SUPPLEMENTARY MATERIALS FOR GRAPH NEURAL NETWORKS WITH INTRA- AND INTER-SESSION INFORMATION FOR SESSION-BASED RECOMMENDATION

Hongying Liu, Tianwen Zhu, Fanhua Shang, Guoliang Ma, Muyao Liu, Yuanyuan Liu*

School of Artificial Intelligence, Xidian University

1. RELATED WORK

In this section, we briefly review some representative related work on session-based recommendations including the conventional methods, and sequential methods. Moreover, some graph neural networks are also introduced.

1.1. General Recommendation

General recommendation is usually implemented on the base of item-to-item recommendation methods. Items that frequently occur together within sessions are considered to be similar. In this setting, a similarity matrix for the item-to-item relation is computed previously with the utilization of session data. For instance, the collaborative filtering method [1] is proposed to capture user's general interests. In addition, the matrix factorization methods [2, 3, 4] are utilized by factorizing the rating matrix of user-item into two low-rank matrices. Each of the low-rank matrices is used to represent general interests with latent vectors of users or items.

1.2. Sequential Recommendation

Sequential recommendation methods use the previous sequential connections between the user behaviors to predict users' next action based on Markov chains and deep learning models. Based on Markov chains, [5] employs Markov decision processes and uses the transition probabilities between items to compute the next recommendation. FPMC [6] can obtain a better prediction result through the factorization of users' personalized probability transition matrices, considering sequential behavior between each two adjacent clicks.

Deep learning has been applied successfully in various fields, such as natural language processing [7, 8], conversation machine [8]. Among numerous deep neural networks, it has been proven that the recurrent neural networks (RNNs) are effective in sequential data, such as sequential next prediction [9], location prediction [10], and next basket recommendation [11]. [12] is the first work to use RNNs for solving session-based recommendation problems. [13] uses parallel RNNs to solve this problem. Both [12] and [13] are fine for modeling sequential data because they can consider the historical behavior of users in predicting the next click. Subsequently, [14] is proposed to improve the performance of session-based recommendation with RNNs, which uses a data augmentation technique and takes into consideration temporal shifts of user behaviors. In [11], RNNs are utilized to obtain the dynamic representation from each basket based on dynamic recurrent model. [15] combines the neighborhood-based method with RNNs to utilize the sequential information. NARM [16] employs the attention mechanism to obtain main purpose of users from the hidden states based on RNNs. STAMP [17] is proposed to obtain users' current interests and general interests.

1.3. Graph Neural Networks

In recent years, graph neural networks (GNNs) have achieved significant development in various areas, e.g., social networks [18, 19], molecular structure [20], knowledge graphs [21]. Any data can be represented as nodes and be constructed edges. DeepWalk [22] is regarded as the first graph embedding method according to the idea of representation learning and word2vec [23], using skip-gram model on the random walks. Meanwhile, other methods such as node2vec LINE [24], TADW [25] and [26] are the most representative.

As for nodes embedding, convolutional methods on graph neural networks can be divided into two categories: spectral and non-spectral domain. Graph convolutional network [18] simplifies the approximation of graph Laplacian. Graph Neural Networks (GNNs) [27, 28] are proposed to generate graph representation. [29] employs gated recurrent units. Different from the tasks handled by Convolutional Neural Networks (CNNs), GNNs focus on graph representation [30], node classification [18] and link prediction [31]. So far, GNNs have been applied in many fields such as image segmentation [32], action recognition [33], and session-based recommendation system [34, 35].

2. OUR INTRA- AND INTER-SESSION INFORMATION APPROACH FOR SESSION-BASED RECOMMENDATION

In this section, we depict our GIISR method in detail.

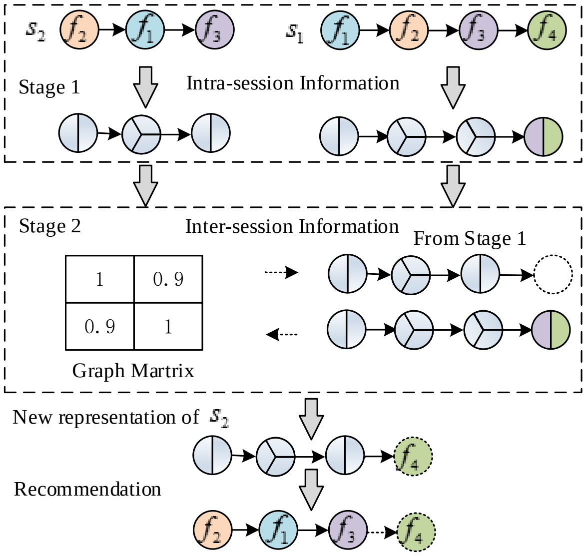


Fig. 1. An example of information propagation in our two stage method GIISR.

