PART A: TIME ANALYSIS

A.1: Number of transactions per month

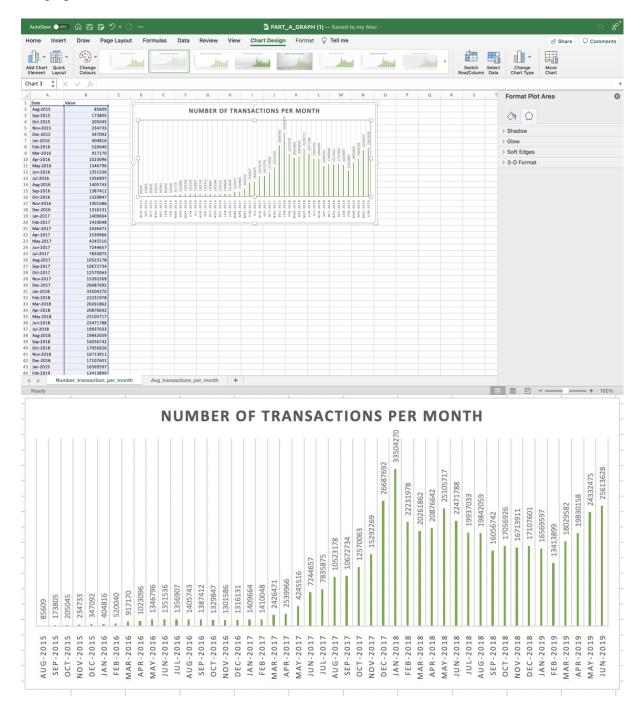
To get the monthly transaction total, we used the mapper's 'datetime.utcfromtimestamp' functionality to extract the date in the desired format, which includes month and year.

In the reducer section, the counts for the various keys are then added together.

Execution command: python no_trans.py -r hadoop --output-dir trans_per_month --no-catoutput hdfs://andromeda.eecs.qmul.ac.uk/data/ethereum/transactions/part-*.csv

```
jmp01@itl211 ~/ecs765/ass1/partA> cat no_trans.py
 from mrjob.job import MRJob
from datetime import datetime
import time
class no_trans(MRJob):
                    def mapper(self, _, line):
                                                         fields = line.split(',')
if len(fields) == 7:
    day = (datetime.utcfromtimestamp(int(fields[6])).strftime('%Y-%m'))
    value = int(fields[3])
    yield (day,1)
                                     except:
                    pass
def reducer(self,u,t):
 if __name_
                    no_trans.run()
 # python no_trans.py -r hadoop --output-dir trans_per_month --no-cat-output hdfs://andromeda.eecs.qmul.ac.uk/data/ethereum/transactions/part-*.csv
# job: http://andromeda.student.eecs.qmul.
Job job_164868358582_6967 completed successfully
Output directory: hdfs:///user/jmp0f/tras_per_month
Gounters
File Input Format Counters
Bytes Red-65389952836
File Output Format Counters
Bytes Wed-65389952836
File System Counters
File: Number of bytes read=321522456
File: Number of bytes written=888852378
File: Number of bytes written=888852378
File: Number of large read operations=8
File: Number of large read operations=8
File: Number of bytes read=30975788
HDFS: Number of bytes read=30975788
HDFS: Number of bytes read=arsure-coded=
HDFS: Number of bytes read erasure-coded=
HDFS: Number of bytes read=32777
HDFS: Number of bytes read=32777
HDFS: Number of read operations=4
Job Counters
 # job: http://andromeda.student.eecs.qmul.ac.uk:8088/proxy/application_1648683650522_6967/
```

Bargraph:



A.2: Average value of transactions per month

In the mapper, we acquired the relevant 'value' field from the transaction's schema along with the date and cumulated these in the reducer phase, like the prior code.

