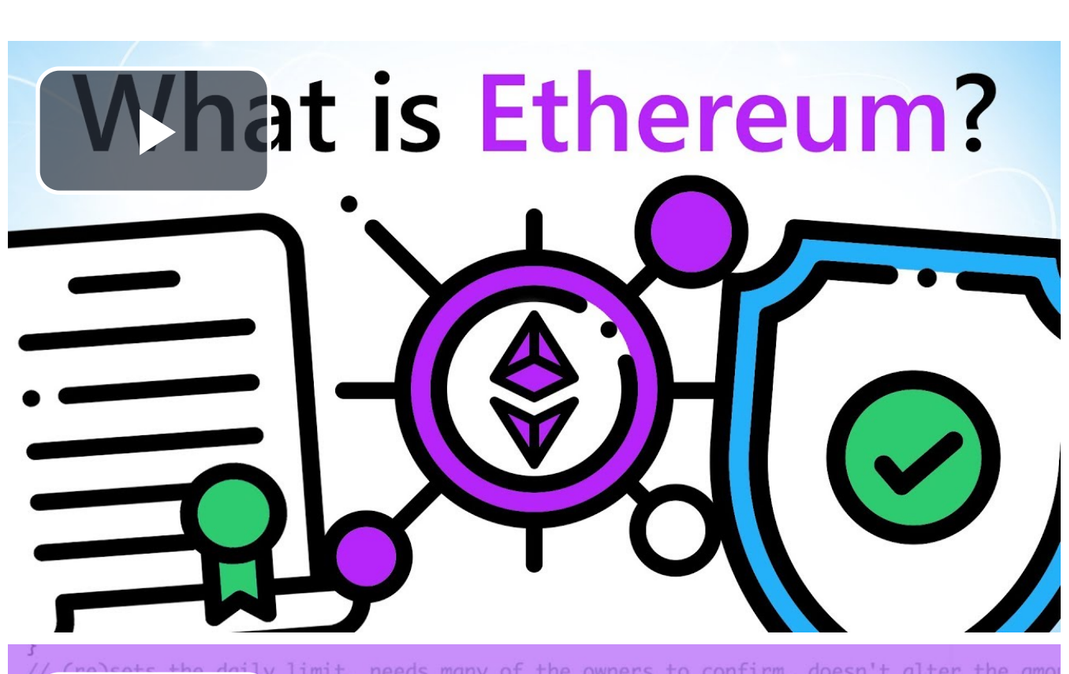
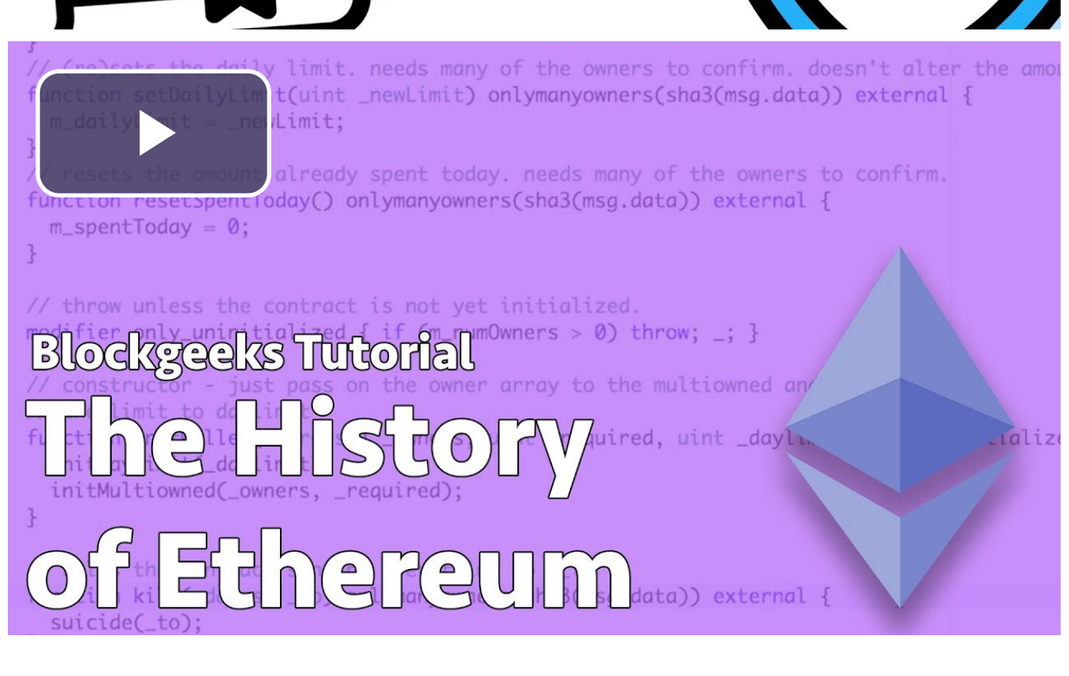
COURSEWORK: ETHEREUM ANALYSIS (40%)

