DEFINE: Friendship Detection Based on Node Enhancement

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Abstract. Network representation learning (NRL) is a matter of importance to a variety of tasks such as link prediction. Learning low-dimensional vector representations for node enhancement based on nodes attributes and network structures can improve link prediction performance. Node attributes are important factors in forming networks, like psychological factors and appearance features affecting friendship networks. However, little to no work has detected friendship using the NRL technique, which combines students' psychological features and perceived traits based on facial appearance. In this paper, we propose a framework named DEFINE (No**d**e **E**nhancement based **Frien**dship D**e**tection) to detect students' friend relationships, which combines with students' psychological factors and facial perception information. To detect friend relationships accurately, DEFINE uses the NRL technique, which considers network structure and the additional attributes information for nodes. DEFINE transforms them into low-dimensional vector spaces while preserving the inherent properties of the friendship network. Experimental results on real-world friendship network datasets illustrate that DEFINE outperforms other state-of-art methods.

Keywords: Node Enhancement · Friendship Detection · Social Network.

1 Introduction

Information networks are general data structures to explore complex relationships in the real-world. Social networks and academic networks have been widely investigated [8, 23, 21]. Mining friendship in networks also has drawn continuous attention in academia. The data collected by mobile phones can form the dynamic evolution of personal relationships and identify friend relationships accurately [5]. Most friendship detection researches are based on the information obtained from online social networks; little friendship prediction studies focus on social network structure and node attributes. However, exploring the hidden friendship among students is challenging. At present, the existing research literature predicts friendship by depicting characters according to the behavior data of students. Attractive appearances and similar psychological characteristics are important factors in the development of friendship [20, 15]. As a kind of social relationship, the formation of friendships is affected by complex social relationships and the students' characteristics. However, little work has been done to detect friendship combining social network structure and node attribute proximity.

To tackle the above challenges, we present a new framework, named No**d**e **E**nhancement based **F**r**i**e**n**dship D**e**tection (DEFINE) for predicting friend relationships. Our framework forms an intelligent solution for detecting friend relationship based on hidden attributes in student social network. As shown in Fig. 1, our framework considers both network structure and node attributes which contain students' psychological features and facial perception information. DEFINE transforms the friendship network into low-dimensional vector spaces while preserving the inherent properties of the friendship network to detect friendship accurately.

In summary, our main contributions are concluded as follows:

(1) We propose a framework named DEFINE based on the NRL technique, to discover students' friend relationships by combining the network structure and node attribute proximity.
(2) DEFINE considers both students' psychological factors and facial perception information as node attributes. Experimental results demonstrate the outstanding capabilities of DEFINE on the friendship detection task.
(3) DEFINE not only considers the structural attributes of the social network but also combines node attribute information, which performs better than other NRL models.

We organize the remainder of this paper as follows. Section 2 summarizes related work which contains the theoretical dimensions of the research. In Section 3, we focus on the details of problem formulation. Section 4 introduces the details of the proposed framework. We present experiments and results in Section 5. In Section 6, we present the conclusion of the research.

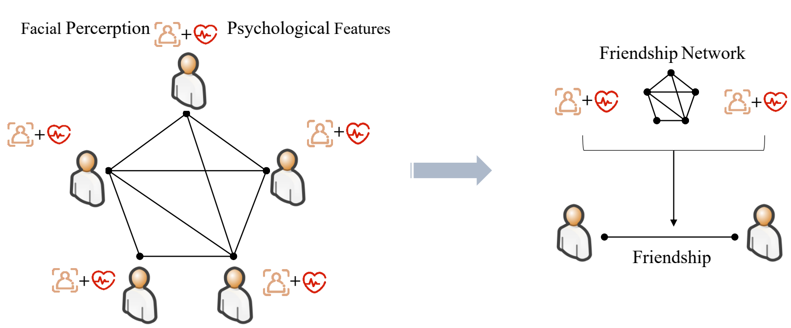


Fig. 1. The overview of friendship detection in our framework.