Execution command: python trans_value.py -r hadoop --output-dir each_month_transaction --no-cat-output hdfs://andromeda.eecs.qmul.ac.uk/data/ethereum/transactions/part-*.csv

ECS765P_JairajPatil_210819108 Ethereum Analysis

```
impel@itl211 -/ecs766/ass1/partA> cat trans_value.py
from mrjob.job import MRJob
from mrjob.job import MRStep
import fileinput
import fileinput
import rileinput
import sys
from time import gmtime , strftime , struct_time
from datetime import datetime

class trans_value(MRJob):

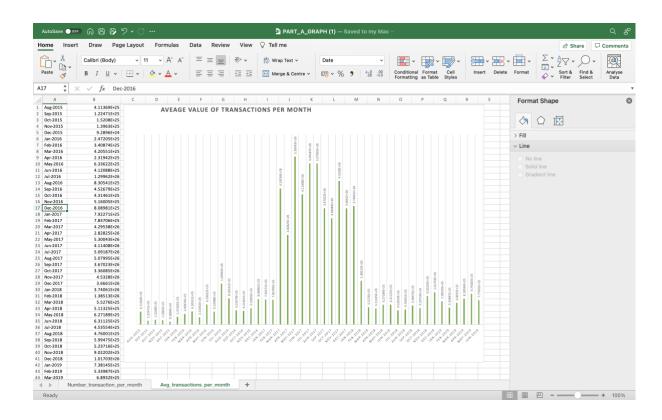
def mapper(self, _,line):
    try:
        fields = line.split(',')
        if len(fields)==7:
            timestamp_val=(datetime.utcfromtimestamp(int(fields[6])).strftime(" %b,%Y "))
        value=int(fields[3])
        yield(timestamp_val,value)
    except:
    pass

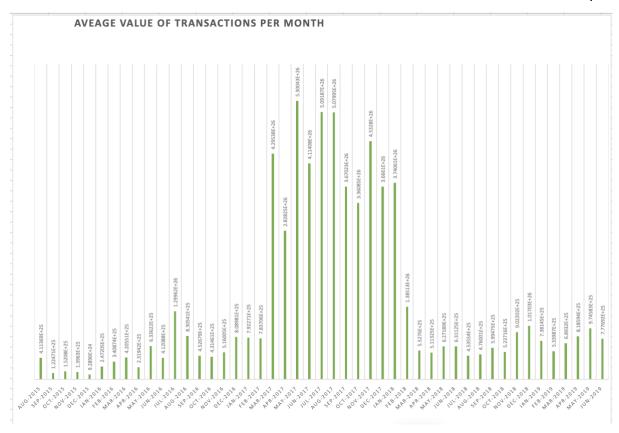
def combiner(self,timestamp_val,value):
    yield(timestamp_val, sum(value))

def reducer(self,timestamp_val,value):
    yield(timestamp_val, sum(value))

if __name__ == "__main__":
    trans_value.run()
```

- # python trans_value.py -r hadoop --output-dir each_month_transaction --no-cat-output hdfs://andromeda.eecs.qmul.ac.uk/data/ethereum/transactions/part-*.csv
- # job: http://andromeda.student.eecs.gmul.ac.uk:8088/proxy/application 1648683650522 7013/





PART B: TOP TEN MOST POPULAR SERVICES

1. Aggregation

The input transaction file is read and split at ',' in the first step of aggregation. We also get the key: to address and the value: value. The entire value for each unique key (to address) is then added.

Execution Command: python agg_trans.py -r hadoop --output-dir agg_trans --no-catoutput hdfs://andromeda.eecs.qmul.ac.uk/data/ethereum/transactions/part-*.csv

```
jmp0l@itl211 ~/ecs765/ass1/partB> cat agg_trans.py
ffrom mrjob.job import MRJob
from mrjob.step import MRStep
import fileinput
import sys
from time import gmtime , strftime , struct_time
from datetime import datetime

class trans_per_m(MRJob):

def mapper(self, _,line):
    try:
        fields = line.split(',')
        if len(fields)==7:
            to_address=fields[2]
            value=int(fields(31))
            yield(to_address,value)

except:
    pass

def reducer(self,to_address,value):
    yield(to_address, sum(value))

if __name__ == "__main__":
    trans_per_m.run()

# python agg_trans.py -r hadoop -_output-dir agg_trans --no-cat-output hdfs://andromeda.eecs.qmul.ac.uk/data/ethereum/transactions/part-*.csv
```

2. Repartition join between aggregate and contracts

'/user/jmp01/aggregate transactions/' and 'data/ethereum/contracts/' are the two input source directories. We look to split the input in the mapper phase based on whether the delimiter is 't' (in aggregate transactions with 2 fields) OR ',' (in contracts with 5 fields). We also get key(address) and values (block number).

