A Parameter Settings

To make a comprehensive comparison, we split each dataset into training, evaluation and test sets with the ratio of $8:1:1$ and $6:2:2$. We apply the early-stop learning strategy on the evaluation set for training, and stop training if MAE stops increasing for continuous 5 steps. We employ Adam as the optimizer. The learning rate lr and batch size are set as $1e-4$ and 512. All embeddings are initialized with normal distributed randoms (mean as 0 and standard deviation as 0.1). We search parameters d, L, η_1, and η_2 in the range of $\{32, 64, 128, 256\}$, $\{1, \cdots, 4\}$, $\{1e-4, 1e-3, \cdots, 1e-1\}$, and $\{5e-5, 5e-4, \cdots, 5e-1\}$. In most cases, $d = 32$, $L = 2$, $\eta_1 = 1e-3$, and $\eta_2 = 5e-4$ lead to the best performance. The temperature parameter in the contrastive module is set as 0.1.

B Additional Experimental Analysis

B.1 Ablation Analysis

Besides MAE and $RMSE$ metrics, we are also interested in *Recall*@K and $NDCG$@K with $K = 5, 10, 20$ to evaluate the ranking performance of our MB-Soc. As we can see in Table 2, MB-Soc consistently outperforms other ablation variants.

Table 2. Ablation Experiment Comparisons.

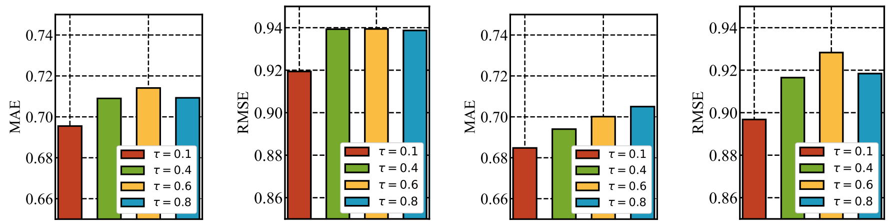
Model	Recall@K			NDCG@K		
	5	10	20	5	10	20
MB-Soc w/o MB&Soc	0.0342	0.0779	0.1445	0.0585	0.0757	0.1047
MB-Soc w/o MB	0.0514	0.0931	0.1706	0.0537	0.0762	0.1151
MB-Soc w/o Soc	0.09	0.1112	0.1907	0.1706	0.151	0.1851
MB-Soc	0.1014	0.1234	0.3251	0.1886	0.2132	0.2815

B.2 Parameter Analysis

We further conduct parameter analysis experiments w.r.t. temperature parameter τ in the SSL module on Ciao 60% and Ciao 80% to find the optimal values. The results are shown in Fig. 6. MB-Soc-τ consistently achieves the best performance with $\tau = 0.1$.

B.3 Smoothing Observations

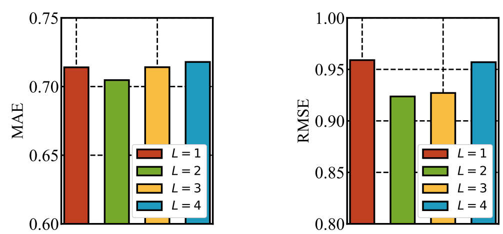
To further explore how the graph aggregation and propagation processes affect the recommendation performance, we conduct additional experiments concerning the aggregation paradigm. Specifically, we investigate the recommendation



(a) MAE on Ciao 60% (b) RMSE on Ciao 60% (c) MAE on Ciao 80% (d) RMSE on Ciao 80%

Fig. 6. Impact of τ.

performance on a MB-Soc variant without smoothing, i.e., $\mathbf{e}_{u,b}^{(l+1)} \leftarrow \sum_{i\in\mathcal{N}_u^b} \mathbf{e}_{i,b}^{(l)}$, $\mathbf{e}_{i,b}^{(l+1)} \leftarrow \sum_{u\in\mathcal{N}_i^b} \mathbf{e}_{u,b}^{(l)}$. We denote the variant as MB-Soc w/o norm, and the performances of MB-Soc w/o norm with varying L are shown in Fig. 7.



(a) MB-Soc w/o norm w.r.t. MAE (b) MB-Soc w/o norm w.r.t. $RMSE$

Fig. 7. Performance of MB-Soc w/o norm on Ciao 60%

Jointly analyzing Fig. 7 with Fig. 4, we can see that MB-Soc w/o norm exhibits a significant performance degradation. This might be because MB-Soc w/o norm easily hits the bottleneck without balancing the varied numbers of neighbors.