2 Related Work

2.1 Network Representation Learning

NRL aims to represent the nodes in the network as low-dimensional vectors that are easy to be the input of machine learning classifier and applied in social network tasks. The common network embedding methods are based on network structure information. Perozzi *et al.* [14] proposed the Deepwalk algorithm in 2014, which is the first to consider the introduction of deep learning techniques to express nodes in vector form in the network. Deepwalk uses the random walk that is a repeatable access depth-first search method, to sample the nodes in the network and learns vector representation of nodes using co-occurrence relation between nodes. Since sampling only depends on local information, Deepwalk is suitable for distributed and online systems.

According to the concept of Deepwalk, lots of scholars proposed improved algorithms. Large-scale Information Network Embedding (LINE) [17] considered neighborhood information of nodes in a network and is designed based on the breadth-first search. It redefines the similarity between nodes that contains first-order proximity and second-order proximity and constructs its unique representation. Grover and Leskovec [6] extended Deepwalk and proposed Node2vec by changing the generation of random walk sequence. Node2vec considers the characteristic of depth-first search and breadth-first search while choosing the next node by adding two parameters p and q to control the jumping direction. It also uses the network structure information to learn suitable node representation in a semi-supervised learning approach.

In addition to network structure information, current researches explore the impact of extra information in the network node, such as texts. Some researches combine both the attributes and the network structure to represent the nodes in the network. Yang *et al.* [24] proposed a text-related Deepwalk model named TADW (text-associated DeepWalk), integrating text information of nodes into NRL. This work proves the Deepwalk algorithm is equivalent to matrix decomposition. Graph2Gauss [2] embedded each node as a Gaussian distribution to capture uncertainty about the representation.

2.2 Friendship Prediction

Analyzing and predicting the social relationship between people by using individual information in the social network is the practical application of network link prediction [22]. Parimi *et al.* [13] applied the Latent Dirichlet Allocation (LDA) topic model to quantify users' interest in social media and predict friendship links based on the similarity of users' interest. Zhang *et al.* [26] quantified the distance between user's frequent movement areas and proved the geographic distance is an effective metric for distinguishing friends and strangers. They experimented with Twitter data and applied machine learning classifiers to predict friendship. Valverde-Rebaza *et al.* [18] reviewed research studies about friendship prediction in location-based social networks, including their approaches, advantages, and disadvantages, emphasizing the role of location in prediction.

Table 1. The description of notations

Notation	Description
n	the number of nodes in the friendship network
$\mathbf{s}$	the score of student's psychological and facial perception for each node
$\mathcal{V}$	the set of n nodes
ε	the set of edges
α	balance module of Skip-gram and the loss of autoencoder
β	the l_2 norm regularizer coefficient
K	the number of encoding layers
T	the weighted average neighbor of each node
$\mathbf{v_i}$	the representations of "context" node.
d	the dimension of node representation
$\mathbf{X} \in \mathbb{R}^{n \times m}$	the node attribute information matrix
$\mathbf{Y} \in \mathbb{R}^{\lvert\mathcal{V}\rvert \times d}$	the final representation of the friendship network

Link prediction has become an interesting focus of friendship prediction, useful models can find the potentially important information in real-world networks. Highly scalable node embedding (HSEM) [1] embedded nodes into a vector with a lower and fix dimension by learning the co-occurrence features of node pairs to solve the link prediction problem in very large-scale networks. Li *et al.* [9] proposed two novel node-coupling clustering approaches and their extensions for link prediction. The models consider the different roles of nodes for prediction and combine the coupling degrees of the common neighbor nodes with the clustering information of a network. DLPA is [4] a novel link prediction approach for dynamic networks using the levels of the related nodes and their attraction force to calculate the connection probability for each potential link.

However, most social network research is based on online social networks; little friendship prediction studies focus on social networks in real life. Zhang *et al.* [25] analyzed the social networks of college students. They collected social networks and appearance data of students and studied the effect of facial perception on social networks. Appearance attributes are considered as features to understand the social status of the student.

