Heterogeneous Graph Neural Network for Session-Based Recommendation with User-Session Constraint

Minjae Park

Abstract—The recommendation system provides users with an appropriate limit of recent online large amounts of information. Session-based recommendation, a sub-area of recommender systems, attempts to recommend items by interpreting sessions that consist of sequences of items. Recently, research to include user information in these sessions is progress. However, it is difficult to generate high-quality user information that includes session information generated by user. In this paper, we consider various relationships in graph created by sessions through HAN. Constraints also force user information to take into account information from the session. It seeks to increase performance through additional optimization in the training process. The proposed model outperformed other methods on various real-world data sets.

Index Terms—Heterogeneous graph neural network, Recommender system, Session-based recommendation

1 INTRODUCTION

The recommendation system is used to provide information that is considered to be preferred by users among the large amount of information that exists online. Session-based recommendation, one of the sub-area of the recommendation system, focuses on a session that consists of a sequence of user interactions with items. Methods that learn using item-user pairs, such as collaborative filtering [1], are not suitable for these scenarios, so there is a growing interest in researching methods optimized for session-based recommendations. The concern with session-based recommendations is to capture patterns of item transitions within a session. To this end, various deep learning-based models [2], [3], that use sessions to learn representations of sessions have been proposed. These models use RNNs to extract sequential features from a sequence of items in a session. However, an issue was raised that only considers item transitions within a single session, not the item transition patterns in other sessions. To solve this problem, there have been attempts [4]–[7] to model the session sequence in the form of a graph and capture their relationship as a GNN. Also, a problem was raised [8], [9] that the user’s preference was not reflected in the session-based recommendation. To solve this problem, [10] creates a heterogeneous graph composed of users and items, and captures their relationship by utilizing a heterogeneous graph neural network. In this way, when the conversion pattern of one session is analyzed, the conversion pattern of another session generated by the user can be utilized, so that the conversion pattern can be captured more efficiently. However, there are limitations to this approach. In heterogeneous graphs, simply averaging aggregate information generated through each meta-path may result in overlooking the importance between meta-path. In addition, if user information is simply aggregated and created, the meaning of the session created by the user may not be considered. For example, interacting with the same books, some users may have preferences in terms of their genre, while others may have preferences in terms of the year of release of those books. Also, since this process simply aggregates the information of the item, it may result in the session’s unique information being ignored. Finally, when simply applying a cross entropy loss when predicting the next session item, other promising candidates may move away from the embedding space. To solve this problem, we use Heterogenous Attention Network [11] to reflect the importance between each meta-path, generate user expressions by reflecting the information of sessions created by each user, and learn by considering candidate items when learning.

2 RELATED WORKS

This section introduces the related works of session-based recommendations.
2.1 Traditional Method
Attempts have been made to create a session-based recommendation system based on collaborative filtering [1] that models the relationship between users and items. Attempts have also been made to interpret the transition pattern of a session based on the Markov chain [12], [13]. These approaches fail to capture the information inherent in complex session switching patterns.

2.2 Deep Learning Method
Deep learning-based methods use RNNs or CNNs to capture the sequential information of a session. GRU4Rec [2] is a prime example of using RNNs for session-based recommendations. In addition to this approach, NARM [3] uses an attention mechanism to focus on more important items. Caser [14] represents the session entries as a matrix and attempts to interpret them as CNNs.

2.3 GNN based Method
Various GNN-based models have been proposed based on the idea of being able to graph the relationships of items within a session. SR-GNN [4] sees transitions between items in a session as nodes in a graph and their relationships between nodes, and uses GNN to try to capture these transition patterns. GC-SAN [7] uses a self-attention mechanism here to try to create a higher quality representation. and LESSR [5] proposes a method that preserves the order of edges in the graph for better representation generation. In GCE-GNN [6], we proposed a method to create two graphs, a session graph and a global entity graph, apply GNN to each, and integrate them.

2.4 Personalized Session-based Recommendation
Personalized session-based recommendations attempt to reflect the user’s information in the session. H-RNN [8] uses hierarchical RNN to capture user preferences from past sessions. A-PGNN [9] transforms each user’s session into a graph and captures session information via GNN. HG-GNN [10] creates a heterogeneous graph of the relationship between users and items and attempts to interpret it using a heterogeneous graph neural network. However, this method does not reflect the session information well in the user’s information.

