A Graph Neural Network Recommendation Method Based on Social Relationship Embedding

Lary Tzeng, Jean Shih, Rimpei Liou, Dely huang, Dan Smolen

Abstract—There is a considerable amount of research in online social networks, most of which focuses on the structural analysis of social graphs. The interpersonal relationships of social networks, especially friend circle, can solve the cold start and sparsity problems, and through the relationship between social networks can effectively recommend users' favorite items (items), such as music , videos, brands/products, preferred tags, location, services, etc. User relationships in social networks are diverse and there are many different perspectives on different social networks. Associations among users can form multi-layered composite networks, and multi-layered social networks present new challenges and opportunities. Different relationships can influence users' preferences to different degrees, which in turn affects their behavior. Therefore, fusing multiple social networks is an effective way to improve recommendation. Although some studies have started to address multiple social network recommendations, simple linear superposition cannot reflect the coupling and nonlinear association between multiple social networks. In this paper, we propose a graph neural network recommendation model under social relationships based on this background. We first propose to compute the 2nd order collaborative signals and their intensities directly from the neighboring matrix for updating the node embedding of the graph convolution layer. Secondly by embedding historical evaluations, various social networks constituting different dimensions, the attention integration of user preferences by different social networks is achieved, and its effectiveness and scalability are demonstrated in theoretical derivation and experimental validation. The theoretical derivation and experimental validation demonstrate its effectiveness and scalability.

Index Terms—Graph Neural Network, Recommendation, Social Relationship.

1 Introduction

With the development of social networks, the method of recommendation using social relationships among users can improve the recommendation results by using relationships such as friends or trust, better simulate the recommendation process in real society, and better reflect the role of people in the recommendation process, so social recommendation has become a research hotspot for industrial applications. The interests between users with certain connections have certain associations, which is the main basis of social recommendation systems [1].

Collaborative filtering (CF) is one of the main methods in recommending systems [2]. It can be divided into: memory-based collaborative filtering [3, 4, 5] and model-based collaborative filtering, depending on whether a machine learning model is used or not. The model-based method learns the embedding representation of entities using models such as matrix hidden space decomposition [6, 7], Markov chain [8], and deep nerve network [9, 10], which can capture the complex connections between entities more effectively from entity interaction operations and auxiliary information, and is the most widely researched recommender method. In recent years, the research of graph convolutional nerve network GCN has been emerging [11]. GCN is the most popular research method in recommendation systems because of its powerful ability to learn embedding representations on graph structures [12, 13, 14, 15, 16]. GCN uses spectral graph theory to define graph convolution operations to propagate and aggregate messages from neighboring nodes on topological graphs, and has the advantage of learning entity embedding representations using both entity features and graph structure features. In essence, it extends the excellent feature learning and representation capabilities of the traditional convolutional nerve network CNN [17] to non-regular graph data.

The entities and their interactions in the recommendation scenario can be naturally represented by topological graphs, and therefore are very suitable for graph-based recommendation tasks using GCN models. In the past years, some recommendation models based on graph convolutional neural networks have been proposed. For example, Berg et al. [12] implemented a GCMC recommendation model using GCN as an encoder in a graph self-coding framework, which uses a single graph convolutional layer to aggregate the collaborative signals of the first-order neighbors on the "user item" bipartite graph to achieve end-to-end rating prediction. Wang et al. [14] proposed an NGCF model, which uses the message passing mechanism of GCN to stack multiple graph convolutional layers to implicitly pass the collaborative signals of higher-order neighbors on the bipartite graph, and finally merges the node embeddings of all layers for recommendation, which can compensate the weakness that the GCMC model can only use the first-order collaborative signals to a certain

*Lary Tzeng is the corresponding author.

- Lary Tzeng, Jean Shih, Rimpei Liou, Dely huang, Dan Smolen are with Vanderbilt University, US. (e-mail: LaryTzeng@hotmail.com).

extent. In addition, some scholars have improved the GCN-based recommendation model in terms of improving the efficiency of graph convolution operation [17], utilizing the attention mechanism [18, 19], introducing auxiliary information [20], improving scalability [21], and overcoming cold start [22]. These studies have shown that GCN-based recommendation models are better able to perform on entity interaction graphs thanks to the powerful learning capability of representation.

