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METHODOLOGIES AND APPLICATION

Link prediction in signed social networks based on fuzzy computational model of trust and distrust

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Abstract

Signed social networks are those in which users of the networks are connected with some interdependencies such as agreement/disagreement, liking/disliking, friends/foes, loving/despising, and companions/enemies. Most individuals in signed social networks have many relations in terms of friends, foes, following and followers. All these relations are usually asymmetric and subjective, thus difficult to predict. To resolve the fundamental problem of sparsity in the networks, substantial amount of research work has been dedicated to link prediction; however, very little work deals with the antagonistic behavior of the users while considering the asymmetric and domain-dependent nature of links. This paper is based on the concept that *All Relations Are Not Equal* and some relations are stronger than other relations. For instance some friends may be acquaintances of an individual, whereas another may be friends who care about him/her. In this paper, a fuzzy computational model is proposed based on trust and distrust, as a decision support tool that dissects relevant and reliable information of the users to distinguish the stronger relations from the weaker ones. Further, we have proposed two different link prediction models based on local information and local–global information to overcome the problem of sparsity in signed social networks. An extensive experimental study is performed on benchmarked synthetic dataset of friends and foes network and publicly available real-world datasets of Epinions and Slashdot. The results obtained are promising and establish the efficacy of our proposed models.

Keywords Signed social networks · Trust · Distrust · Fuzzy · Link prediction · Social balance theory · Positive links · Negative links

1 Introduction

The ubiquity of signed ties can be seen easily in social networks, especially in social networking sites which are commonly used as a platform to express ideas/emotions or views about other users. These users' expressed views or emotions are based on the kind of relationship (positive or negative) they have with other users in the network. Hence, social networks are not untouched with the human antagonistic behavior. The not-so good relation conditions sometimes are visible on social media through user's way of interactions like in poor ratings, disagreements, dislikes, etc., besides the positive relations shown in terms of good ratings, agreements, likes, etc., that lead to the emergence of signed social networks (SSNs). These positive and negative relations represent trust and distrust between users of the network, respectively. To map these relations, the link between users is annotated with + 1 (friends, agreements, likes, etc.), − 1 (foes, disagreements, dislikes etc.), and 0 (non-existing links). Most of the human relations are nebulousness in nature. Moreover, both the terms trust and distrust are quite challenging to define with subjective, asymmetric and domain-dependent aspects as they manifest themselves in many different forms. Thus, crisp modeling of trust and distrust is not appropriate or enough for inferring accurate information about the type of relation among users. Furthermore, people naturally use linguistic

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expressions rather than numeric values to describe their trust or distrust. Thus, the assignments of crisp values $\{+1, 0, -1\}$ to the links in SSNs are somewhat confusing or misleading. For example, a positive link annotated with $+1$ indicates complete trust between two users and -1 annotated link indicates complete distrust which might not be the case as human relations are in essence vague. They can partially trust or distrust each other. So, to overcome the vagueness present in the relations, we have proposed a fuzzy-based trust–distrust model to compute the strength of links (ties). Further, we aim to predict missing links to resolve the problem of sparsity in signed social networks.

In this article, we present two different link prediction models based on the strength of link between users for signed social networks. The fundamental framework for both the proposed models is fuzzy computational model which is based on strength of ties computed in terms of trust–distrust values between users of the network. After fuzzy modeling of trust–distrust, we propose two different link prediction models in this article. The first proposed link prediction model is solely based on strength of ties among users computed in terms of trust–distrust values, which are further calculated on the similarity between users. The similarity is estimated on the basis of interest on common items termed as preference similarity factor and on the virtual encounters happened when users of the network rate same items named as knowledge factor.

In the second proposed link prediction model, for prediction of the missing links, along with the consideration of strength of ties and similarity among the users, we have employed the concept of mutual friends along with the fundamental theory of signed social networks termed as social balance theory which takes into account the social balance of the network. According to this, a triad is said to be balanced if it has odd number of positive links (either one or three positive links). Thus, social balance factor (SBF) is the ratio of number of balanced triads to the number of total triads in the network (Adamic and Adar 2003; Girdhar and Bharadwaj 2016; Patidar et al. 2012).

In this work, we are treating inductive learning-based link prediction (ILLP) approach proposed by Patidar et al. (2012) as the baseline technique to compare our models. This approach initially builds decision tree from the attribute-categories input and generates classification rules by employing C4.5. Then, missing links are predicted as friend/foe based on the classification rules. Next, social balance index (BI) is computed for each user before and after predicting a new link. Finally, recommendation of set of users is one which either maintains or enhances the balance index of that particular user.

Thus, the contributions of this paper are summarized below:

1. Considering the fact that *All Relations Are Not Equal* (Hangal et al. 2010), a fuzzy computational framework based on trust–distrust between users is developed following the approach proposed by Bharadwaj and Al-Shamri (2009) and Kant and Bharadwaj (2013) to resolve the problem of link prediction in signed social networks. Strength of ties based on preference similarity factor, knowledge factor and social balance theory is used to predict the link and the sign of the link among the users of the network.
2. Two novel approaches for link prediction in signed social networks are developed. In particular, our proposed models can incorporate any type of relationships signed or unsigned, weighted or binary and is well suited for directed as well as undirected signed social networks.
3. Extensive experiments are performed on both synthetic benchmarked and on real-world datasets to clearly demonstrate the capability of our proposed models to effectively deal with the sparsity problem of SSNs to achieve link prediction accuracy.

The rest of the article is organized as follows: Sect. 2 summarizes related work in the area of SSNs. The proposed link prediction models are well described in Sect. 3. Section 4 discusses the datasets and evaluation metrics used for analyzing signed social networks and the experimental study of the proposed schemes. Finally, in Sect. 5, we have concluded the findings of our work along with some future research directions.

2 Related work

Being the fundamental research field of social networks, link prediction continues to enthrall the research community. Numerous such efforts focus on the problem of missing links and to tackle the problem of sparsity in signed social networks (Girdhar and Bharadwaj 2016; Leskovec et al. 2010b; Patidar et al. 2012; Tang et al. 2015; Yang et al. 2012). Several methodologies and mathematical models (Backstrom and Leskovec 2011; Fire et al. 2013; Gong et al. 2011; Kleinberg 2002; Quercia and Capra 2009) have been developed to show how people interact with one another and establish link in social networks. Until recently, the link prediction analysis (Kutty et al. 2014; Liben-Nowell and Kleinberg 2007; Patil 2009; Xie 2010; Yang et al. 2013) in social networks has been tackled by modeling only the positive relationships among users, whereas negative ones are completely ignored. However, in the last decade, due to the popularity of SSNs, it has garnered a lot of attention of the research community to develop surge of interest to analyze and examine these networks.

Researchers have encountered a significant change in the nature and complexity of social network once the negative links are introduced in the networks, which signifies the importance of negative links (even more important than positive links) in signed link prediction (Chiang et al. 2011; Kunegis et al. 2009; Leskovec et al. 2010b; Tang et al. 2015; Zhang et al. 2013). A variety of available networks like Epinions, Slashdot, Wikipedia, etc., have also started labeling links explicitly either as friend/foe (Kunegis et al. 2009) or trust/distrust (Jøsang et al. 2006). A number of theories in psychology (Chiang et al. 2011; Leskovec et al. 2010a) provide deeper insight into the fundamental principles which explain how the patterns of negative and positive links resulted into different kinds of relationships.

In a latest work, Leskovec et al. (2010a, b) have examined the applicability of social psychological theories to predict the polarity of links by incorporating machine learning framework. Javari and Jalili (2014) modeled signed network as a bipartite user-item network and applied user-based collaborative filtering (CF) for sign link prediction problem. Chiang et al. (2011) proposed a feature exploitation-based model from longer cycle in social graph in order to benefit the accuracy of sign prediction. With slightly different perspective, Guha et al. (2004) put forward a trust propagation model based on trust–distrust to infer trust between unfamiliar users. Furthermore, Tang et al. (2015) have explored the problem of predicting negative links automatically by investigating only positive links and content-centric interactions in social media. Yang et al. (2012) have exploited the information contained in implicit polarity of the existed positive and negative links as prior information to suggest a user who are more likely to become his friends/foes in near future. Granovetter (1983) proposed the idea of strong and weak ties where he showed that "weak" connections are more useful than connections signifying "strong" bonds of closed friendship or kinship. According to the study conducted on Persuasive Technologies by Ahmad and Ali (2018), emotions (positive and negative) play a vital role in supporting behavior to build trust among users.

One fundamental method used in friend prediction is "number of mutual friends" (Adamic and Adar 2003; Leskovec et al. 2010b; Patil 2009). Undoubtedly, this method suffers severe drawback of interest mismatch, and it is useless in expanding user's network where someone who has many common friends with you probably is already known to you. Also, social networks that are built on friendship relations are modeled as a graph, where each node represents a user and edges represent the friendship links. In this, simply by analyzing the proximity of two members, the system predicts the edges that will be added to the network in the near future. In this strategy, the entire focus remains on the network structure, whereas intrinsic properties of nodes (users) in the network are completely ignored (Adamic and Adar 2003; Kutty et al. 2014; Tang et al. 2016). As most of the traditional link prediction schemes proposed earlier, take into account only positive links, considering network as *All-Friend* relations which is not true (Brzozowski et al. 2008; Kunegis et al. 2009; Zhang et al. 2013) owing to permeating antagonistic links between users of the network (Tang et al. 2015). Thus, these schemes cannot be directly applied to signed social networks due to their brevity of ignoring negative links which plays vita role in evolving of these SSNs.