Only when a key(address) receives values from both 'aggregate transactions' and 'contracts' will the reducer yield in the subsequent reducer phase (address, value). As a result, only smart contracts are allowed to pass.

The result includes a list of smart contracts as well as their total values.

Execution command: python join_task2.py -r hadoop --output-dir part_b_joined_records --no-cat-output hdfs://andromeda.eecs.qmul.ac.uk/data/ethereum/contracts/hdfs://andromeda.eecs.qmul.ac.uk/user/jmp01/aggregate_transactions/

```
| Special Color | Special Colo
```

3. Finding top 10

If the input file is divided along 't' and has two fields, the mapper reads it line by line from the preceding job (/user/jmp01/part b joined records/). We get value(None) and key(None) (address, total transaction value).

All pairs are sorted in descending order in the reducer phase using the sort function. Finally, we run through the sorted data 10 times before stopping.

Execution Command: python part_B_top10.py -r hadoop --output-dir part_B_top10 --no-cat-output hdfs://andromeda.eecs.qmul.ac.uk/user/jmp01/part_b_joined_records

0xaa1a6e3e6ef20068f7f8d8c835d2d22fd5116444 8.415510080996593e+25
0x3f5ce5fbfe3e9af3971dd833d26ba9b5c936f0be 5.834331302252918e+25
0x32be343b94f860124dc4fee278fdcbd38c102d88 5.432072061064933e+25
0xfa52274dd61e1643d2205169732f29114bc240b3 4.578748448318936e+25
0x7727e5113d1d161373623e5f49fd568b4f543a9e 4.56206240013507e+25
0x209c4784ab1e8183cf58ca33cb740efbf3fc18ef 4.317035609226244e+25
0x876eabf441b2ee5b5b0554fd502a8e0600950cfa 4.015767887861935e+25
0x6fc82a5fe25a5cdb58bc74600a40a69c065263f8 2.706892158201953e+25
0x2910543af39aba0cd09dbb2d50200b3e800a63d2 2.6386022236908247e+25
0xcafb10ee663f465f9d10588ac44ed20ed608c11e 2.3078610109547e+25

PARTC: TOP TEN MOST ACTIVE MINERS

The mapper phase reads the file line by line and divides at ',' resulting in key (miner) and value (mapper) fields (size). The size of each miner is aggregated and yielded in the Combiner/Reducer phase.

Command: python partc.py -r hadoop --output-dir part_c_a --no-cat-output hdfs://andromeda.eecs.qmul.ac.uk/data/ethereum/transactions/part-*.csv

hadoop fs -copyToLocal part_c_a inputfor10.txt

Top 10

If the input files are split along '\t' and have two fields, the mapper phase reads them line by line. We get value(None) and key(None) (miner, size). All pairs are sorted in descending order in the reducer phase using the sort function. We then repeat through the sorted values 10 times, yielding them, before stopping.

Command: python part_c_top_10.py inputfor10.txt > part_c_top10.txt

```
jmp01@itl211 ~/ecs765/ass1/partC> cat part_c_top10.py
from mrjob.job import MRJob
class top10_miner(MRJob):
  def mapper(self, _,line):
      fields = line.split(' \t')
     if lends = Interspire( (t)
if len(fields) == 2:
  address = fields[0]
  aggregate = float(fields[1])
  yield (None, (address, aggregate))
    except:
     pass
  def combiner(self, _, values):
  sorted_values = sorted(values, reverse = True, key = lambda x:x[1])
  for idx,value in enumerate(sorted_values):
    yield ("top", value)
    if idx >= 10:
       break
  def reducer(self, _, values):
    sorted_values = sorted(values, reverse = True, key = lambda x:x[1])
for idx,value in enumerate(sorted_values):
    yield ("{} - {}".format(value[0],value[1]),None)
      if idx >= 10:
       break
if __name__ == '__main__':
  top10_miner.run()
# python part_c_top_10.py inputfor10.txt > part_c_top10.txt
```

PART D. DATA EXPLORATION

Scam Analysis

The transaction dataset and the scams.json file were utilised as input files. Because we're dealing with 'json,' we've also imported the json library. Only if the input data set has fields with a length of 7 do we proceed (transactions data set). We'll use address as the key and value as the value from the transaction dataset. Similarly, we take address from the scams data set obtained from the for loop, assign value to it, and set 1 to differentiate it from transactions. The initial reduction phase determines whether the values come from transactions or json files. The reducer then sends the key value pair to the mapper, which includes categories and total values. After that, the second reduction step generates cumulative counts for each category.

