DISSEMINATION REPORT

Action number: CA18232 - Mathematical models for interacting dynamics on networks (MAT-DYN-NET)
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Title: Link Prediction based Recommendation System using Ensemble Framework of Graph Attention Networks

DISSEMINATION OBJECTIVES

This is the dissemination report of the STSM stay at the University of Applied Sciences, Berlin, Germany (HTW). The primary goal of the dissemination of the results is twofold: (1) to give implementation details of the proposed Ensemble Framework of Graph Attention Network model for the recommendation system, and (2) to generate a broader and deeper representation of users, items in the same latent space for generating recommendations and link prediction in heterogeneous graphs .
Towards this direction, its main objectives include:

1. To utilize rating and aspect-based sentiment interactions in a graph embedding framework by using a graph attention networks-based ensemble framework for predicting user-item connections.
2. To adapt recommendation and link prediction algorithms based on graph embeddings using the graph model.

SUMMARY

The majority of currently employed collaborative filtering techniques infer from user ratings to represent users' binary relationships to items. In addition to user ratings, it presents the explanation behind the scoring as well, which often highlights the aspects of the item that are most significant to users. Reviews and user-item interaction have increasingly been recognized as important data for enhancing representation learning skills in the realm of recommender systems. Despite the importance of the reasons underlying user preferences, existing review-based recommendations often neglect the importance of sentiment words linked to related item aspects. This study presents a graph attention network-based ensemble framework with a hierarchical attention technique that incorporates information derived from both textual reviews and user-item bipartite graphs to address these concerns. A node-level graph convolutional network is modeled for each input graph to learn the embeddings derived from the graphs using information from aspect-based sentiments and rating-based text reviews. The graph level attention mechanism is used to learn the relevance of numerous input graphs thus facilitating efficient aggregation of node embeddings from several input graphs. In terms of the accuracy of rating prediction using TripAdvisor datasets, the experiment results clearly indicate that our model greatly surpasses the related approaches. This model also has the advantage

of presenting explanations for user reviews about recommended items which are related to specific aspects.

1. Introduction

Recommender systems, which are often implemented by many websites and applications, are playing a more significant role in reducing information overload as a result of the increasing variety of options available online. Recommendation systems could be used to personalize website content for each unique user. User interactions from various channels drive a recommendation system, improve recommendation precision, and enhance users' satisfaction by offering a personalized experience. Personalized recommendations shorten the time it takes users to find an item, increasing their chances of discovering more items of interest to them. This leads to improved user loyalty and satisfaction. Newsletters targeted promoted content and push alerts to encourage users to return to the platform, increasing the frequency with which regular users visit, reducing customer or user churn, and increasing lifetime value. For these reasons, recommendation systems are extremely valuable to businesses.

Collaborative filtering (CF) capitalizes on collecting and analyzing data on user behaviors, activities, and preferences to create recommendations based on users' similarities with other users. It presents items to recommend based on what is known about the user, without analyzing the content. Even though CF provides recommendations quickly and efficiently without analyzing the content, it has several limitations. For instance, It is challenging to provide perfect recommendations for users with a low volume of ratings or recommend a product with few ratings. Since popular items obtain more recommendations, new items are often overlooked. The underlying assumption in this scenario is that users will like what the majority of other users prefer. One of the primary challenges with CF recommender systems in practice is their inability to provide clear justifications about why an item is recommended [1].

One method to resolve the identified issues is to use review text. The majority of websites that employ recommender systems, such as TripAdvisor, Amazon, and Yelp, allow users to add ratings and free-text reviews. Review text improves ratings by providing in-depth details on products and users' underlying preferences, which means review text explains the thinking behind a user's rating. A combination of all reviews from the reference user allows us to deduce this user's preferences; in the same manner, a collection of reviews for an item indicates crucial aspects of the item that have been rated by several users. When there are few ratings, these user preferences and item features could be used to ease the previously noted issues and present users with explainable recommendations. [2]. Using review text information has recently been demonstrated to enhance rating prediction accuracy, particularly for individuals and items with few ratings. [3, 4]. User feedback, user ratings, and supplementary data are essential for enhancing the efficacy of the recommendation system. An effective combination of these elements could increase the recommendation effect of the recommendation system to a certain extent and address the sparsity issue. However, other recommendation algorithms ignore the usefulness of reviews and instead just consider the importance of user ratings and certain auxiliary data. Therefore, this study focuses on the application of auxiliary data, user reviews, and user ratings to the recommendation system.