ANALYSIS OF ETHEREUM TRANSACTIONS AND SMART CONTRACTS

The goal of this coursework is to apply the techniques covered in the first half of Big Data Processing to analyse the full set of transactions which have occurred on the Ethereum network; from the first transactions in August 2015 till June 2019. You will create several Map/Reduce or Spark programs to perform multiple types of computation. You will submit a report containing your results alongside an explanation of how they were obtained.

There are many resources available for understanding Ethereum and blockchain technology; a good place to start are these two short videos taken from this article, followed up by the Ethereum White Paper . There are also may sites dedicated to providing information about individual blocks, transactions and wallets, such as Etherscan and Ethplorer.





DATASET OVERVIEW

Ethereum is a blockchain based distributed computing platform where users may exchange currency (Ether), provide or purchase services (smart contracts), mint their own coinage (tokens), as well as other applications. The Ethereum network is fully decentralised, managed by public-key cryptography, peer-to-peer networking, and proof-of-work to process/verify transactions.

Whilst you would normally need a CLI tool such as GETH to access the Ethereum blockchain, recent tools allow scraping all block/transactions and dump these to csv's to be processed in bulk; notably Ethereum-ETL. These dumps are uploaded daily into a repository on Google BigQuery. We have used this source as the dataset for this coursework.

A subset of the data available on BigQuery is provided at the HDFS folder **/data/ethereum**. The blocks, contracts and transactions tables have been pulled down and been stripped of unneeded fields to reduce their size. We have also downloaded a set of scams, both active and inactive, run on the Ethereum network via etherscamDB which is available on HDFS at **/data/ethereum/scams.json**.

