Journal of Computing and Electronic Information Management
ISSN: 2413-1660 | Vol. 10, No. 1, 2023

Session-based Recommendation with Preference Interaction

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Abstract: Graph neural network have achieved great success in session-based recommendation. Recently, some works have achieved improvement by incorporating income and outcome adjacent matrices to generate global and local preferences, and directly model the two preferences to build session representation. However, firstly, we observe that the income matrix and outcome matrix of a session have no strong relevance, and their concatenation may introduce noise for building two preferences. Secondly, we find the global and local preferences can benefit from each other, and collaborative information from neighborhood sessions may help to improve recommendation performance. Therefore, we propose a session-based recommendation with preference interaction from separate income adjacent matrix and outcome adjacent matrix framework, which includes two parallel modules: An Income Session Representation Encoder (ISE) and an Outcome Session Representation En-coder (OSE). A fusion gating mechanism is introduced to balance the importance of session representations resulting from ISE and OSE. The experimental results show that our model obviously outperforms other state-of-the-art methods on Yoochoose and Diginetica datasets.

Keywords: Graph neural network; Session-based recommendation; Item-self information.

1. Introduction

Session-based recommendation (SR) is to predict which item a user will click next, only based on his/her current sequential session data without user identification [1]. It plays a significant role in recommendation systems, such as ecommerce and search, since it directly helps users alleviate the problem of infor-mation overload in many web applications.

Due to the highly practical value in both industry and ac-ademic, many approaches have been proposed till the present moment. The classic approach is Markov Chain (MC), which predicts the user's next clicked item based on the previous one. With this assumption, independent combinations of past behaviors restrict the prediction accuracy. Recently, the development of deep learning promotes a proliferation of recommendation using deep neural network [1], [2]. However, these methods model the session representation with single way transitions between adjacent items in a session, which ignore the complex transitions among distant items.

To model the complex item transitions, graph neural network (GNN) has achieved state-of-the-art performance and shown efficiency in SR [3], and these methods get satisfactory results and are proved efficient. However, in each session, we observe that concatenating the income and outcome adjacent matrices may introduce extra relationship between no interactive items. Therefore, it is unreasonable to encode the income and outcome adjacent matrix together into generating the representation of the current item. Beyond that, we discover that global preference is com-posed of local preferences at different time and local pref-erences fluctuate around the global preference, which indi-cates the two preferences are dependent and have mutual influence between them. Additionally, collaborative infor-mation plays an important role in modeling the session representation and has been studied for many years. In order to take preference dependency and collaborative information into consideration simultaneously, we introduce parallel co-attention mechanism into our framework.

In this paper, in order to address the above issues, we propose a session-based recommendation with preference interaction from separate income adjacent matrix and outcome adjacent matrix (SR-IOPI) framework, which contains two parallel modules: an income session representa-tion encoder (ISE) and an outcome session representation encoder (OSE). The ISE models the income information of the session with the help of gated GNN and parallel co-attention mechanism. It learns a unified income session representation by combining two preferences: an income global-aware local preference and an income local-aware global preference. The OSE models the outcome infor-mation of the session with the help of GNN and parallel co-attention mechanism. It also learns a unified outcome ses-sion representation by combining two preferences: an outcome global-aware local preference and an outcome local-aware global preference. The parallel co-attention mechanism in ISE and OSE is based on a block which consists of the ongoing session and its neighborhood sessions. Finally, SR-IOPI introduces a fusion gating mechanism to combine the session representations generating from ISE and OSE, and calculates a recommendation score for each candidate item. The experimental results show our model obviously outperforms other state-of-the-art methods on Yoochoose and Diginetica datasets.

