CrossCBR:Cross-view Contrastive Learning for Bundle Recommendation

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https://github.com/mysbupt/CrossCBR

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Reported by Yabo Yin

Artificial

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Introduction

The cooperative association between these two views (Bundle view, Item view) has been loosely modeled or even overlooked in existing works.

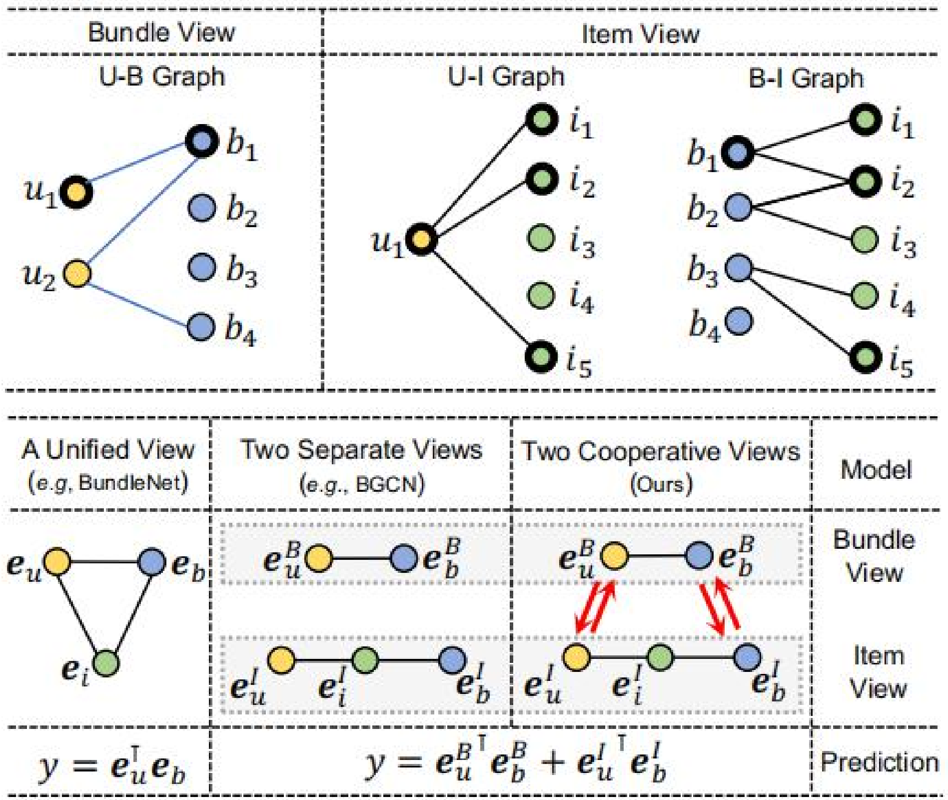


Figure 1: Top: The bundle and item views presented in the U-B, U-I and B-I graphs. Bottom: Our work models the cooperative association between views, where the superscripts B and I denote the bundle and item view, and the subscripts u, b, and i stand for the user, bundle, and item.