3 Problem Formulation

We denote a friendship network $\mathcal{G} = (\mathcal{V}, \varepsilon, \mathbf{X})$, where $\mathcal{V}$ denotes the set of n nodes, and ε is the set of edges. $\mathbf{X} \in \mathbb{R}^{n \times m}$ is a matrix that encodes score s_i for i. $\mathbf{Y} \in \mathbb{R}^{|\mathcal{V}| \times d}$ is the representation of $\mathcal{G}$ in d dimension. The mapping function of $v_i \mapsto y_i \in \mathbb{R}^d$ preserves both network structure and attribute information, where $d \ll |\mathcal{V}|$. z_i is the label in the prediction model. The notations mainly used in this paper are listed in Table 1.

Since we focus on friendship in the student social network, we collect friendship information to construct the friendship network $\mathcal{G} = (\mathcal{V}, \varepsilon, \mathbf{X})$. We assumed that there is a photo of student i and evaluated by attractiveness, trustworthiness, amiableness, and dominance. In the psychological aspect, each student i has extroversion, agreeableness, conscientiousness, and dominance score. Above all, each student i gets score $\mathbf{s}_i$ on psychological features and facial perception dimensions. Our purpose is to detect whether two students will become friends using their psychological features and facial perception information.

Input: Students who are associated with $\mathbf{s}$ and $\mathcal{G}$.

Output: Whether students will become friends?

4 Design of DEFINE

To solve the problem that detects friend relationships in the social network combining psychological features and facial perception, we propose a framework named DEFINE. In this framework, we embed psychological features and facial perception into the network representation, to incorporate both network structure and node attribute information effectively. Then we reconstruct the network via link prediction for the friendship network with node attribute information. DEFINE intelligently combines node attribute information and network construction to detect whether students will become friends. The DEFINE framework is depicted in Fig. 2.

Entropy-based Pre-processing As mentioned before, each photo is evaluated by a certain number of participants. To eliminate the impact of noise from participants evaluating photos, we use the method mentioned in [25], which borrowed the concept of entropy in information theory to remove these meaningless data.

$$E = -\sum p(x) \log p(x) \tag{1}$$

where $p(x)$ represents the probability of occurrence of sample x.

Features Processing Each student has psychological features scores and facial perception scores. We need to convert this information into a matrix which only contains 0 and 1. In the field of network research, the Cora dataset is widely used [10, 16]. The Cora dataset includes 2708 scientific publications. Each publication in the dataset is described by a 0 or 1 valued word vector indicating the absence or presence of the corresponding word from the dictionary. Inspired by the composition of the Cora data set, we map node attributes information into matrix dimensions as follows. First, we made a dictionary according to the psychological features and facial perception scores, each score corresponds to a position in the dictionary. Then, we convert these attributes information score $\mathbf{s}_i$ to a 0 or 1 valued word vector. Finally, we got $\mathbf{x}_i$ for each node to represent node attributes.

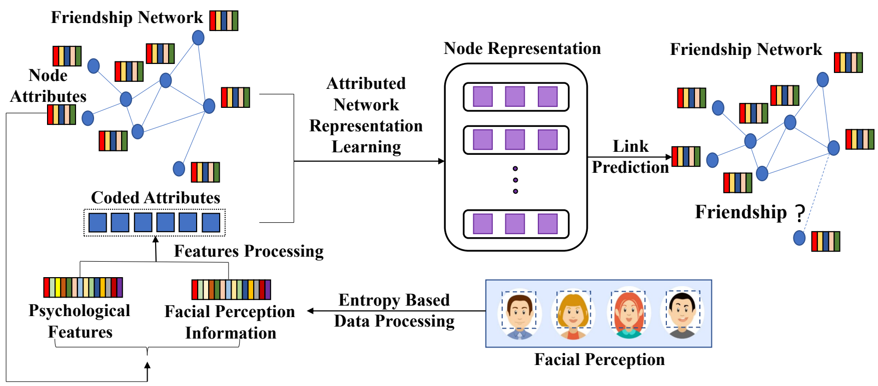


Fig. 2. The framework of DEFINE, which contains four critical components: (1) entropy-based data processing part, (2) feature processing part, (3) attributed network representation part, and (4) link prediction part.

