Abstract:

Token properties in the Etherum blockchain, including price, number of trades, and value in the future, depend on many factors, making it hard to analyze. This is an area where social networks would be of great assistance. They are great tools for analyzing complex systems whose properties are affected by many factors, therefore they can explain changes in the token properties based on the characteristics of the network. In this paper various networks have been generated for two of the popular decentralized exchanges, UniswapV2 and SushiSwap, and the dependencies between the tokens as well as the characteristics of the network have been analyzed.

Introduction:

Social Networks, and Graphs have opened up various research areas for analyzing complex systems, which are hard to simply define them with mathematical notations. Cryptocurrency is not an exception in this regard, and much research has been conducted for finding interesting insights about the crypto world with usage of network analysis. For instance in [2] the small world property of the graph made by transactions has been observed.

Decentralized Exchange is a novel method of exchange that have become popular during these year, and

Methodology:

Dataset:

For the analysis we used data from ethereum blockchain. First of all from the Blockchain all the transfers within block number 10060850 through block number 15076596 had been extracted. After that from these transfers those transfers that at least one of the addresses(buyer or seller) were pool addresses from UniSwapV2 or SushiSwap had been filtered. The pool addresses of UniSwapV2 and SushiSwap had been found while employing some APIs.

Building Swap Graphs:

With the filtered transfers that are made in the data preprocessing step we generate some graphs from the two DEXes.

Weighted Graph:

Nodes in this graph consist of tokens and two tokens have edge two each other if the two tokens have a pool in the checked DEX. The weight of the edge is the number of transfers that have been done through the time.

Without Weight Graph:

For finding some metrics like density and average degree the weighted graph couldn't be useful, therefore we also generate a graph without weights. Nodes in this graph are tokens and there is an unweighted edge between those if there is a pool that contains these tokens.

Graphs During Time:

To analyze the relation between some network properties, and token characteristics in the real world it was necessary to observe the changes in the graph through the time. Therefore we created graphs by slicing the block range to 100 equal intervals, and generating the graphs just for their specific interval. Therefore some properties like centralities have been analyzed within 100 graphs which is equivalent to time.

Results:

Centrality:

The centrality of nodes in these graphs is an interesting property, showing the node's importance, and could be a novel and useful method for raking tokens. For the UniswapV2 and SushiSwap main graph, built for the whole dataset, we have calculated the eigen vector centrality as well as page rank centrality with alpha equals to 0.9. In both graphs WETH is the most central token by a significance difference. Also in both graph based on the centralities USDC, USDT and DAI play important role.

-Eigen Vector Centrality:

Eigen vector centrality is one of the famous centralities could be measured in social networks.

Explanation will be written…

Above is the eight most central tokens and their centrality in the Main graph of UniswapV2 and Sushiswap:

Uniswap:

('WETH', 0.9912290462290068),
('USDT', 0.08766130080471124),
('USDC', 0.08478963367173886),
('DAI', 0.0315343650704104),
('SHIB', 0.01725126620079008),
('SAITAMA', 0.012961603841174644),
('UNI', 0.01082449178594235),
('WBTC', 0.009867950601133909),

SushiSwap:

('WETH', 0.7210405057090393),
('USDC', 0.4148125605644069),
('USDT', 0.31743442143429745),
('SUSHI', 0.23216382577648456),
('DAI', 0.23200965897490583),
('YFI', 0.09122342176106728),
('WBTC', 0.08898564407404234),
('CRV', 0.0863893492462936)

-Page Rank Centrality:

Page rank algorithm used in google search engine for ranking the urls related to the user query in some manner to show the user. This algorithm could be also employed in calculating centralities for the social network.

