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Self-supervised graph learning with target-adaptive masking for session-based recommendation

Key words: Session-based recommendation; Self-supervised learning; Graph neural networks; Target-adaptive masking

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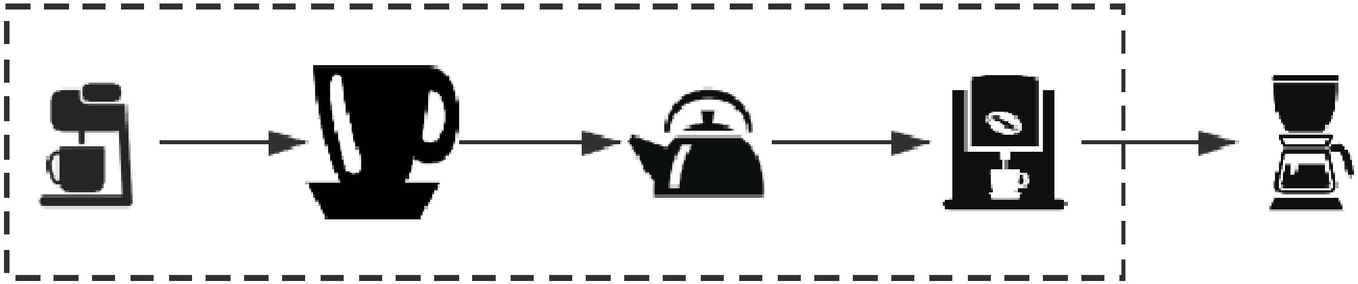
Session-based recommendation

- Traditional recommender systems:
  (1) Pay attention mainly to the long-term preference of users
  (2) Always neglect users' current interaction patterns

- Session-based recommendation aims to predict the next item based on a user's limited interactions within a short period.



