A Self-Supervised Mixture-of-Experts Framework for Multi-behavior Recommendation (Online Appendix)

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A Experimental Details

In this section, we provide several experimental details that are excluded from the main paper due to space limitations.

A.1 Baseline methods

In our work, we use nine baseline methods, which are two single-behavior approaches and seven multi-behavior approaches. We provide details of each baseline method below.

Single-behavior. Here are two single-behavior methods.

- **MF-BPR** [7]: A matrix factorization-based approach that computes user-item inner products for recommendation and optimizes performance using the BPR loss function.
- **LightGCN** [2]: A simplified GCN-based approach that eliminates unnecessary nonlinearities, resulting in improved recommendation performance with reduced model complexity. We leverage LightGCN for target graph propagation, optimized using the BPR loss sampled from the target behavior.

Multi-behavior. Here are eight multi-behavior methods.

- **LightGCN-G** [2]: We utilize LightGCN for global graph propagation, optimized using the BPR loss sampled from the target behavior.
- **MB-GMN** [14]: MB-GMN leverages a meta-learning paradigm with a meta graph neural network to model behavior heterogeneity, preserving behavior semantics through high-order connectivity.
- **CML** [10]: CML leverages a contrastive meta learning framework to model behavior heterogeneity by aligning multi-behavior views and personalizing supervision through meta-contrastive encoding.
- **CIGF** [9]: CIGF models instance-level high-order relations via compressed graph convolution and mitigates gradient conflict in multi-task learning through behavior-specific separate inputs.
- **CRGCN** [15]: CRGCN models behavior sequences by using a residual GCN module for each behavior. It facilitates information flow between modules through embedding propagation, capturing dependency relationships between behaviors.
- **BCIPM** [17]: BCIPM utilizes a global unified graph pre-training method to learn behavior-specific embeddings, which are aggregated with a behavior-contextualized preference network.
- **MB-HGCN** [16]: MB-HGCN proposes a hierarchical behavior propagation method with multi-task learning for each behavior, combining adaptive embedding aggregation across all behaviors.
- **MULE** [4]: MULE proposes target-guided denoising attention to effectively denoise uncertain interactions and a multi-grained aggregator to integrate behavior embeddings.

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A.2 Datasets

We leverage three well-known multi-behavior benchmark datasets.

Tmall Dataset. Tmall[1] is a general e-commerce dataset from Alibaba, containing four user behaviors: click, collect, cart, and purchase. Among these, purchase history is typically considered the target behavior.

Taobao Dataset. Taobao[2] is a general e-commerce dataset from Alibaba, containing three user behaviors: click, cart, and purchase. Among these, purchase history is typically considered the target behavior.

JData Dataset. JData[3] is a general e-commerce dataset from JD, containing four user behaviors: click, collect, cart, and purchase. Among these, purchase history is typically considered the target behavior.

A.3 Evaluation details

Metrics. We use Hit-Ratio@K (HR@K) and Normalized-Discounted-Cumulative-Gain@K (NDCG@K) metrics, whose details are as follows:

- **Hit-Ratio@K (HR@K)**: This metric measures how accurately a recommender system ranks the test items within the top K positions of the ranked list.
- **Normalized-Discounted-Cumulative-Gain@K (NDCG@K)**: This metric evaluates the ranking quality by considering both the relevance of the recommended items and their positions in the ranked list.

Protocol. For the recommendation in the original setting, we rank all candidate items for each user based on s^*_{ui} and select the top K items. To evaluate the performance of each expert separately, we also rank items based solely on:

- **Visited Items Performance:** Rank items from $\mathbb{1}[(u,i) \in C_u^{(V)}]s_{ui}^{(V)}$.
- **Unvisited Items Performance:** Rank items from $\mathbb{1}[(u,i) \in C_u^{(U)}]s_{ui}^{(U)}$.

where $\mathbb{1}[\mathrm{cond}]$ is a indicator function that returns 1 if cond is true; otherwise returns 0.

This dual evaluation enables us to assess the model's ability to recommend both interacted and unvisited items effectively.

A.4 Machines and Implementation

Our experiments were conducted using an NVIDIA RTX A6000 GPU, equipped with 48GB of VRAM. The implementation was done using PyTorch version 1.13.1, which offers efficient handling of deep

[1]https://tianchi.aliyun.com/dataset/140281
[2]https://tianchi.aliyun.com/dataset/649
[3]https://global.jd.com/

Table 1: Performance comparison in terms of HR@50 and ND@50 between single-behavior and multi-behavior models under the standard evaluation setting. Boldface indicates the best performance, and the second-best is <u>underlined</u>.