Recommendation systems have to adapt to the dynamically changing user profile and preferences. The graph data structure keeps track of semantic relationships between entities as edges and semantic entities as nodes. Users, products, product information, and content characteristics can all be referred to as nodes. In contrast to other recommendation systems that examine relationships between users and objects individually, using a graph enables the capture of deeper relationships that may be used to provide better recommendations. [5,6,7]. This results in a more adaptable recommendation system for changing user preferences. In graph-based recommendation systems, users are presented with not just popular items that have been rated or liked by other users, but also new items that have not yet been reviewed [6]. Users are thus presented with more comprehensive recommendations rather than merely popular and advertised items. Additionally, recommender systems should be descriptive and interpretable for users to increase user confidence. Given that users, items, and aspects are all represented in the same latent space, another advantage of graph-based recommender systems is the interpretability of the recommendations [8].

One of the key challenges for recommender systems is cold-start data, which lacks adequate behavioral data about the user or item. Although content-based filtering might be able to overcome this issue, collaborative filtering approaches offer more precise recommendations once adequate behavioral data is available. Recommender systems could offer more accurate recommendations by integrating behavioral data, mainly user ratings and reviews, which indicate the aspects of the items users are interested in. Since ratings merely represent a user's overall satisfaction with the item, deducing the underlying logic of the rating is challenging, as users may be interested in different aspects of the same item. As an outcome, aspect-based opinions have been employed to improve recommender systems. [7,8].
Users and items can be perceived as bipartite networks. We handle recommendations as a link prediction task for heterogeneous sorts of entities, such as users and items. Recent, large recommender systems often include more varied and extensive information. In this study, the TripAdvisor dataset is used, where users could leave reviews for hotels and rate individual aspects such as service, cleanliness, and location.

As illustrated in Figure 1, we present an ensemble framework of graph attention networks in contrast to prior recommender models for the prediction of user-item links. The first thing we do is generate detailed features for both users and items (hotels). The meta-paths in various input graphs are used to predict likely user-item linkages, which is more significant. As seen in Figure 1, we generated the meta-path "user-aspect-item" in the user-aspect-item network. As a result, the GAT would propagate information from the local proximity to learn embeddings and then generate item predictions based on the derived features and meta-path interactions. Besides that, to learn node embeddings from various graphs, we construct a hierarchical attention approach, i.e., node-level attention and graph-level attention [9]. Specifically, we develop a graph attention network with node level attention to learn the nodes' (i.e., users' and items') embeddings in each input graph. We employ graph-level attention to comprehend the importance of various input graphs to successfully aggregate node representations from a variety of input graphs.

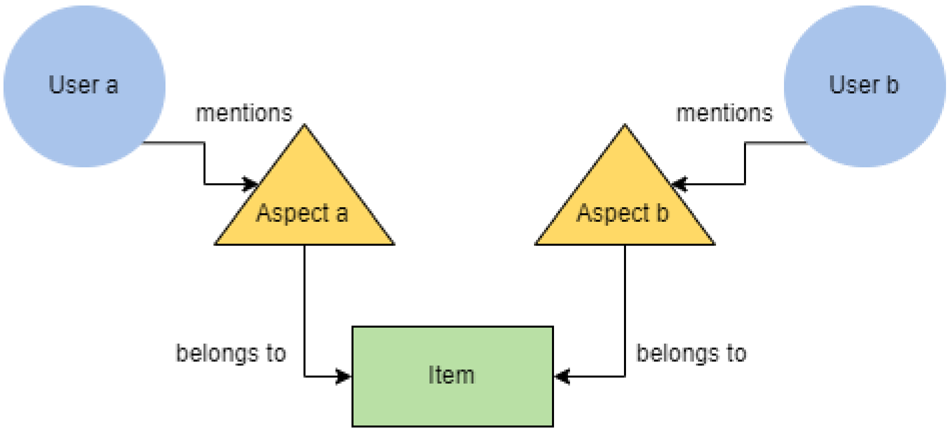

Figure 1: Meta-Paths extracted from the network schemas of the TripAdvisor website. Example of aspect-based opinions meta-path.

Our main contributions to the literatüre could be given as follows:

- To generate broader and deeper embeddings of items, users, and aspect-based sentiment in the same latent space for generating recommendations, our approach merges rating and aspect-based sentiment interactions in a graph embedding framework.
- By combining both aspect-based sentiment information in textual reviews and a user-item interaction graph, we introduced a graph attention network-based ensemble framework for predicting user-item connections.
- To efficiently train node embeddings for the multiple input networks for user-item association prediction, we devised a hierarchical attention method.
- Adapting recommendation algorithms based on graph embeddings using the graph model, demonstrating actual performance increases over baselines.

