南京航空航天大學
NANJING UNIVERSITY OF AERONAUTICS AND ASTRONAUTICS

组会汇报

2024年9月1日

Review-Enhanced Hierarchical Contrastive Learning for Recommendation

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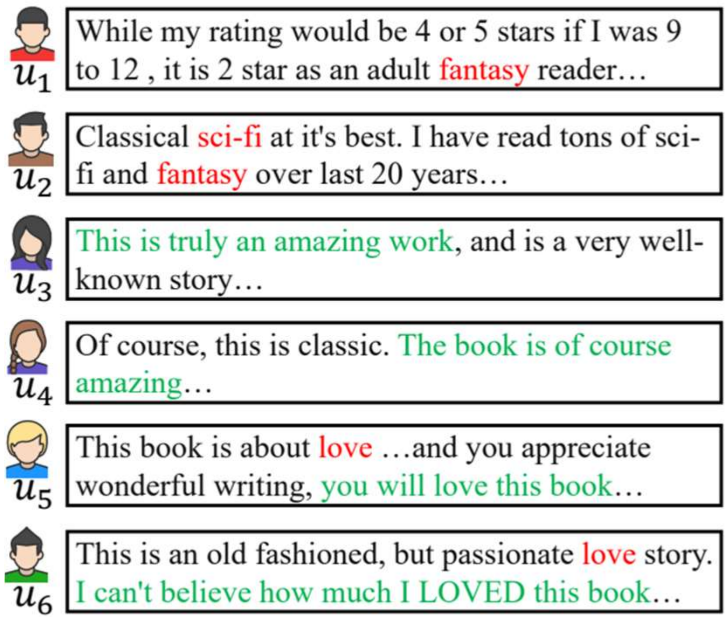
研究背景

