Chongqing University of Technology

ATAI Advanced Technique of Artificial Intelligence

Improving Knowledge-aware Recommendation with Multi-level Interactive Contrastive Learning

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(CIKM-2022) https://github.com/CCIIPLab/KGIC

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Reported by Ke Gan

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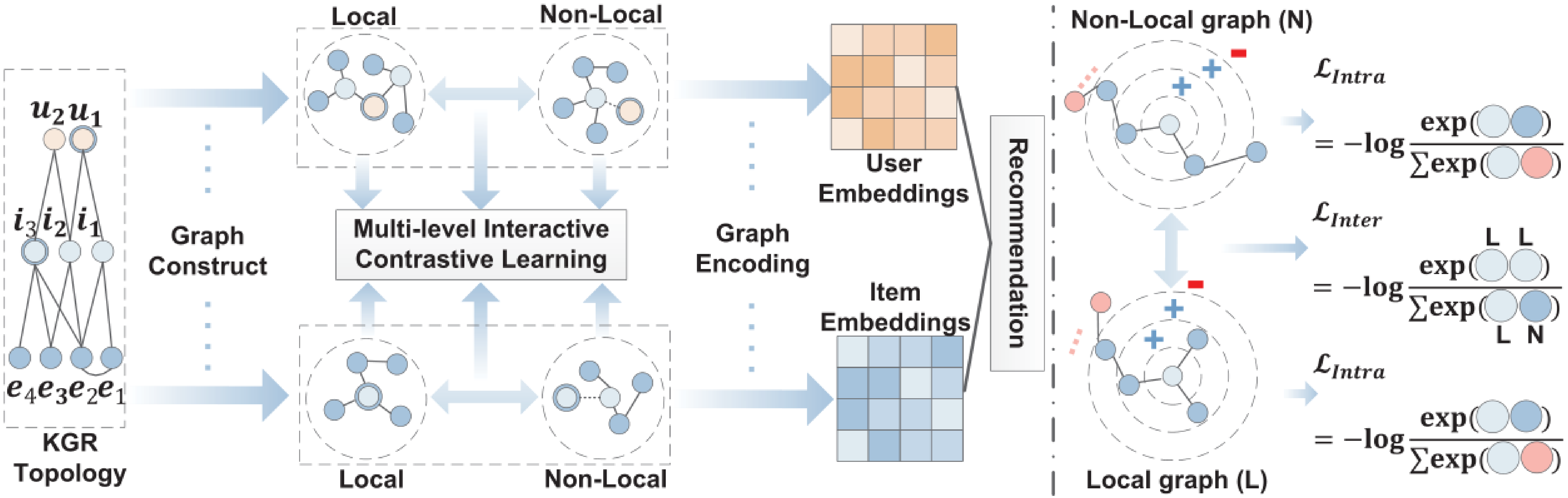
Introduction

Problem:

the GNN-based methods ignores the non-local KG facts (neighboring areas of similar items)

the combination of sparse interactions and redundant KG facts results in an unbalanced information utilization

