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Identifying Interesting Fraudulent Behavior in the Bitcoin Trust Network

Overview

Bitcoin is not only a decentralized system but a grassroots driven technology involving multiple stakeholders (Sas and Khairuddin, 2015). In this report, we describe our analysis of the OTC Bitcoin dataset and Bitcoin transactional dataset. The Bitcoin OTC is an over-the-counter marketplace for trading with bitcoin. Due to the peer-to-peer (p2p) nature of OTC transactions, people are exposed to counterparty risk. To mitigate this risk, OTC offers access to a web of trust service which offers information about the counterparty's reputation and trade history. In order to identify malicious behavior from the Bitcoin trust networks, we first explored our bitcoin data to understand the correlation between trust and value of Bitcoin. We examined Bitcoin market values, bitcoin transactions, average trust (through the web of trust) and count of trust by month to understand *technological trust*, which Bitcoin users experience before, during and after engaging in online transactions (Sas and Khairuddin, 2015). From this exploratory task, we discovered that the price of Bitcoin and the transaction flow provides negative effects on the trust network. As the price and the number of transactions rise, the Bitcoin OTC users tend to receive more negative ratings than positive ratings.

Research Questions and Motivation

Trust is a fundamental foundation for Bitcoin transactions (Mazzella et al. 2016, p. 27). Thus, defining how user trustworthiness is evaluated is an important factor in Bitcoin trading platforms.
Our research questions are:

1. How does trust correlate to the value of Bitcoin?
2. Can we identify which actors are detrimental to trust in the network?

Related Work

- Kumar et al introduce a system to identify fraudulent users through analyzing networks called using REV2 algorithm. They use three independent metrics:

fairness of a user, reliability of a rating and goodness of a product [1]

- Sas et al explains the challenges and opportunities of Bitcoin users face within the Bitcoin network. As Bitcoin uses unregulated and decentralized blockchain technology, individuals have an opportunity to become more empowered and privileged to gain control over their own money. This also means there is a considerable risk factor of dishonest partners with whom one engages in Bitcoin transactions. [2]
- Since users' trust is challenged by their limited knowledge about buyers and whether their payment will be received in time or at all [3], scammers tend to use this risk to cheat or betray their transaction partners.

Datasets and data collection: For this project we collected the following data:

- Reviews: We crawled the OTC platform such that we collect all the posted reviews of the users. There are approximately 6000 users with a total of around 32000 reviews.
- Transactions: We crawled the OTC platform to collect the bitcoin address. For each address find the transactions where that address was involved and find the input and output values in that transaction that corresponds to the address.

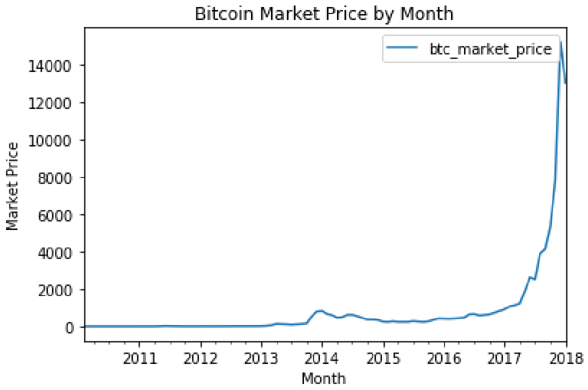
Methods (describe the methods you used in your project)

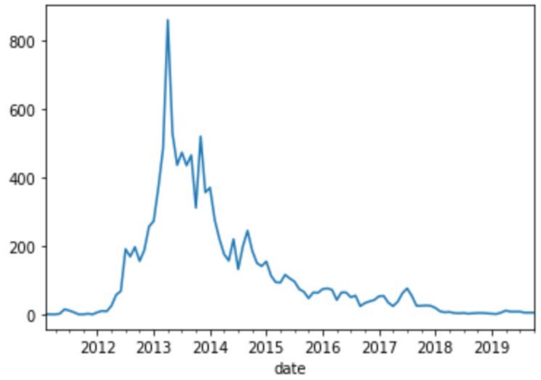
Analyzing Bitcoin transactions

We found a Bitcoin transactional dataset from 2/7/2010 to 1/31/2018. There was a total of 1,951,883 Bitcoin transactions in the data. Unfortunately, we couldn't find transaction ids in the dataset that match to the OTC review dataset. However, we could analyze Bitcoin market values and transaction flow.

