busy_airports_report

April 17, 2017

1 Data Engineer Intern Project - By Chris Canal

1.0.1 Directions:

Check out the data at http://stat-computing.org/dataexpo/2009/the-data.html. This is a large set of aviation data over a couple decades. Create an Apache Spark program that pulls in one year of data.

Create a monthly report for the top 25 busiest airports of that month. For each airport, include the following information in the report: number of flights per day at the airport, the three most common carriers at the airport for the month, average taxi time at the airport, number of weather delays per day, and the top five destinations from the airport.

Use the supplemental data to allow the report to be easier to read and understand (http://stat-computing.org/dataexpo/2009/supplemental-data.html). You can output the data as a CSV file that can be read within Excel. Be prepared to show and discuss your code.

1.0.2 First Steps:

I am going to begin by importing all the libraries I am going to need for this project and initializing my spark context.

```
from pyspark import SparkContext
sc = SparkContext('local[*]','example') # if using locally
from pyspark.sql import SQLContext
sqlContext = SQLContext(sc)
import pandas as pd
```

1.0.3 Importing Data

This block imports data from the interent if it has not been downloaded to the local directory.

```
In [2]: # Import data from the web or from local if available
        dataFiles = {'fileNames': ['flight_data_2008.csv', 'airports.csv', 'carriers.csv', 'plane
                     'fileURLs': ['http://stat-computing.org/dataexpo/2009/2008.csv.bz2',
                                  'http://stat-computing.org/dataexpo/2009/airports.csv',
                                  'http://stat-computing.org/dataexpo/2009/carriers.csv',
                                  'http://stat-computing.org/dataexpo/2009/plane-data.csv']}
       month_list = [(1, 'January'), (2, 'February'), (3, 'March'), (4, 'April'), (5, 'May'), (
        for i in range(len(dataFiles['fileNames'])):
            if not os.path.isfile(dataFiles['fileNames'][i]):
                print("Downloading "+dataFiles['fileNames'][i]+" from "+dataFiles['fileURLs'][i]
                start = time.time()
                response = urllib2.urlopen(dataFiles['fileURLs'][i])
                end = time.time()
                print(dataFiles['fileNames'][i]+" downloaded in "+str(end-start)+" seconds\n")
                print("saving "+dataFiles['fileNames'][i]+"...\n")
                start = time.time()
                data = response.read()
                if dataFiles['fileNames'][i][-3:] == 'csv':
                    dataString = data
                elif dataFiles['fileNames'][i][-3:] == 'bz2':
                    dataString = bz2.decompress(data)
                else:
                    print("Error in filetype")
                new_file = open(dataFiles['fileNames'][i], "w")
                new_file.write(dataString)
                new_file.close()
                end = time.time()
                print(dataFiles['fileNames'][i]+" unzipped and saved in "+str(end-start)+" secon
```

1.0.4 Additional Data

Additional data was used from the Aircraft Registration Database. This data can be found at http://registry.faa.gov/database/ReleasableAircraft.zip

The data from the ACFTREF.txt was used. In order to run the rest of this notebook, you bust download this zip, extract the files, change the name of ACFTREF.txt to ACFTREF.csv and move that file to the local directory.

```
In [3]: # Load all data into Spark DataFrames

flight_data = sc.textFile('flight_data_2008.csv')
    test_flight_data = sc.textFile('flight_data_test_100.csv')
    airports = sc.textFile('airports.csv')
    carriers = sc.textFile('carriers.csv')
    plane_data = sc.textFile('plane-data.csv')
    aircraft_data = sc.textFile('ACFTREF.csv')

In [4]: # view header of the data (column names)
    print(test_flight_data.take(1))
```

[u'Year, Month, DayofMonth, DayOfWeek, DepTime, CRSDepTime, ArrTime, CRSArrTime, UniqueCarrier, FlightNum

1.0.5 Parse Functions

As you can see in the previous cell, there is a lot of data in this main data file. We don't need all of it, so we will get rid of some of that data using the filter and map functions in pyspark.

