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Prediction of Link Weight of bitcoin Network by Leveraging the Community Structure

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Abstract — In this work, the issue of predicting the edge weight in Bitcoin network has been addressed by leveraging community structure that involves members who trust with each other in their transactions. The proposed model consists of two main stages; the first one is the detection of trusted Bitcoin communities by implementing Newman-Girvan algorithm. In the context, the attributes of node have been modeling in different ways to get different structure of communities each time. Secondly, prediction the missing edge weight based on the neighbors of edge-source in community. In other words, the trust values that pointed to edge-target by neighbors are averaged to represent the prediction of missing edge weight. Practically, the model has been evaluated using two real-world datasets; Bitcoin-OTC and Bitcoin-Alpha datasets. The experimental results explicate the effectiveness of the proposed model comparable with other methods, where the minimization percentage for Bitcoin-OTC dataset is 4% and 18% for all and partial edges respectively. As for Bitcoin-Alpha dataset are 0% and 30% for all and partial edges respectively.

Keywords — Bitcoin network, Girvan-Newman algorithm, edge weight prediction, signed networks.

1. INTRODUCTION

Digital coins, cryptocurrency, and electronic money by any given name in the world of digital currencies are an unabashed phenomenon. It's still a big ambiguity to many due to the structure of his labyrinthine (1). The term Bitcoin network relates to the collection of nodes running as a decentralized peer-to-peer payment network (2).

Bitcoin was created on 31 October 2008 by Satoshi Nakamoto, a person whose identity remains undisclosed. While the first transaction to bitcoin happened in January 2009. It has been generated with a view to creating a modern global type of electronic currency can be used instead of euros, US dollars, and other conventional currencies. Nakamoto called Bitcoin an electronic, peer-to-peer cash system. This would be essentially different from the conventional currency structure because of the loss of any central third-party intermediaries (credit card companies, central banks, and other financial intermediaries) (1).

In fact, Bitcoin is one of the most common cryptocurrencies in today's age which is considered as a weighted signed network (WSN) comprising ratings between users (3). Essentially, strong positive and weak negative ties mean the user trusts or distrust the other user respectively. However, WSNs, like any network, is unfulfilled. In other words, there are many relations among users that have not been weighted. The anonymization nature of this network prompted a need to identify untrusted Bitcoin users to avoid risky transactions (4).

Although the existence of a link is known, its weight can still be missing due to restricted data, and the missing weights in this situation need to be predicted (5). Link prediction can be considered as a binary classification problem in machine learning where the edges are either absent or present and weight prediction can also be formed as a regression issue resulting in continuous weight rates (6).

The main challenge is how to predict these weights accurately. Prediction of such weights is meaningful for different reasons. In this work, the community structure has been leveraged to predict the weights of relations among.

2. RELATED WORKS

Link weight prediction makes an effort to predict the weight of edges in the future with missing information on weight or edges. It has prospective uses in recommendation systems, the evolution of networks, analysis of sentiments, etc.

Worthy to mention, the literature that addressed the issue of weight prediction is limited.

Fu et al. (7) treat the problem of link weight prediction as a supervised regression problem where the weight for an undirected network is predicted. The author uses the graph's edge-to-vertex a double representation, called line graph, in which the edges of the original graph are converted into line graph vertices to allow vertex centrality indices to predict link weights. Furthermore, the authors argue that weight information could not be completely occupied using only similarity indices, so a mix of node centrality indices and similarity indices was used to predict weights.

In the weight prediction proposed in signed networks (8), the authors used 11 special properties which include triadic balance, deserve, and bias, along with their proposed new characteristics of node behavior called fairness and goodness measures. In principle, supervised regression has been implemented to predict the weights on the edges.

The node's goodness conceptually measures how much this node is liked/trusted by other nodes, while the node's fairness measures how it is fair in rating the possibility or trust level of other nodes. The standard definitions of goodness and fairness are as follows,

$$g(v) = \frac{1}{|in(v)|} \sum_{u \in in(v)} f(u) \times W(u,v)$$

$$f(u) = 1 - \frac{1}{|out(u)|} \sum_{v \in out(u)} \frac{|W(u,v) - g(v)|}{R}$$

Fairness values are usually in the interval [0,1] and goodness values are in the interval of [1,1]. The highest possible difference in the scale of the score is between edge weight and goodness value differential.

Where W *(u, v)* is the weight of *link u⟶ v,* and in *(v),* out*(u)* are the set of incoming and outgoing neighbors and R=2.

