Real Time Social Attitude Expression Prediction

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***Abstract*—Via online social interactions, users in social networks can form their personal attitudes toward other users. Some of the personal social attitudes will be expressed explicitly, which are represented as the signed social links from the initiators to the recipients. In this paper, we will study the "*social Attitude exPression prEdiction*" (APE) problem, which aims at inferring both the expression activities and the expressed social attitudes simultaneously. The APE problem is very challenging to address due to two reasons: (1) extraction of useful features for predicting social attitude expression activities and the expressed social attitudes, and (2) the prediction model needs to incorporates the correlations between these two tasks covered in the APE problem. To address the APE problem, a novel real-time "*Bayesian network based Integrated Social Attitude exPression inference*" framework BI-SAP is introduced in this paper. Framework BI-SAP extracts a set of features for the expression activities and social attitudes from the networks based on various social closeness measures and social balance theory respectively. In addition, with the extracted features, the integrated social expression prediction framework BI-SAP is built based on the Bayesian network model, in which the dependence relationships between these two tasks covered in APE can be effectively represented and the parameters can be updated in real time. Extensive experiments conducted on real-world signed network datasets have demonstrated the effectiveness of BI-SAP in addressing the APE problem.**

***Index Terms*—Social Attitude Inference; Signed Networks; Data Mining**

I. INTRODUCTION

In recent years, signed networks have gained increasing attentions due to their abilities to represent diverse and contrasting social attitudes among the users. In signed networks, users can express their attitudes freely towards other users, where the explicit expression activities are denoted as the links among users, while the specific expressed social attitudes are represented as the polarities attached to the links. For instance, in online social networks, users can explicitly indicate who are their friends and enemies [20] respectively; meanwhile, in e-commerce review sites, users can express their trustiness towards other users based on their posted reviews [21]. Generally, through certain social interactions over time, users in online social networks can form their personal attitudes toward other users. The social attitudes (i.e., the link polarities) among users are quite diverse, including both *positive* and *negative* attitudes. Depending on specific contexts, the physical meanings of the social attitudes in signed networks can be *friend vs enemy* [20], *positive attitude vs negative attitude* [22], *trust vs distrust* [21], etc.

Given a screen shot of the signed social network structure, inferring the potential social attitudes to be expressed among users in the future can be an interesting problem. Formally, the problem is called the *social attitude expression prediction* (APE) problem in this paper. APE is an important research problem, and it has extensive concrete applications in various social network services, like (1) *friend recommendation*, where people with positive attitudes mutually are more likely to be friends, and (2) *community detection*, where a group of people having positive attitudes toward each other tend to form a community.

Problem Studied: In this paper, we will study the "*social Attitude exPression prEdiction*" (APE) problem in signed networks. More specifically, the *social attitude expression prediction problem* covers two sub-tasks simultaneously:

- *social expression activity prediction*: Various kinds of social attitudes exist among users in signed networks. However, from the social attitude studies perspective, only those explicitly expressed out will make senses and have concrete physical meanings. Therefore, prediction of users' social expression activities is the prerequisite for studying the social attitudes among users.
- *social attitude inference*: Given that users will express their attitudes towards other users in the signed network, inference of the explicit social attitudes to be expressed (e.g., positive or negative) is another important task of the APE problem.

Integrating multiple strongly correlated sub-learning-tasks in a joint learning framework is an important direction in big data studies, which can effectively utilize such correlations to improve the learning results of the sub-tasks synergistically. These two sub-tasks covered in APE have strongly correlations, and *social attitude inference* strongly depends on the *social expression activity prediction* results. To simplify the terminologies, in this paper, we will mis-use the terms "social expression activities" and the "existence of social links", as well as the terms "social attitude" and "link polarity".

The *social attitude expression prediction problem* studied in this paper is a novel problem, which has never been studied before. The *social attitude expression prediction problem* is totally different from the existing works on link prediction and sign prediction in online social networks, like (1) "*link* *prediction for social networks*" [13], which aims at predicting the existence of social links in social networks, and no polarities inference tasks are mentioned in [13]; and (2) "*predicting positive and negative links in social networks*" [9], which focuses on inferring the signs of links based on the assumptions that these links already exist in the network. Distinct from these existing works, in the APE problem, we want to infer both the attitude expression activities (i.e., the links) of users in signed networks, as well as the specific attitudes (i.e., the link polarities) among these users simultaneously.

Besides its importance and novelty, the APE problem is very challenging to address due to the following reasons:

- *feature extraction*: To address the expression activity prediction and attitude inference sub-problems covered in APE, extraction of useful features for these two tasks from the signed networks is desired.
- *real-time integrated prediction model*: The sub-tasks covered in APE have strong dependency relationships. An integrated social attitude expression prediction model which incorporates such correlation between these two tasks and updates the parameters in real time in the training process is required.

To solve the above challenges covered in the APE problem, a new real-time Bayesian network based method named BI-SAP is introduced in this paper. In BI-SAP, a set of diverse features about the historical social expression activities and the expressed attitudes are extracted from the signed networks. With the extracted features, the integrated social expression prediction framework BI-SAP is built based on the Bayesian network model, in which the dependence relationships between these two tasks covered in APE can be effectively represented. Furthermore, the parameters covered in the BI-SAP framework can be updated in real-time as more training data comes in.

The remaining part of this paper is organized as follows. We define the concepts and formulate the APE problem in Section II. The method is introduced in Section III, whose performance is evaluated in Section IV. Finally, Section V talks about the related works, and Section VI concludes this paper.