In our work, proposed models take into account the aforementioned factors of number of mutual friends as well as similarity between users for link prediction in SSNs considering the common interests between users which help in building friendship. Further, since a user's behavior could in turn impact his relationship with others (Yang et al. 2012), this can also be well explained through principle of homophily which advocates "similarity breeds connections," where two socially connected users are tied and reinforced by each other besides the number of mutual links between the users in the network (Leskovec et al. 2010b; Patil 2009). This work further investigates a more realistic case where acquainted users are not necessarily reinforcing each other in decision making. We do so, by modeling sign ties, a much stronger signal that allows us to tie the behavior of a user to whom he trusts rather than whom he knows (Yang et al. 2012).

Moreover, signed social media treats all users at the same level and takes its binary view i.e., either friend $(+1)$ or foe (-1). But, in practice, friendship or antagonism may fall anywhere along the spectrum $[-1, \ 1]$, and further, both the relations between two persons may be asymmetric (Awal and Bharadwaj 2014; Bharadwaj and Al-Shamri 2009; Hangal et al. 2010; Kant and Bharadwaj 2013). Hence, this underpins the idea of fuzzy modeling of strength of ties for link prediction in our proposed models.

3 Proposed link prediction models based on fuzzy modeling of trust–distrust for signed social networks

Trust–distrust measure gives a personalized view of the future encounters with a specific user. In the literature, either trust or distrust is usually used as crisp attributes; however, that does not effectively reflect the social meanings of these concepts where most of the human perceptions are fuzzy. Since trust and distrust concepts are social fuzzy concepts, we have proposed link prediction models grounded on fuzzy computational model that would reflect their actual values for enhancing the link prediction accuracy.

This section will present two different proposed models for link prediction in signed social networks. The first model is based on two major factors: preference similarity factor and knowledge factor. Preference similarity factor implies the trust and distrust established among the users of the network based on social similarities and dissimilarities such as interests on common items or topics. Knowledge factor implies the trust and distrust established among the users based on their past interactions. An interaction is a virtual encounter which takes place when two users rate same item or topic. Both the factors are exploited to find similarity among the users to further compute total trust or distrust among users of the network. Missing links among users are then predicted based on their trust and distrust values. In the second proposed model, besides leveraging the local information about preference similarity and knowledge factors, global information about mutual links among users and social balance theory are also taken into account to predict missing links between users to tackle the problem of sparsity in the network.

Our proposed models follow a two-phase scheme based on the following steps:

Step 1 The primary step of both the models is to perform fuzzy modeling of trust and distrust. It requires computation of strength of ties based on preference similarity and knowledge factors in terms of trust–distrust, which is explained in detail in Sect. 3.1.

Step 2 After fuzzy modeling of trust–distrust, two different link prediction models are proposed (in Sect. 3.2) in this article to overcome the problem of sparsity in the network by predicting missing links among the users of the network.

The detailed descriptions of the two proposed models are given as follows:

3.1 Computation of strength of links in terms of trust–distrust

In this section, we have discussed the fuzzy computational framework developed heeding the approach proposed by Bharadwaj and Al-Shamri (2009) and Kant and Bharadwaj (2013), for trust–distrust computation.

3.1.1 Trust–distrust computation based on preference similarity factor

For the computation of preference-based similarity factor, we have considered common choices of the users based on the ratings given by them to the different items or topics of their interests. The ratings of the users to the items indicate their interest level which is generally given on the scale of 1–5, where values 4 and 5 denote high rating (favored item), 3 denotes neutral rating (indifferent item) and 1 and 2 denote low rating (not-favored item). However, these ratings provided by the users can be imprecise as they depend on the current mood or the situation of the users. Moreover, two users give same rating to a topic, which does not mean that they have same level of interest in that particular topic. Hence, users' interest can be taken as a fuzzy variable which can take up values like strongly liked, liked, neutral, disliked and strongly disliked.

For this, half triangular membership function is used which is expressed in continuum from minimum value (min) to maximum value (max) for fuzzy set Z (Fig. 1) which is defined in Eq. (1), where $R_{(u_i,I_k)}$ is user rating on an item (rating given by ith user for k^{th} item)

$$\mu_Z(I_k) = \begin{cases} 0 & R_{(u_i,I_k)} = \min \\ \dfrac{R_{(u_i,I_k)} - \min}{\max - \min} & \min < R_{(u_i,I_k)} < \max \\ 1 & R_{(u_i,I_k)} = \max \end{cases} \quad (1)$$

Based on the fuzzy set Z, items are classified into three categories: Favored(F), NonFavored items (NF) and Indifferent items (InD).

$$F = \{I_j : \mu_Z(I_j) > 0.5\} \quad (2)$$

$$\mathrm{NF} = \{I_j : \mu_Z(I_j) < 0.5\} \quad (3)$$

$$\mathrm{InD} = \{I_j : \mu_Z(I_j) = 0.5\} \quad (4)$$

Preference similarity factor-based trust and distrust between user u_i and user u_j denoted as $\mathrm{Pref\_Sim\_Trust}(u_i, u_j)$ and $\mathrm{Pref\_Sim\_Distrust}(u_i, u_j)$ are given by Eqs. (5) and (6).

$$\mathrm{Pref\_Sim\_Trust}(u_i, u_j) = \frac{1}{2}\left[\frac{|F_{u_i} \cap F_{u_j}|}{F_{u_i}} + \frac{|NF_{u_i} \cap NF_{u_j}|}{NF_{u_i}}\right] \quad (5)$$

$$\mathrm{Pref\_Sim\_Distrust}(u_i, u_j) = \frac{1}{2}\left[\frac{|F_{u_i} \cap NF_{u_j}|}{F_{u_i}} + \frac{|NF_{u_i} \cap F_{u_j}|}{NF_{u_i}}\right] \quad (6)$$

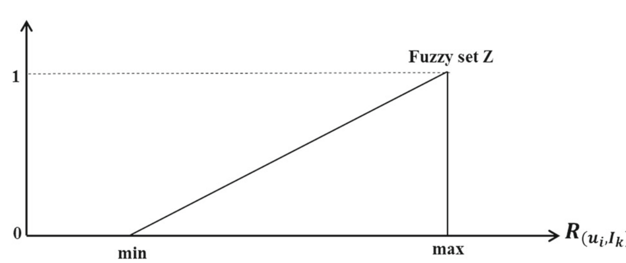


Fig. 1 Membership function for fuzzy set Z

Here, $|F_{u_i}|$ and $|\mathrm{NF}_{u_i}|$ denote number of Favored and NonFavored items by user u_i, respectively.

3.1.2 Trust–distrust computation based on knowledge factor

Considering the fact that the lack of enough experience may result in reduction in degree of trust and distrust, we have also considered the knowledge factor which is related to the repeated "interactions" between users. These repeated interactions are based on the virtual encounters (as users do not meet directly) when two users rate same items (Bharadwaj and Al-Shamri 2009; Kant and Bharadwaj 2013). If user u_i rate item I_k i.e.,$R_{(u_i,I_k)}$, and user u_j also rate same item I_k, i.e., $R_{(u_j,I_k)}$, then a virtual interaction called encounter (let say e) takes place. User rating after this encounter reflects the rater satisfaction about the encounter. Now, rating of user u_i for user u_j after the encounter e, $R_{u_i}^{u_j}(e)$, can be calculated as follows:

$$R_{u_i}^{u_j}(e) = \begin{cases} 5 & 0.0 \leq |R_{(u_j,I_k)} - R_{(u_i,I_k)}| < 0.5 \\ 4 & 0.5 \leq |R_{(u_j,I_k)} - R_{(u_i,I_k)}| < 1.0 \\ 3 & 1.0 \leq |R_{(u_j,I_k)} - R_{(u_i,I_k)}| < 2.0 \\ 2 & 2.0 \leq |R_{(u_j,I_k)} - R_{(u_i,I_k)}| < 3.0 \\ 1 & \text{otherwise} \end{cases} \tag{7}$$

The set of ratings given by user u_i to user u_j is given by $S_{u_i}^{u_j} = \{R_{u_i}^{u_j}(e)|\forall e\}$, and S_{u_i} is the set of all the ratings given by user u_i to remaining users in the system. After completion of encounters for each user u_i, on the basis of ratings given by user u_i to user u_j, these encounters are categorized into three classes: Satisfactory, Unsatisfactory, and Neutral given as:

$$\mathrm{Satisfactory}\left(R_{u_i}^{u_j}(e)\right) = \{R_{u_i}^{u_j}(e)|\forall R_{u_i}^{u_j}(e) \in S_{u_i}^{u_j} \ \ and \ \ R_{u_i}^{u_j}(e) > 3\} \tag{8}$$

$$\mathrm{Unsatisfactory}\left(R_{u_i}^{u_j}(e)\right) = \{R_{u_i}^{u_j}(e)|\forall R_{u_i}^{u_j}(e) \in S_{u_i}^{u_j} \ \ and \ \ R_{u_i}^{u_j}(e) < 3\} \tag{9}$$

$$\mathrm{Neutral}\left(R_{u_i}^{u_j}(e)\right) = \left\{R_{u_i}^{u_j}(e)|\forall R_{u_i}^{u_j}(e) \in S_{u_i}^{u_j} \ \ and \ \ R_{u_i}^{u_j}(e) = 3\right\} \tag{10}$$

