

Big data Processing Assignment

PART A. TIME ANALYSIS (30%)

Create a bar plot showing the number of transactions occurring every month between the start and end of the dataset.

Note: As the dataset spans multiple years and you are aggregating together all transactions in the same month, make sure to include the year in your analysis.

Note: Once the raw results have been processed within Hadoop/Spark you may create your bar plot in any software of your choice (excel, python, R, etc.)

The raw result was being processed within Spark and was obtained as shown below:

def Transaction_data (trans):

try:

fields = trans.split(',')

if len(fields)!=7:

return False

float(fields[6])

return True

except:

return False

The above code snippet returns false if the length of the fields is not equal to 7, else it returns the block_timestamp value of the transaction dataset.

```
transaction=sc.textFile('/data/ethereum/transactions')
clean_trans=transaction.filter(is_good_trans)
timestamp=clean_trans.map(lambda t:int(t.split(',')[6]))
monthyears=timestamp.map(lambda my: (time.strftime("%B-%Y",time.gmtime(my)),1))
transactions=monthyears.reduceByKey(lambda a,b: a+b)
inmem=transactions.persist()
inmem.saveAsTextFile("/user/apk30/BDP_PartA")
```

In the above code snippet, the data is loaded to the variable and a filter is used. Time built in function is used to import the month and year and the output data is obtained is as shown below:

```
('October-2015', 205045)
('October-2016', 1329847)
('October-2017', 12570063)
('October-2018', 17056926)
('March-2017', 2426471)
('March-2016', 917170)
('March-2019', 18029582)
('March-2018', 20261862)
```

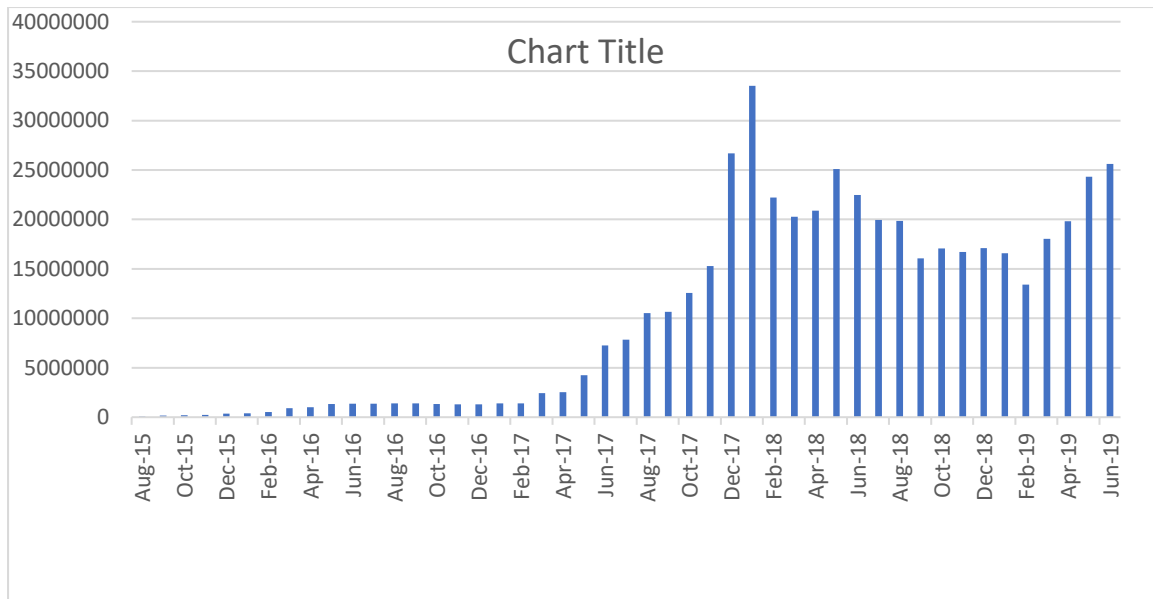
('February-2019', 13413899)
('February-2018', 22231978)
('February-2017', 1410048)
('February-2016', 520040)
('August-2016', 1405743)
('August-2017', 10523178)
('August-2015', 85609)
('August-2018', 19842059)
('July-2017', 7835875)
('July-2016', 1356907)
('July-2018', 19937033)
('May-2019', 24332475)
('May-2018', 25105717)
('April-2016', 1023096)
('May-2017', 4245516)
('April-2017', 2539966)
('May-2016', 1346796)
('April-2018', 20876642)
('April-2019', 19830158)
('January-2016', 404816)
('January-2017', 1409664)
('January-2018', 33504270)
('January-2019', 16569597)
('June-2017', 7244657)
('June-2016', 1351536)
('June-2019', 25613628)
('June-2018', 22471788)
('December-2016', 1316131)
('December-2017', 26687692)
('December-2015', 347092)
('December-2018', 17107601)
('November-2017', 15292269)
('November-2016', 1301586)
('November-2015', 234733)
('November-2018', 16713911)
('September-2015', 173805)
('September-2017', 10672734)
('September-2016', 1387412)
('September-2018', 16056742)

