HIERARCHICAL AND CONTRASTIVE REPRESENTATION LEARNING FOR KNOWLEDGE-AWARE RECOMMENDATION

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Reported by Ke Gan

1. Introduction
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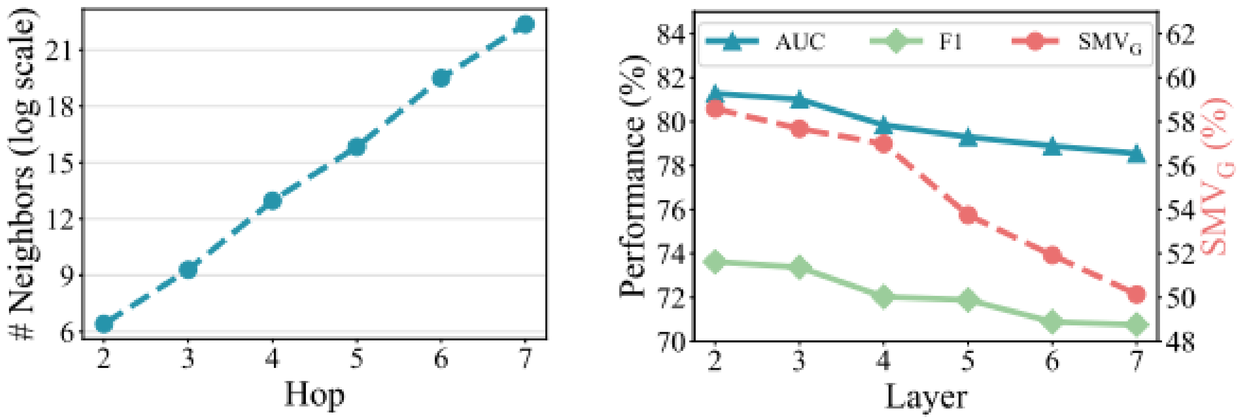
Introduction



(a) Average number of interacted neighbors.

(b) Performance and smoothness metric of KGAT.

1) Selecting and propagating a bundle of valuable neighbors to the central nodes

2) enhancing the selfdiscrimination of node representations in the latent space.