Method

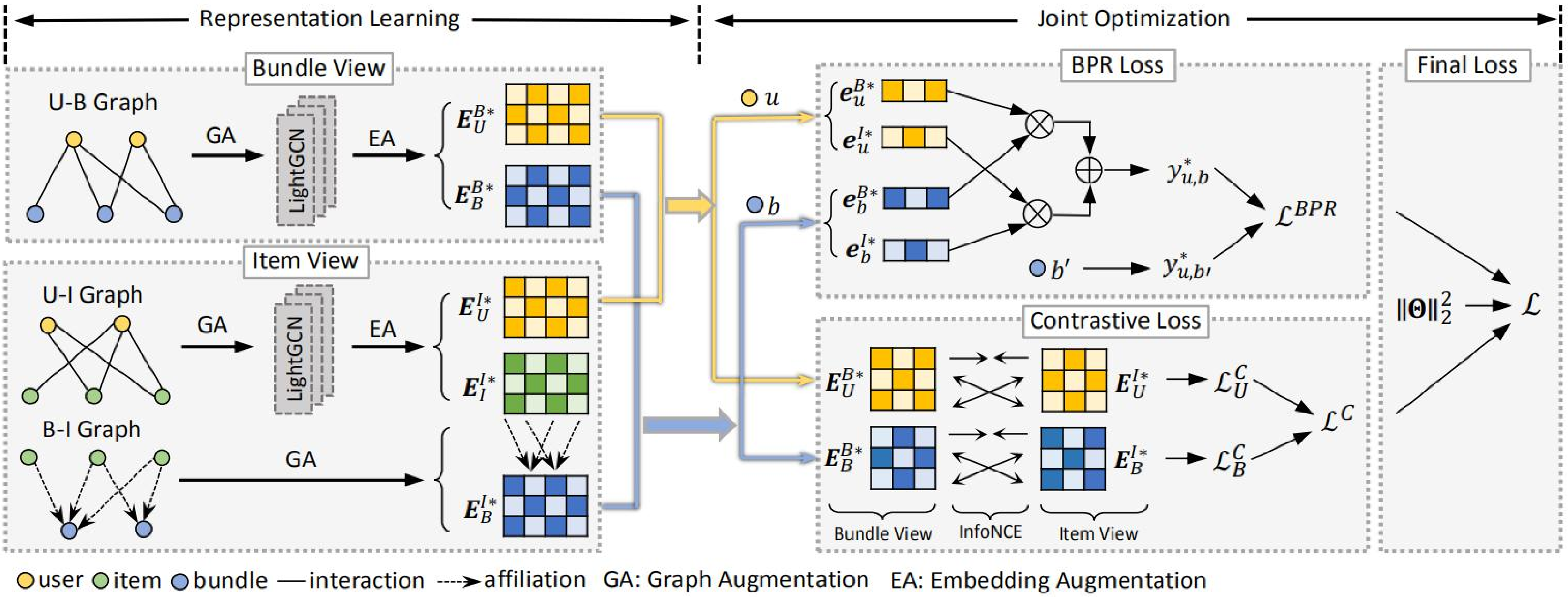


Figure 2: The overall framework of CrossCBR consists of two parts: (1) representation learning for the two views of users and bundles and (2) the joint optimization of the BPR loss $\mathcal{L}^{BPR}$ and contrastive loss $\mathcal{L}^C$.

