Safe Bitcoin Trading by Analyzing Weighted Signed Networks of Reviews

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***Abstract*—A successful platform for cryptocurrency trading relies on the level of trust that is formed in between the two sides of a trade. The higher the number of successful trades, the higher the commissioning fee the platform earns. Having a bad experience on a platform may repel the current traders from the platform and also prevent new traders from joining the platform. Therefore, having a robust suggestion algorithm by implementing different regressions that can predict the outcome experience of a trade between users based on the ratings they have received before, will be of great benefit to the platform. Since Bitcoin users are anonymous, there is a need to maintain a record of users' reputation to prevent transactions with fraudulent and risky users.**

I. Introduction

In 2009, a white paper was published describing a new system called "Bitcoin" that has become a a global currency. Bitcoin is a new technological network, a non-governmental currency, with a global group of users. As Bitcoin involves complex human-technology interactions, it is a complex socio-technical system. Therefore, it is essential that people who use and interact with such systems trust in those systems [1].

Trust refers to the willingness of one party to be liable to the actions of another party based on the expectation that the other party will perform an important action to the trustor, regardless of the ability to supervise or control that other party [2].

Current Bitcoin trading lacks protection against money transfers and it doesn't have an approvable structure by governments. However, it is essential to understand the concept of all digital currency technology [3].

In this research we assume the users are being suggested for a possible trade by the suggestion engine of our trading platform (which is based on the balance theory), we want to make sure that this engine suggests as many successful trades as possible and prevents as many unsuccessful trades as possible. The results from the study of over- or under- presentation of triads are indicative of the robustness of such an engine.

II. DataSet

The Data used in this work are from the Stanford Large Network Dataset Collection (SNAP). Two datasets are used:

- "soc-sign-bitcoin-otc " dataset from the Stanford Large Network Dataset Collection. This dataset lets us know who-trusts-whom to trade using Bitcoin on a platform called Bitcoin OTC. Members of Bitcoin OTC rate other members in a scale of -10 (total distrust) to +10 (total trust) in steps of 1.
  1) SOURCE: node id of source, i.e., rater
  2) TARGET: node id of target, i.e., ratee
  3) RATING: the source's rating for the target, ranging from -10 to +10 in steps of 1
  4) TIME: the time of the rating, measured as seconds since Epoch

Data	Value
Nodes	5,881
Edges	35,592
Range of edge weight	-10 to +10
Percentage of positive edges	89%

Table I
Bitcoin OTC Dataset statistics

Data	Value
Nodes	3,783
Edges	24,186
Range of edge weight	-10 to +10
Percentage of positive edges	93%

Table II
Bitcoin Alpha Dataset statistics

- "soc-sign-bitcoin-alpha " dataset from Stanford Large Network Dataset Collection. Same as the first dataset, this one lets us know who-trusts-whom to trade using Bitcoin on a platform called Bitcoin Alpha. Members of Bitcoin Alpha rate other members in a scale of -10 (total distrust) to +10 (total trust) in steps of 1. This dataset contains following columns:

1) SOURCE: node id of source, i.e., rater
2) TARGET: node id of target, i.e., ratee
3) RATING: the source's rating for the target, ranging from -10 to +10 in steps of 1
4) TIME: the time of the rating, measured as seconds since Epoch.

The brief statistics of the two Datasets is available in Table 1 and 2.

III. Methods and analysis

Two approaches are used to estimate the outcome of a future trade. Shuffling with balance theory, and regression-based models. To perform the tasks, first we extract the number of triads and count the total of each type of triad. Then, keeping the same ratio of the positive and negative edges, we shuffle the edge signs and assign new edge signs to the existing triads and count the new number of each type of triad. The numbers of each type of triad is compared between the original data and the count extracted from the shuffled data. If a triad is over-presented in the original data compared to the shuffled data, it means that the shuffling is less likely to give that type of triad. At the next stage, the data is filtered by the rating value to just keep the strong trust and distrust ratings. Because we don't want the procedure to treat the strong ratings the same as the more neutral ratings. If the filtered data performs better, it means that we can use the same ratio of positive and negative edges to generate the shuffled predictions.

