Safe Bitcoin Trading by Analyzing Weighted Signed Networks of Reviews

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***Abstract*—Cryptocurrency trading platform is a weighted signed networks (WSNs) where the trading among users is based on a who-trusts-whom network. In this network, edges are labeled with positive and negative weights which captures trust/distrust relationships between them. The aim of this work is to develop an algorithm that can predict the outcome of a trade between users based on the ratings they have received before. By maximizing the number of successful trades in the platform, the commissioning fees will be maximized.**

I. INTRODUCTION

In 2009, a white paper was published describing a new system called "Bitcoin", which has grown into a global currency. Bitcoin is a new technological network, a non-governmental currency, with a worldwide group of users. As Bitcoin involves complicated interactions between humans and technologies, it is a complex socio-technical system. Therefore, it is critical that people who use and interact with such systems trust in those systems.

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

A successful platform for cryptocurrency (ex. Bitcoin) 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 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.

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

In order to investigate the idea, the input data and methodology should be defined. As mentioned in the previous section, the input data for analysis contains large-scale data-sets of signed review/relationship records between the Bitcoin traders of a platform, and the methodology for the analysis is balance theory based on which the relationships within networks could be interpreted and forecasted.

The first step would be extracting the number of nodes and edges, the ratio of positive and negative edges, and the total number of triads with focus on the complete triads in the datasets. It should be mentioned that extracting the number of all positive triads representing the trust triangles. These triangles are one of the main sources of commissioning revenues.

These triads are directed, but if we want to go further, in the second step, we should consider four types of triads can occur in the calculating of undirected triads. The occurrence and frequency of +++, +–, ++-, and — triads are calculated in both existing and the randomly signed data.

In the last step of analysis, a surprise value is calculated, representing the deviation of the actual frequency from that of the random-shuffling model.

IV. Results and Discussion

The goal of this work is to maximize the number of successful trades in the platform which will maximize the commissioning fees. This is achieved via supporting trustworthy users and limiting un-trustworthy ones! Furthermore, to keep the trustworthy users happy, the suggestion algorithm of a trade shall never propose an un-trustworthy person for a trade to trustworthy ones. The over- and under- presentation in the network model for certain types of extracted triads are interpreted as risk or value factor for the platform. Finally, the effects of trust level are also investigated both on the robustness and revenue guarantee of the model.

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

TABLE III
R score for prediction model

V. Conclusions

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