Definition of algorithm…

Above is the eight most central tokens and their centrality in the Main graph of UniswapV2 and Sushiswap calculated with this technique:

('WETH', 0.6750021094213728),
('USDT', 0.011101512886777114),
('USDC', 0.005659313258141766),
('DAI', 0.0027044601723589367),
('WBTC', 0.000410946149598066),
('UNI', 0.00034238821637192786),
('DEXTF', 0.00033818870089861666),
('UST', 0.0001588272552079643)

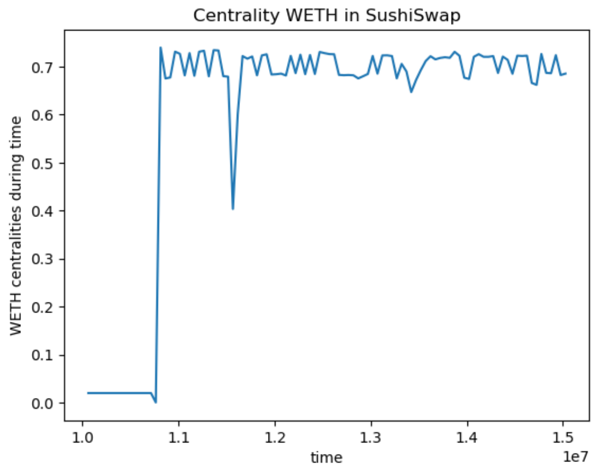
('WETH',0.35397750696443103),
('USDC', 0.05587655078537564),
('USDT', 0.04748929328939108),
('DAI',0.03362380941426781),
('SUSHI', 0.025057445569626222),
('WBTC', 0.013657237010712342),
('OHM', 0.012657063361295861),
('CRV', 0.010106590568482125)

-Centrality Changes During time:

— Interesting events explained with changes in centrality

Changes in centrality of the graphs that are generated during time could show important events in DeFi and Ethereum blockchain, therefore some interesting events have been explained by observing the changes in centralities.

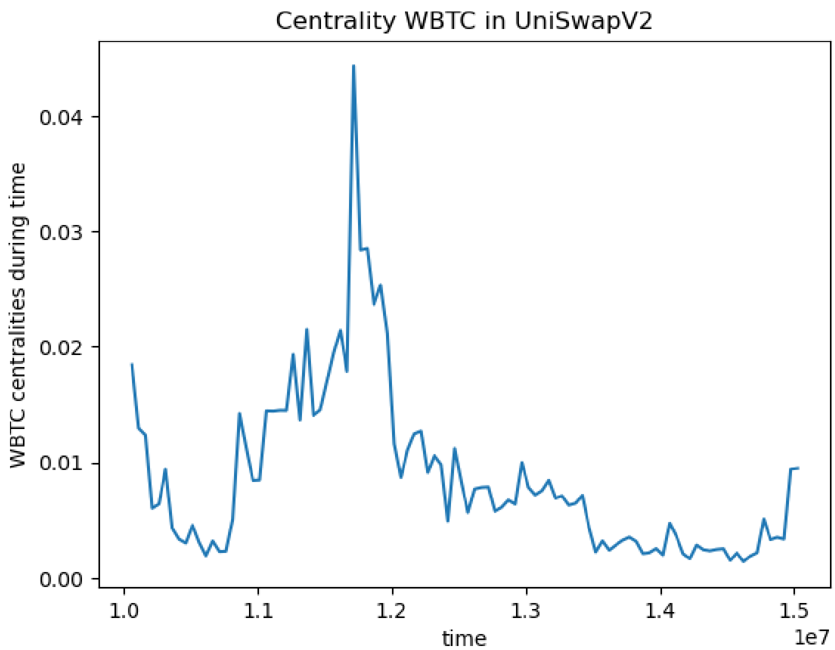
Figure below show the weth centrality in time, and as we could observe there had been a huge drop in centrality of this token between the blocks 11 * 1e6 and 12 * 1e6. After printing the centralities calculated in the graph at the time of the drop, it is observed that a token named ‘Micro’ has become the second most central. Below show the centrality of the tokens in this time:
('USDT', 0.6491668008926491),
('MIC', 0.553542604052636),
('WETH', 0.40337656382533893),
('MIS', 0.2857096686725689),
It means that the MIC token have been severely exchanged probably with a stable coin(USDT).