Dataset	Metric	Single-behavior		Multi-behavior								
		MF-BPR	LGCN	LGCN-G	MB-GMN	CML	CIGF	CRGCN	BCIPM	MB-HGCN	MULE	MEMBER(Ours)
Tmall	HR@50	0.0751	0.0464	0.2810	0.1116	0.1053	0.1285	0.2602	0.4315	0.3843	<u>0.4456</u>	**0.7357**
	NDCG@50	0.0264	0.0156	0.1043	0.0359	0.0313	0.0412	0.0951	0.1580	0.1460	<u>0.1834</u>	**0.2716**
Taobao	HR@50	0.0510	0.0308	0.2491	0.1334	0.0870	0.1592	0.1906	<u>0.4506</u>	0.2660	0.3717	**0.5863**
	NDCG@50	0.0186	0.0109	0.1058	0.0512	0.0272	0.0558	0.0751	0.1748	0.1046	<u>0.1770</u>	**0.2414**
Jdata	HR@50	0.4664	0.4748	0.7124	0.4937	0.4430	0.5603	0.7111	0.7864	<u>0.7888</u>	0.7853	**0.8575**
	NDCG@50	0.2250	0.2140	0.3362	0.2160	0.1553	0.2666	0.3535	0.3719	0.3952	<u>0.4573</u>	**0.4974**

Table 2: Inference time comparison (sec) of multi-behavior recommendation baselines.

Dataset	MB-GMN	CML	CIGF	CRGCN	BCIPM	MB-HGCN	MULE	Ours
Tmall	254	8	26	8	6	8	14	11
Taobao	1095	25	134	14	14	13	27	25
JData	178	7	16	3	3	3	9	6

Table 3: Memory usage comparison(GB) of multi-behavior recommendation baselines.

Dataset	MB-GMN	CML	CIGF	CRGCN	BCIPM	MB-HGCN	MULE	Ours
Tmall	43.8	17.2	4.4	6.6	3.7	3.9	38.4	3.9
Taobao	47.5	34.6	5.7	5.9	6.3	6.3	32.7	6.5
JData	47.5	34.6	8.1	6.3	7.2	6.5	37.7	7.9

learning operations and GPU acceleration. This setup allowed us to handle large datasets and complex model architectures efficiently, ensuring reliable performance during training and evaluation.

B Additional Related Work

<u>**GNN-based Recommender Systems.**</u> Recently, graph neural networks (GNNs) have been proven effective in various recommendation tasks, including multi-behavior recommendation [1, 2, 6, 8]. GNN-based recommender systems use message passing between nodes to aggregate information from neighbors on graphs encoding observed user-item interactions. This process allows them to capture interaction patterns, leading to improved node representations that are useful for recommendation. Among various GNNs, LightGCN [2] is widely employed in multiple models for its simplicity and effectiveness [11, 12, 18]. For GNN-based methods, it is common to leverage self-supervised learning to enhance GNNs' ability to learn user and item representations. To this end, contrastive self-supervised learning aims to maximize the agreement between different views of graphs [6, 19, 20], and generative self-supervised learning aims to generate or reconstructs parts of graphs [5, 13].

Note that the self-supervised learning strategies used in our method are specially designed to tackle our unique challenges (see Section ??), and they differ significantly from those in existing recommender systems.

C Additional Analysis of MEMBER

In this section, we provide further analysis of MEMBER.

C.1 Time Complexity Analysis

We provide an encoding time complexity analysis of MEMBER with respect to the input size. Specifically, MEMBER receives a global graph $\mathcal{G} = (\mathcal{V} = \bigcup_{m\in\mathcal{M}} \mathcal{V}^{(m)}, \mathcal{E} = \bigcup_{m\in\mathcal{M}} \mathcal{E}^{(m)})$ and behavior-specific graphs $\mathcal{G} = (\mathcal{V}^{(m)}, \mathcal{E}^{(m)}), \forall m \in \mathcal{M}$. We encode each graph separately with LightGCN [2]. Note that for a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, LightGCN'S encoding time complexity is $O(|\mathcal{V}|+|\mathcal{E}|)$ with respect to the input graph size [3]. Thus, encoding time complexity of MEMBER is equivalent to

$$O\left(|\bigcup_{m\in\mathcal{M}} \mathcal{V}^{(m)}| + |\bigcup_{m\in\mathcal{M}} \mathcal{E}^{(m)}|\right) + \sum_{m\in\mathcal{M}} O(|\mathcal{V}^{(m)}| + |\mathcal{E}^{(m)}|), \tag{1}$$

$$\equiv O\left(\sum_{m\in\mathcal{M}} |\mathcal{V}^{(m)}| + |\mathcal{E}^{(m)}|\right). \tag{2}$$

