CAGK: Collaborative Aspect Graph Enhanced Knowledge-based Recommendation

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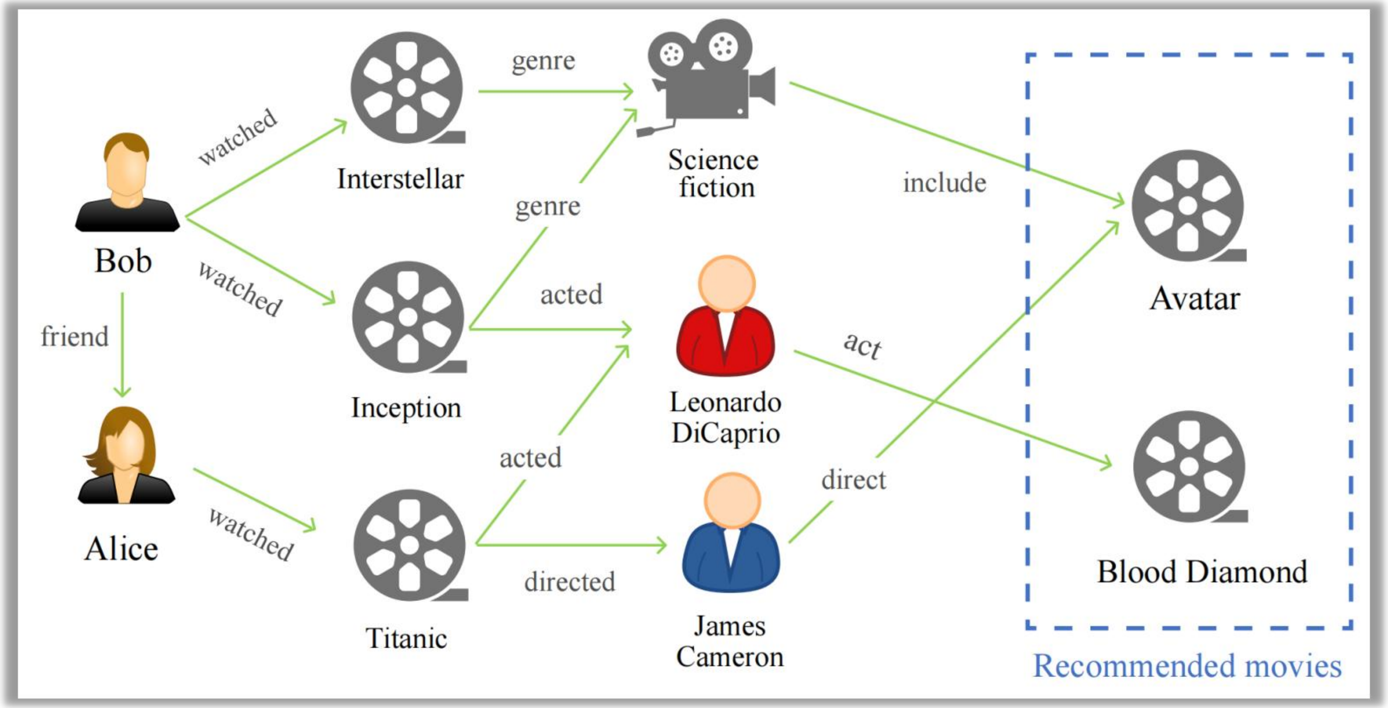
Background(1/4)

Knowledge Graph (KG) based recommendation

- KG contains rich entities and relations, showing great potential in improving recommendation accuracy and interoperability.
- Graph Neural Networks(GNN) can exploit high-order information in KG in an efficient, explicit, and end-to-end manner.



Guo et al.

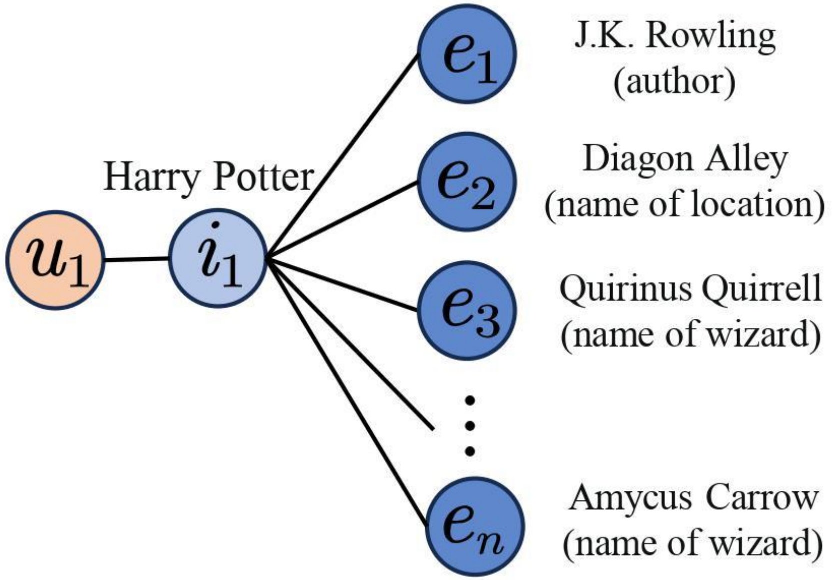
Background(2/4)