Approach

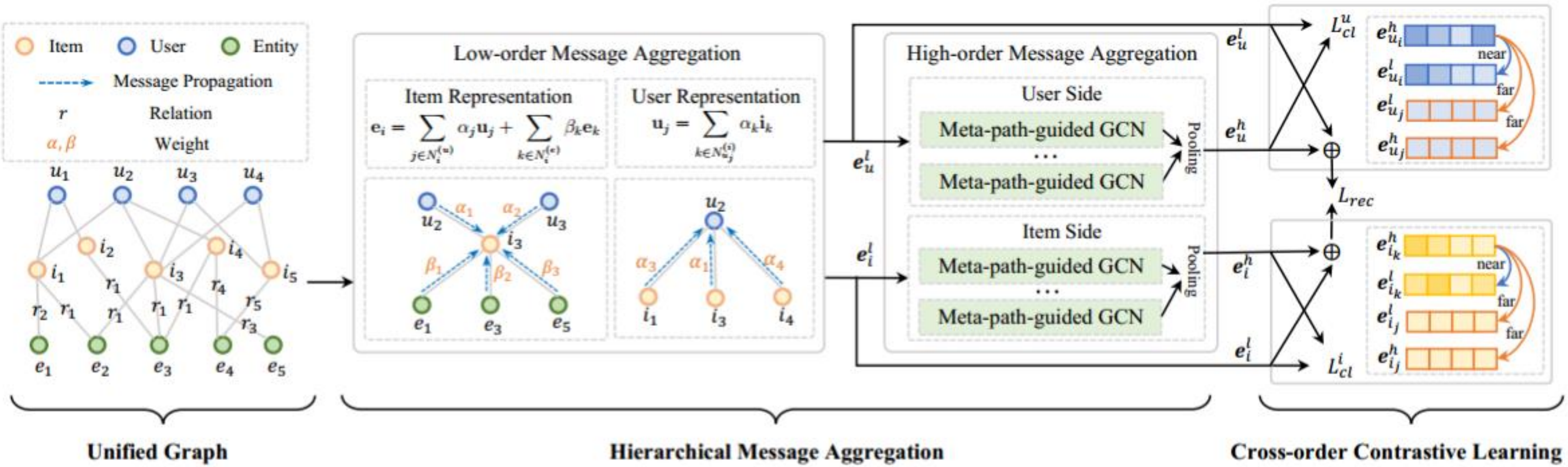
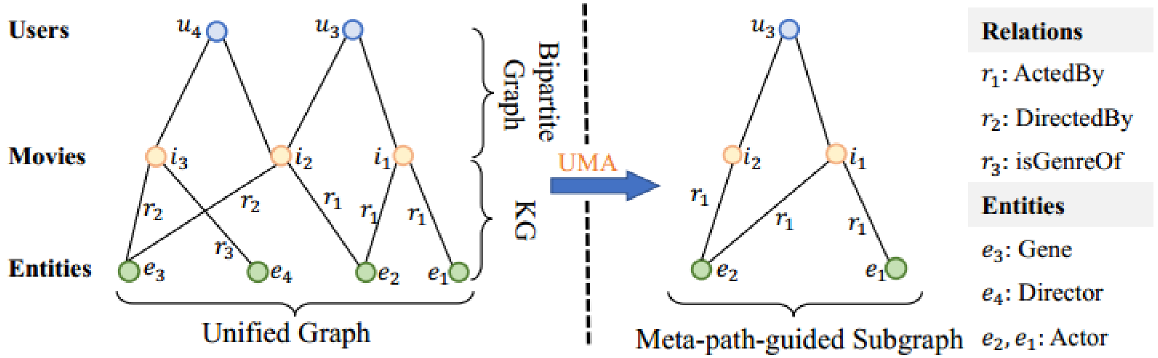
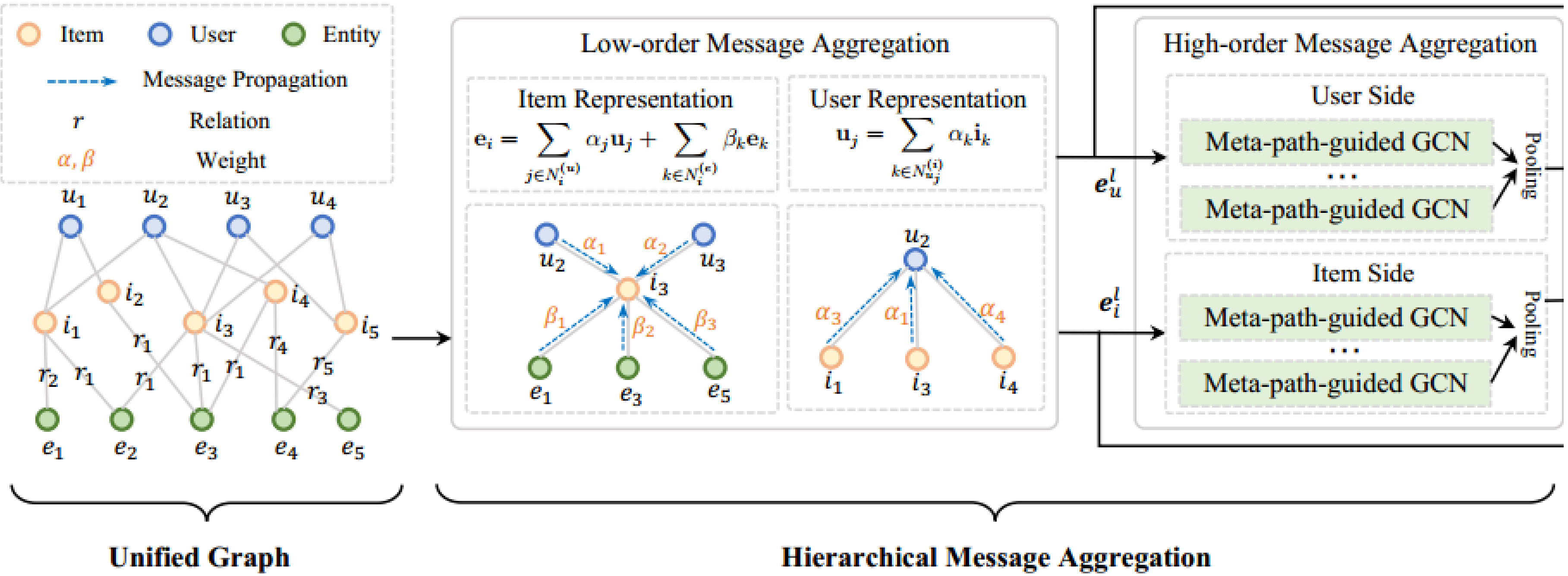


