poly import *
>>> data.map(polynomial).collect()
[101, 530, 257, 50, 145, 1, 2, 2, 5, 10, 26, 65, 2, 1765, 4097, 10202, 10202, 10]
>>>
```

poly.py

```
def polynomial(x):
    return x**2 + 1
```

RDD.map()

Load .py files using the addPyFile() method supplied by sparkContext, then import functions like normal.

```
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/numbers.txt').map(lambda n: int(n))
>>> data.collect()
[10, 23, 16, 7, 12, 0, 1, 1, 2, 3, 5, 8, -1, 42, 64, 101, -101, 3]
>>> doubles = data.map(lambda n: 2*n)
>>> doubles.collect()
[20, 46, 32, 14, 24, 0, 2, 2, 4, 6, 10, 16, -2, 84, 128, 202, -202, 6]
>>> sc.addPyFile('gs://uw-stat606s24-pyspark/poly.py')
>>> from poly import *
>>> data.map(polynomial).collect()
[101, 530, 257, 50, 145, 1, 2, 2, 5, 10, 26, 65, 2, 1765, 4097, 10202, 10202, 10]
>>>
```

poly.py

```
def polynomial(x):
    return x**2 + 1
```

This file is stored in a Google Cloud storage bucket, so we have to specify its path.

RDD.map()

```
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/numbers.txt').map(lambda n: int(n))
>>> data.collect()
[10, 23, 16, 7, 12, 0, 1, 1, 2, 3, 5, 8, -1, 42, 64, 101, -101, 3]
>>> doubles = data.map(lambda n: 2*n)
>>> doubles.collect()
[20, 46, 32, 14, 24, 0, 2, 2, 4, 6, 10, 16, -2, 84, 128, 202, -202, 6]
>>> sc.addPyFile('gs://uw-stat606s24-pyspark/poly.py')
>>> from poly import *
>>> data.map(polynomial).collect()
[101, 530, 257, 50, 145, 1, 2, 2, 5, 10, 26, 65, 2, 1765, 4097, 10202, 10202, 10]
>>>
```

poly.py

```
def polynomial(x):
    return x**2 + 1
```

This file is stored in a Google Cloud storage bucket, so we have to specify its path.

RDD.filter()

```
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/numbers.txt').map(lambda n: int(n))
>>> evens = data.filter(lambda n: n%2==0)
>>> evens.collect()
[10, 16, 12, 0, 2, 8, 42, 64]
>>> odds = data.filter(lambda n: n%2!=0)
>>> odds.collect()
[23, 7, 1, 1, 3, 5, -1, 101, -101, 3]
>>> sc.addPyFile('gs://uw-stat606s24-pyspark/prime.py')
>>> from prime import is_prime
>>> primes = data.filter(is_prime)
>>> primes.collect()
[23, 7, 3, 5, 101, 3]
>>>
```

`filter()` takes a Boolean function as an argument, and retains only the elements that evaluate to `True`.

prime.py

```
def is_prime(n):
    if n < 1: # Primes must be naturals.
        return False
    import math
    if n==1:
        return False
    for x in range(2,max([3,int(math.sqrt(n))])):
        if n%x==0:
            return False
    return True
```

RDD.sample()

```
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/numbers.txt').map(lambda n: int(n))
>>> samp = data.sample(False, 0.5)
>>> samp.collect()
[12, 5, -1, 42, 101, -101]
>>> samp = data.sample(True, 0.5)
>>> samp.collect()
[10, 10, 23, 7, 2, 42, 101, 3]
>>>
```

`sample(`*`withReplacement, fraction, [seed]`*`)`

`RDD.sample()` is mostly useful for testing on small subsets of your data.

Dealing with more complicated elements

What if the elements of my RDD are more complicated than just numbers?...

Example: if I have a comma-separated database-like file

Short answer: RDD elements are always tuples

But what about *really* complicated elements?
Recall that PySpark RDDs are immutable. This means that if you want your RDD to contain, for example, python dictionaries, you need to do a bit of extra work to turn Python objects into strings via **serialization**, which you already know about from the `pickle` module: https://docs.python.org/3/library/pickle.html

Database-like file

