Asymmetrical Context-aware Modulation for Collaborative Filtering Recommendation

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https://github.com/halaoyy/ARBRE_pytorch

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Reported by Ke Gan

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2. Approach
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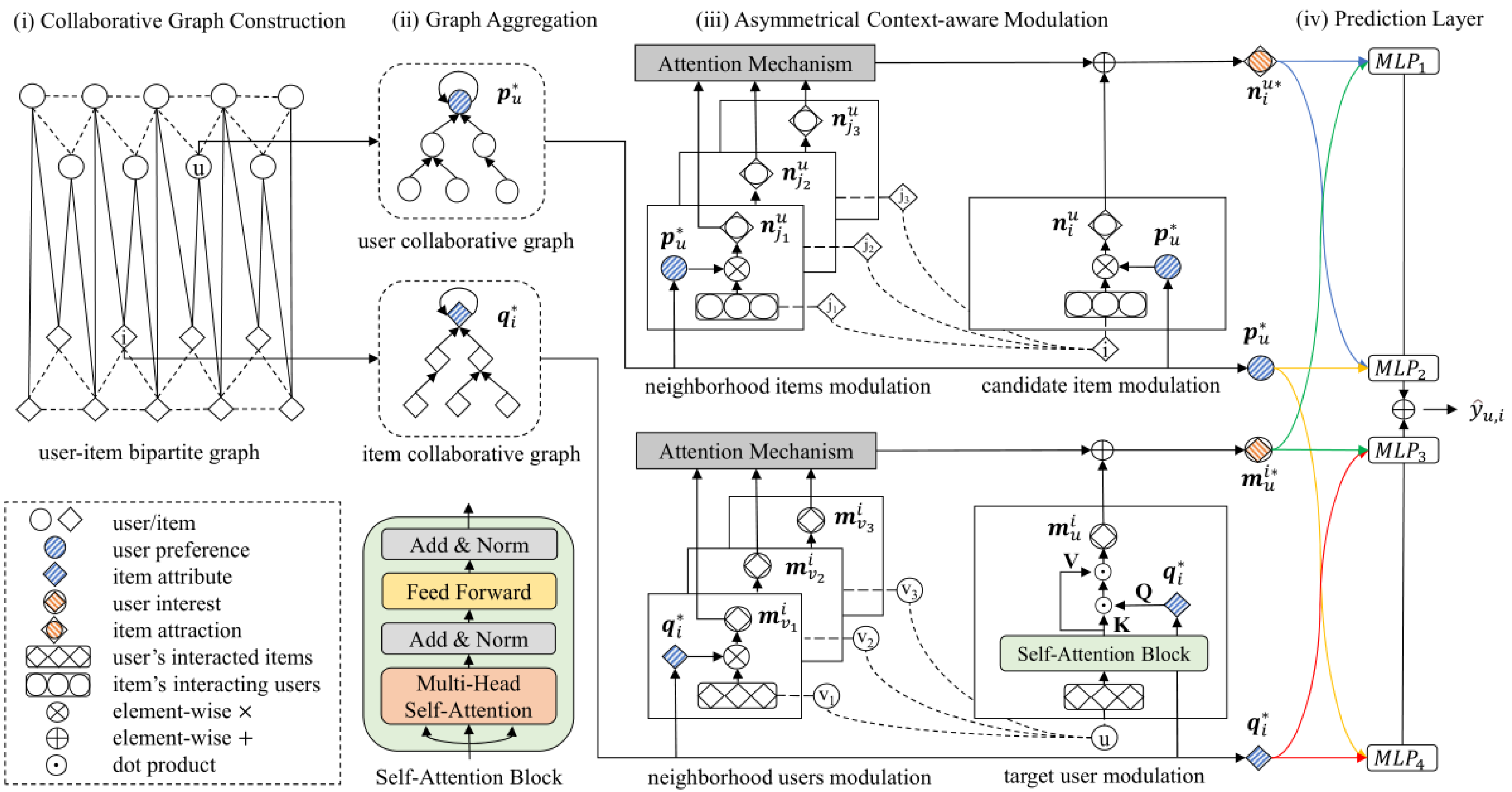
Introduction

Figure 1: Illustration of context-aware user interest and item attraction. The upper part is a user's clicking history, which can be divided into two categories: clothes and computers; the lower part is a MLB varsity jacket's clicked users, which composed of baseball fans and fashionistas.