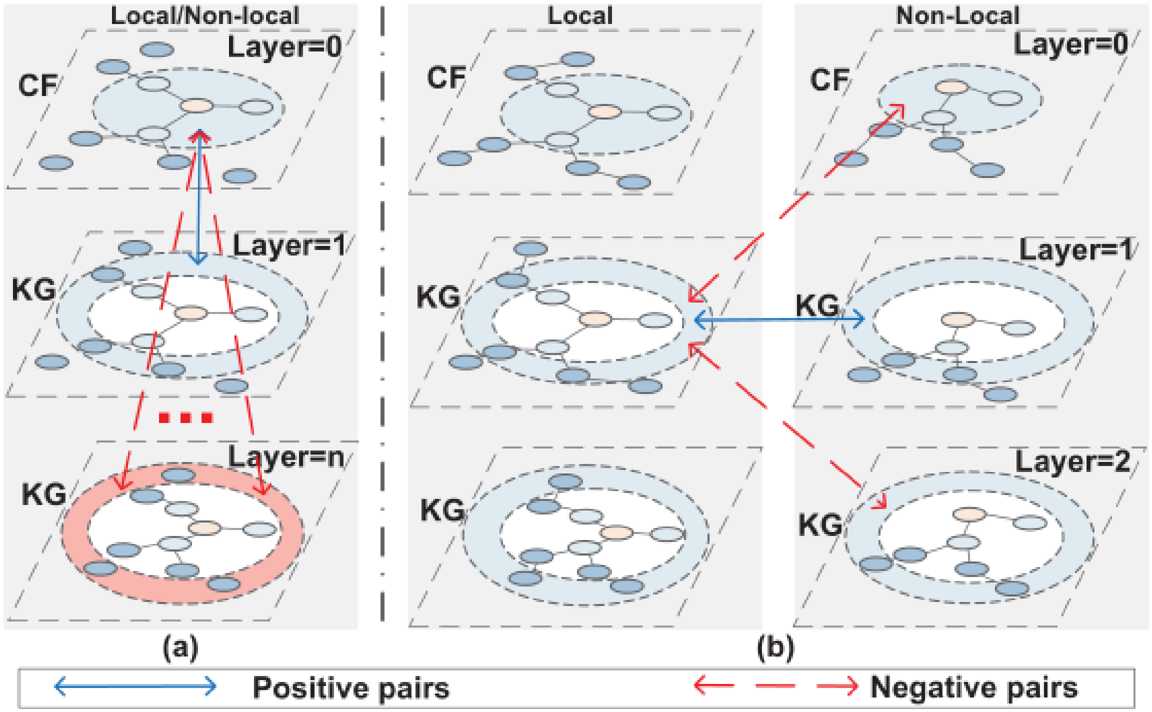
Approach



$$\mathcal{U} = \{u_1, u_2, \ldots, u_M\} \qquad Y \in R^{M\times N}$$

$$\mathcal{V} = \{v_1, v_2, \ldots, v_N\} \qquad \mathcal{A} = \{(v, e) | v \in \mathcal{V}, e \in \mathcal{E}\}$$

Introduction



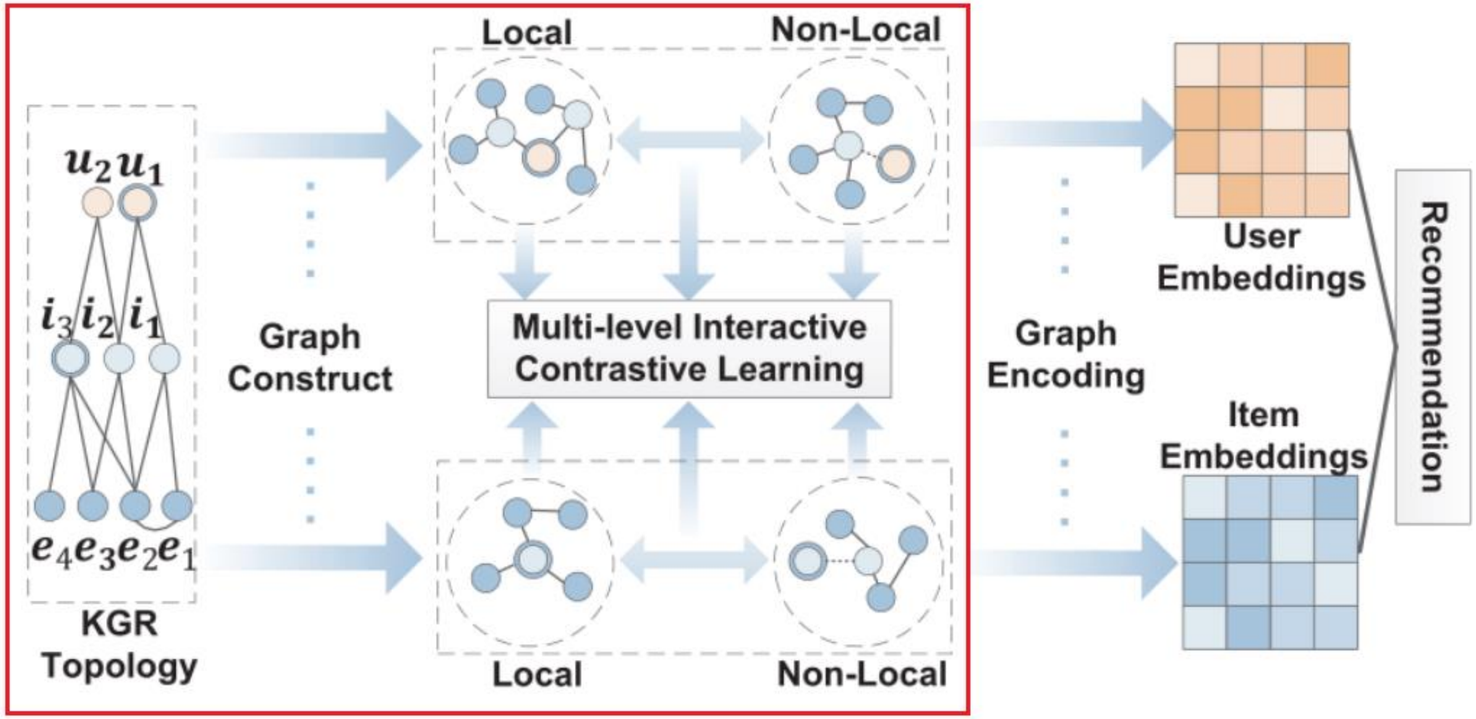
Intra-graph

unifying the CF and KG information,having a consistent and sufficient representation learning