Method

Problem Definition

a set of users $\mathcal{U} = \{u_1, u_2, \cdots, u_M\}$

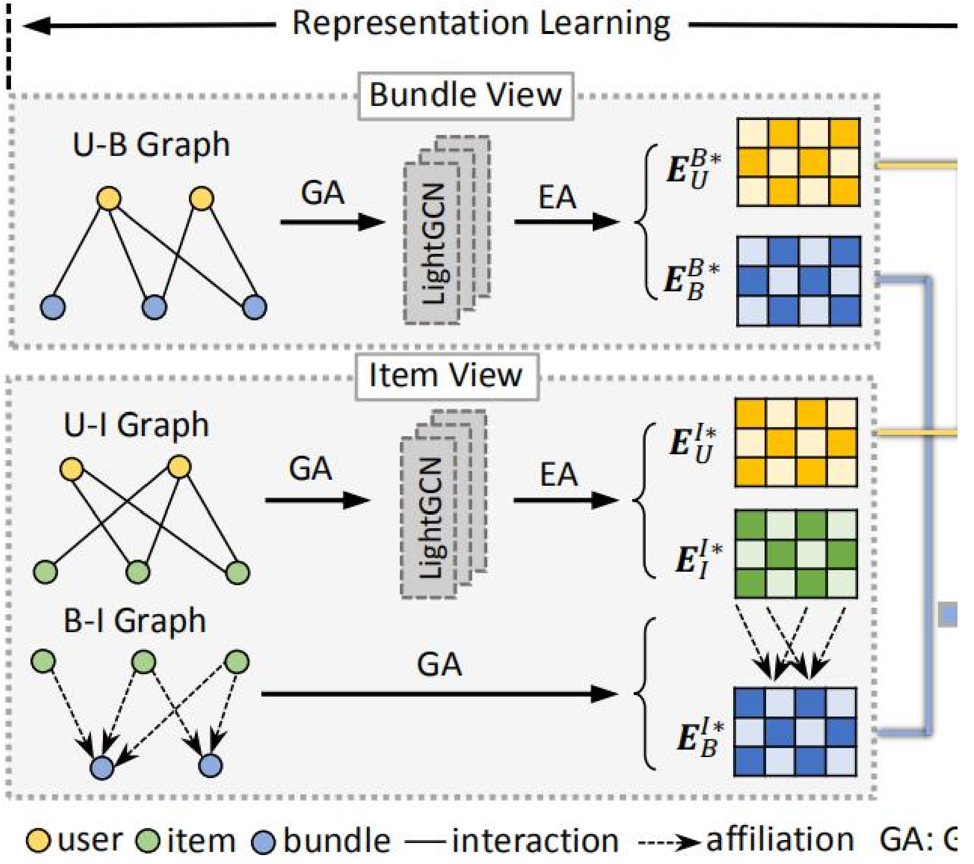
a set of bundles $\mathcal{B} = \{b_1, b_2, \cdots, b_N\}$

a set of items $\mathcal{I} = \{i_1, i_2, \cdots, i_O\}$

$X_{M\times N} = \{x_{ub} | u \in \mathcal{U}, b \in \mathcal{B}\}$

$Y_{M\times O} = \{y_{ui} | u \in \mathcal{U}, i \in \mathcal{I}\}$

$Z_{N\times O} = \{z_{bi} | b \in \mathcal{B}, i \in \mathcal{I}\}$



$$\begin{cases} \mathrm{e}_u^{B(k)} = \sum_{b\in N_u} \frac{1}{\sqrt{|N_u|}\sqrt{|N_b|}} \mathrm{e}_b^{B(k-1)}, \\ \mathrm{e}_b^{B(k)} = \sum_{u\in N_b} \frac{1}{\sqrt{|N_b|}\sqrt{|N_u|}} \mathrm{e}_u^{B(k-1)}, \end{cases} \quad (1)$$