2.1. Two-stage Information Propagation

An example of the two-stage information propagation in our method is illustrated in Figure 1. In Stage 1, two sessions: $s_1 = \{f_1, f_2, f_3, f_4\}$ and $s_2 = \{f_2, f_1, f_3\}$ are processed by GCN and MRGNN. Then the intra-session information has been fused. For example, as f_1 follows f_2 in session s_2, it may contain information of f_2. And similarly, in session s_1, f_2 may fuse information from f_1 and f_3. In Stage 2, the session vectors have similarities as they include intra-session information from Stage 1. Therefore, we can calculate the similarity between sessions and construct an inter-session graph matrix. Then through soft-attention, the final recommended item is attained as f_4 for session s_2.

3. EXPERIMENTAL DETAILS

3.1. Implementation Details

The details of the experimental datasets are shown here. The Yoochoose dataset is released by RecSys Challenge 2015, which consists of a series of user-click events data from an e-commerce website in six months. The Diginetica dataset is obtained from CIKM Cup 2016, for which only the transactional data is used.

For the sake of fair comparison, following [16, 34], we use the items with length larger than 1 and appearing greater than 4 times in all datasets. So that the Yoochoose dataset consists of 7,981,580 sessions and 37,483 items, while the Diginetica dataset consists of 204,771 sessions and 43097 items. Following [14], we use all the session $S = \{s_1, s_2, \cdots, s_n\}$ to split the input sequences and corresponding labels, where n is the number of sessions. The single input sequence is represented as $s_i = \{f_{i,1}, f_{i,2}, \cdots, f_{i,m}\}$, where m is the length of the session s_i. And thus, we generate sequences and labels as $([f_{i,1}], f_{i,2}), ([f_{i,1}, f_{i,2}], f_{i,3}), \cdots, ([f_{i,1}, f_{i,2}, \cdots, f_{i,m-1}], f_{i,m})$, where $[f_{i,1}, f_{i,2}, \cdots, f_{i,m-1}]$ is the sequence and $f_{i,m}$ denotes the label. Following [17, 34], we adopt the common fractions 1/64 and 1/4 for Yoochoose dataset. The statistics of these datasets are shown in Table 1.

Table 1. Statistics of datasets used in this study.

Statistics	Yoochoose 1/64	Yoochoose 1/4	Diginetica
clicks	557,248	8,326,407	982,961
training sessions	369,859	5,917,745	719,470
test sessions	55,898	55,898	60,858
items	16,766	29,618	43,097
average length	6.16	5.71	5.12

3.2. Baseline Methods

POP and S-POP recommend the top-N popular items on the frequency of their occurrences in the training set. Even though they are simplicity, the performance on real-world datasets proved it a strong baseline in certain domains.

Item-KNN [36] recommends the candidate item that is similar to existing items based on the Cosine similarity between them in the sessions. Besides, in order to get rid of the rarely clicked items with coincidental high similarities, a regularization is also utilized in this process.

BPR-MF [37] utilizes stochastic gradient descent to optimize a pairwise ranking objective funciton. The mean of similarities between the candidate's and the existing items' latent factors are used to evaluate the score of recommendation.

FPMC [6] is a hybrid model, predicting sequentially based on Markov chain for the next-basket recommendation. Besides, the latent representations of users will not be considered when evaluating the scores of recommendation.

GRU4Rec [12] consists of many GRU units, which constitutes a deep RNN model to predict user sequences for session-based recommendation. A session-parallel mini-batch training process, as well as ranking-based loss functions, are employed to promote the training.

NARM [16] utilizes the attention mechanism to obtain main purpose from the hidden states of RNN. Then the recommendations are generated by the final representation, which combines with the sequential behavior.

STAMP [38] employs both of users' overall interests for the current session and their interests for the last click currently.

STAN [39] employs recent session and the position of an item in a current session. In inter-session, the recommendable position of the item is also used.

SR-GNN [34] utilizes a GNN and soft-attention mechanism to consider the complex transitions of items.

Table 2. Performance of GIISR with different number of inter-sessions.

Dataset	k=7		k=8		k=9		k=11		k=15		k=20	
	P@20	MRR@20	P@20	MRR@20	P@20	MRR@20	P@20	MRR@20	P@20	MRR@20	P@20	MRR@20
Yoochoose 1/64	70.32	31.07	70.81	31.69	**70.92**	**32.06**	70.67	31.42	70.41	31.26	70.00	30.93
Yoochoose 1/4	71.37	31.96	71.42	32.13	71.62	32.26	71.64	32.29	**71.95**	**32.57**	71.47	32.13
Diginetica	52.31	18.39	52.26	18.37	52.40	18.44	52.41	18.53	**52.48**	**18.55**	52.40	18.62

Both P@20 and MRR@20 are widely used as evaluation metrics. P@20 (Precision) represents the proportion of all test cases which has correctly recommended items amongst the top-20 items. MRR@20 (Mean Reciprocal Rank) is the average of reciprocal ranks of all desire items. We set the reciprocal rank to 0 if the rank exceeds 20. It is important in the field of recommendation systems because it takes into account the ranking order of recommendation list.