研究方法

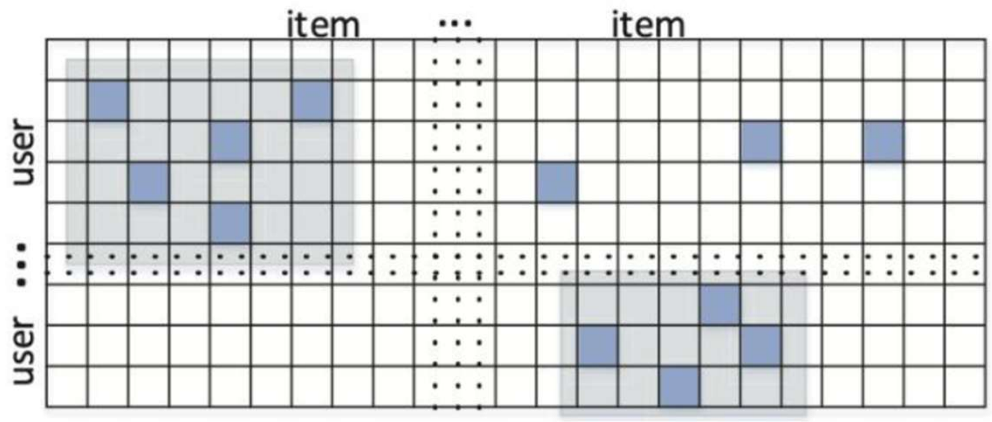
实 验

总 结

研究背景



忽视用户生成内容的丰富信息



数据稀疏性

研究方法 ReHCL架构

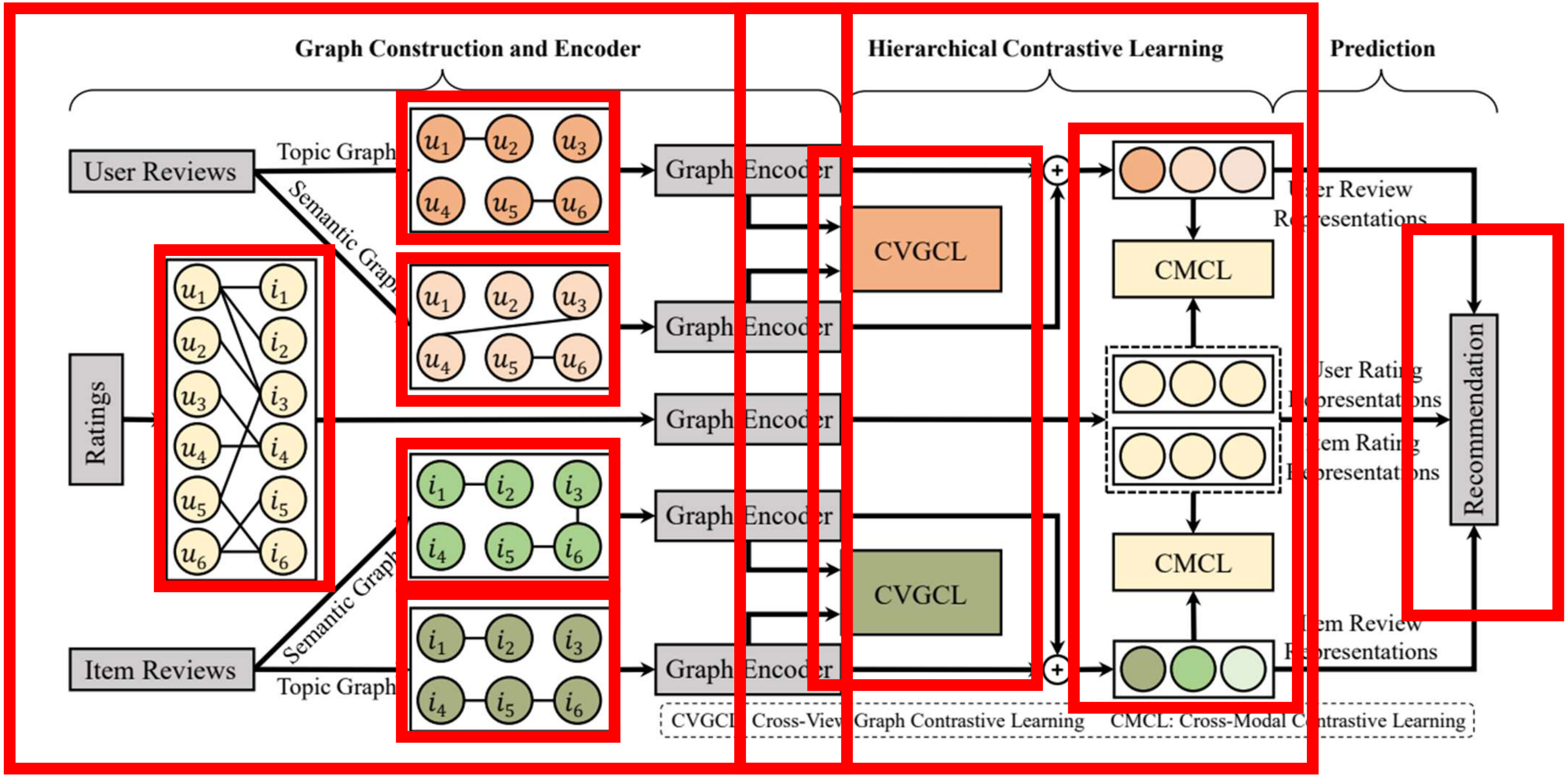


Figure 2: Overview of the proposed review-enhanced hierarchical contrastive learning.

