Construction and Prediction of a Dynamic Multi-relationship Bipartite Network

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Abstract. Bipartite networks are capable of representing complex systems that involve two distinct types of objects. However, there are limitations to the existing bipartite networks: 1) It is inadequate in characterizing multi-relationships among objects in complex systems, as it is restricted to depict only one type of relationship. 2) It is limited to static representations of complex systems, hampering their ability to describe dynamic changes in the interactions among objects over time. Therefore, the Dynamic Multi-Relationship Bipartite Network (DMBN) model is introduced, which not only models the dynamic multi-relationships between two types of objects in complex systems, but also enables dynamic prediction of the intricate relationships between objects. Extensive experiments were conducted on complex systems, and the results indicate that the DMBN model is significantly better than the baseline methods across multiple evaluation metrics, thereby proving the effectiveness of the DMBN.

Keywords: Multi-relationships aggregation · Feature Representation · Dynamic prediction

1 Introduction

With the development of complex network theory, many complex systems can be described by complex networks [1–5]. A typical complex network comprises nodes and edges, wherein nodes are indicative of objects within a complex system, and edges signify the intricate relationships between these objects [6–8]. A distinctive type of network model exists within complex networks, known as bipartite networks. Bipartite networks consist of two distinct types of nodes, wherein edges are solely present between nodes of different types [9–11]. For instance, bipartite network models can be used to represent purchase relationships between users and items, therapeutic relationships between drugs and diseases, as well as invocation relationships between users and services [12–14].

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Traditional bipartite networks are primarily modeled based on a static, single-type relationship between two types of objects. However, in real complex systems, there exist multi-relationships that change over time between two types of objects [15–17]. Each relationship between objects harbors distinct semantic information, making it infeasible to capture the intricate semantic relationship among objects solely based on a singular relationship [18,19]. In addition, traditional bipartite network modeling cannot capture the dynamic interaction information between objects, prompting the need for alternative methodologies in the field of network modeling and analysis.

Therefore, the present paper proposes a novel Dynamic Multi-Relationships Bipartite Network (DMBN) model, designed to effectively model the dynamic multi-relationships that exist between two distinct types of objects in real complex systems. Compared with five existing baseline models, namely DMF, LTSC, TSQP, DLP, and MBN, the DMBN model exhibits superior performance. The main contributions of this paper can be summarized as follows:

(1) A DMBN model is proposed, which can dynamically describe multi-relationships between two types of objects.

(2) Representation methods for multi-relationship aggregation features and preference features are proposed, which can provide features for dynamic prediction.

(3) Experiments on real datasets show that DMBN significantly outperforms baseline methods, proving the effectiveness of the DMBN model.

2 Related Work

A bipartite network is a special type of complex network that consists of two distinct types of nodes and one type of edge, with edges only existing between nodes of different types. The structural characteristics of bipartite networks can be used to describe complex systems consisting of two different types of objects. The characterization and analysis of real complex systems based on bipartite networks can reveal information transmission mechanisms, predict information propagation paths, and explore the relationship between complex system structures and functionalities, providing a scientific basis for decision-making in relevant complex systems. For instance, Fu proposed MVGCN, a robust and effective bipartite network link prediction framework for biomedical applications [20]. The framework is based on bipartite networks in biomedical research and can perform link prediction tasks. Jafari proposed a drug combination strategy method based on bipartite network modeling, which model drug and patient sample (cancer cells) response data as a bipartite network and formulates effective multi-targeted drug combination plans based on community structures [21]. Zhang introduced graph neural on bipartite networks and proposed the BCGNN model for graph classification tasks. This model is able to effectively capture relationships between nodes of the same type in bipartite networks and preserve the structural information of the bipartite graph [22]. Bipartite networks have been proven to be a useful tool for depicting real complex systems and conducting relevant studies and applications. Therefore, this paper implements modeling of multi-relationships between objects in complex systems based on bipartite networks.