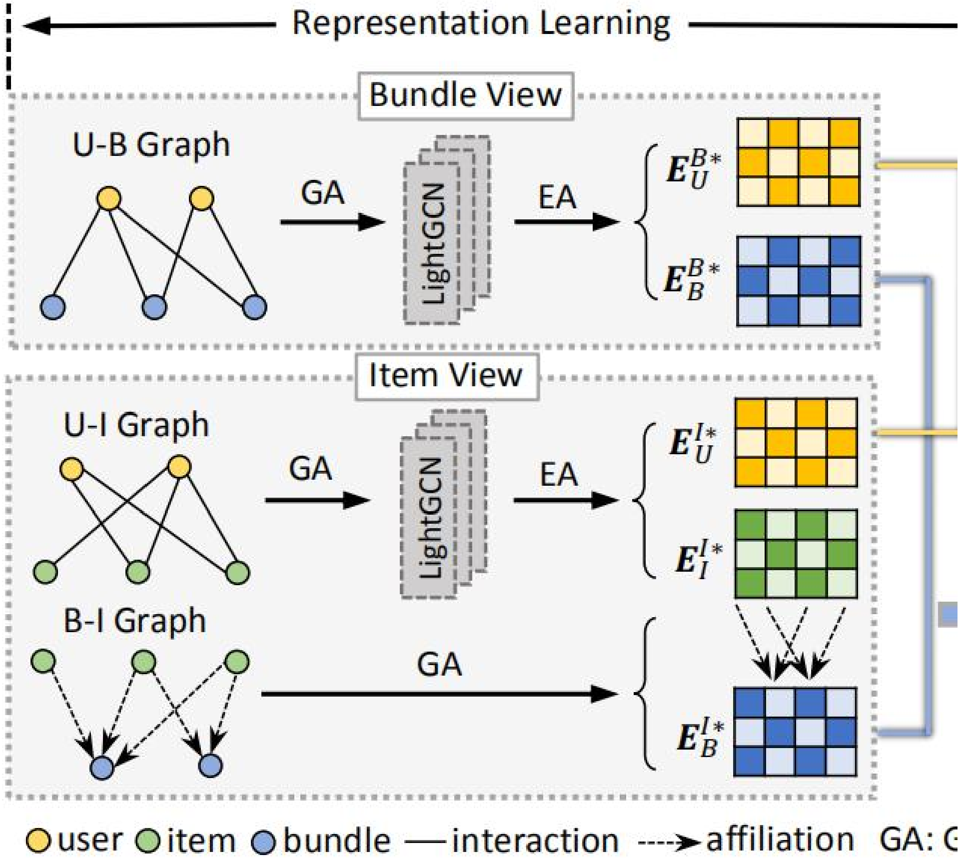
$$\mathrm{e}_u^{B*} = \sum_{k=0}^{K} \mathrm{e}_u^{B(k)}, \quad \mathrm{e}_b^{B*} = \sum_{k=0}^{K} \mathrm{e}_b^{B(k)}. \quad (2)$$

Method

$$\begin{cases} \mathrm{e}_u^{I(k)} = \sum_{i \in \mathcal{N}_u} \frac{1}{\sqrt{|\mathcal{N}_u|}\sqrt{|\mathcal{N}_i|}} \mathrm{e}_i^{I(k-1)}, \\ \mathrm{e}_i^{I(k)} = \sum_{u \in \mathcal{N}_i} \frac{1}{\sqrt{|\mathcal{N}_i|}\sqrt{|\mathcal{N}_u|}} \mathrm{e}_u^{I(k-1)}, \end{cases} \tag{3}$$

$$\mathrm{e}_u^{I*} = \sum_{k=0}^{K} \mathrm{e}_u^{I(k)}, \quad \mathrm{e}_i^{I*} = \sum_{k=0}^{K} \mathrm{e}_i^{I(k)}, \tag{4}$$

$$\mathrm{e}_b^{I*} = \frac{1}{|\mathcal{N}_b|} \sum_{i \in \mathcal{N}_b} \mathrm{e}_i^{I*}, \tag{5}$$



Method

$$\mathcal{L}_U^C = \frac{1}{|\mathcal{U}|}\sum_{u\in\mathcal{U}} -\log \frac{\exp(s(\mathrm{e}_u^{B*}, \mathrm{e}_u^{I*})/\tau)}{\sum_{v\in\mathcal{U}}\exp(s(\mathrm{e}_u^{B*}, \mathrm{e}_v^{I*})/\tau)}, \tag{6}$$