Inter-graph

extract more informative KG signals

Approach



Local

$$\begin{aligned}\mathcal{E}^0_{u,L} &= \{e \mid (v,e) \in \mathcal{A}, \text{ and } v \in \{v \mid y_{uv} = 1\}\},\\ \mathcal{E}^0_{v,L} &= \{e \mid (v,e) \in \mathcal{A}\},\end{aligned} \tag{1}$$

$$\mathcal{S}^l_{o,L} = \left\{(h,r,t) \mid (h,r,t) \in \mathcal{G} \text{ and } h \in \mathcal{E}^{l-1}_{o,L}\right\}, l = 1, \ldots, L, \tag{2}$$

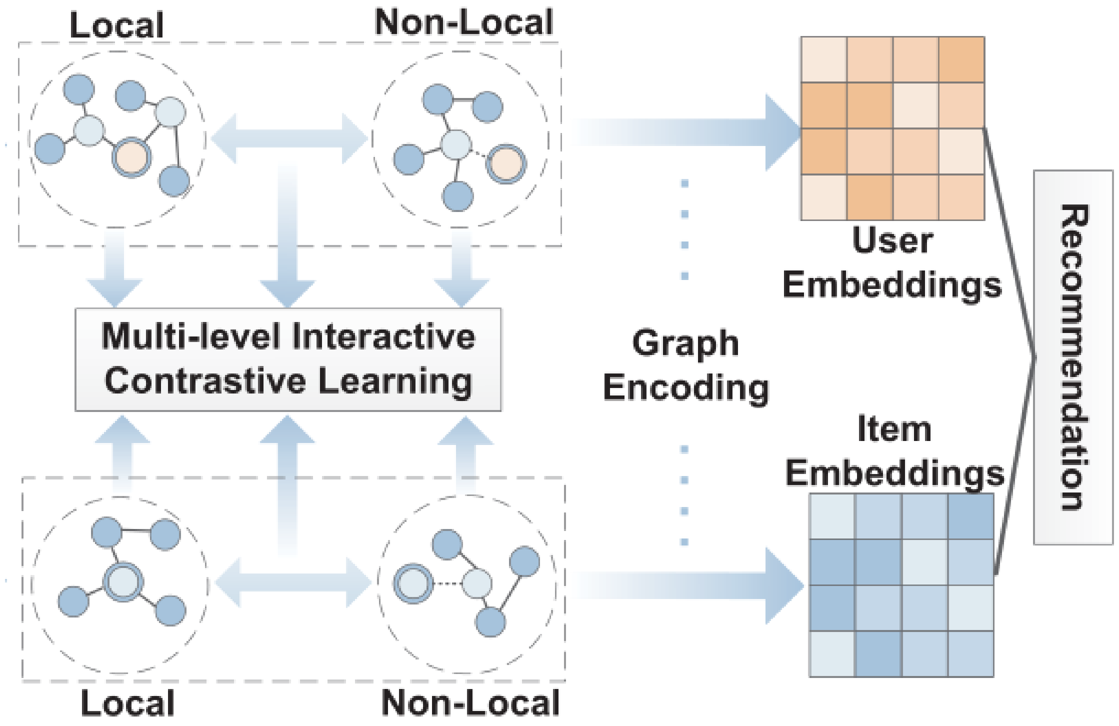
Non-Local

$$\begin{aligned}\mathcal{V}_p &= \left\{v_p \mid u \in \mathcal{U}_{\text{sim}}, \text{ and } y_{uv_p} = 1\right\},\\ \mathcal{U}_{\text{sim}} &= \left\{u_{\text{sim}} \mid v \in \{v \mid y_{uv} = 1\} \text{ and } y_{u_{\text{sim}}v} = 1\right\},\\ \mathcal{V}_u &= \left\{v_u \mid u \in \{u \mid y_{uv} = 1\} \text{ and } y_{uv_u} = 1\right\},\end{aligned} \tag{3}$$

$$\begin{aligned}\mathcal{E}^0_{u,N} &= \left\{e \mid (v_p, e) \in \mathcal{A}, \text{ and } v_p \in \mathcal{V}_p\right\},\\ \mathcal{E}^0_{v,N} &= \left\{e \mid (v_u, e) \in \mathcal{A}, \text{ and } v_u \in \mathcal{V}_u\right\}.\end{aligned} \tag{4}$$

$$\mathcal{S}^l_{o,N} = \left\{(h,r,t) \mid (h,r,t) \in \mathcal{G}\text{and}h \in \mathcal{E}^{l-1}_{o,N}\right\}, l = 1, \ldots, L. \tag{5}$$

