Analysis of Ethereum Transactions and Smart Contracts Report

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Contents

I. Part A – Time analysis

a) Requirement

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

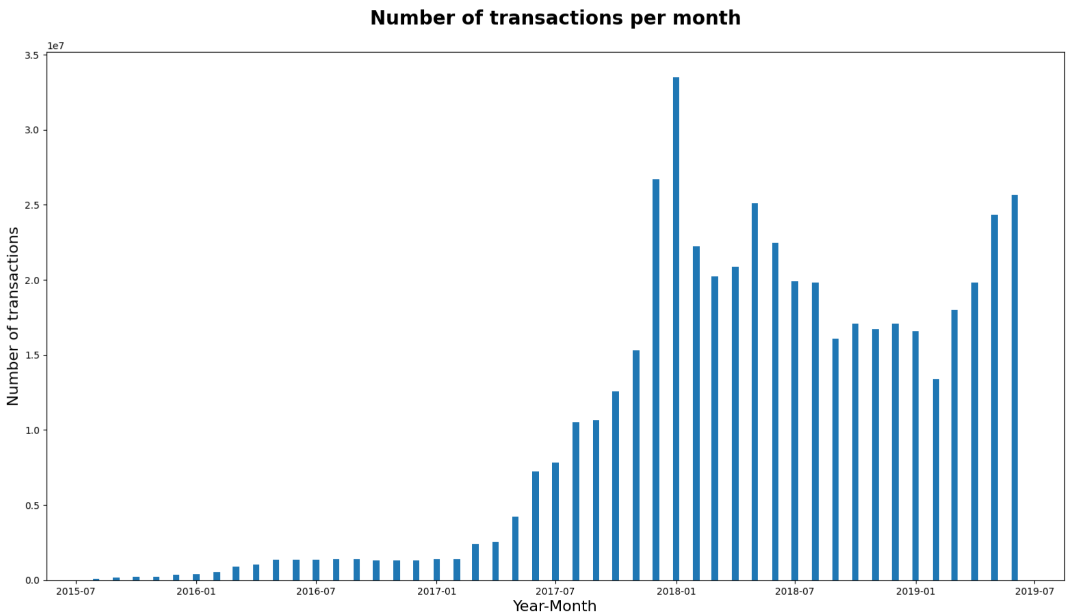
b) Source code (For detailed comments for each step, navigate to the source code file using the hyperlink)

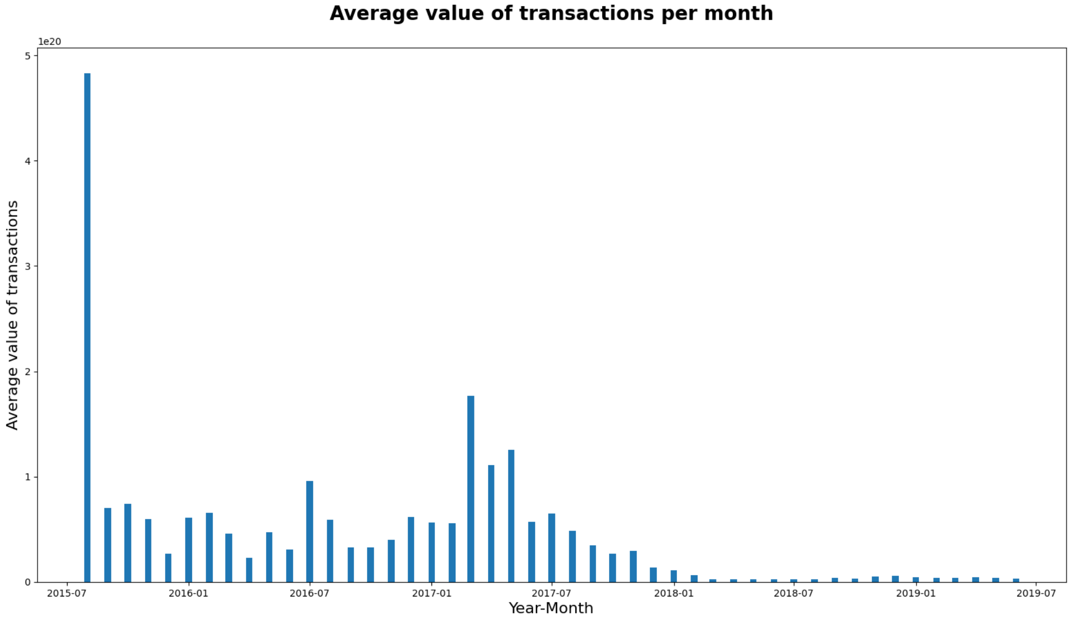
a_part.py - Getting total transactions' values and total occurrence per year-month.

a_part_plot.py - Plotting two required charts from the a_part.py output data.