3 DMBN Model

3.1 Framework Overview

The overall framework of DMBN is shown in Fig. 1. DMBN models and predicts dynamic multi-relationships between two types of objects in complex systems, which includes two parts: DMBN construction and dynamic prediction. In the DMBN construction part: firstly, the DMBN is proposed to describe the dynamic multi-relationships between objects. Then, different relationships with varying degrees of importance are aggregated based on attention mechanisms to obtain multi-relationships aggregated features. In the dynamic prediction part: firstly, the preference features of nodes are mined based on the similarity between same-type nodes in the network. Then, the temporal features of node pairs, which are represented by the concatenation of the multi-relationships aggregated features and preference features, are fed into the prediction model (GRU) to achieve the prediction of relationships.

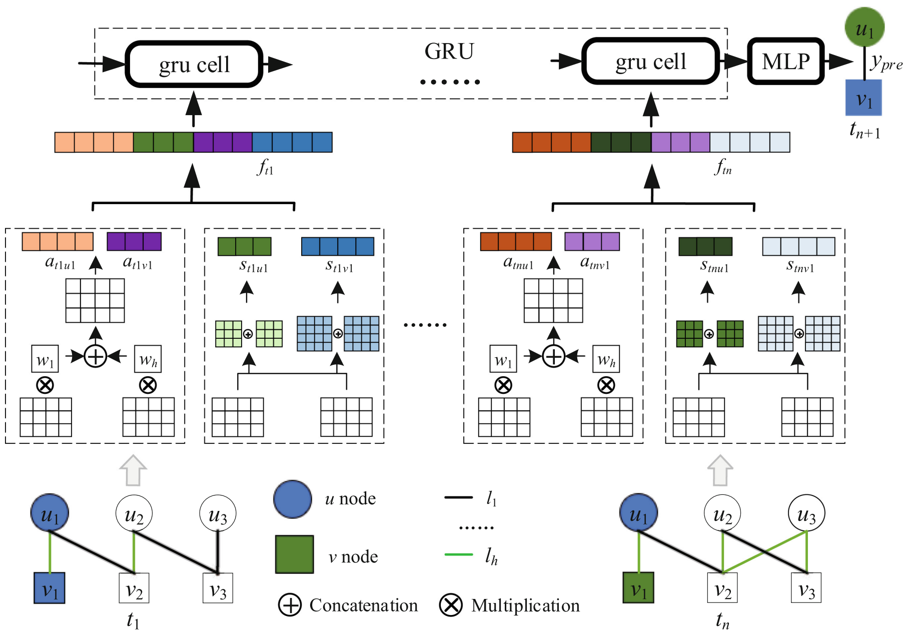

Fig. 1. The overall framework of DMBN.

3.2 DMBN Construction

Definition of DMBN. The DMBN model comprises node sets U and V, type set L, time set T, and edge set E. The DMBN is defined as G_{DMB}=(U, V, L, T, E), where U=$\{u_1, u_2, ...\}$ and V=$\{v_1, v_2, \ldots\}$ respectively represent different types of node sets, L=$\{l_1, l_2, \ldots\}$ represents the set of edge types, T=$\{t_1, t_2, \ldots\}$ represents the set of time instances, and E=$\{e_1, e_2, \ldots\}$ represents the set of edges. The DMBN is represented by the adjacency matrix, A_{DMB}=$\{A_{MB}^{t1}, A_{MB}^{t2}, \ldots\}$, where A_{MB}^{t1}=A_{l1}^{t1} & A_{l2}^{t1} & $\ldots$ denotes the set of adjacency matrices under different relationship at time t_1.

Multi-relationships Aggregation Based on Attention. There are multi-relationships between two types of nodes in a DMBN, and each relationship contains different semantic information. The key to analyzing and researching DMBNs lies in aggregating the relationships that exist with semantic differences between them. Hence, this paper proposes a multi-relationship aggregation method based on the attention mechanism. The method assigns weights to each relationship based on their relative importance, in order to reflect the significance of different relationships, primarily in terms of weights.