2. Methodology

In this paper, we propose a session-based recommendation with preference interaction from separate income adjacent matrix and outcome adjacent matrix framework to make recommendation. The basic idea of SR-IOPI is to separately use income connection data via GNN and parallel co-attention mechanism and outcome connection data with GNN and parallel co-attention mechanism to improve the recommendation performance. As shown in Figure 1, SR-IOPI consists of three main components: an income session representation encoder (ISE), an outcome session representation encoder (OSE), and a recommendation decoder. First of all, a session sequence is modeled as a session graph. For ISE, the session graph is proceeded to build node vectors through gated GNN. Based on node vectors, the income local preference and income global preference of the session are built. Then, with the help of sessions in a block, the two preferences are updated by a preference interaction from the ongoing session itself and its neighborhood sessions through the parallel co-attention mechanism. After that, the two new updated representations (income global-aware local preference and income local-aware global preference) are concatenated to generate a unified income session representation. For OSE, similar to the process of ISE, the OSE generates a unified outcome session representation. Finally, the outputs of ISE and OSE are fed into the recommendation decoder where fusion gating mechanism is used to balance the information from ISE and OSE for recommendation. The output is the recommend probability of each candidate item.

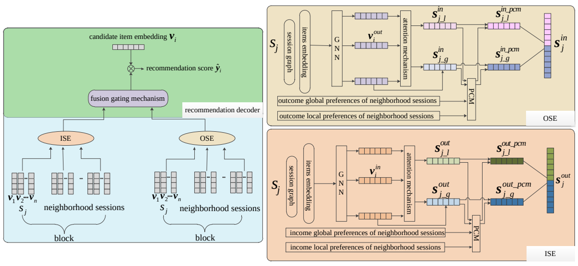

Figure 1. The framework of the proposed SR-IOPI

3. Results and discussion

3.1. Datasets

We conduct experiments on Yoochoose and Diginetica datasets from RecSys Challenge2015 and CIKM Cup 2016, respectively. The training sessions, test sessions and items of Yoochoose 1/64 are 430328, 55464 and 37484, separately. The training sessions, test sessions and items of Yoochoose 1/4 are 6145883, 55861 and 37484, separately. The training sessions, test sessions and items of Diginetica are 719470, 60858 and 43098, separately.

3.2. Model comparisons

The performances of baseline methods and our proposed method SR-IOPI in terms of Recall@20 and MRR@20 are shown in Table 1. The values are average results of five times on each model.

From the Table 1, we can observe that:

In traditional methods, the evaluation metrics of FPMC based on MC are higher than S-POP which are based on co-occurrence items. It indicates consecutive items have dependency relationship. Besides, the performance of Item-KNN is better than FPMC. It denotes the last-clicked item plays a key role in recommendation.

For the methods which only model the ongoing session information, the methods that based on GNN (SR-GNN, TAGNN, and STAN) achieve improvements over the RNN-based methods (GRU4Rec, NARM). This may be because graph-structured data is able to capture more complex item transition patterns, and it verifies that GNN is friendly to model the session information. Despite CSRM achieves the best performance in baseline methods, our proposed SR-IOPI achieves significant results over CSRM. Considering their difference, SR-IOPI not only explores the helpfulness of neighborhood sessions, but also deeply studies the mutual guided relationships between two interests in the ongoing session, whereas CSRM does not make further exploration of dependency relationship between two interests in the ongoing session. It indicates that efficiently explore potential information of a session can assure high recommendation performance.

Table 1. Comparisons with baseline methods

Method	Yoochoose 1/64		Yoochoose 1/4		Diginetica	
	Recall @20	MRR @20	Recall @20	MRR @20	Recall @20	MRR @20
S-POP[4]	30.44	18.35	27.10	17.77	21.06	13.68
FPMC [5]	45.62	15.01	51.52	21.21	26.53	8.95
Item-KNN[6]	51.60	21.44	52.34	21.69	28.75	9.36
GRU4Rec[7]	66.70	22.89	65.66	28.24	44.56	14.32
NARM [8]	68.32	28.34	69.10	29.13	48.32	16.29
CSRM [2]	71.28	30.31	73.12	31.49	51.42	18.47
SR-GNN[3]	69.17	30.12	69.37	29.47	51.03	17.07
TAGNN[9]	71.05	31.12	72.79	32.13	51.09	18.11
STAN [10]	69.45	28.74	70.07	28.89	50.97	18.48
SR-IOPI	**77.41**	**39.82**	**76.72**	**42.44**	**71.19**	**41.32**
improvement	**+8.6%**	**+27.96%**	**+4.9%**	**+32.09%**	**+38.45%**	**+123.59%**

3.3. Influence of different encoders

To illustrate the effect of every encoder in our model, we compare SR-IOPI with three variants SR-I, SR-O, and SR-IO. SR-I denotes the session representation is generated only from income session representation encoder and without preference interaction. SR-O refers that the session representation is built merely from outcome session representation encoder and without preference interaction. SR-IO refers that the session representation is produced merely from income and outcome session representation encoder with fusion gating mechanism, and without preference interaction. Table 2 shows the results of SR-I, SR-O, and SR-IO for SR.