Job ID: http://andromeda.student.eecs.qmul.ac.uk:8088/proxy/application_1649894236110_5371/

c) Deliverable - Charts





II. Part B – Top ten popular services

a) Requirement

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 an MRJob-based approach. This is, however, is not the only way to complete the task, as there are several other viable ways of completing this assignment.

b) Source code (For detailed comments for each step, navigate to the source code file using the hyperlink)

b_part.py - Multi-steps Hadoop/MapReduce task to:

- Perform a repartition left join between contracts and transactions data, filter transactions with value 0.
- Aggregate using sum to get the top 10 most popular services by transaction value.

Job ID:

- http://andromeda.student.eecs.qmul.ac.uk:8088/proxy/application_1649894236110_3685/
- http://andromeda.student.eecs.qmul.ac.uk:8088/proxy/application_1649894236110_3786/

c) Deliverable - Top ten popular services (in wei)

Smart contracts	Total wei received
0xaa1a6e3e6ef20068f7f8d8c835d2d22fd5116444	84155100809965865822726776
0xfa52274dd61e1643d2205169732f29114bc240b3	45787484483189352986478805
0x7727e5113d1d161373623e5f49fd568b4f543a9e	45620624001350712557268573
0x209c4784ab1e8183cf58ca33cb740efbf3fc18ef	43170356092262468919298969
0x6fc82a5fe25a5cdb58bc74600a40a69c065263f8	27068921582019542499882877
0xbfc39b6f805a9e40e77291aff27aee3c96915bdd	21104195138093660050000000
0xe94b04a0fed112f3664e45adb2b8915693dd5ff3	15562398956802112254719409
0xbb9bc244d798123fde783fcc1c72d3bb8c189413	11983608729202893846818681
0xabbb6bebfa05aa13e908eaa492bd7a8343760477	11706457177940895521770404
0x341e790174e3a4d35b65fdc067b6b5634a61caea	8379000751917755624057500

III. Part C – Top ten most active miners

a) Requirement

Evaluate the top 10 miners by the size of the blocks mined. This is simpler as it does not require a join. You will first have to aggregate blocks to see how much each miner has been involved. You will want to aggregate the size for addresses in the miner field. This will be similar to the word count that we saw in Lab 1 and Lab 2. You can add each value from the reducer to a list and then sort the list to obtain the most active miners.

b) Source code (For detailed comments for each step, navigate to the source code file using the hyperlink)

c_part.py - Multi-steps Hadoop/MapReduce task to:

- Perform a map-reduce to get aggregated (None, (Miner address, Size)) for sorting.
- A reducer step to get top 10 miners.

c) Deliverable - Top ten most active miners

Miner's address	Total mined size
0xea674fdde714fd979de3edf0f56aa9716b898ec8	23989401188
0x829bd824b016326a401d083b33d092293333a830	15010222714
0x5a0b54d5dc17e0aadc383d2db43b0a0d3e029c4c	13978859941
0x52bc44d5378309ee2abf1539bf71de1b7d7be3b5	10998145387
0xb2930b35844a230f00e51431acae96fe543a0347	7842595276
0x2a65aca4d5fc5b5c859090a6c34d164135398226	3628875680
0x4bb96091ee9d802ed039c4d1a5f6216f90f81b01	1221833144
0xf3b9d2c81f2b24b0fa0acaaa865b7d9ced5fc2fb	1152472379
0x1e9939daaad6924ad004c2560e90804164900341	1080301927
0x61c808d82a3ac53231750dadc13c777b59310bd9	692942577

IV. Part D

1. Popular scams

a) Requirement

Utilising the provided scam dataset, what is the most lucrative form of scam? Does this correlate with certainly known scams going offline/inactive? For the correlation, you could produce the count of how many scams for each category are active/inactive/offline/online/etc and try to correlate it with volume (value) to make conclusions on whether state plays a factor in making some scams more lucrative. Therefore, by getting the volume and state of each scam, you can make a conclusion whether the most lucrative ones are ones that are online or offline or active or inactive.

b) Source code (For detailed comments for each step, navigate to the source code file using the hyperlink)

Data preprocessing and evaluation d_part_scam_extract_json.py - A python script to locally extract data for all related addresses with each scam from scams.json to text file for ease of use.

d_part_scam_check_dup.py - A small map-reduce job for a sanity check on addresses with several forms of scams/statuses. (With the result there are 15 cases with two types of scams/statuses. Considering the minimal impact, we begin to analyse with a small change in the logic).