DMBNs can be represented by adjacency matrices, which are based on different time periods and various relationships. For example, A_l^t represents the adjacency matrix at time t and relationship type l. This paper adopts an attention mechanism to aggregate multi-relationships, considering the significance of each relationship, as shown in formula (1).

$$A_{MBA}^t = \sum_{i=1}^{h} W_{l_i} A_{l_i}^t \tag{1}$$

A_{MBA}^t represents the adjacency matrix after multi-relationship aggregation at time t. W_{l_i} denotes the importance of relationship type l_i, $A_{l_i}^t$ represents the adjacency matrix corresponding to relationship type l_i at time t, and h is the number of relationship types.

The multi-relationship aggregation based on attention mechanism can effectively capture the significance of diverse relationships. Therefore, this paper aims to extract the multi-relationship aggregation features for nodes u and v. The corresponding methodology is presented in formulas (2)–(3).

$$a_{tu} = A_{MBA}^t(i :) \tag{2}$$

$$a_{tv} = A_{MBA}^t(: j) \tag{3}$$

In this context, a_{tu} and a_{tv} respectively indicate the multi-relationship aggregation features of node u and node v at time t. $A_{MBA}^t(i{:})$ denotes the i-th row of the adjacency matrix, while $A_{MBA}^t({:}j)$ indicates its j-th column.

3.3 Dynamic Prediction

Feature Representation Based on Similarity. In real complex systems, similarities among objects have the potential to influence the evolution of the complex system, as well as the intricate relationships between objects. Therefore, this paper proposes a preference feature representation method based on the similarity among objects. Based on the initial feature and Pearson correlation coefficient (PCC), the similarity between objects of the same type is calculated. As shown in formula (4). The intuitive feature of complex systems is the interactional relationships among their constituent objects, which can reflect the preferences of these objects to some extent. Therefore, this paper is based on the interaction relationship between objects as the initial feature.

$$sim(x, y) = \frac{\sum_{p=1}^{n} (x_p - \bar{x})(y_p - \bar{y})}{\sqrt{\sum_{p=1}^{n} (x_p - \bar{x}) \sum_{p=1}^{n} (y_p - \bar{y})}} \tag{4}$$

Here, x and y represent objects of the same type, p represent the position of the initial feature, and $\bar{x}$ and $\bar{y}$ represent the mean of the initial feature.

Based on the adjacency matrix A_l^t for time t and relationship l, the similarity feature matrices S_{tlu} and S_{tlv} are obtained for u-type nodes and v-type nodes under this time and complex relationship. In this paper, the final similarity feature matrix is obtained by summing the similarity matrices under various complex relationships. The specific formulas are shown in formulas (5)–(6).

$$S_{tu} = \sum_{i=1}^{h} S_{tl_i u} \tag{5}$$

$$S_{tv} = \sum_{i=1}^{h} S_{tl_i v} \tag{6}$$

Here, S_{tu} and S_{tv} represent the similarity feature matrix of u-type nodes and v-type nodes at time t, respectively; $S_{tl_i u}$ represents the similarity feature matrix of u-type nodes under relationship type l_i at time t; h denotes the number of relationship types.

Based on the similarity between nodes of the same type, the preference features of nodes u and v are extracted in this paper, as shown in formulas (7)–(8).

$$s_{tu} = S_{tu}(i:) \tag{7}$$

$$s_{tv} = S_{tv}(j:) \tag{8}$$

Here, s_{tu} and s_{tv} represent the preference features of node u and node v at time t, respectively. (i:) and (j:) represent the i-th and j-th rows of the matrix, respectively.

Dynamic Multi-relationships Prediction. The motivation of this paper is to predict the complex relationships among nodes in DMBNs based on the historical features of the nodes. These historical features include multi-relationship aggregation features and preference features. Multi-relationship aggregation features can reflect the importance of different relationships, while preference features can reflect the preferences of nodes. Therefore, this paper is based on the concatenation of multi-relationship aggregation features and preference features to obtain node features, as shown in formulas (9)–(10).

$$g_{tu} = a_{tu} \oplus s_{tu} \tag{9}$$

$$g_{tv} = a_{tv} \oplus s_{tv} \tag{10}$$

In this context, g_{tu} and g_{tv} respectively denote the features of node u and node v at time t, while the symbol $\oplus$ indicates the concatenation of features.