2. Background and Preliminaries

Link prediction aims at predicting any missing connection between network nodes, or the possibility of the formation of a relationship between any nodes in a network at a later time. It has several applications including friend recommendation, movie recommendation, and knowledge graph completion. Most of the existing link prediction literature tackles homogenous networks where there is a single type of edges or nodes. However, many real-world networks including social, biological, and chemical networks are heterogenous with different types of relationships (edges) between nodes and at times with different types of nodes. The developing e-commerce has availed research with plenty and diverse data, that could be utilized to develop better recommendation systems. A lot of this data is heterogeneous. This raw data is generally characterized by high-dimensional features that limit, some of which might have no or less contribution to the task at hand. Node embedding learn is normally adopted to reduce data dimensions. For recommendation systems, a meta-path has been used to capture the underlying structural interactions in complex networks. For instance, HGRec (Heterogenous Graph neural network for Recommendation) exploits high order semantics underlying complex heterogeneous networks through the aggregation of multi-hops meta-path base neighbors. In addition, it utilizes multiple meta-paths-based attention mechanisms to capture diverse semantics thus yielding enriched node embeddings.

Given the overwhelming efficiency of deep learning in computer vision on images. Researchers have extended deep learning approaches to graphs, a technique termed geometric deep learning. Precisely, Graph convolution networks are widely deployed and have exhibited great performance on several graph-related tasks including node classification, recommendation, and graph clustering.

A single GCN layer is formally defined as $H = \sigma\left(D^{-\frac{1}{2}}A'D^{-\frac{1}{2}}XW\right)$

$$A' = A + I$$

A: graph adjacency matrix,
W: learnable weight matrix,
H: graph output embeddings,
X: node feature matrix
I: identity matrix h
σ: nonlinear function

Different from the fully connected layer, the GCN layer has an extra term $D^{-\frac{1}{2}}A'D^{-\frac{1}{2}}$ that propagates the features of the reference node's neighbor to the reference node. Hence, GCN computes new features of the node as the weighted average of itself and its neighbor. However, the regular GCN layer only learns the local connectivity information but not the global network information. Moreover, it assumes homogenous networks. R-GCN (Relational Graph convolution network) a variant of the regular GCN is usually adopted to model multi relations in heterogeneous networks

The R-GCN layer is defined as

$$h_i^{l+1} = \sigma(W_0^l h_i^l + \sum_{r \in R} \sum_{J \in N_i^r} \frac{1}{c_{ir}} W_r^l h_j^l)$$

Different from the typical GCN, the R-GCN has a different projection matrix (Wr) for each unique relationship r.

GAT (Graph attention Network), a variant of GCN, leverages self-attentional layers to aggregate features of the reference node's neighbor features with different weights. It builds on exploring how important one node's features are for another node. This is achieved through computing the attention coefficient $e_{ij} = \sigma(Wh_i, Wh_j)$.

3. Proposed Approach

Figure 2 shows the proposed ensemble framework of graph attention networks for predicting user-item connections. We begin by extracting graph-specific node embeddings from each user-item network in the input. Second, we combine the learned node embeddings and use graph-level attention to concentrate on crucial data. To anticipate user-item linkages, we then develop a decoder for user-item graph reconstruction using the learned representations.

A useful tool for graph-structured data is a graph convolutional network (GCN), which is effectively being used in a variety of practical applications. Here, by aggregating the representations of a node's close neighbors, we use GCN to learn the node representations. Afterward, the graph convolutional layer is applied for the derivation of node representation. Then, to preserve the importance of neighboring nodes and feature fusion, the graph attention layer is introduced which aims to update the node representation and attention scores using GAT. The information of local neighbors is propagated using GAT which aims to learn representation and generate predictions using meta-path interactions in the network.

Furthermore, a hierarchical attention approach is developed that uses node and graph level attention to learn node representation from different graphs. Especially, for a given graph, the aim is to develop an attention network that learns node representations via the attention mechanism. For this reason, a graph-level attention mechanism is developed which aims to comprehend the information from various input graphs and aggregate the node representation [12]. Finally, the proposed study is considering aspects as well as rating-based relations between the nodes.

The HotelRec dataset is used for training, validation, and testing. The data of the HotelRec dataset is obtained from TripAdvisor, which contains nearly 50 million reviews. Each review has the followings: hotel URL, author, date, rating, review title, review text, and a property dictionary containing sleep quality, value, rooms, service, cleanliness, and location. This is known to be the largest hotel review dataset constructed so far. The data is represented as a bipartite and heterogeneous graph. Then, the data is split into training (80%), validation (10%), and test (10%) sets. Then, each split is represented as sparse tensors by using Python 3.7 and Tensorflow. For evaluating the model, the following metrics are calculated: AUC and AUPR. Under the experimental setup, our proposed model attains the best AUC value of 0.9232 and AUPR value of 0.7955.

