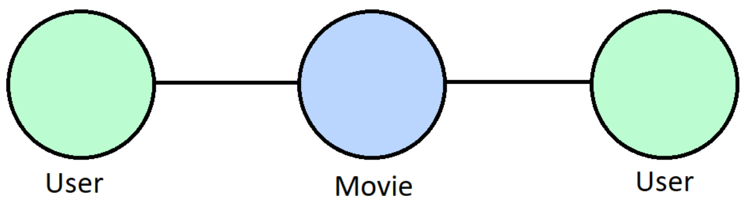
Recommender System with MAGNN Architecture

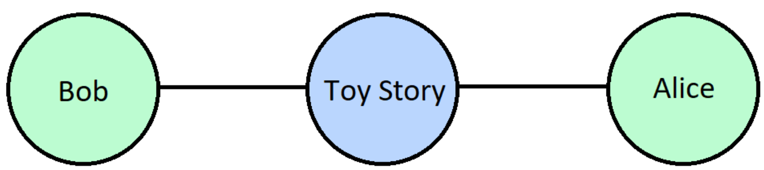
Artyom Makarov

Introduction

Recommender systems play a crucial role in enhancing user experience by providing personalized recommendations based on user preferences. In this report, I present a solution that employs Metapath Aggregated Graph Neural Network (MAGNN) [1] as a recommender system. MAGNN addresses limitations of existing graph models [2], by embedding structural and semantic information from heterogeneous graphs. MAGNN model employs concept of metapath: a metapath is a sequence of edges in a graph that connects two nodes. A metapath instance refers to a specific instance of a metapath in a given graph.



Example of metapath in MovieLens 100k dataset.



Example of metapath instance MovieLens 100k dataset.

Data Analysis

MovieLens 100k dataset provides a heterogeneous graph of users and movies. First of all, I discarded all edges with rating less than 4, because we only want high rated movies to be recommended. I had to drop the ‘zip code’ feature from the user nodes, because it is problematic to encode. Then I applied one hot encoding as well as scaling to remaining features of user nodes and movie nodes. Finally I collected all possible metapath instances for user-movie-user and movie-user-movie metapaths.

Model Implementation

My implementation is a bit simplified implementation of the MAGNN described in the original paper [1]. The MAGNN architecture consists of three key components:

- Node Content Transformation: This encodes input node attributes, so all node types features have the same dimensions.
- Intra-Metapath Aggregation: Encode metapath instances and use self attention to extract only vital features from the given metapath.
- Inter-Metapath Aggregation: Combines messages from multiple metapaths instances. This part is omitted in my work, as there is only one metapath per node.

After all these steps we get node embedding, which captures structural and semantic information from this node. After that I concatenate embedding for the user node with the one for the movie node and perform link prediction.

Model Advantages and Disadvantages

Advantages:

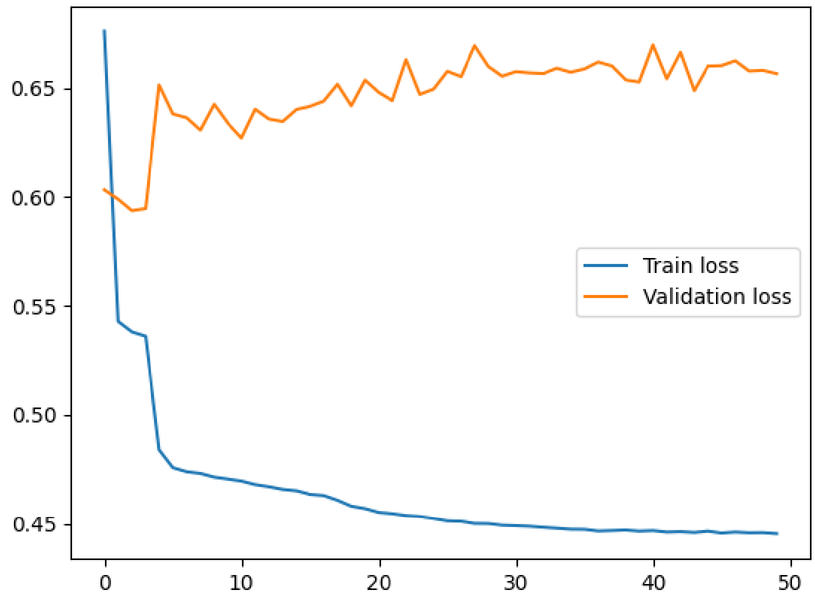
- Information integration: MAGNN effectively captures both structural and semantic information. As mentioned in the original paper [1] “MAGNN achieves state-of-the-art results on three real-world datasets in the node classification, node clustering, and link prediction tasks”.

Disadvantages:

- Computational Complexity: The incorporation of multiple metapaths and the aggregation process can make MAGNN computationally demanding, especially on large graphs. Due to computational limitations, I was only able to use one metapath per node.

Training Process

MovieLens100K was used for training purposes. Training included typical regularization practices for deep learning models, such as dropout and weight decay. As seen on the graph, the model overfit, due to single metapath usage. However it still shows impressive results on test data.



Evaluation
To assess the performance of MAGNN, I employed standard evaluation metrics for recommender systems, including accuracy and mean average precision. To evaluate the performance test dataset graph was used to generate metapaths. All possible combinations of user id and movie id (excluding ones present in the test dataset) was used to evaluate the performance

Results
The model showed an **accuracy score of 0.59** and **mAP of 0.64** on the data described earlier.

In conclusion, the Metapath Aggregated Graph Neural Network (MAGNN) proves to be a powerful solution for recommender systems operating on heterogeneous graphs. Its ability to integrate node content into graph structure contributes to its performance. Despite computational complexity MAGNN is showing promising results on link prediction tasks.