There is a considerable amount of research in online social networks, most of which focuses on the structural analysis of social graphs [23, 24]. The interpersonal relationships of social networks, especially friend circle, can solve the cold start and sparsity problems, and through the relationship between social networks can effectively recommend users' favorite items (items) [25], such as music [26], videos [27], brands/products [28], preferred tags [29], location [30], services [31], etc. User relationships in social networks are diverse and there are many different perspectives on different social networks. Jiang et al. [32] found that personal preferences are also an important factor in social networks. Just as people's ideas influence each other, the potential characteristics of a user constructed by a probability matrix decomposition model should be similar to his friends due to the similarity of preferences [33]. Huang et al. [34] used applied learner's age and class as an important feature in the user relationship. Zheng et al. [35] integrated the textual topic model into social recommendation. Lu et al. [36] found that trust relationships in e-commerce systems have a significant impact on purchase behavior.Yuan et al. [37] explored a social relationship that combines two different types of social relationships, membership and the combined role with friends, into a collaborative filtering-based The decomposition process was used to integrate two different types of social relationships, namely membership and friend bonding, into a collaborative filtering-based recommender. The significant effectiveness of social relationships under sparse data conditions was found.

Associations among users can form multi-layered composite networks, and multi-layered social networks present new challenges and opportunities. Different relationships can influence users' preferences to different degrees, which in turn affects their behavior. Therefore, fusing multiple social networks is an effective way to improve recommendation. Although some studies have started to address multiple social network recommendations [38], simple linear superposition cannot reflect the coupling and nonlinear association between multiple social networks. In this paper, we propose a graph neural network recommendation model under social relationships based on this background. We first propose to compute the 2nd order collaborative signals and their intensities directly from the neighboring matrix for updating the node embedding of the graph convolution layer. Secondly by embedding historical evaluations, various social networks constituting different dimensions, the attention integration of user preferences by different social networks is achieved, and its effectiveness and scalability are demonstrated in theoretical derivation and experimental validation. The theoretical derivation and experimental validation demonstrate its effectiveness and scalability.

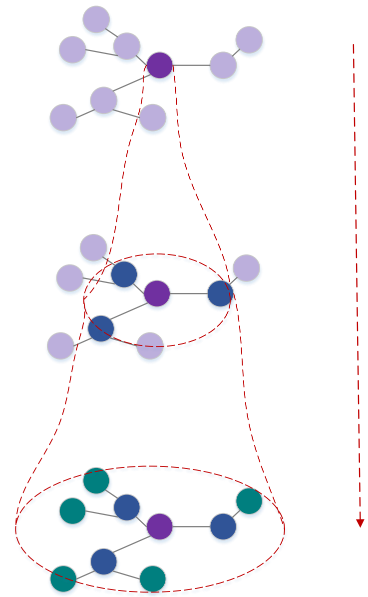

Fig. 1: Demonstration of message passing.

2 Related Work

2.1 Graph Neural Networks

Earlier graph neural network studies [39, 40] were designed based on a recursive approach to learn the representation of vertices by iteratively propagating the neighbor information until reaching the immobile point. It is based on the information propagation mechanism, which updates the state of vertices by periodically exchanging neighborhood information until a stable equilibrium is reached. Each iteration takes the current state of the vertex, the features of the vertex, the features of the vertex neighbors and the features of the edges as the input of the recursive function, and the output of this recursive function is used to update the vertex state, and when the state satisfies the convergence criterion, the vertex state of the last step is input to the output layer. The recurrent graph neural network alternates between vertex state propagation and parameter gradient computation to train the neural network. According to the immobility theory, the recurrent function must be a compressed mapping function to have a unique immobility solution to ensure convergence. Recurrent graph neural networks inspired the later research on space-based convolutional graph neural networks. However, since the computation of each vertex in a graph neural network depends on the neighbors of that vertex, and the parameters of the recursive function are shared at each layer, this training process is very computationally expensive and therefore has few applications in reality [41].