Existing problems for KG-based recommendation

- **Link sparsity**: low link rates between items and KG entities
- **Knowledge redundancy**: edundant knowledge in KG

Linkage ratio	Amazon-book	LFM-1b
Freebase	4.7%	19.4%
YAGO	0.8%	0.8%

(a) Link sparsity.



(b) Knowledge redundancy.

Background(3/4)

KG-based ➡ Aspect Enhanced KG-based

Conceptual Distinction

- **Aspect**: contains high-level semantics, representing keywords about item attributes mentioned by users in reviews, such as "soup" and "cleanliness" from Yelp reviews.
- **Entity**: refers to the representation of various things that exist in the real world, such as "Harry Potter", "KFC", etc.

Review	The soup is delicious but this place was really dirty from floors to tables.
Aspect Extraction	**Aspect and Sentiment**
InstractABSA	$\{soup : 1,\ cleanliness : -1\}$

Background (4/4)

KG-based ➡ Aspect Enhanced KG-based

Chance:

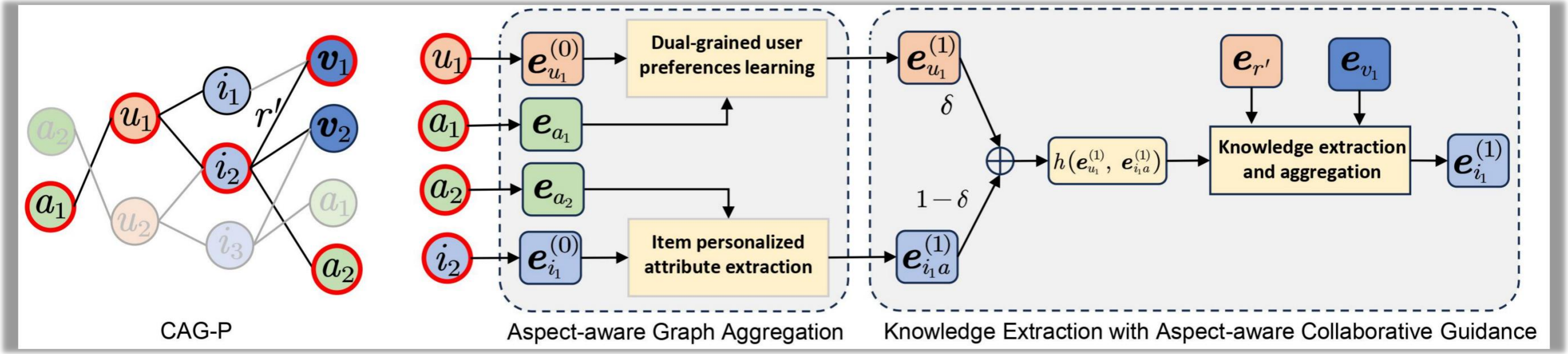
- Most items have reviews that correspond to a set of aspects.
- Aspects contain personalized user preferences.
- Aspects contain negative sentiment information, which can be used as a source of evidence for not recommending.

Challenge:

- There are few high-quality aspect-based recommendation datasets.
- It is still under-explored that how to effectively integrate the interactions and aspect information.
- It is challenging to design the network to solve the problem of **Link sparsity** and **Knowledge redundancy**.

