An Association Based Approach to Propagate Social Trust in Social Networks

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Abstract. The behaviour based trust models generally compute social trust using interactions of a member with other members, referred to as "friends". These models largely ignore the interactions of friends with their friends, referred to as "friendship effects". Results from social studies and behavioural science show that friends have a significant influence on the behaviour of the members in the community. Following the famous Spanish proverb on friendship "Tell Me Your Friends and I Will Tell You Who You Are", we extend our behaviour based trust model by incorporating the "friendship effect". In this paper, we present a trust propagation model based on associations which combines the behaviour of both individual members and their friends. The propagation of trust in our model depends on three key factors: the density of interactions, the degree of separation and the decay of friendship effect. We evaluate our model using a real dataset and make observations on what happens in a social network with models with and without trust propagation. We report the results in this paper.

Keywords: Social networks, Social Trust, Trust Propagation

1. Introduction

With the emergence of social networks such as Facebook, Flickr and Twitter, and an ever growing number of users, researchers have started studying various aspects of social networks as an area of research and development within computer science. In particular, trust, with its different aspects, has become an important research area in social media [20]. There are different aspects of trust: trust between users and social media itself, trust between users and media providers, and trust amongst users. Our focus in this paper is on the trust amongst users in social networks, leading to trust communities. In order to build trust communities in social networks, a number of trust models have been proposed in the literature [25, 26, 27, 28, 21, 23], mostly borrowed from application domains such as peer-to-peer systems [21] and electronic commerce [23]. Many of these trust models do not capture the *social behavioural* aspect of trust [24]. In order to address this issue, we have developed a behaviour social trust model, called *STrust* [18], based on *social capital*. One of the shortcomings of our current trust model is that it only considers the behaviour of an individual member, i.e., the trust computation is localised. It does not consider the "friendship effects", i.e., the influence of friends and friends of friends.

The influence of friends on an individual's attitude, behaviour and decision has been studied in many fields from marketing [2] to behavioural science [1]. The results of these studies indicated that friends shape an individual's behaviour in a direct fashion in any type of social environment. We referred to this influence as "*friendship effects*". Such influence has also been termed as bandwagon effect [3], peer influence [4], neighbourhood effect [5], conformity [6], and contagion [7]. Other terminologies used in literature to describe such influence are imitation, epidemics or herd behaviour. Therefore, it is important to consider friendship effects while computing the social trust based on behaviour. In order to achieve this, we need to devise a mechanism of propagating trust values based on the social trust of friends. This is what we present here.

The propagation of influence has been studied in computer science in different areas of research, such as networking [8], peer-to-peer systems [9], service computing [10], hypertext [11], wireless networks [11] and information retrieval [13]. In recent time, these approaches have been enhanced and applied to social networks. In particular, different types of machine learning approaches have been used to perform post analysis on the influence of friends on the behaviour of members in social networks [14, 15, 16, 17]. All these models follow physical phenomena in the real world, such as the spreading the infectious diseases or the diffusion of heat. The underlying assumption of these models is that, when trust propagates from a source node to a sink node (assuming that the source has a higher value than the sink), the trust value of the source node decreases, and that of the sink node increases. This is not true in the context of a behaviour based social trust model. Consider the following scenario: Bob is the most popular member in the network, and Mary is the least popular one. Bob interacting with Mary may increase the popularity of Mary (e.g., people might decide to start looking at Mary's posts/etc, if Bob does), but does not decrease Bob's popularity. The social trust propagation model should thus reflect this behaviour. We propose such a model here.