 $Command: python \ scam1.py \ -r \ hadoop \ --output-dir \ scam_part_1 \ --no-cat-output \ hdfs://andromeda.eecs.qmul.ac.uk/data/ethereum/transactions/$

```
hdfs://andromeda.eecs.gmul.ac.uk/data/ethereum/scams.json/
jmp01@itl211 ~/ecs765/ass1/partD> cat scam1.py
  rom mrjob.job import MRJob
 from mrjob.step import MRStep
import json
class scams(MRJob):
         def mapper1(self, _, lines):
                  try:
                           fields = lines.split(",")
                           if len(fields) == 7:
address1 = fields[2]
                                    value = float(fields[3])
                                    yield address1, (value,0)
                                    line = json.loads(lines)
keys = line["result"]
                                    for i in keys:
                                             record = line["result"][i]
                                             category = record["category"]
addresses = record["addresses"]
                                             for i in addresses:
                                                      yield j, (category,1)
                           pass
          def reducer1(self, key, values):
                  tvalue=0
                  category=None
                  for k in values:
                           if k[1] == 0:
                                    tvalue = tvalue + k[0]
                                    category = k[0]
                  if category is not None:
                           yield category, tvalue
         def mapper2(self, key, value):
         yield(key,value)

def reducer2(self, key, value):
    yield(key,sum(value))
         def steps(self):
                  return [MRStep(mapper = self.mapper1, reducer=self.reducer1), MRStep(mapper = self.mapper2,
if __name__ == '__m
scams.run()
```

```
Output1:

jmp01@itl210 ~/ecs765/ass1/partD> cat scamout1.txt

"Scamming" 3.833616286244431e+22

"Fake ICO" 1.35645756688963e+21

"Phishing" 2.699937579408742e+22

"Scam" 0
```

Part 2

Similarly to the previous section, we import the json library and use the input files 'transactions.json' and'scams.json'. To ensure that we are utilising the correct dataset, we check the length of the fields. The first mapper works in the same way as the previous code.

In the first reducer, we utilise address as a key, which is retrieved using a for loop, and category and status of the scam as the value, which is used to distinguish between them. Furthermore, it checks for the values and adds them if they are 1, else, the reducer will add them to categories and status as they are from the json file containing scam categories and values. The second mapper takes the values from the previous reduction and passes them on to the next reducer, which sums them up to tally the overall number of scams in a category.

Command: python scam2.py -r hadoop --output-dir scam_part_2 --no-cat-output hdfs://andromeda.eecs.qmul.ac.uk/data/ethereum/transactions/

```
hdfs://andromeda.eecs.qmul.ac.uk/data/ethereum/scams.json/
[jmp01@itl210 ~/ecs765/ass1/partD> cat scam2.py
 from mriob.iob import MRJob
 from mrjob.step import MRStep
import json
class scams2(MRJob):
  def mapper1(self, _, lines):
    fields = lines.split(",")
    if len(fields)
     address1 = fields[2]
     yield address1, (1,0)
     line = ison.loads(lines)
     keys = line["result"]
     for i in keys:
  record = line["result"][i]
  category = record["category"]
  addresses = record["addresses"]
      status = record["status"]
      for j in addresses:
       yield j, (2, category, status)
   except:
    pass
  def reducer1(self, key, values):
   tvalue=0
   category=None
   status = None
for k in values:
if k[0] == 1:
     tvalue = tvalue + k[0]
     category = k[1]
status = k[2]
  if category is not None and status is not None: yield (status,category), tvalue
  def mapper2(self, key, value):
   vield(kev.value)
  def reducer2(self, key, value):
  yield(key,sum(value))
   return [MRStep(mapper = self.mapper1, reducer=self.reducer1), MRStep(mapper = self.mapper2, reducer = self.reducer2)]
if __name__ == '__main__':
         scams2.run()
```

The output below shows the total number of frauds in various categories.

