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Interpretable Relation Prediction of Undirected Hypergraphs with Dynamic Bipartite Graphs

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Abstract

Predicting the number of new relationships based on combinations of people is a helpful task for decision-making. This paper proposes an **I**nterpretable **R**elation **P**rediction (**IRP**) framework to predict the complex relationships between individuals and groups. Our two-stage framework uses a dynamic bipartite graph as an input to simplify increasing sets of nodes over time. The framework's high interpretability in handling temporal dynamics and intuitive features provides insights into the underlying factors driving the predictions, making it useful for decision-making in various domains, such as recommendation systems, social networks, and academic co-authorship networks.

1. Introduction

In real-world situations, many complex relationships can be represented by undirected hypergraphs consisting of sets of nodes. Hypergraphs are effective in representing social networks because an edge can contain multiple nodes. Thus, hypergraphs are suitable for containing group information between people such as movies-actors and papers-authors.

Predicting the relations between who is in each group and how many times that group has occurred can be a good indicator for recommending which combination of people to organize. For example, the relation prediction shows which combination of actors produces many movies or which author's cooperation produces many papers. Moreover, providing the criteria by which this prediction is made would benefit decision-makers. Therefore, in this paper, we propose an **I**nterpretable **R**elation **P**rediction (**IRP**) framework to predict upcoming sets of nodes.

Although hypergraph refers to sets of nodes, dynamic bipartite graphs are used in the IRP framework to smoothly deal with input information about hypergraphs. Dynamic bipartite graphs change the relations between two different types of node sets over time. Therefore, these network structures are useful in modeling interactions between users and various entities. Dynamic bipartite graphs are widely used in recommendation systems. In e-commerce, the systems are utilized to forecast new interactions between users and items and then give users personalized lists of items.

To deal with our problem, two node sets of the bipartite graph represent the hypergraph's input nodes and set information, respectively. For instance, in an academic co-authorship network, authors and papers are represented by nodes and sets in hypergraphs, respectively. However, in the bipartite graph, authors and papers are nodes, and the connections between authors and papers are edges.

To this end, this paper introduces a two-stage framework to predict future sets of nodes. The input of the framework is a dynamic bipartite graph containing information about sets of nodes. After pre-processing, the embedding module deals with weight logs and projected graphs to extract temporal dynamics and intuition factors. Then, the application module uses concatenated embedding results to predict a number of sets under a particular combination of nodes.

* This work was supported by Institute of Information & Communications Technology Planning & Evaluation (IITP) grant funded by the Korea government (MSIT) (No. 2022-0-00157, Robust, Fair, Extensible Data-Centric Continual Learning).

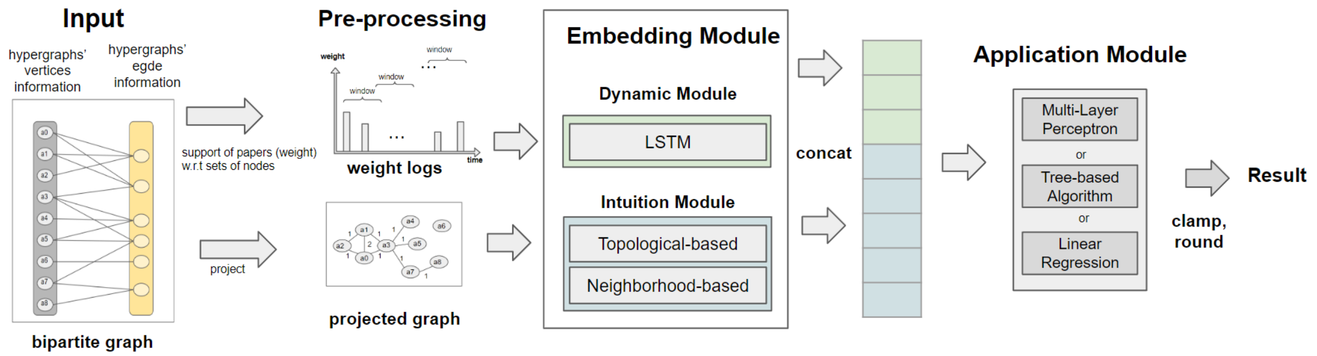

Figure 1. IRP framework

2. Related Work

To preserve the semantics of the graph and handle bipartite graphs efficiently, many papers utilize node embedding to extract features for networks and utilize the embedded results in various applications [1]. Thus, we also adopt these two-stage methods to capture meaningful information from data.