These parse functions divide the csv data into a useable format while dropping the unwanted fields.

```
In [5]: def parseLineByMonth(line):
    fields = line.split(',')
    Month = int(fields[1])
    return Month
```

```
def parseLineByOrigin(line):
    fields = line.split(',')
    Month = int(fields[1])
    Day = int(fields[2])
    Origin = fields[16] .encode('utf8')
    Dest = fields[17].encode('utf8')
    Carrier = fields[8].encode('utf8')
    TaxIn = fields[19].encode('utf8')
    TaxOut = fields[20].encode('utf8')
    Weather = fields[25].encode('utf8')
#TODO Add in weather
    return (Origin, (Dest, Month, Carrier, TaxIn, TaxOut, Weather, Day))
```

1.0.6 Find busiest month

I thought it would be most adventageous to look at the busiest month in the year. The following block removes the header from the RDD and then removes all data except the month when the flight occured. The we use countByValue to count all occurences of each month. Since there are only 12 rows after in the returned python object, I will sort using pure python instead of spark.

The busiest month is July with 627931 flights

1.0.7 Find the busiest airports

Next, I am interested in finding the 25 busiest airports. Now that we are going to be reusing some of the data when we do other calculations on these 25 airports, it is important to use the cache() function in order to maximize our effeciency and minimize the ammount of work we redo. I also love using this trick where you flip the key and value in a key value pair in orde to use the sort by key function built into pyspark, so baller.

```
In [8]: rdd = data.map(parseLineByOrigin)
    rdd_busy_month = rdd.filter(lambda (x,y): y[1] == busiest_month[0] ).cache()
    rdd_top_25 = rdd_busy_month.flatMap(lambda x: [(x[0],1),(x[1][0],1)])
    rdd_top_25 = rdd_top_25.reduceByKey(lambda x, y: x + y)
    rdd_top_25 = rdd_top_25.map(lambda x: (x[1], x[0])).sortByKey()
    sorted_25_airports_and_flights = rdd_top_25.collect()[-25:]
```

1.0.8 Main Spark Program

This part of the script can look a little intimidating. After spending a little time with the code though, it is very simple and easy to understand. Most imporant part of this block is the use of the cache() function. This function allows for an immense speed gain because spark doesn't have to recalculate costly steps with lots of data.

At a high level, this block iterates over the 25 busy airports we found earlier and exctracts a bit of data from each of them. There are a couple odd filters, you might notice. I used ".filter(lambda (x,y): y)" as a simple way to check for empty data. For some reason, there were some missing fields in the data. This filter helped me ignore those before I try to put some sort of transformation on that data. Everything else is fairly straight forward.

I store all the data that I find in a dictionary, where the airport code is the key to the data that lies within.

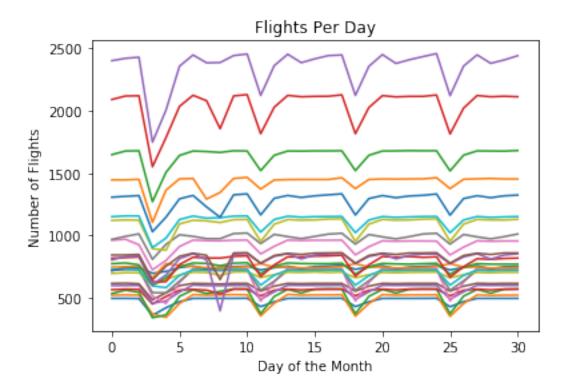
```
In [11]: gathered_data = {}
                        for airport in sorted_airports_25:
                                   this_airport_rdd = rdd_busy_month.filter(lambda (x,y): (x == airport) or (y[0] == airport)
                                   flights_per_day = this_airport_rdd.map(lambda (x,y): y[-1]).countByValue()
                                   top_3_carriers_rdd = this_airport_rdd.map(lambda (x,y): (y[2],1)).reduceByKey(lambda
                                   top_3_carriers = top_3_carriers_rdd.map(lambda x: (x[1], x[0])).sortByKey().collectors_rdd.map(lambda x: (x[1], x[1], x[1])).sortByKey().collectors_rdd.map(lambda x: (x[1], x[1], x[1], x[1])).sortByKey().collectors_rdd.map(lambda x: (x[1], x[1], x[1
                                   landing_flights_rdd = this_airport_rdd.filter(lambda (x,y): y)
                                  landing_flights_rdd = landing_flights_rdd.filter(lambda (x,y): y[3] != "NA" and y[0]
                                  landing_flights_rdd = landing_flights_rdd.map(lambda (x,y): (1,(int(y[3]),1)))
                                   landing_flights_rdd = landing_flights_rdd.reduceByKey(lambda x,y: (x[0]+y[0],x[1]+y
                                   average_taxi_in = landing_flights_rdd.mapValues(lambda y: float(y[0])/y[1]).collect
                                   departing_flights_rdd = this_airport_rdd.filter(lambda (x,y): y)
                                  departing_flights_rdd = departing_flights_rdd.filter(lambda (x,y): y[4] != "NA" and
                                  departing_flights_rdd = departing_flights_rdd.map(lambda (x,y): (1,(int(y[4]),1)))
                                   departing_flights_rdd = departing_flights_rdd.reduceByKey(lambda x,y: (x[0]+y[0],x[
                                   average_taxi_out = departing_flights_rdd.mapValues(lambda y: float(y[0])/y[1]).coll
```