Attributed Network Representation Learning Attributed network representation learning via deep neural networks (ANRL) can uninterruptedly integrate node attributes affinity and network structural proximity into low-dimensional representation spaces [27]. Therefore, we input each node v_i in friendship network $\mathcal{V}$ and node attributes $\mathbf{X}$ into the ANRL model to get the node representations $\mathbf{Y}\epsilon\mathbb{R}^{|\mathcal{V}|\times d}$.

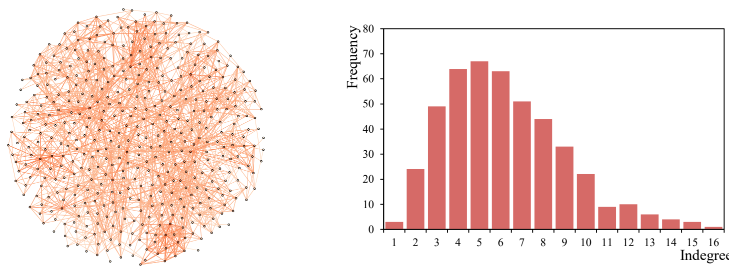
The goal of the ANRL model is to minimize the objective function:

$$\mathcal{L} = \mathcal{L}_{sg} + \alpha\mathcal{L}_{ae} + \frac{\beta}{2}\sum_{k=1}^{K}(\left\|\mathbf{W}^{k}\right\|_F^2 + \left\|\hat{\mathbf{W}^{(\mathbf{k})}}\right\|_F^2) \tag{2}$$

where $\mathcal{L}_{sg}$ and $\mathcal{L}_{ae}$ are defined in Equations (3) and (6), respectively. For the rest of the formula, α is the hyper parameter which can balance Skip-gram module $\mathcal{L}_{sg}$ and the loss of autoencoder module $\mathcal{L}_{ae}$, and β is the l_2 norm regularizer coefficient. $\mathbf{x}_i$ represents node v_i's feature vector, which includes student psychological features and facial perception information. $\mathbf{y}^{(K)}$ is the representation for node v_i after encoding with K layers. $\mathbf{W}^{(k)}$ is weight matrix in the k-th layer for encoder, and $\hat{\mathbf{W}^{(\mathbf{k})}}$ is same for decoder. u_v corresponds to the v-th column in the weight matrix $\mathbf{U}$ for graph context prediction.

$$\mathcal{L}_{sg} = -\sum_{i=1}^{n}\sum_{c\epsilon C}\sum_{-b\leq j\leq b, j\neq 0}\log p(v_{i+j}|\mathbf{x}_i) \tag{3}$$

where n is the total number of nodes, C is the set of node sequences generated by random walks, and b is the window size. $p(v_{i+j}|\mathbf{x}_i)$ is the likelihood of the target context given the node attributes, and is defined as:



(a) Friendship Network (b) Histogram of Indegree

Fig. 3. (a) a sketch of friendship network. (b) histogram of indegree for friendship network.

$$p(v_{i+j}|\mathbf{x}_i) = \frac{\exp(\mathbf{v'}_{i+j}^T f(\mathbf{x}_i))}{\sum_{v=1}^{n} \exp(\mathbf{v'}_v^T f(\mathbf{x}_i))} \tag{4}$$

where $\mathbf{v'}_i$ is the representations when node v_i is regarded as "context" node.

When directly optimizing Equation 4, the summation over the entire set of nodes is computationally expensive. Therefore, sampling multiple negative samples according to some noisy distributions [11] is convenient. In detail, for a specific node-context pair $(v_u,\, v_{i+j})$, the objective is as follows:

$$\log \sigma(\mathbf{v'}_{i+j}^T f(\mathbf{x}_i)) + \sum_{s=1}^{|\mathrm{neg}|} \mathbb{E}_{v_n \sim P_n(v)} [\log \sigma(-\mathbf{v'}_n^T f(\mathbf{x}_i))] \tag{5}$$

where $|neg|$ is the number of negative samples and $\sigma(x) = 1/(1+\exp(x))$ is the sigmoid function. $Pn(v) \propto d_v^{3/4}$ is set as suggested in [11], where d_v is the degree of node v.

$$\mathcal{L}_{ae} = \sum_{i=1}^{n} \|\hat{x} - T(v_i)\|_2^2 \tag{6}$$

where $\hat{x}$ is the reconstruction output decoder. $T(v_i)$ is adopted by a weighted average neighbor and incorporates prior knowledge into the model to return the target neighbors of v_i. That is to say, $T(v_i) = \frac{1}{|\mathcal{N}(i)|} \sum_{j \epsilon \mathcal{N}(i)} \omega_{ij} \mathbf{x}_j$, where $\mathcal{N}_(i)$ is the neighbors of node v_i in the friendship network, $w_{ij} = 1$ for unweighted friendship network, and x_j is the attributes associated with node v_j.

