A Novel Approach to Trust based Identification of Leaders in Social Networks

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Abstract

Recommender Systems has been a research hotspot in recent times as an efficient information filtering tool, to filter out useful required information from ever expanding web. The characteristics of social networks play a very important role towards behavioral modeling of a trust network based Recommender System (RS). Similar to real world, in a social network also, it is important to objectively identify a member with high reputation who is heavily trusted by many members and hence his suggestions and inputs are most trust worthy for the whole community; that is, objective identification of leader is extremely important. In this paper, we propose a method to objectively identify leaders in a social network, we introduce new terms: Leadership score, prominence trust, peer inclusive factor, trust spread factor, trust maturity factor and trust penetration factors to portray a member more appropriately in a social network. We have calculated the leadership score using the real world dataset. Leadership score is taken as a linear additive function of prominence trust, engagement trust and peer inclusive factors with different weightage values. In our experiment, we have considered that leaders not only are followed by others, they are also socially engaged from their end to others in the social network. Prominence trust is a detailed characterization to get more accurate value of trust. Along with overall trust score, it is imperative to analyze more attributes to derive a more objective interpretation of the same. These attributes take care of trust score/reputation over period of time, number of trusting members, peer level interactions and also absolute score. To validate our leadership model in social network, we remove top 5%, 10% and top 20% of the members with high ‘leadership score’ and findout the reduction in the overall interactions. As further improvements to this work, a social network to be built with users and items and collect the data using positive and negative responses; use multiprogramming concepts to determine the optimum function for leadership score. This will aid towards further analysis and fine tuning of the models.

Keywords: Data Mining, Recommender System, Social Network, Trust, Web Mining

1. Introduction

Social networks and the analysis of them is intrinsically an interdisciplinary field which emerged from social psychology, sociology, statistics, and graph theory and is gaining lot of interest in both academia, as well as in industry. Web based Social networking sites initially started and used by individual users to keep in touch with their friends and families. With the unprecedented popularity and exponential growth of social networks, many commercial organizations started using social networks to offer better services to the customers and thereby enhancing their business opportunities. Many non-commercial organizations also use social networks to fulfill their objectives more effectively. Some of the example popular social networking sites are facebook, linkdin etc. Social network is made up of individual entities of varying trust levels and all entities will not have same standing/reputation in the network. Social relationships established by popular Social Networking Services (SNS), such as Facebook, Twitter, are all based on ego social networks—every user is building his/her own social network by