The weight of the link *(u, v)* can be predicted by-product the fairness *f(u)* and goodness *g(v).*

$$W(u,v) = f(u) \times g(v)$$

This approach is efficient and reliable but they assume it can be limited to using goodness and fairness (with only 2 ways of good or bad) for weight prediction.

The main idea of (4) is mapping node properties into vectors and using the inner product to predict the weights of the link. Influenced by collaborative filtering, the weight matrix of the network is approximated by matrix decomposition, and optimized by gradient descent.

Predict weights of the link using vectors for node u. $p_u \in \mathbb{R}^k$, $q_u \in \mathbb{R}^k$.

They use the inner product $p_u^T q_v$ to predict the W_{uv} edge weight and to model their similarity using cosine distance.

$P = F \in \mathbb{R}^{n\times 1}, Q = G \in \mathbb{R}^{n\times 1}$, follows the same concept as the Fairness and Goodness algorithm, where P represents the fairness of each node (how fair is a node in rating others), and Q denotes the goodness of each node (how probably is the node to be trusted by other nodes).

$$P = (p_1, p_2, \dots, p_n)^T \in \mathbb{R}^{n\times K}$$
$$Q = (q_1, q_2, \dots, q_n)^T \in \mathbb{R}^{K\times n}$$

The goal is to find P, Q

$$W = PQ$$

Where $W \in \mathbb{R}^{n\times n}$ denotes the weight matrix of a WSN, and W_{uv} is the weight of link *u* ⟶ *v* in the network.

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In the case of $\big(f(u)g(v)\big) \neq sign\ (W_{uv})$ or minimizing $|f(u)g(v) - W_{uv}|$, the model metrics can be enhanced by correcting the wrong predicted signs. Consequently, apart from finding the fairness and goodness metrics P and Q, the model allows the weights of the known links to be corrected to the fairness and goodness scores. The parameters in their model are initialized first with the result of the Fairness-Goodness method (rather than initializing all parameters to 0), and gradient descent is carried out.

In (5) the authors suggest a novel weight prediction approach based on the local network structure, which includes the neighbor set of each node.
In the first case, some links are completely missing along with their weights, whereas in the second case all links are known and for some links weight information is missing.
The prediction in the first case consists of two steps: link prediction and weight prediction.

During the first one, the goal is to estimate the probability that links exist in a given network. To do this, we assign a score, S_{xy}, to each candidate node pair (x, y) ∈ U − E, where U stands for the universe of possible edges to determine the likelihood of connecting the node pair (x, y) with a higher score implying a more probable connection while E represent the observed links. Then, every pair of candidates is sorted in descending order by their ratings. The model predicts the weights for the highest-rated links in the second step. In neighbor set A, nodes a and b appear together, the weight of (a, b) is related to the weights of other similar links in A. Because there is only one other link (b, c). The weight of (b, c) is associated with the weights of links to common α node. On this basis, one can predict definitely

$$w_{ab} = \frac{w_{bc}}{w_{\alpha b} w_{\alpha c}} W_{\alpha a} \,.\, W_{\alpha b}$$

If there are other similar links, the predictions will be integrated using an averaging strategy. Likewise, the weight of the link (d, e) may be used to infer the weight of the link (a, f) in neighboring sets A and B by estimating the value of $w_{af} =$ as follow in this eq.

$$w_{af} = \frac{w_{de}}{w_{\alpha d} w_{\beta e}} W_{\alpha a} \,.\, W_{\beta f}$$

Prediction of weight in unsigned networks: unsigned weighted networks contain only positive edges. Some methods include some information on communication between individuals (9). Others instead use non-communication based techniques, some of the current algorithms are listed below.
Reciprocal (10): predicts the weight of the edge (u; v) as the reciprocal of the edge (v; u) (0 where there is no reciprocal edge).
Triadic balance (11): extends balance theory, predicts edge weight (u; v) as the average edge weight product for all incomplete triads that edge (u; v) is part of.
Triadic status (12): extends status theory, the predicted weight of the transitive edge in a transitive triad is a sum of the two non-transitive edge weights.