Approach

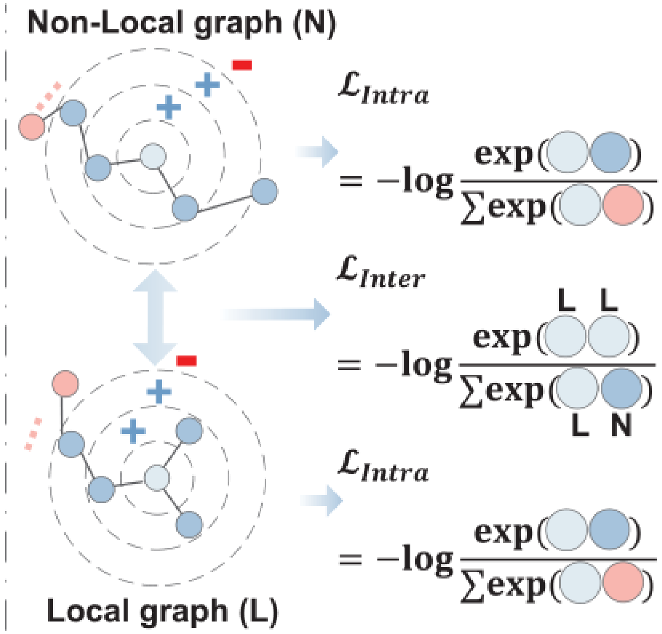


$$\mathrm{E}_{o,D}^{l} = \sum_{i=1}^{m} \pi\left(e_i^h, r_i\right) e_i^t, \tag{6}$$

$$\pi\left(e_i^h, r_i\right) = \sigma\left(W_1\left[\sigma\left(W_0\left(e_i^h \| r_i\right) + b_0\right)\right] + b_1\right),$$

$$\pi\left(\mathrm{e}_i^h, \mathrm{r}_i\right) = \frac{\exp\left(\pi\left(\mathrm{e}_i^h, \mathrm{r}_i\right)\right)}{\sum_{(h',r',t')\in\mathcal{S}_{o,D}^{l}} \exp\left(\pi\left(\mathrm{e}_i^{h'}, \mathrm{r}_i'\right)\right)}, \tag{7}$$