After LightGCN encoding, we average the embeddings from the behavior-specific graphs. This computation has the complexity of $O\left(|\bigcup_{m\in\mathcal{M}} \mathcal{V}^{(m)}| + |\bigcup_{m\in\mathcal{M}} \mathcal{E}^{(m)}|\right)$. Since this complexity is bounded by Eq (2), still the overall complexity is equivalent to Eq (2). This is the end of the encoding, and thus, the encoding time complexity is equivalent to $O\left(\sum_{m\in\mathcal{M}} |\mathcal{V}^{(m)}| + |\mathcal{E}^{(m)}|\right)$.

C.2 Inference time Comparison

As shown in Table 2, we compared inference times against multi-behavior baseline methods, and our inference time is competitive. Note that our method also achieves the best performance.

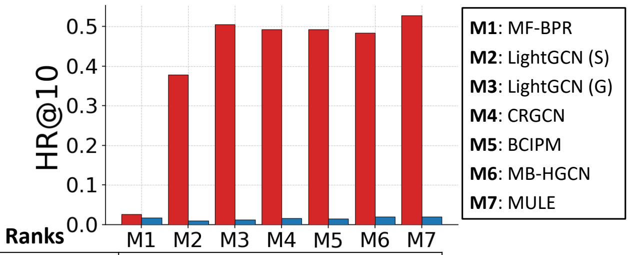
C.3 Memory Usage Comparison

As shown in Table 3, MEMBER 's memory usage remains competitive against other multi-behavior recommender models. Note that our method also achieves the highest performance.

C.4 Additional Real-world Data Analysis

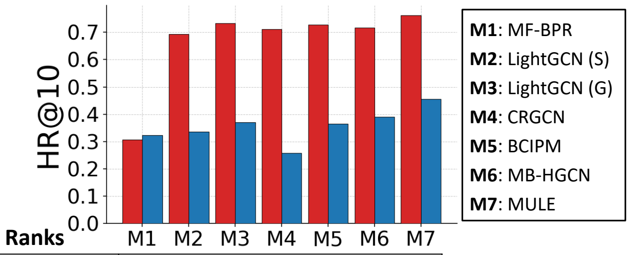
We present an additional real-world data analysis on Taobao and Jdata in Figure 1 and 2, respectively. The results confirm that our observation remains consistent across these two datasets.

<u>**(O1) Performance gap between visited and unvisited items.**</u> All methods experience significant absolute performance drop in the unvisited-item recommendation compared to the visited-item recommendation.



Ranks	M1	M2	M3	M4	M5	M6	M7
Visited 🟥	7	6	2	3	4	5	1
Unvisited 🟦	3	7	6	4	5	1	2

Figure 1: Performance comparison of visited vs. unvisited item recommendation on the Taobao dataset across two single-behavior and five multi-behavior recommender systems. Rank (lower is better) indicates model effectiveness in each setting.



Ranks	M1	M2	M3	M4	M5	M6	M7
Visited 🟥	7	6	2	5	3	4	1
Unvisited 🟦	6	5	3	7	4	2	1

Figure 2: Performance comparison of visited vs. unvisited item recommendation on the Jdata dataset across two single-behavior and five multi-behavior recommender systems. Rank (lower is better) indicates model effectiveness in each setting.

Table 4: RQ3. Effectiveness of the key components of MEMBER under the standard evaluation protocol. The best performance is highlighted in bold, and the second-best one is underlined. H@10: Hit Ratio@10. N@10: NDCG@10.