Bitcoin market values by month (2011 - 2018)

Number of transactions in the OTC network (2011 - 2019)

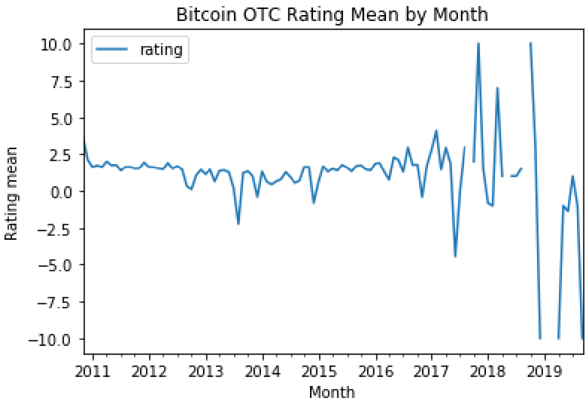




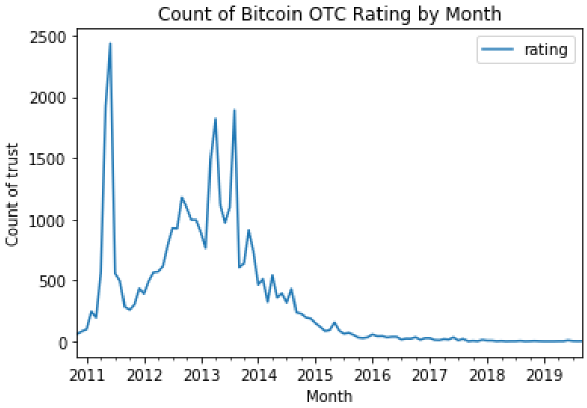
Analyzing review in the OTC trust network

We collected the Bitcoin OTC review data of 5,959 users, which has a total 37,610 net ratings points. In total, 32,388 positive ratings and 3,476 negative ratings were sent among OTC users. We converted the collected JSON files to pandas dataframe and examined average trust and count of trust within OTC network by visualizing the trust network.

Average trust ratings by month (2011-2019)



Count of trust by month (2011 - 2019)



Analyzing the evolution of the trust network over time and the correlation with the transaction flow and price of Bitcoin

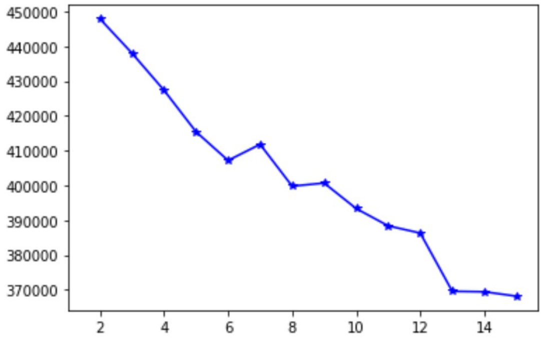
Considering the lags in our time series, we used cross correlation functions (CCF) to compute synchrony metrics using Pearson correlation. For this exploratory analysis, we measured the correlation between average OTC rating and Bitcoin market price, average OTC rating and number of transactions, and count of ratings and number of transactions. We analyzed two variables by day, by week, by month as well as by year.

Analyzing clusters

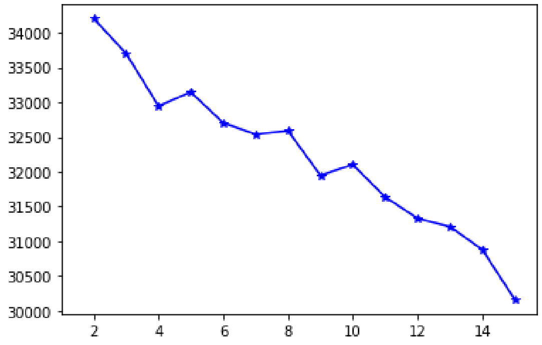
Using the network's adjacency matrix

We used two approaches for running clustering based on the network's adjacency matrix: a weighted matrix where each edge cell i,j is filled with the review one node i gave to a node j, and an unweighted matrix where each edge cell i,j is filled with a 1 if node i reviewed node j and 0 otherwise.

Weighted adjacency matrix elbow plot



Unweighted adjacency matrix elbow plot



According to the elbow plots we set the number of clusters for both cases to be 4.

To visualize the clusters, we used Principal Component Analysis (PCA) reduction dimensionality method.

Using features of each node

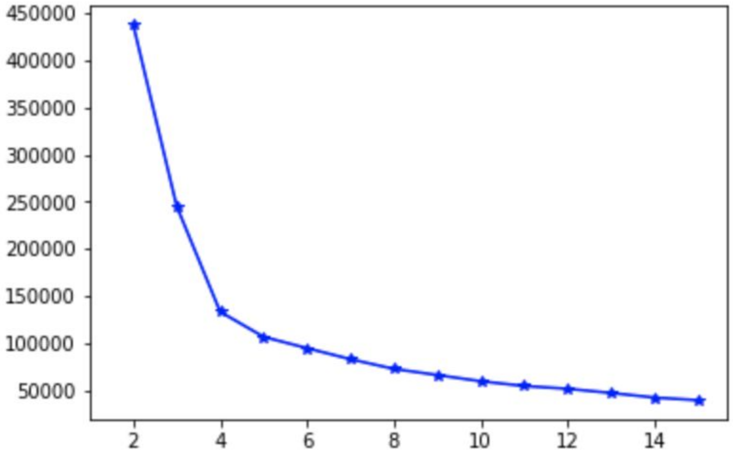
Features for each node (5952 nodes) are found using graph features and transaction values. These features are:

1. Closeness centrality
2. Betweenness centrality
3. Clustering coefficient
4. Out degree
5. In degree

6. Average transaction sent in USD
7. Average transaction received in USD
8. Mean transaction in USD
9. Number of transactions

There are some null values in the dataset, therefore we used SimpleImputer in the scikit-learn library to fill the nulls with mean values and indicated which row are nulls.