Our approach extends the behaviour based trust model (STrust) to include friendship effects by propagating the trust values from friends. STrust was developed with the aim of building trust communities. It considers two aspects of trust: *Popularity Trust* (PopTrust) and *Engagement Trust* (EngTrust). Popularity trust refers to the acceptance and approval of a member by others in the community, while engagement trust captures the involvement of someone in the community. Popularity trust can be seen to reflect the trustworthiness of a member in the community, while engagement trust reflects how much a member trusts other members in the community. Our model separates these trust values as they can be used to recommend different things and identify different roles (for example, leaders and mentors) in the community. However, the current model computes the social trust of a member by computing members' behaviour with their direct friends. The model does not consider the neighbourhood (or friendship) effects. To address this issue, ,this paper presents an association based trust propagation approach for behaviour based social trust models. The novelty of our extended model is that the trust propagation follows association rules deeply rooted in social networks, e.g., having less popular members following more popular members does not have any effect on the popularity of the popular members. We evaluate our proposed propagation model in a real data set and present our results.

The rest of the article is organised as follows. Section 2 motivates the trust propagation model using example scenarios, and Section 3 shows how it can be theoretically modelled. Section 4 presents the evaluation of the theoretical model, and some observations of its impact using a real social network. The final section draws some concluding remarks and discusses potential future work.

2. Motivation

Why do we need to propagate the trust value in social networks? The aim of this section is to provide intuitive answers to this question, walking through a couple of examples. Intuitively, we believe that the popularity and engagement trust of a node in the networks depends not only to the density of interactions it has with its “friend” nodes, but also the interactions of friend nodes with their friends, in line with a famous proverb “Tell me what company thou keepst, and I'll tell thee what thou art” by Spanish novelist Miguel de Cervantes. In this context, a node is called “friend” of another node if there is an interaction between them, whether the nature of the interaction is positive or negative.

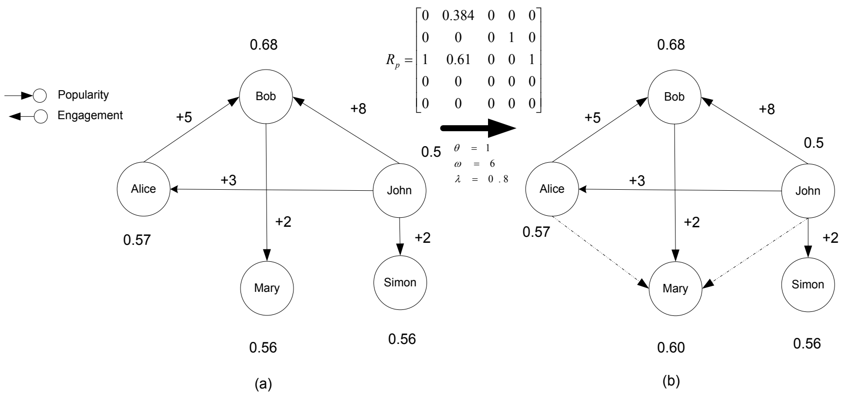

Figure 1: An example illustrating the need for propagation of popularity trust

Figure 1 shows an example network that is used to explain the motivation behind the need to propagate popularity trust. The network has five nodes (or members): Alice, Bob, John, Mary and Simon. John has 8, 3 and 2 positive interactions with Bob, Alice and Simon respectively. Alice has 5 positive interactions with Bob, and Bob has 2 positive interactions with Mary. We calculated the popularity trust of the nodes using the social trust model in [18] (Equation 2 in Section 3 below). Figure 1 (a) shows the popularity trust values for four nodes. Bob is the most popular member in the network with popularity trust value 0.68, and John is the least popular member with value 0.5 (the default/bootstrapping value, in our scenario). The popularity trust value of Bob is calculated using his popularity based interactions (see the direction of arrow in the figure) with Alice and John. Similarly, Mary’s popularity trust (0.56) is calculated solely based on her interactions with Bob. Simon's trust value is equal to that of Mary, as both of them have a similar number of friends and interactions. A drawback of this model is that it does not consider the popularity of the friend nodes. In fact, Mary should have higher popularity trust value than Simon, as Mary has a popularity interaction with the most popular member Bob and Simon with the least popular member John. However, this is not captured by the trust model calculated based on direct interactions. In order to address this problem, we have to look beyond direct interactions. Indirect interactions can be captured through the popularity values of immediate friend nodes. We extend our model accordingly. Figure 1(b) shows the result of the application of the extended trust propagation model (Equation 9 in Section 3 below) for the example scenario in Figure 1 (a). As expected, after propagation of trust, Mary's trust value is increased to 0.60, whereas Simon's trust vale remains the same. Another interpretation of this is that, if Alice and John follow Bob, and Bob follows Mary, it is likely that Alice and John will follow Mary in future (as shown by dotted lines in Figure 1(b)).