Datasets	Tmall		Taobao		JData	
Metrics	H@10	N@10	H@10	N@10	H@10	N@10
MEMBER-MoE.	0.1404	0.0747	0.1748	0.1014	0.5072	0.3203
MEMBER-$\mathcal{L}_{\text{SSL}}^{(V)}$.	0.3646	0.1745	0.3022	0.1554	0.6515	0.4193
MEMBER-$\mathcal{L}_{\text{CL}}^{(U)}$.	0.3699	0.1813	0.3067	0.1579	0.6196	0.3843
MEMBER-$\mathcal{L}_{\text{GEN}}^{(U)}$.	**0.3766**	**0.1853**	0.3184	0.1705	0.6277	0.3964
MEMBER	0.3764	0.1850	**0.3371**	**0.1808**	**0.6618**	**0.4425**

(O2) No one-size-fits-all model. The rankings based on performance for visited-item recommendation differ from those for unvisited-item recommendation. This discrepancy demonstrates the challenge of achieving strong recommendation performance for both item types within a single recommender system.

D Additional Experimental Results of MEMBER

We now provide additional experimental results of MEMBER.

D.1 Additional Results of MEMBER

We compare the performance of MEMBER against those of baseline methods in terms of additional evaluation metrics. We use HR@50 and NDCG@50 evaluation metrics (refer to Sec. ?? for details of HR and NDCG). As shown in Tables 1, MEMBER outperforms other methods in all settings. Thus, the superiority of MEMBER is not limited to particular evaluation metrics.

We also present the ablation study results for key components in Table 4. Our method consistently outperforms its variants, with the mixture-of-experts architecture proving to be the most critical component.

D.2 Gating function analysis

Recall that MEMBER combines the scores of the two experts based on the item types; using the score of the visited-item expert for visited items, while using that of the unvisited-item expert for unvisited items. In this section, we demonstrate that this simple, intuitive approach outperforms the following approaches:

- **MEMBER w/ AVG.** This approach combines the score via mean pooling. Formally, the score for recommending item i to user u is computed as $s^*_{ui} = (s^{(V)}_{ui} + s^{(U)}_{ui})/2$.
- **MEMBER w/ L.G.** This variant generates dynamic, user-specific expert weights by first concatenating the two expert-derived embeddings and then passing them through a linear layer followed by Softmax. Let
$$\mathbf{e}_u^{(V)},\ \mathbf{e}_u^{(U)} \in \mathbb{R}^d$$
be the embeddings produced by the visited-item and unvisited-item experts for user u. From the concatenated vector, we compute unnormalized logits as follows:
$$\mathbf{e}_u^{(\text{cat})} = \left[\mathbf{e}_u^{(V)};\, \mathbf{e}_u^{(U)}\right] \in \mathbb{R}^{2d}.$$
$$\left[\tilde{\alpha}_u^{(V)},\ \tilde{\alpha}_u^{(U)}\right]^\top = \mathbf{W}\,\mathbf{e}_u^{(\text{cat})} + \mathbf{b},$$
where $\mathbf{W} \in \mathbb{R}^{2\times 2d}$ and $\mathbf{b} \in \mathbb{R}^2$ are learnable. Normalize with the softmax function:
$$\left[\tilde{\alpha}_u^{(V)},\ \tilde{\alpha}_u^{(U)}\right] = \text{softmax}\!\left(\left[\alpha_u^{(V)},\ \alpha_u^{(U)}\right]\right),$$
ensuring $\alpha_u^{(V)} + \alpha_u^{(U)} = 1$. Finally, the recommendation score is
$$s^*_{ui} = \alpha_u^{(V)}\, s_{ui}^{(V)} + \alpha_u^{(U)}\, s_{ui}^{(U)}.$$

Other architectural designs of these variants are the same as that of MEMBER. As shown in Table ??, MEMBER outperforms these two variants, demonstrating the effectiveness of our score combination strategy in multi-behavior recommendation.