After that, we ran these features in an unsupervised K-Means clustering. Before choosing the clusters, we used an elbow method to choose the number or clusters. According to the elbow method, 4 clusters are the best number of clusters.



To visualize the clusters, we used Principal Component Analysis (PCA) reduction dimensionality method.

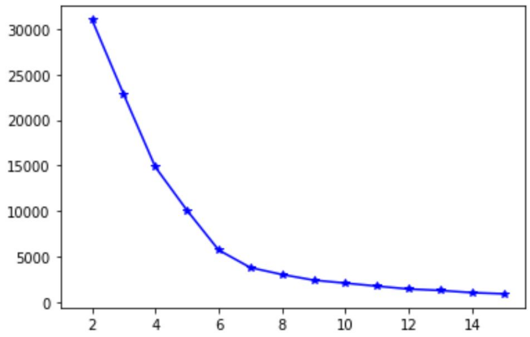
Using combined matrix and transaction features

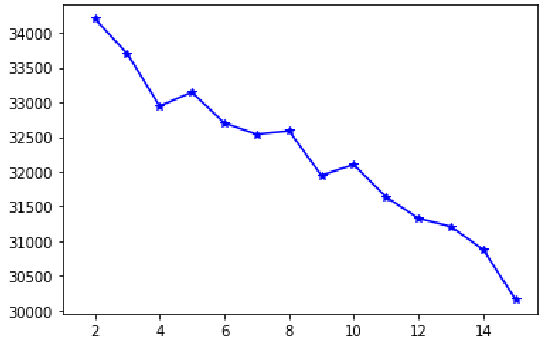
We combined the transaction features of the nodes with the output of clustering with the adjacency matrix to avoid a situation where the adjacency features overpower the transaction features.

1. Average transaction sent in USD
2. Average transaction received in USD
3. Mean transaction in USD
4. Number of transactions

We also made use of imputed values based on the average and signaled with 1 and 0 in an additional column (0 when the value is not present) to overcome the lack of transaction values of some nodes.

We used the elbow method to determine the number of clusters in this case 6 for the weighted and 4 for the unweighted.


Weighted adjacency matrix elbow plot

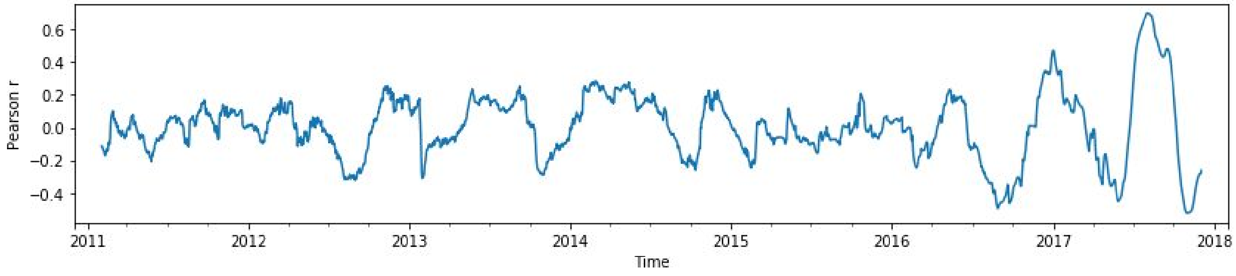

Unweighted adjacency matrix elbow plot

Results

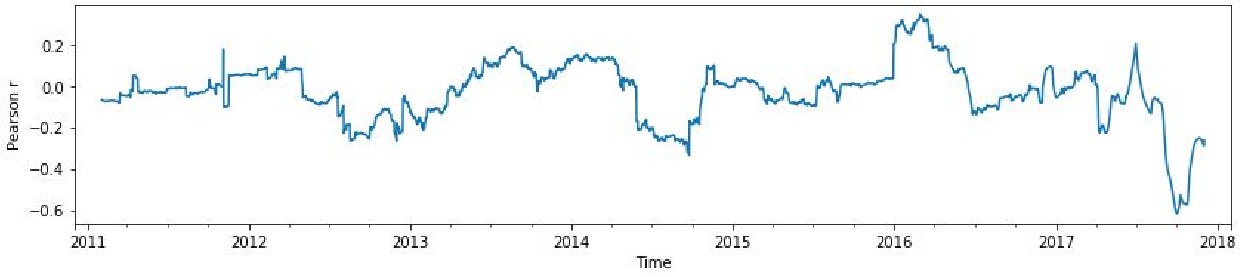
<u>Analyzing the evolution of the trust network over time and the correlation with the transaction flow and price of Bitcoin</u>

Trust has been described as the subjective belief in the character, ability, strength, reliability, honesty or truth of someone or something (Grandison and Sloman, 2000). In order to identify any correlations between trust and Bitcoin market, we analyzed the Bitcoin market values, bitcoin transactions, average trust and count of trust to identify some patterns. Using CCF and measuring the pearson correlation, we couldn’t find a distinct relationships between OTC trust ratings and transactions. The overall pearson coefficient of average ratings and Bitcoin market price was 0.11. Whereas, the correlation of average ratings and number of transactions indicated -0.02. Even if we measured in different time scales such as by day, by week and by year, the results ranged from as low as -0.2 to as high as -0.01.