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explicitly defining connections with other people. On the other hand, connections between users in implicit social networks are based on analyzing over user profiles by third party, resulting in connecting users with similar profiles. Trust is one of the very important parameter in social networks as this encourages and enables members to join and freely interact with each other. Also this trust, in a major way influences individual members towards determing their preference of particular service or products, in line with social and behavioral science. Many a times, it is important to determine the members with high reputation. This analysis is required in many applications. The characteristics of social network plays a very important role towards behavioral modeling a trust network based Recommender System (RS). Based on the standing of members in social network, the recommendation for a particular service/product for other members in the network can effectively be determined. In real life, for getting appropriate suggestions on movies, doctors, books etc, we seek inputs from our circle of trusted friends, relatives etc. In real life social domain also, if we can identify an expert (or a most trusted) person who is trusted heavily by many in our social circle, we at the individual level also tend to be more inclined and confident of him and he is standout to be more trust worthy although we would not have any direct experience with him in the past. Similarly in a social network also, it is important to identify a member with high reputation who is trusted high by many members and hence his suggestions and inputs are most trust worthy for the whole community. Also identification of such members is important from the sustenance, growth and usability of the social network point of view. Thus trust plays a pivotal role in any collaborative applications in a scenario where any entity may not know all other entities individually. Social trust is very complex and depends on man factors, which makes it difficult to model in computational system. Some factors which influence trust are, past experience with a person, psychological factors impacted by history, events, rumors and influenced by others opinion. This collective intelligence helps in increasing the accuracy of trust based recommender system by enhancing traditional collaborative filtering based recommender system. There are various works done on trust based RS. Based on trust information, the accuracy and coverage of RS has greatly improved compared to traditional rating based RS. Increasing popularity of online social network has brought in new dimensions to the concept of trust in computational intelligence and can enhance traditional recommendation models. As pointed out by social psychology theory, the role of a person in a specific domain has significant influences on trust evaluation if the person recommends a person or an object. Thus, the role of the user should also be taken into account in making recommendations. Follow the leader in dynamic social networks, is a model of opinion formation with dynamic confidence in agentmediated social networks where the profiling of agents as leaders or followers is possible. An opinion leader is specified as a highly self-confident agent with strong opinions. An opinion follower is attracted to those agents in which it has more confidence. The “Follow the Leader” model provides a formal probabilistic approach and we have provided a URL to a paper that describes it in detail for those who are not familiar with it. The underlying basis of such approaches is that users are linked with each other in a social network tend to share some degree of trust among members themselves, shares similar taste and interest which can help to increase prediction accuracy of RS. In, introduced the concept of Trust in Recommender system. Several trust based recommendation models have been proposed. The accuracy of Recommender Sytem is increased greatly by incorporating trust in collaborative filtering algorithms. These works uses trust information however donottaketo considerations the social network based trust relationships. In takes into consideration, social trust information. In, a trust model for social networks is proposed where trust communities are build to inspire members share their experience, feelings and opinions objectively. The concept of social capital is introduced in. Sustainability of social networks using trust is detailed in. Here the concept of engagement trust and popularity trust to derive social trust is modeled. Two aspects of trust are considered here, popularity trust and engagement trust. Popularity trust refers to the acceptance and approval of a member by others in the community; while engagement trust depicts howmuch a member trust other members in the community. The impact trusted members on sustainability of social neworkisanalyzed. In, Random Walk with Restarts model is adopted to provide a more natural and efficient way to represent a social network. Social recommender is a new type among recommender systems, whose emergence was enabled by proliferation of web-based social networking. Social recommender
system will recommend the consumer products/services that consumer’s best friends (i.e., those friends in the social network whom consumer trusts most) liked in the past. In\textsuperscript{22} presents a system for recommending content within social networks. The main goal of the system is to identify and filter the recently published valuable resources while taking into account the interactions and the relationships the user has within social structures. In\textsuperscript{8} details the influence of social network leaders in recommender systems. The behavioral qualities of leaders in general and identification of opinion leaders in social networks is described in\textsuperscript{23}. In\textsuperscript{24} describes data mining and social networks, the concept of social network profile based search engines are given in\textsuperscript{25}. Recommender systems based on social data is presented in\textsuperscript{26}, blocking schemes in social sites are described in\textsuperscript{27}. Although there are substantial literature available on social networks, trust based Recommender System, however no comprehensive literature has been found on social trust models that takes into considerations trust scoring distribution over time and number of members along with peer interaction pattern and overall score.

In this paper, we propose a method to determine the leaders in a social network. Also in this paper, we propose the term prominence trust similar to popularity trust. Prominence trust is decomposed further to get more accurate value. We introduce new terms – trust spread factor, trust maturity factor and trust penetration factors, peer inclusive factor to characterize a member more appropriately in a social network.

2. Proposed Approach

Our objective isto identify the leaders in a trust based social network and this identification has a direct repercussion on the accuracy of trust based recommender system.

The importance for identification of leaders to have efficient recommender system is based on the premise as given by Goldbaum’s model. The characteristics of experts can be extrapolated to leaders in this context as leaders are expected to be expert and major influencer in a given domain. Goldbaum’s\textsuperscript{26} model explains three types of consumers that seek input from experts/leaders:

- The consumer has a set of preferences but suboptimal information concerning the available product. The expert offers input or advice that helps the consumer buy the product.
- The consumer possesses some preference over the available products, but can be influenced by the opinion of others (peers) and experts/leaders. The “expert/leader” has high standing in the community who can provide advice that is consistent with the underlying preferences of a group of consumers.
- Third type is where the consumer has no preferences. The consumer’s tastes are fully fashioned by the influence of peers and experts. In this case, the expert shapes opinion.

