Heterogeneous Graph Neural Network for Personalized Session-Based Recommendation with User-Session Constraints

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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 representation that includes session representations generated by user. In this paper, we consider various relationships in graph created by sessions through Heterogeneous attention network. Constraints also force user representations to consider the user’s preferences presented in the session. It seeks to increase performance through additional optimization in the training process. The proposed model outperformed other methods on various real-world datasets.

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

1 INTRODUCTION

The recommender 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 which is 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 item sequence in the form of a graph and capture their relationship as a graph neural network. 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 same 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 representation is simply aggregated item representations, 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 vector space. To solve this problem, we use Heterogeneous Attention Network [11] to reflect the importance between each meta-path. And we generate user representation by reflecting the information of sessions created by each user, and learn by considering candidate items.

- We encode heterogeneous graph using a HAN to reflect the importance of each meta-path. In this process, HAN captures the importance of the relationships between item and item, items and users to create higher-quality representations.
- When we create user representations, we ensure that each user includes a representation of the session created by user. Specifically, the constraints maximizes the amount of mutual information between the user and session.
- We try to make learning more stable by excluding items similar to the next item from the learning process.

2 RELATED WORKS

This section introduces the related works of session-based recommendations. The content of related works is largely composed of traditional methods, deep learning methods, graph neural network-based methods, and personalized session-based recommendations.
2.1 Traditional Method
Attempts have been made to create a session-based recommendation system based on collaborative filtering [11] 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] transforms transitions between items in a session into a graph and attempts to capture patterns within these transitions using GGNN. 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 item graph, apply GNN to each, and integrate them.

2.4 Personalized Session-based Recommendation
Personalized session-based recommendations attempt to reflect the user’s preference 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 representation.

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 \( S_{u_i} = \{s_{u_i,1}, \ldots, s_{u_i,L}\} \) where \( s_{u_i,j} \) is \( j \)-th sessions of user \( u_i \). Session \( s_{u_i,j} \) is consists of items \( \{v_{1j}, \ldots, v_{lj}\} \).

Given these items and session information, and current session \( S_{u_i,t} \), predicting the next item \( v_{i,t+1} \) 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 heterogeneous graph neural network model for personalized session-based recommendations with user-session constraints. Using the method proposed in previous study [10], create heterogeneous graphs that reflect item conversion in each session and all user-item interactions. Specifically, the edges in the graph represent user-item interactions or item-item interactions. A heterogeneous graph attention network selectively captures information of neighbor 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 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 \( V \) consists of user and item and Edge set \( E \) 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, we 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 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 \((u_i, v_i, r_{clicked})\) which means the user \( u_i \) clicked on an item \( v_j \) and vice versa \((v_i, u_i, r_{clicked\_by})\).

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, \( R = \{r_{in}, r_{out}, r_{clicked, by}\} \). 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 meth-path.

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

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

\[
w_{r_x} = \frac{1}{|V|} \sum_{v_i \in V} a^T \cdot \text{tanh} \left( Wp^{(k+1)}_{v_i,r_x} + b \right)
\]

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

4.3.2 User representation

User node \( u \) has only one meta-path \( r_{clicked} \), so user node representation \( q_u \), calculated by Eq 3 final user representation \( q^{(k)}_u \) be final propagation representations \( q^{(k)}_{u,v_i} \).

\[
q^{(k+1)}_{u,v_i} = \frac{1}{|N(u_i)|} \sum_{n \in N(u_i)} f^{(k)}(p^{(k)}_n)
\]

\[
r^{(k+1)}_{u,v_i} = g^{(k)}(q^{(k)}_u) + \sum_{r_x \in R} \beta_{r_x} \cdot r^{(k+1)}_{v_i,r_x}
\]

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 [16] 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 \( \{v^1, ..., v^j\} \), 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 \( p_{v_i} \) but also the sequence embedding \( l_j \in \mathbb{R}^d \) are important, so combine them like Eq 4

\[
p_{v_i} = W_e[p_{v_i}, l_j]
\]

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

\[
e_i = \sigma(v_0^T p_{v_i} + W^ce_t + b^c)
\]

\[
\alpha_i = \frac{\exp(e_i)}{\sum_{j=1}^{l} \exp(e_j)}
\]

\[
Z = \sum_{i=1}^{l} \alpha_i p_{v_i}
\]

Obtain local session preference \( C_u \) to calculate Eq 5 using \( p_{v_i} \) which obtained through the Eq 6 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 \( S_u \).