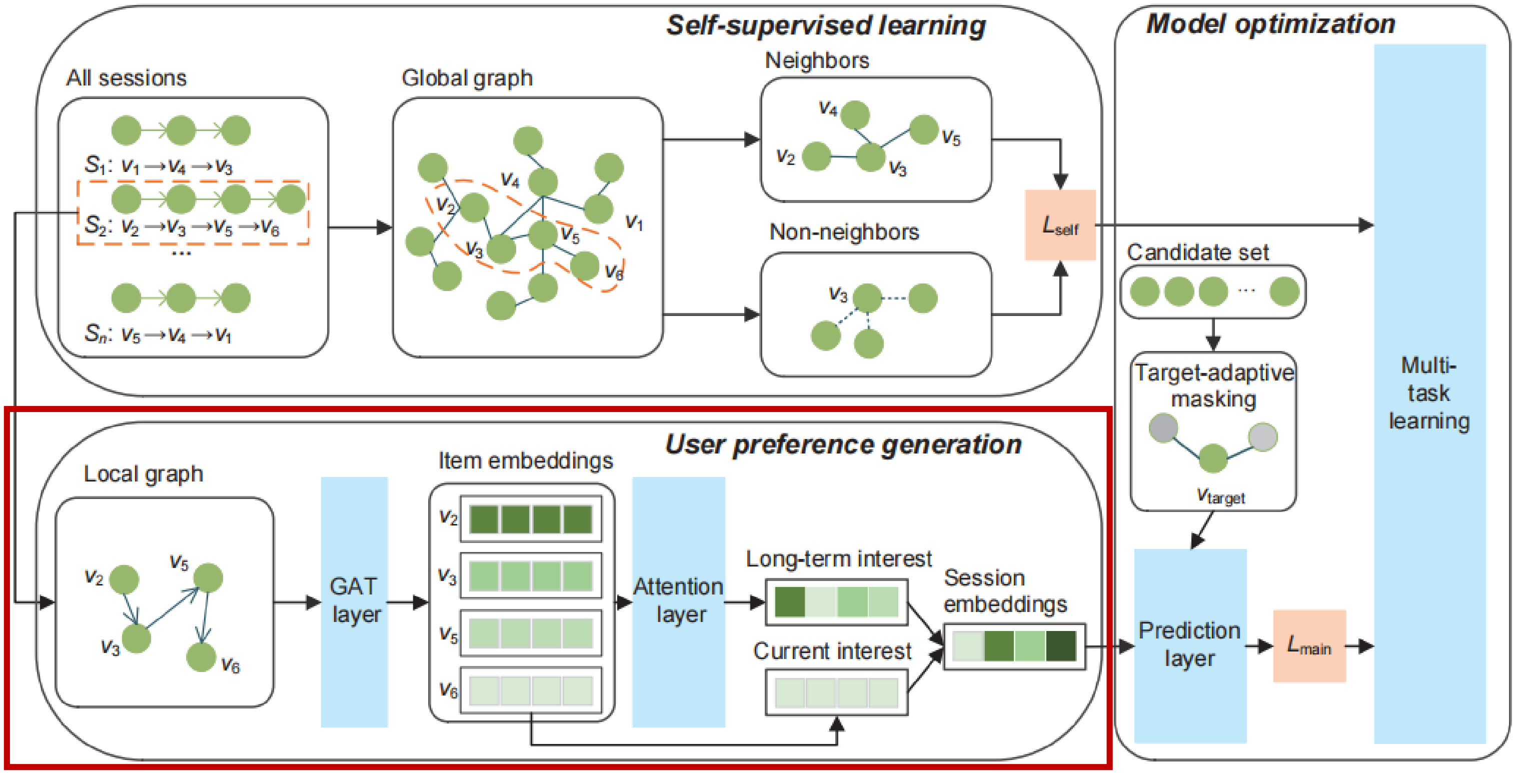
Motivation

- Existing recommendation models always use graph neural networks (GNNs) to obtain item representations. Deep GNNs may lead to an over-smoothing issue, in which the learned representations of adjacent items in the session are highly similar, making the item features indistinguishable.

- The training objective of existing models is to minimize the cross-entropy loss. In the training process, the target item score will continually increase while other items, including the neighbors of the target item, are treated as negative samples with decreasing scores. However, items adjacent to each other in the graph should be similar; i.e., it is unreasonable that the scores of the neighbors of the target item are continuously decreased. Thus, it leads to an over-fitting problem and model performance degradation.