The expert in all previous cases can be considered as an experienced user who gives objective and high quality feedback on products. According to\textsuperscript{26}, in a social network a member is either a leader or a follower who adopted another leader’s opinion or recommendation to use a product. Thus user trust is the determinant relationship between two friends.

As detailed in\textsuperscript{23}, Rogers identified following characteristics of opinion leaders:

- Opinion leaders have higher exposure to mass media than others in the social network.
- Opinion leaders are more socially diverse than their followers.
- Opinion leaders have higher contact with change agents than others in the social network.
- Opinion leaders have greater social participation.
- Opinion leaders have higher socioeconomic status compared to their followers.
- Opinion leaders are more innovative.
- When a social system’s norms favor change, opinion leaders are more innovative, but when the system’s norms do not favor change, opinion leaders are less innovative.

In another comprehensive study, Weimann listed the attributes of leaders and are grouped into three sub-categories as:

1. Personal attributes
   - Innovativeness.
   - Individuation with social conformity.
   - Domain knowledge and interest.
   - Cosmopolitaness.
   - Higher level of Personal involvement.
2. Social attributes

- Sociable and socially active.
- Centrality in social networks.
- Social accessibility.
- Social recognition.
- Credibility.

3. Socio-demographic attributes

- Profiles change according to domains.
- Dynamic profiles based on social, cultural contexts and time variant.
- Tendency to similarity of influential/influence profiles.

These attributes of opinion leaders give researchers a general idea of who opinion leaders are, however practically it is difficult to actually identify opinion leaders in a social network with these general attributes because all social networks have their own specific characteristics and uniqueness. It is not always possible to characterise a social network and its leaders by taking into consideration all the attributes. The modelling and experimentations are not possible with all the attributes due to lack of dataset. Some of the attributes are combined together and a more meaningful and measureable attribute is modeled. Among he social attributes of opinion leaders, peer level interaction is considered to be a very important attribute as per social and personal psychology and reflects other social attributes directly or indirectly.

In this paper, we propose a method to objectively identify leaders in a social network, we introduce new terms: Leadership score, prominence trust, peer inclusive factor, trust spread factor, trust maturity factor and trust penetration factors to portray a member more appropriately in a social network. Prominence trust is a detailed characterisation to get more accurate value of trust. Along with overall trust score, it is imperative to analyze more attributes to derive a more objective interpretation of the same. These attributes take care of trust score/reputation over period of time, number of trusting members, peer level interactions and also absolute score.

2.1 Prominace and Leadership based Trust Calculation

As given in\(^9\), the popularity trust gives the popularity of a member in the social network. The engagement trust gives the involvement of a member in the social network. Trust score is combination of popularity trust (how many messages/feedbacks received) and engagement trust (how many messages/feedbacks provided). The nodes in the graph represent community members and the edges represent the interactions between them. In the Figure 1 node A has 4 incoming lines and 2 outgoing lines. The outgoing lines represent engagement trust, and the incoming lines represent the popularity trust. Each arrowed line gives information for popularity trust for sink side (receiving end) and engagement trust on the source side (initiating end).

**Figure 1.** Nodes in a network.

**Popularity Trust:**

The popularity trust \((PopTrust)\) of a member \(u \in U\) for a particular context \((x)\) is defined as:

\[
Poptrust (uix) = \sum_{j=1}^{M} \left( PT_{ij}^x + PT_{ij}^{-x} \right) + 1
\]

The aggregation over all contexts gives the popularity trust of the member in the community as follows:

\[
Poptrust (ui) = \sum_{x=1}^{X} \left( Poptrust (uix) \right)
\]

Where,

\[
|A| \quad PT_{a,\infty} = \sum_{a=1}^{+1}
\]
|A| 

\[ \text{PT}_{ij} = \sum_{a=1}^{X} \text{ET}_{ij} \]

|X| represents the number of contexts, and \(|A|\) represents the number of activities in each context. M is the total number of members.