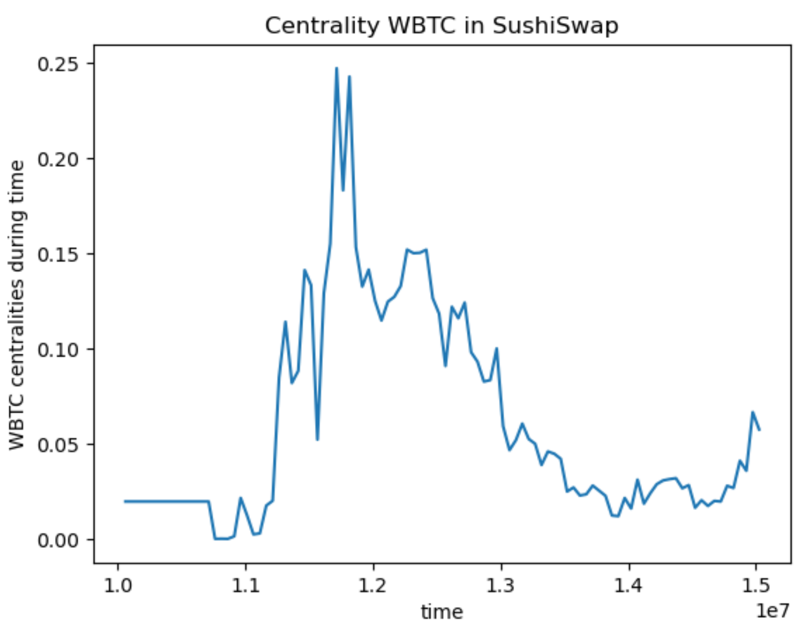


–Similarity of tokens centrality during time between two DEXes and its relation with price

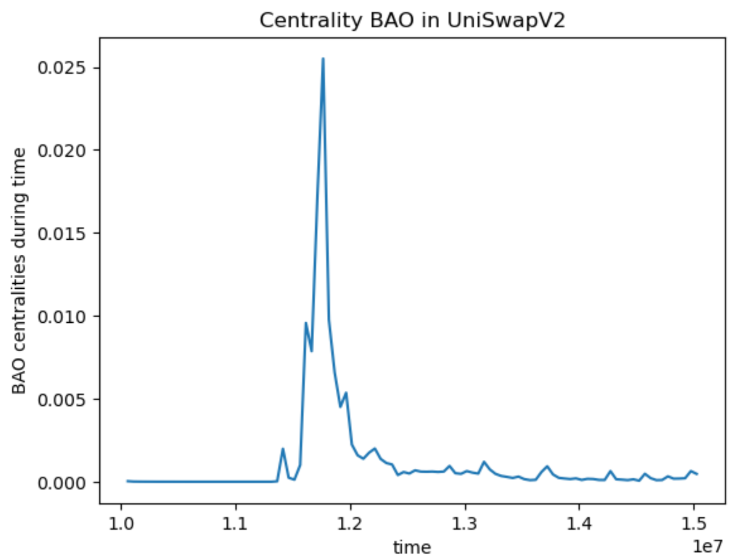
For most of the tokens it is exepted that the relation of the centrality in the graph could be related to the price changes, we draw the plot of changes for some tokens

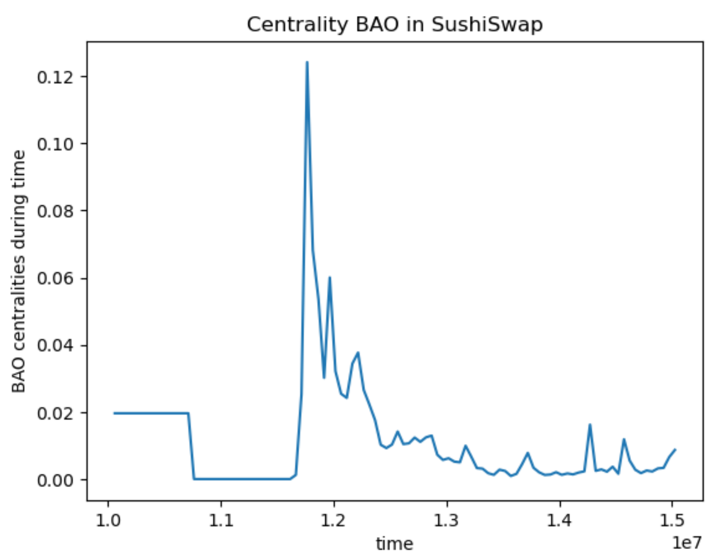
WBTC token:



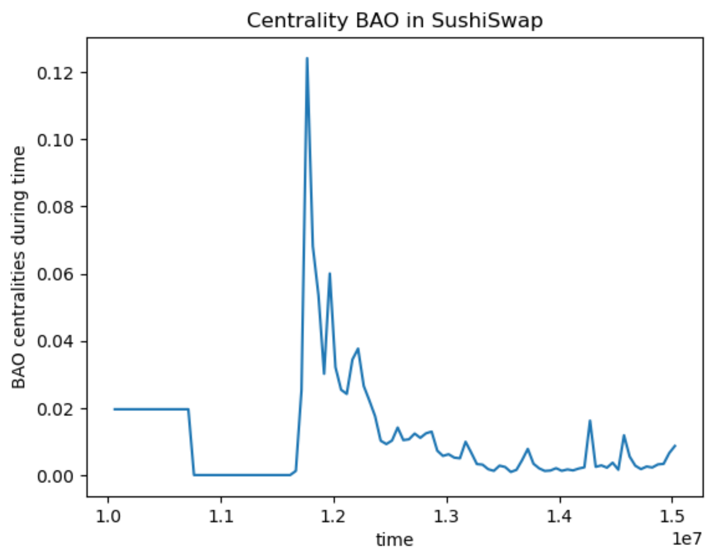


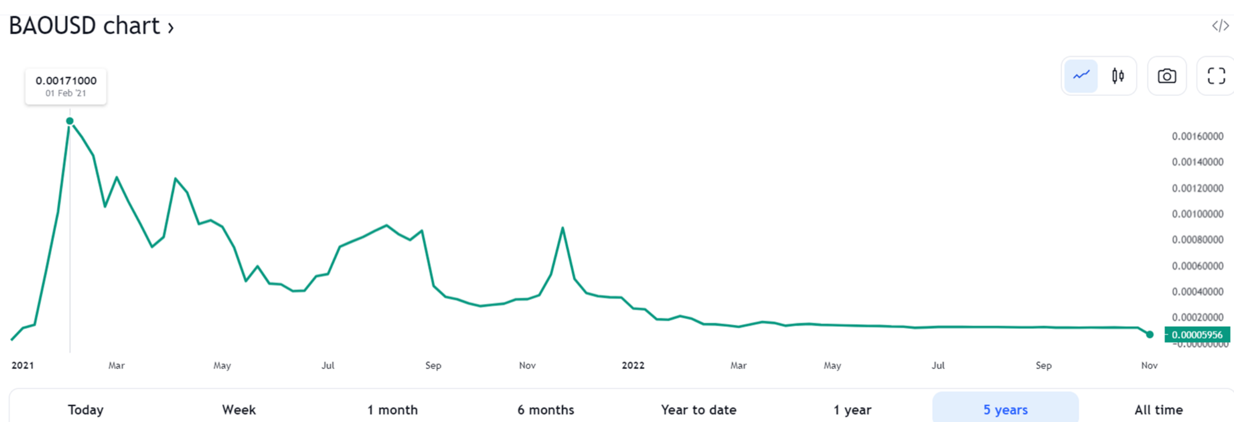
BAO token:





–Relation Price With Centrality

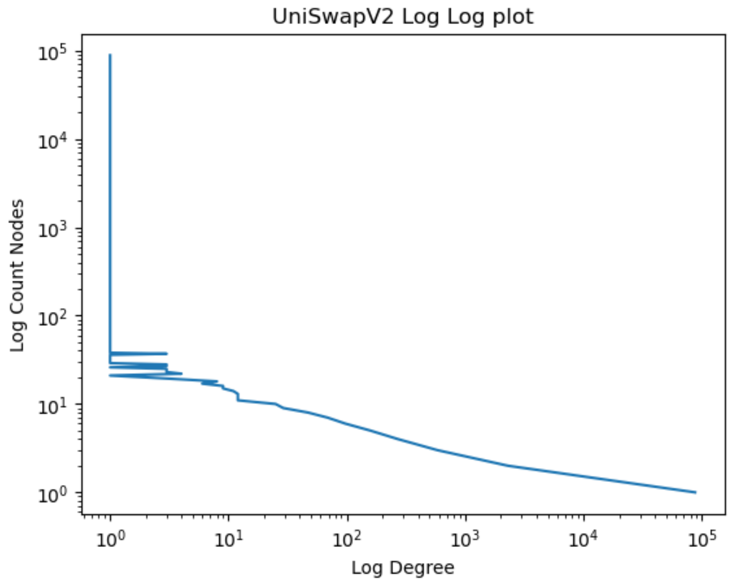


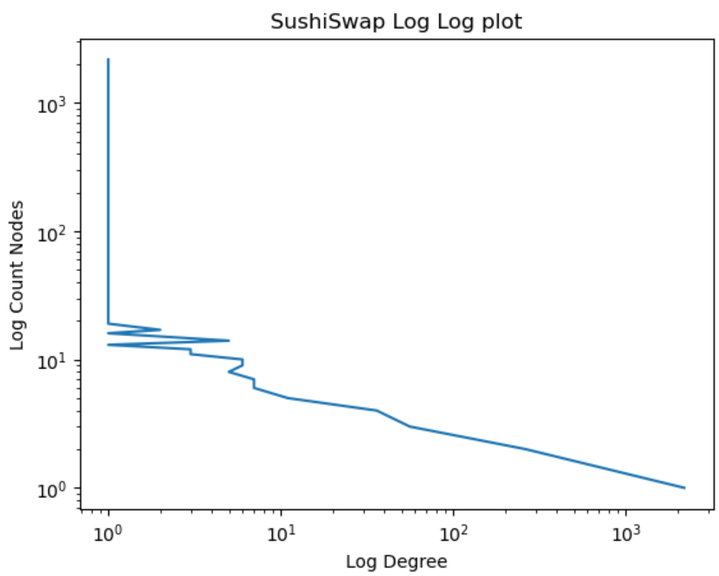


The peak in the graph is the centrality of the graph made from the date February 1st of 2021 till about February 7th of 2021, and as it could be observed in the price chart above in this date the BAO token price has become the maximum price. The reason is related to the fact that when the price of a token decreases or increases people would exchange these tokens more(sell or buy).

Degree Distribution:

Degree distribution for both graphs is calculated in the graph without considering the weights. For checking and fitting the power law distribution the log function has applied to both xaxis and yaxis. For the power law distribution the log function converts the curve to line(i.e ax + b), therefore for both UniSwapV2's and SushiSwap's log degree distribution with linear regression we fitted a line and calculated the p-value.





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                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.437
Model:                            OLS   Adj. R-squared:                  0.425
Method:                 Least Squares   F-statistic:                     37.24
Date:                Wed, 15 Feb 2023   Prob (F-statistic):           1.75e-07
Time:                        20:08:24   Log-Likelihood:                -99.493
No. Observations:                  50   AIC:                             203.0
Df Residuals:                      48   BIC:                             206.8
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          4.5974      0.546      8.413      0.000       3.499       5.696
x1            -0.8435      0.138     -6.103      0.000      -1.121      -0.566
==============================================================================
Omnibus:                       27.729   Durbin-Watson:                   0.209
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               49.789
Skew:                           1.740   Prob(JB):                     1.54e-11
Kurtosis:                       6.434   Cond. No.                         8.89
==============================================================================
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                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.544
Model:                            OLS   Adj. R-squared:                  0.523
Method:                 Least Squares   F-statistic:                     26.20
Date:                Wed, 15 Feb 2023   Prob (F-statistic):           3.95e-05
Time:                        21:47:23   Log-Likelihood:                -40.562
No. Observations:                  24   AIC:                             85.12
Df Residuals:                      22   BIC:                             87.48
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          3.9980      0.556      7.186      0.000       2.844       5.152
x1            -0.8778      0.171     -5.119      0.000      -1.233      -0.522
==============================================================================
Omnibus:                        9.359   Durbin-Watson:                   0.430
Prob(Omnibus):                  0.009   Jarque-Bera (JB):                7.271
Skew:                           1.230   Prob(JB):                       0.0264
Kurtosis:                       4.106   Cond. No.                         6.93
==============================================================================
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As it could be seen in the above figures the p-value for both tests is lower than 0.05 so the degree distribution of both graph obeys the powerlaw distribution.