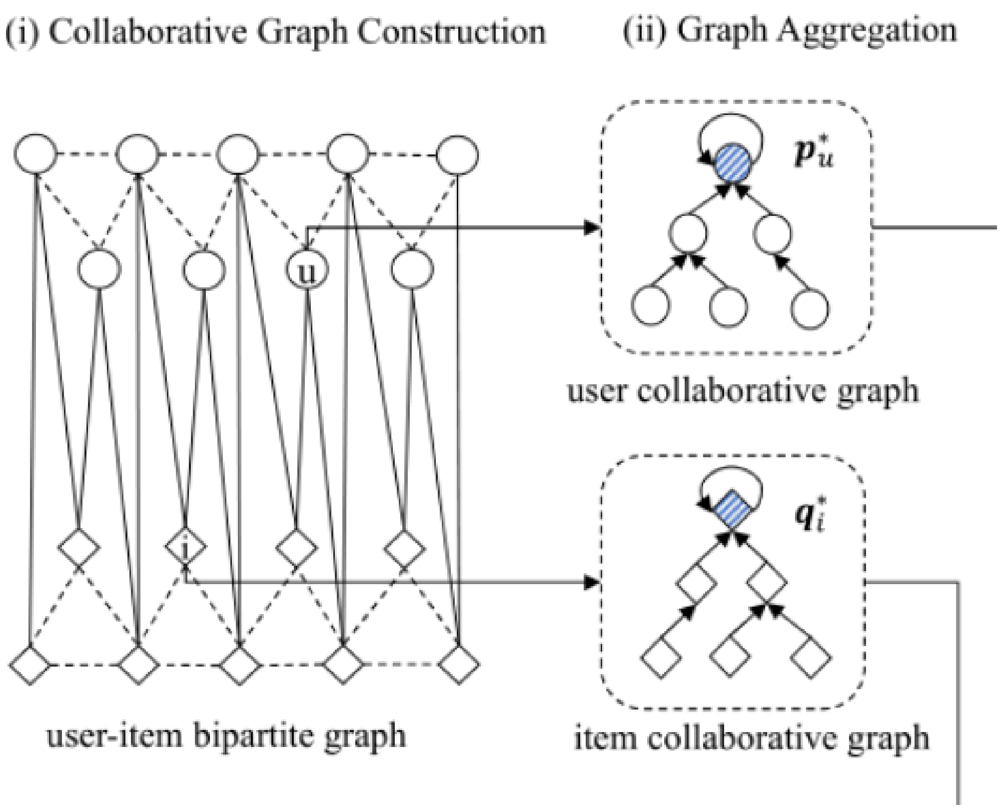
the learned representation of a user (resp. item) is static for diverse items (resp. users)

learn representations by symmetrical dual methods which have identical or similar operations

Approach


(i) Collaborative Graph Construction
(ii) Graph Aggregation
(iii) Asymmetrical Context-aware Modulation
(iv) Prediction Layer
user-item bipartite graph
user collaborative graph
item collaborative graph
Attention Mechanism
neighborhood items modulation
candidate item modulation
Attention Mechanism
neighborhood users modulation
target user modulation
Self-Attention Block
Add & Norm
Feed Forward
Add & Norm
Multi-Head Self-Attention
Self-Attention Block
user/item
user preference
item attribute
user interest
item attraction
user's interacted items
item's interacting users
element-wise ×
element-wise +
dot product
MLP_1
MLP_2
MLP_3
MLP_4
$\hat{y}_{u,i}$