Link Prediction We generate the labeled dataset of edges [19, 6, 27], which holds out existing links as positive instances randomly. We also sample an equal number of non-existing links randomly to get negative instances. Then, we use the network to train the ANRL model. After having obtained the representations for each node, we use these representations $\mathbf{Y} \in \mathbb{R}^{|\mathcal{V}| \times d}$ to perform link prediction task in the labeled edge dataset. We choose linear SVC as the link prediction model to deal with this task [3, 12, 25], that is,

$$\begin{cases} max_{\mathbf{w},b} & \dfrac{2}{\|\mathbf{w}\|} \\ \quad s.t. & \mathbf{y}_i(\mathbf{w}^T z_i) \geq 1, \quad i = 1, 2, 3 \cdots, \end{cases} \tag{7}$$

where $\mathbf{w}$ is the normal vector of the hyperplane, node representations $\mathbf{y}_i$ is the feature of the ith sample, and z_i is label in the train set.

5 Experiments

In this section, we describe all the data we used in our research and evaluate our framework by comparing it with some classical methods.

5.1 Datasets

We use 454 students' online survey results, which include the Big Five Personality questionnaire results, the dominance scale scores [7], facial images, and questionnaire results about listing their friends. We also collect facial perception scores by recruiting volunteers to rate the facial images. Fig. 3(a) shows the sketch of the friendship network. The node represents student i, and the color depth of the nodes in the friendship indicates the indegree of nodes. The darker the color, the higher the indegree. Fig. 3(b) is the distribution of indegree for each node in the friendship network which looks like left-skewed bell-shaped curves. Tables 2, 3, and 4 are Pearson's correlation coefficient for psychological features and facial perception information. To distinguish these two features, we marked namesake in Table 3 using P to represent psychological features.

5.2 Prediction

Comparison with DEFINE Variants The first competitor considers node attributes information only, which is used to verify the validity of NRL in the link prediction task. Then we use competitors to learn low-dimensional vector representations for nodes based on network structure and node attributes.

Table 2. Pearson's correlation coefficient for psychological features

	Dominance	Extroversion	Agreeableness	Conscientiousness
Dominance	-	-	-	-
Extroversion	-0.209**	-	-	-
Agreeableness	-0.488**	0.446**	-	-
Conscientiousness	-0.315**	0.551**	0.580**	-

*$p < 0.05$; **$p < 0.01$

Table 3. Pearson's correlation coefficient for facial perception

	Attractiveness	Trustworthiness	Agreeableness	Dominance
Attractiveness	-	-	-	-
Trustworthiness	0.664**	-	-	-
Agreeableness	0.425**	0.583**	-	-
Dominance	0.569*	0.470**	-0.012	-

*$p < 0.05$; **$p < 0.01$

We compare DEFINE with the node attributes that only include psychological features or facial perception. The DEFINE variants are used to verify the performance of our proposed framework.

Comparison with Baseline Methods To prove the advantages of our framework combining network structure and node attributes, we compare DEFINE framework with several classical NRL methods as follows:

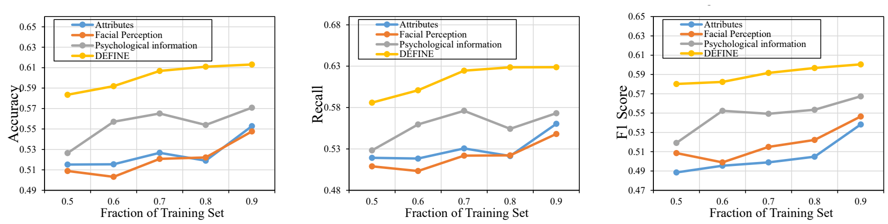
- **Structure-only**: This group competitors ignore the node attributes and leverage network structure information only. Node2vec [6] and Deepwalk [19] generate node sequences by using truncated random walks and obtain the latent node representations by feeding them into the Skip-gram model.
- **Attribute + Structure**: The competitor of this group is competitive because it tries to preserve node attributes information and network structure proximity. We consider TADW [24] as our competitor, the detailed descriptions can be found in Section 2. It is also used to verify the effectiveness of the Skip-gram model because the main idea of TADW is matrix decomposition.