Approach



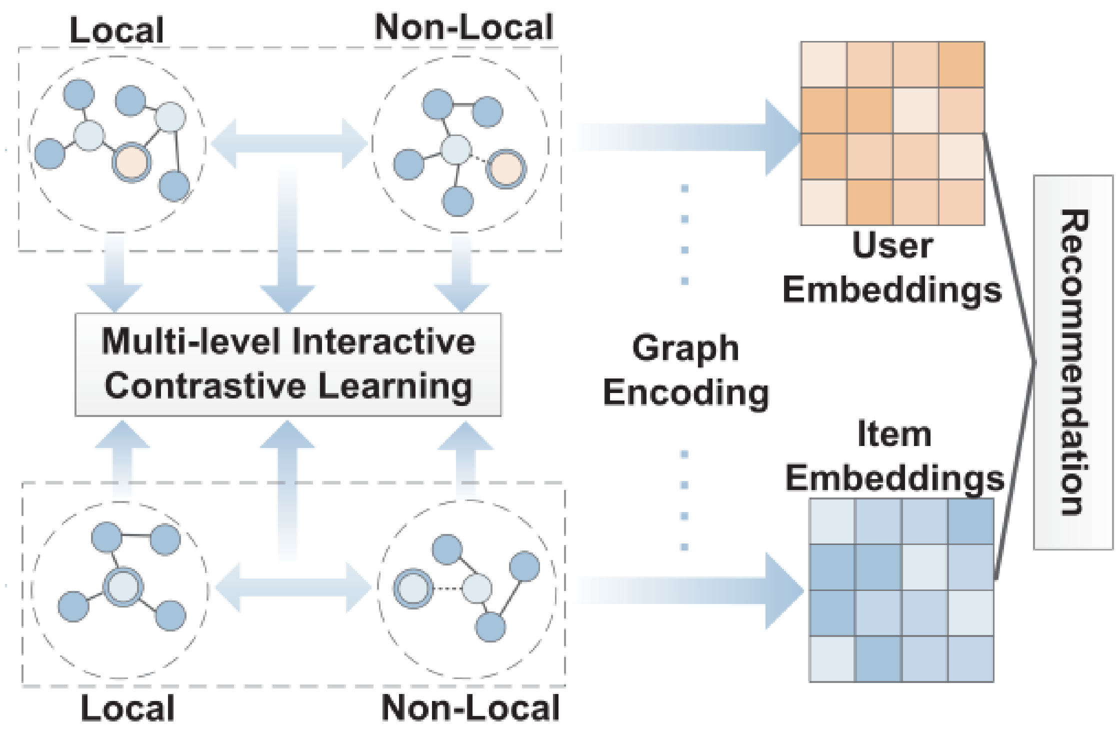
$$\mathcal{L}^{U}_{Intra} = \sum_{u\in\mathcal{U}} -\log \frac{\sum_{k\in L} e^{\left(\left(\mathbf{E}^{(0)}_{u,L}\cdot \mathbf{E}^{(k)}_{u,L}/\tau\right)\right)}}{\underbrace{\sum_{k\in L} e^{\left(\left(\mathbf{E}^{(0)}_{u,L}\cdot \mathbf{E}^{(k)}_{u,L}/\tau\right)\right)}}_{\text{positive pair}} + \underbrace{\sum_{k'>L} e^{\left(\left(\mathbf{E}^{(0)}_{u,L}\cdot \mathbf{E}^{(k')}_{u,L}/\tau\right)\right)}}_{\text{intra-graph negative pair}}} + \sum_{u\in\mathcal{U}} -\log \frac{\sum_{k\in L} e^{\left(\left(\mathbf{E}^{(0)}_{u,N}\cdot \mathbf{E}^{(k)}_{u,N}/\tau\right)\right)}}{\underbrace{\sum_{k\in L} e^{\left(\left(\mathbf{E}^{(0)}_{u,N}\cdot \mathbf{E}^{(k)}_{u,N}/\tau\right)\right)}}_{\text{positive pair}} + \underbrace{\sum_{k'>L} e^{\left(\left(\mathbf{E}^{(0)}_{u,N}\cdot \mathbf{E}^{(k')}_{u,N}/\tau\right)\right)}}_{\text{intra-graph negative pair}}}, \quad (8)$$

$$\mathcal{L}_{Intra} = \mathcal{L}^{U}_{Intra} + \mathcal{L}^{I}_{Intra}. \quad (9)$$

$$\mathcal{L}^{U}_{Inter} = \sum_{u\in\mathcal{U}} \sum_{k\in L} -\log \frac{e^{\left(\left(\mathbf{E}^{(k)}_{u,L}\cdot \mathbf{E}^{(k)}_{u,N}/\tau\right)\right)}}{\underbrace{e^{\left(\left(\mathbf{E}^{(k)}_{u,L}\cdot \mathbf{E}^{(k)}_{u,N}/\tau\right)\right)}}_{\text{positive pair}} + \underbrace{\sum_{k'\neq k} e^{\left(\left(\mathbf{E}^{(k)}_{u,L}\cdot \mathbf{E}^{(k')}_{u,N}/\tau\right)\right)}}_{\text{inter-graph negative pair}}}. \quad (10)$$

$$\mathcal{L}_{Inter} = \mathcal{L}^{U}_{Inter} + \mathcal{L}^{I}_{Inter}. \quad (11)$$

Approach



$$\mathbf{e}_u = \mathbf{E}^0_{u,L} \| \dots \| \mathbf{E}^L_{u,L} \| \mathbf{E}^0_{u,N} \| \dots \| \mathbf{E}^L_{u,N},$$
$$\mathbf{e}_i = \mathbf{E}^0_{i,L} \| \dots \| \mathbf{E}^L_{i,L} \| \mathbf{E}^0_{i,N} \| \dots \| \mathbf{E}^L_{i,N}, \tag{12}$$
$$\hat{\mathbf{y}}(u, i) = \mathbf{e}_u^\top \mathbf{e}_i .$$

$$\mathcal{L}_{\text{BPR}} = \sum_{(u,i,j) \in O} - \ln \sigma \left(\hat{\mathbf{y}}_{ui} - \hat{\mathbf{y}}_{uj} \right), \tag{13}$$

$$\mathcal{L}_{KGIC} = \mathcal{L}_{\text{BPR}} + \lambda 1 (\alpha \mathcal{L}_{Intra} + \mathcal{L}_{Inter}) + \lambda 2 \|\Theta\|^2_2, \tag{14}$$