Fig. 3: The framework of our proposed HiCON model.



Approach



$$\alpha_{i,j} = \frac{1}{\sqrt{|\mathcal{N}_{u_i}^{(v)}|}\sqrt{|\mathcal{N}_{v_i}^{(u)}|}}, \quad \mathbf{h}_{v_i}^{(k+1)} = \sum_{j\in\mathcal{N}_{v_i}^{(u)}} \alpha_{i,j}\mathbf{e}_{u_j}^{(k)}, \quad (1)$$

$$\beta_{v_i,t}^{(k)} = \frac{\exp(\pi_{v_i,t}^{(k)})}{\sum_{(v_i,r,t)\in\mathcal{N}_{v_i}^{(e)}} \exp(\pi_{v_i,t}^{(k)})}, \quad \pi_{v_i,t}^{(k)} = \mathbf{s}_{v_i}^T \mathbf{s}_t, \quad (2)$$

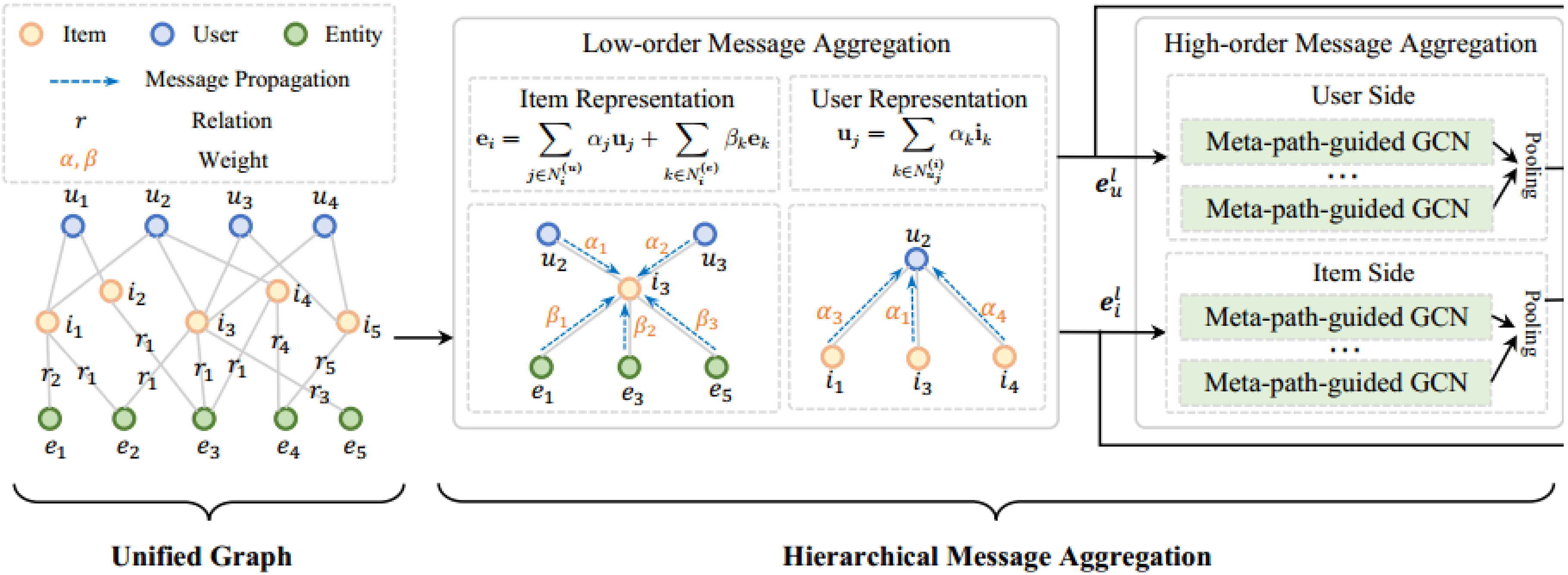
$$\mathbf{e}_{v_i}^{(k+1)} = \mathbf{h}_{v_i}^{(k+1)} + \mathbf{g}_{v_i}^{(k+1)}$$