DATASET SCHEMA - BLOCKS

number: The block number

hash: Hash of the block

miner: The address of the beneficiary to whom the mining rewards were given

difficulty: Integer of the difficulty for this block

size: The size of this block in bytes

gas_limit: The maximum gas allowed in this block

gas_used: The total used gas by all transactions in this block

timestamp: The timestamp for when the block was collated

transaction_count: The number of transactions in the block

```
+-------+--------------------+--------------------+----------------+-----+---------+--------+----------+-----------------+
| number|                hash|               miner|      difficulty| size|gas_limit|gas_used| timestamp|transaction_count|
+-------+--------------------+--------------------+----------------+-----+---------+--------+----------+-----------------+
|4776199|0x9172600443ac88e...|0x5a0b54d5dc17e0a...|1765656009004680| 9773|  7995996| 2042230|1513937536|               62|
|4776200|0x1fb1d4a2f5d2a61...|0xea674fdde714fd9...|1765656009037448|15532|  8000029| 4385719|1513937547|              101|
|4776201|0xe633b6dca01d085...|0x829bd824b016326...|1765656009070216|14033|  8000000| 7992282|1513937564|               99|
|4776202|0x2ec4b8235923a59...|0x52bc44d5378309e...|1765656009102984|29386|  8000029| 7851362|1513937573|              238|
|4776203|0x41f604b680e98d9...|0xea674fdde714fd9...|1765656009135752|28954|  8000029| 7608807|1513937582|              218|
|4776204|0x5cbbf6a7d477d8e...|0x52bc44d5378309e...|1766518145891730|21030|  8000029| 7851625|1513937587|              168|
|4776205|0xbfc7b7c3e60871d...|0x5a0b54d5dc17e0a...|1767380703612921|14168|  7992222| 7835129|1513937591|              103|
|4776206|0x753989a3805ef53...|0xea674fdde714fd9...|1765654745927319|29125|  7999992| 7989266|1513937624|              217|
|4776207|0x6f05105a6f8bc79...|0x829bd824b016326...|1767379018172905|27294|  8003884| 7996284|1513937632|              199|
|4776208|0x0f4a563b90f8dfe...|0xea674fdde714fd9...|1768241996241890|17090|  8000029| 7981114|1513937636|               67|
|4776209|0x5d62c54adb1cf9f...|0x829bd824b016326...|1769105395686885|31756|  8003909| 7999420|1513937646|              152|
|4776210|0x61f378b94ee93e5...|0xea674fdde714fd9...|1769105395719653|17215|  8000029| 4861724|1513937661|               93|
|4776211|0xaf0bd62dbb54a5f...|0xb2930b35844a230...|1769969216746424|22572|  8000029| 7980777|1513937667|              107|
|4776212|0xc378e5b0cb56015...|0x6a7a43be33ba930...|1766512245652736|32834|  8000029| 7981744|1513937718|              194|
|4776213|0x70a7e0f71e4ae02...|0xea674fdde714fd9...|1763924581263163|37277|  8000029| 7992002|1513937761|              255|
|4776214|0xfb19cfa052d0f9f...|0xea674fdde714fd9...|1764785872595375|13740|  8000029| 4704474|1513937763|               72|
|4776215|0x2d127b5cbc681c0...|0xb75d1e62b10e4ba...|1765647584479996|26482|  7992222| 6630351|1513937767|              163|
|4776216|0xc4e242278d153b5...|0xb2930b35844a230...|1766509717122373|18248|  7984452| 7965327|1513937774|               76|
|4776217|0xde24c6f461a79da...|0x829bd824b016326...|1765647163582328|31649|  7992248| 7986059|1513937796|              180|
|4776218|0x1689f0d2ea89886...|0xea674fdde714fd9...|1767371428423280|25953|  8000029| 7415731|1513937802|              146|
```

DATASET SCHEMA - TRANSACTIONS

block_number: Block number where this transaction was in

from_address: Address of the sender

to_address: Address of the receiver. null when it is a contract creation transaction

value: Value transferred in Wei (the smallest denomination of ether)

gas: Gas provided by the sender

gas_price : Gas price provided by the sender in Wei

block_timestamp: Timestamp the associated block was registered at (effectively timestamp of the transaction)

```
+------------+--------------------+--------------------+-------------------+------+-----------+---------------+
|block_number|        from_address|          to_address|              value|   gas|  gas_price|block_timestamp|
+------------+--------------------+--------------------+-------------------+------+-----------+---------------+
|     6638809|0x0b6081d38878616...|0x412270b1f0f3884...| 240648550000000000| 21000| 5000000000|     1541290680|
|     6638809|0xb43febf2e6c49f3...|0x9eec65e5b998db6...|                  0| 60000| 5000000000|     1541290680|
|     6638809|0x564860b05cab055...|0x73850f079ceaba2...|                  0|200200| 5000000000|     1541290680|
|     6638809|0x8e5bb92b98c0cf4...|0x9eec65e5b998db6...|                  0| 60000| 5000000000|     1541290680|
|     6638809|0x6908856f565e5b6...|0x9eec65e5b998db6...|                  0| 60000| 5000000000|     1541290680|
|     6638809|0x00cdc153aa8894d...|0x8d5a0a7c555602f...| 984699000000000000|940000| 5000000000|     1541290680|
|     6638809|0x71e5e2114561d30...|0xe36df5bb57e8062...|                  0| 60000| 5000000000|     1541290680|
|     6638809|0x9cbbc2c728863d9...|0x9eec65e5b998db6...|                  0| 60000| 5000000000|     1541290680|
|     6638809|0x33ca0295811747f...|0x9eec65e5b998db6...|                  0| 60000| 5000000000|     1541290680|
|     6638809|0xbcf32771090aecb...|0x32623916bd5e735...| 257315840000000000| 21000| 5000000000|     1541290680|
|     6638809|0xc21a44550926c9a...|0x9eec65e5b998db6...|                  0| 60000| 5000000000|     1541290680|
|     6638809|0x405353c90852e9c...|0x9eec65e5b998db6...|                  0| 60000| 5000000000|     1541290680|
|     6638810|0xeee28d484628d41...|0x8dd5fbce2f6a956...|                  0| 90000|64000000000|     1541290720|
|     6638810|0x96f9706e01caba2...|0x490c95be16384e1...|                  0| 37804|50100000000|     1541290720|
|     6638810|0xca83c8e5ff93fa0...|0x5bc8854dd4a7d5b...|2292738000000000000| 21000|41000000000|     1541290720|
|     6638810|0xf73c3c65bde10bf...|0x13e8640a2f06ef1...|1000000000000000000|400000|40000000000|     1541290720|
|     6638810|0x2cefcf6a903d863...|0xd9c8ae68aa8ff1f...|                  0|200000|33000000000|     1541290720|
|     6638810|0x521db06bf657ed1...|                null|                  0|210000|32608136662|     1541290720|
|     6638810|0x3f5ce5fbfe3e9af...|0xdf2c7238198ad8b...|                  0| 75138|30000000000|     1541290720|
|     6638810|0x3f5ce5fbfe3e9af...|0xdf2c7238198ad8b...|                  0| 75138|30000000000|     1541290720|
```