Many approaches to redefine the concept of graph convolution have been proposed in recent years, mainly divided into two categories. The spectral-based graph neural networks [42, 43, 44, 45] introduce a signal processing approach to define graph convolution by transforming vertex features into the spectral domain and

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then transforming the result into the spatial domain, while the spatial-based graph neural networks [44, 46] define graph convolution directly by information aggregation in the node domain. The main idea of graph convolutional neural network is to generate the vertex representation by aggregating the features of the vertex itself and the features of the vertex neighbors, which is different from the recurrent graph neural network in that the graph convolutional neural network computes the vertex representation by stacking multiple graph convolutional layers and using different parameters in each layer to solve the problem of high computational cost due to the sharing of parameters in the recurrent graph neural network.

The spectral approach transforms the signal on the graph to the spectral domain, implements the definition of the graph convolution in the spectral domain, and then transforms the result to the spatial domain. The early ChebyNet is a graph convolutional neural network based on the spectral approach, which reduces the parameters by parameterizing the convolution kernel in the spectral domain and approximating the kernel with polynomial functions, and reduces the computational cost by eliminating the need for feature decomposition. In addition, there are also AGCNs, which belong to graph convolutional neural networks based on spectral methods. The spatial approach defines the graph convolution by aggregating the information on the graph and updating the central vertex features by convolving the features of the central vertex with those of its neighbors. The spatial approach to graph convolution is essentially propagating vertex information along edges. One representative work is GCN, which is both the starting point of spatial methods and a special case of spectral methods. Other works based on spatial methods include GraphSAGE, GAT, etc. GraphSAGE updates vertices by sampling a fixed number of neighbors for each vertex and aggregating the information obtained. GAT calculates the corresponding hidden information for each vertex, and by introducing an attention mechanism, the model can be applied to data with unknown graph structure. GAT computes the corresponding hidden information for each vertex, and by introducing the attention mechanism, the model can be applied to data with unknown graph structure and achieve better results in vertex classification tasks.

3 METHODOLOGY

In this section, a new model is proposed to address the shortcomings of the GCN-based recommendation model.

3.1 Input layer

The input layer is responsible for encoding the entity features of the user or project, and the generated low-dimensional embedding vector is used as the input to the graph convolution layer. It uses an encoding function as follows:

$$e_u^0 = W_u^{in} \cdot x_u, \tag{1}$$

$$e_v^0 = W_v^{in} \cdot x_v, \tag{2}$$

where $W_u^{in} \in \mathbb{R}^{h \times d_u}$ and $W_v^{in} \in \mathbb{R}^{h \times d_v}$ are the encoding matrices to be learned for the user and the item, respectively.

We adopt the method of encoding the original entity features of users or items directly to obtain their initial embedding vectors. This method can encode the semantically richer entity features or auxiliary information and input them to the graph convolution layer, which is more conducive to learn the embedding representation of nodes accurately; moreover, since only the optimization encoding matrix is required, it makes the optimization parameters of the model less.

3.2 Enhanced graph convolution layer

The model in this paper achieves layer-by-layer refinement of the node embedding representation by stacking L graph convolutional layers to achieve layer-by-layer refinement of the node embedding representation. However, we enhance the existing model by fusing the 2nd-order synergy signals and user preferences.

Let $u_i \to v_k \to u_j \ldots$ be any connectivity path from user u_i on a bipartite graph $\mathcal{G}$. The subscripts i,k,j, denote the node numbers. We call v_k the first-order neighbor of u_i, u_j the second-order neighbor of u_i, and so on, according to the number of hops from user u_i on the path.