Engagement Trust: We define the engagement trust model in a similar way to the popularity trust model as follows.

\[ \text{Engtrust (ui)} = \frac{\sum_{x=1}^{M} \left| \text{ET}_{ij} \right| + 1}{\sum_{x=1}^{M} \left| \text{ET}_{ij} \right| + 1} \]

Where \(|ET_{ij}| = 1, |ET_{ij}| \leq AA_{aa} = 0, \ldots, \ldots, 1\).

As given in \(^9\),

Trust = \( \mu \). Popularity Trust + (1-\( \mu \)). Engagement Trust

We derive the term prominence trust (similar to popularity trust). Prominence trust is decomposed further to get more accurate value. It is not sufficient that a member in a social network has high overall trust score, it is important to analyze more attributes of the same. We introduce the term “\( \eta \)” that characterizes an individual member in a social network in a better way that will be closer to the real life social eco-system. Trust Spread Factor is a function of Trust Maturity Factor and Trust Penetration Factor.

Prominence trust =

\[ \text{Trust Spread factor} = f \left( \text{Trust Maturity factor, Trust Penetration factor} \right) \]

(1)

Trust Maturity factor (TM) = Distribution over time (distribution of trust score of the member over a period of time, recently trusted has more weightage than trusted backward in the time axis). This takes care of trust dynamism over time.

Trust Penetration factor (TP) = Distribution of trust score of the member as given by number of other members. That is, if the av. Trust is same, a member who is trusted by more number of members in the social network, the weightage will be higher.

We have considered a harmonic mean function for Equation (4). Trust Spread Factor is taken as harmonic mean of trust Maturity Factor and Trust Penetration Factor. The advantage of using harmonic mean is that it is robust to large differences between the inputs, so a high value will be calculated only if both Trust Maturity factors and trust Penetration factor are high.

\[ \frac{2 \cdot \text{TM} \cdot \text{TP}}{\text{TM} + \text{TP}} \]

We consider Trust Maturity Factor as a linear growth function over time. That is, with progress in time, the factor increases its value.

\[ \text{Trust Maturity Factor (TM)} = \eta \cdot \frac{t}{T} \]

where, \( 0 < \eta < 1 \)

Example: let there are total of 5 time intervals (\( T = 5 \)) and an individual member in the social network is last interacted during time slot \( t = 3 \). Let \( \eta = 0.5 \).

Then trust maturity factor = \( 0.5 \times 3/5 = 0.3 \).

We consider Trust Maturity Factor as a linear growth function. That is, if an individual member in a social network is trusted (i.e., followed) by more number of member, rather than few members providing lot of messages/feedbacks on that member, it is more trust worthy and needs to be factored in the overall calculation of trustworthiness/reputation of members.

\[ \text{Trust Penetration Factor (TP)} = \eta \cdot \frac{m}{M} \text{ where, } 0 < \delta < 1 \]

\( M = \text{Total number of members.} \)

\( m = \text{The number of members followed/provided feedbacks/given messages to the individual member.} \)

Let \( M = 1000; m = 100; \nu = 0.5 \)

\[ \text{Trust Penetration Factor} = 0.9 \times \frac{100}{1000} = 0.05 \]

Prominence trust = Popularity Trust Value \( \times \) Trust Spread Factor (1-\( \mu \)). Engagement Trust

Thus prominence trust is a better and more accurate representation for a given social network.

Some of the important characteristics of leaders in general and specific to social networks are Humility, Passion, inclusive attitude, engaging, deep niche...
knowledge, prolific content producers and most importantly consistent. That means it is important for leaders to be followed by others as well as being engaging with others in the social network. To be a good leader in the context of social network, it is important to have a non-competitive, inclusive approach. A leader will recommend and endorse his/her peers. We introduce a term ‘peer inclusive factor’ to represent this quality/behaviour of a leader. We define this terms as:

\[
\text{Peer inclusive factor} = \frac{\sum_{i=m+1}^{m+k} I_p}{\sum_{i=1}^{m+k} I_p}
\]

Where,

- \( m \) = trust score rank of a particular member \( p \).
- \( I_p \) = interactions (both in and out types) of the member \( p \).
- \( k \) = neighbouring leaders considered (<n).
- \( n \) = total number of members in the network.