Experiment

		Book-Crossing	MovieLens-1M	Last.FM
User-item Interaction	# users	17,860	6,036	1,872
	# items	14,967	2,445	3,846
	# interactions	139,746	753,772	42,346
Knowledge Graph	# entities	77,903	182,011	9,366
	# relations	25	12	60
	# triplets	151,500	1,241,996	15,518
Hyper-parameter Settings	# η	4×10^{-3}	4×10^{-3}	4×10^{-3}
	# $\lambda 1$	1×10^{-6}	1×10^{-7}	1×10^{-6}
	# $\lambda 2$	1×10^{-4}	1×10^{-5}	1×10^{-4}

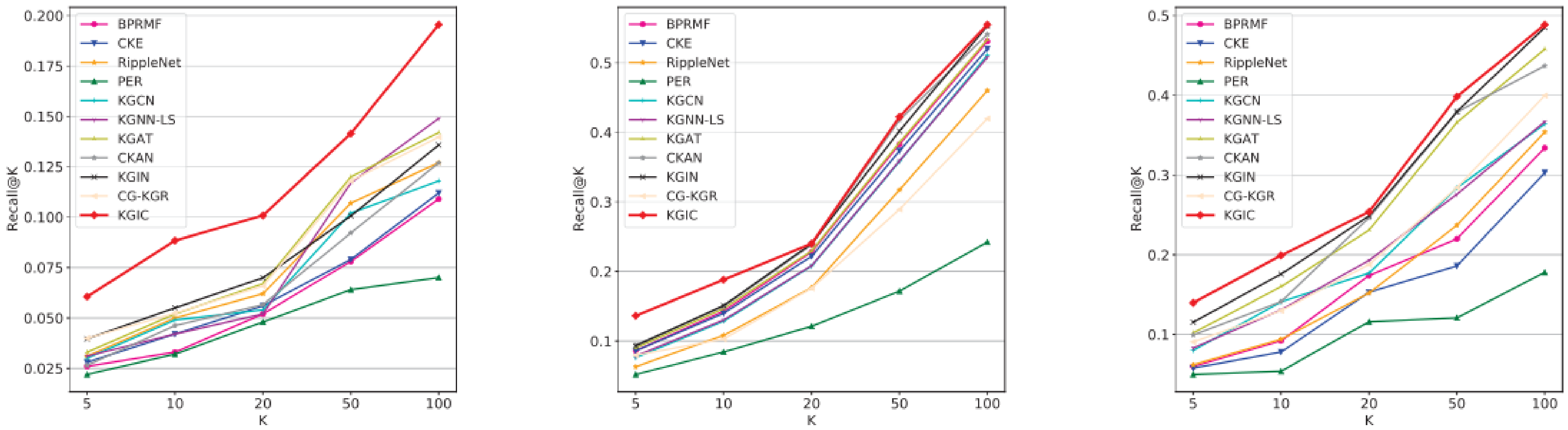
Table 1: Statistics and hyper-parameter settings for the three datasets. (η: learning rate, $\lambda 1$: constrastive loss weight, $\lambda 2$: L2 regularizer weight.)

Experiment

Model	Book-Crossing		MovieLens-1M		Last.FM	
	AUC	*F1*	*AUC*	*F1*	*AUC*	*F1*
BPRMF	0.6583(−11.66%)	0.6117(−6.95%)	0.8920(−3.32%)	0.7921(−6.38%)	0.7563(−10.29%)	0.7010(−7.43%)
CKE	0.6759(−9.90%)	0.6235(−5.77%)	0.9065(−1.87%)	0.8024(−5.35%)	0.7471(−11.21%)	0.6740(−10.13%)
RippleNet	0.7211(−5.38%)	0.6472(−3.40%)	0.9190(−0.62%)	0.8422(−1.37%)	0.7762(−8.30%)	0.7025(−7.28%)
PER	0.6048(−17.01%)	0.5726(−10.86%)	0.7124(−21.28%)	0.6670(−18.89%)	0.6414(−21.78%)	0.6033(−17.20%)
KGCN	0.6841(−9.08%)	0.6313(−4.99%)	0.9090(−1.62%)	0.8366(−1.93%)	0.8027(−5.65%)	0.7086(−6.67%)
KGNN-LS	0.6762(−9.87%)	0.6314(−4.98%)	0.9140(−1.12%)	0.8410(−1.49%)	0.8052(−5.40%)	0.7224(−5.29%)
KGAT	0.7314(−4.35%)	0.6544(−2.68%)	0.9140(−1.12%)	0.8440(−1.19%)	0.8293(−2.99%)	0.7424(−3.29%)
CKAN	0.7420(−3.29%)	0.6671(−1.41%)	0.9082(−1.70%)	0.8410(−1.49%)	0.8418(−1.74%)	0.7592(−1.61%)
KGIN	0.7273(−4.76%)	0.6614(−1.98%)	<u>0.9190</u>(−0.62%)	<u>0.8441</u>(−1.18%)	<u>0.8486</u>(−1.06%)	<u>0.7602</u>(−1.51%)
CG-KGR	<u>0.7498</u>(−2.51%)	<u>0.6689</u>(−1.23%)	0.9110(−1.42%)	0.8359(−2.00%)	0.8336(−2.56%)	0.7433(−3.20%)
KGIC	**0.7749***	**0.6812***	**0.9252***	**0.8559***	**0.8592***	**0.7753***