Data processing d_part_scam_data.py - Multi-steps Hadoop/MapReduce task to:

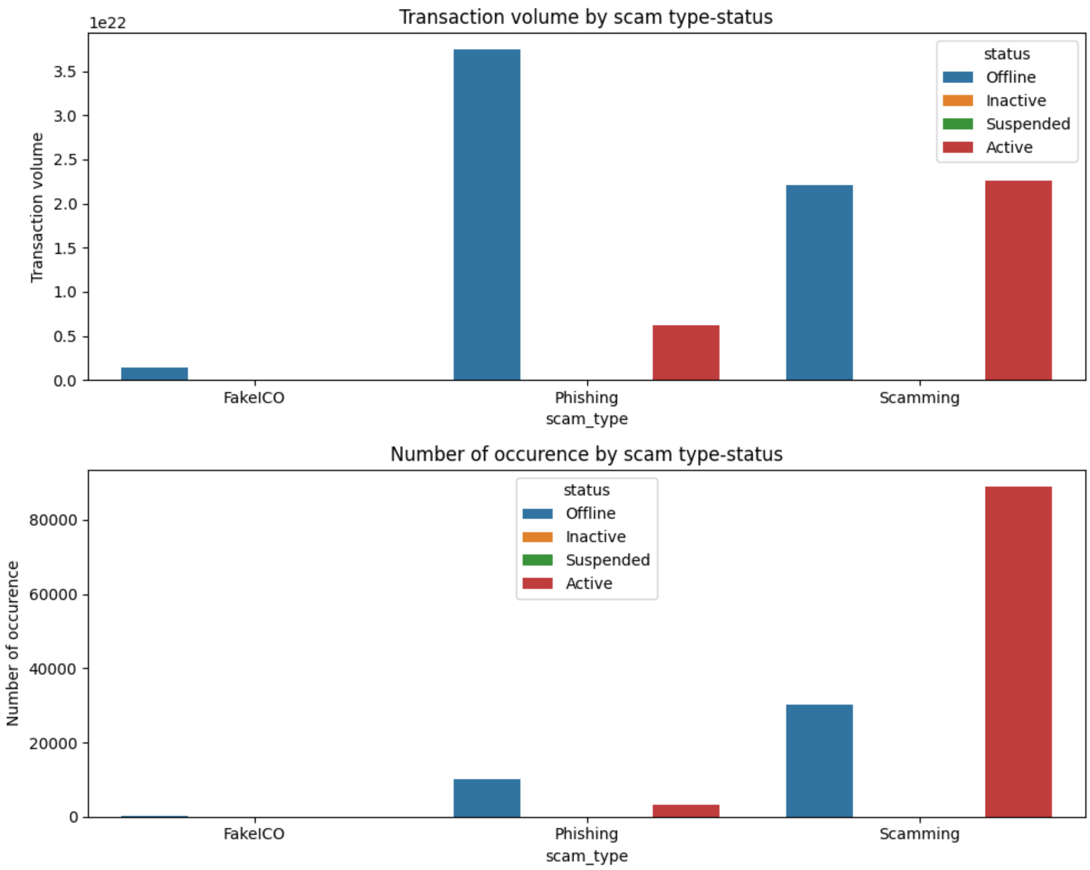
- Do a repartition join between transactions and scams (extracted from the previous step) data set by address key.
- Change dimension from address to scam type, status to aggregate total transaction volume, the number of occurrences (per address related).

Reporting data d_part_scam_report.py - A python script to aggregate data from previous step for reporting insights.

c) Deliverable - Report

Scam type	Metric	Volume
FakeICO	count	1.210000e+02
	sum	1.356458e+21
Phishing	count	1.331100e+04
	sum	4.372701e+22
Scamming	count	1.194640e+05
	sum	4.471581e+22

What is the most lucrative form of scam? From the data table above, in terms of both occurrence and transaction volume, the “Scamming” type is the most lucrative form of scam. However, “Scamming” is an umbrella term. Therefore, we could safely infer that “Phishing” is the most lucrative form.



Does this correlate with certainly known scams going offline/inactive?