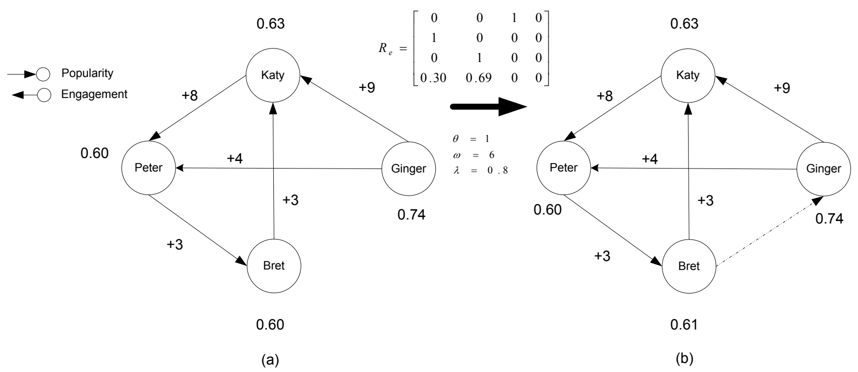

Figure 2: An example illustrating the need for propagation of engagement trust

We have just described the logic behind the propagation of popularity trust value through an example. Next we describe the intuition behind the propagation of engagement trust, using the example given in Figure 2. In this example, there are four members: Peter, Katy, Bret and Ginger. Figure 2(a) shows the number of positive interactions between them, with the engagement trust values (calculated using Equation 3 in Section 3). Ginger is the most highly engaged member with engagement trust value 0.74, whereas Peter and Bret are the least engaged members with trust value 0.60. Ginger and Katy are engaged with Peter, and Peter has lower engagement value than both of them. Peter is engaged with Bret, but Bret has lower engagement than Peter. However, Bret is engaged with Katy who has higher engagement value than Bret. Intuitively, Bret should have higher engagement trust value than Peter, as Bret is engaged with the most highly engaged members in the network. Another interpretation is that, if Bret is engaged with the most highly engaged members in the network, it is likely that Bret will engage with other members in future, as shown by the dotted lines in Figure 2(b). It is important to note that the engagement trust works in an opposite way to the popularity trust in terms of following the arrow, as it is based on the source nodes rather than the sink nodes. We apply the trust propagation model proposed in Section 3 (Equation 9), and the result is shown in Figure 2(b).

3. Social Trust Propagation Model

This section first briefly reviews *STrust*, our social trust model presented in [18]. We then propose an association based approach to propagate social trust in social networks to implement the behaviour described in Section 2.

3.1 STrust: Social Trust Model

Let U be the set representing the number of members in the community. The social trust (STrust) of an individual member $u_i \in U$ in the community is given by.

$$STrust(u_i) = \alpha.PopTrust(u_i) + (1-\alpha).EngTrust(u_i) \quad (1)$$

where *PopTrust* and *EngTrust* refer to the popularity and engagement trust of an individual member in the community, and α represents the value of a weight in the range of 0 to 1. The popularity trust (*PopTrust*) of a member $u_i \in U$ is calculated as:

$$PopTrust(u_i) = \frac{\sum_{\substack{j=1 \\ except(i)}}^{|M|-1} \frac{|PT_{ij}^{+}|+1}{|PT_{ij}^{+}|+|PT_{ij}^{-}|+2}}{|M|-1} \quad (2)$$

where $|PT_{ij}^{+}|$ and $|PT_{ij}^{-}|$ is the total number of positive and negative popularity interactions a member $u_i \in U$ has with the member $u_j \in U$, and M is the total number of members in the community. Referring to Figure 1, $|PT_{ij}^{+}|$ = 8 between John and Bob. Similarly, the popularity trust of Mary using Equation 2 is 0.56. Similarly, the engagement trust is calculated as:

$$EngTrust(u_i) = \frac{\sum_{\substack{j=1 \\ except(i)}}^{|M|-1} \frac{|ET_{ij}^{+}|+1}{|ET_{ij}^{+}|+|ET_{ij}^{-}|+2}}{|M|-1} \quad (3)$$

where $|ET_{ij}^{+}|$ and $|ET_{ij}^{-}|$ is the total number of positive and negative engagement interactions a member $u_i \in U$ has with the member $u_j \in U$. Referring to Figure 2, $|ET_{ij}^{+}|$= 9 between Ginger and Katy, and the engagement trust of Ginger is 0.74 using Equation 3. We refer readers to [18] for further details.

3.2 Association Based Trust Propagation Model

The model describe above does not consider the nature of friends and their influence. Yet, as explained in Section 2, a highly popular node should have an influence on the popularity of the node with which it has interacted, by association.

Nodes with the same level of interactions, but with highly popular friends should have higher popularity trust than those with not so popular friends. Therefore, the model should consider the propagation of trust in the networks. In order to address this problem, the model needs to be modified to incorporate the effect of friends (the friendship effects). In the following, we extent the model and propose an association based trust propagation model. Our model considers three factors: the density of interactions, the degree of separation and the decay of influence. The density of interactions is used to calculate the localised popularity and engagement trust, as described in Section 3.1. We also use the density of interactions to calculate the rate of propagation from a member to other members. The basic idea is that the more interactions you have with your friend, the more influential your friend becomes on your behaviour. In a nutshell, the rate of propagation represents the friendship effects. The second factor is the degree of separation. The degree of separation is how far trust can be propagated in a network. If we choose the value based on the small world problem, the value of the maximum degree of separation would be six. The friendship effect decays with the degree of separation. That is, a propagation of trust to a member from friends will be higher than friends of friends. We next define the social trust propagation model considering all these three factors.

Not all friends interact at the same rate. Some friends have positive interactions, and some have negative interactions. Similarly, some friends have higher number of interactions, and some have fewer interactions. In order to propagate the popularity trust of the friends to a node, we need to consider the rate of propagation. We calculate the rate of propagation using the following popularity and engagement interaction values: positive popularity interactions between friends (PT_{ij}^{+}), negative popularity interactions between friends (PT_{ij}^{-}), positive engagement interactions between friends (ET_{ij}^{+}) and negative engagement interactions between friends (ET_{ij}^{-}).

Let R_p and R_e be the rate of propagation matrix for popularity and engagement trust, respectively. The matrix is normalised in such a way that the sum of the column of R_p is equal to 1, and the sum of the row of R_e is equal to 1. Figure 1 and 2 showed the matrices associated with the examples.

The popularity propagation rate (an element in R_p) by association is defined as follows:

$$\gamma_{ji}^{p} = \begin{cases} 0 & \text{if} \quad i = j \\ 0 & \text{if} \quad \sum_{k=1;k\neq i}^{|M-1|} PT_{ki}^{+} + PT_{ki}^{-} = 0 \\ \dfrac{PT_{ji}^{+} + PT_{ji}^{-}}{\sum_{k=1;k\neq i}^{|M-1|} PT_{ki}^{+} + PT_{ki}^{-}} & \text{otherwise} \end{cases} \qquad (4)$$

Similarly, the engagement propagation rate (an element in R_e) by association is defined as follows:

$$\gamma_{ij}^{e} = \begin{cases} 0 & \text{if} \quad i = j \\ 0 & \text{if} \quad \sum_{k=1;k\neq i}^{|M-1|} ET_{ik}^{+} + ET_{ik}^{-} = 0 \\ \dfrac{ET_{ij}^{+} + ET_{ij}^{-}}{\sum_{k=1;k\neq i}^{|M-1|} ET_{ik}^{+} + PT_{ik}^{-}} & \text{otherwise} \end{cases} \quad (5)$$

The degree of separation is an important aspect of trust propagation. For example, if we consider the propagation by one "hop" (from John to Bob in Figure 1), we are just considering the immediate friend nodes (with one degree of separation). While propagating the trust value, it is important to consider how far we would like to propagate the trust values. Let ω represent the degree of separation to be considered.