3 PRELIMINARY
Among the sub-areas of session-based recommendations [15], we are going to cover next item recommendation which aims to predict which item the user will click next in the active session. In this paper, we aim to accurately encode the user’s information with respect to the session in which it was performed for personalized recommendations.

Let $V = \{v_1, \ldots, v_N\}$ and $U = \{u_1, \ldots, u_M\}$ denotes set of items and users. We also denotes session record list of each user as $S_{u_i} = \{s_{u_i,1}, \ldots, s_{u_i,w}\}$ where $s_{u_i,j}$ is $j$-th sessions of user $u_i$. Session $s_{u_i,j}$ is consists of items $\{v_{i,1}, \ldots, v_{i,l}\}$.

Given these items and session information, and current session $S_{u_i,l}$, predicting the next item $v_{i,l+1}$ is the goal of next item prediction. When the information described above is given, the model predict scores $\hat{Y} = \{\hat{y}_1, \ldots, \hat{y}_N\}$ for all items.

4 METHODOLOGY
4.1 Overview
This section details the design of a user-session constrained heterogeneous graph neural network model for personalized session-based recommendations. Using the method proposed in previous study [10], create a heterogeneous graph that takes into account all item interactions of the user and item conversions for each session. Specifically, the edges in the graph represent user-item interactions or item-item interactions. A heterogeneous graph attention neural network selectively captures information of neighboring nodes in a given graph according to their relationship. It uses an encoder that uses a personalized session representation by combining the user’s general preferences and local session preferences. This encoder makes a discriminator to check if a given session was created by the user to generate high-quality user information. Next, we introduce these modules in detail.

4.2 Heterogeneous Global Graph Construction
This subsection describes how to transform training session sequence into a directed heterogeneous graph $G = (V, E)$. Node set $V$ is consists of user and item and Edge set $E$ is consists of two meta-paths item-user and item-item. Each edge is represented by $(v_i, v_j, r)$.

4.2.1 Item-to-Item
In the existing graph-based session recommendation system, a graph was created by considering the relationship between the previous item and the next item. This is because switching between items implies similarity between two items. Referring to previous studies, this paper also creates graphs by reflecting these relationships. This relationship is specifically expressed as two relationships. $(v_i, v_j, r_{out})$ represents the relationship between the previous item $v_i$ and the next item $v_j$, and also creates an inverse relationship $(v_j, v_i, r_{in})$.

4.2.2 Item-to-User
This relationship represents a direct interaction between a user and an item. Specifically, the item node clicked by the user and the user node are connected through this meta-path. It consists of a relationship $(u_i, v_j, r_{clicked,by})$ which means the user $u_i$ clicked on an item $v_j$ and vice versa $(v_j, u_i, r_{clicked,by})$.

In conclusion, the generated graph effectively represents the relationship between items and the relationship between those items and users.

4.3 Heterogeneous Attention Network
We apply Heterogeneous Attention Network to efficiently encode user-item heterogeneous graph. In graph neural network, each user $u_i$ and item $v_i$ represents as embedding $q_{u_i} \in \mathbb{R}^d$ and $p_{v_i} \in \mathbb{R}^d$. $q_{u_i}^{(k)}$ or $p_{v_i}^{(k)}$ means $k$-layer propagation node representations.
4.3.1 Item representation

In heterogeneous graph, there are three meta path connected with item, $R = \{r_{in}, r_{out}, r_{clicked, bg}\}$. First, for each meta path $r_x$, we calculate meta-path specific item representations using Eq (1). $N_r_x(v_i)$ is neighbor nodes of node $v_i$ connected by meta-path $r_x$. $e_n$ can be item $p$ or user $q$ by meta-path.

$$p^{(k+1)}_{v_i, r_x} = \frac{1}{|N_{r_x}(v_i)|} \sum_{n \in N_{r_x}(v_i)} f^{(k)}_{r_x}(e_n)$$

$$p^{(k+1)}_{v_i} = g^{(k)}(p^{(k)}_{v_i}) + \sum_{r_x \in R} \beta_{r_x} \cdot p^{(k+1)}_{v_i, r_x}$$