Output2:

```
Output(2:

[jmp01@it1210 ~/ecs765/ass1/partD> cat scamout2.txt
["Active", "Scamming"] 88444

["Inactive", "Phishing"] 22
["Offline", "Fake ICO"] 121
["Offline", "Phishing"] 7022
["Offline", "Scam"] 0
["Suspended", "Phishing"] 11
["Active", "Phishing"] 1584
["Offline", "Scamming"] 24692
["Suspended", "Scamming"] 56
jmp01@it1210 ~/ecs765/ass1/partD>
```

Contract types (identify contract types):

Extraction of features Top 5 transaction datasets with the most transactions We can give award points to addresses that have the highest amount of transactions, and we can refer to them as loyal users.

2 jobs at the same time:

- 1. Here, the "address" field is yielded, and the reducer aggregates it to the number of transactions. The output is saved in the "Part_D_contracts_part_1" file.
- 2. In the second task, we used the sorted method in Python to apply the sorting algorithm to find the top 5 transactions.

Command: python Part_D_contracts_part_1.py -r hadoop --output-dir Part_D_contracts_part_1 --no-cat-output hdfs://andromeda.eecs.gmul.ac.uk/data/ethereum/transactions/

```
[jmp01@itl210 ~/ecs765/ass1/partD> cat Part_D_contracts_part_1.py
from mrjob.job import MRJob
class number_of_transactions(MRJob):
         def mapper(self, _, line):
                            fields = line.split(",")
                            if len(fields) == 7:
key = fields[2]
yield (key, 1)
                  except:
         def combiner(self, k, 1):
                  yield k, sum(1)
         def reducer(self, u, t)
                 yield (u, sum(t))
         me__ == '__main__':
   number_of_transactions.run()
jmp01@itl210 ~/ecs765/ass1/partD> ||
```

```
from mrjob.job import MRJob
fields = line.split()
                      key = fields[0]
                      value = int(fields[1])
                      yield (None, (key, value))
               except:
       def reducer(self,
                        _, val):
              sorted_values = sorted(val, reverse = True, key = lambda tup: tup[1])
               i = 0
               for i in sprted_values:
                      yield i
                      j += 1
                      if j >= 5:
                             break
if _ _name_
           == '
                  _main_
       number_of_transacions.run()
jmp01@itl210 ~/ecs765/ass1/partD>
```

Output:

```
"\"0x8d12a197cb00d4747a1fe03395095ce2a5cc6819\"" 11089018
"\"0x2a0c0dbecc7e4d658f48e01e3fa353f44050c208\"" 7160876
"\"0x3f5ce5fbfe3e9af3971dd833d26ba9b5c936f0be\"" 5952175
"\"0x174bfa6600bf90c885c7c01c7031389ed1461ab9\"" 5797049
"\"0x06012c8cf97bead5deae237070f9587f8e7a266d\"" 3995252
```

Is_erc721_contract:

Erc721 is an ethereum token that may be used to identify contracts that adhere to the erc721 contract rules. Smart contracts are another name for them. By simply adding a "if" condition that checks for the truth value in the relevant column of the dataset, we can filter the contract by determining if it is an er721 contract.