D.3 Hyperparameter Sensitivity Analysis

TODO

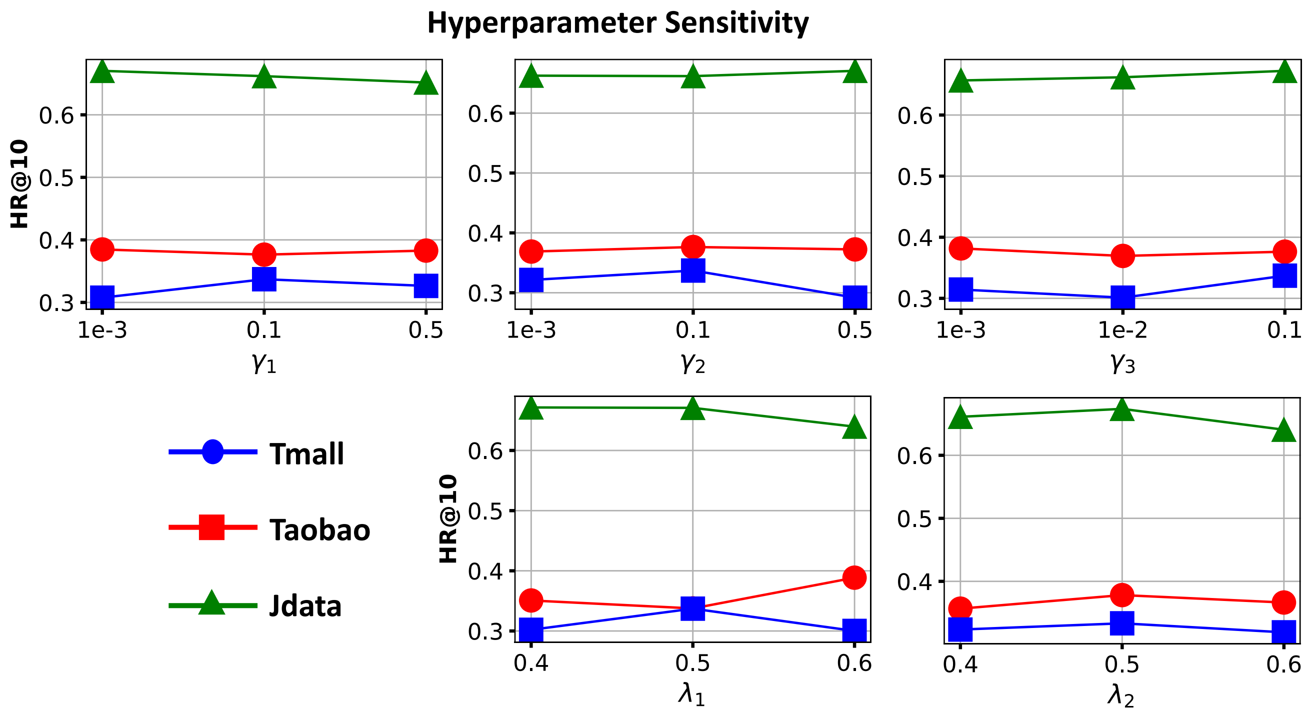


Figure 3: TODO

Table 7: Effectiveness of various gating functions under the unvisited-item recommendation setting. The best performance is highlighted in bold. H@10: Hit Ratio@10. N@10: NDCG@10.

Datasets	Tmall		Taobao		JData	
Metrics	H@10	N@10	H@10	N@10	H@10	N@10
MEMBER w/ AVG.	0.1404	0.0747	0.1748	0.1014	0.5072	0.3203
MEMBER w/ L.G.	0.2465	0.2769	0.2920	0.1616	0.5887	0.3549
MEMBER	**0.3764**	**0.1850**	**0.3371**	**0.1808**	**0.6618**	**0.4425**

Table 5: Effectiveness of various gating functions under the standard evaluation setting. The best performance is highlighted in bold. H@10: Hit Ratio@10. N@10: NDCG@10.

Datasets	Tmall		Taobao		JData	
Metrics	H@10	N@10	H@10	N@10	H@10	N@10
MEMBER w/ AVG.	0.1404	0.0747	0.1748	0.1014	0.5072	0.3203
MEMBER w/ L.G.	0.2465	0.2769	0.2920	0.1616	0.5887	0.3549
MEMBER	**0.3764**	**0.1850**	**0.3371**	**0.1808**	**0.6618**	**0.4425**

Table 6: Effectiveness of various gating functions under the visited-item recommendation setting. The best performance is highlighted in bold. H@10: Hit Ratio@10. N@10: NDCG@10.

Datasets	Tmall		Taobao		JData	
Metrics	H@10	N@10	H@10	N@10	H@10	N@10
MEMBER w/ AVG.	0.1404	0.0747	0.1748	0.1014	0.5072	0.3203
MEMBER w/ L.G.	0.2465	0.2769	0.2920	0.1616	0.5887	0.3549
MEMBER	**0.3764**	**0.1850**	**0.3371**	**0.1808**	**0.6618**	**0.4425**

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