Let u_j be the 2nd order neighbor of the target user u_i on the graph $\mathcal{G}$ and $u_i \to v_k \to u_j$ be an arbitrary connected path of length 2 between them, then the 2nd order cooperative signal propagating from u_j to u_i is defined as:

$$s_{ij}^l = \sum_{k \in N_i} p_{i,j,k} (e_{u,j}^{(l-1)} + e_{u,i}^{(l-1)}), \tag{3}$$

where, $e_{u,j}^{(l-1)}$ is the embedding of user u_j at layer $l-1$. $p_{i,j,k}$ is the 2nd order collaborative signal strength coefficients of the graph convolutional neural network, which are related to the degree of nodes on the path.

$N_i^{(2)}$ denotes all the 2nd order neighbors of the target user u_i, then all the 2nd order cooperative signals converging to u_i are:

$$s_{u,i}^{l(2)} = \sum_{j \in N_i^{(2)}} s_{ij}^l, \tag{4}$$

Similarly, it is easy to introduce the 2nd order co-signal $s_{v,i}^{l(2)}$ of the lth layer converging to the project v_j. Let $E^{(l-1)} \in \mathbb{R}^{(m+n) \times h}$ be the matrix of all embedded vectors in layer $l-1$, and s denote the 2nd-order co-signal matrix of all nodes in layer l. The row vectors are composed of $s_{u,i}^{l(2)}$ or $s_{v,i}^{l(2)}$. Based on the theoretical knowledge of spectrograms [31], a concise form of the 2nd-order co-signal matrix $s^{l(2)}$ can be expressed as follows:

$$s^{l(2)} = L^{l(2)} E^{(l-1)} + L^{l(2)} E^{(l-1)} \odot E^{(l-1)}, \tag{5}$$

where, $L^{l(2)}$ is a de-diagonalized canonical 2nd order adjacency matrix.

And $L^{l(2)}$ is the normalized 2nd order adjacency matrix, which measures the 2nd order signal strength based on the node degree, and is in the form of a matrix of signal strength coefficients $p_{i,j,k}$:

$$L^{l(2)} = (D^{-\frac{1}{2}} \cdot A \cdot D^{-\frac{1}{2}})^2, \tag{6}$$

wHere, D is the diagonal matrix composed of node degrees. A is the adjacency matrix of graph $\mathcal{G}$ of the adjacency matrix.