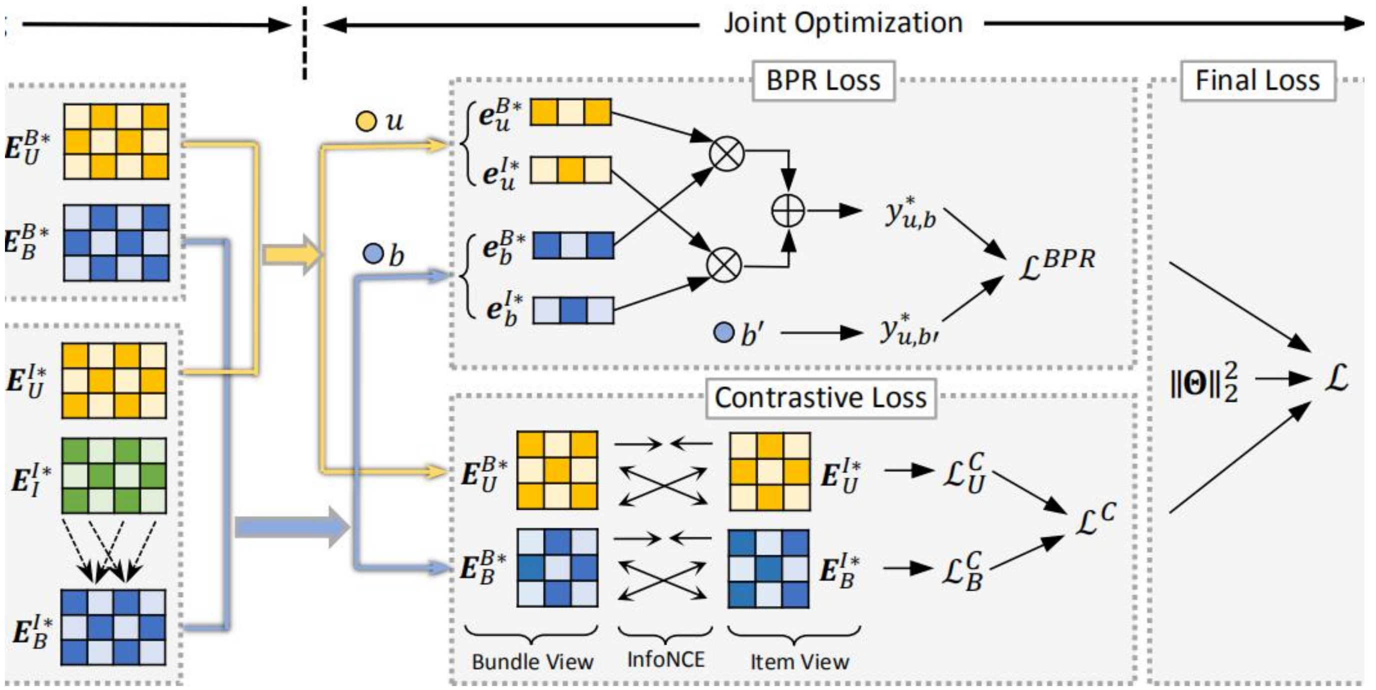
$$\mathcal{L}_B^C = \frac{1}{|\mathcal{B}|}\sum_{b\in\mathcal{B}} -\log \frac{\exp(s(\mathrm{e}_b^{B*}, \mathrm{e}_b^{I*})/\tau)}{\sum_{p\in\mathcal{B}}\exp(s(\mathrm{e}_b^{B*}, \mathrm{e}_p^{I*})/\tau)}, \tag{7}$$

$$\mathcal{L}^C = \frac{1}{2}(\mathcal{L}_U^C + \mathcal{L}_B^C). \tag{8}$$

$$y^*_{u,b} = \mathrm{e}_u^{B*\top}\mathrm{e}_b^{B*} + \mathrm{e}_u^{I*\top}\mathrm{e}_b^{I*}. \tag{9}$$

$$\mathcal{L}^{BPR} = \sum_{(u,b,b')\in Q} -\ln\sigma(y^*_{u,b} - y^*_{u,b'}). \tag{10}$$

$$\mathcal{L} = \mathcal{L}^{BPR} + \lambda_1\mathcal{L}^C + \lambda_2\|\Theta\|_2^2, \tag{11}$$



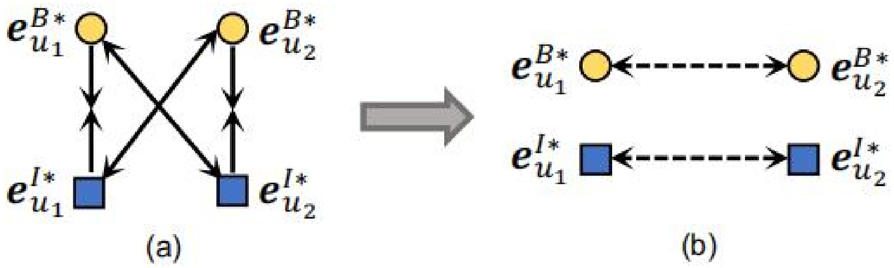


Figure 3: The illustration of the direct (a) and indirect (b) effects of the cross-view contrastive loss.