3. Newman-Girvan Algorithm

Historically, the Girvan-Newman algorithm is significant because it represented in the area of community detection as the beginning of a new era, a top-down hierarchical community detection algorithm suggested by Girvan and Newman, but it requires a time O(n3) on a sparse graph. It is a divisive method where the number of shortest paths passing through the edge. The value is called edge betweenness and is a generalize of the central betweenness of the vertex which specifies the impact of the vertex on other vertices of the network (13). In other words, vertex betweenness is the number of shortest paths that pass through the vertex, while the edge betweenness is the number of shortest paths that go through the edge endpoints (14). When 2 geodesic paths (shortest) cross a given pair of vertexes, then each one counts as half of a path, and likewise for 3 or more (15).
In practice, the Girvan-Newman algorithm starts by calculating the edge betweenness of all the edges in weighted graph use betweenness algorithm mentioned in (16). It is important to say, that when 2 or more edges have the same highest betweenness, they have to be removed both. Then, the betweenness of all edges is recalculated on the remaining network and the process is repeated. In fact, the recalculation is necessary for the proper operation of the algorithm (13), as it allows for the common situation in which there is more than one edge between a given pair of community.
The algorithm's main steps as illustrated in (16):

1) Calculate edge betweenness for every edge in the graph.

2) Remove all edges with the highest edge betweenness.

3) Recalculate edge betweenness for remaining edges.

4) Repeat 2-4 until the graph becomes empty.

Firstly, the algorithm calculates the edge betweenness in a network based on the betweenness theory as in eq. (1).

$$B_{u_i} = \sum_{u_i \neq u_j \neq u_k} \frac{\sigma_{u_j u_k (u_i)}}{\sigma_{u_j u_k}} \qquad (1)$$

where B_{u_i} is the betweenness centrality value at node u_i, $\sigma_{u_j u_k(u_i)}$ is the number of the shortest path between node u_i and u_k that pass through the node u_i. As for $\sigma_{u_j u_k}$, it is the number of the shortest path between node u_j and u_k.Therefore, if the edges with high betweenness scores have been removed that leads to eliminate the edges of the intercommunity and leave only the communities themselves (15).

Girvan-Newman algorithm's main problem is that it's not really an algorithm that has a graph as input and a community structure as output. In other words, if the labeling of the graph vertices is reconfigured, then the outcome of the Girvan- Newman algorithm may change. Therefore, a given input (which would be a result of any algorithm) does not have a unique output. New provisions change this. New modification modifies this drawback of the Girvan-Newman algorithm so that the community structure does not depend on the vertices of the graph being labeled. Additionally, this modification can reduce the number of operations of the Girvan-Newman algorithm. However, it relies greatly on the graph found, where there are graphs for which no improvements can be made (14).

A modularity concept described in (16) gives a measure of the quality of a given network partitioning. That quantifies the intensity of the community by comparing the fraction of edges within the community to the fraction of edges when random connections between the nodes are made. The argument is that a community would have more relations within its than a random grouping of nodes. Thus, the Q value close to zero indicates that the fraction of edges within communities is not good than the random case and the value of 1 indicates that a network community structure has the highest possible intensity (17).

Modularity is described as the difference in the value obtained by the fraction of the edges inside the module to the predicted fraction if the edges are distributed randomly. The numerous modularity optimization approaches include greedy strategies (hierarchical clustering), spectral optimization, extreme optimization, and simulated annealing. Newman-Girvan is the most common modularity method used, in which each network partition is divided into n disjoint modules, the value Q is computed in each step of the divisible algorithms. The highest value Q gives us the graph's best partition of the graph (18).

Newman has generalized the modularity maximization equation (19):

$$Q = \sum_{l=1}^{k} \sum_{i \in c_l} \sum_{i \in c_l} A_{ij} - \frac{d_i d_j}{2m} \qquad (2)$$

Given a network with *m* edges, the expected number of edges between 2 nodes i and j with degrees *di* and *dj* respectively *is di dj / 2m*. As for Aij, it is the link weight between node i and j. Basically, when, the value of the modularity Q larger, the partition is better.

4. HOW BITCOIN WORKS

Bitcoin works like an electronic cash kind where the people can buy Bitcoins on special websites.

The digital currency blockchain stores all transactions since the system has been established. The database is stored in a decentralized way in a peer-to-peer network that erases dual-spending attempts and authenticates legal transactions in a long-term blockchain created using a hash-based proof-of-work method. There is no central third party that manages the database as it is distributed all over the entire database (20).