研究方法　图构建——主题图的构建及其作用

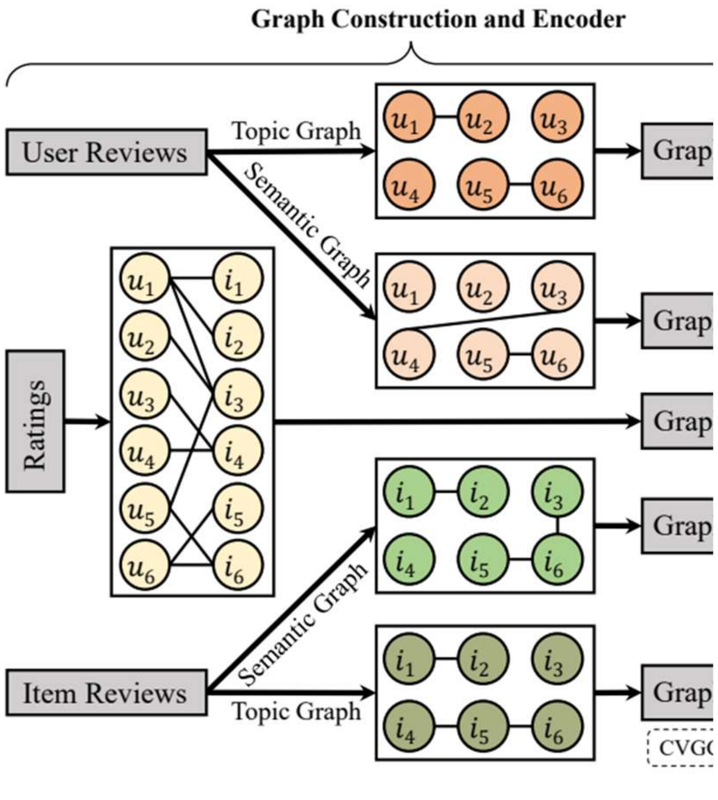
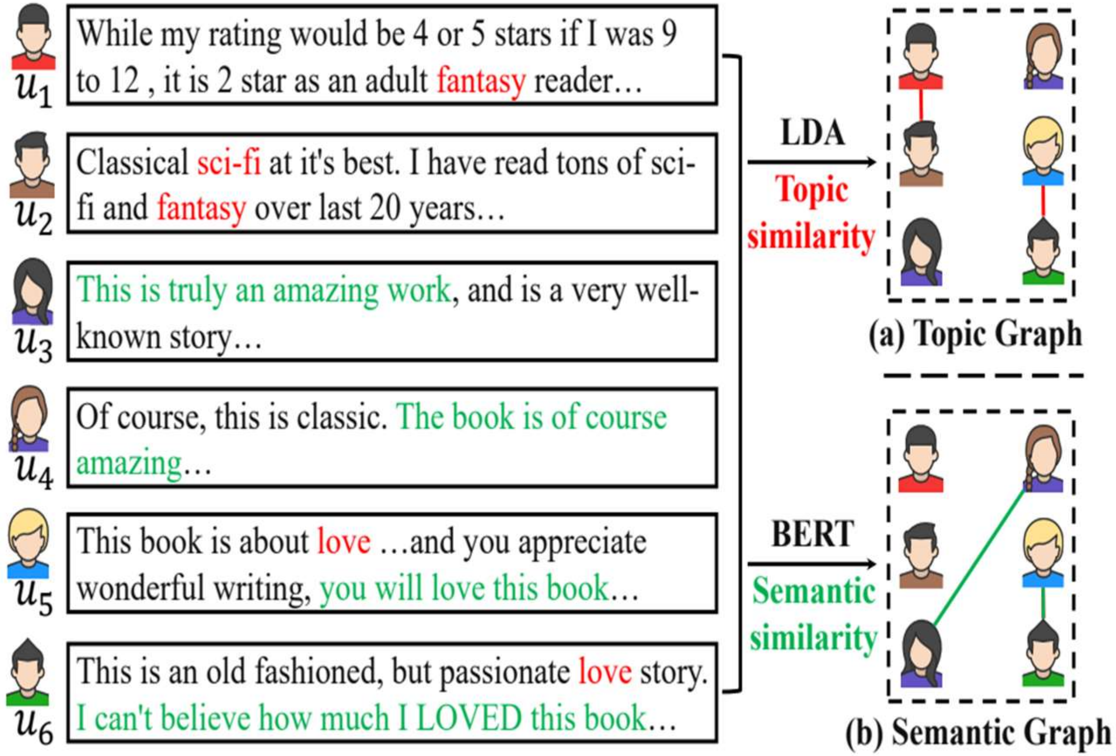


Figure 2: Overview of the proposed re



研究方法　图构建——主题图的构建及其作用

用户u_1评论数据D_{u_1}

用户u_2评论数据D_{u_2}

⋮

用户u_i评论数据D_{u_i}

→ 隐含狄利克雷分配 LDA →

$\theta_{u_1} = \{\theta_{1u_1}, \theta_{2u_1}, \dots, \theta_{Ku_1}\} = LDA(D_{u_1})$

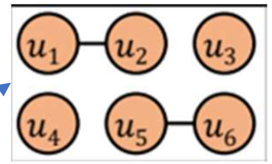
$\theta_{u_2} = \{\theta_{1u_2}, \theta_{2u_2}, \dots, \theta_{Ku_2}\} = LDA(D_{u_2})$

⋮

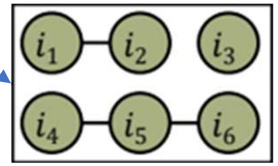
$\theta_{u_i} = \{\theta_{1u_i}, \theta_{2u_i}, \dots, \theta_{Ku_i}\} = LDA(D_{u_i})$