Approach



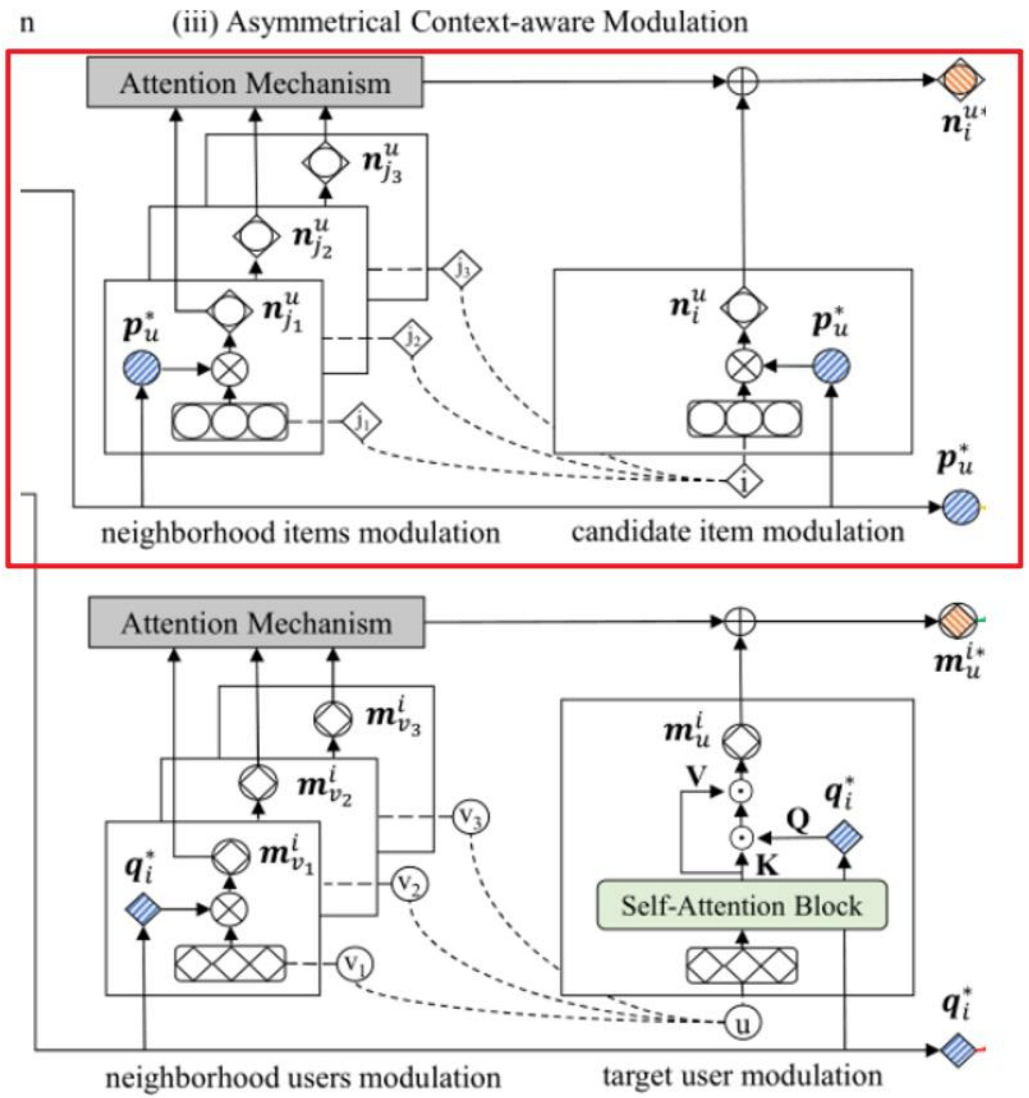
$$sim_{\mathrm{U}}(u,v) = \frac{|\mathcal{R}_{\mathrm{I}}(u)| \cap |\mathcal{R}_{\mathrm{I}}(v)|}{|\mathcal{R}_{\mathrm{I}}(u)| \cup |\mathcal{R}_{\mathrm{I}}(v)|} \tag{1}$$

$$\begin{aligned} \mathbf{P} &= \mathbf{W}_{\mathrm{U}}\mathbf{U} \\ \mathbf{Q} &= \mathbf{W}_{\mathrm{I}}\mathbf{I} \end{aligned} \tag{2}$$

$$\boldsymbol{p}_u^{l+1} = LN\left(\sum_{v \in \mathcal{N}_{\mathrm{U}}(u)} \boldsymbol{p}_v^l\right) \tag{3}$$

$$\boldsymbol{q}_i^{l+1} = LN\left(\sum_{j \in \mathcal{N}_{\mathrm{I}}(i)} \boldsymbol{q}_j^l\right) \tag{4}$$