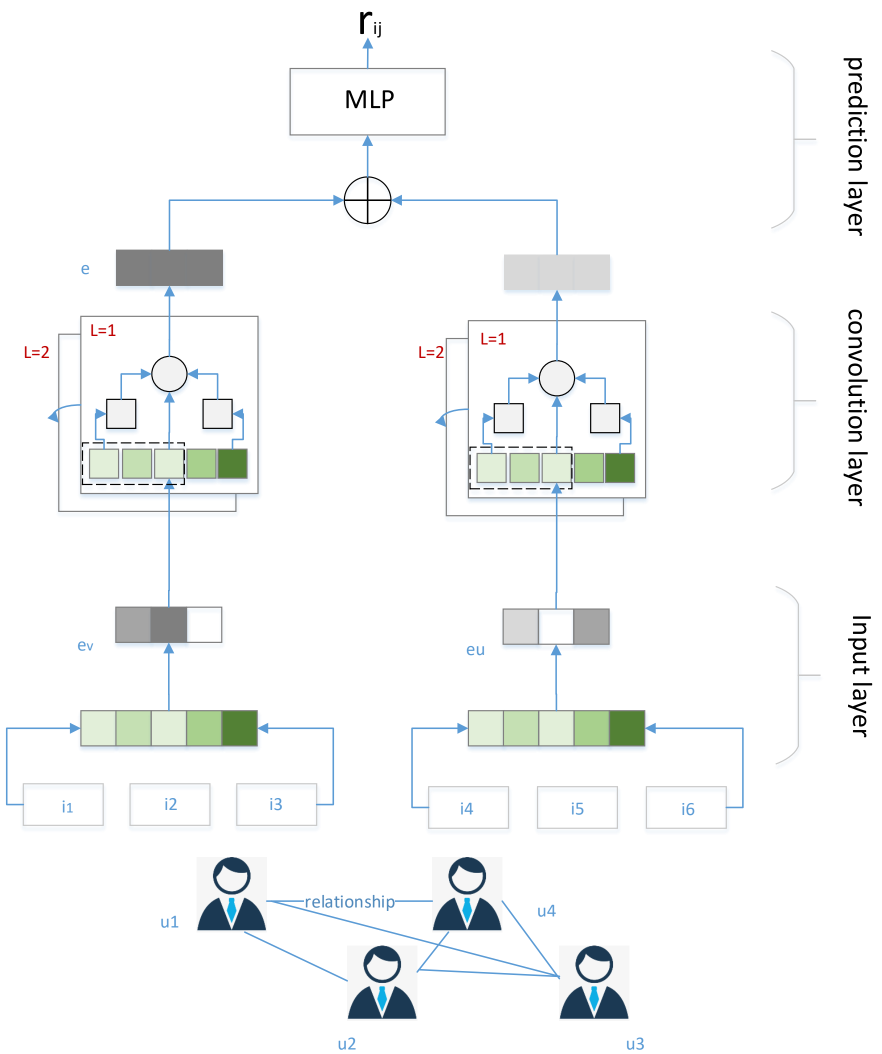

Fig. 2: The general architecture of our model.

We propose a method for constructing a first-order synergistic signal with user's viewpoint, borrowing from GCN's message transmission mechanism. It defines the first-order co-signal converged to the user u_i as:

$$s_{u,i}^{l(1)} = \sum_{j \in N_i} c_{i,j} p_{i,j} W_1^l e_{v,j}^{(l-1)}, \quad (7)$$

3.3 User social relationship embedding

In the social relationship model, considering the influence of multiple social relationships on users' behaviors, this paper introduces a concern influence mechanism to select representative friends in each dimension of the social network to characterize users' social information. For the social network in the dth dimension, the potential factor s_i^d of each user u_i is the potential factor that aggregates all his neighbors N (i) in this network, and thus can be expressed as follows:

$$s_i^d = f(W \cdot Aggre_n(UA_a) + b) = f(W \cdot (\sum_{j \in N_i} \beta(UA_a)) + b), \quad (8)$$

where, $Aggre_n$ denotes the aggregation of users' neighbors, and the same weighted average function is used to construct this network; UA_a denotes the preference feature vector calculated by the ath user according to the user preference model; β denotes the influence of user a on the interest of user i. Since there are strong and weak influences among users, mixing them together can identify users' interests more widely. The learning process of β can be expressed as follows:

$$\beta = w_2^T \cdot f(W_1 \cdot A_a + b_1) + b_2, \quad (9)$$

$$\beta = \frac{exp(\beta^*)}{\sum_{i \in N_i} exp(\beta^*)}, \quad (10)$$

3.4 Non-linear prediction layer

The final learned node embeddings e_u^L and e_v^L from the graph convolution layer are connected and fed into a 2-layer MLP network to predict the unknown score r between user u and item v:

$$r = W_4(ReLU(W_3(e_u^L \oplus e_v^L))), \quad (11)$$

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TABLE 1: statistical information of the two datasets.

Dataset	users	items	ratings	density
Yelp	13729	62759	388132	0.05%
Douban	10359	88437	1052364	0.11%

where $W_3 \in \mathbb{R}^{2h \times d'}$, $W_4 \in \mathbb{R}^{d' \times 1}$ are the MLP weight matrix to be learned weight matrix; d' is the number of neurons in MLP layer l (hidden layer).

4 EXPERIMENTS

4.1 Dataset

To evaluate the proposed approach, this paper conducts experiments using two datasets, Yelp and Douban Movie. The statistical information of the datasets is shown in Table 1.

4.2 Baselines

Probabilistic Matrix Factorization (PMF): This is a basic recommendation method [16] that uses only the user item matrix for recommendations.

Context Matrix Factorization (CMF): This method goes beyond the traditional probability matrix decomposition by adding to the PMF posterior distribution by adding item-user item sender matrix, user-user preference similarity matrix, and item-content similarity matrix to the PMF and item-content similarity matrices.