For each user u_i, based on the set of ratings given by user u_i to user u_j for all encounters, two fuzzy sets $\mathrm{Satisfied}(u_i)$ and $\mathrm{Unsatisfied}\ (u_i)$ are formed that follow simple triangular membership function as shown in Fig. 2, and can be calculated as from Eqs. (11) and (12), respectively.

$$\mathrm{Satisfied}(u_i) = \begin{cases} 0 & R_{u_i}^{u_j}(e) = 1 \\ \dfrac{R_{u_i}^{u_j}(e) - 1}{4} & 1 < R_{u_i}^{u_j}(e) < 5 \forall R_{u_i}^{u_j}(e) \in S_{u_i} \\ 1 & R_{u_i}^{u_j}(e) = 5 \end{cases} \tag{11}$$

$$\mathrm{Unsatisfied}(u_i) = \begin{cases} 1 & R_{u_i}^{u_j}(e) = 1 \\ \dfrac{5 - R_{u_i}^{u_j}(e)}{4} & 1 < R_{u_i}^{u_j}(e) < 5 \forall R_{u_i}^{u_j}(e) \in S_{u_i} \\ 0 & R_{u_i}^{u_j}(e) = 5 \end{cases} \tag{12}$$

One of the ideas behind computing trust and distrust based on these encounters is experience, which effect a user of anything or everything owed to his past encounters with other users. On the basis of positive and negative encounters, experience is categorized as $\mathrm{Trust\_Exp}(u_i,\ u_j)$ and $\mathrm{Distrust\_Exp}(u_i,\ u_j)$ between user u_i and user u_j, given by Eqs. (13) and (14), respectively.

$$\mathrm{Trust\_Exp}(u_i,\ u_j) = \frac{\left|S_j^+\right|}{\max\{|S_i|, |S_j|\}} * \frac{\left|S_j^+\right|}{\max\{\ |S_i||\forall i\}} \tag{13}$$

$$\mathrm{Distrust\_Exp}(u_i,\ u_j) = \frac{\left|S_j^-\right|}{\max\{|S_i|, |S_j|\}} * \frac{\left|S_j^-\right|}{\max\{\ |S_i||\forall i\}} \tag{14}$$

where $\left|S_j^+\right|$ and $\left|S_j^-\right|$ denote the cardinality of positive and negative interactions, respectively, of user j.

Similar to experience, the other idea is phenomenon of reciprocity which states the probability of mutual deeds, viz. favor or revenge increases if two persons trust or distrust each other. Reciprocity is also classified as trust reciprocity $\mathrm{Trust\_Rec}(u_i, u_j)$ and distrust reciprocity $\mathrm{Distrust\_Rec}(u_i, u_j)$ between user u_i and user u_j calculated by Eqs. (15) and (16):

$$\mathrm{Trust\_Rec}(u_i,\ u_j) = \mathrm{Agr}(u_i,\ u_j)\left(1 - \mathrm{Disagr}(u_i,\ u_j)\right) * \mathrm{Rel}(u_i,\ u_j) \tag{15}$$

$$\mathrm{Distrust\_Rec}(u_i,\ u_j) = \mathrm{Disagr}(u_i,\ u_j)\left(1 - \mathrm{Agr}(u_i,\ u_j)\right) * \mathrm{Rel}(u_i,\ u_j) \tag{16}$$

Here, $\mathrm{Rel}(u_i,\ u_j)$ denotes the reliability which is the ignorance or uncertainty in the reciprocity value of trust and distrust between user u_i and user u_j that can be computed as Eq. (17)

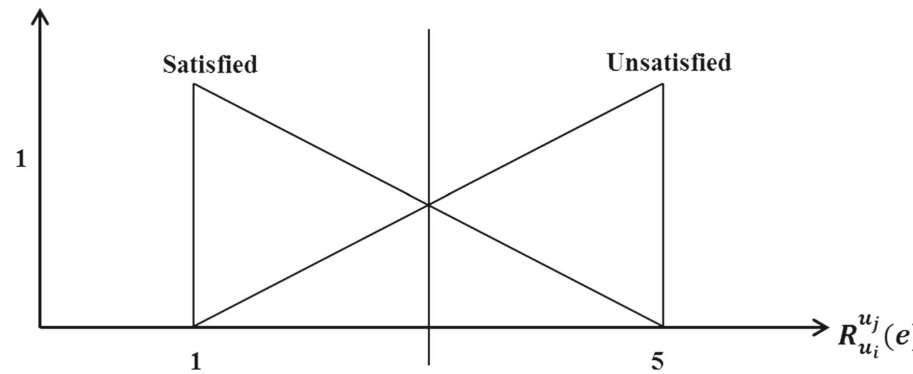


Fig. 2 Membership function for satisfied and unsatisfied fuzzy sets

$$\mathrm{Rel}(u_i,u_j) = 1 - \frac{\left|\mathrm{Neutral}\left(R_{u_i}^{u_j}(e)\right)\right| + \left|\mathrm{Neutral}\left(R_{u_j}^{u_i}(e)\right)\right|}{\left|S_{u_i}^{u_j}\right| + \left|S_{u_j}^{u_i}\right|} \tag{17}$$

$\mathrm{Agr}(u_i,\ u_j)$ is agreement value computed between user u_i and user u_j, Eq. (18), when both the users either get satisfied $\mathrm{SS}(u_i,\ u_j)$, Eq. (19) or unsatisfied $\mathrm{UU}(u_i,\ u_j)$, Eq. (20).

$$\mathrm{Agr}(u_i,\ u_j) = \frac{\mathrm{SS}(u_i,\ u_j) + \mathrm{UU}(u_i,\ u_j)}{2} \tag{18}$$

$$\mathrm{SS}(u_i,u_j) = \frac{\mathrm{Satisfied}(u_i) \cap \mathrm{Satisfied}(u_j)}{\mathrm{Satisfied}(u_i) \cup \mathrm{Satisfied}(u_j)} \tag{19}$$

$$\mathrm{UU}(u_i,u_j) = \frac{\mathrm{Unsatisfied}(u_i) \cap \mathrm{Unsatisfied}(u_j)}{\mathrm{Unsatisfied}(u_i) \cup \mathrm{Unsatisfied}(u_j)} \tag{20}$$

Likewise, disagreement $\mathrm{Disagr}(u_i,u_j)$ between user u_i and user u_j can be computed as Eq. (21), when one of the users gets satisfied, while other is unsatisfied $\mathrm{SU}(u_i,\ u_j)$, Eq. (22) or vice versa $\mathrm{US}(u_i,\ u_j)$, Eq. (23).

$$\mathrm{Disagr}(u_i,\ u_j) = \frac{\mathrm{SU}(u_i,\ u_j) + \mathrm{US}(u_i,\ u_j)}{2} \tag{21}$$

$$\mathrm{SU}(u_i,u_j) = \frac{\mathrm{Satisfied}(u_i) \cap \mathrm{Unsatisfied}(u_j)}{\mathrm{Satisfied}(u_i) \cup \mathrm{Unsatisfied}(u_j)} \tag{22}$$

$$\mathrm{US}(u_i,u_j) = \frac{\mathrm{Unsatisfied}(u_i) \cap \mathrm{Satisfied}(u_j)}{\mathrm{Unsatisfied}(u_i) \cup \mathrm{Satisfied}(u_j)} \tag{23}$$

Knowledge factor-based trust and distrust between user u_i to user u_j is termed as interaction trust $\mathrm{Interaction\_Trust}(u_i,\ u_j)$ and interaction distrust $\mathrm{Interaction\_Distrust}(u_i,\ u_j)$, respectively, that can be computed as follows:

$$\mathrm{Interaction\_Trust}(u_i,\ u_j) = \frac{2 * \mathrm{Trust\_Rec}(u_i,\ u_j) * \mathrm{Trust\_Exp}(u_i,\ u_j)}{\mathrm{Trust\_Rec}(u_i,\ u_j) + \mathrm{Trust\_Exp}(u_i,\ u_j)} \tag{24}$$

$$\mathrm{Interaction\_Distrust}(u_i,\ u_j) = \frac{2 * \mathrm{Distrust\_Rec}(u_i,\ u_j) * \mathrm{Distrust\_Exp}(u_i,\ u_j)}{\mathrm{Distrust\_Rec}(u_i,\ u_j) + \mathrm{Distrust\_Exp}(u_i,\ u_j)} \tag{25}$$

The total strength of links in terms of trust and distrust is given by overall trust $\mathrm{Overall\_Trust}(u_i,\ u_j)$ and distrust values $\mathrm{Overall\_Distrust}(u_i,\ u_j)$ that are amalgamation of both preference similarity-based trust or distrust and interaction-based trust or distrust that are calculated as follows:

$$\mathrm{Overall\_Trust}(u_i,\ u_j) = \frac{w_1 * \mathrm{Interaction\_Trust}(u_i,\ u_j) + w_2 * \mathrm{Pref\_Sim\_Trust}(u_i,\ u_j)}{w_1 + w_2} \tag{26}$$

$$\mathrm{Overall\_Distrust}(u_i,\ u_j) = \frac{w_1 * \mathrm{Interaction\_Distrust}(u_i,\ u_j) + w_2 * \mathrm{Pref\_Sim\_Distrust}(u_i,\ u_j)}{w_1 + w_2} \tag{27}$$

Here, the values of weights w_1 and w_2 are determined empirically and normalized in the range $[0,\ 1]$.