Bitcoin payment can be done between anyone on their device, smartphone, or tablet with the appropriate software, the software is known as a wallet. However, Bitcoin should not be seen as a kind of digital cash. because it is not digital value units saved on a computer. Therefore, it is not a digital note or coin and should not be compared with regular bills and coins (21). Instead, it should have appeared as funds in the account. Thus, when a payment is made, the payer does not send digital notes and coins to the receiver; rather, the payment occurs by debiting the sender's account and crediting the receiver 's account. Payments are made by exchanging encrypted messages and checked within the user network. Suppose there are two persons A and B as shown in figure 1, person A should pay 1 Bitcoin (BTC) to person B. A as well as B has on their devices wallets that have a private encryption key and a public one. A wallet is associated with its public encryption key, which serves as an address or account number. The two persons communicate with their wallets (21).

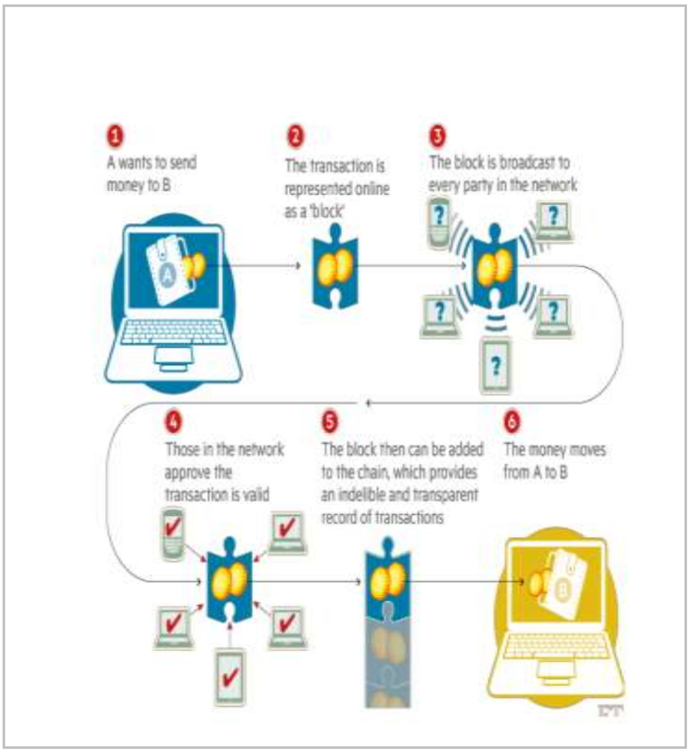

Figure1: *How a blockchain works*[1]

In order to have and transfer digital currency, one has to have an alternative account number. Those account numbers are governed by a public and private cryptographic key. To issue Bitcoins for the given account, one needs to know the public key (an alphanumeric string, somewhat analogous to an account number) of the person. On the other hand, it is essential to keep the private key to transfer the account (i.e., the password associated with that address) as well the recipient's public address to create a transaction with a cryptographically secure signature that can encrypt transactions. When a person sends and receives digital currency, their identity is not identified, but achieving acceptable anonymity with Bitcoin can be really challenging, and complete anonymity can be impossible (20).

Bitcoin is innovative though since the issue of double-spending can be solved without a third party being needed. The double-spending issue in computer science refers to the question that more than once could be easily spent on digital capital. Consider the situation where digital money is just like a digital document, just like a computer file, Alice could send $10 to Bob by giving him a money file, and it can simply do so by email. Nevertheless, I know that sending a file will send a copy of the file and will not erase the original file from the machine. When Alice adds a money file to Bob in an email, it still maintains a copy of the money file even though it was submitted and so Alice could simply transfer out the same $10 to another user, Charlie, without a trusted third-party intermediary to make sure otherwise. Bitcoin addresses the problem of double-spending by keeping a balanced ledger, called the blockchain (3).

The recorded information in the blockchain is the sender's and recipient's public keys, the amount, and a timestamp. Every transaction has been recorded in Bitcoin 's history and will be recorded on the blockchain, and is available to the public (3).

5. COMMUNITY STRUCTURE BASED WEIGHT LINK PREDICTION

Mainly, the proposed algorithm involves two main stages.

I. Newman-Girvan Algorithm

Firstly, the Newman-Girvan algorithm for detecting Bitcoin communities. Essentially, the quality of the detection algorithm depends on how the features of nodes are represented. Thus, the features of Bitcoin nodes have been modeled in different ways.

Weight matrix or adjacency matrix is considering as a core of the Newman- Girvan algorithm. Generally, the matrix A (see eq. 2) based on the representation of nodes.