Table 2. Performance comparison with different encoders

Models	Yoochoose 1/64		Yoochoose 1/4		LastFM	
	Recall @20	MRR @20	Recall @20	MRR @20	Recall @20	MRR @20
SR-I	70.48	31.00	70.04	29.88	50.99	16.99
SR-O	70.56	31.08	69.72	29.80	51.14	16.90
SR-IO	71.40	31.59	70.71	30.44	51.52	17.12

From the Table 2, we can observe that all three models perform better than GRU4Rec, NARM, and STAMP, which indicates again that modeling the session as graph-structured data is friendly to recommendation. Compared with SR-GNN, TAGNN, STAN, and SR-IEM, the result of SR-IO is higher. It demonstrates that individually encoding income connection and outcome connection is reasonable. Additionally, SR-I performs worse than SR-O on Yoochoose 1/64 dataset, and SR-O performs worse than SR-I on Yoochoose 1/4 dataset. This demonstrates that SR-I and SR-O are irrelevance and both important for SR tasks. Additionally, the result of SR-IO confirms the usefulness of fusion gating mechanism for better recommendation.

3.4. Influence of parallel co-attention mechanism

To investigate the effect of PCM in each encoder, we also conduct independent income session representation encoder (SR-ISE) and outcome session representation encoder (SR-OSE). Table 3 shows the results of SR-ISE, SR-OSE and SR-IOPI for SR.

Table 3. Performance comparison on different encoders

Models	Yoochoose 1/64		Yoochoose 1/4		LastFM	
	Recall @20	MRR @20	Recall @20	MRR @20	Recall @20	MRR @20
SR-ISE	75.64	39.15	5.52	40.14	70.35	40.00
SR-OSE	76.85	39.32	75.06	40.12	71.06	41.01
SR-IOPI	77.41	39.82	76.72	42.44	71.19	41.32

From the Table 3, we can observe that compared to SR-I, SR-O, and SR-IO which ignore the inter-relationship between global preference and local preference, SR-ISE, SR-OSE, and SR-IOPI achieve obviously improvements, which verify the rationality of exploring the mutual interaction between preferences and of introducing neighborhood sessions into SR. The results also show the PCM is able to explore more useful information for recommendation. The outcome connection in formation is more useful than income connection information on Yoochoose 1/64 dataset, and with opposite on Yoochoose 1/4 dataset. These trends are consistent with the results in Table 3. It indicates the PCM does not take any negative influence on original feature.

3.5. Influence of session length

We compare diverse sessions with different lengths on Diginetica in SR-IOPI and SR-GNN to analysis the influence of session length. For Table 4, the numbers in the second column and third column are the number of sessions whose ground-truth items are ranked amongst the top-20 items in each length interval.

Table 4. Comparison of different session lengths on Diginetica

Length	SR-GNN	SR-IOPI	Performance
1-5	24283	29080	+19.75%
6-10	5213	6626	+27.11%
11-15	1228	1643	+33.80%
16-20	323	426	+31.89%
21-25	68	101	+48.53%
26-30	27	49	+81.48%
31-	14	32	+128.57%

From the Table 4, we can observe that: (1) SR-IOPI performs consistently better than SR-GNN in all lengths. It demonstrates that separately encoding income matrix and outcome matrix with are suitable to design node representations and preference interaction makes more precise preferences. (2) The results of SR-IOPI are relatively stable under arbitrary lengths. It means that our SR-IOPI model has good generalization.

4. Conclusion

We develop a novel session-based recommendation with preference interaction from separate income adjacent matrix and outcome adjacent matrix framework. By individually encoding income connection with preferences interaction and outcome connection with preferences interaction, the proposed SR-IOPI jointly incorporates complex item transition, preference dependency, and collaborative information. We conduct thorough empirical experiments to investigate SR-IOPI. The experiments on three datasets show the effectiveness of our model.

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