3.1.3 Fuzzy modeling of trust and distrust

Mostly in trust networks, users specify their belief (trust) or disbelief (distrust) in crisp values. Nonetheless, this is not the actual case as people in real-world prefer to express their views in words not in values. To deal with the problem comprising linguistic terms gives rise to the need for computing with words. Thus, to handle the semantics of the linguistic terms our computational model is based on the extension principle (Bharadwaj and Al-Shamri 2009; Kant and Bharadwaj 2013). Accordingly, each trust and each distrust are fuzzified into seven normal triangular fuzzy sets. Trust is fuzzified as: No Trust (NT), Very Low Trust (VLT), Low Trust (LT), Average Trust (AT), High Trust (HT), Very High Trust (VHT) and Complete Trust (CT) as shown in Fig. 3. Similarly, distrust is fuzzified as:

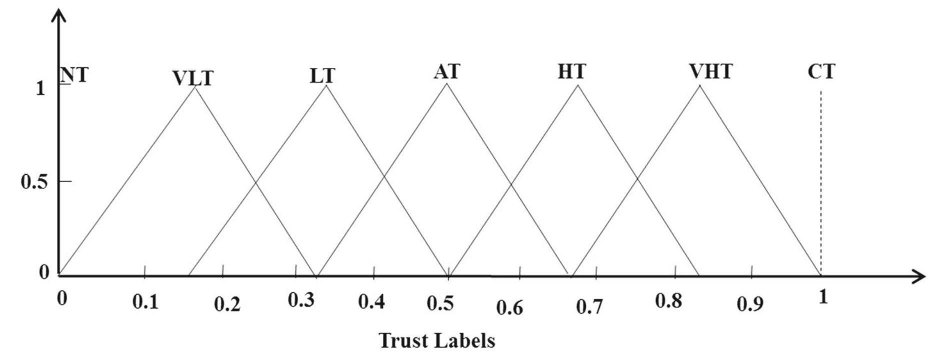


Fig. 3 Membership functions for trust

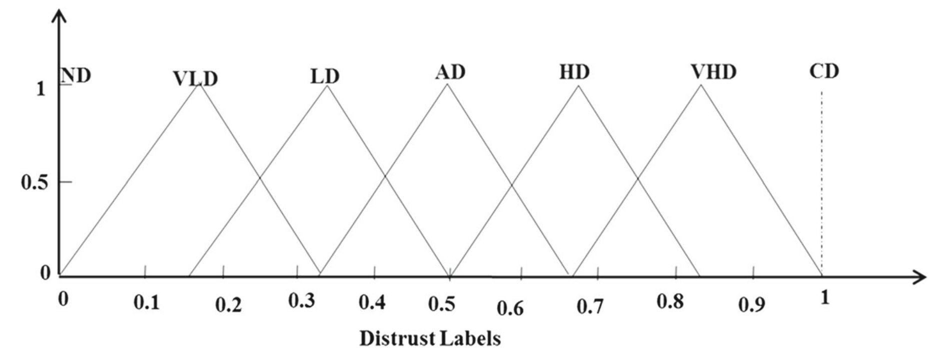


Fig. 4 Membership functions for distrust

No Distrust (ND), Very Low Distrust (VLD), Low Distrust (LD), Average Distrust (AD), High Distrust (HD), Very High Distrust (VHD) and Complete Distrust (CD) as shown in Fig. 4.

The key point here to note is that in social network we consider both trust and distrust values for two users as one user can show both trust and distrust for other user. Also, the type of relationship existing between users is not known, but in the case of signed social networks where the information about the relationship existing between two users is explicitly available, we will cogitate either trust if positive link is present or distrust if negative link is present but not both.

The details of the proposed models are given as follows:

3.2 Link prediction based on fuzzy computational model

In a social network, link prediction involves only prediction of missing/future links. Unlike to this, in signed social networks in addition to predict the missing link between two users, prediction of the type of missing link, i.e., sign of the link (positive or negative), is also required. To serve this purpose, we have proposed two different link prediction models for signed social networks. For prediction of missing link, strength of tie between pair of users is computed and for the type of link likely to appear is predicted on the basis of how much they trust or distrust (link strength value) on each other, that are explained as follows:

3.2.1 Model 1: Local Information based Link Prediction (LILP)

In the first model, we have tried to predict missing links between users on the basis of local information available about the ratings given by the users to the items of their interests to compute the preference similarity factor between users and information about common rated items by different users resulting in virtual interactions (as they do not meet physically) termed as encounters to compute the knowledge factor among them. Both these factors, preference similarity and knowledge factors, are then used to compute total trust or distrust between users that are descriptively explained in Sect. 3.1. Further, a fuzzy computational model is developed based on these trust–distrust values. Next, after fuzzy modeling of trust and distrust, prediction of missing links as shown diagrammatically in Fig. 5.

The step-by-step description of the proposed Local Information based Link Prediction model (LILP) is as follows:

Step 1 Initially, based on the local information available about the users (user-item ratings and common items rated by different users), we will figure out how much similar the users are based on their preferences. For this, we have used

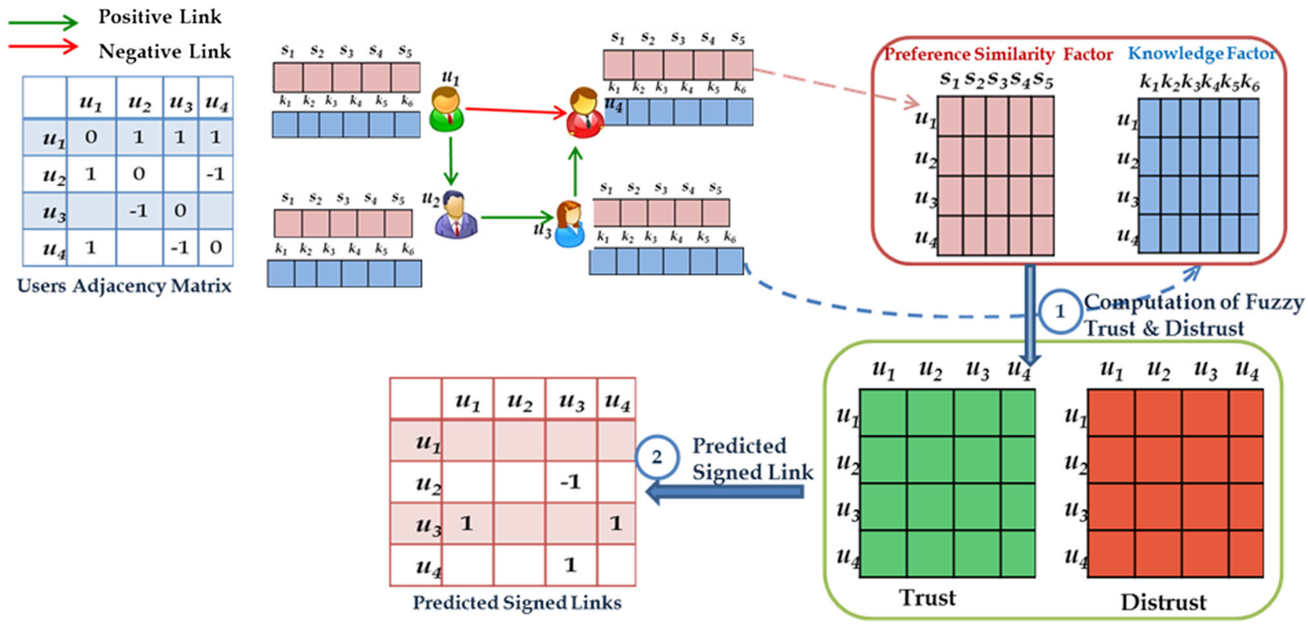


Fig. 5 Local information based link prediction model for signed social networks

Pearson correlation coefficient (PCC) to compute similarity between two users u_i and u_j denoted as Similar(u_i, u_j) that can be defined as:

$$\text{Similar}(u_i, u_j) = \frac{\sum_{k \in I_{ij}} (R_{u_i} I_k - \bar{i}).(R_{u_j} I_k - \bar{j})}{\sqrt{\sum_{k \in I_{ij}} (R_{u_i} I_k - \bar{i})^2}.\sqrt{\sum_{k \in I_{ij}} (R_{u_j} I_k - \bar{j})^2}} \tag{28}$$

where $\bar{i}$, $R_{u_i} I_k$ denote the average rating and rating given to item k by user i, respectively. I_i denotes the set of items rated by user i, and I_{ij} denotes the set of items rated by both the users, u_i and u_j.