Experiments

Table 1: Dataset Statistics.

Dataset	#U	#I	#B	#U-I	#U-B	#Avg.I/B
Youshu	8,039	32,770	4,771	138,515	51,377	37.03
NetEase	18,528	123,628	22,864	1,128,065	302,303	77.80
iFashion	53,897	27,694	42,563	2,290,645	1,679,708	3.86

Experiments

Table 2: The overall performance comparison, where Rec is short of Recall. Note that the improvement achieved by CrossCBR is significant (p-value $\ll 0.05$).

Model	Youshu				NetEase				iFashion			
	Rec@20	NDCG@20	Rec@40	NDCG@40	Rec@20	NDCG@20	Rec@40	NDCG@40	Rec@20	NDCG@20	Rec@40	NDCG@40
MFBPR	0.1959	0.1117	0.2735	0.1320	0.0355	0.0181	0.0600	0.0246	0.0752	0.0542	0.1162	0.0687
LightGCN	0.2286	0.1344	0.3190	0.1592	0.0496	0.0254	0.0795	0.0334	0.0837	0.0612	0.1284	0.0770
SGL	0.2568	0.1527	0.3537	0.1790	0.0687	0.0368	0.1058	0.0467	0.0933	0.0690	0.1389	0.0851
DAM	0.2082	0.1198	0.2890	0.1418	0.0411	0.0210	0.0690	0.0281	0.0629	0.0450	0.0995	0.0579
BundleNet	0.1895	0.1125	0.2675	0.1335	0.0391	0.0201	0.0661	0.0271	0.0626	0.0447	0.0986	0.0574
BGCN	0.2347	0.1345	0.3248	0.1593	0.0491	0.0258	0.0829	0.0346	0.0733	0.0531	0.1128	0.0671
CrossCBR	**0.2813**	**0.1668**	**0.3785**	**0.1938**	**0.0842**	**0.0457**	**0.1264**	**0.0569**	**0.1173**	**0.0895**	**0.1699**	**0.1080**
%Improv.	9.57	9.26	7.02	8.28	22.57	24.33	19.48	21.96	25.76	29.63	22.33	26.85

Experiments

Table 4: The cross-view alignment and dispersion analysis of the representations. A denotes *Alignment*; D denotes *Dispersion*; superscripts (C, B, I) denote the cross, bundle, and item view; subscripts (U, B) stand for users and bundles.

Metrics	NetEase		iFashion	
	CrossCBR-CL	CrossCBR	CrossCBR-CL	CrossCBR
A_U^C	0.638	0.932	0.878	0.950
D_U^B	0.313	0.049	0.331	0.014
D_U^I	0.044	0.004	0.193	0.004
A_B^C	0.351	0.632	0.635	0.910
D_B^B	0.040	0.042	0.052	0.033
D_B^I	0.075	0.016	0.011	0.030