Finally linear regression, and gradient boosting regression models are used to predict the weight of edges.

IV. Results and Discussion

As seen in Table III, the T3 types are slightly over-presented (by 1 and 13 percent) while the T2 types are under-presented (by 27 and 59 percent). This means that if we want to estimate the outcome of a future trade, just by shuffling the signs of the current edges (while preserving the ratio of positive and negative edges) we are likely to identify the triad containing the trade as a ++- while we are less likely to identify it as a +++ compared to the actual outcome of the future trade. As the ++- triads are undesirable (resulting in bad experience of two users who had already been trusted by others), over-estimating them by a trade suggestion engine helps saving the good reputation of the platform but at the cost of a possible successful trade.

Data	Ti	$\|Ti\|$	P(Ti)	P0(Ti)	s(Ti)	P0(Ti)$_{filtered}$
Alpha	T3 +++	98349	0.841	0.829	11.40	0.445
	T2 ++-	13634	0.117	0.16	-40.8	0.41
	T1 +–	4590	0.039	0.011	95.6	0.127
	T0 —	331	0.003	0	61.2	0.018
OTC	T3 +++	135845	0.826	0.726	91.1	0.186
	T2 ++-	16868	0.103	0.246	-134.9	0.422
	T1 +–	11095	0.067	0.027	99.9	0.325
	T0 —	659	0.004	0.001	36.4	0.067

Table III
NUMBER OF UNDIRECTED TRAIDS FOR THE TWO DATASETS

In Table III, the T3 type is highly over-presented in the data compared to the shuffled graph generated based on the filtered data (—Rating— ¿ 3) while the T2 is highly underpresented. This means that if we just reshufle the edge signs with the ratio of positive and negative edges existent in the filtered data, we would be very safe as we are highly over-estimating the number of T2s. It shall be noted that this comes as a cost: the T3 type is highly under-estimated. However, keeping in mind that the goal of a suggestion engine is to gurantee good experiences, this challenge can be justified.

R scores for Bitcoin OTC		
	Two features	Five features
Linear Regression	0.0427	0.2791
GradientBoostingRegressor	0.4117	0.5724

Table IV
R SCORE FOR PREDICTION MODEL

V. Conclusions

Two approaches were used in this project to estimate the outcome of a trade in a crypto-currency trading platform. The first approach was based on the balance theory in which the edge signs of generated triads were shuffled and the distribution of actual triad types were compared to the distribution of the triad types gnerated through the shuffling method. The outcome of this prediction can be used by a suggestion engine to suggest a trader to another trader. The goal of this suggestion engine is to gurantee successful trades for the users of the trading platform.

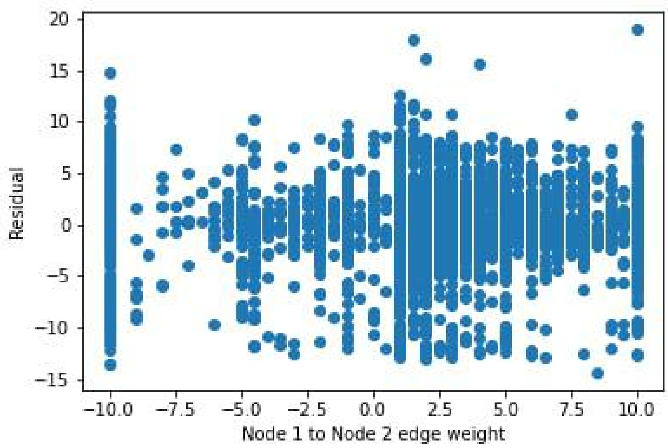

Figure 1. Residuals of GradientBoostingRegressor for R=0.57 in Bitcoin OTC regression

As a result, the higher the confidence in the result, the better. If the undesirable triad types are under-presented in the actual data compared to the shuffle data, it means that by shuffling the edge signs we are more likely to get an undesirable estimation than it may happen in reality. This means that the engine works on the safe side!

Finally, two regression-based models were used to estimate the rating outcome of a future trade. The linear regression-based model was not so successful in estimating the weights, scoring very low. However, the gradient boosting regressor was able to give better results even by using low number of features (just the total ratings of the two sides of a trade).

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