Then, we will see whether it is possible to predict future link between user u_i and user u_j by checking the similarity between them. If similarity between two users is more or equal to the threshold value as given by Eq. (29), then it is possible to predict future link; otherwise, if similarity is less than the threshold value, then it is not possible to predict link with the available information and hence there will be no prediction.

$$\text{if Similar}(u_i,\ u_j) = \begin{cases} \geq 0.6 & \text{future link can be predicted} \\ < 0.6 & \text{prediction not possible} \end{cases} \tag{29}$$

Higher is the threshold value, more similar are the users (and vice versa) and thus, the accuracy of prediction of missing link between users will increase. However, since the real-world datasets are very sparse and with high threshold value, the chances to find similar users decrease. It will result in no similar users found situation and there will be no prediction. In order to deal with the problem to find similar users in the network while maintaining the accuracy in the prediction of missing link between users, we have chosen the threshold value of similarity more than the average, i.e., 0.6 (60%).

Step 2 Next, after ensuring the prediction possibility with available information, we find whether the link will be positive or negative. For this, the results from the first step are incorporated to compute overall trust (based on preference similarity trust and interaction trust) and overall distrust (based on preference similarity distrust and interaction distrust) between users as described earlier in Sects. 3.1.1 and 3.1.2, respectively.

Step 3 Then, based on previously discussed trust–distrust values among users, a fuzzy implementation of trust–distrust is modeled as described in Sect. 3.1.3 and shown by Figs. 3 and 4.

Step 4 Finally, based on above fuzzy computational model grounded on trust and distrust values (strength of ties) among users, positive and negative links are predicted, respectively. If two users have high strength of trust value and its membership belongs to any of the fuzzified terms {HT, VHT, CT, ND, VLD}, then we label the predicted link as positive. On contrast, if two users have high strength of distrust value and its membership belongs to any of the fuzzified terms {NT, VLT, HD, VHD, CD}, then the predicted link is annotated with negative sign as given by Eq. (30):

$$\text{Link\_Predicted}(u_i, u_j) = \begin{cases} +1 & \text{HT, VHT, CT, ND, VLD} \\ -1 & \text{NT, VLT, HD, VHD, CD} \end{cases} \quad (30)$$

3.2.2 Model 2: Local and Global Information based Link Prediction (LGILP)

In the second proposed model, besides the local information about the users, global information about the common neighbors of the users (i.e., common mutual links among users) and social balance theory are also taken into consideration while predicting missing links among users in signed social network as shown in Fig. 6. Similar to LILP model, *Step 1* to *Step 3* (Sect. 3.2.1) are the same for LGILP model. After, fuzzy modeling of trust–distrust in *Step 3*, the following step is employed:

Step 4 We have users either with high trust values { HT, VHT, CT, ND, VLD } or high distrust values {NT, VLT, HD, HD, CD}. Now, to predict missing link between a pair of users, we will consider number of links they have in common (mutual links) and social balance factor before and after the prediction of missing link, details of which are as follows:

Case I: Users with high trust values For each pair of users (let say user u_i and user u_j) with high strength of trust value whose membership belongs to any of the fuzzified terms { HT, VHT, CT, ND, VLD }, we will find mutual links between these two users. Now, for each mutual link (let say m_{ij}), we will add a positive link (as trust strength is high) between user u_i and user u_j, thus forming a triad ($\Delta_{u_i,u_j}^{m_{ij}}$) between user u_i, user u_j and mutual link m_{ij}. Next, we will compute social balance factor of the triad formed $\Delta_{u_i,u_j}^{m_{ij}}$ before and after insertion of the positive link, i.e., SBF_{old} and SBF_{new}, respectively. Then, we will check if $\text{SBF}_{\text{new}} \geq \text{SBF}_{\text{old}}$, then the new link will be predicted as

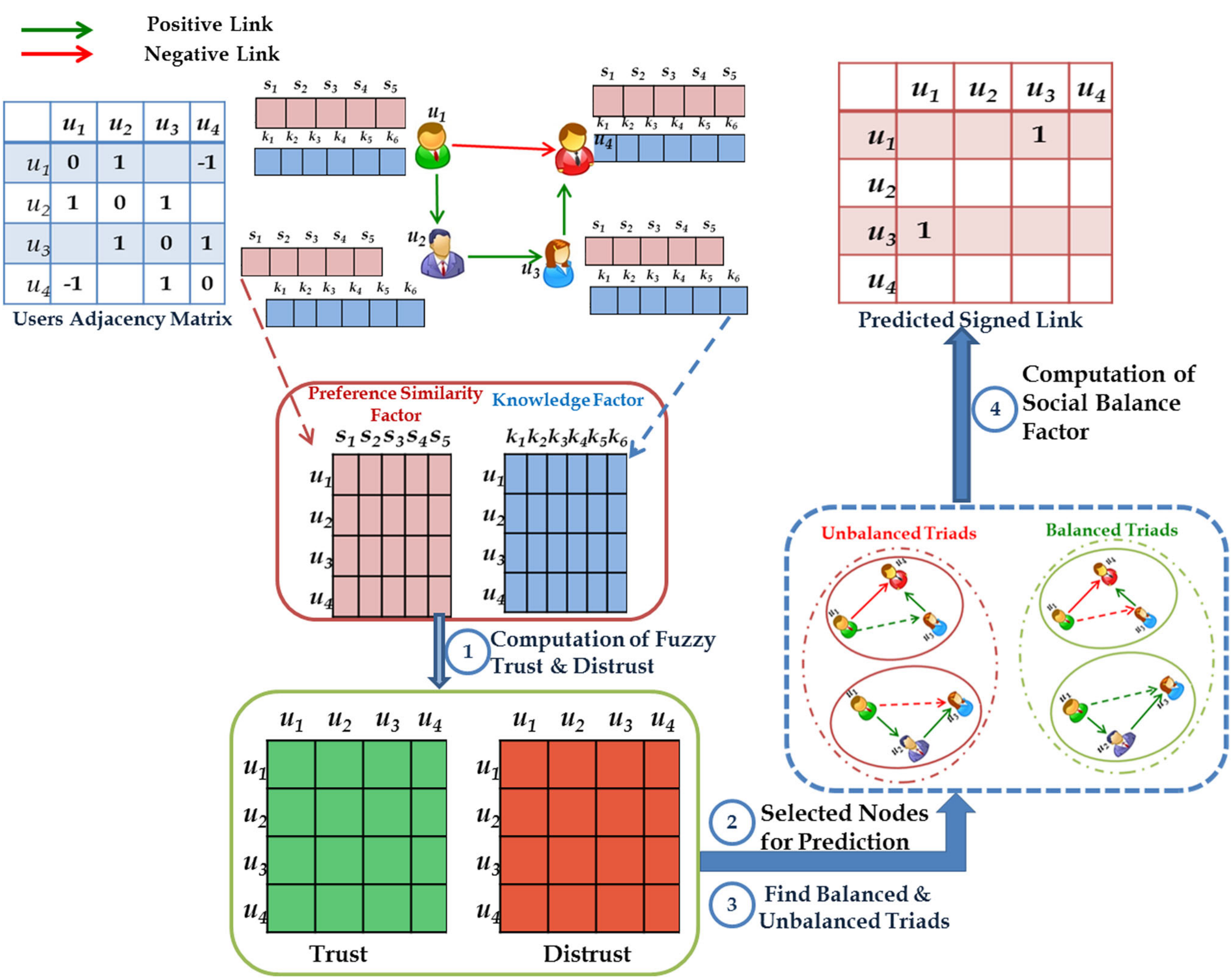


Fig. 6 Local and global information based link prediction model for signed social networks

positive link between user u_i and user u_j which either maintains or enhances the SBF of these users.

Case II: Users with high distrust values Likewise, for each pair of users (let say user u_i and user u_j) with high strength of distrust value whose membership belongs to any of the fuzzified terms {NT, VLT, HD, HD, CD }, we will find mutual links between these two users. Now, for each mutual link (let say m_{ij}), we will add a negative link (as distrust strength is high) between user u_i and user u_j, thus forming a triad ($\Delta^{m_{ij}}_{u_i,u_j}$) between user u_i, user u_j and mutual link m_{ij}. Next, we will compute social balance factor of the triad formed $\Delta^{m_{ij}}_{u_i,u_j}$ before and after insertion of the negative link, i.e., SBF_{old} and $\mathrm{SBF}_{\mathrm{new}}$, respectively. Then, we will check if $\mathrm{SBF}_{\mathrm{new}} \geq \mathrm{SBF}_{\mathrm{old}}$, then the new link will be predicted as negative link between user u_i and user u_j which either maintains or enhances the SBF of these users.

$$\mathrm{Link\_Predicted}(u_i, u_j) = \begin{cases} +1 & \mathrm{SBF}_{\mathrm{new}} \geq \mathrm{SBF}_{\mathrm{old}}, \text{provided} \quad \text{high trust value} \\ -1 & \mathrm{SBF}_{\mathrm{new}} \geq \mathrm{SBF}_{\mathrm{old}}, \text{provided} \quad \text{high distrust value} \end{cases} \tag{31}$$

4 Experimental study

This section illustrates the details of datasets used for experimental setup and metrics used to evaluate the performance of the proposed models. Further, it describes various experiments conducted on benchmarked synthetic dataset of friends and foes network (FFN) (Patidar et al. 2012) as well as real-world datasets of Epinions (Girdhar and Bharadwaj 2016) and Slashdot (Girdhar and Bharadwaj 2016) to study the performance of our proposed scheme. We have study the effectiveness of our proposed models with respect to the following baseline technique.