Social Network Regularization (SoReg): It defines a regularization specification to capture social relationships, which combines a user-item matrix, a user-user similarity matrix and outgoing friendship relationship matrix.

4.3 Evaluation Metrics

The average indicator uses 2 widely used indicators: Root Mean Square Error, RMSE and Mean Absolute Error, MAE, calculated as follows:

$$RMSE = \sqrt{\frac{1}{\tau}\sum(R_{ij} - \hat{R}_{ij})^2}, \tag{12}$$

$$MAE = \frac{1}{\tau}\sum(R_{ij} - \hat{R}_{ij}), \tag{13}$$

where τ is the set of rating data in the test set; $\hat{R}_{ij})$ is the prediction of the user's product rating in τ according to the method in this paper. The smaller the RMSE and MAE, the better the prediction performance. Based on the analysis of the experimental results, it was found that using social network information for recommendation improves significantly in terms of RMSE and MAE. For example, either method can improve more accuracy compared to the basic PMF; and the richer the application of social connections, the better the performance of the algorithm tends to be. The performance of the Yelp dataset is significantly weaker than that of Douban movies because the mean variance of item scores in the Yelp dataset is larger than that of Douban movies, which results in a flatter Gaussian distribution of score prediction values. Therefore, the RMSE and MAE metrics depend heavily on the dataset itself. The larger the training set is, the better the prediction is. It is worth noting that our model achieves the best performance when the proportion of the training set is equal to 50

4.4 Result Analysis

The criteria used to evaluate the accuracy of each algorithm in this paper are MAE and RMSE. Several experiments were conducted by choosing different sizes of training sets (30%, 50%) and different potential factor dimensions k (k=10, 20), and the comparison results are shown in Table2-5.

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5 CONCLUSION AND FUTURE WORK

GCN is the most popular research method in recommendation systems because of its powerful ability to learn embedding representations on graph structures. GCN uses spectral graph theory to define graph convolution operations to propagate and aggregate messages from neighboring nodes on topological graphs, and has the advantage of learning entity embedding representations using both entity features and graph structure features. In essence, it extends the excellent feature learning and representation capabilities of the traditional convolutional nerve network CNN to non-regular graph data. There is a considerable amount of research in online social networks, most of which focuses on the structural analysis of social graphs. The interpersonal relationships of social networks, especially friend circle, can solve the cold start and sparsity problems, and through the relationship between social networks can effectively recommend users' favorite items (items), such as music , videos, brands/products, preferred tags, location, services, etc. User relationships in social networks are diverse and there are many different perspectives on different social networks.

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TABLE 2: Performance comparison on Douban Movie with proportion of 30%.

Baseline	k	RMSE	MAE	k	RMSE	MAE
PFM	10	0.736	0.576	20	0.721	0.563
CMF	10	0.676	0.504	20	0.629	0.487
SoReg	10	0.716	0.571	20	0.677	0.554
Ours	10	0.631	0.498	20	0.572	0.469

TABLE 3: Performance comparison on Yelp with proportion of 30%.

Baseline	k	RMSE	MAE	k	RMSE	MAE
PFM	10	0.979	0.776	20	0.938	0.757
CMF	10	0.869	0.654	20	0.833	0.638
SoReg	10	0.941	0.725	20	0.914	0.729
Ours	10	0.793	0.642	20	0.732	0.617

TABLE 4: Performance comparison on Douban Movie with proportion of 50%.

Baseline	k	RMSE	MAE	k	RMSE	MAE
PFM	10	0.731	0.573	20	0.718	0.553
CMF	10	0.657	0.497	20	0.622	0.477
SoReg	10	0.707	0.580	20	0.656	0.534
Ours	10	0.627	0.487	20	0.565	0.450

TABLE 5: Performance comparison on Yelp with proportion of 50%.

Baseline	k	RMSE	MAE	k	RMSE	MAE
PFM	10	0.966	0.767	20	0.922	0.750
CMF	10	0.862	0.649	20	0.831	0.623
SoReg	10	0.935	0.715	20	0.902	0.718
Ours	10	0.788	0.638	20	0.723	0.600

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