Table 2: The result of *AUC* and *F*1 in CTR prediction. The best results are in boldface and the second best results are underlined. * denotes statistically significant improvement by unpaired two-sample t-test with $p < 0.001$.

Experiment



(a) Book-Crossing (b) MovieLens-1M (c) Last.FM

Figure 3: The result of Recall@K in top-K recommendation.

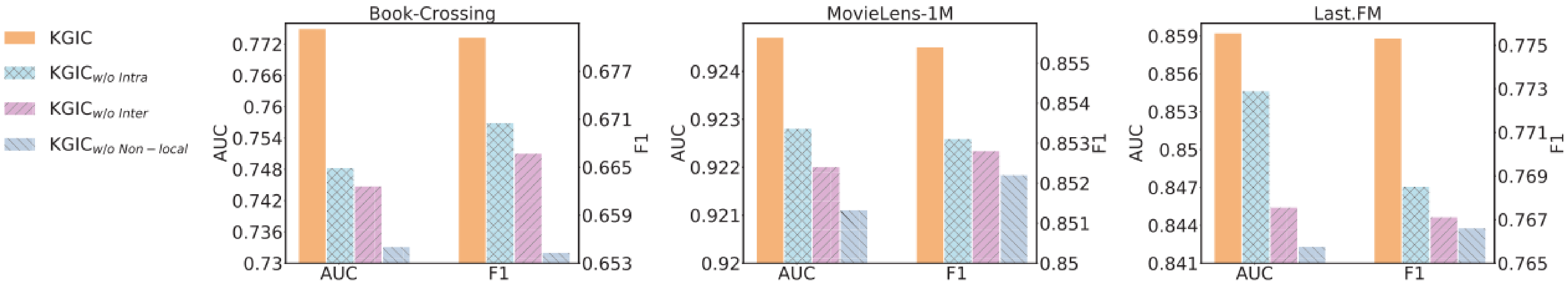
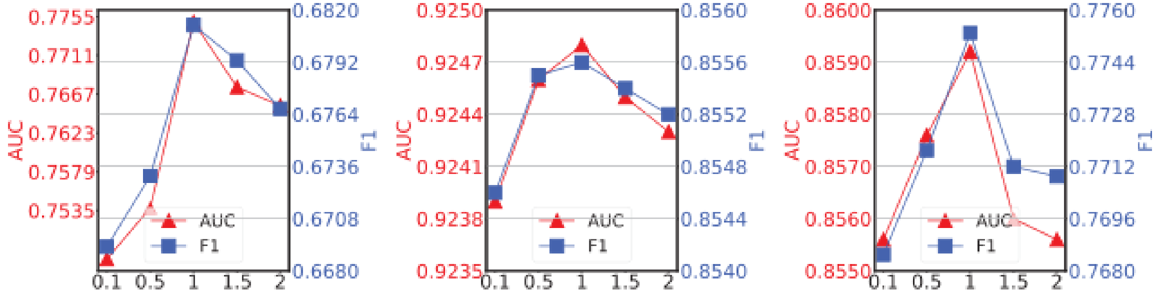


Figure 4: Effect of ablation study.