Inductive Learning based Link Prediction (ILLP) As described earlier in Sect. 1, in ILLP approach (Patidar et al. 2012) existing patterns among users of the signed social networks are utilized to predict the unknown links through inductive learning approach. Further, it uses social balance theory to avoid the imbalance in extended signed social network while predicting new missing links in the network.

Our proposed models LILP and LGILP are compared with the aforementioned baseline approach on benchmarked synthetic and real-world datasets. Performance assessments of models are done on the basis of their ability to predict missing links; for this, we have evaluated our proposed models on different metrics (Sect. 4.1) and the results are shown in Sect. 4.2. To check the accuracy and effectiveness of proposed models on larger datasets, we have performed experiments on real-world datasets of Epinions and Slashdot with varying sizes that are shown in Sects. 4.3 and 4.4, respectively.

4.1 Evaluation metrics

To validate the performance of our proposed models, we have used confusion matrix which is well suitable for accuracy computation and classification problems. A confusion matrix is basically a square matrix and consists of four parameters: TP (True Positive) is number of positive cases correctly predicted as positive, TN (True Negative) is the number of negative cases correctly predicted as negative, FP (False Positive) is the number of negative cases incorrectly predicted as positive, and FN (False Negative) is the number of positive cases incorrectly predicted as negative.

Prediction accuracy (PA) The prediction accuracy (Agarwal and Bharadwaj 2015) of a model can be computed as the ratio of total correctly predicted cases to the total number of predicted cases, as given in Eq. (32)

$$\mathrm{Prediction\_Accuracy} = \frac{(\mathrm{TP}+\mathrm{TN})}{(\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN})} \tag{32}$$

Precision, recall and F_β*_score* The major goal of prediction accuracy is to improve recall without conceding precision. However, because of conflicting nature of precision and recall, it is difficult to improve recall without compromising precision. F_β_score (Agarwal and Bharadwaj 2015) is a metric which shows "the goodness of a classifier," and trade-off between precision and recall is computed using Eq. (34).

$$\mathrm{Precision} = \frac{\mathrm{TP}}{(\mathrm{TP}+\mathrm{FP})} \quad \mathrm{Recall} = \frac{\mathrm{TP}}{(\mathrm{TP}+\mathrm{FN})} \tag{33}$$

$$F_\beta\_\mathrm{score} = \frac{(1+\beta^2) * \mathrm{Precision} * \mathrm{Recall}}{\beta^2 * \mathrm{Recall} + \mathrm{Precision}} \tag{34}$$

where β is positive real value which signifies importance of recall to precision. We have taken $\beta = 1$ for experimental purpose.

G_measure is the geometric mean of precision and recall (Agarwal and Bharadwaj 2015), computed as Eq. (35)

$$G\_\mathrm{measure} = \sqrt{\mathrm{Precision} * \mathrm{Recall}} \tag{35}$$

Specificity (S) metric determines how often the prediction model correctly predicts the negative instances in the sample (i.e., predicts negative when it actually is negative). Specificity is given as the ratio of the number of correctly predicted negative cases to the total number of negatives cases in the sample, as given in Eq. (36)

$$S = \frac{TN}{(TN + FP)} \tag{36}$$

Balance Error Rate (BER) is used to compute the misclassification error, which is composed of two types of error termed as: False Positive Rate (FPR) and False Negative Rate (FNR) (Agarwal and Bharadwaj 2015). FPR is the fraction of negative cases which are incorrectly classified as positive out of total negative cases, and FNR is the fraction of positive cases incorrectly classified as negative out of total positive cases, given by Eq. (37):

$$BER = \frac{1}{2(FPR + FNR)} \tag{37}$$

where $FPR = \frac{FP}{FP+TN}$ and $FNR = \frac{FN}{FN+TP}$.

4.2 Experiments on friends and foes network (FFN) dataset

In this section, we have described benchmarked synthetic dataset of friends and foes network (FFN) and show the results with discussion.

4.2.1 Dataset description

Friends and foes network (FFN) (Patidar et al. 2012) is an undirected signed social network of 10 nodes and 20 edges. Each node represents a user profile consisting set of attributes information about Gender, Career Interest, Hometown, Movies, Thinking, Religion, SES, Activities and categorical information about Friends or Foes. Each edge connecting two nodes is assigned either a positive or a negative sign representing Friend or Foe relation between these two users, respectively.

4.2.2 Results and discussion

The results obtained by performing experiments on benchmarked synthetic dataset of FFN are shown in Fig. 7, based on Precision, Recall, F_score and $G\_measure$. It can be observed from the results that obtained value by our proposed LILP and LGILP for aforementioned metrics are far better than the ILLP approach. Also, Fig. 8 shows that our proposed models have achieved higher accuracy value compared to ILLP scheme. Moreover, results in Fig. 9 show that our proposed models have outperformed the ILLP approach in terms of misclassification rate and negative instances prediction accuracy. Hence, it can be seen easily that both the proposed models LILP and LGILP outperforms ILLP approach and are able to predict missing links and their sign more accurately and efficiently.

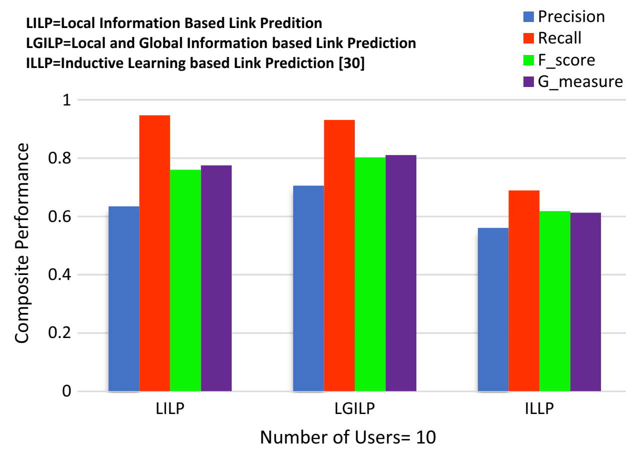


Fig. 7 Composite performance of proposed models on FFN dataset

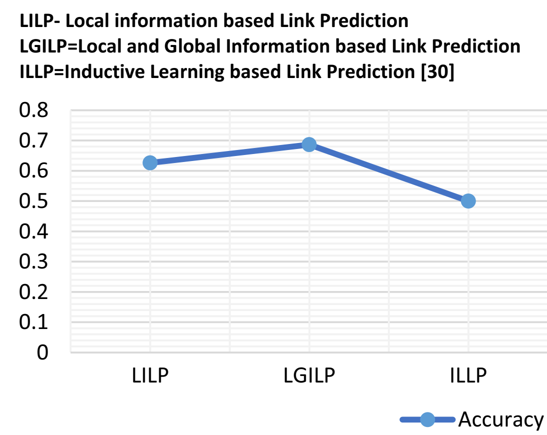


Fig. 8 Accuracy on FFN dataset

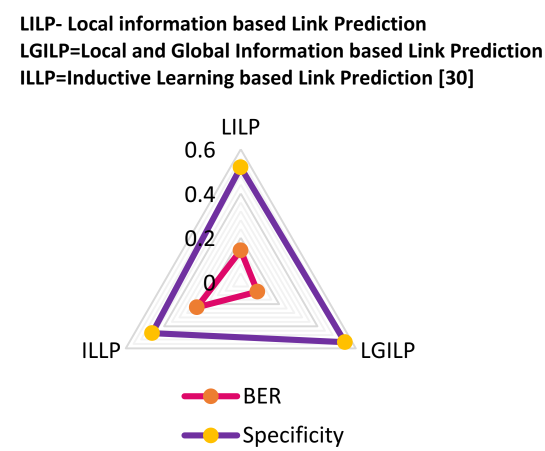


Fig. 9 BER and specificity on FFN dataset

Next, we have conducted experiments on real-world datasets of Epinions and Slashdot to validate the performance of our proposed models on larger datasets. We have also tried to establish the efficiency of the proposed models by performing the experiments on different varying