$$\mathbf{g}_{v_i}^{(k+1)} = \sum_{(v_i,r,t)\in\mathcal{N}_{v_i}^{(e)}} \beta_{v_i,t}^{(k)}(\mathbf{e}_r^{(k)} \odot \mathbf{e}_t^{(k)})$$

$$\mathbf{s}_{v_i} = \mathbf{e}_{v_i}^{(k)} \odot \mathbf{e}_r^{(k)} / \|\mathbf{e}_{v_i}^{(k)} \odot \mathbf{e}_r^{(k)}\|$$

$$\mathbf{e}_{v_i} = \mathbf{e}_{v_i}^{(0)} + \mathbf{e}_{v_i}^{(1)} + \mathbf{e}_{v_i}^{(2)}$$

Approach

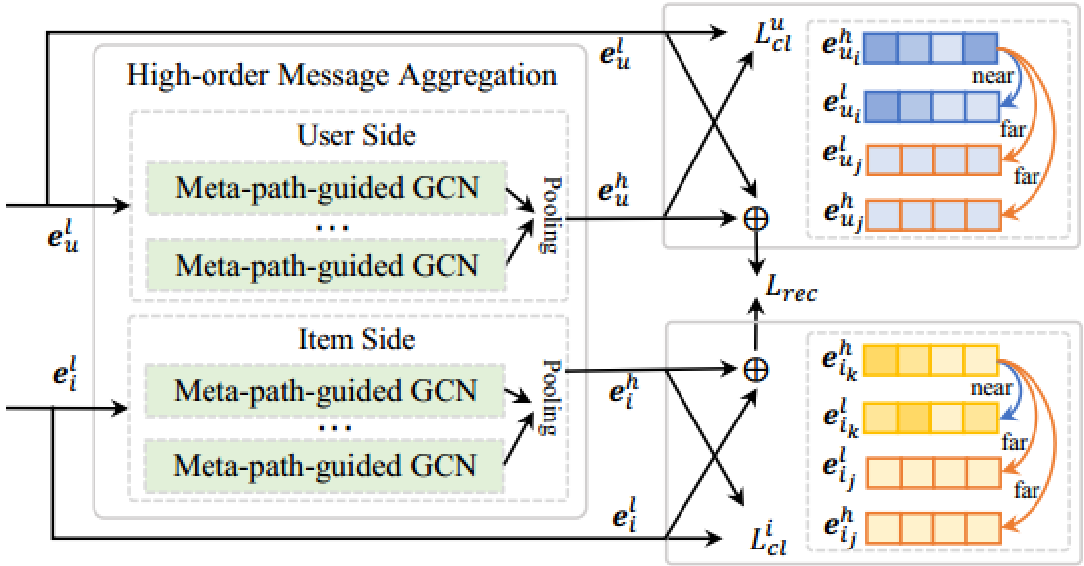


$$\mathbf{z}^{(k+1)}_{m,u_i} = \sigma\left(\sum_{j\in\mathcal{N}^{(m)}_{u_i}} \frac{1}{\sqrt{|\mathcal{N}^{(m)}_{u_i}|}\sqrt{|\mathcal{N}^{(m)}_{j}|}} \mathbf{z}^{(k)}_{m,j}\mathbf{W}^{(k)}_m\right), \quad (3)$$