Correlation between average OTC trust ratings vs Bitcoin market price



Correlation between average OTC trust ratings vs number of transactions



As Bitcoin uses unregulated and decentralized blockchain technology, individuals have an opportunity to become more empowered and privileged to gain control over their own money. This also means there is a considerable risk factor of dishonest partners with whom one engages in Bitcoin transactions. (Sas and Khairuddin, 2017) Since users' trust is challenged by their limited knowledge about buyers and whether their payment will be received in time or at all (Shcherbak, 2014), scammers tend to use this risk to cheat or betray their transaction partners. However, from this exploratory analysis, we could not find any distinct negative effects on the trust network from the price of Bitcoin and the transaction flow.

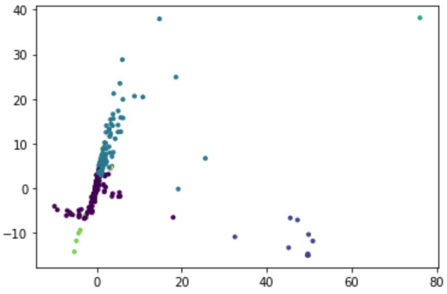
Analyzing clusters

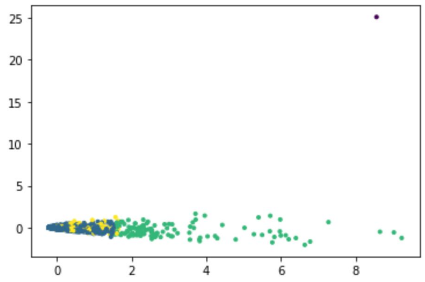
Using adjacency matrix

Below is the representation of the K-Means clustering using 4 clusters and a PCA method to reduce the dimension for visualizations for both weighted and unweighted adjacency matrices.