- As we could see, there are some positive correlations between the numbers of occurrences and transaction volume for Phishing/FakeICO. However, it is not the same for Scamming type.
- For the Scamming type, the most lucrative one is Active.
- For the Phishing type, the most lucrative one is Offline.

2. Fork the Chain

a) Requirement

There have been several forks of Ethereum in the past. Identify one or more of these and see what effect it had on price and general usage. For example, did a price surge/plummet occur, and who profited most from this?

b) Source code (For detailed comments for each step, navigate to the source code file using the hyperlink)

d_part_fork_analysis.py - A Spark job to:

- Differentiate different fork events based on block number[1]

[1] Wikipedia Ethereum

- Join with close price data of Ethereum scraping from Coinmarketcap in USD[2]

d_part_fork_analysis_report.py - A Python script to cleanse the output data, plot chart and extracting insights for the report

c) Deliverable - Analysis report

Date	**Event**	**Average price last two weeks**	**Average price next two weeks**	**% Change in average price**
2015-09-08	Ice Age	1.267857	0.947571	-25.26%
2016-03-15	Homestead	11.167143	11.133571	-0.30%
2016-07-20	DAO Fork	11.206429	12.275714	9.54%
2016-10-18	Tangerine Whistle	12.197143	11.495	-5.76%
2016-11-23	Spurious Dragon	9.936429	8.245	-17.02%
2017-10-16	Byzantium	311.609286	301.816429	-3.14%
2019-02-28	Constantinople	140.043893	135.030217	-3.58%

Table 1. Comparing the average price change within the last and next two weeks from the fork date

Date	**Event**	**Total wei transaction last two weeks**	**Total wei transaction last next two weeks**	**% Change in total transaction**
2015-09-08	Ice Age	5.58E+24	5.52E+24	-0.98%
2016-03-15	Homestead	2.47E+25	1.38E+25	-44.01%
2016-07-20	DAO Fork	3.86E+25	1.08E+26	180.02%
2016-10-18	Tangerine Whistle	2.52E+25	1.69E+25	-32.75%
2016-11-23	Spurious Dragon	2.00E+25	3.03E+25	51.25%
2017-10-16	Byzantium	1.48E+26	1.58E+26	6.69%
2019-02-28	Constantinople	3.20E+25	2.94E+25	-8.20%

Table 2. Comparing the total usage (transaction amount) within the last and next two weeks from the fork date

Commentary

- Considering every fork could make a huge impact on the usage/price of Ethereum. This could be an instrument to drive the Ethereum market.
- Furthermore, every Ethereum owner would receive the new token with the same amount as their Ethereum amount after the fork. This could be an incentive for holding/hoarding

[2] There were days with unavailable price data being filled with the nearest date's price

Ethereum before each fork. And, Potentially, huge sell-outs after each fork which were reflected in table 1.

- In conclusion, the more Ethereum an owner had, the more profit they gained from each fork.

3. Gas guzzlers

*** a) Requirement**

For any transaction on Ethereum, a user must supply gas. How has the gas price changed over time? Have contracts become more complicated, requiring more gas, or less so? Also, could you correlate the complexity for some of the top-10 contracts found in Part B by observing the change in their transactions