```
[keith@m ~]$ gsutil cat gs://uw-stat606s24-pyspark/scientists.txt
John Bardeen 3.1 EE 1908
Eugene Wigner 3.2 Physics 1902
Albert Einstein 4.0 Physics 1879
Ronald Fisher 3.25 Statistics 1890
Emmy Noether 2.9 Physics 1882
Leonard Euler 3.9 Mathematics 1707
Jerzy Neyman 3.5 Statistics 1894
Ky Fan 3.55 Mathematics 1914
[keith@m ~]$
```

Database-like file

```
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/scientists.txt')
>>> data.collect()
['John Bardeen 3.1 EE 1908', 'Eugene Wigner 3.2 Physics 1902', 'Albert Einstein
4.0 Physics 1879', 'Ronald Fisher 3.25 Statistics 1890', 'Emmy Noether 2.9 Physics
1882', 'Leonard Euler 3.9 Mathematics 1707', 'Jerzy Neyman 3.5 Statistics 1894',
'Ky Fan 3.55 Mathematics 1914']
>>> data2 = data.map(lambda line: line.split())
>>> data2.collect()
[['John', 'Bardeen', '3.1', 'EE', '1908'], ['Eugene', 'Wigner', '3.2', 'Physics',
'1902'], ['Albert', 'Einstein', '4.0', 'Physics', '1879'], ['Ronald', 'Fisher',
'3.25', 'Statistics', '1890'], ['Emmy', 'Noether', '2.9', 'Physics', '1882'],
['Leonard', 'Euler', '3.9', 'Mathematics', '1707'], ['Jerzy', 'Neyman', '3.5',
'Statistics', '1894'], ['Ky', 'Fan', '3.55', 'Mathematics', '1914']]
>>>
```

Database-like file

On initial read, each line is a single element in the RDD.

```
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/scientists.txt')
>>> data.collect()
['John Bardeen 3.1 EE 1908', 'Eugene Wigner 3.2 Physics 1902', 'Albert Einstein
4.0 Physics 1879', 'Ronald Fisher 3.25 Statistics 1890', 'Emmy Noether 2.9 Physics
1882', 'Leonard Euler 3.9 Mathematics 1707', 'Jerzy Neyman 3.5 Statistics 1894',
'Ky Fan 3.55 Mathematics 1914']
>>> data2 = data.map(lambda line: line.split())
>>> data2.collect()
[['John', 'Bardeen', '3.1', 'EE', '1908'], ['Eugene', 'Wigner', '3.2', 'Physics',
'1902'], ['Albert', 'Einstein', '4.0', 'Physics', '1879'], ['Ronald', 'Fisher',
'3.25', 'Statistics', '1890'], ['Emmy', 'Noether', '2.9', 'Physics', '1882'],
['Leonard', 'Euler', '3.9', 'Mathematics', '1707'], ['Jerzy', 'Neyman', '3.5',
'Statistics', '1894'], ['Ky', 'Fan', '3.55', 'Mathematics', '1914']]
>>>
```

Note: `RDD.collect()` returns a list, but internal to the RDD, the elements are **tuples**, not lists.

After splitting each element on whitespace, we have what we want-- each element is a tuple of strings.

RDD.distinct()

```
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/scientists.txt')
>>> data2 = data.map(lambda line: line.split())
>>> fields = data2.map(lambda t: t[3])
>>> fields_distinct = fields.distinct()
>>> fields_distinct.collect()
['EE', 'Statistics', 'Physics', 'Mathematics']
>>>
```

RDD.distinct()

Each tuple is of the form
(first_name, last_name, GPA, field, birth_year)

```
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/scientists.txt')
>>> data2 = data.map(lambda line: line.split())
>>> fields = data2.map(lambda t: t[3])
>>> fields_distinct = fields.distinct()
>>> fields_distinct.collect()
['EE', 'Statistics', 'Physics', 'Mathematics']
>>>
```

`RDD.distinct()` does just what you think it does!

RDD.flatMap()