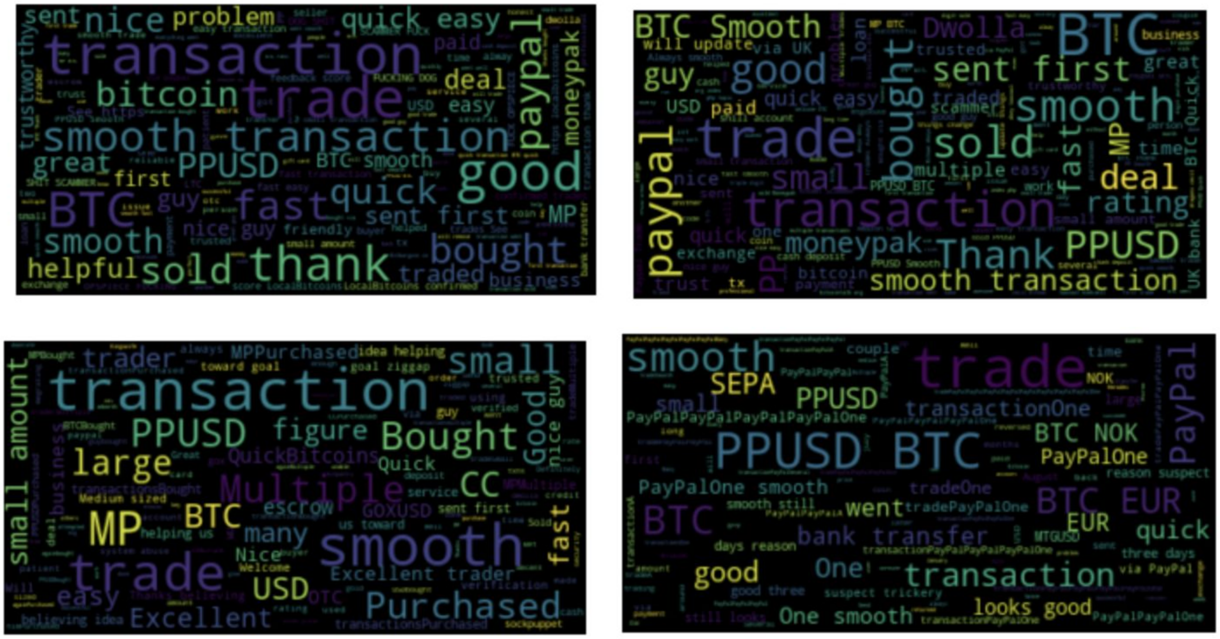
Weighted adjacency matrix PCA

Unweighted adjacency matrix PCA

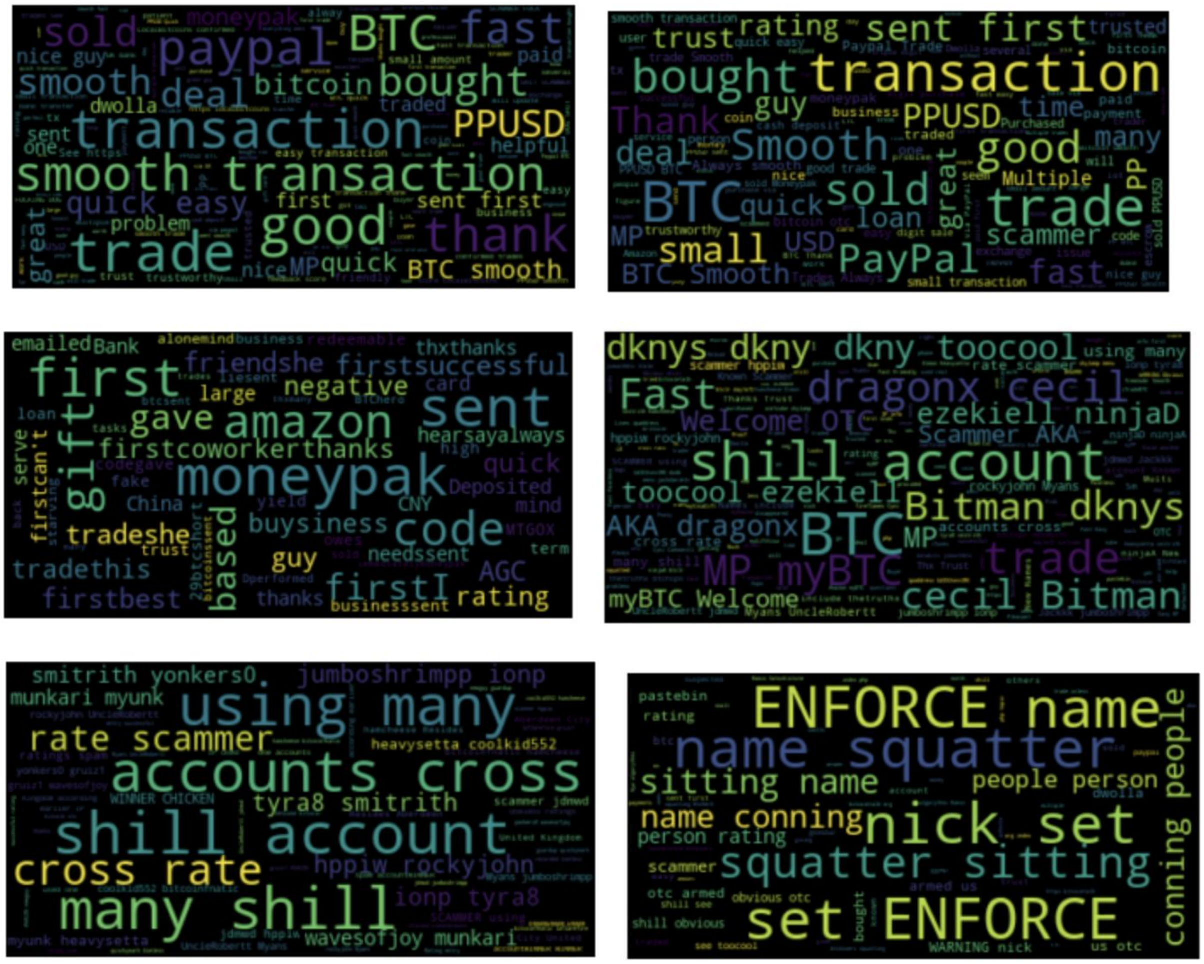




We’ve included word clouds that describe some commonly used words in the identified weighted and unweighted adjacency matrix clusters. Upon initial exploration, it is evident that the weighted network is doing a better job at identifying reviews related to fraudulent behaviour as the word ‘shill’, for example, is clearly dominant in two clusters.



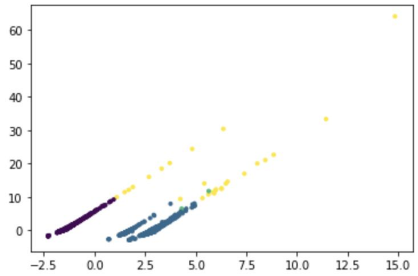
Resulting word clouds of the **unweighted** adjacency matrix clusters