$$\mathbf{z}^m_{u_i} = \mathbf{z}^{(l)}_{m,u_i}$$

$$\mathbf{z}_{u_i} = \sum_{m\in\mathcal{M}_u}\mathbf{z}^m_{u_i},$$

Approach



$$\mathcal{L}^I_{cl} = -\sum_{v_i \in \mathcal{I}} \log \frac{\exp((\mathbf{e}_{v_i} \cdot \mathbf{z}_{v_i})/\tau)}{\sum\limits_{v_j \in \mathcal{C}_{v_i} \cup \{v_i\}} \exp((\mathbf{e}_{v_i} \cdot \mathbf{h}_{z_j})/\tau)}),$$

$$\mathcal{L}_{cl} = \mathcal{L}^U_{cl} + \mathcal{L}^I_{cl}.$$

$$\mathcal{L}_{HiCON} = \mathcal{L}_{bpr} + \lambda \mathcal{L}_{cl}, \qquad (4)$$

$$\mathcal{L}_{bpr} = \sum_{u \in \mathcal{U}} \sum_{i \in \mathcal{N}_u} \sum_{i' \notin \mathcal{N}_u} -\log \sigma(\hat{y}_{u,i} - \hat{y}_{u,i'})$$

$$\hat{y}_{u,i} = [\mathbf{e}_u \parallel \mathbf{z}_u]^T [\mathbf{e}_i \parallel \mathbf{z}_i]$$

Experiment

Model	Book-Crossing		MovieLens-1M		Last.FM	
	AUC	*F1*	*AUC*	*F1*	*AUC*	*F1*
BPRMF	0.6583	0.6117	0.8920	0.7921	0.7563	0.7010
LightGCN	0.6134	0.6469	0.8800	0.8091	0.8300	0.7439
CKE	0.6759	0.6235	0.9065	0.8024	0.7471	0.6740
PER	0.6048	0.5726	0.7124	0.6670	0.6414	0.6033
RippleNet	0.7211	0.6472	0.9190	0.8422	0.7762	0.7025
KGCN	0.6841	0.6313	0.9090	0.8366	0.8027	0.7086
KGNN-LS	0.6762	0.6314	0.9140	0.8410	0.8052	0.7224
KGAT	0.7314	0.6544	0.9140	0.8440	0.8293	0.7424
CKAN	0.7420	0.6671	0.9082	0.8410	0.8418	0.7592
KGIN	0.7273	0.6614	0.9190	0.8441	0.8486	0.7602
MCCLK	0.7625	0.6777	<u>0.9351</u>	<u>0.8631</u>	<u>0.8763</u>	<u>0.8008</u>
KGIC	<u>0.7749</u>	<u>0.6812</u>	0.9252	0.8559	0.8592	0.7753
HiCON	**0.8045***	**0.7169***	**0.9410***	**0.8718***	**0.9045***	**0.8186***

Experiment

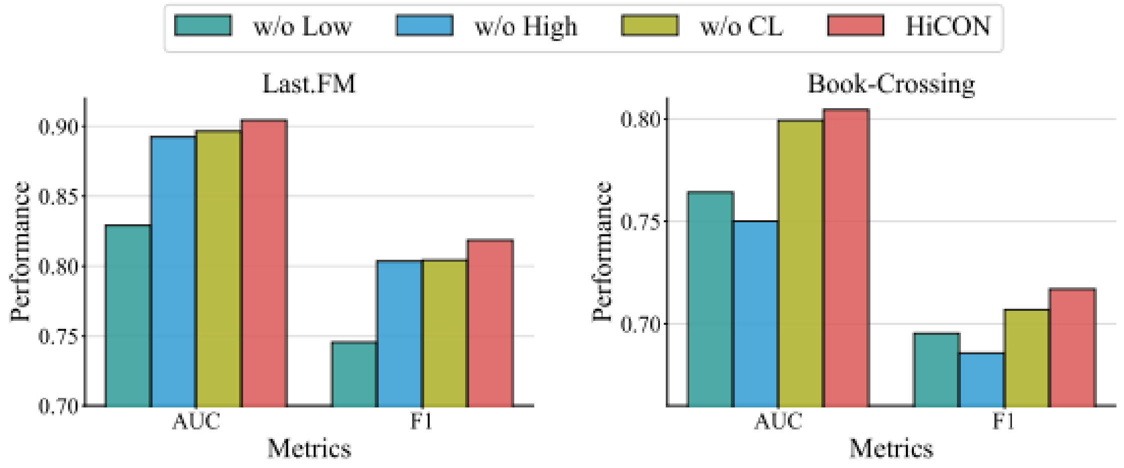


Fig. 5: The performance of HiCON and its variants on the LastFM and Book-Crossing datasets.

