ANSWER: Generating Information Dissemination Network on Campus

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Abstract. Information dissemination matters, both on an individual and group level. For college students who are physically and mentally immature, they are more sensitive and susceptible to unnormal information like rumors. However, current researches focus on large-scale online message sharing networks like Facebook and Twitter, rather than profile the information dissemination on campus, which fail to provide any references for daily campus management. Against this background, we propose a framework to generate the information dissemination network on campus, named ANSWER (cAmpus iNformation diSsemination netWork gEneRation), based on multimodal data including behavior data, appearance data, and psychological data. The construction of the ANSWER is listed as four steps. First, we use a convolutional autoencoder to extract the students' facial features. Second, we process the behavior data to construct a friendship network. Third, heterogeneous information is embedded in the low-dimensional vector space by using network representation learning to obtain embedding vectors. Fourth, we use the deep learning model to predict. The experiment results show that ANSWER outperforms other methods in multiple feature fusion and prediction of information dissemination relationship performance.

Keywords: Information dissemination · Attribute network · Network generation.

1 Introduction

Information dissemination matters, both on an individual and group level. The sharing of good news can spread happiness [12], while the diffusion of bad news, like rumors, could cause serious consequences [27]. For example, during this pandemic, the spread of misinformation about COVID-19 is impeding healthy behaviors and promoting erroneous practices that facilitate the spread of the virus and result in poor physical and mental health situation among individuals [25]. College students are a very special group of people in their emerging adulthood. In this stage, teenagers pursue personality exploration and may play many roles such as college students, full-time employees. Commonly, they are leaving their families and toward independence [21]. Thus, various information will affect their physical and mental health deeply. In this case, simulating information dissemination patterns on campus and exploring the mechanisms behind them is an urgent research topic for education-related research fields.

However, exploring the hidden modes of information dissemination among students is a complex issue. Serving as the traditional method of collecting data for information dissemination, the amount of data collected by the questionnaire is small and time-consuming. At present, the researches on massive data are mainly based on online platforms such as Twitter [14], Facebook [12]. Due to privacy and security issues, researchers in the school administration fail to access these data, and cannot regard these data as a reference for academic research [9, 13]. Moreover, the information itself is so private that the previous research is not enough to analyze the information dissemination between students.

Different from traditional data mining, multimodal data presents more complex information [4, 15]. Furthermore, the advancement of network science has provided us with great help in analyzing social relationships, enabling us to abstract real-world relationships into the structure of the network [10]. These two major advancements provide us with an opportunity to analyze the hidden relationships behind students' information dissemination. Nevertheless, new challenges have emerged. The choices they make when choosing friends to disseminate information affected by many factors [29], thus need to select the appropriate approach. Moreover, the underlying network structure of information dissemination between students is invisible, and there must be an interaction between two people, which can be inferred from the information flow. But it is difficult to obtain disseminated data among students because of its privacy. Yet information dissemination is closely related to the common friendship network. People usually tell friends when they know information, but not each friend. Therefore, the prediction of information dissemination relationships can be developed by using the friendship network.

In this paper, we focus on students' friendship networks and combine students' facial and psychological attributes to construct a friend attribute network to complete the prediction of campus information dissemination relationships. The model named ANSWER (cAmpus iNformation diSsemination netWork gEneRation) is divided into four parts, as shown in Fig.1. First, through the co-occurrence processing of the consumption record data of the student's campus card, the adjacency matrix of the friendship network is constructed. Secondly, we use the convolutional autoencoder to extract features from student facial images and express them as dense vectors. Thirdly, we use Network Representation Learning to embed the adjacency matrix of the friend attribute network. The network structure and node attributes of two heterogeneous information sources are processed in the same vector space. Fourth, a three-layer neural network is used to predict the information dissemination relationships.

In summary, our contributions can be summarized as follows:

(1) Based on the spatial and temporal behavioral data recorded by the campus card, we build a friendship network adjacency matrix containing only 0 or 1 by using the co-occurrence processing.