II. Problem Formulation

In this section, we will first introduce the definition of signed network, based on which, we will formulate the APE problem.

A. Terminology Definition

The networks studied in this paper are signed networks, where the links are associated with certain polarities denoting the expressed social attitudes among users.

Definition 1 (Signed Network): A signed network can be formally represented as $G = (\mathcal{V}, \mathcal{E}, s)$, where set $\mathcal{V}$ represents the set of users in the network, set $\mathcal{E}$ denotes the set of existing attitude expression activities among users in $\mathcal{V}$, and mapping $s : \mathcal{E} \to \{-1, +1\}$ projects the expression activities in $\mathcal{E}$ to the expressed positive/negative attitudes respectively.

B. Problem Statement

Given a signed network G, the APE problem aims at inferring both the social expression activities and the specific attitudes expressed simultaneously.

Problem Definition: Formally, let $\mathcal{V}$ and $\mathcal{E}$ be the sets of users and the existing attitude expressions in network G. The set of potential social expressions (which have not been expressed yet) can be represented as $\mathcal{L} = \mathcal{V} \times \mathcal{V} \setminus \mathcal{E}$.

Sub-Problem 1: Social Expression Prediction In the first sub-problem covered in the APE, we aim at building a mapping $y : \mathcal{L} \to \{-1, +1\}$. For potential social expression $l \in \mathcal{L}$, if the expression activity l will take place, then $y(l) = +1$; otherwise, $y(l) = -1$.

Sub-Problem 2: Social Attitude Prediction Based on the existing attitude expressions $\mathcal{E}$ and the expressed attitudes $\{s(e)\}_{e \in \mathcal{E}}$, we aim at building another mapping $p : \bar{\mathcal{L}} \to \{-1, +1\}$ to obtain the specific attitudes of the expression activities in $\mathcal{L}$, where $\bar{\mathcal{L}} = \{l | l \in \mathcal{L} \wedge y(l) = +1\}$ contains the expressions predicted to take place in Sub-Problem 1.

According to the problem statement, we can observe that the *social attitude prediction* task heavily depends on the results of the *social expression prediction* task, and only the attitudes clearly expressed will make sense and have the concrete physical meanings.

III. Proposed Methods

In this section, we will introduce the integrated signed link prediction framework BI-SAP in detail. The features extracted to build BI-SAP are introduced in Section III-A, and detailed information about the model is available in Section III-B.

A. Feature Extraction

In this part, we will introduce the features extracted for the *social expression prediction* and *social attitude prediction* sub-problems respectively.

1) Feature Extraction for Social Expression Prediction: With the known social expressions among users within the network, we can represent the users that a given user u has expressed his attitudes to as set $\Gamma_{out}(u) = \{w | w \in \mathcal{V}, (u, w) \in \mathcal{E}\}$. Meanwhile, the set of users who express their attitudes to u can be represented as set $\Gamma_{in}(u) = \{w | w \in \mathcal{V}, (w, u) \in \mathcal{E}\}$. $\Gamma_{out}(u)$ together with $\Gamma_{in}(u)$ can be used to define the set of users having expression activities with u, i.e., $\Gamma(u) = \Gamma_{in}(u) \cup \Gamma_{out}(u)$, who are called the expression neighbor of u in this paper. Based on the notations $\Gamma_{out}(u)$, $\Gamma_{in}(u)$ and $\Gamma(u)$, a set of features for potential social expression from u to v, i.e., (u, v), are extracted from the network.

(1) Degree based Features: Social degree is an important hint about users' social activeness and popularity, and active users are more likely to express their attitudes with other users. Therefore, the first category of features extracted for the social expression prediction problem is the social degrees of users in the networks. Meanwhile, considering that the social expression among users are all directed, both the out-going and in-coming social degrees should be considered. We propose to extract 3 different degree based features:

- *in-degree*: For a social expression (u, v), the in-degrees of u and v (i.e., $|\Gamma_{in}(u)|$ and $|\Gamma_{in}(v)|$) show their popularity, and are used as as two degree based features.
- *out-degree*: Meanwhile, the out-degrees of u and v (i.e., $|\Gamma_{out}(u)|$ and $|\Gamma_{out}(v)|$) show the activeness of u and v in the network, which are also used as two features for expression prediction.
- *all-degree*: To take the activeness and popularity of users into consideration concurrently, we also count the number of expression neighbors of users u and v, i.e., $|\Gamma(u)|$ and $|\Gamma(v)|$, and use them as another two features.

(2) Preferential Attachment (PA) based Features: Besides the degree based features, to denote the popularity and activeness of users simultaneously, we also propose to extract features with the product of the in/out degrees of users u and v as a proximity measure. Due to the directions of social expressions, 3 different PA based features are extracted as follows:

- *PA*: For a social expression (u, v), the out-degree of u and the in-degree of v denote the activeness and popularity of u and v respectively. We extract the PA based feature for (u, v) to be $|\Gamma_{out}(u)| \times |\Gamma_{in}(v)|$.
- *reverse-PA*: Generally, in social networks, if user u shows his attitude towards v, user v will be highly likely to show his attitude to u as well. Another PA-based feature extracted for expression (v, u) is the *reverse-PA*, which can be represented as $|\Gamma_{in}(u)| \times |\Gamma_{out}(v)|$.
- *all-PA*: By considering the in-coming and out-going neighbors of u and v at the same time, we introduce a new feature named all-PA, which can be represented as all-PA$(u, v) = |\Gamma(u)| \times |\Gamma(v)|$.