Approach

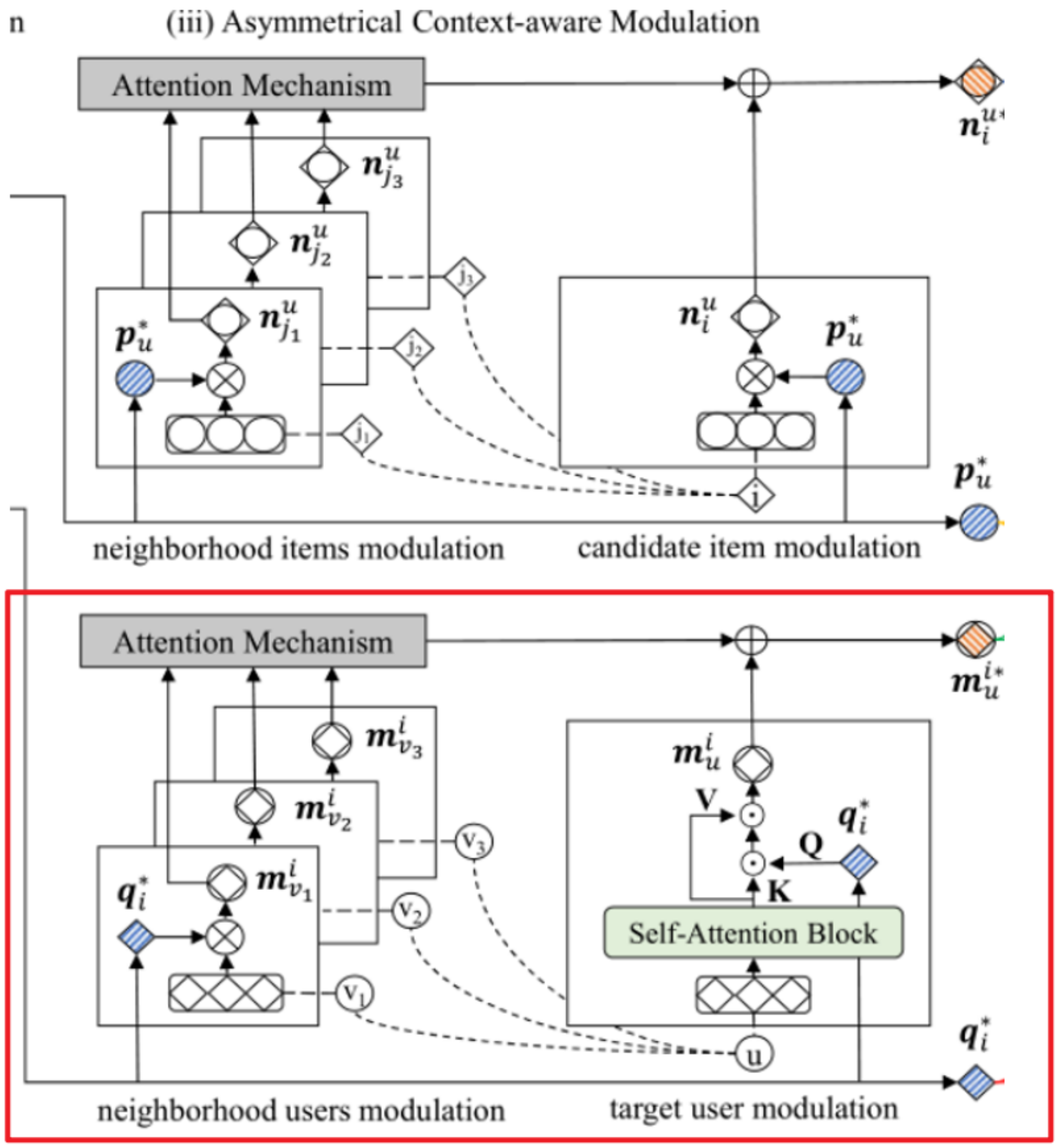


$$\boldsymbol{n}_i^u = MP_{v \in \mathcal{R}_U(i)} \left(\{ \boldsymbol{p}_u^* \otimes \boldsymbol{p}_v^* \} \right) \quad (5)$$