Job ID :

http://andromeda.student.eecs.qmul.ac.uk:8088/cluster/app/application_1575381276332_3832

Elapsed: 2mins, 55sec

The graph was plotted in excel as shown below, after the processing of raw results in spark.



PART B. TOP TEN MOST POPULAR SERVICES (40%)

Evaluate the top 10 smart contracts by total Ether received. An outline of the subtasks required to extract this information is provided below, focusing on a MRJob based approach. This is, however, only one possibility, with several other viable ways of completing this assignment.

JOB 1 - INITIAL AGGREGATION

To workout which services are the most popular, you will first have to aggregate transactions to see how much each address within the user space has been involved in. You will want to aggregate value for addresses in the `to_address` field. This will be similar to the wordcount that we saw in Lab 1 and Lab 2.

JOB 2 - JOINING TRANSACTIONS/CONTRACTS AND FILTERING

Once you have obtained this aggregate of the transactions, the next step is to perform a repartition join between this aggregate and contracts (example [here](#)). You will want to join the `to_address` field from the output of Job 1 with the `address` field of contracts

Secondly, in the reducer, if the address for a given aggregate from Job 1 was not present within contracts this should be filtered out as it is a user address and not a smart contract.

JOB 3 - TOP TEN

Finally, the third job will take as input the now filtered address aggregates and sort these via a top ten reducer, utilising what you have learned from lab 4.

Job 1 : initial Aggregation .

```
def mapper(self, _, trans):
```

```
try:
    fields = trans.split(',')
    if len(fields) == 7 :
        ad=fields[2]
        val=int(fields[3])
        yield(ad,val)
except:
    pass
```

```
def combiner(self, ad, val):
```

```
    yield(ad,sum(val))
```

```
def reducer(self, ad, val):
```

```
    yield(ad,sum(val))
```

The above code snippet is used aggregate the to_address and the value of the transaction data set. The output of this is taken to the second job for joining transaction/contracts and filtering.

Job ID :

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Elapsed:33mins, 16sec

Job 2 :

Following is the code snippet for mapper and reducer that is used to join the key and value as shown below.

```
Spyder (Python 3.7)
File Edit Search Source Run Debug Consoles Projects Tools View Help
Editor - C:\Users\Akshatha\Pictures\job2.py
partA.py partB.py job2.py Job3.py Partb_spark.py job1.py BD_partB.py scam.py PartAB.py
1 # -*- coding: utf-8 -*-
2 """
3 Created on Mon Dec  2 15:31:03 2019
4
5 @author: Akshatha
6 """
7 #Part B
8
9 from mrjob.job import MRJob
10
11 class job2(MRJob):
12
13     def mapper(self, _,line):
14         try:
15             if len(line.split(',')) ==5 :
16                 fields = line.split(',')
17                 join_key_value_1 = fields[0]
18                 join_value_1 = fields[3]
19                 yield(join_key_value_1,(join_value_1,1))
20             if len(line.split('\t')) ==2:
21                 fields = line.split('\t')
22                 join_key2 = fields[0]
23                 join_key2= join_key2[1:-1]
24                 join_value = int(fields[1])
25                 yield (join_key2, (join_value,2))
26         except:
27             pass
28     def reducer(self,ad,val):
29         block = None
30         amt = None
31         for value in val:
32             if value[1] ==1:
33                 block = value[0]
34             if value[1] ==2 :
35                 amt = value[0]
36         if block is not None and amt is not None:
37             yield((ad,block),amt)
38
39 if __name__ == '__main__':
40     job2.run()
41
42
```