Our CAGK Approach (1/4)

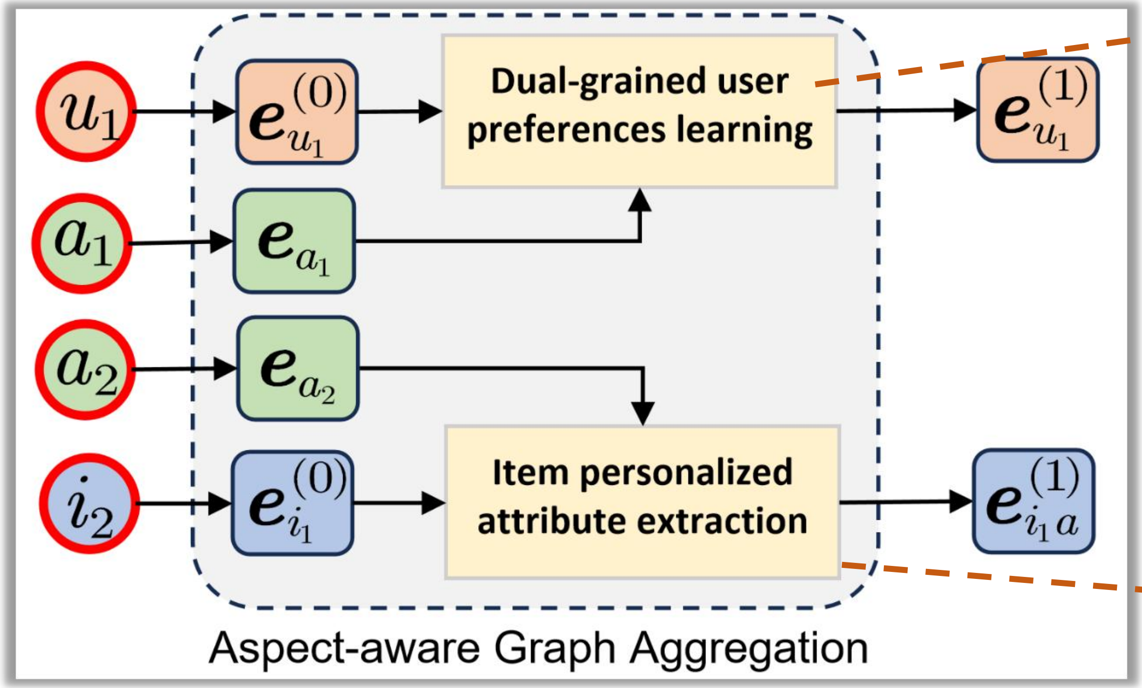
Collaborative Aspect Graph Enhanced Knowledge-based Network (CAGK)



- **Aspect-aware graph aggregation** (CAG-P)
- **Knowledge extraction with aspect-aware collaborative guidance** (CAG-P)
- **Negative sentiment modeling** (CAG-N)

Our CAGK Approach (2/4)

- **Aspect-aware graph aggregation**： model user preferences and item characteristics based on aspects, alleviating the problem of **Link sparsity**.



- Dual-grained user preferences learning

$$e_{ui}^{(1)} = \frac{1}{|N_u^i|} \sum_{i \in N_u^i} e_r \odot e_i^{(0)}$$

$$\alpha(u,a) = \frac{\exp(e_a^T e_u^{(0)})}{\sum_{a' \in N_u^a} \exp(e_{a'}^T e_u^{(0)})} \qquad e_{ua}^{(1)} = \sum_{a \in N_u^a} \alpha(u,a) \mathrm{e}_a$$

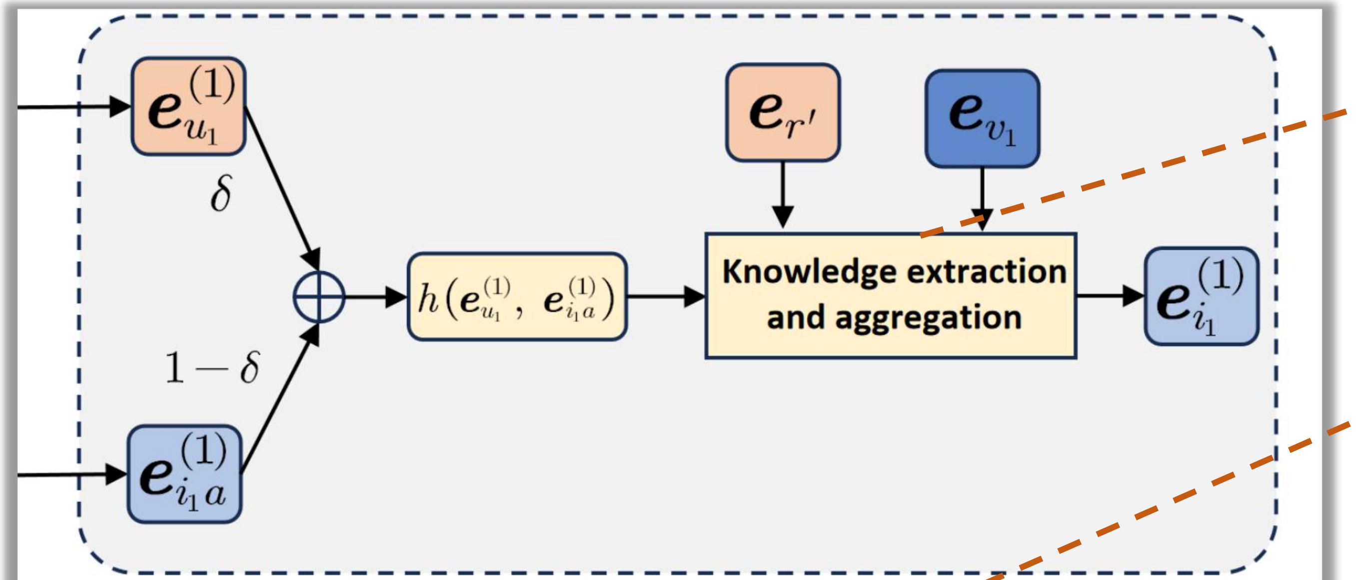
$$e_u^{(1)} = e_{ui}^{(1)} + e_{ua}^{(1)}$$