Let PT^0 and ET^0 be the vectors representing the initial popularity and engagement trust calculated using Equations (2) and (3) (see Figures 1 (a) and 2(a)). They represent the localised trust values for the members. The trust value considering 1 degree of separation is then calculated as:

$$PT^1 = \begin{cases} PT^0 & \text{if} \quad \| PT^0 R_p - PT^0 \| < 0 \\ PT^0 + PT^0 R_p & \text{otherwise} \end{cases} \quad (6)$$

It can be generalised for θ degree of separation as follows:

$$PT^{\theta} = \begin{cases} PT^{\theta-1} & \text{if} \quad \| PT^{\theta-1} R_p - PT^{\theta-1} \| < 0 \\ PT^{\theta-1} + PT^{\theta-1} R_p & \text{otherwise} \end{cases} \quad (7)$$

Similarly, $$ET^{\theta} = \begin{cases} ET^{\theta-1} & \text{if} \quad \| T^{\theta-1} R_e^{\,T} - ET^{\theta-1} \| < 0 \\ ET^{\theta-1} + ET^{\theta-1} R_e^{T} & \text{otherwise} \end{cases} \quad (8)$$

Where R_e^T is the transformation of the matrix R_e.

The value $(PT^{\theta-1} R_p - PT^{\theta-1})$ represents the popularity gain due to association. If there is no gain in the popularity, the popularity remains the same. However, the gain in popularity depends on the degree of separation. This means if the nodes are separated by higher degree of separation, the propagation will be decreased proportionally. By incorporating the decay factors, we define our social trust model at θ degree of separation as follows:

$$PT^{\theta} = \begin{cases} PT^{\theta-1} & \text{if} \quad \| PT^{\theta-1} R_p - PT^{\theta-1} \| < 0 \\ PT^{\theta-1} + PT^{\theta-1} R_p \lambda^{(\omega-\theta)} & \text{otherwise} \end{cases} \quad (9)$$

$$ET^{\theta} = \begin{cases} ET^{\theta-1} & \text{if} \quad \| ET^{\theta-1} R_p - ET^{\theta-1} \| < 0 \\ ET^{\theta-1} + ET^{\theta-1} R_e^{\,T} \lambda^{(\omega-\theta)} & \text{otherwise} \end{cases}$$

where λ is the decay factor, ω the total degree of separation considered. Figure 1(b) and 2 (b) show the result of applying equation 9 where λ =0.8, ω = 6 and θ =1.

The social trust value after considering θ degree of separation is given by

$$STrust^{\theta} = \alpha.PT^{\theta} + (1-\alpha) ET^{\theta} \quad (10)$$

Where $STrust^{\theta} = \alpha.PT^{\theta} + (1-\alpha)ET^{\theta}$ is the vector representing the social trust of each member in the networks after considering association up to θ degree of separation.

4. Evaluation

We evaluate the propagation model presented above using a real dataset representing the exchange of messages between university students over a facebook-like social network. We first look at whether we have achieved behaviour we wanted to model. We then look at the impact of propagating the popularity trust.

The data for our evaluation was obtained from the web(http://toreopsahl.com/datasets) and was also used to study network analysis of online community in [29] and network clustering in [30]. The network consists of 1899 nodes exchanging a total of 59835 messages through 20296 unique interactions between them. Size of the network and density of interaction between the members makes this network suitable for our study to observe propagation of trust. The primary objective of this evaluation is to study the impact of trust propagation on nodes along various degree of separation between them. We calculate the popularity trust of nodes by considering the propagation of trust from other nodes and analyse the change in popularity trust of the nodes that are connected to the popular nodes. The evaluation result suggests the effectiveness of our model in propagating trust in a Social Network setting.