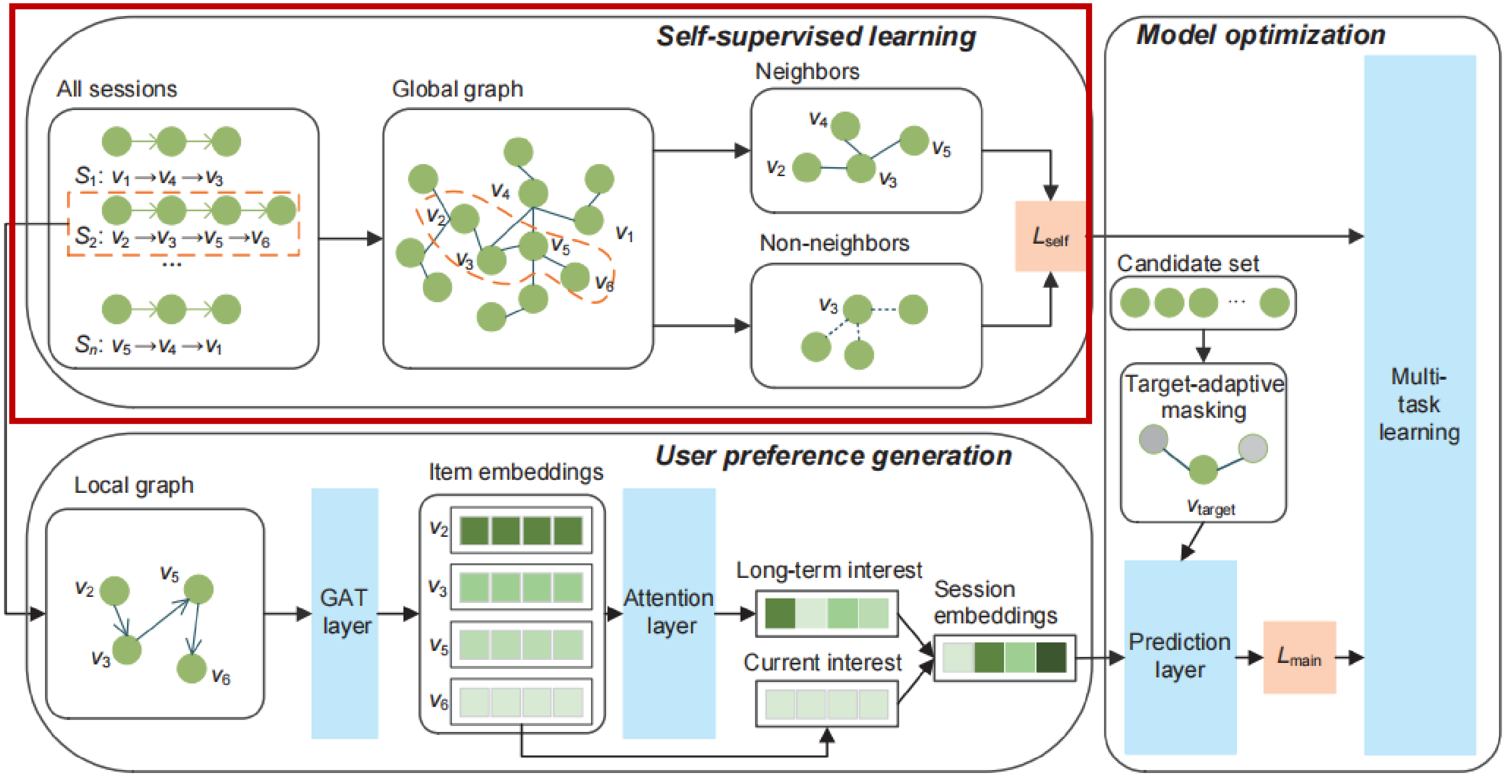
Method

Given a current session, we first learn the item embeddings by the information propagation of a graph attention network (GAT). Then we obtain the user's long-term and current interests in the session, and concatenate them to generate the final session representation.