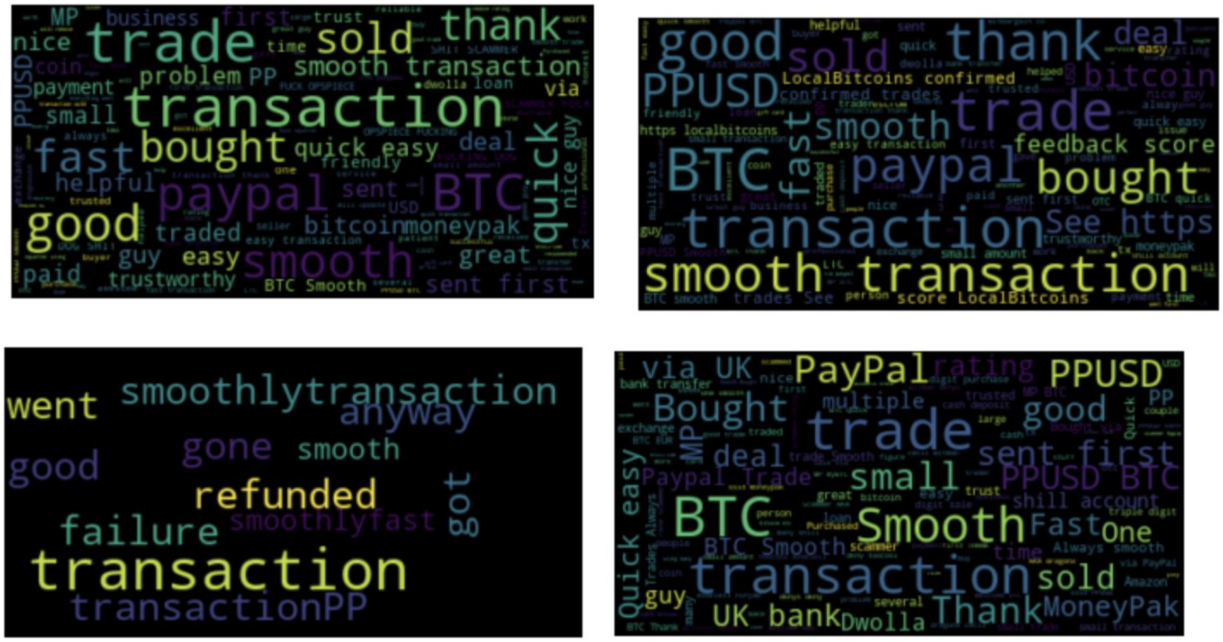
Resulting word clouds of the **weighted** adjacency matrix clusters

Using features of each node

Below is the representation of the K-Means clustering using 4 clusters and a PCA method to reduce the dimension for visualizations.



Using the feature matrix alone, we can also see a cluster emerge with more fraudulent behaviour. However, it is important to note the scarcity of nodes identified in this cluster.

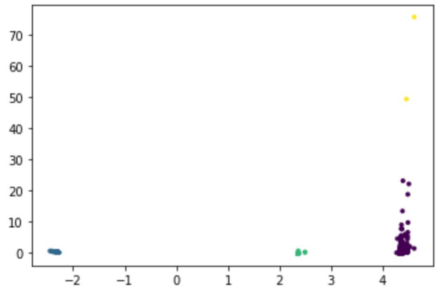


Resulting word clouds of the feature matrix clusters

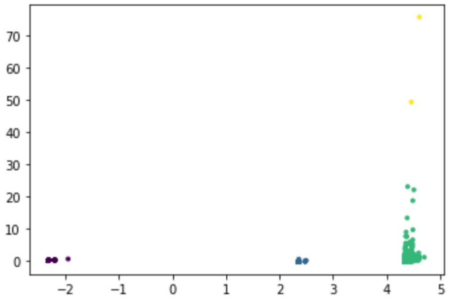
Using combined features matrix

Below is the representation of the K-Means clustering using 6 and 4 clusters and a PCA method to reduce the dimension for visualizations for both weighted and unweighted adjacency matrices.