(3) Common Neighbor (CN) based Features: Besides the activeness and popularity factors, new social attitudes are more likely to be expressed between users who are close to each other. The social closeness among users can be measured by various metrics, e.g., common neighbor. Depending on the direction of social expressions, the common neighbor can be defined in 3 different forms:

- *in-CN*: The common in-coming neighbors shared by u and v can be represented as $|\Gamma_{in}(u) \cap \Gamma_{in}(v)|$.
- *out-CN*: The common out-going neighbors shared by u and v can be represented as $|\Gamma_{out}(u) \cap \Gamma_{out}(v)|$.
- *all-CN*: Regardless of the directions, the common neighbors shared by u and v can be denoted as $|\Gamma(u) \cap \Gamma(v)|$.

(4) Jaccard's Coefficient (JC) based Features: Considering that the common expression neighbors shared by u and v can be very large because both u and v have a lot of neighbors rather than they are strongly related to each other, we introduce 3 Jaccard's Coefficient based features in the paper. Jaccard's Coefficient consides both the shared neighbors between u and v, as well as the degrees of u and v when inferring potential social expression (u, v). Depending on the expression direction, the Jaccard's Coefficient based features extracted for link (u, v) include:

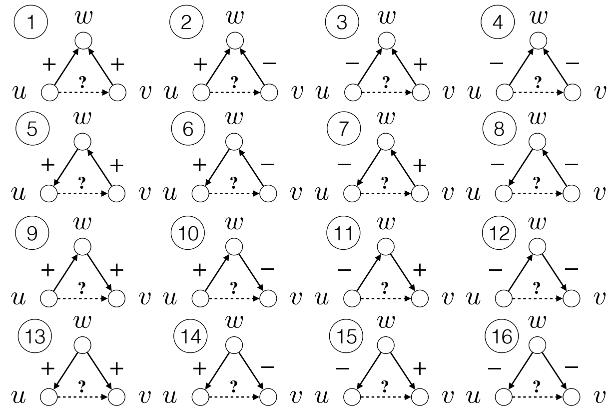


Fig. 1. Different triad patterns in signed networks.

- *in-JC*: The JC score extracted for (u, v) based on the incoming neighbors can be represented as $\frac{|\Gamma_{in}(u) \cap \Gamma_{in}(v)|}{|\Gamma_{in}(u) \cup \Gamma_{in}(v)|}$.
- *out-JC*: The JC score extracted for (u, v) based on the out-going neighbors can be represented as $\frac{|\Gamma_{out}(u) \cap \Gamma_{out}(v)|}{|\Gamma_{out}(u) \cup \Gamma_{out}(v)|}$.
- *all-JC*: Regardless of the directions, the JC score extracted for (u, v) can be represented as $\frac{|\Gamma(u) \cap \Gamma(v)|}{|\Gamma(u) \cup \Gamma(v)|}$.

(5) Admic/Adar (AA) based Features: In the JC-based features, the shared common neighbors are assigned with the same weight, i.e., $\frac{1}{|\Gamma(u) \cup \Gamma(v)|}$. However, in the real scenarios, the common neighbors with lower degree will indicate stronger closeness between u and v. Therefore, we propose to extract 3 AA based features for social expression (u, v)

- *in-AA*: The AA score extracted for (u, v) based on the in-coming expression neighbors can be represented as $\sum_{w \in \Gamma_{in}(u) \cap \Gamma_{in}(v)} \frac{1}{|\Gamma_{out}(w)|}$.
- *out-AA*: The AA score extracted for (u, v) based on the out-going expression neighbors can be represented as $\sum_{w \in \Gamma_{out}(u) \cap \Gamma_{out}(v)} \frac{1}{|\Gamma_{in}(w)|}$.
- *all-AA*: Regardless of the expression directions, The AA score extracted for (u, v) can be represented as $\sum_{w \in \Gamma(u) \cap \Gamma(v)} \frac{1}{|\Gamma(w)|}$.

Based on the above descriptions, we can represent the feature vector extracted for potential social expression (u, v) as $\mathbf{x}^l(u, v)$, whose length can be represented as $|\mathbf{x}^l(u, v)|$. In the social expression prediction task, a potential expressions among users, e.g., (u, v), can actually be represented as a tuple $(\mathbf{x}^l(u, v), y(u, v))$, where $y(u, v)$ denotes the expression label of (u, v) in the network.

2) Feature Extraction for Social Attitude Prediction: We have introduced the features extracted for the social expression prediction task, and we will talk about the features to be extracted for the *social attitude prediction* task in this part.

By considering the attitudes in the existing social expressions, the expression neighbor sets of each user (e.g., u) can be divided into two separate subsets, e.g., the neighbors connected by positive and negative attitudes. For instance, given the out-going neighbor set of user u, i.e., $\Gamma_{out}(u)$, we can represent the subset of neighbors u connects to via positive expressions as $\Gamma^{+}_{out}(u) = \{w | w \in \mathcal{V}, (u,w) \in \mathcal{E}, s(u,w) = +1\}$. Similarly, we can define the negative out-going neighbor set as $\Gamma^{-}_{out}(u)$, in-coming neighbor sets $\Gamma^{+}_{in}(u)$ and $\Gamma^{-}_{in}(u)$, as well as neighbor sets regardless of the directions $\Gamma^{+}(u)$ and $\Gamma^{-}(u)$.