↓

生成主题图



$\mathcal{G}_u^1$



$\mathcal{G}_i^1$

作用：

增强对用户偏好的理解：通过分析用户的评论中的主题，可以更深入地了解用户的兴趣和需求。

提高个性化推荐的相关性：主题图可以帮助系统识别并推荐那些与用户已表现出兴趣的主题相相关的项目，从而提高推荐的个性化。

研究方法　图构建——语义图的构建及其作用

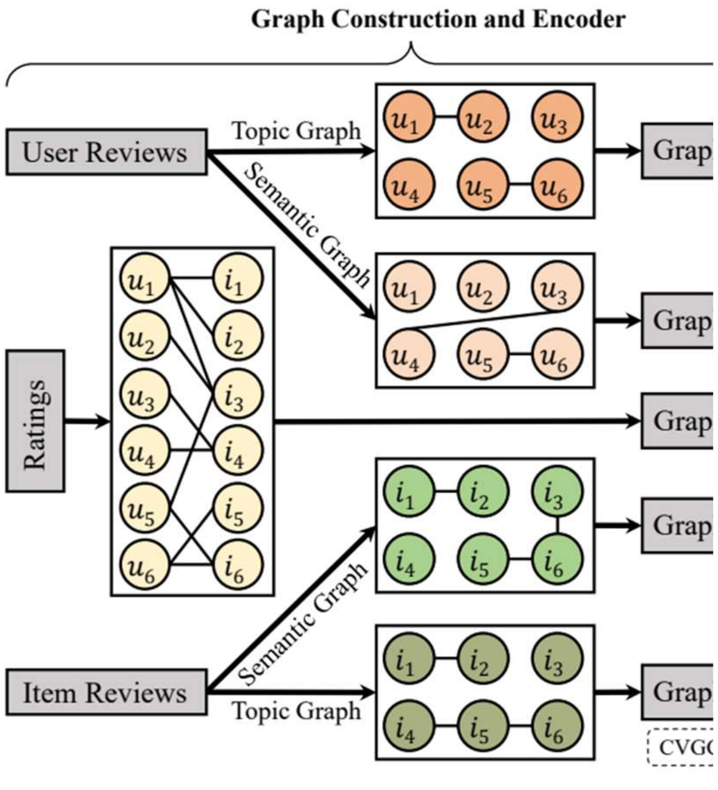
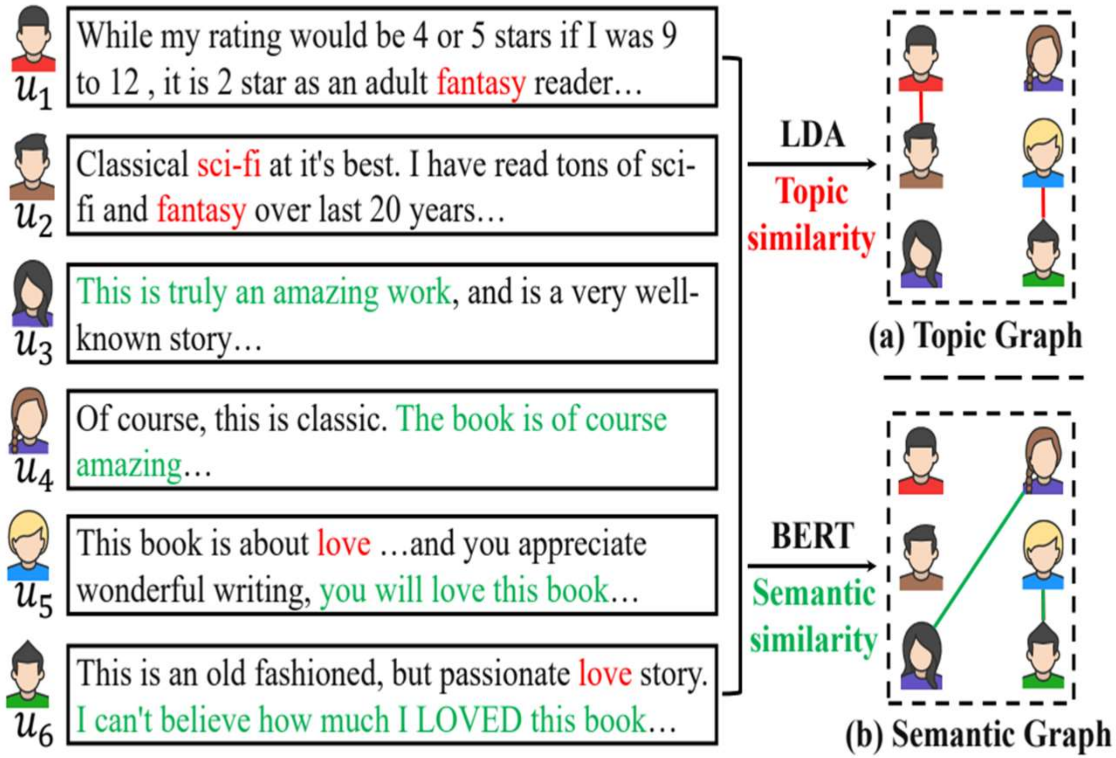


Figure 2: Overview of the proposed re



研究方法　图构建——语义图的构建及其作用

用户u_1评论数据D_{u_1}

用户u_2评论数据D_{u_2}

⋮

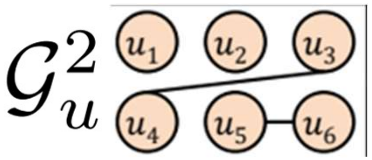
用户u_i评论数据D_{u_i}

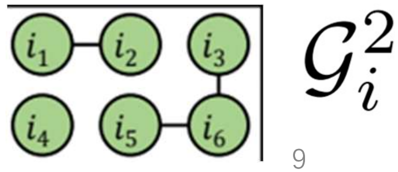
→ 孪生BERT网络 →

$$\boldsymbol{p}_u = \frac{1}{|\mathcal{D}_u|}\sum_{i \in \mathcal{D}_u} \boldsymbol{p}_{u,i} + MaxPooling(\boldsymbol{p}_{u,1}, \ldots, \boldsymbol{p}_{u,|\mathcal{D}_u|})$$

$$Sim(u, u') = ReLU\left(\frac{\boldsymbol{p}_u \boldsymbol{p}_{u'}}{\|\boldsymbol{p}_u\| \, \|\boldsymbol{p}_{u'}\|}\right)$$