$$\alpha_{i,j} = \left(\boldsymbol{n}_i^u \right)^T \cdot \left(\boldsymbol{n}_j^u \right) \quad (6)$$

$$\boldsymbol{n}_i^{u*} = 0.5 \times \left(\boldsymbol{n}_i^u + \sum_{j \in \mathcal{N}_I(i)} \alpha'_{i,j} \cdot \boldsymbol{n}_j^u \right)$$
$$\alpha'_{i,j} = \frac{\exp(\alpha_{i,j})}{\sum_{j \in \mathcal{N}_I(i)} \exp(\alpha_{i,j})} \quad (7)$$

Approach



$$\mathbf{Q}_u = \left[\boldsymbol{q}_{i_1}^*, \boldsymbol{q}_{i_2}^*, \ldots, \boldsymbol{q}_{i_{|\mathcal{R}_I(u)|}}^* \right] \in \mathbb{R}^{d \times |\mathcal{R}_I(u)|}$$

$$\begin{aligned} \mathbf{H}_u &= LN\left(\mathbf{Q}_u' + FFN\left(\mathbf{Q}_u'\right)\right) \\ \mathbf{Q}_u' &= LN\left(\mathbf{Q}_u + MultiHeadAttn\left(\mathbf{Q}_u\right)\right) \end{aligned} \tag{10}$$

$$\begin{aligned} MultiheadAttn\left(\mathbf{Q}_u\right) &= \mathbf{W}^{\mathrm{O}} \cdot Concat(\mathbf{head}_1, \ldots, \mathbf{head}_h) \\ \mathbf{head}_i &= Attention\left(\mathbf{W}_i^{\mathrm{Q}} \mathbf{Q}_u, \mathbf{W}_i^{\mathrm{K}} \mathbf{Q}_u, \mathbf{W}_i^{\mathrm{V}} \mathbf{Q}_u\right) \end{aligned} \tag{8}$$

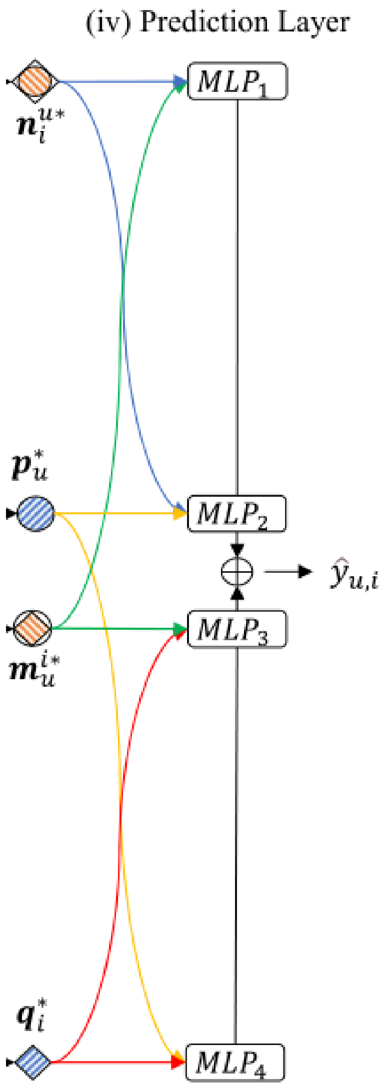
$$Attention(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \mathbf{V} \cdot softmax\left(\frac{\mathbf{K}^T \mathbf{Q}}{\sqrt{d_h}}\right) \tag{9}$$

$$\boldsymbol{m}_u^i = \left(\mathbf{W}^{\mathrm{V}} \mathbf{H}_u\right) \cdot softmax\left(\frac{\left(\mathbf{W}^{\mathrm{K}} \mathbf{H}_u\right)^T \left(\mathbf{W}^{\mathrm{Q}} \boldsymbol{q}_i^*\right)}{\sqrt{d}}\right) \tag{11}$$

$$\boldsymbol{m}_v^i = MP_{j \in \mathcal{R}_{\mathrm{I}}(v)}\left(\{\boldsymbol{q}_i^* \otimes \boldsymbol{q}_j^*\}\right) \tag{12}$$