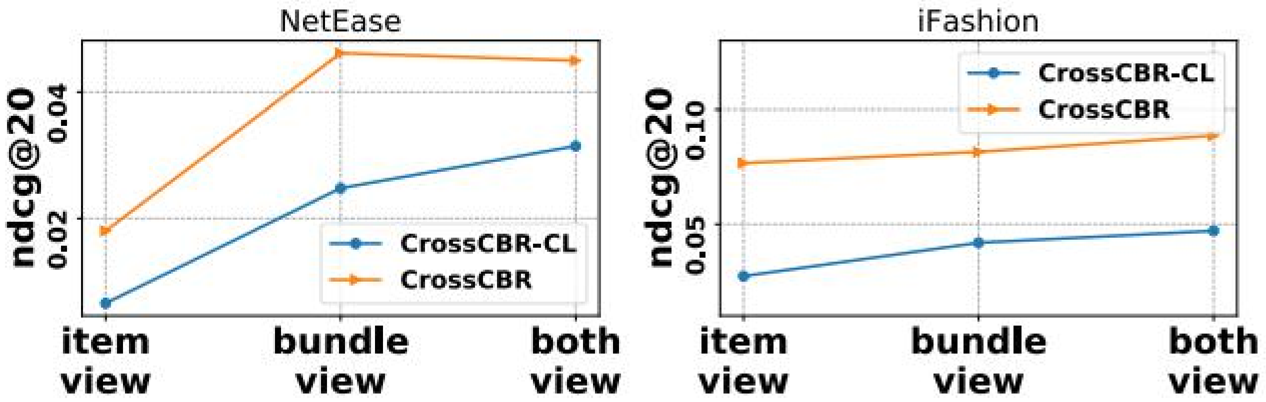


Figure 4: The performance of CrossCBR and CrossCBR-CL *w.r.t.* predictions based on different views.

Experiments

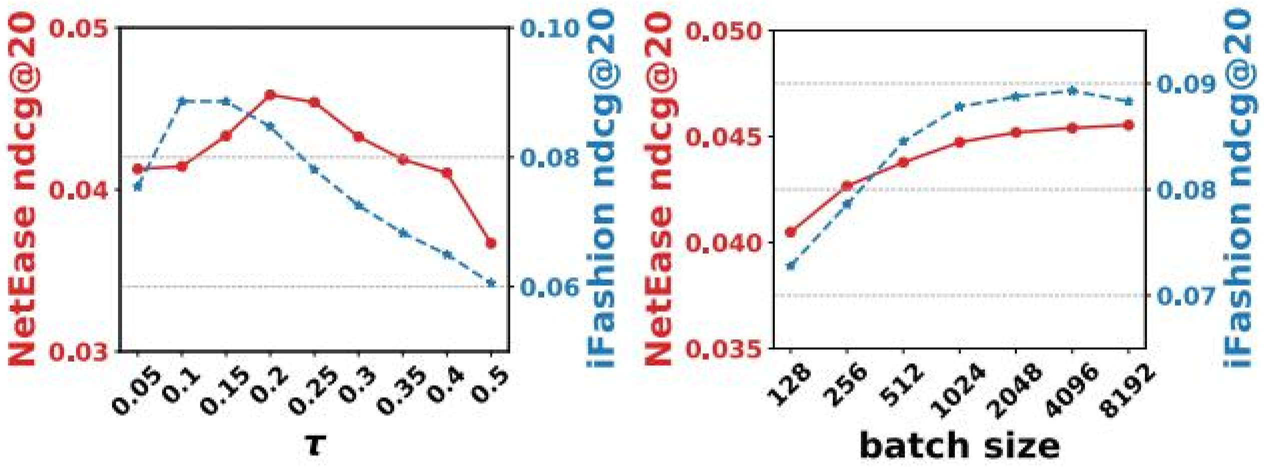


Figure 5: The performance (NDCG@20) variance of CrossCBR *w.r.t.* the temperature τ and the batch size on both datasets of NetEase and iFashion.

Table 5: The statistics of one-epoch training time (seconds) for CrossCBR and baselines on different devices, where the "Cr" is short of "CrossCBR".

Device	Dataset	BGCN	Cr-CL	**Cr_OP**	Cr+SC	Cr+BB
Titan XP	NetEase	32.05	6.80	7.04	7.27	28.02
	iFashion	63.47	46.05	46.74	47.61	56.42
Titan V	NetEase	20.76	4.67	5.09	5.48	18.59
	iFashion	38.76	29.48	30.02	30.31	35.01