取相似度前Q的节点对连成边构成语义图





作用：

捕获深层语义关联：通过分析评论的深层语义内容，语义图能够捕捉用户情感和更细微的意见差异，这些在传统方法中可能被忽略。

提高推荐的准确性：利用用户和项目之间更复杂的语义关系，可以为用户推荐其更喜好的项目。

研究方法 层次对比学习——交叉视图对比学习

$$\widetilde{\boldsymbol{E}}^1 = Dropout(BatchNorm(\boldsymbol{E}^1), \gamma)$$

1 $$\widetilde{\boldsymbol{E}}^2 = Dropout(BatchNorm(\boldsymbol{E}^2), \gamma)$$

Embedding-based Data Augmentation

$$\mathcal{L}_{gcl} = \sum_{v \in \{\mathcal{U} \cup \mathcal{I}\}} -\log \left(\frac{\overbrace{exp(sim(\tilde{\boldsymbol{e}}_v^1, \tilde{\boldsymbol{e}}_v^2)/\tau)}^{\text{inter-view positive pair}}}{\sum_{v' \in \{\mathcal{U} \cup \mathcal{I}\}} exp(sim(\tilde{\boldsymbol{e}}_v^1, \tilde{\boldsymbol{e}}_{v'}^2)/\tau)} + \frac{\overbrace{\sum_{v^+ \in \mathcal{N}_v^+} exp(sim(\tilde{\boldsymbol{e}}_v^1, \tilde{\boldsymbol{e}}_{v^+}^1/\tau)}^{\text{intra-view positive pairs}}}{\sum_{v' \in \{\mathcal{U} \cup \mathcal{I}\}} exp(sim(\tilde{\boldsymbol{e}}_v^1, \tilde{\boldsymbol{e}}_{v'}^2)/\tau)} \right),$$

2

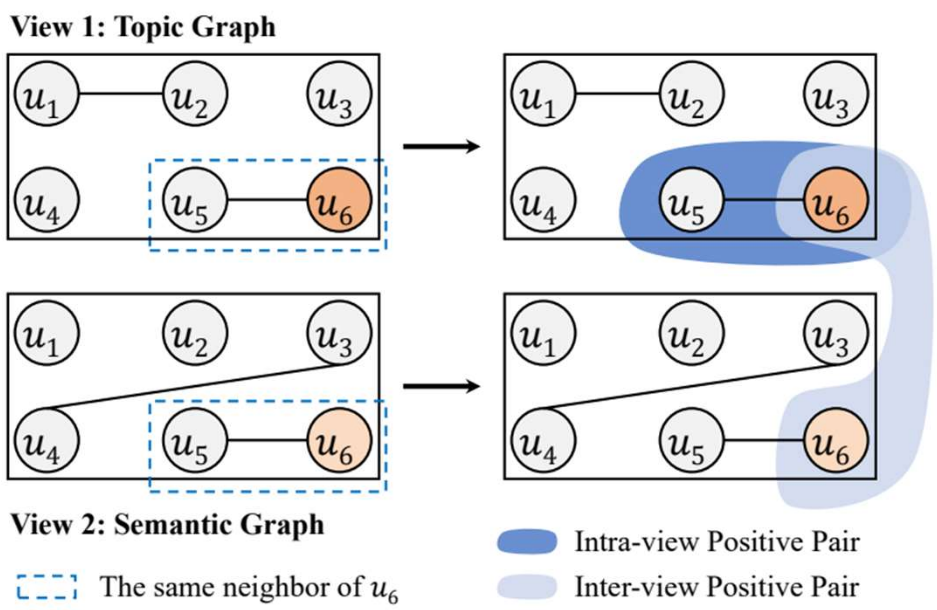


Figure 3: A toy example of neighbor-based positive samples.