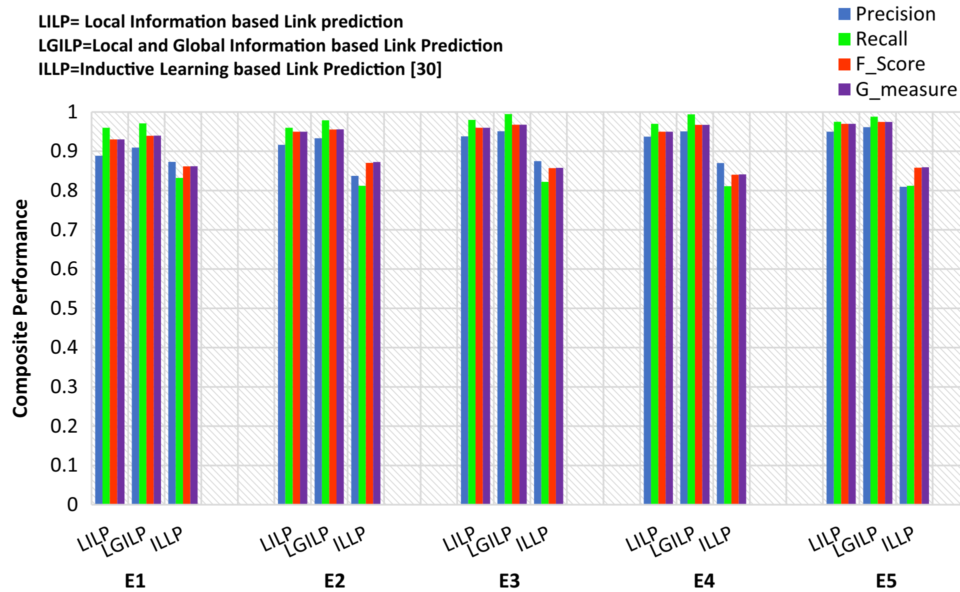


Fig. 10 Composite performance on different partitions of Epinions dataset

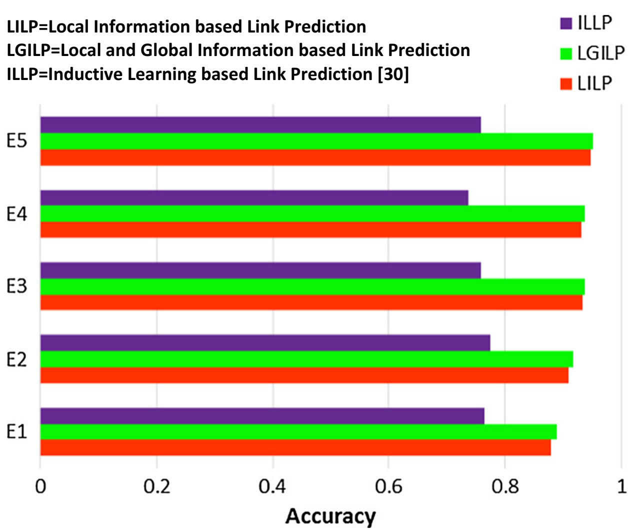


Fig. 11 Accuracy on different partitions of Epinions dataset

partitions of data sizes having 500, 1000, 2000, 3000 and 5000 users.

4.3 Experiments on Epinions dataset

In this section, we have described real-world dataset of Epinions[1] and presented the obtained results with discussion.

4.3.1 Dataset description

Epinions is a general consumer review Web site of "*who-trust-whom*" on which users can post reviews about the various products and services of their interests. The reviews to the items are provided in terms of ratings. The dataset consists of 139,738 different items with 664,823 ratings of 49,290 users. Rating is provided on the rating score of [1–5] where1 denotes the lowest and 5 denotes the highest rating that can be given to an item by a user. We have mapped ratings [4–5] as high ratings,3 as neutral rating and [1–2] as low ratings. Among 664,823 ratings, high ratings are 495,392(74.5%), low ratings are 93,906(14.1%), and 75,525(11.4%) are neutral ratings (Tang et al. 2016).

In our experimental setup, for each dataset, we have performed experiments on randomly selected varying number of users $E1(500), E2(1000), E3(2000), E4(3000), E5(5000)$, to show the effectiveness and flexibility of our proposed models.

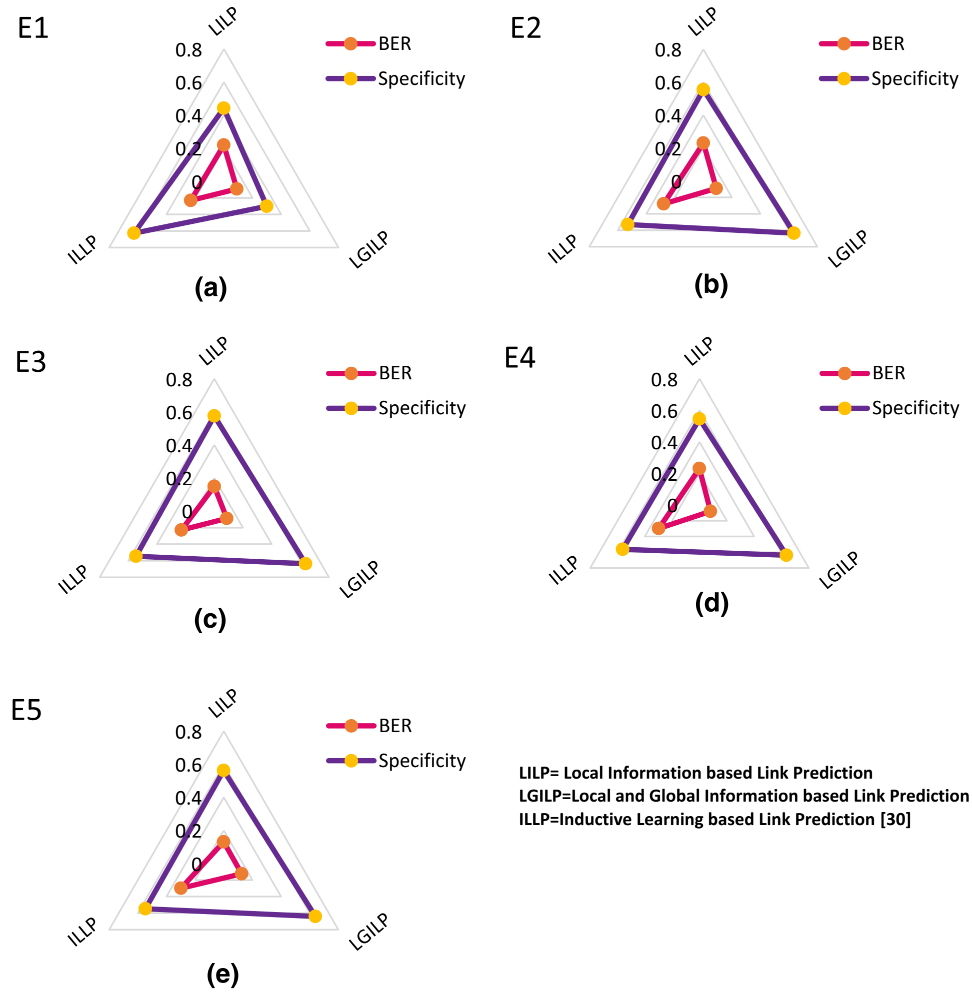
4.3.2 Results and discussion

We investigate the performance of our proposed models LILP and LGILP on real-world dataset of Epinions based on the metrics discussed in Sect. 4.1. Figure 10 shows the value of precision, recall, F_score and $G\_measure$ metrics on varying number of users, $E1$, $E2$, $E3$, $E4$ and $E5$, respectively. It can be easily observed that both our proposed models LILP and LGILP have outperformed the ILLP for each metric. Moreover, as the number of users is increased, LILP and LGILP have constantly performed better than the ILLP approach, thus validating the performance of our models on larger datasets.

Figure 11 shows the accuracy value of our proposed models against ILLP approach on varying number of users $E1$, $E2$, $E3$, $E4$ and $E5$, respectively, which clearly indicates that LILP and LGILP have achieved better accuracy

[1] http://snap.stanford.edu/data/soc-sign-epinions.html.

Fig. 12 BER and specificity performance on different partitions of Epinions dataset



values compared to ILLP approach, thus establishing the efficacy of proposed models.

Next, we have shown the effectiveness of our proposed models based on how correct it predicts the negative instances and misclassification errors by computing specificity and BER (balance error rate) for varying number of users. As shown in Fig. 12, it can be seen that the LILP and LGILP have shown better performance in handling negative instances besides the positive instances as compared to ILLP approach.

4.4 Experiments on Slashdot dataset

In this section, we have described real-world dataset of Slashdot[2] and show the obtained results with discussion.

4.4.1 Dataset description

Instead of consisting user ratings to the items, Slashdot dataset contains ratings given to the users by tagging them as *"friend"* (high rating) or *"foe"* (low rating). There is no neutral rating in this dataset. Here, items are the users of the network themselves who are receiving ratings and users are the people who are giving at least one rating. Slashdot dataset contains total of $82,144$ users with $44,044(53.6\%)$ users who give at least one rating and $70,284(85.6\%)$ users who receive at least one rating. The difference between the users who give at least one rating and the users who receive at least one rating is $26,240$, which shows that some users give many ratings. There are $549,202$ signed relations having $425,072(77.4\%)$ high ratings and $124,130(22.6\%)$ low ratings in them (Tang et al. 2016). This shows that users in Slashdot give much more high ratings than low ratings.

4.4.2 Results and discussion

In another set of experiments conducted on varying size partitions of Slashdot dataset $S1(500), S2(1000), S3(2000), S4(3000)$ and $S5(5000)$, results obtained proves the effectiveness of our proposed models LILP and LGILP

[2] http://snap.stanford.edu/data/soc-sign-Slashdot090221.html.