The output of this code is obtained as a .txt file , as shown below :

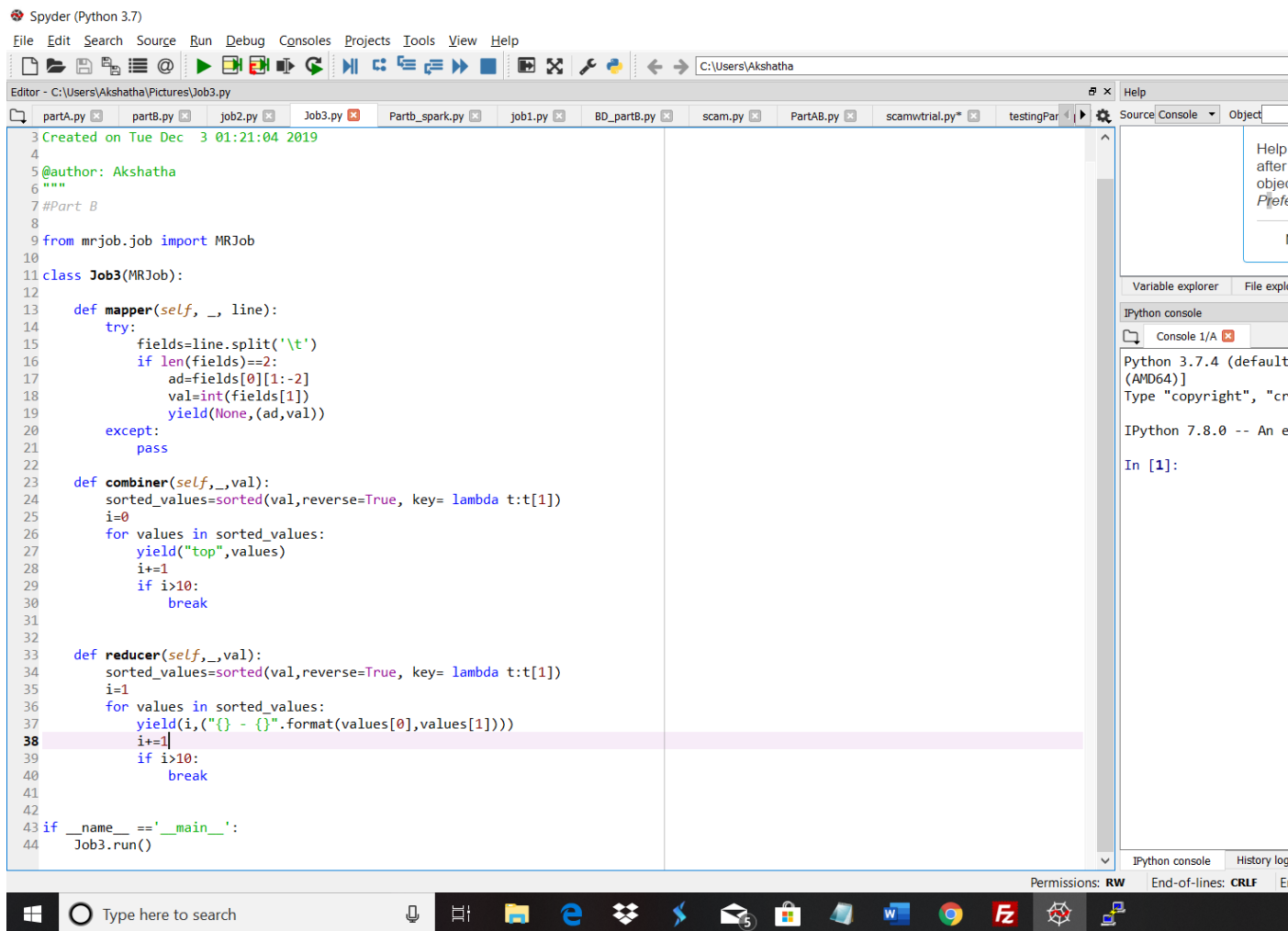
FileZilla interface showing a connection to sftp://apk30@bert.eecs.qmul.ac.uk. The interface displays the local site (C:\Users\Akshatha\Desktop) and the remote site (sftp://apk30@bert.eecs.qmul.ac.uk). The remote site contains a directory listing of /homes/apk30, showing files like Lab0Tutorial..., Logistic regr..., Microsoft E..., MI_Assignm..., My Orders..., plot_cost.py, plot_hypoth..., Presentation..., Project Plan..., scam.py, scammer.py, scamwtrial.py, testing1.txt, timings.txt, ~\$.etherum..., ~WRL0005.t..., and ~WRL1739.t... The interface also shows a list of files and directories with their sizes and types.

