The Supplementary Material of MB-TGAT

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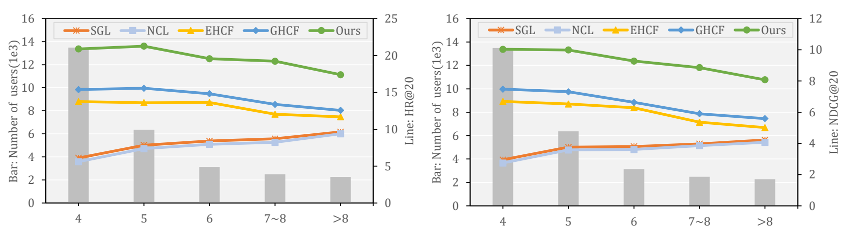
1 Model Time Complexity Analysis.

The time cost of MB-TGAT mainly comes from three parts. 1) For the local user-item aggregation layer, users and items aggregating the first-order neighbors has computational complexity $O(|\mathcal{G}|d)$. 2) For the global user and item propagation layer, the graph-based message passing mechanism has computational complexity $O((|\mathcal{E}_u|+|\mathcal{E}_v|)Ld)$. 3) For the dynamic interaction evolution learning, the time cost of evolution squence self-attention is $O(T^2d)$, and the behavior-wise fusion is $O(T(N+M)d)$. In conclusion, our MB-TGAT could achieve comparable time complexity with the GNN-based multi-behavior recommendations.

2 Benefits of MB-TGAT in Alleviating Data Sparsity

Data sparsity is a big challenge for recommender systems, and multi-behavior recommendation is a typical solution of it. Thus, we study how our proposed MB-TGAT alleviates the data sparsity issue for those users having few interactions of target behavior. Specifically, we split users of Taobao into five groups according to the interaction number of target behavior : $\{4, 5, 6, 7 \sim 8, > 8\}$. The reported model performance measured by HR@20 and NDCG@20 (as shown in the right side of y-axis in Fig. 1) is averaged over all users in each group. The total number of users belonging to each group is shown in the left side of y-axis in Fig. 1.



(a) HR@20.

(b) NDCG@20.

Fig. 1: Performance comparison w.r.t different data sparsity degrees on Taobao.

The results are presented in Fig. 1. We have the following observations: 1) The multi-behavior recommendations outperform the single-behavior recommendations on all groups, which indicates that the auxiliary behaviors effectively assist in modeling users' preferences and alleviate data sparsity issue of target behavior. 2) Our MB-TGAT outperforms other multi-behavior recommendations under different data sparsity degrees. This observation reveals that MB-TGAT solves the data sparsity issue better, by sufficiently differentiating and leveraging various behaviors. 3) It is worthwhile pointing out that the performance of multi-behavior recommendations have a slight descent in $\{6, 7 \sim 8, > 8\}$ groups, we think it is because of the size difference of auxiliary behavior data. In the last three groups, users with more target behaviors have more auxiliary behaviors, which could introduce more noise into the user preferences, thus leading to the negative effect.