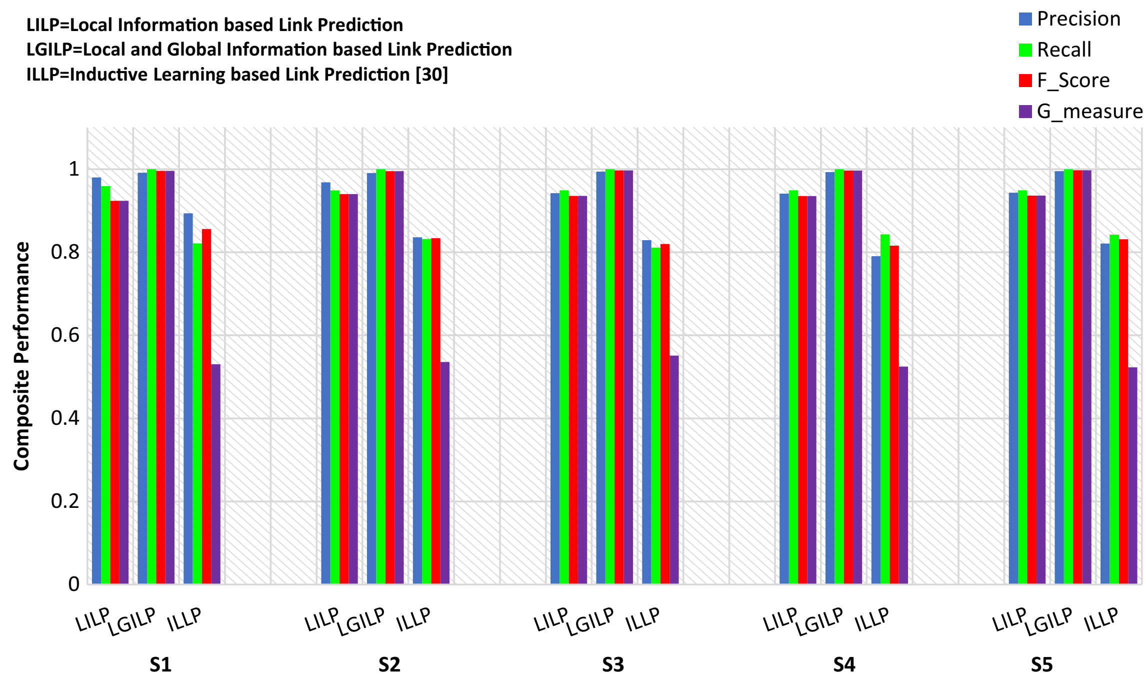


Fig. 13 Composite performance on Slashdot dataset

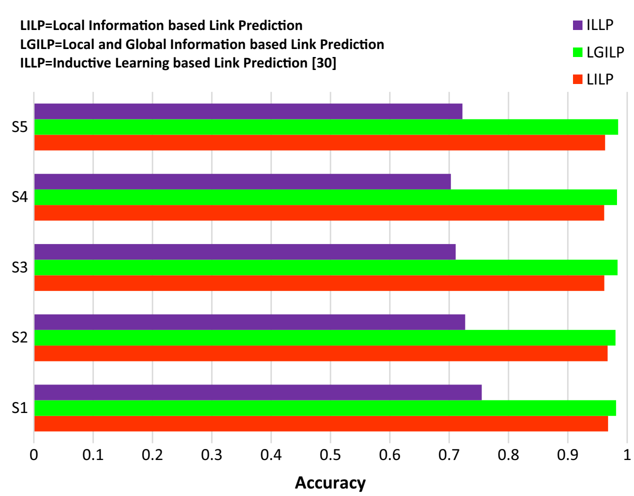


Fig. 14 Accuracy on different partitions of Slashdot dataset

over compared ILLP approach. Figure 13 shows the values of Precision, Recall, F_score and G_measure on varying instances of Slashdot dataset. Results obtained clearly show the better performance of proposed models over ILLP approach.

Figure 14 presents the different accuracy values obtained for the ILLP approach and the proposed models LILP and LGILP for varying dataset sizes. The results clearly show that our models LILP and LGILP have consistently achieved better accuracy values even for larger datasets compared to the baseline ILLP approach.

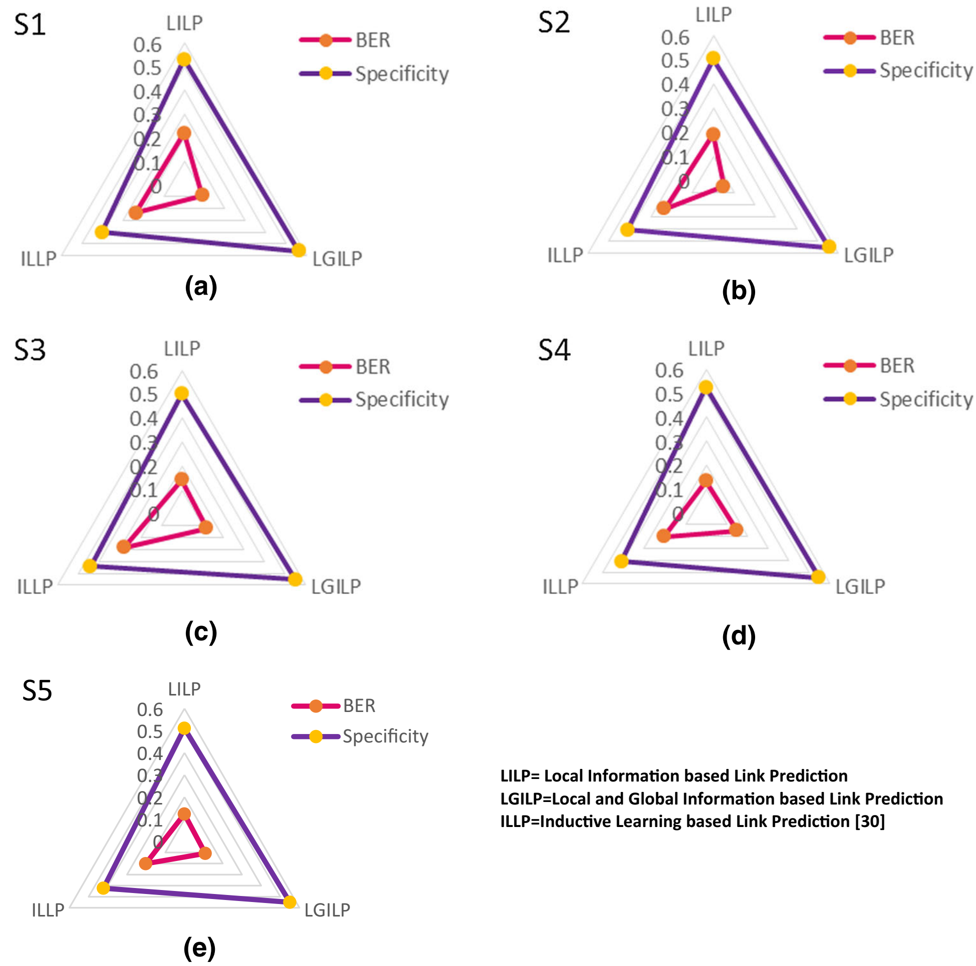
Furthermore, Fig. 15 shows that the BER values for varying number of users are considerably less, thus clearly indicating that our proposed models LILP and LGILP are well suited for correctly predicting the negative instances. Moreover, our models have achieved better specificity values compared to ILLP, thus showing that misclassification errors are less compared to the ILLP approach.

It can be clearly seen that both the proposed models LILP and LGILP have performed better than the ILLP approach on consistent basis. As a whole, we can conclude that LILP and LGILP models withstand their performance and have shown considerably better results for all aforementioned metrics for varying number of users, thus establishing their effectiveness on larger datasets and hence validating the fact that they are well suited to solve the problem of sparsity in signed social networks.

5 Conclusion and future work

Our work focuses on the prediction of missing links among the users of the signed social network based on their trust–distrust on other users to handle the problem of sparsity in signed social networks. We have proposed two novel link prediction models LILP and LGILP grounded on fuzzy modeling of trust–distrust which is a twofold scheme based on strength of ties between users and social balance theory. Signed social networks mimic the real-world scenario where users have different relations with different users, and moreover, *All Relations Are Not Equal*. In the first

Fig. 15 BER and specificity on different partitions of Slashdot dataset



step, the generic fuzzy framework is developed for these relationships in our proposed models that take into account the relative importance of these relationships and also the fact that users are more comfortable in using linguistic expressions to show their trust or distrust rather numeric values (binary either trust (+ 1) or distrust (− 1)). In the second step, missing link prediction is deployed based on trust–distrust values computed among users based on their similarity with each other. The results of experiments conducted on benchmarked synthetic dataset of friends and foes network and real-world datasets of Epinions and Slashdot on different partitions reaffirm that our proposed models are well capable of handling larger datasets with high prediction accuracy. Moreover, better results of BER and specificity metrics clearly establish the efficacy of our proposed models LILP and LGILP. Furthermore, our proposed models find their applicability in both directed and undirected signed social networks.

In future work, we would consider the trust–distrust propagation mechanism (Anand and Bharadwaj 2013) to further enhance the link prediction accuracy. Also, we would like to extend our link prediction scheme in signed social networks to include multi-relations (Brzozowski et al. 2008; Davis et al. 2013; Peters et al. 2012), multiple dimensions like spatial, temporal, etc. (Kashoob and Caverlee 2012), and multiple social networks (Ahmad et al. 2010; Reguieg and Taghezout 2017). Another interesting future research challenge would be to address the dynamic properties of signed relations of these networks (Beigi et al. 2016; Ibrahim and Chen 2015).

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical standard This article does not contain any studies with human participants or animals performed by any one of the authors.

Informed consent Informed consent was obtained from all the individual participants included in the study.

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