We model leaders as:

\[
\text{Leadership score} = \mu \cdot \text{Prominence Trust} + (1-\mu) \cdot \text{Engagement Trust} + \beta \cdot \text{Peer inclusive factor.} \quad \ldots \ldots (4)
\]

### 3. Experiments and Datasets

We have chosen a social network dataset for the experiment. ToreOpsahl is a facebook-like social network dataset. For trust calculation in social network, we carried out experiments using real datasets representing Facebook-like social networks. The datasets for the experiments were obtained from http://www.toreopsahl.com/datasets/ and represent interactions between students in an online community at the University of California, USA. These dataset have also been used to study network analysis of online community in Panzarasa et al. (2009) and network clustering in Opsahl and Panzarasa (2009). The dataset includes the users that sent or received at least one message (1,899). A total number of 59,835 online messages were sent over 20,296 directed ties among these users. Although the original dataset contains many nodal attributes (e.g., gender, age, and course attended), these are not made available to public as it would be possible to reverse engineer the anonymisation procedure of users.

Self-loops in the longitudinal edgelistsignal the time that users registered on the site.

The details of the datasets (D1 and D2) are described below.

- Total number of members: 1,899 (D1); 899 (D2)
- Total number of interactions: 59,835 (D1); 1,113,924 (D2)
- Number of unique interactions: 20,296(D1); 142,760(D2)

From theory of social and human behavioural science, it is a well understood proposition that, leaders play a very important role in influencing the actions of masses. The suggestions by leaders are followed largely by others in the society and also the leader’s choice of a particular commodity/act becomes the defacto choice for others. This is one of the driving force towards many commercial success also. Extrapolating the same concept in computational social network, it becomes imperative to identify leaders in a social network. The suggestions or choice of leaders in the social network plays a very important role in deciding for other members of the society. In this dataset, the types of responses (positive or negative) are not mentioned. Hence for our analysis all the responses are taken as positive. As already discussed. We model leaders as:

\[
\text{Leadership score} = \mu \cdot \text{Prominence Trust} + (1-\mu) \cdot \text{Engagement Trust} + \beta \cdot \text{Peer inclusive factor.} \quad \ldots \ldots (4)
\]

Initially we calculate the trust score without considering the ‘peer inclusive factor’ and identify top K in the list. After that, we calculate the ‘peer inclusive factors’ for top K members taking into consideration association with remaining K-1 members of the list. Then we calculate the leadership score and rank them in the order of the same.

As per our model, leaders are characterized by heavy interactions with varying weightages for different types of interactions. So, if a leader is removed from the community, there will be reduction in the overall interactions in the social network.

### 4. Results and Discussion

We have calculated the leadership score using the dataset as mentioned. Leadership score is taken as a linear additive function of prominence trust, Engagement trust and peer inclusive factor as given in the equation 4. For our experiment we have considered, \( \mu = 0.5 \) and \( \beta = 0.1 \). In this experiment, we have considered that leaders not only are followed by others, they are also socially engaged from their end to others in the social network. Table 1 and Table 2 shows the leadership score values and data statistics as calculated.
Table 1. Leadership score for top 5% members