Experiment

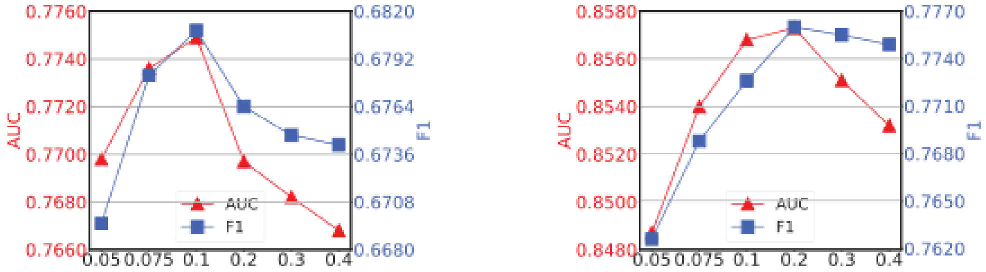
	Book		Movie		Music	
	Auc	F1	Auc	F1	Auc	F1
L=1	**0.7749**	**0.6812**	0.9241	0.8551	0.8482	0.7692
L=2	0.7689	0.6705	**0.9252**	**0.8559**	**0.8592**	**0.7753**
L=3	0.7513	0.6718	0.9203	0.8521	0.8511	0.7694

Table 3: Impact of model depth.



(a) Book (b) Movie (c) Music

Figure 5: Impact of coefficient α.



(a) Book (b) Music

Figure 6: Impact of temperature τ

Experiment

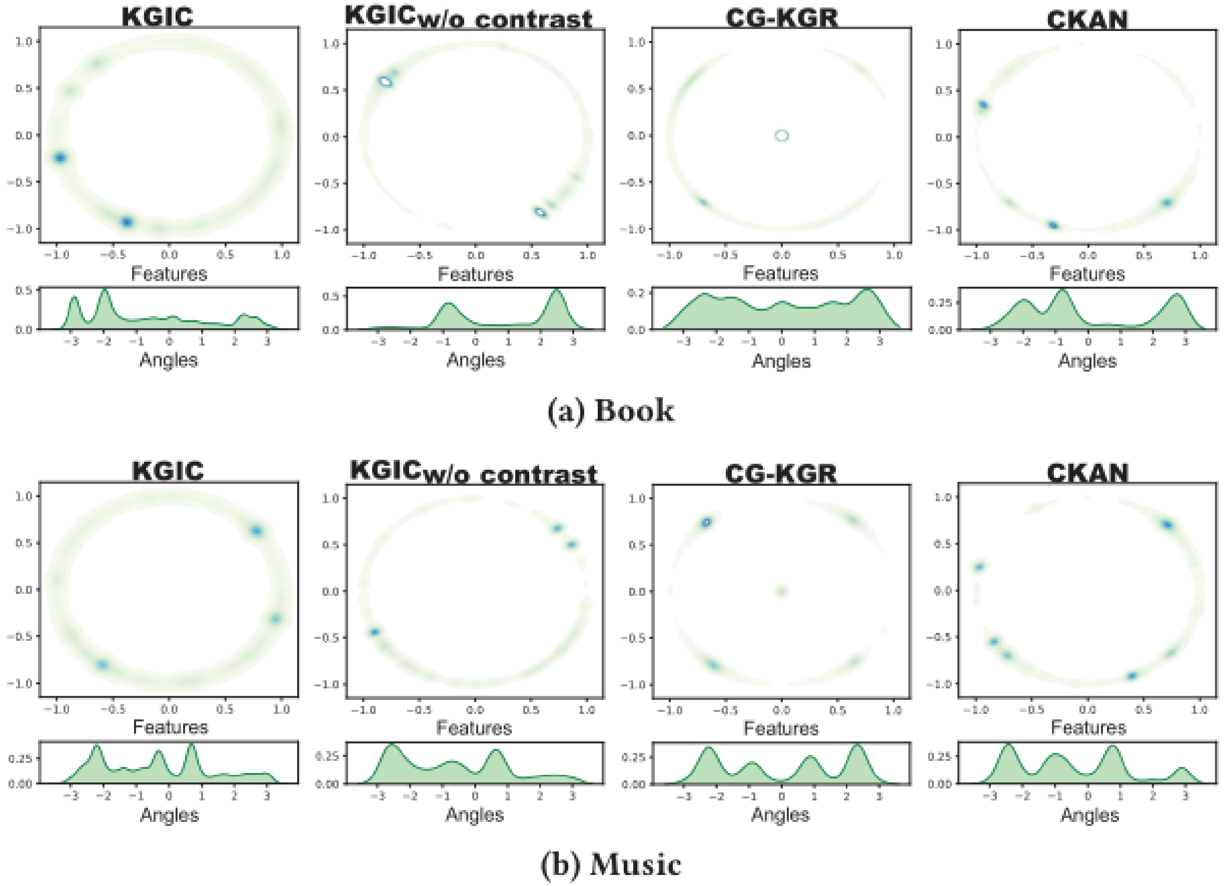


Figure 7: Visualization for the distribution of item embeddings.

Thank you!