Job ID : http://andromeda.student.eecs.qmul.ac.uk:8088/cluster/app/application_1575381276332_3445

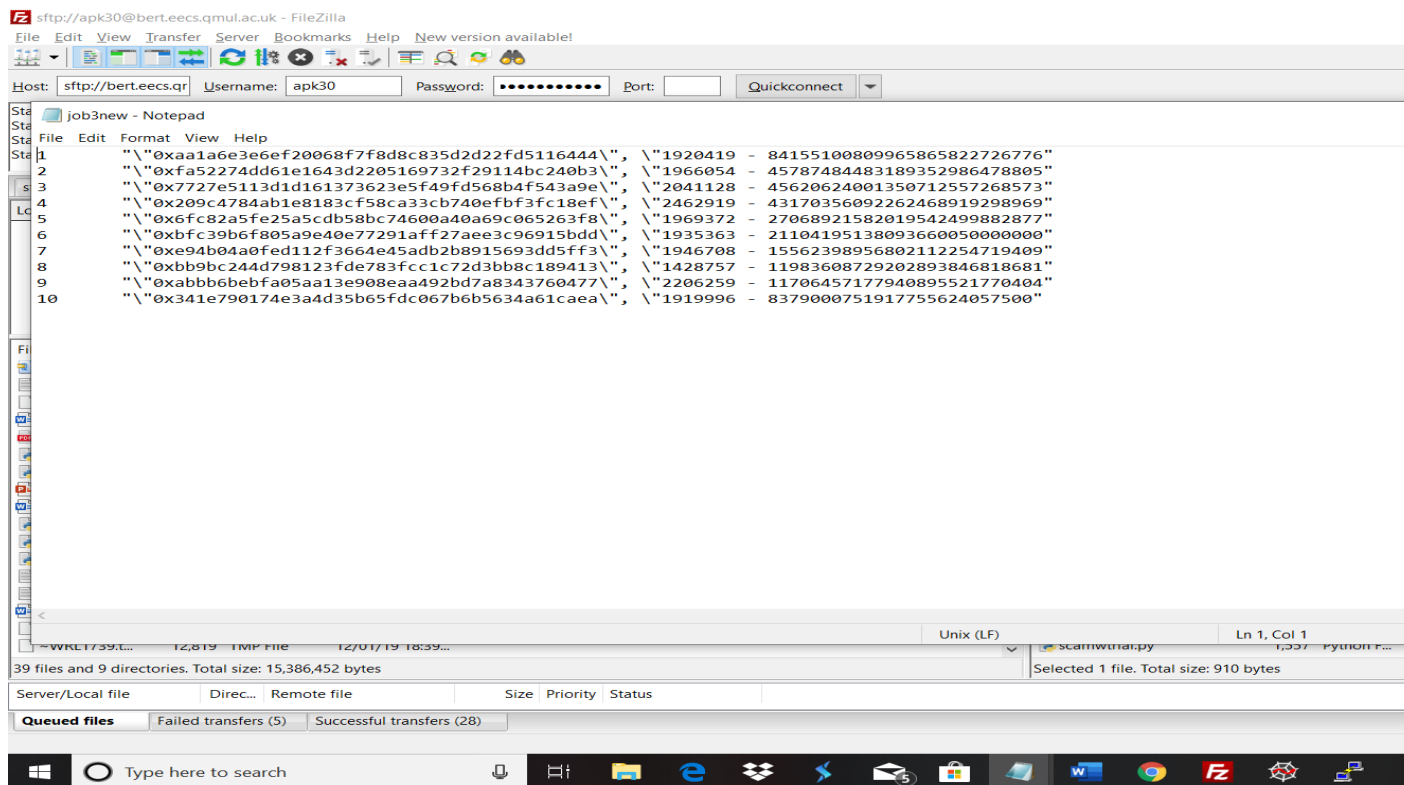
Elapsed: 7mins, 42sec

Job 3 :

The Mapper reads all the fields by splitting the line and yielding /emitting it to combiner. Split function is used eliminate '\ ' and ',' .Combiner is used for sorting the values from each mapper, also yields the top 10 values . Reducer sorts the values relieved from the cobiner and yields the top 10 global values.



The output of this code is obtained as shown below:



Job ID :

http://andromeda.student.eecs.qmul.ac.uk:8088/cluster/app/application_1575381276332_3529

Elapsed:35sec

PART C. DATA EXPLORATION (30%)

SCAM ANALYSIS

1. **Popular Scams:** Utilising the provided scam dataset, what is the most lucrative form of scam? How does this change throughout time, and does this correlate with certain known scams going offline/inactive? (20/30)

MISCELLANEOUS ANALYSIS

Comparative Evaluation

Reimplement Part B in Spark (if your original was MRJob, or vice versa). How does it run in comparison? Keep in mind that to get representative results you will have to run the job multiple times, and report median/average results. Can you explain the reason for these results? What framework seems more appropriate for this task? (10/30)

Spyder (Python 3.7)

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C:\Users\Akshatha

Editor - C:\Users\Akshatha\Pictures\PartC_spark.py

```
PartC_spark.py x job1.py x BD_partB.py x scam.py x scamwtrial.py x scammer.py x
5 @author: Akshatha
6 """
7
8 import pyspark
9
10 sc = pyspark.SparkContext()
11