This paper obtains the temporal feature f_t of node pair u-v at time t based on feature concatenation, as shown in formula (11).

$$f_t = g_{tu} \oplus g_{tu} \tag{11}$$

This paper employs the Gate Recurrent Unit (GRU) model to mine implicit information. As a variant of LSTM, this model features a simpler structure, fewer parameters, and faster training speed. By feeding the vector h_k obtained from the final time step output of GRU into a fully connected network, the predicted relationship between nodes u and v can be obtained, as shown in formula (12).

$$\hat{y} = Relu\,(Wh_k + b) \tag{12}$$

Here, W and b are weight matrices for adaptive learning, and $\hat{y}$ represents the predicted value.

In this paper, predicting relationships among objects is regarded as a regression problem, and its loss function is shown in formula (13).

$$L = \alpha^* \frac{1}{M} \sum_{i=1}^{M} (y_i - \hat{y}_i)^2 + (1 - \alpha)^* \sum_{j} w_j^2 \tag{13}$$

In this equation, y_i represents the true relationship between nodes u and v, $\hat{y}$ represents the predicted relationship, M denotes the number of samples, w_j is a learnable parameter, $\sum_j w_j^2$ represents the regularization term, α is used to balance the importance of the regularization term.

4 Experiment and Results

4.1 Dataset

This paper constructs DMBN based on various complex relationships among complex objects, and performs dynamic prediction of target relationships. The dataset is sourced from various complex relationships between users and items on the Taobao platform [23], including browse (Pv), favorite (Fav), add-to-cart (Cart) and purchase (Buy), among others. The experiments in this paper follow the experimental setup of MBN [28], and three datasets were obtained as experimental data using the same preprocessing method. Moreover, the complex relationships between users and items in the three datasets were rearranged based on their temporal order. In the experimental process, each dataset was divided into five equal parts, where one part was used as a testing set and the remaining parts were used as training sets. This process was repeated five times.

4.2 Evaluation Metrics

This paper constructs a DMBN based on various relationships between users and items, and dynamically predicts the relationships based on the temporal features of DMBN. In the real world, merchants are more concerned with the purchasing relationships. Therefore, this paper regards the purchasing relationship as the ultimate goal. To address the issue of imbalanced data resulting from using negative samples that do not have any relationships between users and items, this paper adopts a regression model-based evaluation metric to measure the performance of DMBN. This approach allows for a more accurate assessment of the predictive performance of the model when dealing with highly imbalanced datasets. The mean absolute error (MAE) and root mean square error (RMSE) were used to evaluate the performance of the predictions in the experiments.

4.3 Baseline Methods

The effectiveness of DMBN is evaluated based on the following five baseline methods. DMF [24]: DMF is a matrix factorization model based on neural network structures. LTSC [25]: LTSC is a feature-enhanced service classification model based on attention mechanisms and convolutional neural networks (CNN). TSQP [26]: TSQP is a QoS prediction method based on deep learning, which aims to perform time-aware service QoS prediction tasks through feature integration. DLP [27]: DLP is a link prediction model that employs the local structures of a bipartite network. MBN [28]: MBN is a network model that is designed to model the various complex relationships between two types of objects in the real world.

4.4 Results

Performance Comparison. The performance comparison results between DMBN and baseline methods based on two evaluation metrics, namely MAE and RMSE, are presented in Table 1. The experimental results demonstrate that DMBN outperforms the baseline methods on all the evaluation metrics. The performance improvements are primarily attributed to the following reasons: 1): Modeling based on the DMBN can characterize the existence of multi-relationships in complex systems. 2): Dynamic modeling can effectively retain both historical and current information among objects. 3): Feature representation based on similarity can to some extent reflect the preference features of objects. Moreover, the following observation results were further summarized:

Table 1. Performance comparison of DMBN and baseline methods.