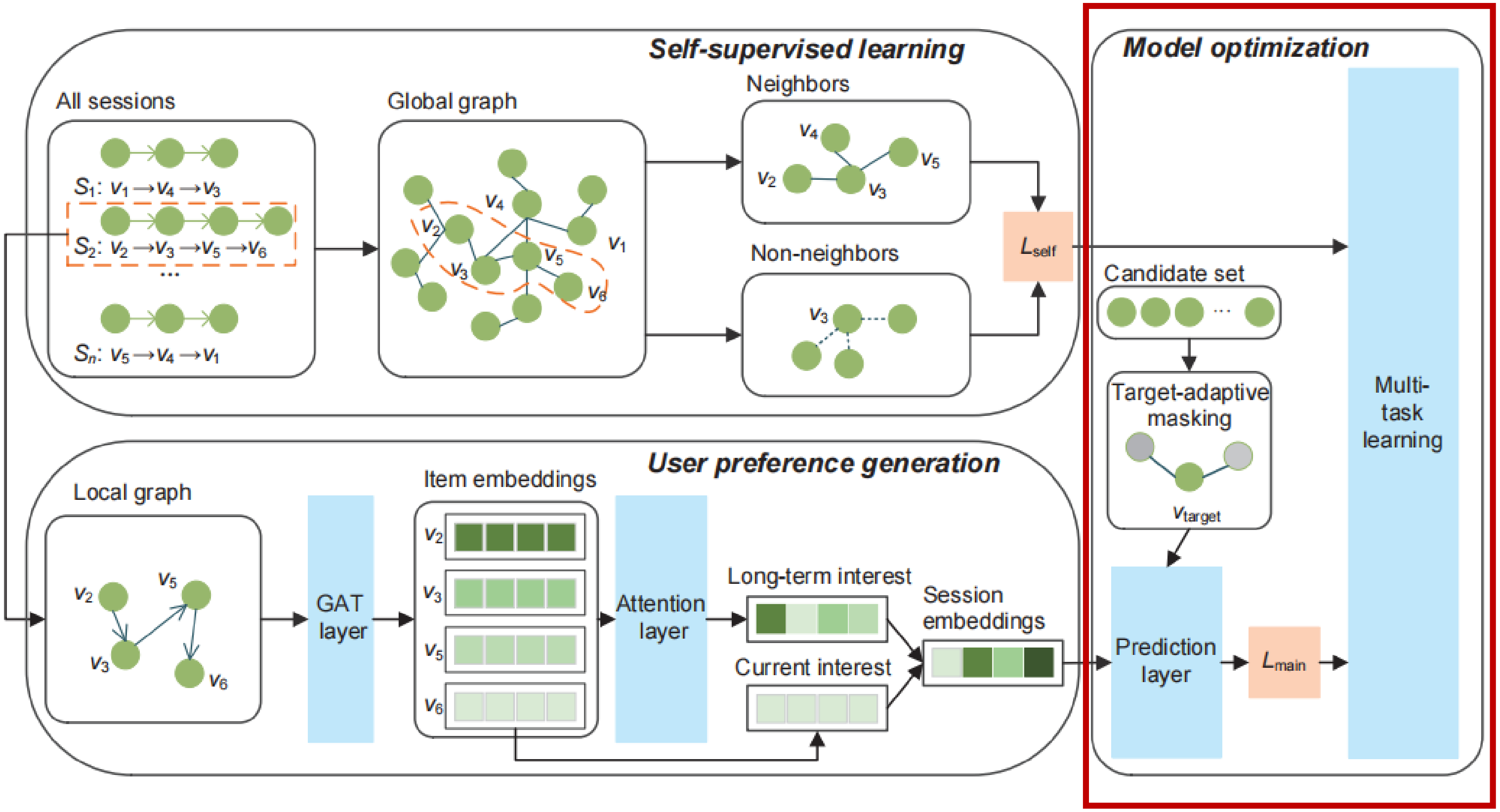
Method (Cont'd)

- Specifically, we establish a global graph to reveal the transition relations between items among different sessions according to all sessions in the training set. Then, we obtain the self-supervised signals from the global-level connections between items to calculate the self-supervised loss.



Method (Cont'd)

- We calculate the prediction scores of all items in the candidate set, which are then adjusted by the designed target-adaptive masking module to obtain the cross-entropy loss as the main supervised loss. Finally, the main supervised loss and self-supervised loss are combined to generate the final loss for model optimization.



Major results

- Our method SGL-TM is superior to the competitive baselines in terms of both Recall@20 and MRR@20 on both datasets, revealing its effectiveness for the session-based recommendation task.

Table 2 Model performance

Method	Recall@20 (%)		MRR@20 (%)	
	Gowalla	Diginetica	Gowalla	Diginetica
FPMC	29.91	28.50	11.45	7.67
NextItNet	45.15	45.41	21.26	15.19
NARM	50.07	49.80	23.92	16.57
FGNN	50.06	50.03	24.12	17.01
SR-GNN	50.32	50.81	<u>24.25</u>	17.31
GCE-GNN	51.51	51.66	23.52	17.53
S^2-DHCN	<u>51.96</u>	<u>52.58</u>	23.47	<u>17.91</u>
SGL-TM	**52.26**$^\triangle$	**53.02**$^\triangle$	**25.29**$^\triangle$	**18.38**$^\triangle$

The results of the best performing model and the best baseline in each column are boldfaced and underlined, respectively. $^\triangle$ indicates a statistical significance of SGL-TM against the best baseline applying a paired t-test ($p < 0.01$)

Major results (Cont'd)

- According to Table 3, it can be found that both self-supervised learning and target-adaptive masking modules contribute to the improvement of model performance. Besides, the contribution of the self-supervised learning module on ranking the target items at the correct location is larger than that on hitting them in the recommended list.