With these notations, we propose to extract two sets of features for the *social attitude prediction* task:

(1) Degree based Features: Based on the expressed social attitudes, we can infer the personal characteristics of users in the network. For instance, assume some users like to trust others and all the social attitudes expressed by him are positive, then the future expressions from him to other users are highly likely to be positive. On the other hand, for users who have very bad fame and all his/her nearby users distrust him/her, the future social attitudes towards to him/her will also be negative with a high probability. Therefore, for a potential social expression (u, v), a set of degree-based features are extracted in this paper:

- *positive degree*: Depending on the direction of social expressions between users and their neighbors, the positive degree features extracted for (u, v) involves three different categories: positive in degree ($|\Gamma^{+}_{in}(u)|$, $|\Gamma^{+}_{in}(v)|$), positive out degree ($|\Gamma^{+}_{out}(u)|$, $|\Gamma^{+}_{out}(v)|$) and positive all degree ($|\Gamma^{+}(u)|$ and $|\Gamma^{+}(v)|$).
- *negative degree*: Similarly, a set of negative degree based features have also been extracted for (u, v), i.e., $|\Gamma^{-}_{in}(u)|$, $|\Gamma^{-}_{out}(u)|$, $|\Gamma^{-}(u)|$, as well as $|\Gamma^{-}_{in}(v)|$, $|\Gamma^{-}_{out}(v)|$ and $|\Gamma^{-}(v)|$.

(2) Social Balance Theory based Features: The social attitudes among the users in signed networks often obey some interesting laws. For instance, in the real world, "friend of my friend is my friend", "enemy of my friend is my enemy" but "enemy of enemy is my friend", etc. These social patterns can be represented and explained with the *social balance theory* [1], [9]. In this paper, we propose to extract a set of social balance theory based features for the *social attitude prediction* task.

Three users u, v and w who have shown their attitudes towards each other are referred to as a *social triad*. When inferring the attitude from u to v (i.e., the attitude of (u, v)), depending on the direction and attitudes between w, u and v respectively, where 16 different *social triads* can be defined, which are shown in Figure 1. In this paper, we propose to extract the number of *social triads* involving (u, v) as the set of *social balance theory based features*. For instance, based on the first *social triad* shown at the top left of Figure 1, we can represent the extracted feature to be $|\{w | w \in \mathcal{V}, (u,w) \in \mathcal{E}, s(u,w) = +1, (v,w) \in \mathcal{E}, s(v,w) = +1\}|$, i.e., the number of w in the network that together with the expressed attitudes to u and v that can fit the first *social triad*. Similarly, for other *social triads*, we also can extract a set of other *social balance*

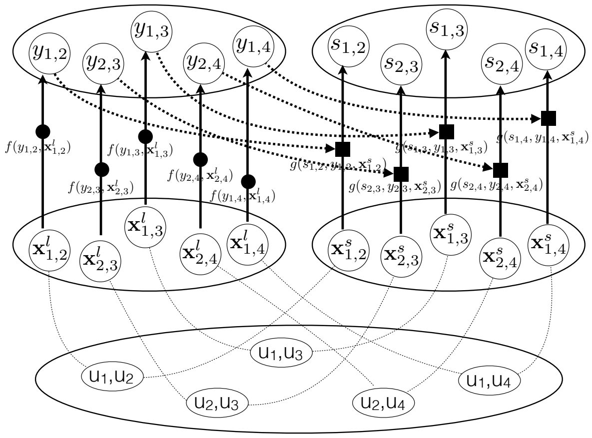


Fig. 2. The BI-SAP Framework.

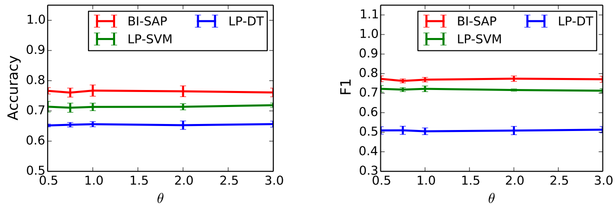
theory based feature from the network.

Based on the above descriptions, we can represent the set of features extracted in the *social attitude prediction* task for expression (u, v) as vector $\mathbf{x}^s(u, v)$, whose length can be represented as $|\mathbf{x}^s(u, v)|$. In the *social attitude prediction* task, each potential social attitude expression between users u and v can be represented as a tuple involving the feature vector and the attitude of it, i.e., $(\mathbf{x}^s(u, v), s(u, v))$, where $s(u, v)$ represents the sign of link (u, v) in the network.

B. Social Attitude Expression Prediction Model

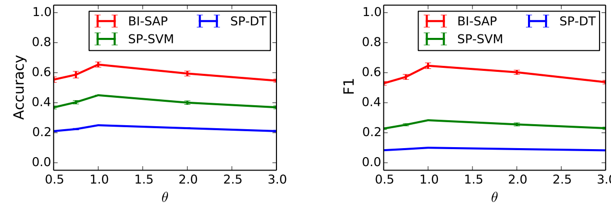
In the previous section, we have introduced the set of features extracted for the *social expression prediction* and *social attitude prediction* tasks respectively. Meanwhile, these two sub-problems covered in the *social attitude prediction* problem are actually strongly correlated with each other, as we aim at inferring the attitudes that are explicitly expressed in the social networks. In other words, for certain potential social expression (u, v), its attitude prediction result significantly depends on its expression prediction result. With the extracted features, in this section, we will introduce an integrated *social attitude expression prediction* framework based on the Bayesian network model in detail.