Average Degree:

Average Degree in these graphs shows that in average how many pools with each token is created. Average Degree in UniswapV2 is about 2.126 and in Sushiswap is 2.432, Therefore in both cases for each token on average there is between 2 or 3 pools that contain it.

Number of Components:

Like other social networks this network in both UniswapV2 and Sushiswap is consist of one giant component and some small components.

Uniswap Components:

[87585 2297 584 271 158 97 69 47 29 25 12 12 12 11 9 9 6 8 4 2 1 4 3 3 1 3 3 1 1 1 1 3 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]

SushiSwap Components:

[2184 263 56 36 11 7 7 5 6 6 3 3 1 5 1 2 1 1 1 1 1 1 1 1]

As it could be observed, the giant component in uniswap consists of 87585, and in Sushiswap is 2184.

Maximum Clique:

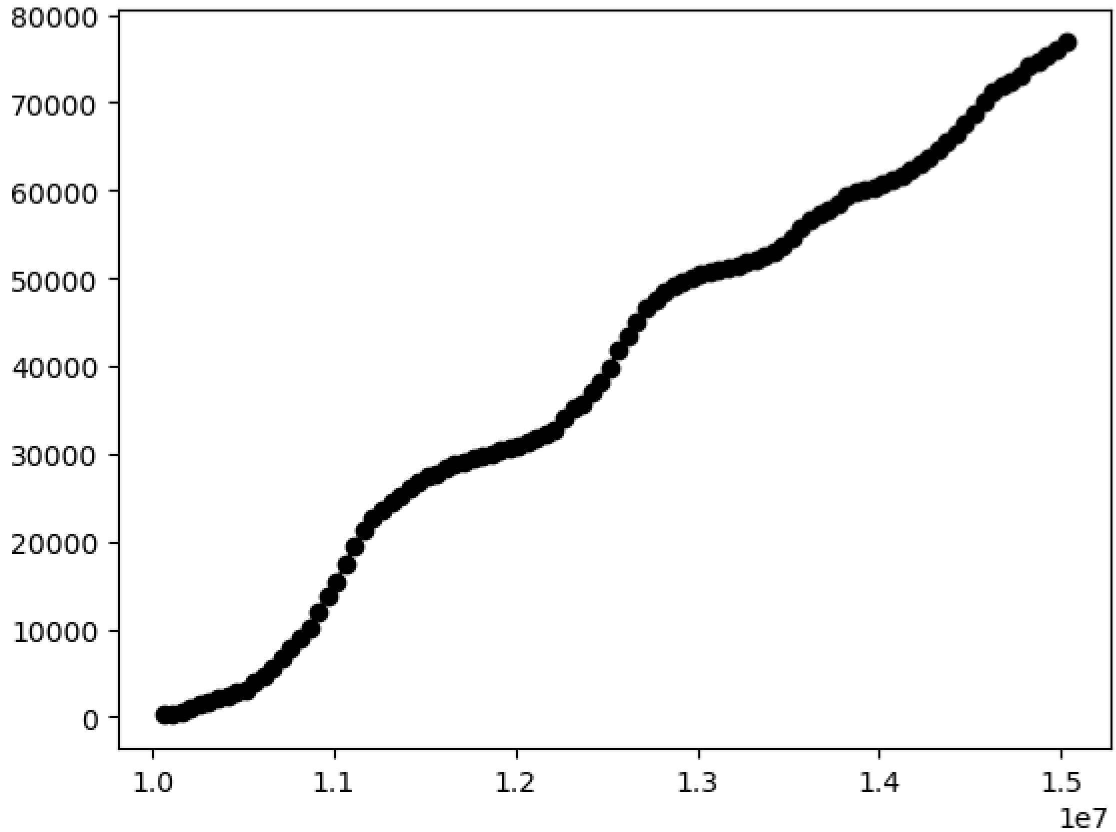
Maximum Clique size in the uniswap unweighted graph is 8 and in the sushiswap the is 10.