$$\begin{aligned} \boldsymbol{m}_u^{i*} &= 0.5 \times \left(\boldsymbol{m}_u^i + \sum_{v \in \mathcal{N}_{\mathrm{U}}(u)} \alpha_{u,v}' \cdot \boldsymbol{m}_v^i\right) \\ \alpha_{u,v}' &= \frac{\exp\left(\alpha_{u,v}\right)}{\sum_{v \in \mathcal{N}_{\mathrm{U}}(u)} \exp\left(\alpha_{u,v}\right)} \\ \alpha_{u,v} &= \left(\boldsymbol{m}_u^i\right)^T \cdot \left(\boldsymbol{m}_v^i\right) \end{aligned} \tag{13}$$

Approach



$$
\begin{aligned}
y_{u,i}^1 &= MLP_1\left(\boldsymbol{m}_u^{i*}, \boldsymbol{n}_i^{u*}\right) \\
y_{u,i}^2 &= MLP_2\left(\boldsymbol{p}_u^*, \boldsymbol{n}_i^{u*}\right) \\
y_{u,i}^3 &= MLP_3\left(\boldsymbol{m}_u^{i*}, \boldsymbol{q}_{i*}\right) \\
y_{u,i}^4 &= MLP_4\left(\boldsymbol{p}_u^*, \boldsymbol{q}_i^*\right)
\end{aligned} \tag{14}
$$

$$
\hat{y}_{u,i} = \sum_{k=1}^{4} \lambda_k y_{u,i}^k \tag{15}
$$

$$
\mathcal{L} = -\sum_{(u,i)\in\mathbb{D}} y_{u,i} \log \hat{y}_{u,i} + \left(1 - y_{u,i}\right) \log\left(1 - \hat{y}_{u,i}\right) \tag{16}
$$

Experiment

Table 3: Comparisons of different models on three datasets. The best results are in boldface and the second best results are underlined. "Impv." indicates the relative improvement of the best results compared to the second best results.

Datasets	Metric	**BPR**	**GCMC**	**NGCF**	**LightGCN**	**UltraGCN**	**IMP-GCN**	**DICER**	**ARBRE**	Impv.
Beauty	Recall@5	0.3554	0.3714	0.4310	0.4733	0.4690	0.4812	0.4718	**0.5223**	8.54%
	Recall@10	0.4436	0.4901	0.5395	0.5814	0.5644	0.5925	0.5903	**0.6465**	9.11%
	Recall@15	0.5006	0.5642	0.6022	0.6406	0.6291	0.6539	0.6573	**0.7202**	9.57%
	NDCG@5	0.3165	0.2981	0.3561	0.3914	0.3939	0.3972	0.3799	**0.4249**	6.97%
	NDCG@10	0.3543	0.3400	0.3947	0.4297	0.4286	0.4367	0.4232	**0.4704**	7.72%
	NDCG@15	0.3738	0.3618	0.4130	0.4472	0.4477	0.4549	0.4431	**0.4923**	8.22%
Video	Recall@5	0.4781	0.5470	0.6187	0.6341	0.6355	0.6332	0.6105	**0.7024**	10.53%
	Recall@10	0.6032	0.6924	0.7473	0.7558	0.7582	0.7541	0.7479	**0.8227**	8.51%
	Recall@15	0.6753	0.7703	0.8123	0.8192	0.8221	0.8145	0.8206	**0.8836**	7.48%
	NDCG@5	0.4172	0.4420	0.5166	0.5338	0.5351	0.5331	0.4970	**0.5957**	11.33%
	NDCG@10	0.4697	0.4935	0.5623	0.5769	0.5802	0.5760	0.5476	**0.6395**	10.22%
	NDCG@15	0.4948	0.5169	0.5819	0.5959	0.5995	0.5943	0.5697	**0.6580**	9.76%
Yelp	Recall@5	0.4210	0.4389	0.4693	0.4884	0.6002	0.5522	0.5264	**0.6266**	4.40%
	Recall@10	0.5731	0.6277	0.6528	0.6645	0.7472	0.7337	0.7012	**0.7910**	5.86%
	Recall@15	0.6466	0.7325	0.7494	0.7585	0.8335	0.8268	0.8113	**0.8784**	5.39%
	NDCG@5	0.4253	0.4044	0.4329	0.4568	0.5287	0.5153	0.4452	**0.5469**	3.44%
	NDCG@10	0.4785	0.4665	0.4935	0.5140	0.5866	0.5748	0.5148	**0.6120**	4.33%
	NDCG@15	0.5066	0.5015	0.5258	0.5453	0.6174	0.6064	0.5540	**0.6439**	4.29%