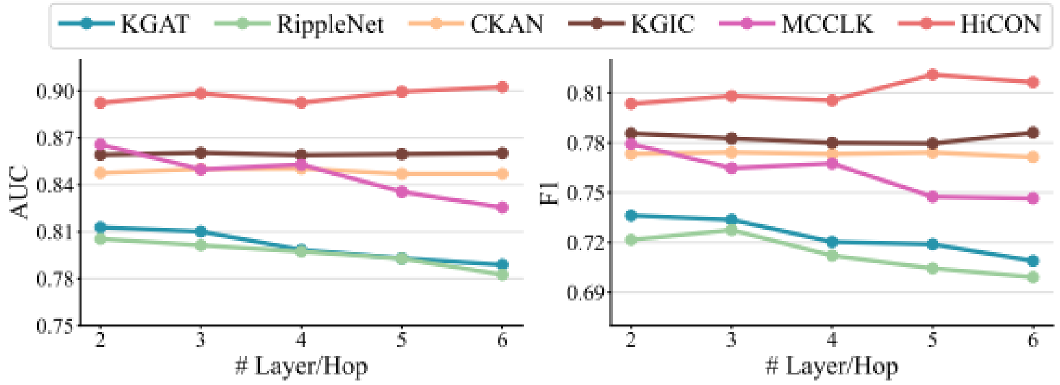
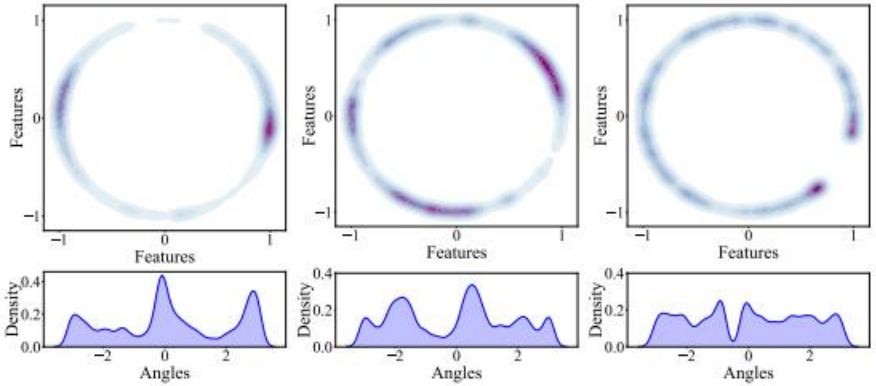


Fig. 6: The performance of HiCON and baselines at different layers (hops) on the LastFM dataset.

Experiment

		Last.FM	Book-Crossing	MovieLens-1M
Bipartite Interaction	# users	1,872	17,860	6,036
	# items	3,846	14,967	2,445
	# interactions	42,346	139,746	753,772
Knowledge Graph	# entities	9,366	77,903	182,011
	# relations	60	25	12
	# triplets	15,518	151,500	1,241,996