Graph Contrastive Learning——Neighbor-based Positive Sampling

基于邻居的
正样本采样

$$\mathcal{L}_{gcl} = \mathcal{L}_{gcl}^{user} + \mathcal{L}_{gcl}^{item}$$

研究方法 层次对比学习——交叉模态对比学习

$$\mathbf{e}_v^{re} = [\mathbf{e}_v^1 || \mathbf{e}_v^2]$$

$\mathbf{e}_v^{ra}$ 通过LightGCN编码交互图得到

$$\tilde{\mathbf{e}}_v^{re} = MLP(\mathbf{e}_v^{re})$$

$$\mathcal{L}_{cro} = \sum_{v \in \mathcal{U}/\mathcal{I}} -\log \frac{exp(sim(\mathbf{e}_v^{ra}, \tilde{\mathbf{e}}_v^{re})/\tau)}{exp(sim(\mathbf{e}_v^{ra}, \tilde{\mathbf{e}}_v^{re})/\tau) + \rho Neg}$$

$$Neg = \sum_{v' \in \{\mathcal{U} \cup \mathcal{I}\}, v' \neq v} exp(sim(\mathbf{e}_v^{ra}, \tilde{\mathbf{e}}_{v'}^{re})/\tau)$$

研究方法 预测

$$\hat{y}_{u,i} = \boldsymbol{e}_u \boldsymbol{e}_i^\top$$

$$e_u、e_i = e_v^{ra} + e_v^{re}$$

研究方法 学习目标

$$\mathcal{L}_{rec} = \sum_{(u,i,j)\in\mathcal{P}} -\ln\sigma(\hat{y}_{u,i} - \hat{y}_{u,j})$$

$$\mathcal{P} = \{(u,i,j) | (u.i) \in \mathcal{P}^{+}, (u.j) \in \mathcal{P}^{-}\}$$

$$\mathcal{L} = \mathcal{L}_{rec} + \beta_1\mathcal{L}_{gcl} + \beta_2\mathcal{L}_{cro} + \beta_3||\Theta||_2^2$$

实验 实验设置

数据集（Amazon）	用户数	项目数	交互数	稀疏度
Instrument	1429	900	10261	0.798%
Music	5541	3568	64706	0.327%
Toy	19412	11924	167597	0.072%

category	Baseline Model
Rating-based GNN	GCN、LightGCN、NGCF
Rating-based GCL	SCL
Review-based topic	TopicMF、ALFM
Review-based CNN	DeepCoNN、NARRE
Review-based GNN	HGNR、SSG
Review-based GCL	RGCL

超参数设置:
- 嵌入向量大小为64
- L2正则化参数为10e-4
- 传播层数为3
- 使用Adam优化器
- 学习率为0.001

实验 与其他模型比较

Model		Instrument			Music			Toy		
		H@10	M@10	N@10	H@10	M@10	N@10	H@10	M@10	N@10
(1) Rating-based GNN	GC-MC	0.2451	0.0682	0.1080	0.4614	0.1609	0.2308	0.3304	0.1237	0.1717
	NGCF	0.2500	0.0957	0.1317	0.4729	0.1854	0.2523	0.3379	0.1428	0.1841
	LightGCN	0.2661	0.0933	0.1336	0.4839	0.2156	0.2783	0.3459	0.1478	0.1906
(2) Rating-based GCL	SGL	0.2773	0.0941	0.1367	0.4889	0.2170	0.2794	0.3549	0.1507	0.2044
(3) Review-based topic	TopicMF	0.2969	0.1118	0.1575	0.4408	0.1765	0.2381	0.2796	0.1072	0.1472
	ALFM	0.3249	0.1419	0.1849	0.4848	0.1946	0.2618	0.3090	0.1218	0.1653
(4) Review-based CNN	DeepCoNN	0.3213	0.1427	0.1847	0.5376	0.2505	0.3180	0.3478	0.1427	0.1905
	NARRE	0.3432	0.1492	0.2033	0.5647	0.2637	0.3346	0.3617	0.1493	0.1987
(5) Review-based GNN	SSG	0.2605	0.0853	0.1259	0.4733	0.1944	0.2596	0.3469	0.1476	0.1919
	HGNR	0.2780	0.0999	0.1414	0.4958	0.2232	0.2873	0.3692	0.1556	0.2091
(6) Review-based GCL	RGCL	0.2731	0.0914	0.1335	0.4935	0.2042	0.2717	0.3636	0.1531	0.2049
(7) OURS	**ReHCL**	**0.3936***	**0.1612***	**0.2155***	**0.6116***	**0.2797***	**0.3570***	**0.3885***	**0.1833***	**0.2313***
Improv.		14.68%	8.03%	6.00%	8.30%	6.07%	6.71%	5.23%	17.80%	10.62%

Table 2: Performance results. The row of "Improv." indicates the improvement of the best result of ReHCL (boldface) compared with the best baseline (underscore). * indicates the statistical significance for $p < 0.05$ compared with the best baseline.

实验

消融实验

使用交叉视图的方法会比单一视图的方法有性能提升

	Graph	Instrument	Music	Toy
(2)	$\mathcal{G}_u^1 + \mathcal{G}_i^1$	0.2906	0.4847	0.3371
	$\mathcal{G}_u^2 + \mathcal{G}_i^2$	0.2808	0.4523	0.3147
(3)	$\mathcal{G}_u^1 + \mathcal{G}_i^1 + \mathcal{G}_u^2 + \mathcal{G}_i^2$	0.3165	0.5121	0.3469
(6)	**ReHCL**	**0.3936**	**0.6116**	**0.3885**

Table 3: Comparison of different graphs in terms of HR@10. The results with the best performance are marked in bold.