Command: python Part_D_Is_erc721_contract.py -r hadoop --output-dir Part_D_Is_erc721_contract --no-cat-output hdfs://andromeda.eecs.qmul.ac.uk/data/ethereum/contracts/

```
[jmp01@itl210 ~/ecs765/ass1/partD> cat Part_D_contracts_part_2.py
from mrjob.job import MRJob
class number_of_transactions(MRJob):
         def mapper(self)
                  try:
                           fields = line.split()
                           key = fields[0]
                           value = int(fields[1])
                           yield (None, (key, value))
                  except:
                           pass
         def reducer(self,
                              _, val):
                  sorted_values = sorted(val, reverse = True, key = lambda tup: tup[1])
                  j = 0
                  for i in sprted_values:
                           yield i
j += 1
if j >= 5:
                                    break
              _ == '_ _main_
if _ _name_
         number_of_transacions.run()
[jmp01@itl210 ~/ecs765/ass1/partD> nano Part_D_Is_erc721_contract.py
[jmp01@itl210 ~/ecs765/ass1/partD> cat Part_D_Is_erc721_contract.py
from mrjob.job import MRJob
class erc721_contract(MRJob):
         def mapper(self, _, line):
                  try:
                           fields = line.split(',')
                           if len(fields) == 5:
                                   if fields[2] == "true":
                                             yield fields [0], 1
                  except:
                           pass
         def reducer(self, u, t):
                  yield (u, sum(t))
                  main ':
if name
         erc721_contract.run()
jmp01@itl210 ~/ecs765/ass1/partD>
```

```
"0x000edf42475e7ceb32f82ee11f9733231a67b2be"
                                                 1
"0x00136a57574c805312d4ee875b0bc2e56984f00d"
                                                 1
"0x003203f31def0aa63b895b8599c9b81ddce8939b"
"0x003ad9c18bc279f40632e7e5de2fd213931215d0"
                                                 1
"0x0063f8d3537ec9cd23b08357494d3e0ee63a8f4a"
                                                 1
"0x00650ea64d5c226755a6a6976a774a6f2fdf8c13"
                                                 1
"0x006bf2f5cc930eed50e14c66605ac95767133bec"
                                                 1
"0x00b218fd2db515392f2a2d78b658c913f2eebf2d"
                                                 1
"0x00bf70e1ddfb8984d0af9af4b29ad3ec40d4b84e"
                                                 1
"0x00d2be2c7e509515cdba64051a643a5220f1f241"
"0x0111ac7e9425c891f935c4ce54cf16db7c14b7db"
"0x01144cad63687f9d06c46854c810366b28a84d73"
"0x0131c575be43586c5346435273035c8709a3fd34"
                                                 1
"0x01d8a618ba50232e73b7e0c3254bfa0802a75b56"
                                                 1
"0x01f96d3376acae2fc4f9077f03fa9d997797ed5c"
                                                 1
"0x0211621fb78c85ee44b12d2f04e2e2f16334a9fe"
                                                 1
"0x0213c2c85315299c6074fc4a6d779121284e9f42"
                                                 1
```

Outflow addresses:

Simply apply wordcount to the transaction dataset to obtain a unique outflow address. This allows us to retrieve all of the transaction dataset's unique addresses.

Command: python Part_D_outflow.py -r hadoop --output-dir Part_D_outflow --no-cat-output hdfs://andromeda.eecs.qmul.ac.uk/data/ethereum/transactions/

```
"0x014d3c3de0696c4e1662cd5e913d833e9181af89" 1
"0x014d3c62d7d8d41936773b186be11af.2d2e6ac16" 1
"0x014d3cd32875eb5fab7cdc383398fe8b8.28181d8" 3
"0x014d3cd43567dac810aba9e0eec6ff084bb0159d" 1
"0x014d3d3cd0d2f6334a7d70b26a72038118875df9"
"0x014d3d762587bc8f33fd2eff618cc8505d45a290" 5
"0x014d3dc71911e397602c3991b830bdal7c5a8a71" 1
"0x014d3de457357bcf065d5897e905cac292bc452c"
"0x014d3e9e5216d77067af40fce741e0aaf2bedc90" 1
"0x014d3eb929c0f449345c87dcde4a4e13f91c7246" 1
"0x014d3ed7a70692491a832aac8.2d.241ed967c8401" 1
"0x014d3f101261d1b7221492946123017d786a5f6d" 1
"0x014d3f2be1c647a725742cdb917f235bcd0e2074" 64
"0x014d405b8dcd1723eec901b078d481928805d103" 15
"0x014d40d44c31f7f4f1795bf4eb00ca385cdfa92d"
"0x014d40f86e343c298b03446a8d86f7022af1465e"
"0x014d42589bfbde32b84190d7fdbce618c4a4d9c2" 1
"0x014d42bfcbe9c00fb956af2b837caf231ffebd8d"
"0x014d43a3b18f0944fee6622a5815ba0321d6440a" 9
"0x014d4517ecd1e4bb9e7c0c7020del6b9f68c7faa"
"0x014d45d33b131b4ecda18c3a4924a7ac15c58220" 1
"0x014d46c6eff0e04a2.278f017671f73ea7ed2ca9d" 1
"0x014d47e551cac04db2ab4980d81f29cb38acl6b3" 1
"0x014d47fc325050fe37347d96e3a5726284ef664a" 1
"0x014d48483f5b111e397974a75322dbbd1a6b0cce"
"0x014d495cd68302745445fda7cd42ce1d9e033f29" 1
"0x014d49efeb2a7fbca43705b4eaf957a02813df19" 2
"0x014d4a2cd11519245ca78d30b68a5e935e518e12" 22
"0x014d4a2fedlaabe08e82edfa28343c94d3800442" 1
"0x014d4b916c71cdcb0122d8c5605ff7a1d500a518"
"0x014d4be25067f7dde1187b5dffa9c2ace3e395d6" 81
"0x014d4bf25039f4f47b74ea73db42399b97288ca2" 2
"0x014d4bfa1886b969ede482fa7af5045f333dd59b"
"0x014d4cf0721be83114alac9d321664cc3084cd3c" 2
```