Prediction Results In this part, we evaluate the ability of our framework by comparing it with other baseline methods and DEFINE variants. Our goal is to reconstruct the friendship network structure via link prediction. First of all, we learn the representation based on different representation learning algorithms and DEFINE variants. Secondly, we generate the labeled dataset of edges by holding out existing links as positive instances and randomly sample an equal

Table 4. Pearson's correlation coefficient for psychological features and facial perception

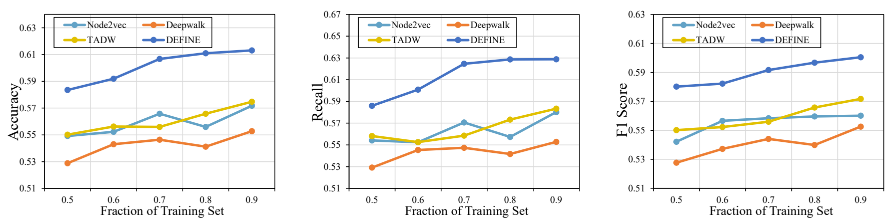
	Dominance(P)	Extroversion	Agreeableness(P)	Conscientiousness
Attractiveness	-0.079	0.129**	0.132**	0.063
Trustworthiness	-0.118**	0.078	0.122**	0.049
Agreeableness	-0.145**	0.088	0.102*	0.039
Dominance	-0.029	0.068	0.062	0.074

*$p < 0.05$; **$p < 0.01$



(a) Accuracy (b) Recall (c) F1 Score

Fig. 4. The results of the DEFINE variants link prediction experiment with the fraction of the training set.



(a) Accuracy (b) Recall (c) F1 Score

Fig. 5. Link prediction performance comparison of different baseline methods with the fraction of the training set.

number of non-existing links for negative instances. Then, we use linear SVC to make link prediction. Finally, we divide the labeled nodes into the training set and testing set. The portion ratio of training nodes varies from 50% to 90%. To evaluate the framework quality and the results, we employ the Accuracy, Recall, and F1 score, and higher value indicates a better performance.

- We can observe that DEFINE performs well than DEFINE variants. Fig. 4 presents the result. Even though node attributes can detect friendship, this competitor performs not very well because of lacking NRL.
- Link prediction using each part of node attributes also performs worse, even though converting these attributes and network structure into low-dimensional vectors by the NRL model.
- We can observe that the performance of DEFINE is better than other baseline methods, as seen in Fig. 5.
- Node2vec and Deepwalk both use Skip-gram to represent nodes in the friendship network. Their performance is not good enough because they only consider network structure.
- TADW combines both network structure and node attributes. However, this model is not as good as DEFINE because it is based on matrix decomposition instead of Skip-gram, which does not consider network structure very well.

6 Conclusion

In this paper, we focus on the problem of student friendship detection by developing an effective framework called DEFINE based on Node Enhancement. To our best knowledge, we are the first to combine students' psychological features and facial perceptions with friendship in this problem. Our experiment indicates DEFINE performs well in the prediction of student friendship while compared with the NRL models which use the structure information as the only consideration, such as Deepwalk and Node2vec. Even when both node attributes and network structure are taken into account, our framework still performs better than the NRL model without the leverage of Skip-gram. Compared to the DEFINE variant, experimental results on the real-world friendship network show the outstanding performance of our proposed framework. With its effective and accurate detection in our student friendship network, we consider deploying the framework on larger friendship networks. We also intend to extend DEFINE to the networks with other social relationships such as academic collaboration and trustworthy networks.

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