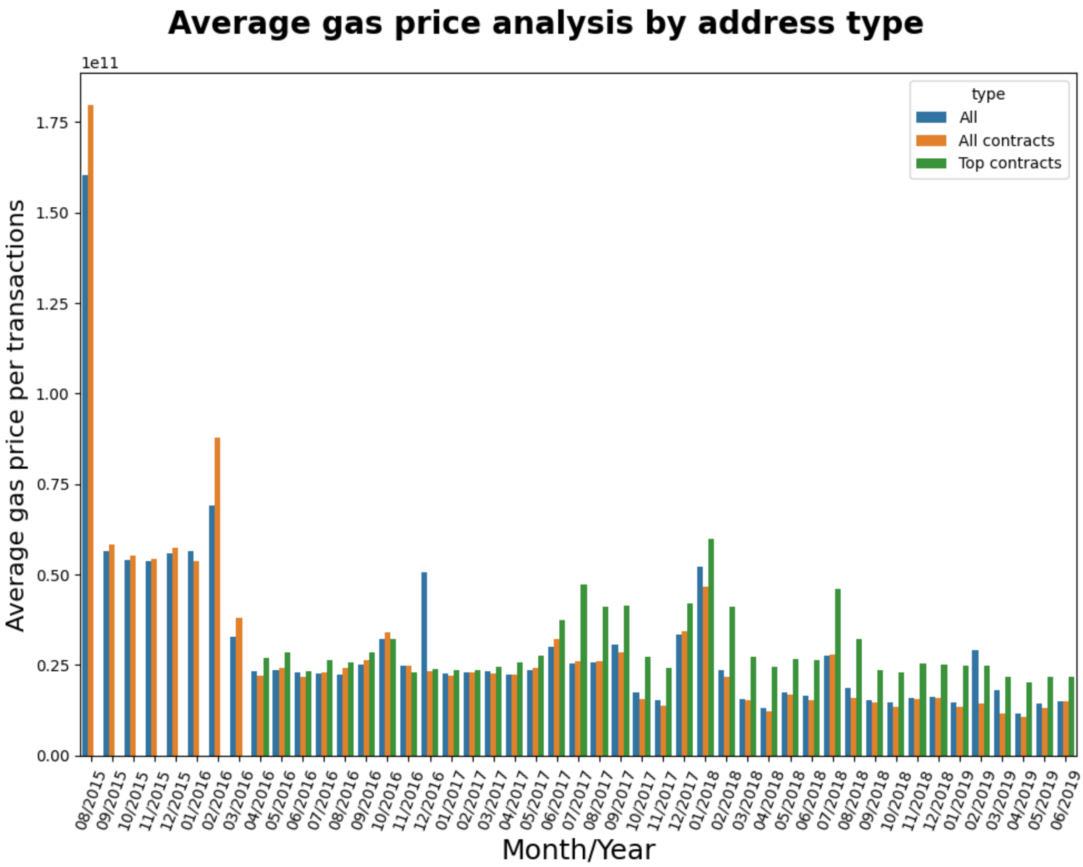
b) Source code (For detailed comments for each step, navigate to the source code file using the hyperlink)

d_part_gas_guzzler.py - A spark job to:

- Map between transactions, contracts, and top contracts (result from part B) data sets
- Generate an address type dimension on the way to do the gas price analysis between each type

d_part_gas_guzzler_analysis.py - A quick code to generate a barplot for analysing the gas price trend between each address type through time

c) Deliverable - Chart & Commentary
Chart



Commentary

How has the gas price changed over time? Overall, we could see the downtrend in the gas price.

Have contracts become more complicated, requiring more gas, or less so?

- There are 3 distinct periods that could be observed from this period. Before Q2 2016, where smart contracts were usually more complicated than normal wallets on average.
- After Q2 2016, the average gas price for smart contracts and normal wallets stayed roughly the same. The average price per transaction for smart contracts sometimes was slightly higher during this period.
- Except for Dec 2016, where there was a pump in gas price for normal wallets.

Also, could you correlate the complexity for some of the top-10 contracts found in Part B by observing the change in their transactions.

- As we could see, the top ten popular contracts of this data set were from Q2 2016.
- During the period Q2 2016 to the end of Q1 2017, the average gas price per transaction had stayed roughly the same for all three types except for Dec 2016.
- From Q2 2017, the average gas price per transaction of the top ten popular contracts had been consistently higher than the other two with an exception of Feb 2019.

4. Comparative evaluation

*** a) Requirement**

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?

b) Source code (For detailed comments for each step, navigate to the source code file using the hyperlink)

d_part_comparative_evaluation.py - A spark job with the same objective as Part B to evaluate performance

d_part_comparative_evaluation.txt - An output text file to log the runtimes of different executions

c) Deliverable - Performance report & Commentary

Runtime	Spark	MapReduce
1st	110.663076878	125.119294405
2nd	122.247198551	112.667238644
3rd	104.098869553	120.955614206
4th	108.583358127	122.505109383
5th	113.403694996	118.575467115
Average	111.799239621	119.964544750
Median	110.663076878	120.955614206

Chart 1. Benchmarking based on a subset of transactions & contracts data set

	Spark	MapReduce
Runtime	124.950928926	2076.626327991

Chart 2. Benchmarking based on whole transactions & contracts data set

Commentary

- **Observation**: In chart 1, Spark job ran slightly better than MapReduce.
- **Observation**: Spark ran significantly faster compared to Hadoop/MapReduce with chart 2. In this case, we could safely assume that the variance in performance due to network traffic could be ignored.
- **Reason**: The MRjob job consisted of 2 steps. Therefore, it needed to write a large amount of data into the HDFS with the intermediate results. This was the reason for the huge difference in performance.
- **Conclusion**: For this task, Spark seems to be more appropriate.