MISCELLANEOUS

Gas Guzzlers:

Using MapReduce, obtain the average Gas Price and Average Gas Limit for each month in the dataset by running the following two tasks.

GasPrice.py

```
[jmp01@it1210 ~/ecs765/ass1/partD> cat GasPrice.py
from mrjob.job import MRJob
import time
class Gas(MRJob):
    def mapper(self,_,line):
         val = float(fields[5])
date = time.localtime(float(fields[6]))
if len(fields) == 7:
                  yield ((date.tm_mon,date.tm_year),(1,val))
                                                                    #Number of transaction
         except:
             pass
    def combiner(self,key,val):
         count = 0
         for v in val:
             count+=v[0]
         total+=v[1]
yield (key,(count,total))
    def reducer(self,key,val):
         count = 0
total = 0
         for v in val:
             count+=v[0]
              total+=v[1]
         yield (key,(total/count))
if __name__=='__main__':
    Gas.run()
jmp01@itl210 ~/ecs765/ass1/partD>
```

GasLimit.py

```
[jmp01@itl210 ~/ecs765/ass1/partD> cat GasLimit.py
from mrjob.job import MRJob
import time
class Gas_limit(MRJob):
    def mapper(self,_,line):
         try:
fields = line.split(',')
             val = float(fields[4])
date = time.localtime(float(fields[6]))
if len(fields) == 7:
                  yield ((date.tm_mon,date.tm_year),(1,val))
                                                                     #Number of transaction
         except:
             pass
     def combiner(self,key,val):
         count = 0
         total = 0
         for v in val:
    count+=v[0]
              total+=v[1]
         yield (key,(count,total))
     def reducer(self,key,val):
         count = 0
total = 0
         for v in val:
             count+=v[0]
             total+=v[1]
         yield (key,(total/count))
if __name__=='__main__':
     Gas_limit.run()
jmp01@it1210 ~/ecs765/ass1/partD>
```

```
jmp01@it1210 ~/ecs765/ass1/partD> cat Gas_Price_output.txt
[1, 2017]
[1, 2019]
                       22507570807.719795
14611816445.785261
[10, 2015]
[10, 2017]
[11, 2016]
                       53898497955.07804
                       17509171844.77064
                       24634294365.279037
[11, 2016]
[11, 2018]
[12, 2015]
[12, 2017]
[2, 2016]
[2, 2018]
                       16034859008.681648
                       55899526672.35498
                       33423472930.407898
                       69180681134.38954
                       23636574203.828873
[3, 2017]
[3, 2019]
                       23232083087.910202
18091340267.2465
[4, 2016]
[4, 2018]
                       23359978331.676765
                       13149523170.45877
[5, 2017]
                       23568661138.035046
[5, 2019]
[6, 2016]
                       14480574461.419468
23021831286.57488
[6, 2018]
                       16536952425.540333
[7, 2017]
[8, 2016]
                       25463022668.143833
                       22407628763.365406
[8, 2018]
[9, 2015]
[9, 2017]
                       18478650928.737164
56512934320.01927
                       30676555381.728436
[1, 2016]
[1, 2018]
                       56596270931.316185
                       52106060636.844185
[10, 2016]
[10, 2018]
                       32113146198.891758
14527572489.59486
[11, 2015]
                       53607614201.79755
[11, 2017]
[12, 2016]
                       15312465314.693539
                       50318068074.687996
[12, 2018]
[2, 2017]
[2, 2019]
                       16338844844.014513
23047230327.254387
                       28940599438.1487
[3, 2016]
[3, 2018]
                       32805967466.947445
                       15554999714.874079
[4, 2017]
[4, 2019]
[5, 2016]
                       22357075153.737774
11573133401.384796
                       23747073761.79113
[5, 2018]
                       17414613148.43696
[6, 2017]
[6, 2019]
[7, 2016]
                       30201664896.657127
                       15067557451.33386
                       22619213302.825947
[7, 2018]
                       27520561081.0211
[8, 2015]
                       160356354969.0592
[8, 2017]
                       25903650367.89669
[9, 2016]
[9, 2018]
                       25262249340.11566
15208159827.250359
```