Table 3 Ablation study

Method	Recall@20 (%)		MRR@20 (%)	
	Gowalla	Diginetica	Gowalla	Diginetica
Base	50.68	51.14	24.17	17.32
Base-TM	51.61	52.07	24.30	17.69
Base-SSL	52.05	52.65	24.87	18.27
SGL-TM	52.26	53.02	25.29	18.38

Major results (Cont'd)

- Based on Fig. 2, the introduction of self-supervised signals with an appropriate λ effectively improves the performance of recommender systems.

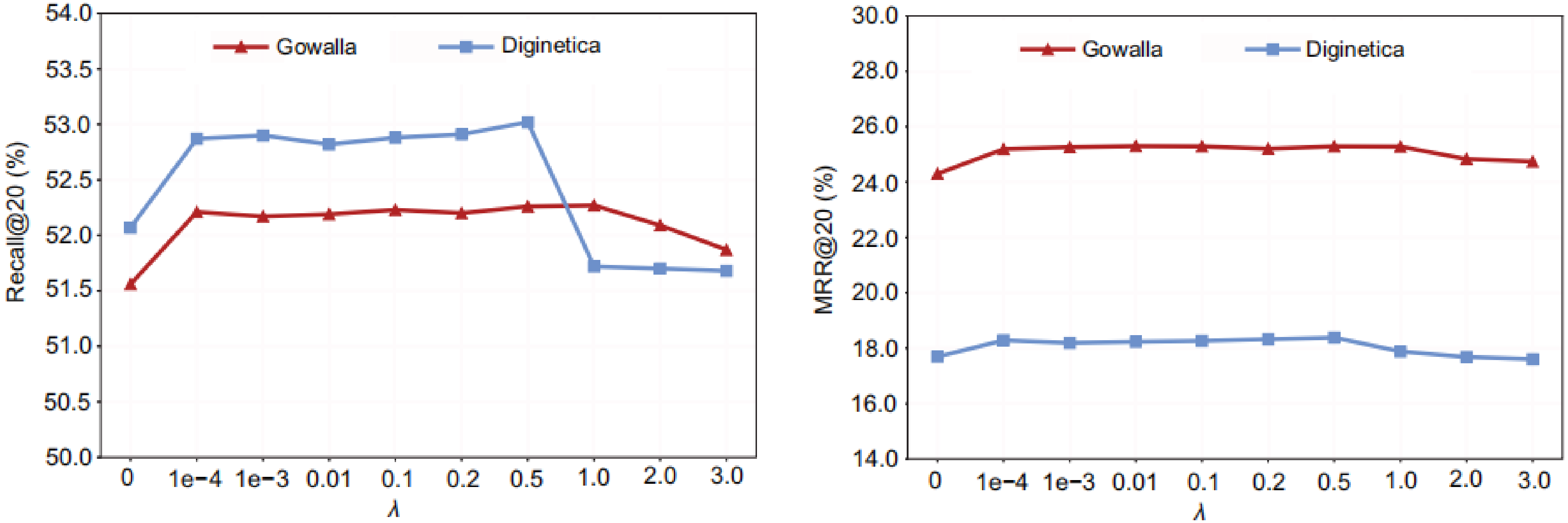


Fig. 2 Impact of the magnitude of self-supervision

Major results (Cont'd)

- SGL-TM outperforms the baselines in terms of both Recall@20 and MRR@20 at different session lengths, demonstrating the effectiveness of our proposal on dealing with sessions of various lengths.