(2) We use the convolutional autoencoder to process the facial image data, to get the vector representation of facial features.
(3) We use facial features and psychographic data as the node attributes of the friendship network. The experimental results highlight the outstanding capabilities of ANSWER for information dissemination prediction.
(4) ANSWER is designed to solve the problem of information dissemination in the campus environment, mainly utilizes the friend attribute network to complete the construction of the information dissemination network. It combines the network topology and node attributes, and its performance is significantly better than other approaches.

This paper is organized as follows. In the next Section, we discuss the latest researches developments in relevant theoretical work. In Section 3, we describe the details of the problem formulation. In Section 4, we present the methodology in the proposed framework. In Section 5, we introduce the dataset and the analysis of the experimental results. We conclude the paper in Section 6.

2 Related work

2.1 Network Representation Learning (NRL)

Network Representation Learning (also known as graph embedding) is based on a mapping function that is dedicated to solving the problem of data sparsity. The mapping function converts nodes into low-dimensional vectors to intuitively represent the relationship between the nodes in the original graph and finally used for downstream network analysis tasks. Perozzi et al. [22] carried out the first method of embedding, namely DeepWalk based on network structure. Its core draws on the Word2vec and the collinear relationship between nodes, uses a random walk strategy to generate node sentences based on the weight of edges, and uses Skip-gram training to obtain word vectors. Based on the Deepwalk theory, many researchers have made improvements [24, 32].

These approaches are all based on the network structure to obtain the vector representation of nodes. However, there are also attribute features. Hou et al. [8] conducted a graph representation learning framework called Property Graph Embedding (PGE), which considers the relationship between the network structure and the attribute features.

2.2 Social Relationship

In social sciences, relationships are divided into two types: one-way (celebrities and ordinary people) and two-way (friends) [7]. Social structure is mainly connected by social relationships. By analyzing the formation in social relationships, we can better understand the dynamic changes in the social structure. Previous researches on social relationships can be divided into two categories, link prediction [20] and relation type prediction [16, 11]. Link prediction occupies an

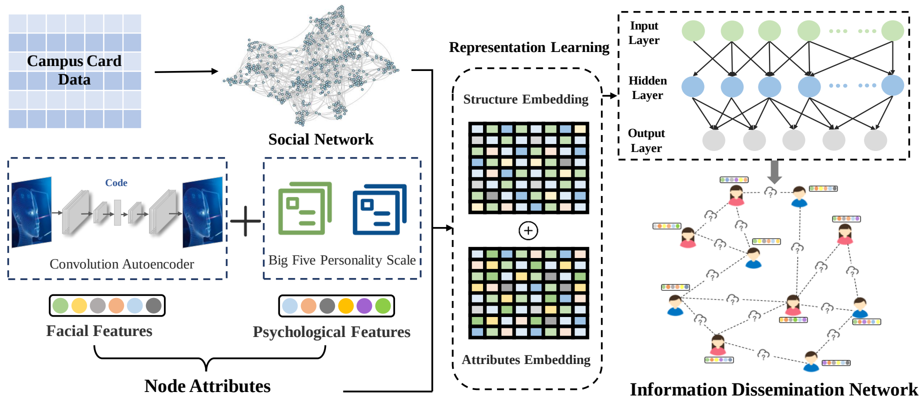


Fig. 1. Illustration of prediction framework ANSWER.

important role in social networks, which can be used to reconstruct complex networks. The types of social relationships are segmented into two types according to their nature, one is the blood relationship, etc., the other is the relationship formed by many social behaviors such as academic collaboration, information dissemination. Zhao et al. [31] identified vulnerable relationships in the information dissemination network, and showed that vulnerable relationships can largely affect information sharing, but have little impact on the information exchange network.

2.3 Information Dissemination Network

Existing literature exploring information dissemination focuses on online social platforms such as Twitter [14], Facebook [12]. Lerman et al. [14] constructed the social network for active users on Digg and Twitter, and analyzed the patterns of information dissemination. Elisa et al. [19] reconstructed the information dissemination network using natural language processing to study the dynamics of information dissemination and found that the dynamics were similar to epidemic SIR. Campan et al. [2] studied the dissemination of fake news in online social networks and analyzed its dissemination and influence. The commonality of the above-mentioned literature researches is that the network construction depends on large-scale online information dissemination.