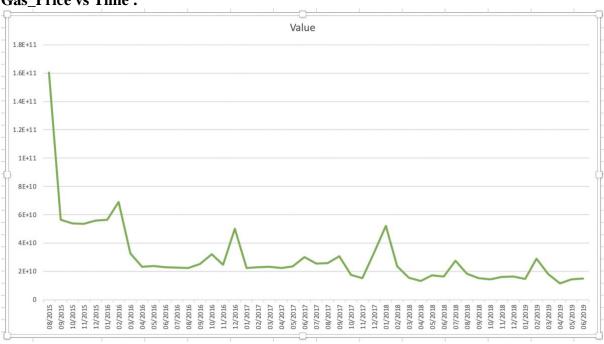
jmp01@it1210 ~/ecs765/ass1/partD>

ECS765P_JairajPatil_210819108 Ethereum Analysis

```
jmp01@itl210 ~/ecs765/ass1/partD> cat Gas_Limit_output.txt
                    144585.8323444452
[1, 2019]
[10, 2015]
                    213715.9605048934
                    124898.76345065859
[10, 2017]
[11, 2016]
                    139870.05913735816
                    118474.20698056064
[11, 2018]
                    224208.95181702235
[12, 2015]
[12, 2017]
                    202883.632316504
                    125269.51047898784
[2, 2016]
[2, 2018]
                    130175.52141758327
131824.6970378884
 [3, 2017]
                    147228.19778654756
[3, 2019]
                    248217.42927149552
[4, 2016]
                    95083.47755021007
[4, 2018]
                    236204.97904008476
152449.08294623252
[5, 2017]
[5, 2019]
                    183094.5693197547
[6, 2016]
                    130112.21626908527
[6, 2018]
                    180795.02085380582
[7, 2017]
[8, 2016]
                    132790.34469405047
119958.22676283357
 [8, 2018]
                    185752.46188363043
[9, 2015]
                    99880.37666969116
[9, 2017]
                    146371.34922749794
                    140463.7812759377
102167.12354317823
[1, 2016]
[1, 2018]
[10, 2016]
                    117078.86856704934
[10, 2018]
                    202550.24404083
 [11, 2015]
                    209520.94340378218
[11, 2017]
[12, 2016]
                    146613.7212948582
134463.8302327048
 [12, 2018]
                    228197.0665342265
[2, 2017]
[2, 2019]
                    185771.26611789103
                    246776.93062665823
[3, 2016]
[3, 2018]
                    103585.96288806947
                    156114.3435117928
[4, 2017]
                    156866.61651822302
[4, 2019]
                    210658.60478696763
[5, 2016]
                    119737.9383389679
[5, 2018]
[6, 2017]
                    149300.75953211795
129488.39504908556
 [6, 2019]
                    153578.42011967467
[7, 2016]
[7, 2018]
                    114490.23118436741
                    160946.32119566188
[8, 2015]
                    73133.53050098693
[8, 2017]
                    139510.6310349726
     2016]
                    139595.43180709172
[9, 2018]
                    202264.51543298518
```

jmp01@itl210 ~/ecs765/ass1/partD> ||

Bar charts & Observation Gas Price vs Time:



According to the graph above, the average price of gas has reduced from 2015 to 2019, and we can also see that each year, prices have risen in the last few months or the first few months of the year.

Contract_gas vs Time:



Observation from the graph above - Despite some ups and downs, there has been a general pattern of steadily increasing gas requirements (from 80000 to 250000 approx)