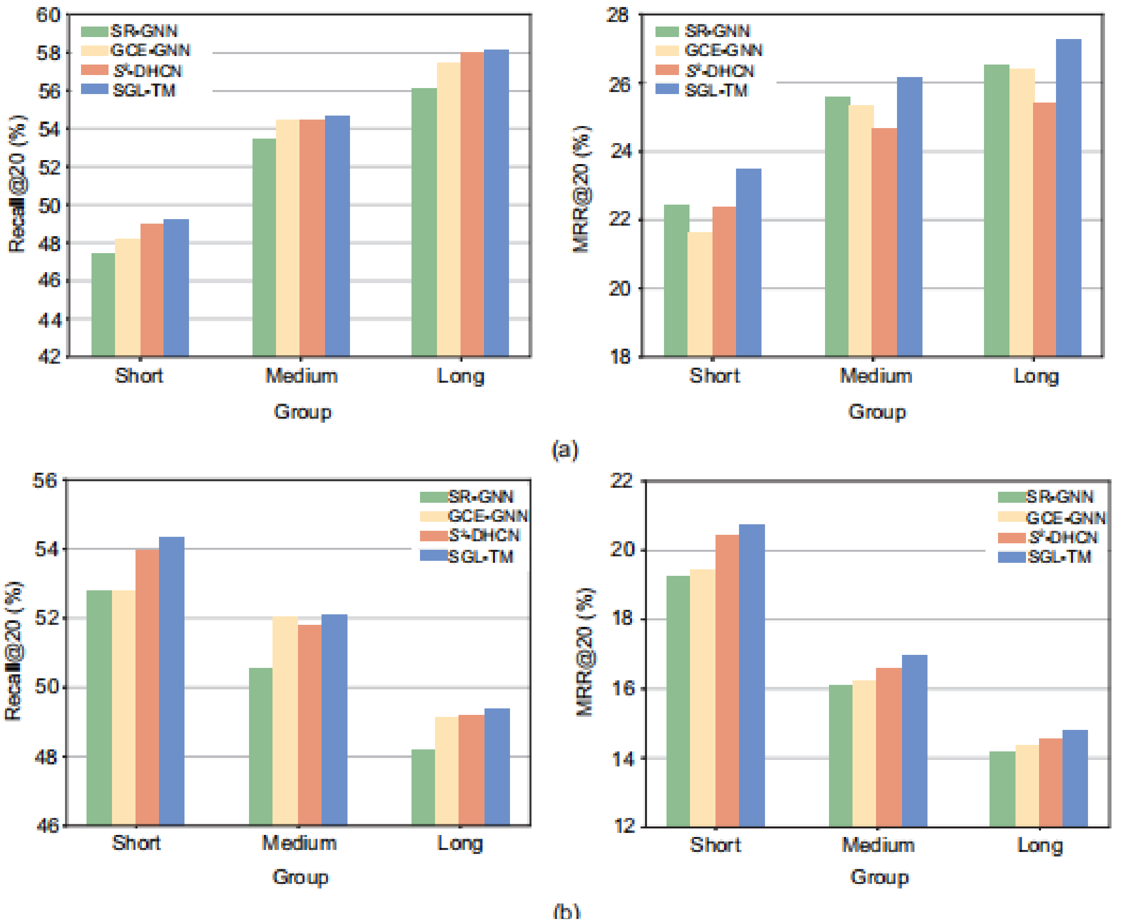
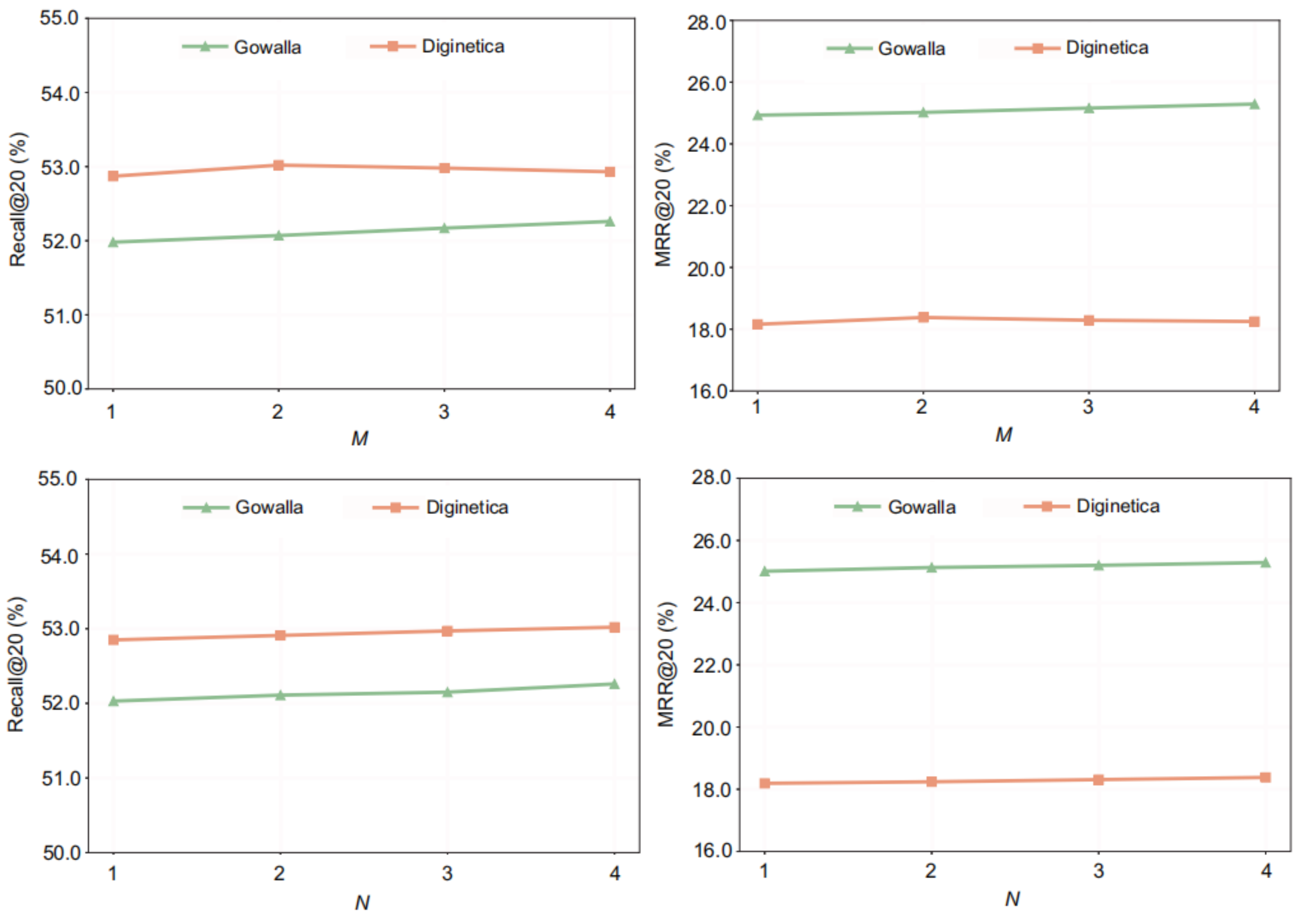


Fig. 3 Impact of the session length on Gowalla (a) and Diginetica (b). References to color refer to the online version of this figure

Major results (Cont’d)

- We examine the influence of some important hyper-parameters (including *M* and *N*, which are introduced in the self-supervised learning and target-adaptive masking components, respectively) on the performance of SGL-TM.



Conclusions

- In this paper, we have proposed a self-supervised graph learning with target-adaptive masking (SGL-TM) method for session-based recommendation.
- Specifically, we have employed self-supervised learning to tackle the over-smoothing issue of GNNs by introducing the global-level transition relations between items.
- Moreover, we have designed a target-adaptive masking module to effectively overcome the over-fitting problem of a cross-entropy loss with a softmax layer.
- The results of the experiments implemented on two real-world datasets, namely, Gowalla and Diginetica, have verified the effectiveness of our SGL-TM in terms of Recall@20 and MRR@20.

Yitong WANG is now pursuing the master degree in management science and engineering at the National University of Defense Technology, Changsha, China. Her research focuses on session-based recommendation. She received her BS degree in Ocean University of China, Qingdao, China, in 2020.