| Prominence Trust | µ* Prominence Trust | Engagement Trust | (1-µ)* Engagement Trust | Peer Inclusive factor | β* Peer inclusive factor | Leadership Score |
|------------------|----------------------|------------------|--------------------------|----------------------|--------------------------|------------------|
| 0.82             | 0.41                 | 0.42             | 0.21                     | 0.71                 | 0.07                     | 0.69             |
| 0.78             | 0.39                 | 0.40             | 0.20                     | 0.82                 | 0.08                     | 0.67             |
| 0.80             | 0.40                 | 0.40             | 0.20                     | 0.62                 | 0.06                     | 0.66             |
| 0.72             | 0.36                 | 0.48             | 0.24                     | 0.59                 | 0.06                     | 0.66             |
| 0.70             | 0.35                 | 0.48             | 0.24                     | 0.69                 | 0.07                     | 0.66             |
| 0.64             | 0.32                 | 0.56             | 0.28                     | 0.62                 | 0.06                     | 0.66             |
| 0.66             | 0.33                 | 0.54             | 0.27                     | 0.61                 | 0.06                     | 0.66             |
| 0.68             | 0.34                 | 0.50             | 0.25                     | 0.58                 | 0.06                     | 0.65             |
| 0.66             | 0.33                 | 0.52             | 0.26                     | 0.58                 | 0.06                     | 0.65             |
| 0.60             | 0.30                 | 0.56             | 0.28                     | 0.71                 | 0.07                     | 0.65             |
| 0.66             | 0.33                 | 0.48             | 0.24                     | 0.81                 | 0.08                     | 0.65             |
| 0.66             | 0.33                 | 0.52             | 0.26                     | 0.62                 | 0.06                     | 0.65             |
| 0.78             | 0.39                 | 0.42             | 0.21                     | 0.54                 | 0.05                     | 0.65             |
| 0.66             | 0.33                 | 0.54             | 0.27                     | 0.53                 | 0.05                     | 0.65             |
| 0.56             | 0.28                 | 0.64             | 0.32                     | 0.49                 | 0.05                     | 0.65             |
| 0.42             | 0.21                 | 0.74             | 0.37                     | 0.58                 | 0.06                     | 0.64             |
| 0.74             | 0.37                 | 0.42             | 0.21                     | 0.54                 | 0.05                     | 0.64             |
| 0.54             | 0.27                 | 0.60             | 0.30                     | 0.62                 | 0.06                     | 0.63             |
| 0.58             | 0.29                 | 0.54             | 0.27                     | 0.49                 | 0.05                     | 0.63             |
| 0.36             | 0.18                 | 0.78             | 0.39                     | 0.61                 | 0.06                     | 0.63             |
| 0.70             | 0.35                 | 0.46             | 0.23                     | 0.60                 | 0.06                     | 0.62             |
| 0.64             | 0.32                 | 0.48             | 0.24                     | 0.52                 | 0.05                     | 0.62             |
| 0.70             | 0.35                 | 0.44             | 0.22                     | 0.44                 | 0.04                     | 0.62             |
| 0.38             | 0.19                 | 0.74             | 0.37                     | 0.61                 | 0.06                     | 0.62             |
| 0.46             | 0.23                 | 0.64             | 0.32                     | 0.53                 | 0.05                     | 0.62             |
| 0.68             | 0.34                 | 0.38             | 0.19                     | 0.52                 | 0.05                     | 0.61             |
| 0.44             | 0.22                 | 0.64             | 0.32                     | 0.59                 | 0.06                     | 0.61             |
| 0.42             | 0.21                 | 0.66             | 0.33                     | 0.68                 | 0.07                     | 0.60             |
| 0.38             | 0.19                 | 0.70             | 0.35                     | 0.59                 | 0.06                     | 0.60             |
| 0.62             | 0.31                 | 0.46             | 0.23                     | 0.59                 | 0.06                     | 0.60             |
| 0.64             | 0.32                 | 0.44             | 0.22                     | 0.54                 | 0.05                     | 0.59             |
| 0.54             | 0.27                 | 0.54             | 0.27                     | 0.51                 | 0.05                     | 0.59             |
| 0.66             | 0.33                 | 0.42             | 0.21                     | 0.50                 | 0.05                     | 0.59             |
| 0.40             | 0.20                 | 0.66             | 0.33                     | 0.63                 | 0.06                     | 0.59             |
| 0.26             | 0.13                 | 0.82             | 0.41                     | 0.53                 | 0.05                     | 0.59             |
| 0.62             | 0.31                 | 0.44             | 0.22                     | 0.61                 | 0.06                     | 0.59             |
| 0.46             | 0.23                 | 0.62             | 0.31                     | 0.49                 | 0.05                     | 0.59             |
| 0.34             | 0.17                 | 0.68             | 0.34                     | 0.67                 | 0.07                     | 0.58             |
| 0.46             | 0.23                 | 0.58             | 0.29                     | 0.64                 | 0.06                     | 0.58             |
| 0.74             | 0.34                 | 0.38             | 0.19                     | 0.53                 | 0.05                     | 0.58             |
| 0.54             | 0.27                 | 0.50             | 0.25                     | 0.61                 | 0.06                     | 0.58             |
| 0.38             | 0.19                 | 0.72             | 0.36                     | 0.54                 | 0.05                     | 0.58             |
| 0.58             | 0.29                 | 0.46             | 0.23                     | 0.62                 | 0.06                     | 0.58             |
| 0.54             | 0.27                 | 0.52             | 0.26                     | 0.51                 | 0.05                     | 0.58             |
| 0.36             | 0.18                 | 0.68             | 0.34                     | 0.64                 | 0.06                     | 0.58             |
| 0.60             | 0.30                 | 0.44             | 0.22                     | 0.53                 | 0.05                     | 0.57             |
Table 2. Data statistics for top 5% leaders