12 def transactions_data(trans):
13     try:
14         fields = trans.split(',')
15         if len(fields)!=7:
16             return False
17         int(fields[3])
18         return True
19     except:
20         return False
21
22
23 def contracts_data(contract):
24     try:
25         fields = contract.split(',')
26         if len(fields)!=5:
27             return False
28         return True
29     except:
30         return False
31
32 transaction = sc.textFile("/data/ethereum/transactions")
33 trans_filter = transaction.filter(transactions_data)
34 address=trans_filter.map(lambda l: (l.split(',')[2], int(l.split(',')[3]))).persist()
35 partbjob1 = address.reduceByKey(lambda a,b:(a+b))
36 partbjob1_join=partbjob1.map(lambda f:(f[0], f[1]))
37
38 contracts = sc.textFile("/data/ethereum/contracts")
39 contrts_filter = contracts.filter(contracts_data)
40 contracts_join = contrts_filter.map(lambda f: (f.split(',')[0],f.split(',')[3]))
41
42 partbjob2 = partbjob1_join.join(contracts_join)
43
44 t10=partbjob2.takeOrdered(10, key = lambda x:-x[1][0])
45 for record in t10:
46     print("{}: {}".format(record[0],record[1][0]))
```



Type here to search



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Job ID : http://andromeda.student.eecs.qmul.ac.uk:8088/cluster/app/application_1575381276332_4230

Spark executes jobs faster than when compared to MR job, as per the elapsed time as well spark is quicker. Spark uses in memory processing which is better than map reduce codes which gets stored in a disk, this is a disadvantage for map reduce since the next job depends on the previous job output, which will consume a lot a time.