实验

消融实验

使用交叉视图的方法会比单一视图的方法有性能提升

	Graph	Instrument	Music	Toy
(4)	$\mathcal{G}^R + \mathcal{G}_u^1 + \mathcal{G}_i^1$	0.3242	0.5531	0.3541
	$\mathcal{G}^R + \mathcal{G}_u^2 + \mathcal{G}_i^2$	0.3522	0.5782	0.3657
(5)	$\mathcal{G}^R + \mathcal{G}_u^1 + \mathcal{G}_u^2$	0.3789	0.5848	0.3799
	$\mathcal{G}^R + \mathcal{G}_i^1 + \mathcal{G}_i^2$	0.3817	0.5830	0.3733
(6)	**ReHCL**	**0.3936**	**0.6116**	**0.3885**

Table 3: Comparison of different graphs in terms of HR@10. The results with the best performance are marked in bold.

实验 消融实验

交互图、语义图和主题图都会对模型产生增益效果

	Graph	Instrument	Music	Toy
(1)	$\mathcal{G}^R$	0.2941	0.4897	0.3483
(2)	$\mathcal{G}_u^1 + \mathcal{G}_i^1$	0.2906	0.4847	0.3371
	$\mathcal{G}_u^2 + \mathcal{G}_i^2$	0.2808	0.4523	0.3147
(4)	$\mathcal{G}^R + \mathcal{G}_u^1 + \mathcal{G}_i^1$	0.3242	0.5531	0.3541
	$\mathcal{G}^R + \mathcal{G}_u^2 + \mathcal{G}_i^2$	0.3522	0.5782	0.3657
(6)	**ReHCL**	**0.3936**	**0.6116**	**0.3885**

Table 3: Comparison of different graphs in terms of HR@10. The results with the best performance are marked in bold.

消融实验

	Graph	Instrument	Music	Toy
(1)	$\mathcal{G}^R$	0.2941	0.4897	0.3483
(5)	$\mathcal{G}^R + \mathcal{G}_u^1 + \mathcal{G}_u^2$	0.3789	0.5848	0.3799
	$\mathcal{G}^R + \mathcal{G}_i^1 + \mathcal{G}_i^2$	0.3817	0.5830	0.3733
(6)	**ReHCL**	**0.3936**	**0.6116**	**0.3885**

通过组合来自评论的用户-用户和项目-项目图，用户和项目两方面均对性能有所贡献。

Table 3: Comparison of different graphs in terms of HR@10. The results with the best performance are marked in bold.