3 Problem Formulation

With the collected data of students' campus card consumption, the friendship network $\mathcal{G}_f = (\mathcal{X}, \mathcal{V}_f)$ is constructed, where $\mathcal{X}$ is the set of nodes and $\mathcal{V}_f$ is the set of edges. For each node i in the network, $\boldsymbol{S}_i = [s_{i1}, s_{i2}, ...s_{in}]$ retains node attributes. The d-dimensional embedded representation matrix $\boldsymbol{E} \in R^{(|\mathcal{X}| \times d)}$ of $\mathcal{G}_f$ is obtained by using the mapping function $f(x)$ (where d means embedding spatial dimension). The resulting matrix $\boldsymbol{E} \in R^{(|\mathcal{X}| \times d)}$ is used as the input of the three-layer neural network. We train the model to predict whether there will be an information dissemination relationship (ℓ_{st}) between two nodes s and t. Ultimately, we get the information dissemination network $\mathcal{G}_n(\mathcal{G}_n = (\mathcal{X}, \mathcal{V}_n))$, $\mathcal{V}_n$ is the set of ℓ_{st}.

Information dissemination network generation problem: Given the friendship network $\mathcal{G}_f$ and facial features data, psychological features data $\boldsymbol{S}$, to generate the corresponding campus information dissemination network $\mathcal{G}_n$.

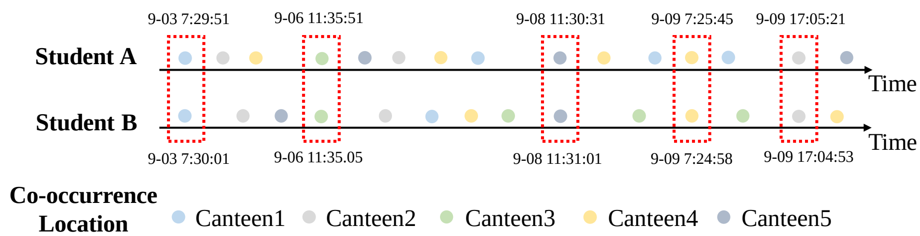


Fig. 2. Illustration of two students' co-occurrence.

4 Design of ANSWER

4.1 Construction of Friendship Network

Digital information management systems in 21st-century universities have dramatically improved the convenience of campus life for students. Temporal and spatial-based behavioral data provide us with the opportunity to discover potential social ties [3, 23]. This paper utilizes students' campus card consumption records to construct a friendship network. Fig.2 explains what is co-occurrence. Student A and B co-occurs five times.

In our work, we focus on analyzing the consumption records of students in six different canteens. The process can be reformulated with more details as follows. Set the time interval to one minute [28], collect the consumption records of two students in the same canteen, and use the probability model to calculate the co-occurrence probability. The higher the probability is, the closer the relationship between friends is. The probability formula is calculated as [3]:

$$p(F|C_k) = \frac{P(F)P(C_k|F)}{P(C_k)} \approx \frac{1}{M} e^{klog\beta(N-1)+1} \tag{1}$$

where N represents geographic units, M individuals, joint visit probability β, prior probability $P(F) = \frac{1}{M-1}$, likelihood function $P(F) = p_1^k$, $p_1 = \beta + \frac{1-\beta}{N}$.

4.2 Processing of Node Attributes

Previous studies have shown that face images can be used to identify relationships [1]. To eliminate the effect of noise and obtain the vector representation of students' facial cognitive features, the convolutional autoencoder has been widely applied [18, 26]. Convolutional autoencoder learns the sample features without labels and incorporates the properties of the convolutional neural network to complete unsupervised feature extraction. For the input layer x, it's corresponding i_{th} convolution is denoted as:

$$h^i = \sigma(x * \mathbf{W}^i + b^i), i = 1, 2, 3...k \tag{2}$$

$*$ is a convolution operation determined by context, and $\sigma(.)$ is the sigmoid function. And then the feature reconstruction process is represented as:

$$y = \sigma(\sum_{i \in H} h^i * \tilde{\mathbf{W}}^i + C) \tag{3}$$

$\tilde{\mathbf{W}}^i$ indicates filter weight, C indicates a bias vector. We use BP (Error Back Propagation) algorithm to optimize the loss function:

$$E(\theta) = \frac{1}{2n} \sum_{j=1}^{n} (x_j - y_j)^2 \tag{4}$$

Another attribute of nodes is psychological evaluation data, which is collected by questionnaires. There are some invalid, redundant, and missing data. First of all, for the invalid questionnaire, we will find the same participant and ask him to fill it out again. Then, the abnormal score data are detected by the box graph, and some missing data are filled by the median, and the unreasonable score data of students' individual tests are filled by mean. These data are recorded and encrypted corresponding to the student's ID, to protect their privacy.