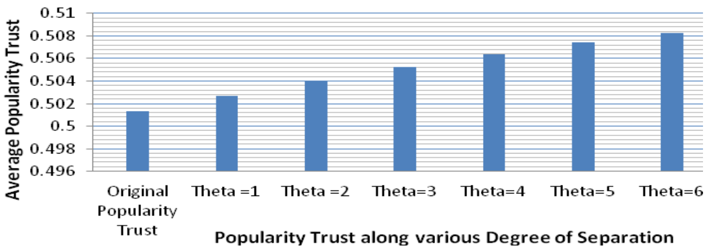

Figure 3: Growth of Average Popularity Trust along the Degree of Separation

The association based propagation model presented in section 3.2 assumes that the popularity of nodes in a network increases as trust propagates through the nodes. To observe this, an average of Popularity Trust of the whole network is computed and the trend observed. Figure 3 presents the growth in average popularity trust of the community when we consider higher degree of separation in the network. We also look at an individual node and find that its popularity trust value always increases.

We next study how the popularity trust of some individual nodes changes when we consider propagation of trust from other nodes to which they are connected. We evaluate the popularity trust of each node in the network for six degrees of separation using Equation 7 in section 3.2. Finally, we pick some specific node to observe: the top five nodes (in terms of popularity trust) at degree of separation one, and the top five at degree of separation six. Table 1 presents the rank of nodes and the changes in position occurred with the impact of propagation through the degree of separation between them.

Node	Original PopTrust position	Position at Θ=1	Position at Θ=2	Position at Θ=3	Position at Θ=4	Position at Θ=5	Position at Θ=6
32	1	1	1	1	1	1	1
76	822	1139	28	5	2	2	2
129	896	1411	36	9	6	6	3
1495	1721	1699	45	13	9	9	5
1680	1235	1648	41	12	8	8	5
372	2	2	2	2	11	12	13
103	3	3	3	3	12	15	15
598	4	4	4	4	13	16	17
42	5	5	5	11	16	18	33

Table 1. Changes in position of nodes along the degree of separation

Table 1 provides insights into how the propagation improves the popularity of nodes in the network. In general, the node positions have changed significantly with the increase in the degree of separation. The most popular node in the network is 32, and its position does not change, as no other nodes can get a value higher due to the constraint in Equation 7. Figure 4 presents interaction views of node 32 with one and two degree of separations. It is clearly seen that the density of interactions with node 32 is high in one degree of separation, and it further increases rapidly when nodes separated by two degrees are also considered. Node 32 has 958 interactions with a 318 unique nodes when looking at first degree of separation, and it reaches to 6987 interactions with 1935 unique nodes at the second degree of separation.