```
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/numbers_weird.txt')
>>> data.collect()
['10 23 16', '7 12', '0', '1 1 2 3 5 8', '-1 42', '64 101 -101', '3']
>>>
```

Same list of numbers, but they’re not one per line, anymore...

From PySpark documentation:
flatMap(*func*) Similar to map, but each input item can be mapped to 0 or more output items (so *func* should return a Seq rather than a single item).
https://spark.apache.org/docs/latest/rdd-programming-guide.html#transformations

RDD.flatMap()

```
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/numbers_weird.txt')
>>> data.collect()
['10 23 16', '7 12', '0', '1 1 2 3 5 8', '-1 42', '64 101 -101', '3']
>>> flattened = data.flatMap(lambda line: [x for x in line.split()])
>>> flattened.collect()
['10', '23', '16', '7', '12', '0', '1', '1', '2', '3', '5', '8', '-1',
'42', '64', '101', '-101', '3']
>>> flattened.map(lambda n: int(n)).reduce(lambda x,y: x+y)
196
>>>
```

So we can think of `flatMap()` as producing a list for each element in the RDD, and then concatenating those lists. But crucially, the output is another RDD, **not** a list. This kind of operation is called **flattening**, and it's a common pattern in functional programming.

Example RDD Actions

`reduce`: aggregate elements of the RDD using a function

`collect`: return all elements of the RDD as an array at the driver program.

`count`: return the number of elements in the RDD.

`countByKey`: Returns <key, int> pairs with count of each key.

Only available on RDDs with elements of the form <key,value>

More: https://spark.apache.org/docs/0.9.0/scala-programming-guide.html#actions

RDD.count()

```
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/ps_demo_file.txt')
>>> data_flat = data.flatMap(lambda line: line.split())
>>> words = data_flat.map(lambda w: w.lower())
>>> words.collect()
['this', 'is', 'just', 'a', 'demo', 'file.', 'normally,', 'a', 'file',
'this', 'small', 'would', 'have', 'no', 'reason', 'to', 'be', 'on',
'hdfs.']
>>> uniqwords = words.distinct()
>>> uniqwords.count()
17
>>>
```

RDD.countByKey()

```
>>> data = sc.textFile('gs://uw-stat606s24-pyspark/ps_demo_file.txt')
>>> data_flat = data.flatMap(lambda line: line.split())
>>> words = data_flat.map(lambda w: (w.lower(), 0))
>>> words.countByKey()
defaultdict(<class 'int'>, {'this': 2, 'is': 1, 'just': 1, 'a': 2,
'demo': 1, 'file.': 1, 'normally,': 1, 'file': 1, 'small': 1, 'would': 1,
'have': 1, 'no': 1, 'need': 1, 'for': 1, 'had
oop.': 1})
>>>
```

Note: In the example above, each word had a key 0, but note that in the dictionary produced by `countByKey`, the values correspond to how many times that key appeared. This is because `countByKey()` counts how many times each key appears and **ignores their values**.

Sidenote: Shared Variables

You won't need these in this course, but they're extremely useful for more complicated jobs, especially ones that are not embarrassingly parallel.

Spark supports shared variables!

Allows for (limited) communication between parallel jobs

Two types:

Broadcast variables: used to communicate value to all nodes

Accumulators: nodes can only "add"

(or multiply, or… any operation on a **monoid**)

https://en.wikipedia.org/wiki/Monoid

https://spark.apache.org/docs/latest/rdd-programming-guide.html#accumulators

Running PySpark on the Cluster

So far, we've just been running in interactive mode.

Problem: Interactive mode is good for prototyping and testing…

- ...but not so well-suited for running large jobs.

Solution: PySpark can also be submitted to a cluster and run there.

- Cluster with PySpark server: instead of `pyspark`, use `spark-submit`
  - This will be cluster-specific, so we won't discuss it here
- GCP: submit pyspark job to a Dataproc server
  - https://cloud.google.com/sdk/gcloud/reference/dataproc/jobs/submit/pyspark

Submitting to the queue: `spark-submit`

ps_wordcount.py