3.3. Analysis on the Similarity Metrics for Inter-session Graph

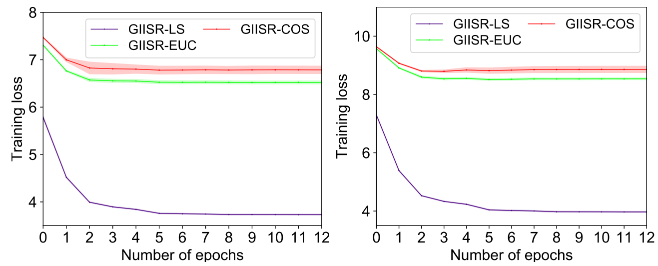
In this subsection, we analyse our GIISR with different similarity metrics for constructing the inter-session graph as shown in Table 3. The following three metrics are compared: (1) similarity with the cosine distance (GIISR-COS); (2) similarity with the Euclidean distance (GIISR-EUC); (3) Euclidean distance is calculated at first, and then utilize local-scaling method to compute the similarity (GIISR-LS).This is also our original GIISR. Note that we fix batch size to 100, and $k = 10$ for all these datasets.

It can be observed that the performance of GIISR-LS is superior to the other two methods. The values of P@20 and MRR@20 are higher than GIISR-COS and GIISR-EUC. This validates the effectiveness of our GIISR with the metric of local scaling. Furthermore, the table shows that the performance of GIISR-ECU is better than GIISR-COS, which indicates that the Euclidean distance is more suitable for these relative low-dimensional datasets.

In addition, the training loss of GIISR-COS, GIISR-EUC, and GIISR-LS are shown in Figure 2. It can be seen that the training loss of both GIISR-COS and GIISR-EUC is much higher than GIISR-LS, which demonstrates that the GIISR with local scaling metric obtains better convergence results. Moreover, the standard errors of each studied metric show that the GIISR-LS is more stable than other metrics. This also verifies the effectiveness of the local scaling metric for construction of the inter-session graph.

3.4. Analysis on the Number of Inter-sessions

In this subsection, we analyze the influence of the number of inter-sessions k (in Eq.(8) in the main paper) on performance of GIISR in Table 2. We also fix batch size to 100. It can be seen that the optimal number of inter-sessions varies with



(a) Yoochoose 1/64 (b) Diginetica

Fig. 2. The training loss of GIISR with different similarity metrics. Note that the standard error is also plotted for each case.

Table 3. The performance of GIISR with different similarity metrics in constructing inter-session graph.

Method	Yoochoose 1/64		Yoochoose 1/4		Diginetica	
	P@20	MRR@20	P@20	MRR@20	P@20	MRR@20
GIISR-COS	25.70	6.47	24.58	6.48	5.35	1.18
GIISR-ECU	31.23	8.05	33.45	11.38	8.29	1.90
GIISR-LS	**70.86**	**31.61**	**71.67**	**32.42**	**52.47**	**18.87**

different datasets. For Yoochoose 1/64, when the value of k is around 9, the performance is highest. And when k is around 15, the performance of Yoochoose 1/4 and Diginetica is better than that of other settings. In summary, the value of k can be set around 10 for other datasets.

Table 4. The performance of GIISR with different structure in the inter-session stage.

Method	Diginetica		Yoochoose 1/64	
	P@20	MRR@20	P@20	MRR@20
GIISR-FCN	20.08	3.8	30.82	19.10
GIISR (Graph)	**52.48**	**18.55**	**70.92**	**32.06**

3.5. The Ablation of the Graph in Inter-session Stage

In the second stage of our GIISR, we utilize a local sensitive inter-session graph to aggregate the relation between different sessions. In order to show its effectiveness, we replace the graph with a three-layer fully connected neural network (FCN). Note that consider the size of the datasets, we do not use deeper networks for this experiment. The experimental results are provided on yoochoose 1/64 and yoochoose 1/4 datasets, listed in Table 4. Obviously, the performance of our GIISR with the graph is much higher than that with a three-layer neural network, since our local sensitive inter-session graph is devised for accurate computation for the similarity between sessions. This result confirmed the importance and the effectiveness of our local sensitive inter-session graph in the second stage.

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