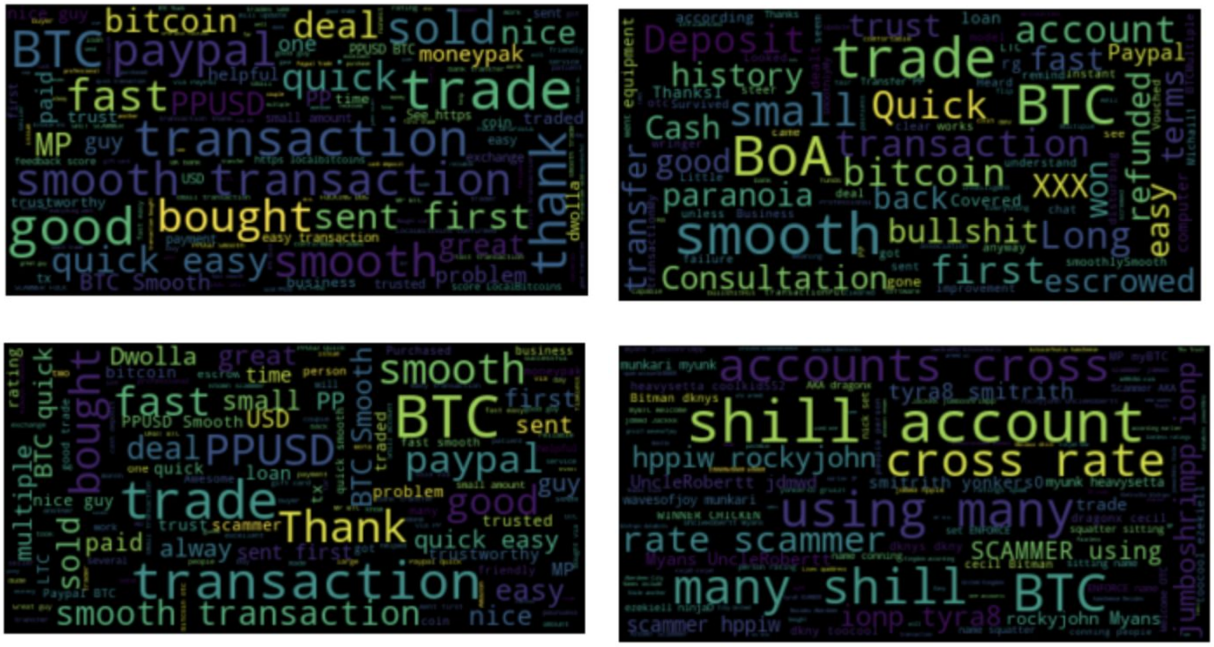
Weighted adjacency matrix PCA



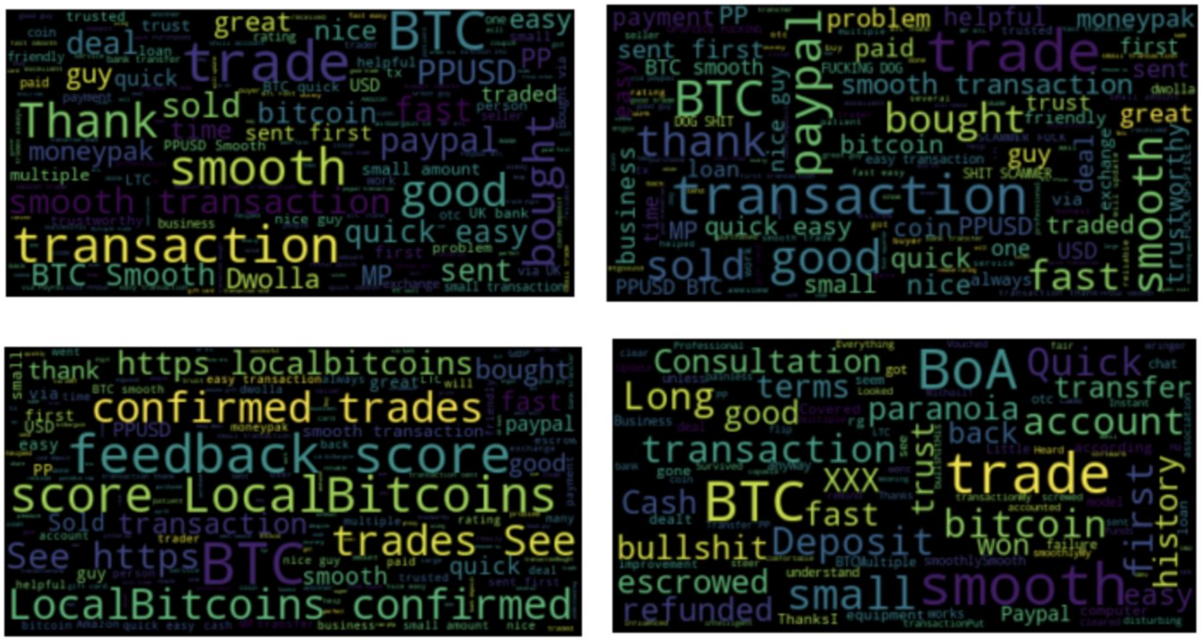
Unweighted adjacency matrix PCA



Upon exploring the corresponding word clouds, we find that having no null indicator (no indicator that missing values were imputed with means) performed better. Although the bottom right with the null indicators seems to indicate reviews of fraudulent behaviour, it seems to be mixed with other types of reviews.

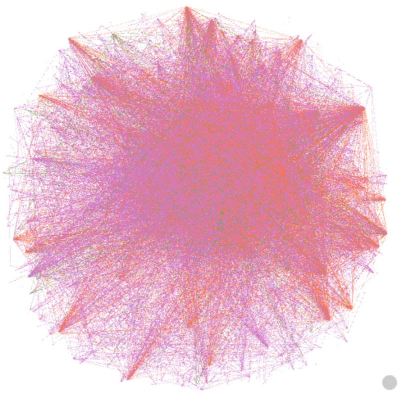

BTC paypal bitcoin deal sold nice quick trade fast PPUSD moneypak MP transaction smooth transaction good bought sent first thank quick easy smooth great problem
Deposit trust account trade history fast Paypal small Quick BTC Cash BoA transaction bitcoin good paranoia XXX back smooth bullshit Long transfer refunded easy Consultation first escrowed
Dwolla great time smooth fast small PP USD BTC first sent deal PPUSD paypal bought trade good quick Thank transaction easy smooth transaction nice
accounts cross shill account hppiw rockyjohn cross rate using many rate scammer SCAMMER using many shill BTC scammer hppiw lonp tyra8