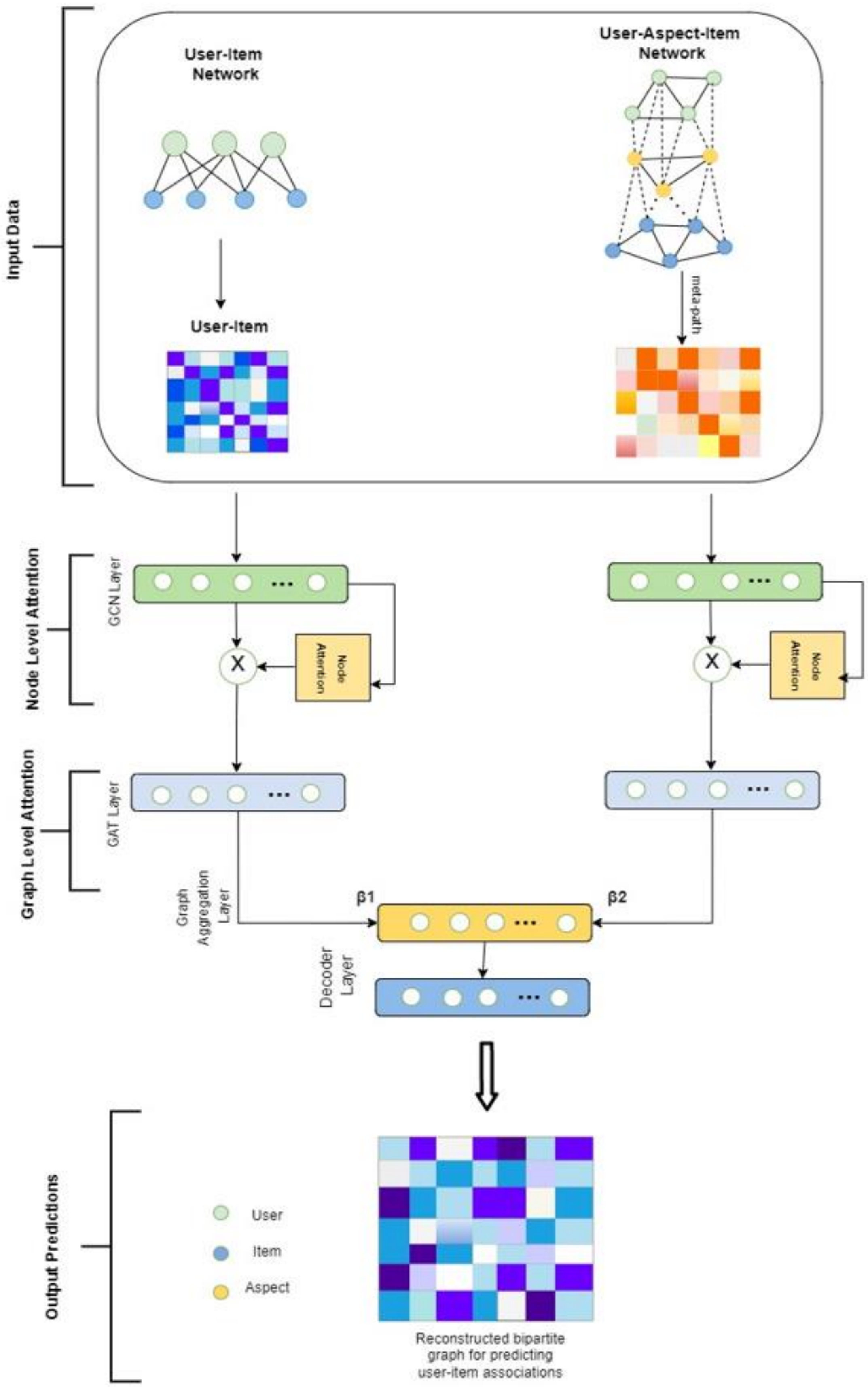

Figure 2: Proposed Graph Attention Networks for Graph Recommendation and Link Prediction

4. Conclusion and Future work

Overall, the STSM stay at the University of Applied Sciences, Berlin focused on the following aspects: (1) to implement the Ensemble Framework of Graph Attention Network model for recommendation and (2) to generate a broader and deeper representation of users, items in the same latent space for generating recommendations and link prediction in heterogeneous graphs.

For future activities, it has been planned to summarise the findings and conclusions of this STSM, with more details, in a conference paper, as a collaboration of the two institutions and COST CA 18232. In this conference paper, we aim at designing and implementing new explainable and transparent recommender systems for complex products that combines multiple criteria, namely past preferences of users, friendship relation among users and check-in time information. Also, if the proposed model can be extended to different domains, it is planned to build the proposed model into SaaS applications.

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