1) BI-SAP *Framework:* To predict the social expressions and attitudes simultaneously, a novel social attitude expression prediction framework, BI-SAP, is proposed in this paper. To illustrate the model more clearly, we also give an example in Figure 2. At the bottom of Figure 2, we show a group of social expressions, which include both existing expressions and some potential ones to be predicted. Based on the features introduced in the previous section, the feature vectors extracted for a potential social expression (u, v) in the expression and attitude prediction tasks can be represented as $\mathbf{x}^l(u, v)$ and $\mathbf{x}^s(u, v)$ respectively. Meanwhile, the expression label and attitude sign of (u, v) in the BI-SAP model are represented as $y(u, v)$ and $s(u, v)$. The correlation among the variables can be quantified with functions $f\left(y(u, v), \mathbf{x}^l(u, v)|\alpha\right)$ and $g\left(s(u, v), y(u, v), \mathbf{x}^s(u, v)|\beta\right)$, where α and β are the parameter vectors in the model. The probability for expression (u, v) to achieve expression label $y(u, v)$ and attitude $s(u, v)$ based



(a) Accuracy (b) F1

Fig. 3. Expression prediction results at different θ.



(a) Accuracy (b) F1

Fig. 4. Attitude inference results at different θ.

on information in G can be represented as

$$\begin{aligned} & P(y(u,v), s(u,v)|G) \\ & = P\left(y(u,v), s(u,v)|\mathbf{x}^l(u,v), \mathbf{x}^s(u,v)\right) \\ & = f\left(y(u,v), \mathbf{x}^l(u,v)|\alpha\right) \cdot g\left(s(u,v), y(u,v), \mathbf{x}^s(u,v)|\beta\right), \end{aligned}$$

where $f\left(y(u,v), \mathbf{x}^l(u,v)|\alpha\right)$, $g(s(u,v), y(u,v), \mathbf{x}^s(u,v)|\beta)$ quantify the probability of achieving the expression label $y(u,v)$ and attitude $s(u,v)$ based on the extracted features $\mathbf{x}^l(u,v)$ and $\mathbf{x}^s(u,v)$ respectively. These two factors can be instantiated in various ways, and in this paper, we propose to model them in a way similar to the Markov random field. For the expression prediction function $f\left(y(u,v), \mathbf{x}^l(u,v)|\alpha\right)$, we can represent as a full-joint distribution

$$\begin{aligned} & f\left(y(u,v), \mathbf{x}^l(u,v)|\alpha\right) \\ & = \frac{1}{Z_\alpha} \exp\left(\sum_i \alpha_i f\left(y(u,v), x_i^l(u,v)\right)\right), \end{aligned}$$

where $Z_\alpha = \sum_{x_i^l(u,v) \in \mathcal{X}} \exp\left(\sum_i \alpha_i f\left(y(u,v), x_i^l(u,v)\right)\right)$ is the expression prediction normalization term, $x_i^l(u,v)$ denotes the i_{th} feature in vector $\mathbf{x}^l(u,v)$ and $\mathcal{X}$ denotes all the potential values of feature $x_i^l(u,v)$.

Meanwhile, we can define the attitude prediction function $g(s(u,v), y(u,v), \mathbf{x}^s(u,v)|\beta)$ in a similar way, so that its full-joint distribution can be represented as

$$\begin{aligned} & g\left(s(u,v), y(u,v), \mathbf{x}^s(u,v)|\beta\right) = \\ & \frac{1}{Z_\beta} \exp\left(\beta_0 g\left(s(u,v), y(u,v)\right) + \sum_j \beta_j g\left(s(u,v), x_j^s(u,v)\right)\right), \end{aligned}$$

where Z_β represents the attitude prediction normalization term. The attitude prediction function depends on the expression prediction result a lot, and the expression label $y(u,v)$ is also involved as a feature with weight β_0 in the equation.

Therefore, based on the concrete instantiation of functions $f\left(y(u,v), \mathbf{x}^l(u,v)|\alpha\right)$ and $g\left(s(u,v), y(u,v), \mathbf{x}^s(u,v)|\beta\right)$, we can define the log-likelihood objective function $\mathbb{O}(\alpha, \beta)$ of the training set $\mathcal{T}$ as follows:

$$\begin{aligned} & \mathbb{O}(\alpha, \beta) = \log \prod_{(u,v) \in \mathcal{T}} P\left(y(u,v), s(u,v)|\mathbf{x}^l(u,v), \mathbf{x}^s(u,v)\right) \\ & = \sum_{(u,v) \in \mathcal{T}} \left(\sum_i \alpha_i f\left(y(u,v), x_i^l(u,v)\right) + \beta_0 g\left(s(u,v), y(u,v)\right)\right. \\ & \left. + \sum_j \beta_j g\left(s(u,v), x_j^s(u,v)\right)\right) - \log Z_\alpha - \log Z_\beta. \end{aligned}$$

In the aforementioned function, α and β are the parameters configuration. In the next subsection, we will focus on learning these two parameter vectors from the data, and apply the built model to infer the labels and attitudes of potential social expression in the network.