- Item personalized attribute extraction

$$e_{ia}^{(1)} = \sum_{a \in N_i^a} \alpha(i,a) \boldsymbol{e}_a$$

Our CAGK Approach (3/4)

➢ **Knowledge extraction with aspect-aware collaborative guidance:** alleviating the problem of **Knowledge redundancy.**



Knowledge Extraction with Aspect-aware Collaborative Guidance

- Knowledge extraction and aggregation

$$e_{r'}^{\langle u,i,a\rangle} = h(e_u^{(1)}, e_{ia}^{(1)}) \odot e_{r'}$$

$$\beta(\langle u,i,a\rangle, i, r', v) = (\mathbf{W}e_v^{(0)})^T \tanh(\mathbf{W}e_i^{(0)} + e_{r'}^{<u,i,a>})$$

$$e_{iv}^{(1)} = \sum_{(i,r',v)\in N_i^v} \beta'(\langle u,i,a\rangle, i, r', v) e_v^{(0)}$$

$$e_i^{(1)} = e_{ia}^{(1)} + e_{iv}^{(1)}$$

- Aspect-aware Guidance Encoding

$$h(e_u^{(1)}, e_{ia}^{(1)}) = \delta e_u^{(1)} + (1-\delta) e_{ia}^{(1)}$$

Our CAGK Approach (4/4)

- **Negative sentiment modeling**: inputs the CAG-P into the MLP network to obtain the negative representations of users and items.

$$\boldsymbol{e}_u^N, \boldsymbol{e}_i^N = MLP(G_{CAG-N})$$

- **Model Prediction**

$$\boldsymbol{e}_u^P = \boldsymbol{e}_u^{(0)} + \cdots + \boldsymbol{e}_u^{(L)}, \boldsymbol{e}_i^P = \boldsymbol{e}_i^{(0)} + \cdots + \boldsymbol{e}_i^{(L)}$$

$$\hat{y}(u,i) = \boldsymbol{e}_u^P \boldsymbol{e}_i^P - \boldsymbol{e}_u^N \boldsymbol{e}_i^N + 1$$

which $e_u^P e_i^P$ reflects the similarity between user preferences and item characteristics, and $e_u^N e_i^N$ reflects the similarity between user dislike and item defects.

Datasets

High-quality Aspect-based Recommendation Datasets

- **Recommdation datasets**:
  - Amazon-book
  - Yelp2018
- **Aspect**
  - Rource: reviews from Amazon-book and Yelp2018
  - Extraction method: InstructABSA
- **Knowledge Graph**
  - Amazon-book: Freebase
  - Yelp2018: Extract knowledge from the local business information network (He et al.)

		Amazon-book	Yelp2018
Interaion	# users	70,679	45,919
	# items	24,915	45,538
	# interactions	847,733	1,185,068
KG	# entities	88,572	90,961
	# relations	39	42
	# triples	2,557,746	1,853,704
Aspect	# aspects	207734	190521
	# linkage ratio	96.3%	98.4%