Experiment

Table 4: Effect of context-aware modulation on Beauty

Model	Recall@5	Recall@10	Recall@15	NDCG@5	NDCG@10	NDCG@15
ARBRE-m	0.4196	0.5373	0.6074	0.3299	0.3730	0.3937
ARBRE-n	0.4769	0.6093	0.6894	3853	0.4331	0.4568
ARBRE-m-n	0.3604	0.4924	0.5627	0.2753	0.3239	0.3449
ARBRE	**0.5223**	**0.6465**	**0.7202**	**0.4249**	**0.4704**	**0.4923**

ARBRE-m: ignoring user interest $\boldsymbol{m}_u^{i*}$.

Table 5: Effect of asymmetrical structure on Beauty

Model	Recall@5	Recall@10	Recall@15	NDCG@5	NDCG@10	NDCG@15
ARBRE-α	0.4657	0.5832	0.6486	0.3761	0.4192	0.4387
ARBRE-β	0.4652	0.5840	0.6612	0.3789	0.4213	0.4440
ARBRE	**0.5223**	**0.6465**	**0.7202**	**0.4249**	**0.4704**	**0.4923**

ARBRE-α: learning target user interest by conducting element-wise product and max pooling operations

Experiment

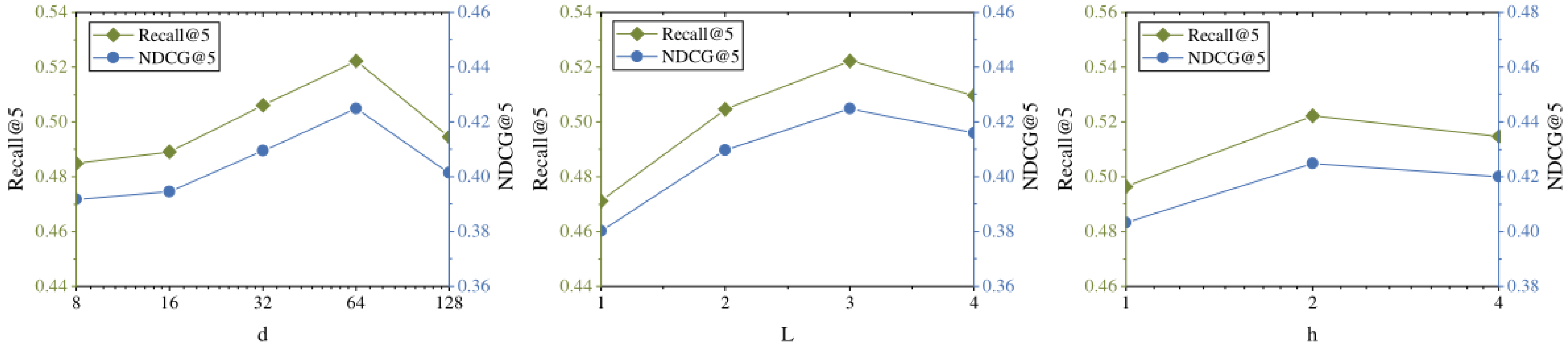


Figure 3: Performance of ARBRE on Beauty w.r.t different hyper-parameters

Table 6: Effect of the interaction between user interest and item attraction in the prediction layer on Video

Model	Recall@5	Recall@10	Recall@15	NDCG@5	NDCG@10	NDCG@15
ARBRE-MLP_1	0.6180	0.7554	0.8285	0.5111	0.5612	0.5832
ARBRE	**0.7024**	**0.8227**	**0.8836**	**0.5957**	**0.6395**	**0.6580**

Thank you!