实验 消融实验

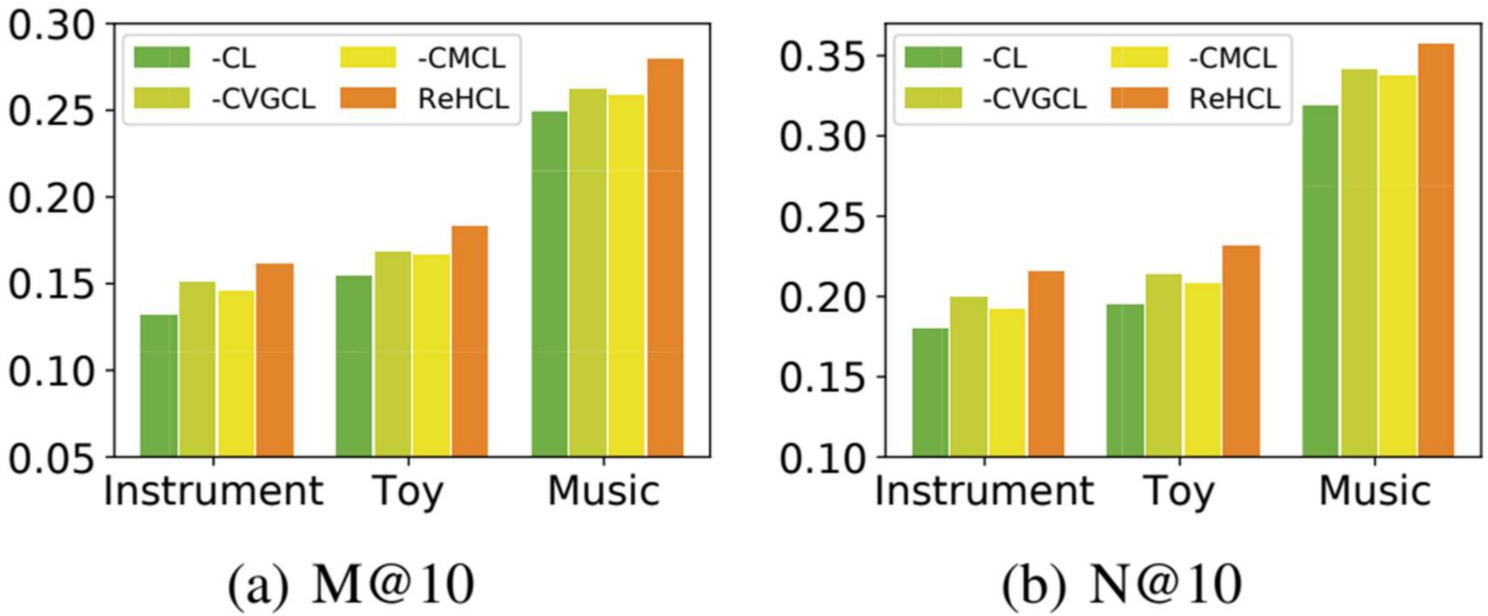


Figure 4: Performance comparison over different contrastive learning tasks on M@10 and N@10.

实验　模型研究

不同图编码器对模型的影响

不同图增强策略对模型的影响

交叉视图对比学习中正样本采样对模型的影响

Model		Instrument	Music	Toy
(1)	ReHCL_GCN	0.3578	0.5601	0.3484
	ReHCL_NGCF	0.3690	0.5831	0.3606
(2)	ReHCL_NA	0.3873	0.6031	0.3788
	ReHCL_ED	0.3898	0.6022	0.3821
	ReHCL_ND	0.3824	0.5951	0.3785
(3)	ReHCL_Info	0.3908	0.6042	0.3806
(4)	ReHCL	0.3936	0.6116	0.3885

Table 4: Comparison of variants in terms of H@10.

总结

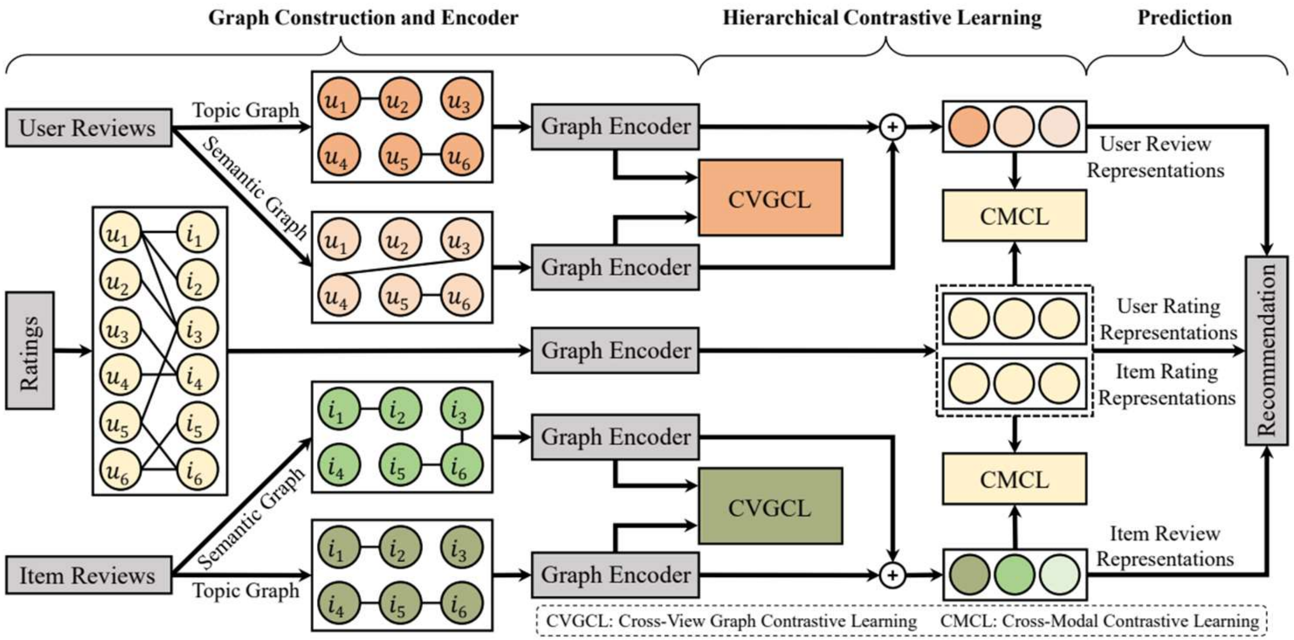


Figure 2: Overview of the proposed review-enhanced hierarchical contrastive learning.

通过引入层次对比学习和复杂图结构，ReHCL为推荐系统提供了一个创新的解决方案，特别是在充分利用用户生成内容的背景下。这种方法明显提高了推荐的精度。

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Thanks！

2024年9月1日