top_5_dest_rdd = this_airport_rdd.map(lambda (x,y): (y[0],1)).reduceByKey(lambda x,

1.0.9 Now for the fun part

Spark has completed its magic, now we get to reap the reward. The following few code blocks are graphs that help us visualize the data.

In this first graph you can see that there are fewer flights on Fridays and that the 4th of this month had many fewer flights. This is probably because it is July in the US in this graph and the 4th is a holiday.



In []:

```
In [13]: # bar graph of the data
    ATL = gathered_data['ATL']['top_3_carriers']
    DFW = gathered_data['DFW']['top_3_carriers']
    ORD = gathered_data['ORD']['top_3_carriers']

    n_groups = 3
    std = (1,1,1)

ATL_carriers = (ATL[0][0],ATL[1][0],ATL[2][0])

DFW_carriers = (DFW[0][0],DFW[1][0],DFW[2][0])

ORD_carriers = (ORD[0][0],ORD[1][0],ORD[2][0])

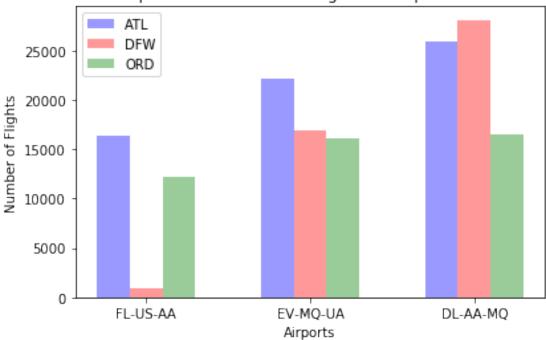
fig, ax = plt.subplots()

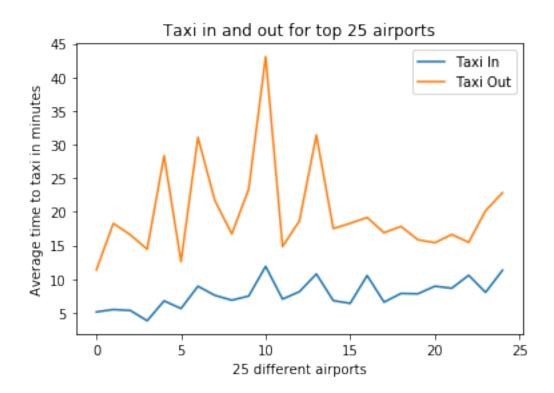
index = np.arange(n_groups)
bar_width = 0.20

opacity = 0.4
error_config = {'ecolor': '0.3'}
```