4.3 Attributed Network Representation Learning (ANRL)

Through ANRL [30] of the deep neural network, node attributes, and network topology structure can be uninterruptedly integrated into the low-dimensional representation space. Therefore, in this paper, the network structure $\mathcal{G}_f$ and node attributes $\boldsymbol{S}$ of each node in the friendship network are input into the model to obtain the vector representation of each node.

The ANRL is mainly composed of the autoencoder and the Skip-gram model, the final optimization cost function is:

$$\mathcal{L} = \mathcal{L}_{sg} + \alpha \mathcal{L}_{ae} + \beta \mathcal{L}_{reg} \tag{5}$$

where $\mathcal{L}_{ae}$ is the loss function of the autoencoder and $\mathcal{L}_{sg}$ is the loss function of the Skip-gram. α is the hyper-parameter to balance the two losses and β is the l_2 parametric regularization factor.

The autoencoder is a neighbor-enhanced model that addresses the noise problems. The optimized loss function is:

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

where $\hat{\mathbf{x}}_i$ is the reconfigured output decoder. The reconstructed target $T(v_i)$ is the peculiarities of the target neighbor, which can be computed in two ways: weighted average of neighbor characteristics, $T(v_i) = \frac{1}{|\mathcal{N}(i)|}\sum_{j\in\mathcal{N}(i)} w_{ij}\mathbf{x}_j$ and median neighbor of element, $T(v_i) = \tilde{\mathbf{x}}_i = [\tilde{x}_1, \tilde{x}_2, ..., \tilde{x}_m], \tilde{x}_k = \text{Median}(w_{i1}\mathbf{x}_{1k}, w_{i2}\mathbf{x}_{2k}, ..., w_{i|\mathcal{N}(i)|}\mathbf{x}_{|\mathcal{N}(i)|k})$. $\mathcal{N}(i)$ is the neighbors of node v_i in the friendship network, and $\mathbf{x}_j$ is the feature vector of node v_i, including student facial cognition and psychological data, where w_{ij} indicates whether to weight or not.

The cost function $\mathcal{L}_{sg}$ for the Skip-gram model minimization is:

$$\mathcal{L}_{sg} = -\sum_{i=1}^{n}\sum_{c\in C}\sum_{-b\leq j\leq b, j\neq 0} \log p(v_{i+j}|\mathbf{x}_i) \tag{7}$$

where n indicates the total number of nodes, C is the collection of node sequences and b means the window size. $p(v_{i+j}|\mathbf{x}_i)$ is the conditional probability. Since the model extracts information about node attributes and global structure, it is computationally expensive and then we use negative sampling optimization [17]. For each specific node pair (v_i, v_{i+j}), the optimization goal is:

$$\log\sigma(\mathbf{v}_{i+j}^{'T} f(\mathbf{x}_i)) + \sum_{s=1}^{|\text{neg}|} \mathbb{E}_{v_n\sim P_n(v)}[\log\sigma(-\mathbf{v}_n^{'T} f(\mathbf{x}_i))] \tag{8}$$

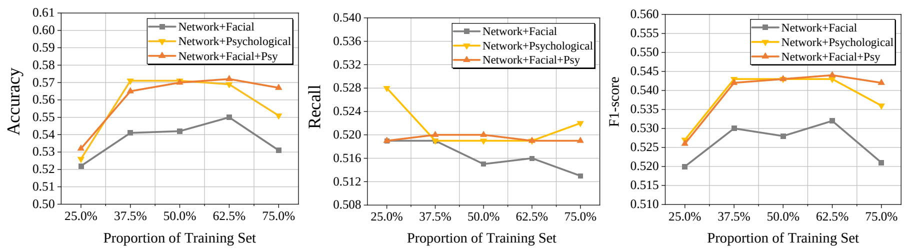
$\sigma(.)$ is the sigmoid function, the value is $1/(1+\exp(x))$. $\mathcal{L}_{reg}$ is formulated as:

$$\mathcal{L}_{reg} = \frac{1}{2}\sum\nolimits_{k=1}^{K}(||\mathbf{W}^{(k)}||_F^2 + ||\hat{\mathbf{W}}^{(k)}||_F^2) \tag{9}$$