Density:

Density could show us how sparaceness of the graph density
UniswapV2 Density: 4.658826306545306e-05
SushiSwap Density: 0.0018689294462905556

Network Diameter:

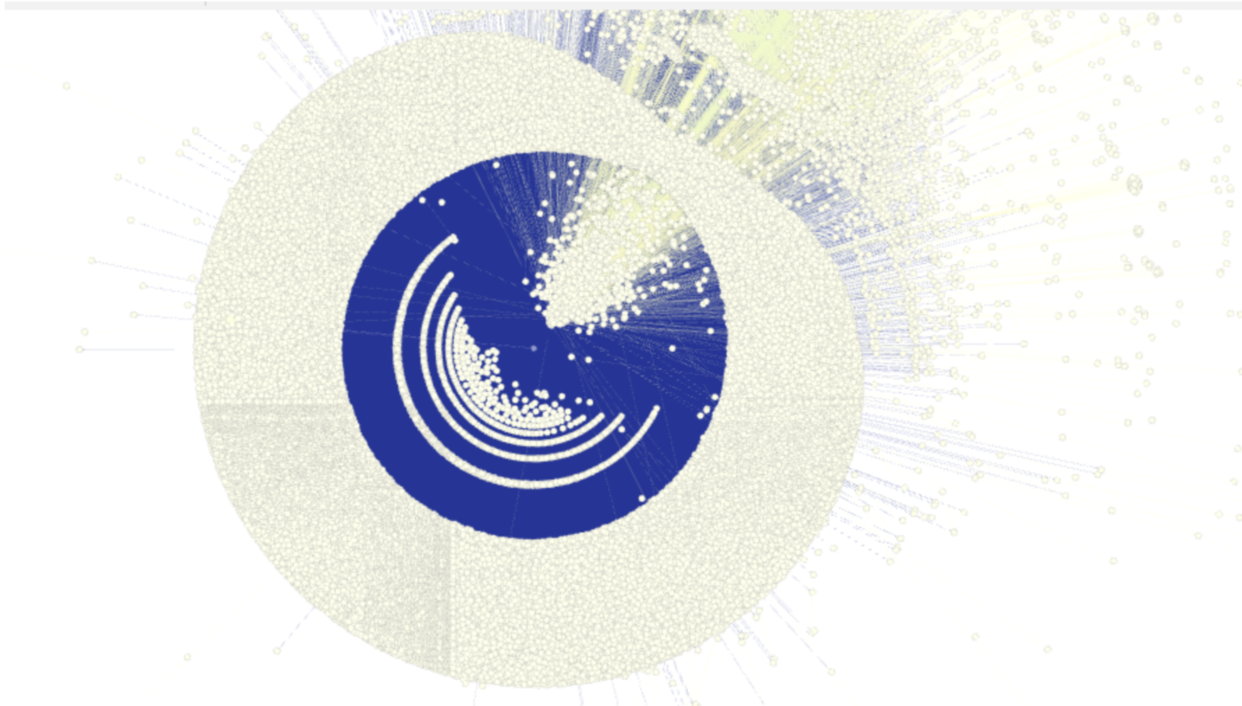
Number of edges during time(Number of pools during time):



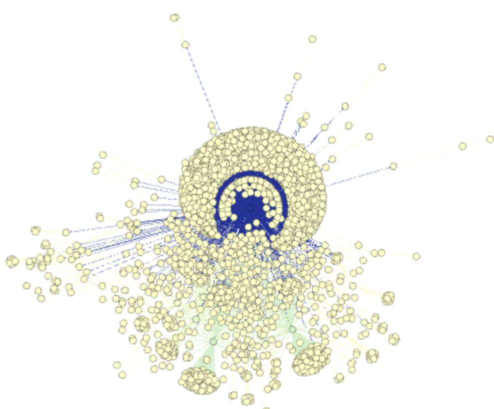
Visualization of the graph:

Weighted graph for both dexes have been visualized. Both graph have a core and most of the edges are between these nodes in the core, and this is visible in the visualizations.

–-UniswapV2 weighted graph Visualization



—SushiSwap weighted graph Visualization:



Future Works:

From the properties of these graphs some ML models and predictors could be created and predict the graph through the future and based on the predicted graphs the price of the tokens could be predicted. Also with usage of centrality in these graphs it is possible to find out the reason for some events that could not be explained with just economic science.

References:

1. Coinmarketcap. https://coinmarketcap.com/
2. Cryptocurrencies activity as a complex network: Analysis of transactions graphs https://link.springer.com/article/10.1007/s12083-021-01220-4
3.