2) Real Time BI-SAP *Learning:* In the log-likelihood objective function, two parameter vectors α and β are involved, which can be learnt from the historical data. The optimal parameters $\hat{\alpha}$ and $\hat{\beta}$ which can maximize the objective function can be represented as

$$\hat{\alpha}, \hat{\beta} = \arg\max_{\alpha, \beta} \mathbb{O}(\alpha, \beta).$$

The objective function is convex, and has closed-form solution. In this paper, we propose to address the objective function with the stochastic gradient decent method, which can adjust the model in real time as new training data comes in. For each of the user (u,v), we can represent the objective function for the link as $\mathbb{O}_{(u,v)}(\alpha, \beta)$. The iterative updating equation of α_i, β_0, and β_j can be represented as

$$\begin{cases} \alpha_i^{(\tau+1)} = \alpha_i^{(\tau)} - \gamma_{\alpha_i} \frac{\partial \mathbb{O}_{(u,v)}}{\partial \alpha_i}, \\ \beta_0^{(\tau+1)} = \beta_0^{(\tau)} - \gamma_{\beta_0} \frac{\partial \mathbb{O}_{(u,v)}}{\partial \beta_0}, \\ \beta_j^{(\tau+1)} = \beta_j^{(\tau)} - \gamma_{\beta_j} \frac{\partial \mathbb{O}_{(u,v)}}{\partial \beta_j}, \end{cases}$$

where γ_{α_i}, γ_{β_0} and γ_{β_j} are the learning rates, which are assigned with very small constant values in this paper.

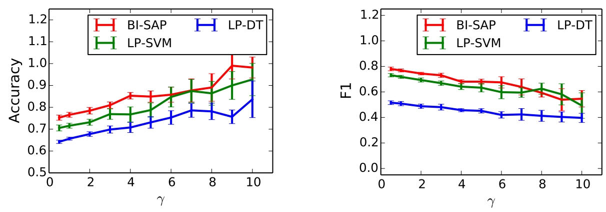
The partial derivative of the objective function $\mathbb{O}_{(u,v)}(\alpha, \beta)$ with regard to α_i can be represented as

$$\begin{aligned} & \frac{\partial \mathbb{O}_{(u,v)}}{\partial \alpha_i} = f\left(y(u,v), x_i^l(u,v)\right) - \frac{\partial \log Z_\alpha}{\partial \alpha_i} \\ & = f\left(y(u,v), x_i^l(u,v)\right) \\ & \quad - \mathbb{E}_{P_{\alpha_i}(y(u,v)|x_i^l(u,v))}\left[f\left(y(u,v), x_i^l(u,v)\right)\right], \end{aligned}$$

where $\mathbb{E}_{P_{\alpha_i}(y(u,v)|x_i^l(u,v))}[f\left(y(u,v), x_i^l(u,v)\right)]$ is the expectation of the factor function $f\left(y(u,v), x_i^l(u,v)\right)$ under the distribution $P_{\alpha_i}(y(u,v)|x_i^l(u,v))$. Considering that the factor graph model introduced in this paper is represented as a tree-structured graph in Figure 2, the conditional probability $P_{\alpha_i}(y(u,v)|x_i^l(u,v))$ can be obtained by calculating the marginal probability $P_{\alpha_i}(y(u,v), x_i^l(u,v))$ first, which is obtained with the belief propagation effectively.

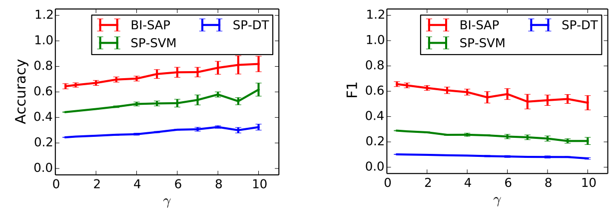
In a similar way, we can obtain the partial derivative of the objective function $\mathbb{O}(\alpha, \beta)$ with respect to β_0 and β_j as follows:

$$\begin{aligned} & \frac{\partial \mathbb{O}_{(u,v)}}{\partial \beta_0} = g\left(s(u,v), y(u,v)\right) - \frac{\partial \log Z_\alpha}{\partial \alpha_i} \\ & = g\left(s(u,v), y(u,v)\right) \\ & \quad - \mathbb{E}_{P_{\beta_0}(s(u,v)|y(u,v))}[g\left(s(u,v), y(u,v)\right)]; \end{aligned}$$



(a) Accuracy (b) F1

Fig. 5. Expression prediction results at different γ.



(a) Accuracy (b) F1

Fig. 6. Attitude inference results at different γ.

$$\frac{\partial \mathbb{O}_{(u,v)}}{\partial \beta_j} = g\left(s(u,v), x_j^s(u,v)\right) - \frac{\partial \log Z_\alpha}{\partial \alpha_i}$$
$$= g\left(s(u,v), x_j^s(u,v)\right)$$
$$- \mathbb{E}_{P_{\beta_j}(s(u,v)|x_j^s(u,v))}[g\left(s(u,v), x_j^s(u,v)\right)].$$

The marginal probability introduced in the second terms in the above equations can both be obtained with the belief propagation effectively, which will not be introduced here due to the limited space. Such a alternative updating process continues until all these parameters converge, which are used as the final parameters in the framework BI-SAP. As more data comes into the system, the parameters in BI-SAP can be updated in real time, which makes BI-SAP applicable to the dynamic social network setting.

IV. EXPERIMENTS

To test the effectiveness of the proposed framework BI-SAP, extensive experiments have been conducted on real-world signed network datasets. In this section, we will describe the datasets used in the experiments first, and then talk about the experiment setting in detail. Finally, we will show the experiment results and give detailed analysis.

A. Dataset Descriptions

The signed network dataset used in the experiments is the Epinions network, which can be downloaded from site[1]. The Epinions network dataset used in this paper include $313,828$ users and $841,372$ directed links. Among these $841,372$ social links, $717,667$ are positive links and $123,705$ are negative links.

B. Experiment Settings

In this part, we will talk about the experiment settings in detail, which include the detailed experiment setup, comparison methods, and the evaluation metrics applied to measure the performance of the methods.