K is the number of layers of the encoder and the decoder. For the encoder, $\mathbf{W}^{(k)}$ is the k-th layer weighted matrix, and $\hat{\mathbf{W}}^{(k)}$ is the k-th layer weighted matrix of the decoder. The final representation of y_i^K extracts the node v_i attribute characteristics and network structure information.

4.4 Link Prediction

In this paper, the problem of reconstructing an information dissemination network is changed to a link prediction problem. We use ANRL to train the friendship network with node attributes, and obtain a low-dimensional representation of each node $\boldsymbol{E} \in R^{(|\mathcal{X}|\times d)}$, which is input in the deep learning model for training. In addition, we adopt the real information dissemination relationships as the labels for training. The three-layer neural network is selected as the information dissemination prediction model for the prediction task.



(a) Accuracy (b) Recall (c) F1-score

Fig. 3. Performance comparison of different inputs of ANSWER. The horizontal coordinate is the proportion of the training set.

5 Experiments

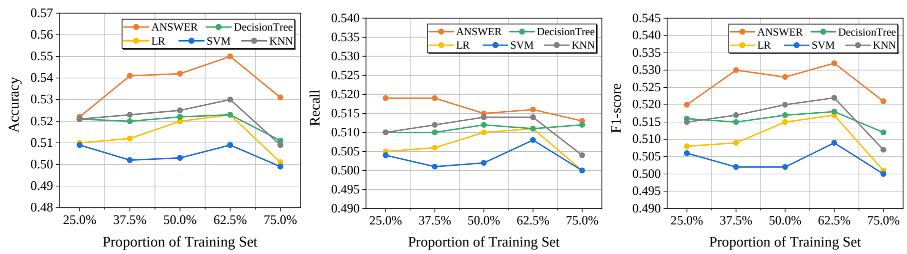
5.1 Dataset

We collect data from freshmen in the same major at a university in China. The data includes the facial image of students, psychological evaluations, and data in the information dissemination scene and students' campus card records. The students were notified about the use of these data and signed a consent form to confirm their participation in the research. They were noticed that these data were only used for academic research and were stored encrypted in encoded form, no intuitive information exists, and only relevant researchers could access.

The dataset includes three parts: real information dissemination data, student psychological level data, and campus card record. (A) In order to obtain the real information dissemination relationships of students, the questionnaire was adopted. Students need to answer: who will they voluntarily share the information with? Students need to write down 6-8 people. (B) The psychological level data of the students were collected by completing the Dominance Test Scale [6] and the Big Five Personality Scale [5]. There are different scoring standards for the scale, so the psychological characteristic data needs to be normalization processing before used. (C) Formally obtain student campus card information from the school's digital campus management department, and legally obtain facial photos of participating volunteers.

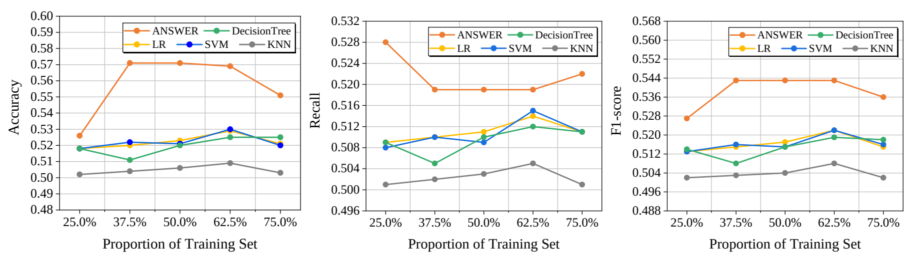
5.2 Prediction

Performance comparison of different inputs of ANSWER: The student features include facial and psychological attributes. To verify the effect of facial and psychological attributes in the prediction task, we compare the network structure by including only facial or psychological attributes and both. Following that, we adopted three different combinations to learn different vector representations of nodes, and finally completed the prediction of the information dissemination network. For the performance of ANSWER framework, we use F1-score,



(a) Accuracy (b) Recall (c) F1-score

Fig. 4. Comparison of the performance of different prediction algorithms on friendship networks combined with face attributes.