(1)

Attention $\beta_{r_x}$ is calculated by Eq (2) and final item representation $p_{v_i}$ be final propagation representations $p^{(k)}_{v_i}$.

$$w_{r_x} = \frac{1}{|V|} \sum_{v_j \in V} a^{\top} \cdot \tanh(W_p^{(k+1)} + b)$$

$$\beta_{r_x} = \frac{\exp(w_{r_x})}{\sum_{r_y \in R} \exp(w_{r_y})}$$

(2)

4.3.2 User representation

User node $q$ has only one meta-path $r_{clicked}$, so user node representation $q_{u_i}$ calculated by Eq (3) final user representation $q_{u_i}$ be final propagation representations $q_{u_i}^{(k)}$.

$$q^{(k+1)}_{u_i, r} = \frac{1}{|N_{r}(u_i)|} \sum_{n \in N_{r}(u_i)} f^{(k)}(p^{(k)}_{n})$$

$$q^{(k+1)}_{u_i} = g^{(k)}(q^{(k)}_{u_i}) + q^{(k+1)}_{u_i, r}$$

(3)

4.4 Personalized Session Encoder

In order to model a user’s preference for the current session, we need to consider the general preferences and the preferences presented in the session. It is natural to think that the user’s representations contains general preferences because it created with the items the user has interacted with. Preference that appear in a session can be captured in the sequence of items contained in the session. We use the personalized session encoder introduced in the previous study [10] to generate a representation that includes all of the aforementioned information, and use this representation to predict the next item.

4.4.1 Session Preference Representation

Given the current session $\{v^1, ..., v^t\}$, generate a session embedding $Z$ that reflects the preference through the attention mechanism using the preference query $e_t$ for the session. In this process, not only the item embedding $p_{v_t}$ but also the sequence embedding $l_i \in \mathbb{R}^d$ are important, so combine them like Eq (4)

$$p'_{v_i} = W_c [p_{v_i} | l_i]$$

(4)

Finally, the two pieces of information are combined using a soft attention mechanism using Eq (5) $\sigma$ means sigmoid function.

$$\epsilon_t = v_0^{\top} (W'^c_{r_t} p'_{v_t} + W_{e_t} + b^e)$$

$$\alpha_t = \frac{\exp(\epsilon_t)}{\sum_{j=1}^{t} \exp(\epsilon_j)}$$

$$Z = \sum_{i=1}^{t} \alpha_t p'_{v_i}$$

(5)

Obtain local session preference $C_u$ to calculate Eq (6) using $p'_s$ which obtained through the Eq (5) as the query $e_t$ and get global session preference $O_u$ to calculate Eq (5) using $q_u$ as the query $e_t$. After that, we combine the two preference via Eq (7) to get the final session embedding $S_u$.

$$p'_s = \frac{1}{l} \sum_{i=1}^{l} p'_{v_i}$$

(6)

$$\alpha_c = \sigma (W_s [C_u | O_u])$$

$$S_u = \alpha_c \cdot C_u + \alpha_c \cdot O_u$$

(7)

4.4.2 Discriminator for User-Session Constraint

A discriminator is used which inspired by [16] to ensure that the user’s representation contains not only simply a representation of the items they interacted with, but also the session representation. Discriminator can be used to increase or decrease the amount of mutual information between two representations. Here, the amount of mutual information between the user representations and the user’s session representations is maximized, and the amount of mutual information between the session representations of other users is minimized. The positive and negative scores between the user representations and the session representations are obtained through the following equation. $B$ means training batch.

$$d_{pos} = \sigma (p'_s^{\top} W_d q_u)$$

$$d_{neg} = \prod_{s_n \in B \backslash s} (1 - \sigma (p'_s^{\top} W_d q_{u_n}))$$

(8)

4.5 Prediction and Training

Finally, we directly combine session preference with each item or user representations to get a score for predicting the next item using Eq (9)

$$\hat{y}_t = \text{softmax}(S^{\top} e^{(0)})$$

(9)

The model is optimized by add the two objective functions. The classification loss $L_{cls}$ is optimized via cross entropy loss. $y$ is one-hot vector of ground truth. Another objective function $L_{disc}$ which constraints the user representations is optimized via discriminator loss.