Method	User Behavior 1		User Behavior 2		User Behavior 3	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
DMF	0.477	0.438	0.488	0.434	0.472	0.424
LTSC	1.503	1.212	1.541	1.502	1.536	1.511
TSQP	1.371	0.784	1.675	0.915	1.583	0.886
DLP	2.718	1.437	2.566	1.051	2.393	1.251
MBN	0.471	0.387	0.473	0.393	0.470	0.388
DMBN	0.319	0.270	0.277	0.197	0.351	0.282

(1) Based on RMSE evaluation metric, the DLP model exhibits the worst performance. DLP predicts the link relationships between nodes based on the local structural information of the bipartite network. This methodology necessitates a significant quantity of edge relationships within the bipartite network to extract more structural features that can distinguish differences in target node. However, the relationships present in real complex systems are typically sparse. When constructing bipartite networks based on complex relationships and extracting local structural features, the limited structural information contained in the features may not be sufficient to provide accurate and effective information for predictions, which consequently may result in suboptimal performance.

(2) Based on the MAE evaluation metric, the LTSC model exhibits poor performance. The LTSC model extracts feature representations based on a word embedding model, and enhances the embedding representation using a label attention mechanism. However, the users and items in the dataset of this paper are mainly represented in the form of IDs, which cannot extract features based on word embedding models. Therefore, utilizing solely the IDs of users and items as features would not be effective in extracting meaningful information.

(3) MBN exhibits superior performance when compared to the other baseline methods. MBN has the ability to model a variety of complex relationships among objects in a complex system and can overcome the limitations of traditional bipartite networks, which can only model a single type of edge relationship. At the same time, an attention mechanism based on the relationship level is designed to fuse multiple relationships and realize the importance distinction of each relationship. Moreover, the superior performance of DMBN relative to MBN indicates that incorporating dynamic factors into modeling can significantly enhance the predictive performance of the model.

Impact of Multi-relationship. In this work, we examine the effects of multi-relationship modeling strategies on performance, with a primary focus on DMBN modeling based on double and multiple relationships.

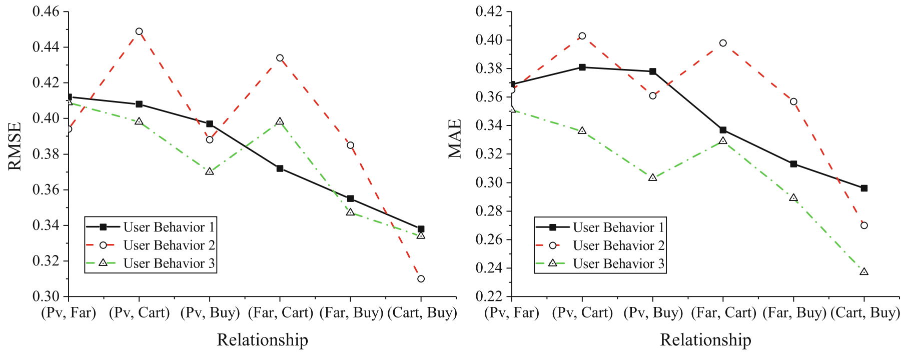

Fig. 2. Modeling based on double relationships.

Initially, we investigate the modeling strategy based on double relationships, where the network is modeled based on two types of relationships. The experimental results demonstrated in Fig. 2 show that the model achieves optimal performance when modeled based on "Cart" and "Buy" relationships. In addition to the "Buy" relationship, adding other relationships still achieves good predictive performance, demonstrating the importance of the "Buy" relationship in enhancing the model performance. Moreover, when modeling is based on a combination of two relationships, that without the "Pv" relationship performs better than that with the "Pv" relationship, indicating the limitations of the "Pv" relationship in improving the model performance.