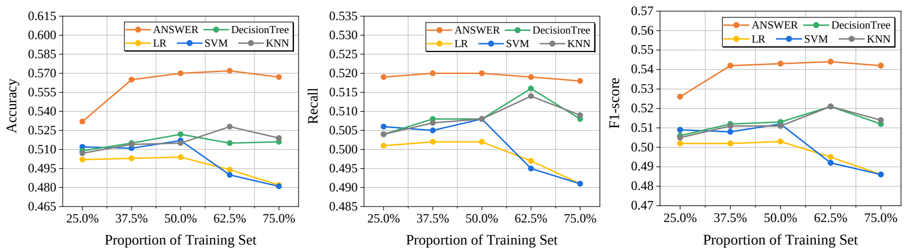


(a) Accuracy (b) Recall (c) F1-score

Fig. 5. Comparison of the performance of different prediction algorithms on friendship networks combined with psychological attributes.

Recall, and Accuracy to evaluate. Through the control of different model inputs, the effectiveness of the ANSWER framework is proved.

From Fig.3, the prediction performance of the friendship network and facial attributes on the information dissemination relationship is significantly inferior to that of the friendship network combined with psychological attributes or all three attributes. When the training ratio of the training set and the test set is 1:1, the predictive performance results of the friendship network combined with psychological attributes are similar to that combined with the facial and psychological attributes. But then as the training set ratio increases, the combination of all three is more effective. Through the input variant control of the ANSWER, the network topology combined with the facial and psychological attributes is more effective for information dissemination relationship prediction.
Comparison of differences in results with different prediction algorithms: The three-layer neural network in the ANSWER model is replaced by Logistic Regression (LR), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Decision Tree (DT) algorithms for information dissemination relationship prediction, and three different input combinations of the ANSWER framework are tested for comparison. The results are shown in Fig.4, 5, 6.



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

Fig. 6. Comparison of the performance of different prediction algorithms on friendship networks combined with facial as well as psychological attributes.

★ The ANSWER has strong nonlinear fitting capabilities and multi-layer feature fusion with neural networks. The findings of all experiments indicate the outstanding performance of the ANSWER in predicting information dissemination relationships.

★ The KNN algorithm without feature fusion uses Euclidean Distance to calculate sample similarity, which depends largely on the number of selected neighbors, and the performance lower than ANSWER.

★ From Fig.6, We found that LR and SVM results are much lower than when the network structure contains only one attribute. ANRL combines facial and psychological features into embedding vectors through nonlinear learning. But LR and SVM are linear models. When the eigenvector increases, they may not make full use of the embedding vector after being combined in a nonlinear manner.

★ As the training set proportion increases, the model is better trained. However, when it reaches 62.5%, we observe that the effect starts to gradually decrease. The reason may be the scarcity of sample data. As a result, the test set at this time is smaller, so the strengths and weaknesses of the model cannot be reflected more effectively.

6 Conclusion

In this paper, our goal is to solve the problem of campus information dissemination network generation. Based on the friendship network, combining the students' facial features and psychological features to create an attribute network, we use the friend attribute network to build an effective framework ANSWER for campus information dissemination relationship prediction. As far as we know, our work is the first to make predictions about campus information dissemination relationship. We compensate for this limitation in a novel way. And the results show that, compared with other predictive relationship algorithms, ANSWER composed of network representation learning and deep learning model fuses various features through nonlinear learning, which has outstanding performance in generating and forecasting campus information dissemination relationship. The sample volume for this paper is relatively small because of the privacy issues involved in the data and calling for more volunteers is very challenging. Future plans are to obtain larger datasets and to enhance the generalizability of the framework for other campus social relationships, such as academic cooperation networks.

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