Experiment

- **Overall comparison**

Datasets	Model	recall@10	recall@20	ndcg@10	ndcg@20
Amazon-book	NFM	0.1266	0.1366	0.0794	0.0913
	CKE	0.1264	0.1342	0.0522	0.0698
	RippleNet	0.1256	0.1336	0.0796	0.091
	KGAT	0.1325	0.1489	0.0833	0.1006
	KGIN	0.1441	0.1687	0.0875	0.1095
	ANR	0.124	0.132	0.0727	0.0801
	CARP	0.1292	0.1441	0.0801	0.0923
	CG-KGR	0.1299	0.145	0.0859	0.1079
	SiReN	0.1175	0.1302	0.0823	0.0986
	CAGK	**0.1501**	**0.1788**	**0.092**	**0.1204**
Yelp2018	NFM	0.048	0.066	0.0591	0.081
	CKE	0.0479	0.0657	0.058	0.0805
	RippleNet	0.0484	0.0664	0.057	0.0858
	KGAT	0.0543	0.0712	0.0602	0.0867
	KGIN	0.0588	0.0754	0.0668	0.088
	ANR	0.0497	0.0672	0.0524	0.0771
	CARP	0.0521	0.0703	0.0598	0.0813
	CG-KGR	0.0513	0.0698	0.0633	0.0847
	SiReN	0.0574	0.074	0.0559	0.0792
	CAGK	**0.0622**	**0.0814**	**0.0717**	**0.0943**

Experiment

➢ **Ablation study**

method	Amazon-book		Yelp2018	
	recall@20	ndcg@20	recall@20	ndcg@20
w/o AGA	0.1712	0.1107	0.0736	0.0891
w/o KEACG	0.1754	0.1148	0.0786	0.0882
w/o NSM	0.1769	0.1155	0.0793	0.0933
w/o PLMs	0.1673	0.1050	0.0722	0.0871
CAGK	**0.1788**	**0.1204**	**0.0814**	**0.0943**

- **w/o AGA**: Aspect-aware Graph Aggregation is disabled.
- **w/o KEACG**: Knowledge Extraction with Aspect-aware Collaborative Guidance is disabled.
- **w/o NSM**: Negative Sentiment Modeling is disabled.
- **w/o PLMs**: Extract aspects with traditional method (LDA), not PLMs (InstructABSA).

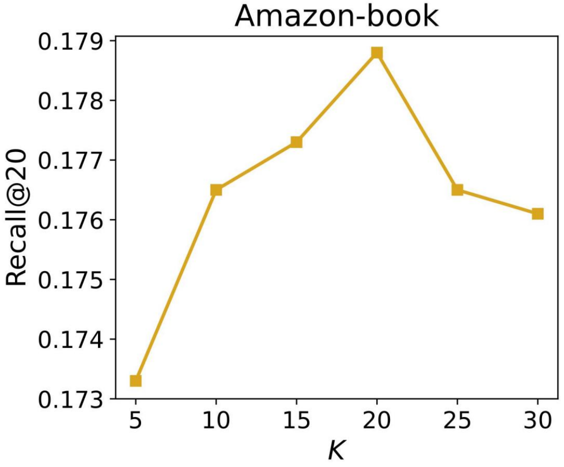
Experiment

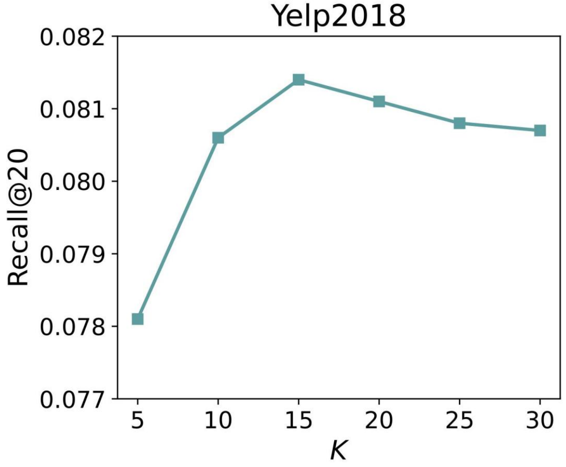
➢ Hyperparameter Analysis

- Effect of embedding propagation layer number (L).

	Amazon-book		Yelp2018	
	recall@20	ndcg@20	recall@20	ndcg@20
CAGK-1	0.1613	0.1103	0.0771	0.0911
CAGK-2	0.1705	0.1127	0.0806	0.0927
CAGK-3	0.1779	0.1132	0.0804	0.0925
CAGK-4	**0.1788**	**0.1204**	**0.0814**	**0.0943**

- Effect of the number of aspects sampled (K).





Discussion

Contributions:

- As far as we know, we are the first to exploit the potential of aspects in KG-based recommendation.
- We propose a novel framework named Collaborative Aspect Graph enhanced Knowledge based Network (CAGK), which alleviates the challenges posed by sparse links and redundant knowledge and makes full use of the negative sentiment information.
- Extensive experiments on two widely used benchmark datasets demonstrate the superiority of our method.

Future exploration:

- Introducing aspects to improve the diversity of RecSys.

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Thank you