4.5.1 Tuning Loss

When calculate cross entropy loss, It is not calculated for items similar to the next items. This is to avoid semantic confusion. Examples of items similar to the following items are items that users who interacted with the next items have commonly interacted with, or items that have been part of the same session.
\[ L_{cls}(\hat{y}) = - \sum_{i=1}^{V} y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i) \]  
\[ L_{div}(d) = - \log(d_{pos}) - \log(d_{neg}) \]  

5 EXPERIMENT

We perform experiments on three real-world data sets. Last.fm, Xing, and Reddit are widely used in session-based recommendation research and contain user information about each session. The overall data processing and experimental setup method detail followed the method of [10].

5.1 Dataset

- **Last.fm**: Music listening records of about 1000 users collected from a music-related site Last.fm. The goal of this dataset is to recommend artists out of 40,000 artists and groups that users might be interested in. It is processed and used in the same way as in [10].
- **Xing**: The goal of this database is to recommend job openings that users may be interested in. The dataset consists of interaction data between users and job openings. Session records are created using the same method as mentioned in [8].
- **Reddit**: The goal of this dataset is to recommend subreddit pairs where users have commented. This dataset consists of subreddit pairs where users have commented. We treat this dataset in the same approach as [17].

5.2 Baseline

To evaluate the performance of our model, we compare its performance with various previously proposed models.

- **Item-KNN** [1] uses the KNN to recommend items similar to those in the session.
- **GRU4Rec** [2] uses GRU, a type of RNN, to capture information inherent in a session sequence.
- **NARM** [3] uses the Attention mechanism in addition to GRU.
- **SR-GNN** [4] transforms the session sequence into an unweighted directed graph and encodes it using a GGNN layer [18].
- **LESSR** [5] captures sequence information within a graph neural network using GNN and GRU.
- **GCE-GNN** [6] creates a graph considering both the global context and item sequence of the current session, and then creates a session embedding through the graph neural network.
- **H-RNN** [8] uses hierarchical RNNs to capture user preferences between sessions.
- **A-PGNN** [9] converts the session to a graph and encodes it into a GGGN model. It also uses an attention mechanism to reflect the user’s past preferences in session encoding.
- **HG-GNN** [10] transforms sessions and users into a heterogeneous graph and encodes them through a heterogeneous graph neural network. The user’s representation is used as the global session representation and the session representation is used as the local session representation to capture information about the current session through the attention mechanism.

5.3 Comparison

The results of compared to the latest model is presented in Table 1. HG-GNN does not capture user preferences that appear in the session when encoding user information. This aspect is even more pronounced in the Last.fm dataset. Music listening session sequences reflect the unique preferences of users. Even if you listen to the same item, different users may have different reasons for listening to the item. Our constraint forces user expressions to reflect the session’s unique preferences, creating more efficient user expressions. Also, when calculating cross-entropy loss, removing similar items from negative pairs is one of the main factors to improve performance. For example, if a user selects an artist in the same genre as the previous artist when selecting the next artist, there may be more than one answer. This prevents the next item candidates from moving away from the embedding space, enabling more stable learning. In addition, when referring to neighboring nodes to generate item information, reflecting different ratios depending on the relationship leads to an increase in the quality of the item expression and leads to an increase in performance. Also, on other datasets, our model performs better than the other models.

The results of experimenting with various variants of our model are shown in Table 2. wo-HAN means that the Attention module is subtracted from the HAN model, and wo-Discrim means that User-session Constraint using Discriminator is not applied. wo-Loss-Tune means no loss tuning. As a result, it can be seen that all three contributed significantly to the performance improvement.

6 Conclusion

In this paper, we propose a session-based recommendation method through a heterogeneous graph neural network with user representation constraints. In addition to the previous method, the Attention mechanism was applied to create a better item representation, and session constraints were applied to the user representation to produce a higher quality user representation. Finally, we tried to make the training more stable by excluding similar items from the prediction. Experiments have shown that our model is more efficient compared to other session-based models.