1) Experiment Setup: In the experiments, the existing links are treated as the expressed social attitudes. As shown in the datasets, the number of positive links is larger than that of the negative links. From the Epinions network, we treat all the negative links as the negative instance set, and a set of positive instances are extracted from the positive links whose number is controlled by the positive-negative ratio $\theta = \frac{\#\text{positive}}{\#\text{negative}}$ and $\theta \in \{0.5, 0.75, 1.0, 2.0, 3.0\}$. Ratio $\theta = 1.0$ denotes that the positive and negative link sets are of the same size, while ratio $\theta = 0.5$ means that the number of extracted positive links is only half of the negative links. In the experiments, the positive links are assigned with sign $+1$, while the negative links are assigned with sign -1. The extracted positive together with the negative links are treated as the existing links.

Meanwhile, in the networks, besides the existing links, most potential social connections among users are actually unknown and non-existing (as introduced in Section II). Therefore, a set of non-existing social links are extracted from the network controlled by the missing ratio $\gamma = \frac{\#\text{missing}}{\#\text{existing}}$, where $\gamma \in \{0.5, 1.0, 2.0, \cdots, 10.0\}$. The missing ratio $\gamma = 1.0$ denotes that the number of non-existing links is the same as the known links, while ratio $\gamma = 10.0$ represents the number of non-existing links is 9 times larger than the known links. In the experiments, the non-existing links are assigned with label -1, while the existing links are assigned with label $+1$.

These positive, negative and non-existing links are partitioned into two sets according to ratio $4:1$ in the 5-fold cross validation, where the 4 folds are used as the training set and the other 1 fold is used as the test set. Based on the training set, we will build the BI-SAP framework, which is applied to the test set to infer both the labels and signs of the links.

2) Comparison Methods: The comparison methods used in the experiment include:

- BI-SAP: Framework BI-SAP is the Bayesian network based social attitude prediction model proposed in this paper, which considers the correlation between the attitude inference and expression prediction tasks. The results of BI-SAP include both the expression labels and attitudes of the links to be inferred.
- LP-SVM: LP-SVM is a supervised expression prediction method proposed in [5], where SVM is used as the base classifier. The features used to build LP-SVM include the topological features proposed in [5]. LP-SVM will only output the expression labels of links in the test set.
- SP-SVM: SP-SVM is a SVM-based attitude prediction method with the features extracted based on the link polarities [9]. SP-SVM will merely output the attitudes of the links in the test set.
- LP-DT: Based on the same set of features as LP-SVM, another social expression prediction method LP-DT is built by using the decision tree as the base classifier.
- SP-DT: The attitude prediction method SP-DT is identical to SP-SVM except that decision tree is used as the base classifier in SP-DT.

[1] http://snap.stanford.edu/data/index.html#signnets

TABLE I

IMPORTANCE OF SOCIAL EXPRESSION PREDICTION FEATURES FOR (u, v).

Rank	Exp. Pred. Feature	Rank	Exp. Pred. Feature
1	*PA*	10	*all-CN*
2	*u degree*	11	*all-JC*
3	*v in degree*	12	*in-JC*
4	*u out degree*	13	*out-CN*
5	*all-PA*	14	*out-AA*
6	*u in degree*	15	*in-AA*
7	*v degree*	16	*out-JC*
8	*v out degree*	17	*in-CN*
9	*reverse-PA*	18	*all-AA*

3) Evaluation Metrics: In the experiments, the existing social links among the users are used as the ground truth for evaluation. For both the expression prediction and attitude inference tasks, the comparison methods' performance are evaluated with two frequently used metrics: F1 and Accuracy.

C. Experiment Results

Based on the results obtained in each fold in cross-validation, we show the mean±std Accuracy and F1 scores achieved by different methods in Figures 3-6.

The plots in Figure 3 and Figure 4 are the expression prediction and attitude inference results obtained by different comparison methods at different positive-negative ratios θ. As shown in Figure 3, in predicting the expression activates in signed networks, the change of positive-negative ratio θ has very limited affects on different comparison methods. For instance, the Accuracy scores achieved by BI-SAP is around 0.78 constantly for different θs. In addition, BI-SAP can outperform the comparison methods LP-SVM and LP-DT with significant advantages when evaluated by F1.

From Figure 4, we can observe that θ can affect the comparison methods' performance in the attitude inference task. Generally, when the positive and negative instances are balanced (i.e., the ratio $\theta = 1.0$), the comparison methods can achieved the best performance. In addition, by utilizing the dependence relationship between attitude and expression activities, BI-SAP can perform better in inferring the attitudes than LP-SVM and LP-DT. For example, the Accuracy score achieved by BI-SAP at $\theta = 1.0$ is 0.68, which is 54% higher than the Accuracy score obtained by LP-SVM and almost two times larger than that achieved by LP-DT.

Besides the positive-negative ratio θ, we also analyze the effects of the missing ratio γ on the performance of different methods, and the results are shown in Figures 5-6.

As shown in Figure 5, as the missing ratio γ increases (i.e., more non-existing links are added), the Accuracy scores obtained by all the comparison methods increases steadily, while F1 scores achieved by the methods keep decreasing instead. The potential reasons is that, as more non-existing links are involved, the ratio of known links (including both positive and negative links) vs non-existing links is becoming more and more imbalanced. Predicting all the links to be non-existing links can still achieve high Accuracy scores, while it will become more and more difficult to infer known link correctly, which is the reasons why F1 decreases. Similar phenomenon can be observed in Figure 6.

TABLE II

IMPORTANCE OF ATTITUDE INFERENCE FEATURES FOR (u, v).