DATASET SCHEMA - CONTRACTS

address: Address of the contract

is_erc20: Whether this contract is an ERC20 contract

is_erc721: Whether this contract is an ERC721 contract

block_number: Block number where this contract was created

```
+--------------------+--------+---------+------------+--------------------+
|             address|is_erc20|is_erc721|block_number|     block_timestamp|
+--------------------+--------+---------+------------+--------------------+
|0x9a78bba29a2633b...|   false|    false|     8623545|2019-09-26 08:50:...|
|0x85aa7fbc06e3f95...|   false|    false|     8621323|2019-09-26 00:29:...|
|0xc3649f1e59705f2...|   false|    false|     8621325|2019-09-26 00:29:...|
|0x763fe69be6c6ec1...|   false|    false|     8621263|2019-09-26 00:16:...|
|0xcd05b1405efa69f...|   false|    false|     8621206|2019-09-26 00:05:...|
|0xdeb220a2403e653...|   false|    false|     5363203|2018-04-01 21:23:...|
|0x0de0e9971ad93b3...|   false|    false|     5359109|2018-04-01 05:10:...|
|0x58c38ad83417e7b...|   false|    false|     5362728|2018-04-01 19:37:...|
|0xadce4fe9b3c2ed0...|   false|    false|     5362995|2018-04-01 20:39:...|
|0x6fe77efba17afa5...|   false|    false|     5363518|2018-04-01 22:49:...|
|0x391db5cb42e918b...|   false|    false|     5359958|2018-04-01 08:35:...|
|0x61d0e4402996bd3...|   false|    false|     5358721|2018-04-01 03:37:...|
|0x356db362d67e065...|   false|    false|     5359534|2018-04-01 06:56:...|
|0x80c676fbba74643...|   false|    false|     5363162|2018-04-01 21:12:...|
|0x2f73ea1b261dfa7...|   false|    false|     5358309|2018-04-01 02:04:...|
|0x8bdb0567c9db489...|   false|    false|     5359093|2018-04-01 05:05:...|
|0x128e9904959629d...|   false|    false|     5357919|2018-04-01 00:30:...|
|0x1d601b70f3d8489...|   false|    false|     8377968|2019-08-19 01:43:...|
|0xc0ce6542be0df27...|   false|    false|     8378020|2019-08-19 01:54:...|
|0xdb98e880a574766...|   false|    false|     8380961|2019-08-19 13:01:...|
```

DATASET SCHEMA - SCAMS.JSON

id: Unique ID for the reported scam

name: Name of the Scam

url: Hosting URL

coin: Currency the scam is attempting to gain

category: Category of scam - Phishing, Ransomware, Trust Trade, etc.