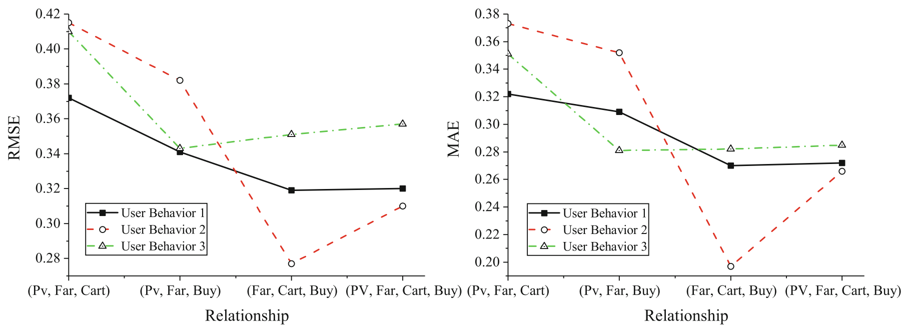

Fig. 3. Modeling based on multiple relationships.

Next, we investigate the modeling strategy based on multi-relationships, where the network is modeled based on a variety of relationships.

The experimental results in Fig. 3 demonstrate that the modeling of the "Far", "Cart", and "Buy" relationships yields the best predictive performance. This indicates the importance of these three relationships for predicting the target relationship. However, it is noteworthy that the predictive performance is not optimal when modeling based on the four relationships. It is proposed that the "Pv" relationship is a ubiquitous factor between users and items. Therefore, including this relationship in the modeling may introduce unnecessary noise, interfere with the model's recognition of the target relationship, and result in a decrease in predictive performance. Furthermore, incorporating the "Buy" relationship in the multi-relationship modeling yields significantly superior performance, thereby underscoring the paramount importance of this relationship in augmenting the predictive capabilities of model.

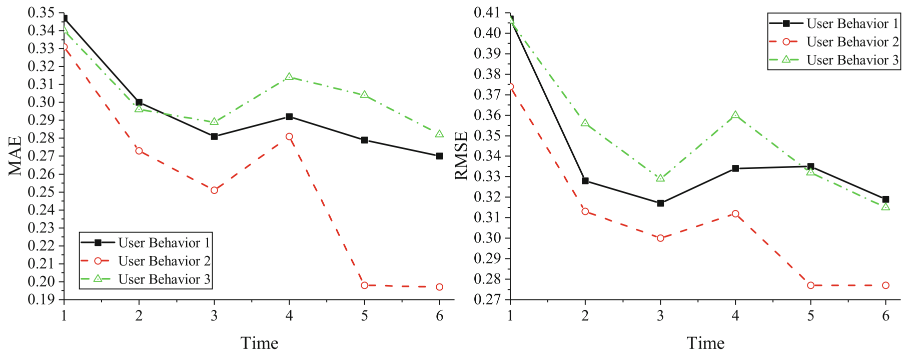

Fig. 4. The impact of time on model performance.

The Impact of Time. This paper performs temporal segmentation of the dataset based on a 24-hour cutoff for partitioning. As illustrated in Fig. 4, the predictive performance of the model improves with the increase of time, which indicates that incorporating historical information can effectively enhance the predictive capability of model. In addition, the introduction of historical information leads to a remarkable improvement in the performance of the model within a short time frame. This could be attributed to the model's incapability of capturing enough historical cues when the temporal window is too brief. At time interval of 4, the model's performance temporarily decreases, possibly due to the redundant interaction information between users and items present in the historical data at that moment. As the time interval increases, the model's performance further improves, highlighting the significant impact of historical information on enhancing model performance.

5 Conclusion

This paper proposes a DMBN model to address the challenge of modeling dynamic multi-relationships between objects in complex systems. The main innovation of DMBN can be summarized as follows: 1) A novel framework, the DMBN model, is proposed to tackle the formidable task of modeling intricate and diverse dynamic relationships that exist between two types of objects in complex systems. 2) A multi-relationship aggregation feature representation method and a preference feature mining method are proposed, and the dynamic prediction of the target relationship is achieved by concatenating these features. 3) Experimental results on a real complex system demonstrate the DMBN's modeling ability and outstanding performance in predicting target relationships. In our future endeavors, we intend to incorporate more intricate objects within the network modeling framework, aiming to enhance the comprehensive characterization of real complex systems.

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