| Variable      | X1    | X2    | X3    | Y     |
|---------------|-------|-------|-------|-------|
| Number of Points | 46    | 46    | 46    | 46    |
| Missing Points | 0     | 0     | 0     | 0     |
| Maximum Value  | 0.41  | 0.41  | 0.08  | 0.69  |
| Minimum Value  | 0.13  | 0.19  | 0.04  | 0.57  |
| Range          | 0.28  | 0.22  | 0.04  | 0.12  |
| Average        | 0.2880434 | 0.2721739 | 0.0578260 | 0.619347 |
| Standard Deviation | 0.0701940 | 0.05819175 | 0.00840979 | 0.032207 |

To validate our leadership model in social network, we remove top 5%, 10% and top 20% of the members with high 'leadership score' and find out the reduction in the overall interactions. We determine the leadership score of the members and plot them as shown in Figure 2. We also find that reduction of outgoing interactions is more as compared to incoming interactions in the whole social network after the removal of top score members. This shows that the leaders are modeled appropriately. Figure 3 shows the percentage reduction with removal of leaders from social network. As we find that there is considerable reduction. Thus the behavioural attributes of leaders in social networks are verified.

5. Conclusions and Future Works

In this paper, we have modeled the behavior of leaders in the social network considering various parameters namely trust spread factor, trust maturity factor and trust penetration factors. Determination of leadership score is important in determining the leaders in the social network who influences other members in the social network. We have analyzed the effect of removing the leaders from the social network and thereby validating our model. As we could not find a readily available dataset that contains social network data with time stamping and items with user ratings, we could not perform testing of our leadership model on a recommender system. We plan to build a social network with users and items, collect the data using positive and negative responses and use the collected data to comprehensively apply towards building a leadership model with more attributes and validate the same on a recommender system. Multiprogramming concepts can be applied to determine the optimum function for leadership score. This will enable us to do further analysis and fine tuning of the models.

6. References

1. Mika P. Social networks and the semantic web. New York: Springer; 2007.
2. Zappen JP, Harrison TM, Watson D. A new paradigm for designing e-government: Web 2.0 and experience design. Proceedings of the International Conference on Digital Government Research; Montreal, Canada: Digital Government Society of North America. 2008.

3. Hassan O, Brunie L, Pierson JM, Bertino EB. Elimination of subjectivity from trust recommendation. The 3rd IFIP International Conference on Trust Management (TM 2009); West Lafayette, IN, USA. 2009 Jun. p. 15–9.

4. Ma H, King I, Lyu MR. Learning to recommended with social trust ensemble. Proceedings of the 32nd SIGIR; 2009.

5. Jamali M, Ester M. A matrix factorization technique with trust propagation for recommendation in social networks. Proceedings of the 4th ACM Conference on Recommender Systems; 2010.

6. Walter FE, Battistone S, Schweitzer F. A model of a trust-based recommendation system on a social network. Autonomous Agents and Multi-Agent systems. 2008; 16(1):57–4.

7. Liu F, Lee HJ. Use of social network information to enhance collaborative filtering performance. Expert Systems with Applications. 2010 Jul; 37(7):4772–8.