subcategory: Subdivisions of Category

description: Description of the scam provided by the reporter and datasource

addresses: List of known addresses associated with the scam

reporter: User/company who reported the scam first

ip: IP address of the reporter

status: If the scam is currently active, inactive or has been taken offline

```
0x11c058c3efbf53939fb6872b09a2b5cf2410a1e2c3f3c867664e43a626d878c0: {
    id: 81,
    name: "myetherwallet.us",
    url: "http://myetherwallet.us",
    coin: "ETH",
    category: "Phishing",
    subcategory: "MyEtherWallet",
    description: "did not 404.,MEW Deployed",
    addresses: [
        "0x11c058c3efbf53939fb6872b09a2b5cf2410a1e2c3f3c867664e43a626d878c0",
        "0x2dfe2e0522cc1f050edcc7a05213bb55bbb36884ec9468fc39eccc013c65b5e4",
        "0x1c6e3348a7ea72ffe6a384e51bd1f36ac1bcb4264f461889a318a3bb2251bf19"
    ],
    reporter: "MyCrypto",
    ip: "198.54.117.200",
    nameservers: [
        "dns102.registrar-servers.com",
        "dns101.registrar-servers.com"
    ],
    status: "Offline"
},
```

ASSIGNMENT

Write a set of Map/Reduce (or Spark) jobs that process the given input and generate the data required to answer the following questions:

PART A. TIME ANALYSIS (20%)

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 transaction in each 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.)

PART B. TOP TEN MOST POPULAR SERVICES (20%)

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.

PART C. TOP TEN MOST ACTIVE MINERS (10%)

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 in. You will want to aggregate **size** for addresses in the **miner** field. This will be similar to the wordcount 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.

PART D. DATA EXPLORATION (50%)

The final part of the coursework requires you to explore the data and perform some analysis of your choosing. These tasks may be completed in either MRJob or Spark, and you may make use of Spark libraries such as MLlib (for machine learning) and GraphX for graphy analysis. Below are some suggested ideas for analysis which could be undertaken, along with an expected grade for completing it to a *good* standard. You may attempt several of these tasks or undertake your own. However, it is recommended to discuss ideas with Joseph before commencing with them.

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? (15/50)

MACHINE LEARNING

1. **Price Forecasting**: Find a dataset online for the price of ethereum from its inception till now. Utilising Spark mllib build a price forecasting model trained on this, the coursework dataset and any other useful information sources you can find. How accurate can you get your forecast within the coursework window to June 2019? How far past June 2019 does your forecast remain accurate? (20-25/50)

GRAPH ANALYSIS

For these challenges you can use Spark GraphX to build the transactions dataset into a directed graph where the `from` and `to` addresses are the vertices and each transaction is an edge. Label the edges with the value of each transaction and the time of transaction.

1. **Triangle Count/Clustering coefficient**: Triangle Count is a community detection graph algorithm that is used to determine the number of triangles passing through each node in the graph. A triangle is a set of three nodes, where each node has a relationship to all other nodes. Write your own triangle count algorithm using GraphX's pregel API and report your findings (20/50). You can expand upon this to calculate local and global clustering coefficients (25/50)
2. **Scammer Graph Traversal**: Once Ether have been scammed what happens to it afterwards? Utilising GraphX's Pregel API implement a graph traversal algorithm to find addresses where scammers are accumulating ether. It is common for stolen crypto to be tumbled, can your algorithm mitigate against this? From your results can you identify several separate scams in the dataset which appear to be the same bad actor/group? This is a **hard** challenge (25/50)

MISCELLANEOUS ANALYSIS

1. **Fork the Chain**: 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? (10/50)
2. **Gas Guzzlers**: For any transaction on Ethereum a user must supply gas. How has gas price changed over time? Have contracts become more complicated, requiring more gas, or less so? How does this correlate with your results seen within Part B. (10/50)
3. **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? (10/50)

SUBMISSION

You have to submit a single compressed file (in zip format) containing all the requested materials:

- A short report in **PDF format** detailing your answer to each of the questions (A,B,C,D). Your answer must include the requested plots, as well as the explanation of the MapReduce / Spark programs that obtained these results. Additionally, for each job, you must include the id of the job as reported by YARN when launching the job. e.g. `http://andromeda.student.eecs.qmul.ac.uk:8088/proxy/application_1572204863710_0404/`
- The source code for all the jobs you have implemented in this exercise.

For generating the plots you can use any visualisation toolkit; Python's matplotlib, R, gnuplot, Matlab, or excel.

SUBMISSION STATUS

Attempt number	This is attempt 1.
Submission status	No attempt
Grading status	Not graded
Due date	Friday, 4 December 2020, 10:00 AM
Time remaining	20 days 11 hours 10 mins 15 secs
Last modified	-
Submission comments	Comments (0)

Add submission

You can still make changes to your submission.