Rank	Attitude Infer. Feature	Rank	Attitude Infer. Feature
1	*u negative degree*	15	*v negative out degree*
2	*u positive out degree*	16	*triad:* $u \xrightarrow{+} w \xleftarrow{+} v$
3	*u negative out degree*	17	*triad:* $u \xleftarrow{-} w \xrightarrow{-} v$
4	*u positive degree*	18	*triad:* $u \xleftarrow{+} w \xrightarrow{+} v$
5	*v positive in degree*	19	*triad:* $u \xrightarrow{-} w \xrightarrow{+} v$
6	*v positive degree*	20	*triad:* $u \xleftarrow{+} w \xleftarrow{+} v$
7	*v negative in degree*	21	*triad:* $u \xrightarrow{-} w \xrightarrow{-} v$
8	*u positive in degree*	22	*triad:* $u \xrightarrow{-} w \xleftarrow{+} v$
9	*v positive out degree*	23	*triad:* $u \xrightarrow{-} w \xleftarrow{-} v$
10	*v negative degree*	24	*triad:* $u \xleftarrow{-} w \xleftarrow{+} v$
11	*triad:* $u \xrightarrow{+} w \xrightarrow{-} v$	25	*triad:* $u \xleftarrow{-} w \xrightarrow{+} v$
12	*triad:* $u \xrightarrow{+} w \xrightarrow{+} v$	26	*triad:* $u \xleftarrow{+} w \xleftarrow{-} v$
13	*u negative in degree*	27	*triad:* $u \xrightarrow{+} w \xleftarrow{-} v$
14	*triad:* $u \xleftarrow{+} w \xrightarrow{-} v$	28	*triad:* $u \xleftarrow{-} w \xleftarrow{-} v$

D. Feature Analysis

In addition, we also analyze the importance of different social expression prediction features in building the models, and the results is available in Table I. For all the 18 features extracted for pair (u, v) in the expression prediction task, the top 5 most effective features are "*PA*", "*degree of u*", "*in degree of v*", "*out degree of u*" and "*all PA*". The features extracted based on measures, like "*CN*" "*JC*" and "*AA*", are less useful for the expression prediction task. Therefore, individuals' activeness and popularity play an important role in the social attitude expression activities.

Meanwhile, for the attitude inference task, among the 28 extracted attitude inference features shown in Table II, the most useful features about the degree based features. Among all the features extracted based on the 16 triads, the most useful ones are u $\xrightarrow{+}$ w $\xrightarrow{-}$ v, u $\xrightarrow{+}$ w $\xrightarrow{+}$ v, and u $\xleftarrow{+}$ w $\xrightarrow{-}$ v, and the other ones are less useful for the attitude inference task. Viewed in this perspective, individuals' personal characteristics (e.g., like to trust/distrust others) determine their future attitudes towards other users.

V. RELATED WORKS

In recent years, signed networks have gained increasing attention. Kunegis et al. analyze the corpus of user relationships of the Slashdot site, where users of the website can tag other users as friends and foes, providing positive and negative endorsements [7]. Leskovec et al. [10] develop an alternate theory of status that better explains the observed edge signs based on the traditional structural balance theory, which provides insights into the underlying social mechanisms.

Based on signed networks, various application problems have been studied already, like link prediction [9], [17], community detection [2], [8], information diffusion [11], [12], [23], and trust hole detection [24]. Symeonidis et al. [17] define a basic node similarity measure that captures effective local graph features for link prediction in signed networks. Based on the structural balance theory, Leskovec et al. propose to study the link prediction problems in signed networks in [9]. Doreian et al. [2] and Kunegis [8] propose to partition the network into different social groups to detect the signed social community structures. Li et al. [12] studied the influence diffusion dynamics and influence maximization in signed social networks, and a similar problem is studied in [11], where a new diffusion model P-IC is proposed. To depict the information diffusion process in signed networks, Zhang et al. introduce a new diffusion model called MFC and propose to discover the rumor initiators from the infected signed network [23]. A new research problem for the signed network, called "trust hole detection", is introduced by Zhang et al. in [24]. In [24], Zhang et al. propose to discover the users occupying positions with great advantages in the networks, which are denoted as the positive/negative trust holes respectively.

Link prediction in online social networks first proposed by D. Liben-Nowell et al. [13] has been a hot research topic in recent years and many different methods have been proposed [14]–[16], [19]. D. Liben-Nowell et al. [13] propose many unsupervised link predicators to predict the social connections among users. M. Hasan et al. [5] propose to predict links by using supervised learning methods. An extensive survey of other link prediction methods is available in [4], [6]. Most of the existing works focus on studying the link prediction problem with one single information source. Nowadays, the researchers's attention has been shifted to the link prediction across multiple sources. For instance, Tang et al. [18] propose to infer certain type of links across multiple heterogeneous information networks and develop a method for predict the types of social ties. To deal with the domain differences, i.e., information distribution differences of different networks, Qi et al. [3] propose to use biased cross-network sampling to predict links across networks.

VI. Conclusion

In this paper, we have studied the *social attitude expression prediction* problem, which aims at predicting both the attitude expression activities as well as explicit social attitudes among users in signed networks. To address the problem, a novel integrated social attitude expression prediction framework BI-SAP is introduced based on the Bayesian network model. In framework BI-SAP, the *social attitude prediction* task depends on the prediction results of specific *social expression*a lot. Extensive experiments conducted on real-world signed networks have demonstrated the effectiveness of BI-SAP in addressing the APE problem.

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