Similarity Measures

The most important step in any community detection algorithm is creating the profile of the nodes which reflected on the algorithm performance. According to that, several methods have been used to extract the features of nodes. Thus, the selection of the similarity measure is also based on the representation of the nodes which could be in numeric or binary form.

For each user has extracted all the outgoing edges to represent the profile for him. Doing so gives communities of the shared transactions among users in Bitcoin networks. To get more trust communities in terms of transactions, only outgoing edges that have been rated (>3) are kept for each user to represent the profile in another way. Worthy to mentioned the attributes of nodes in both ways above are represented as categorical form.

Besides, the profile can be built-in in terms of weights value of the edges, the outgoing edges rated (>1) are considered in an experiment. In other words, the node is represented as a numeric form.

Let u and v are two users, where u and v have n and m relations transactions respectively:

$$u = \{w_1, w_2, w_3, \dots., w_n\}$$

$$v = \{w_1, w_2, w_3, \dots., w_m\}$$

Pearson correlation (r) coefficient can be used to compute the similarity among users as follows:

$$r(u,v) = \frac{N(\sum uv) - (\sum u) - (\sum v)}{\sqrt{[N\sum u^2 - (\sum u)^2] - [N\sum v^2 - (\sum v)^2]}} \quad (3)$$

where N represents the length of the profile. As well as, the Cosine similarity has been used to calculate the similarity matrix as below:

$$cos(u,v) = \frac{u.v}{\|u\| \times \|v\|} = \frac{\sum_{i=1}^{N} u_i \times v_i}{\sqrt{\sum_{i=1}^{n} u^2{}_i} \times \sqrt{\sum_{i=1}^{n} v^2{}_i}} \quad (4)$$

Pearson and Cosine similarity have been used with the numeric representation of node.

Finally, Jaccard index is also applied, however for categorical representation of attributes: -

$$J(u,v) = \frac{|u \cap v|}{|u \cup v|} \quad (5)$$

In practice, the similarity matrix T that obtained from the previous step can be used in this stage rather than A. Actually, TR is representing the transactions among users in networks whether they are categorical or numerical form.

By applying eq. (1), all edge betweenness among nodes can be obtained. Then, the modularity Q is computed using Eq. (2)

$$Q = \frac{1}{4m} \sum_{i} \sum_{l}^{k} \sum_{u_i \in l, u_j \in l} \left(TR_{u_i u_j} - \frac{d_{u_i} d_{u_j}}{2w2m} \right) s_{u_i} s_{u_j} \quad (6)$$

Where $TR_{u_i u_j}$ represents the similarity in terms of transactions or the trust between the two users u_i and u_j when the representation of a node in binary or numeric form respectively.

Practically, most of the communities are small. Figure (2) shows the distribution of community size.

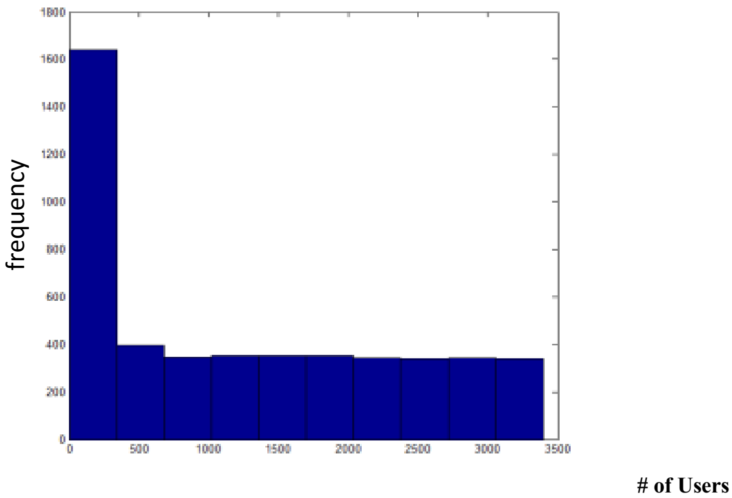

Figure2: *Histogram of community sizes (OTC dataset)*

II. Prediction Link Model

Given the *community structure* of a *network* as a set of k communities:

$$C = \{c_1, c_2, \ldots., c_K\}$$

let edge (u, v) has missing weight in the original graph, where the u and v are the source and destination respectively. To predict the weight of the edge:

if $u \in c_k$

$$\widehat{w} = \begin{cases} \sum_{z \in c_k} \delta(E(z,v))\, w_{zv} / N & if\ N \geq 1 \\ \sum_{k=1}^{K} \sum_{z \in c_k} \delta(E(z,v))\, w_{zv} / M & otherwise \end{cases}$$

where $\delta(E(z,v))$ is 1if there is an edge from z to v and it is 0 otherwise. While N represents the neighbors in a community which u is considered as a member in and M is the number of nodes in other communities.