```python
from pyspark import SparkConf, SparkContext
import sys

# This script takes two arguments, an input file and output directory.
if len(sys.argv) != 3:
    print('Usage: ' + sys.argv[0] + ' <in> <out>')
    sys.exit(1)
inputlocation = sys.argv[1]
outputlocation = sys.argv[2]

# Set up the configuration and job context
conf = SparkConf().setAppNamr('WordCount')
sc = SparkContext(conf=conf)

# Read in the dataset and immediately transform all the lines into arrays.
data = sc.textFile(inputlocation)
data_flattened = data.flatMap(lambda line: line.split())
wordkeys = data_flattened.map(lambda w: (w.lower(),1) )
wordcounts = wordkeys.reduceByKey(lambda x,y: x+y)

# Save the results in the specified output directory.
wordcounts.saveAsTextFile(outputlocation)
sc.stop() # Let Spark know that the job is done.
```

Submitting to the queue: `spark-submit`

ps_wordcount.py

```
from pyspark import SparkConf, SparkContext
import sys

# This script takes two arguments, an input file and out
if len(sys.argv) != 3:
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# Save the results in the specified output directory.
wordcounts.saveAsTextFile(outputlocation)
sc.stop() # Let Spark know that the job is done.
```

We’re not in an interactive session, so the SparkContext isn’t set up automatically. SparkContext is set up using a SparkConf object, which specifies configuration information. For our purposes, it’s enough to just give it a name, but in general there is a lot of information we can pass via this object.

Submitting to the queue: `spark-submit`

ps_wordcount.py

```
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import sys

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# Save the results in the specified output directory.
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sc.stop() # Let Spark know that the job is done.
```

Load the modules we need and read an input filename and output location from the command line.

Submitting to the queue: `spark-submit`

ps_wordcount.py

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import sys

# This script takes two arguments, an input file and output directory.
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wordcounts = wordkeys.reduceByKey(lambda x,y: x+y)

# Save the results in the specified output directory.
wordcounts.saveAsTextFile(outputlocation)
sc.stop() # Let Spark know that the job is done.
```

Load the modules we need and read an input filename and output location from the command line.

Do the actual work. Read in the data, create (word,1) keys, and sum up the counts for each key.

Submitting to the queue: `spark-submit`

```
[keith@cluster ~]$ spark-submit ps_wordcount.py hdfs:/stat606/demo.txt wc_demo
```

Run our `ps_wordcount.py` script on the file `demo.txt`, stored on HDFS, and store the output in a directory called `wc_demo` (which will also be created on HDFS).

This will submit our script to be run on the PySpark server (assuming we have one available on the cluster we ssh'd to…). We are also assuming that our data is on HDFS. This will only work if you are on a cluster that has HDFS configured.

Submitting to the queue: `spark-submit`

```
[keith@cluster ~]$ spark-submit ps_wordcount.py hdfs:/stat606/demo.txt wc_demo
[...lots of status information from Spark...]
[keith@cluster ~]$ hdfs dfs -ls wc_demo/
```

List the contents of our newly-created directory `wc_demo` on HDFS.
If all went well, this should contain the results of our computation.