\[
p'_s = \frac{1}{T} \sum_{i=1}^{l} p'_{v_i}
\]

\[
\alpha_c = \sigma(W_s[C_u,O_u])
\]

\[
S_u = \alpha_c \cdot C_u + (1 - \alpha_c) \cdot O_u
\]

4.4.2 Discriminator for User-Session Constraints

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. 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.

\[
d_{pos} = \sigma(p'_s^T W_d q_u)
\]

\[
d_{neg} = \prod_{s_n \in B \setminus s} (1 - \sigma(p'_s^T W_d q_u))
\]

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

\[
\hat{y}_i = \text{softmax}(S^T e^{(0)})
\]

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 constrains 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.
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 constraints forces user representations to reflect the session’s unique preferences, creating more efficient user representations. 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 vector space, enabling more stable learning.

In addition, when referring to neighbor nodes to generate item representations, reflecting different items depending on the relationship leads to an increase in the quality of the item representation 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 not used in the HAN model, and wo-Discrim means that User-session Constraints 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 personalized 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 constraints were applied to the user representation to produce a higher quality 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.

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| Datasets | Metric | @5       | @10      | HR       | MRR      | HR       | MRR      | HR       | MRR      | HR       | MRR      | HR       | MRR      | Ours     |
|----------|--------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| Last.fm  |        |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | ItemKNN | 6.73     | 8.47     | 10.29    | 11.89    | 12.96    | 12.83    | 13.92    | 13.10    | 13.09    | 13.80    | 13.88    | 17.25    | 17.38    |
|          | GRU4REC | 10.90    | 12.86    | 15.03    | 16.90    | 17.88    | 18.28    | 15.83    | 17.13    | 19.39    | 19.95    | 12.43    | 12.99    |          |
|          | NARM    |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | LESSK   | 4.02     | 4.71     | 6.09     | 7.23     | 8.24     | 7.60     | 6.71     | 7.31     | 7.35     | 7.75     | 8.38     |          |          |
|          | GCE-GNN | 4.81     | 5.29     | 6.71     | 7.85     | 8.82     | 8.32     | 7.39     | 8.01     | 8.18     |          |          | 12.99    |          |
|          | H-GNN   |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | A-PGNN  |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | HG-GNN  |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | Ours    |          |          |          |          |          |          |          |          |          |          |          |          |          |
| Xing     |        |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | ItemKNN | 8.70     | 10.35    | 13.51    | 13.38    | 14.84    | 16.98    | 10.72    | 14.23    | 17.25    | 17.38    |          |          |          |
|          | GRU4REC | 11.65    | 13.15    | 17.31    | 16.71    | 16.77    | 20.86    | 14.36    | 17.01    | 20.30    | 20.77    |          |          |          |
|          | NARM    | 3.04     | 3.94     | 5.97     | 8.87     | 11.98    | 11.14    | 10.26    | 12.25    |          |          |          |          |          |
|          | LESSK   | 5.42     | 6.36     | 9.37     | 9.39     | 12.13    | 11.65    | 7.74     | 10.58    | 12.79    |          |          |          |          |
|          | GCE-GNN |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | H-GNN   |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | A-PGNN  |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | HG-GNN  |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | Ours    |          |          |          |          |          |          |          |          |          |          |          |          |          |
| Reddit   |        |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | ItemKNN | 21.71    | 33.72    | 33.25    | 34.96    | 36.03    | 36.30    | 44.76    | 49.10    | 51.08    | 51.28    |          |          |          |
|          | GRU4REC | 30.32    | 41.73    | 40.52    | 42.38    | 43.27    | 45.16    | 53.44    | 58.23    | 60.51    |          |          |          |          |
|          | NARM    | 12.74    | 24.36    | 24.56    | 25.90    | 26.45    | 26.65    | 32.13    | 33.54    | 35.46    |          |          |          |          |
|          | LESSK   | 12.88    | 25.42    | 25.52    | 26.88    | 27.41    | 27.70    | 33.29    | 34.62    | 36.89    |          |          |          |          |
|          | GCE-GNN |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | H-GNN   |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | A-PGNN  |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | HG-GNN  |          |          |          |          |          |          |          |          |          |          |          |          |          |
|          | Ours    |          |          |          |          |          |          |          |          |          |          |          |          |          |

**TABLE 1:** Experiment results for three datasets

| Datasets | Metric | @5       | @10      | HR@5     | MRR@5    | HR@10    | 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     |          |          |

**TABLE 2:** Experiment results with model variants

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