8. Al-Sharawneh J, Williams MA. Credibility-aware web-based social network recommender: Follow the leader. Proceedings of the 2nd ACM RecSys’10 Workshop on Recommender Systems and the Social Web; 2010.

9. Jiang M, Cui P, Liu R, Yang Q, Wang F, Zhu W, Yang S. Social contextual recommendation. Proceedings of the 21st CIKM; 2012.

10. Ma H, Yang H, Lyu MR, King I. Sorec: Social recommendation using probabilistic matrix factorization. Proceedings of the 17th CIKM; 2008.

11. Ma H, King I, Lyu MR. Recommender system with social regularization. Proceedings of the 4th WSDM; 2010.

12. O’Donovan J, Smyth B. Trust in recommender systems. Proceedings of the 10th International Conference on Intelligent user Interfaces; 2005. p. 167–74.

13. Massa P, Avesani P. Trust-aware recommender systems. Proceedings of the 2007 ACM Conference on Recommender systems, RecSys ’07; New York, NY, USA. 2007. p. 17–24.

14. Lathiya N, Hailes S, Capra L. Trust-based collaborative filtering. Joint iTrust and PST Conferences on Privacy, Trust Management and Security (IFIPTM); Trondheim, Norway. 2008.

15. Golbeck J, Hendler J. Accuracy of metrics for inferring trust and reputation in semantic web-based social networks. Proceedings of EKAW’04, LNAI 2416; 2004. p. 278.

16. Liu X. Towards context aware social recommendation via trust networks. WISE Part I, LNCs. 2013; 8180:121–34.

17. Nepal S, Sherchan W, Paris C. Strust: A trust model for social networks. IEEE 10th International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom); Changsha, China. 2011. p. 841–6.

18. Nepal S, Paris C, Bista SK, Sherchan W. A trust model based analysis of social networks. International Journal of Trust Management in Computing and Communications. 2013; 1:3–22.

19. Caverlee J, Liu L, Webb S. The social trust framework for trusted social information management: architecture and algorithms. Information Sciences. 2010; 180(1):95–112.

20. Konstas I, Stathopoulos V, Jose JM. On social networks and collaborative recommendation. Proceedings of the 32nd International ACM SIGIR Conference on Research and Development in Information Retrieval, ACM; New York, NY, USA. 2009. p. 195–202.

21. Podobnik V, Striga D, Jandras A, Lovrek I. How to calculate trust between social network users? Proceedings of the 20th International Conference on Software, Telecommunications and Computer Networks (SoftCOM 2012); 2012.

22. Mican D, Mocan I, Tomai N. Building a social recommender system by harvesting social relationships and trust scores between users. Lecture Notes in Business Information Processing. 2012; 127:1–12.

23. Kim DK. Identifying opinion leaders by using social network analysis: A synthesis of opinion leadership data collection methods and instruments [PhD dissertation]. School of Communication Studies, Ohio University; 2007.

24. Chakradeo SN, Abraham RM, Rani BA, Manjula R. Data mining: Building social network. Indian Journal of Science and Technology. 2015 Jan; 8(S2). DOI: 10.17485/ijst/2015/v8iS2/60482.

25. Ramesh N, Andrews J. Personalized search engine using social networking activity. Indian Journal of Science and Technology. 2015 Feb; 8(4). DOI: 10.17485/ijst/2015/v8i4/60376.

26. Reddy CA, Subramaniyaswamy V. An enhanced travel package recommendation system based on location dependent social data. Indian Journal of Science and Technology. 2015 Jul; 8(16). DOI: 10.17485/ijst/2015/v8i16/63571.

27. Nivedha R, Sairam N. A machine learning based classification for social media messages. Indian Journal of Science and Technology. 2015 Jul; 8(16). DOI: 10.17485/ijst/2015/v8i16/63640.

28. Adamkani J, Nirmala K. A content filtering scheme in social sites. Indian Journal of Science and Technology. 2015 Dec; 8(33). DOI: 10.17485/ijst/2015/v8i11/80128.