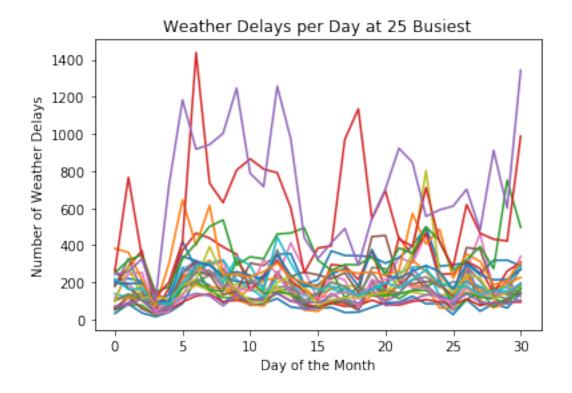
```
rects1 = plt.bar(index, ATL_carriers, bar_width,
                 alpha=opacity,
                 color='b',
                 yerr=std,
                 error_kw=error_config,
                 label='ATL')
rects2 = plt.bar(index + bar_width, DFW_carriers, bar_width,
                 alpha=opacity,
                 color='r',
                 yerr=std,
                 error_kw=error_config,
                 label='DFW')
rects3 = plt.bar(index + bar_width*2, ORD_carriers, bar_width,
                 alpha=opacity,
                 color='g',
                 yerr=std,
                 error_kw=error_config,
                 label='ORD')
plt.xlabel('Airports')
plt.ylabel('Number of Flights')
plt.title('Airports and Number of Flights for Top 3 Airlines')
plt.xticks(index + bar_width, ('FL-US-AA', 'EV-MQ-UA', 'DL-AA-MQ'))
plt.legend()
plt.tight_layout()
plt.show()
```







```
In [15]: #View which days of the month airlines had the most weather delays
    for airport in sorted_airports_25:
        weather_list = []
        for i in gathered_data[airport]['weather_delays_per_day']:
            weather_list.append(i[1])
        plt.plot(weather_list)
        plt.xlabel('Day of the Month')
        plt.ylabel('Number of Weather Delays')
        plt.title('Weather Delays per Day at 25 Busiest')
        plt.show()
```



```
MDW [(315, 'LAS'), (317, 'STL'), (321, 'MCI'), (396, 'DEN'), (7431, 'MDW')]
DCA [(636, 'ATL'), (636, 'ORD'), (756, 'BOS'), (1000, 'LGA'), (7561, 'DCA')]
CVG [(292, 'DFW'), (293, 'DTW'), (329, 'LGA'), (508, 'ORD'), (8105, 'CVG')]
SAN [(484, 'LAS'), (620, 'SFO'), (663, 'PHX'), (999, 'LAX'), (8613, 'SAN')]
PHL [(577, 'BOS'), (597, 'ORD'), (617, 'MCO'), (623, 'ATL'), (8896, 'PHL')]
BWI [(340, 'PVD'), (411, 'MCO'), (446, 'BOS'), (537, 'ATL'), (9303, 'BWI')]
LGA [(930, 'ATL'), (935, 'ORD'), (996, 'DCA'), (1080, 'BOS'), (10506, 'LGA')]
BOS [(652, 'ORD'), (729, 'JFK'), (760, 'DCA'), (1079, 'LGA'), (10591, 'BOS')]
SEA [(531, 'SFO'), (612, 'DEN'), (678, 'ANC'), (686, 'LAX'), (10728, 'SEA')]
CLT [(477, 'ORD'), (504, 'LGA'), (517, 'ATL'), (525, 'EWR'), (10821, 'CLT')]
JFK [(478, 'MCO'), (607, 'SFO'), (737, 'LAX'), (745, 'BOS'), (11499, 'JFK')]
MCO [(412, 'EWR'), (477, 'JFK'), (618, 'PHL'), (802, 'ATL'), (11578, 'MCO')]
MSP [(484, 'DEN'), (490, 'DTW'), (514, 'ATL'), (866, 'ORD'), (11684, 'MSP')]
EWR [(412, 'MCO'), (520, 'CLT'), (643, 'ORD'), (774, 'ATL'), (12244, 'EWR')]
SLC [(436, 'LAX'), (471, 'LAS'), (663, 'PHX'), (769, 'DEN'), (12476, 'SLC')]
SFO [(558, 'SAN'), (607, 'LAS'), (638, 'JFK'), (1290, 'LAX'), (12842, 'SFO')]
DTW [(408, 'LGA'), (424, 'MSP'), (499, 'ATL'), (640, 'ORD'), (14392, 'DTW')]
LAS [(607, 'SFO'), (672, 'DEN'), (935, 'PHX'), (1047, 'LAX'), (15226, 'LAS')]
IAH [(416, 'ATL'), (430, 'DEN'), (488, 'DFW'), (512, 'ORD'), (16877, 'IAH')]
PHX [(663, 'SLC'), (664, 'DEN'), (857, 'LAX'), (903, 'LAS'), (17390, 'PHX')]
```