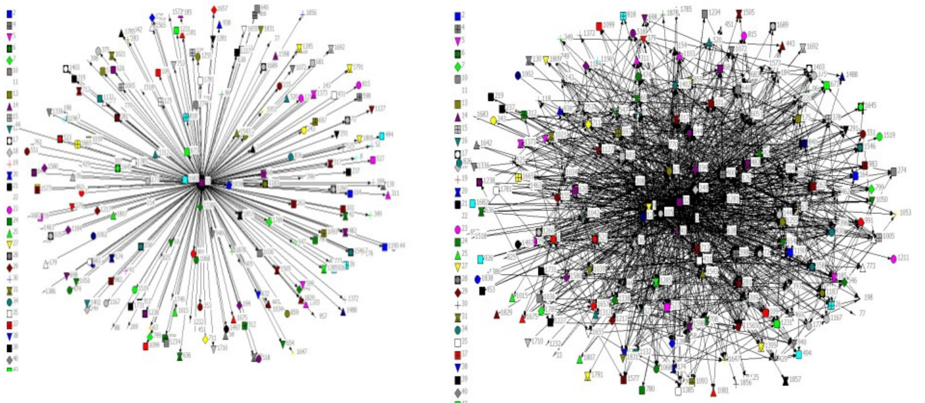

Figure 4 One Degree View (left) and Two Degree View (right) of node 32

Node 76 is one of the nodes whose popularity trust changed significantly when propagation was considered. It climbs up to the second position with six degree of separation as compared to its 1139th position at the first degree of separation. Figure 5 (a) presents an interaction view with one degree of separation for node 76. It has a few incoming and outgoing connections at the beginning. Interestingly, when two degree of separation is considered, the network becomes significantly denser due to the friendship effect (i.e. due connection of its friend nodes to some highly popular nodes) as shown in Figure 5 (b). We can see that it is connected with node 32 (the most popular node in the network) through nodes 400 and 9, and they are connected to other nodes connected to 76. This means by three degree of separation most nodes connected to 76 are transmitting the value from 32. This can be seen in Table 1 with the change in position of 76 from 1139th position at first degree of separation to 2nd position at six degrees of separation. This clearly shows that our model is propagating trust along the connected nodes as desired.

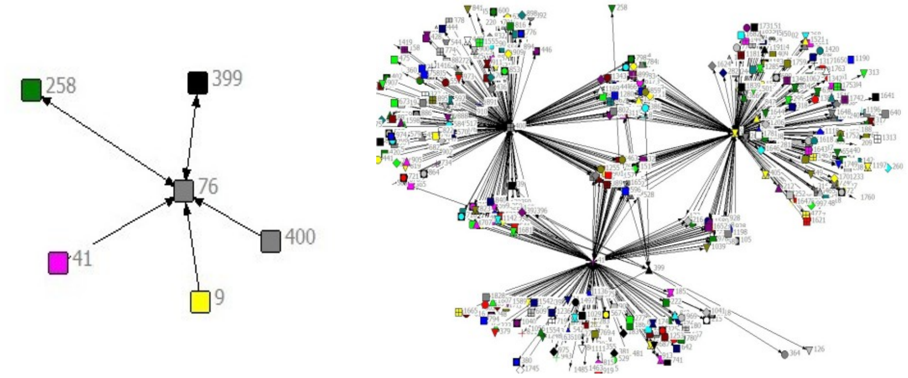

Figure 5 a. One Degree View (left) b. Two Degree View (right) of node 76

We have also gained some insights into how our proposed trust propagation model works. The trust propagation model follows the small world phenomenon. That is everyone is connected. In the data set we analysed, node 76 reaches the popularity value of 32 with five degree of separation. Node 76 is also a good example of showing the friendship effect. Node 76 is not directly connected with 32, but most of 76's friends and their friends are connected with 32. Therefore, 76 gets value closer to 32 faster than other nodes directly connected to 32. This is due to the friendship effect described in Section 2. That is, in future, 76 is likely to have a high number of interactions with 32. It is also observed that after certain degree of separation, a cluster starts to form around the most popular node in the network. This feature could be further exploited to extract trust communities within a social network. It is also seen that if there exists a loop, it helps to reach the popularity value of the most popular node faster (the rate depends on the degree of separation in the loop).

5. Discussions and Future Work

We described an association based trust propagation model for social networks where trust is evaluated based on the behaviour of the members. The model considers three factors while propagating trust: the density of interaction between members, the degree of separation and the decay of friendship effect due to the distance between the members in the network. We presented an initial evaluation of the model using a real dataset and found that "*friendship effects*" does exist in real networks and our model can capture the effects following the intuition (i.e., a person followed by a popular person may likely to have more follower). Our evaluation at the moment is limited to analysing only the popularity based propagation of trust. Further insights are likely to be gained if we also consider the propagation of engagement and observe its impact on the overall social trust of nodes in the network, which we will do in our future work. In addition, the current evaluation only considers positive interactions. In future, we intend to evaluate the model on a dataset where there are a significant number of negative interactions to study the effect of negative interactions on the propagated trust. We also propose to study the effect of propagation on passive nodes (nodes that do not have popularity interactions with any other nodes, e.g., forum posts, articles, etc.). In addition, we plan to analyse the model further from the point of view of building trust communities and obtaining sustainable communities. Finally, we will be applying our model to an online community which we have designed to support a specific group of users, and we will study the effect of trust and the trust model in that community.

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