To extract semantics from the graphs, there are two approaches. One approach involves extracting meaningful metrics from graphs. For example, distance-based metrics focus on evaluating paths between nodes such as the shortest path, and Katz's index. Relation-based metrics aim to infer relations between nodes by predicting the degree of contribution of individuals to the groups. The relationship between specific nodes is analyzed by Coherence, Cosine, and Kulc [2].

Another approach is representation learning. Ranran Bian et al. [3] divided previous studies on heterogeneous network representation learning algorithms into semantic unit-based, path-based, and other algorithms. Many studies focus on analyzing static graphs [4]. However, there have also been studies on embedding dynamic graphs to capture the temporal characteristics of graphs that change over time [5].

These embedded results can be utilized as an input value in various applications. Link prediction, anomaly detection, link reconstruction, network clustering, similarity search, recommendation, and so on are examples of the applications [4, 5]. Among these, we approach the problem by focusing on link prediction. However, most of the existing studies of link prediction predict the probability of edge connection between two nodes. In order to apply to the problem, we are trying to solve, it was necessary to consider how to appropriately transform and use the link prediction result.

3. Methodology: *IRP* Framework

3.1 Overall Framework

Figure 1 illustrates the overall structure of the proposed IRP framework. First, there is an embedding module that describes the graph. Embedding modules can be divided into two main categories: dynamic (LSTM) and intuitive modules. In the intuitive module, it utilizes various indicators to describe the characteristics of nodes in a graph. The results generated by these two modules are passed to the input of the model.

In our framework, we use the input that is transformed from an undirected hypergraph into a bipartite graph. The information about the vertices and edges of the hypergraph incorporates the information about the nodes of the bipartite graph.

3.2 Preprocessing

The base graph is a bipartite graph that comprises the hypergraph's vertices information and edge information. This bipartite graph can be projected to form a new graph consisting consists of nodes from the hypergraph's vertices information and edges from relations between nodes. Moreover, we can extract the weights of the dynamic bipartite graph.

3.3 Embedding Module

The *intuitive module* defines features that can be intuitively explained in a network extracted by projecting from a base graph. The simplest topological feature is the degree of each node. Metrics based on neighbors focus on evaluating the overlap of neighbors between nodes. The three most frequently used indicators are common Neighbors, Jaccard's coefficient, and Adamic/Adar [6] is most frequently used for indicators.

The *dynamic module* aims to capture temporal dynamics from a dynamic bipartite graph. In our implementation, we utilize LSTM, one of the popular deep learning models, to predict time series. The model gets inputs from weights of the dynamic bipartite graph at an interval of a time window.

3.4 Application Module

The two outputs from the embedding module are concatenated, and the concatenated results are used as input for the application module which can be referred to as an inference stage. The embedding module considered various semantics concerning their characteristic. Therefore, simple models such as MLP, linear regression, tree-based algorithms, and so on can be used in the application module to predict the relationship.

4. Experiments

To predict relationships in a hypergraph, we used data on dynamic academic collaboration networks that consist of an author set and their corresponding number of papers. Given information about combinations of authors, the aim is to make predictions about the support of their papers at the next timestamp. To predict the information, the IRP framework was implemented by adopting the MLP model among various application modules. The use of simple DL models such as MLP can be interpretable with many existing eXplainable AI methods.

In order to verify the effectiveness of the IRP framework, we conduct a comparison between our method and baseline. The baseline is the case that all of the answers from queries are set by the most common value, which is constructed in 52% of the test queries. Although the validation MSE is quite high, the IRP framework (Mean Squared Error: 59.45) is better than the baseline (Mean Squared Error: 65.68).

4. Conclusion

We propose a two-stage IRP framework. In the first stage, the embedding module extracts both traditionally important features and hidden information from the dynamic bipartite graph. In the second stage, the result of the intuition module is used for weight prediction. To solve these tasks, we use the embedding module and a simple application model. This process enhances the interpretability of the results of prediction. Subsequently, we considered how to incorporate intuitive features. Our implemented approach achieved superior performance compared to the baseline.

Our framework provides an approach for predicting relations between individuals and groups and can enable decision-makers to identify important combinations of users that can produce many results of the collaboration. Furthermore, the framework's high interpretability to handle intuitive features can provide insights into the underlying factors driving the predictions, making it useful in real-world decision-making contexts.

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