(a) HiCON$_{w/o\ Hie}$ (b) HiCON$_{w\ Hie}$ (c) HiCON

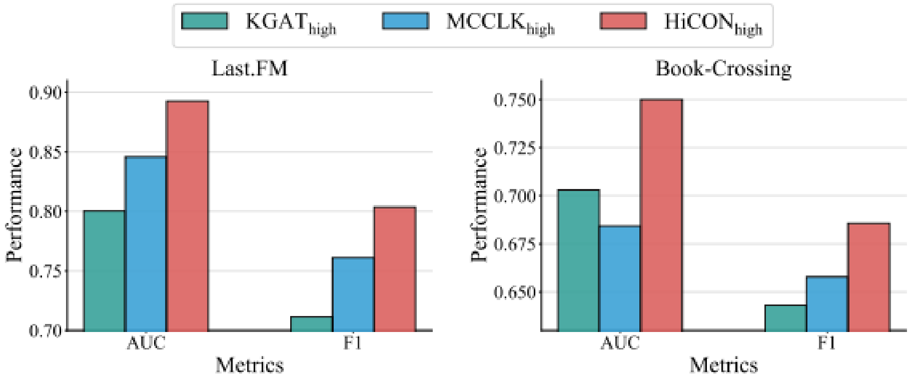


Fig. 8: The performance of KGAT, MCCLK, and HiCON in modeling the high-order semantic relatedness on the LastFM and Book-Crossing datasets.

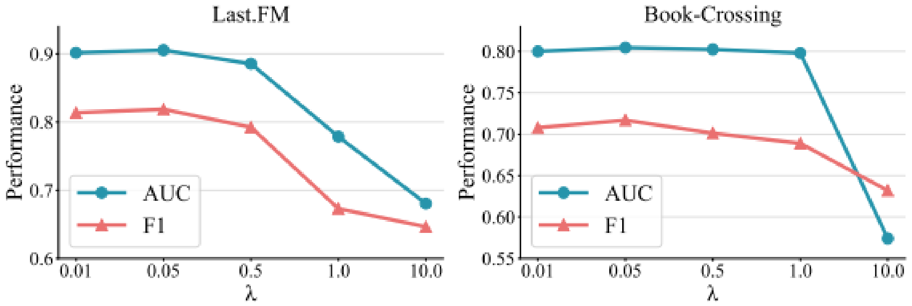


Fig. 10: The impact of the hyper-parameter λ.

Experiment

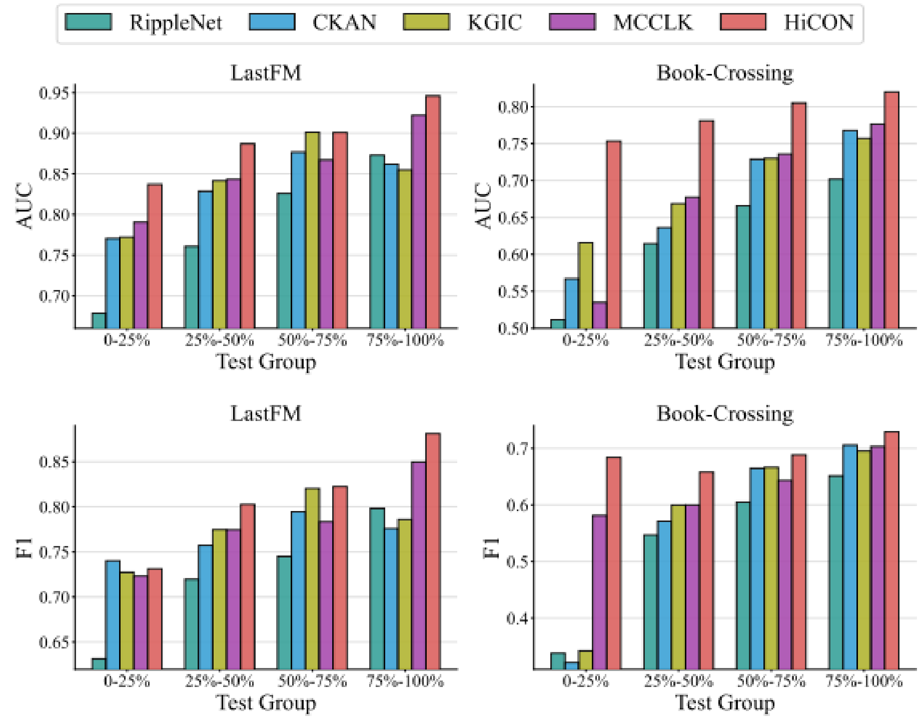


Fig. 9: The performance of HiCON and baselines at different interaction sparsity levels. 25%-50% is a user group sampled from the test set, including the users whose number of interacted items ranges from the 25th to 50th percentile.

Thank you!