Submitting to the queue: `spark-submit`

```
[keith@cluster ~]$ spark-submit ps_wordcount.py hdfs:/stat606/demo.txt wc_demo
[...lots of status information from Spark...]
[keith@cluster ~]$ hdfs dfs -ls wc_demo/
Found 3 items
-rw-r--r--   3 klevin hdfs        0 2019-03-12 11:58 wc_demo/_SUCCESS
-rw-r--r--   3 klevin hdfs        94 2019-03-12 11:58 wc_demo/part-00000
-rw-r--r--   3 klevin hdfs        108 2019-03-12 11:58 wc_demo/part-00001
[keith@cluster ~]$
```

Submitting to the queue: `spark-submit`

```
[keith@cluster ~]$ spark-submit ps_wordcount.py hdfs:/stat606/demo.txt wc_demo
[...lots of status information from Spark...]
[keith@cluster ~]$ hdfs dfs -ls wc_demo/
Found 3 items
-rw-r--r--   3 klevin hdfs          0 2019-03-12 11:58 wc_demo/_SUCCESS
-rw-r--r--   3 klevin hdfs         94 2019-03-12 11:58 wc_demo/part-00000
-rw-r--r--   3 klevin hdfs        108 2019-03-12 11:58 wc_demo/part-00001
[keith@cluster ~]$ hdfs dfs -cat wc_demo/*
```

PySpark splits our script's output into pieces, called `part-#####`. The file `_SUCCESS` is an empty file to signal that everything ran successfully. To get our actual answer, we need to combine these different "part" files.

Submitting to the queue: `spark-submit`

```
[keith@cluster ~]$ spark-submit ps_wordcount.py hdfs:/stat606/demo.txt wc_demo
[...lots of status information from Spark...]
[keith@cluster ~]$ hdfs dfs -ls wc_demo/
Found 3 items
-rw-r--r--   3 klevin hdfs          0 2019-03-12 11:58 wc_demo/_SUCCESS
-rw-r--r--   3 klevin hdfs          94 2019-03-12 11:58 wc_demo/part-00000
-rw-r--r--   3 klevin hdfs          108 2019-03-12 11:58 wc_demo/part-00001
[keith@cluster ~]$ hdfs dfs -cat wc_demo/*
('this', 2)
('is', 1)
('just', 1)
[...]
('hdfs.', 1)
[keith@cluster ~]$
```

Submitting to the queue: `spark-submit`

```
[keith@cluster ~]$ spark-submit ps_wordcount.py hdfs:/stat606/demo.txt wc_demo
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-rw-r--r--   3 klevin hdfs          94 2019-03-12 11:58 wc_demo/part-00000
-rw-r--r--   3 klevin hdfs          108 2019-03-12 11:58 wc_demo/part-00001
[keith@cluster ~]$ hdfs dfs -cat wc_demo/*
('this', 2)
('is', 1)
('just', 1)
[...]
('hdfs.', 1)
[keith@cluster ~]$
```

Just like our example run locally, only this time it ran on the Spark server, working with a file stored on HDFS.

Submitting to the queue: `spark-submit`

```
[keith@cluster ~]$ spark-submit ps_wordcount.py hdfs:/stat606/demo.txt wc_demo
[...lots of status information from Spark...]
[keith@cluster ~]$ hdfs dfs -ls wc_demo/
Found 3 items
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[keith@cluster ~]$ hdfs dfs -cat wc_demo/*
('this', 2)
('is', 1)
('just', 1)
[...]
('hdfs.', 1)
[keith@cluster ~]$
```

Of course, this is a fictional example-- the specifics of how you call PySpark will depend on how your cluster is configured. For example, you may need to pass flag arguments to `spark-submit` to specify a **queue** or which resource manager to use.

More: https://spark.apache.org/docs/latest/submitting-applications.html

PySpark on GCP

Step 1: spin up a compute cluster

```
gcloud dataproc clusters create CLUSTNAME --region=REGION
```

Details: https://cloud.google.com/dataproc/docs/guides/create-cluster

Step 2: submit your job to the cluster

```
gcloud dataproc jobs submit pyspark --cluster=CLUSTER --region=REG ps_script.py -- SCRIPT-ARGS
```

https://cloud.google.com/sdk/gcloud/reference/dataproc/jobs/submit/pyspark

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https://cloud.google.com/sdk/gcloud/reference/dataproc/jobs/submit/pyspark

This `--` is important! It tells `gcloud` that you are done giving arguments to the dataproc submission process, and the remaining arguments are to be passed to Python.