6. Implementations and Results

The datasets (Bitcoin networks) that have been used in this work are available in [1], which are the first public weighted signed network. A weighted signed network is a directed weighted graph. Bitcoin Alpha (Alpha for short) and Bitcoin OTC (OTC for short) are two major Bitcoin rating datasets. Both datasets are a user-to-user trust. In addition, the dataset has been provided with a time of rating, measured as seconds. The dataset starts on November

[1] https://snap.stanford.edu/data/

8th, 2010, and ends on January 25th, 2016, starts on March 26th, 2013, and ends on August 8th, 2014, OTC and Alpha respectively. Table I shows data statistics.

TABLE I. DATASET STATISTICS

No	**Network**	**#Nodes**	**#Edges addresses**	**Range of edge weight**	**Percentage of positive edges**
1	OTC	5,881	35,592	-10 to +10	89%
2	Alpha	3,783	24,186	-10 to +10	93%

TABLE II EXPERIMENTAL RESULTS

Methods	**Bitcoin-OTC**		**Bitcoin-Alpha**	
	RMSE			
Reciprocal	0.34		0.28	
Triadic Status	0.65		0.65	
Fairness-Goodness	0.32		0.29	
Matrix Decomp	0.27		0.23	
The proposed model				
Models	**RMSE**			
	$\boldsymbol{Edge_{all}}$	$\boldsymbol{Edge_{partial}}$	$\boldsymbol{Edge_{all}}$	$\boldsymbol{Edge_{partial}}$
TR>1_{pear}	**0.26**	0.24	**0.23**	0.22
TR>1_{cos}	0.26	0.24	0.24	0.22
TR>3_{Jacc}	0.28	**0.22**	0.25	**0.16**
TR>1_{Jacc}	0.3	0.27	0.24	0.22

Table II displays the averaged RMSE of each dataset for the proposed model. Further, the table states the comparative with baseline and other methods. Experimentally, **10% to 90%** of links have been removed in steps of **30%** to examine the robustness of the model in predicting the missing values.

As mentioned previously, the proposed model has been used a different representation of node attributes and corresponding similarity measures to get the different structure of communities each time. Table II demonstrates that our proposed model has been conducted in two experiments. Firstly, the proposed model could not predict all missing weights of edges (**$Edge_{partial}$**) for different reasons such as; some of the nodes are lonely in their communities, or the neighbors of some other are had not a transaction with edge-target. Hence, **17%-40%** and **18%-33%** of missing links have not predicted relate to Bitcoin-OTC and Bitcoin-Alpha; respectively.

Secondly, the model can address the missing links (**$Edge_{All}$**) issue that could not benefit from community structure by predicting the weights without considering the community structure, however the whole network.

As illustrated, the best performance is recorded when the high percentage of missing links has not been predicted (part of edges) which indicates the effectiveness of community structure in the prediction process. To predict these missing links, the model has to regardless of the community structure (all edges) which leads to increasing the error, however, it is still competitive.

As for the proposed model taking into account all edges, it reports the best performance when the attributes of a node have been represented by trust values of only transactions with trust values >1 for Bitcoin-OTC dataset, however, the model presents the same performance and best than for Matrix Decomp and other models respectively for Bitcoin-Alpha. Specifically, the performance of Pearson similarity (bold values) is superior on the Cosine similarity for the same representation of attributes, of course, when all missing edges have been predicted. In contrast, Jaccard's similarity is best in the case of part of edges are not take advantage of community structure. Indeed, the representation of trust as numeric values to be featured for each node can give good structure for communities, thus; affect the accuracy of the prediction. In the proposed model the quality of a community is a crucial point because it depends on the convergence degree of the target user in a community with the members in the same community.

7. CONCLUSION

In this work, it is demonstrated that community structure has the effectiveness in prediction comparably with baseline methods and competitively with the recent methods. Moreover, the representation way of the attribute of the node a bit of effect on the accuracy of results.

In other words, forming the trust communities in Bitcoin networks in terms of how each node evaluates the others has a vital role in minimizing the error, particularly when taking into account only the nodes that taking the advantage of community structure. Unfortunately, because of the short period in that the dataset has been collected, most communities are small which in turn affects the performance.

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