References

[1] B. Sarwar, G. Karypis, J. Konstan, and J. Riedl, “Item-based collaborative filtering recommendation algorithms,” in WWW, 2001, pp. 285–295.
[2] B. Hidasi, A. Karatzoglou, L. Baltrunas, and D. Tikk, “Session-based recommendations with recurrent neural networks,” arXiv preprint arXiv:1511.06939, 2015.
[3] J. Li, P. Ren, Z. Chen, Z. Ren, T. Lian, and J. Ma, “Neural attentive session-based recommendation,” in CIKM, 2017, pp. 1419–1428.
[4] S. Wu, Y. Tang, Y. Zhu, L. Wang, X. Xie, and T. Tan, “Session-based recommendation with graph neural networks,” in AAAI, vol. 33, no. 01, 2019, pp. 346–353.
[5] T. Chen and K. C.-W. Wong, “Handling information loss of graph neural networks for session-based recommendation,” in KDD, 2020, pp. 1172–1180.
### Table 1: Experiment results for three datasets

| Datasets | Metric | @5 | ItemKNN | GRU4REC | NARM | SR-GNN | LESSK | GCE-GNN | H-GNN | A-PGNN | HG-GNN | Ours |
|----------|--------|----|---------|---------|------|--------|-------|---------|-------|--------|--------|------|
| Last.fm  | HR     | 5  | 10.90   | 8.47    | 10.29 | 11.89  | 12.96 | 12.83   | 15.83 | 17.13  | 19.39  | 13.80 |
|          |        | 10 | 8.47    | 10.29   | 11.89 | 12.96  | 12.83 | 15.83   | 17.13 | 19.39  | 13.80  | 13.09 |
|          | MRR    | 5  | 4.02    | 4.71    | 6.09  | 7.23   | 8.24  | 7.60    | 6.71  | 7.34   | 7.35   | 7.75 |
|          |        | 10 | 4.81    | 5.29    | 6.71  | 7.85   | 8.82  | 8.32    | 7.39  | 8.01   | 8.18   | 8.38 |
| Xing     | HR     | 5  | 8.70    | 10.35   | 13.51 | 13.38 | 14.84 | 16.98   | 10.72 | 14.23  | 17.25  | 17.58 |
|          |        | 10 | 11.85   | 13.15   | 17.31 | 16.71 | 16.77 | 20.86   | 14.36 | 17.01  | 20.30  | 20.77 |
|          | MRR    | 5  | 3.54    | 5.94    | 8.87  | 11.05 | 11.65 | 12.32   | 10.16 | 12.23  | 12.53  | 12.43 |
|          |        | 10 | 5.42    | 6.36    | 9.37  | 9.39  | 12.13 | 11.65   | 7.74  | 10.58  | 12.79  | 12.99 |
| Reddit   | HR     | 5  | 21.71   | 33.72   | 33.25 | 34.96 | 36.03 | 36.30   | 44.76 | 49.10  | 51.08  | 51.28 |
|          |        | 10 | 30.32   | 41.73   | 40.52 | 42.38 | 43.27 | 45.16   | 53.44 | 58.23  | 60.51  | 61.01 |
|          | MRR    | 5  | 11.74   | 24.36   | 24.56 | 25.90 | 26.45 | 26.65   | 32.13 | 35.34  | 35.46  | 35.58 |
|          |        | 10 | 12.88   | 25.42   | 25.52 | 26.88 | 27.41 | 27.70   | 33.29 | 34.62  | 36.89  | 36.95 |

### Table 2: Experiment results with model variants

| Datasets | Metrics | HR@5 | HR@10 | MRR@5 | MRR@10 |
|----------|---------|------|-------|-------|--------|
| Last.fm  | wo-HAN  | 13.76| 19.94 | 7.64  | 8.23   |
|          | wo-Discrim | 13.74| 19.65 | 7.58  | 8.26   |
|          | wo-Loss-Tune | 13.59| 19.64 | 7.45  | 8.21   |
|          | Ours    | 13.80| 19.95 | 7.75  | 8.38   |