Clusters from combining features and weighted adjacency matrix with no indicator of imputed values



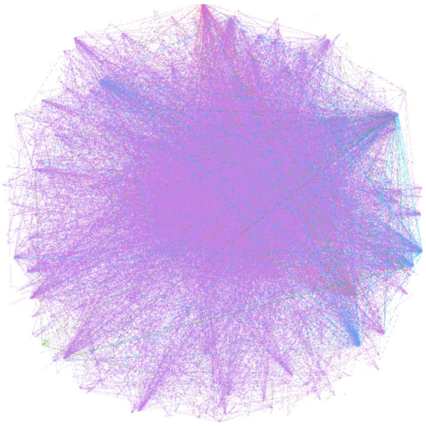
Clusters from combining features and weighted adjacency matrix with indicator of imputed values

Network clusters visualizations:

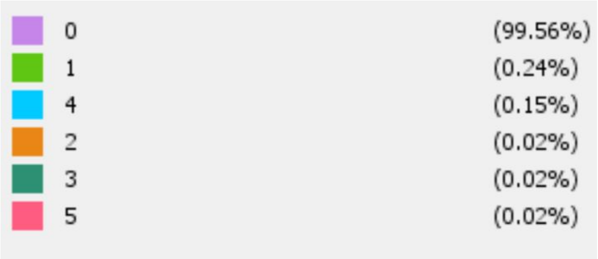


Adjacency matrix unweighted

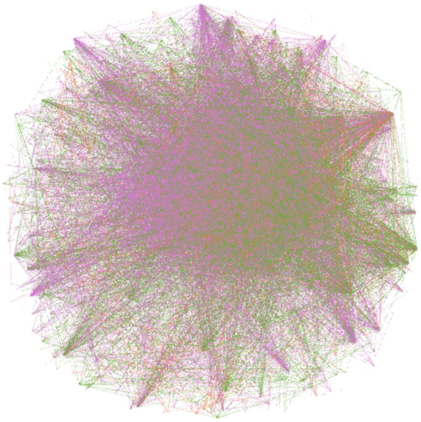
🟪	1	(89.43%)
🟩	3	(8.52%)
🟧	2	(2.03%)
🟦	0	(0.02%)



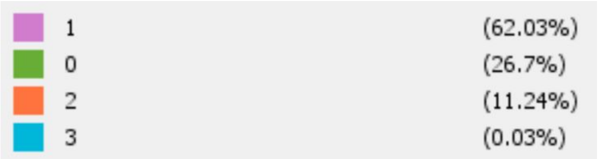
Adjacency matrix weighted



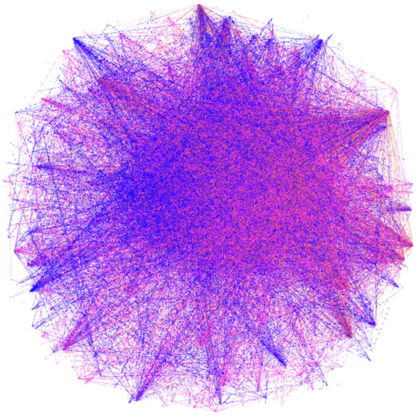
🟪	0	(99.56%)
🟩	1	(0.24%)
🟦	4	(0.15%)
🟧	2	(0.02%)
🟩	3	(0.02%)
🟥	5	(0.02%)



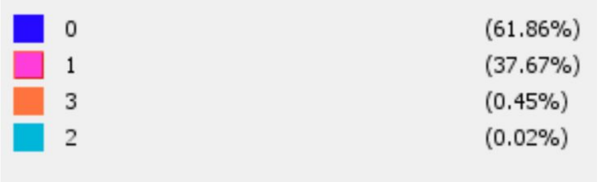
Combined cluster unweighted/weighted



🟪	1	(62.03%)
🟩	0	(26.7%)
🟧	2	(11.24%)
🟦	3	(0.03%)



Network structural attributes + transactions



🟦	0	(61.86%)
🟪	1	(37.67%)
🟧	3	(0.45%)
🟦	2	(0.02%)

Challenges

- Initial hypothesis about the positive correlation between the trust network and Bitcoin market price did not hold
    - We used multiple strategies to look at the cross correlation function between ratings given and the Bitcoin market price that includes daily,

monthly and yearly but all proved either no correlation or negative correlation.

- Lack of ground truth
    - Our exploratory analysis was based on the contrast of different sources of information and observing the effects of using different properties in others that we consider descriptive of certain behaviours, like the comments made in the reviews that we used for descriptive word clouds
- Lack of transactions for all users in the OTC network
    - We imputed values but also complemented this approach with flags that penalize weights for data points that lack information.

Conclusions

We concluded our subset of members of the bitcoin Network presents in OTC is not representative to explain any of the global price variations. Additionally, the rating behaviour over time seems unrelated to the number of transactions between these individuals in the OTC network. And because the clusters that could characterize fraudulent behaviour are a very small proportion of the total nodes of the graph, we find that removing these nodes does not have a significant impact on our previous correlation analysis.

References

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