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An Aspect Performance-aware Hypergraph Neural Network for Review-based Recommendation

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Introduction

Background: Online reviews allow consumers to provide detailed feedback on various aspects of items. Existing methods utilize these aspects to model users' fine-grained preferences for specific item features through graph neural networks.

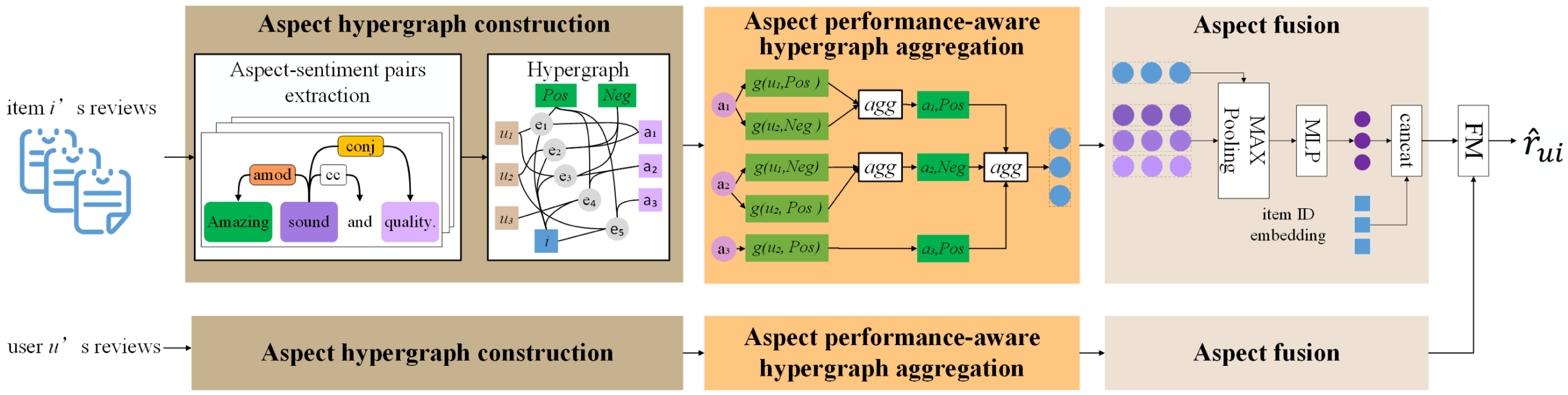
Challenge: Not all the performances can be directly obtained.

Motivation: The reviews encompass users' sentiments on a specific aspect of an item, which partially reflect the item's performance in that aspect.

Contribution: We propose an aspect performance-aware hypergraph neural network (APH) for the review-based recommendation, which learns the performance of items from the conflicting sentiment polarity of user reviews.

Methodology

APH first extracts aspects and user sentiments from reviews to construct a hypergraph. Then, to learn the true relationship between an item and an aspect from conflicting user sentiments, APH considers user preferences to identify the weight of their sentiments. Likewise, we use a similar way to calculate the aspect-based user representations. Finally, APH fuses items, neighbor aspect nodes, and their ID embeddings to make predictions.



(1) Aspect Hypergraph Construction

- Extracting aspect-sentiment pairs from reviews

Table 1: Extracting aspects based on dependency relations

No.	Dependency relations	Aspect	Sentiment
1	Adj. (x) ← amod – Noun (y)	y	x
2	Noun (x) ←nsubj– Linking Verb (y) – – acomp → Adj. (z)	x	z
3	Verb (x) – dobj → Noun (y)	(x,y)	x

- Constructing aspect hypergraph

(2) Aspect Performance-aware Hypergraph Aggregation

For each item, aggregating conflicting user sentiments by considering their performance:

$$\hat{\mathbf{x}}_i = \sum_{\mathcal{E}_{i,a} \in \mathcal{E}_i} \sum_{e \in \mathcal{E}_{i,a}} w(e)\mathbf{x}_a \mathbf{W}_4$$

$$w(e) = w(u, i, a, s)$$

$$= \frac{exp[\pi(\mathbf{x}_i, q_i(\mathbf{x}_u, \mathbf{x}_s), \mathbf{x}_a)]}{\sum_{e' \in \mathcal{E}_i} exp[\pi(\mathbf{x}_i, q_i(\mathbf{x}_{u'}, \mathbf{x}_{s'}), \mathbf{x}_a)]}$$

$$\pi(\mathbf{x}_i, \mathbf{x}_q, \mathbf{x}_a) = LeakyRelu[(\mathbf{x}_i \mathbf{W}_1)(\mathbf{x}_q \mathbf{W}_2 + \mathbf{x}_a \mathbf{W}_3)] \qquad \mathbf{x}_q = q_i(\mathbf{x}_u, \mathbf{x}_s) = MLP(\mathbf{x}_u, \mathbf{x}_s)$$

(3) Aspect Fusion

Learning more about the role of aspects in user-item interactions

$$\hat{\mathbf{g}}_i = max_{t=1}^{d_2} \mathbf{X}_i(:, t),$$

$$\mathbf{g}_i = ReLU(\hat{\mathbf{g}}_i \mathbf{W}_6 + b_6),$$

$$\mathbf{m}_i = ReLU(\hat{\mathbf{x}}_i \mathbf{W}_7 + b_7),$$

$$\mathbf{y}_i = \mathbf{m}_i \oplus \mathbf{g}_i,$$

Experiment

We do a series of experiments to identify the performance of our method, including analysis extracted aspects, model comparison, ablation study, and case study.

(1) Model Performance

MSE results

Dataset	Music	Office	Toys	Games	Beauty	Yelp
PMF	1.8783	0.9635	1.6091	1.5260	2.7077	1.4217
SVD++	0.7952	0.7213	0.8276	1.2081	1.2129	1.2973
CDL	1.2987	0.8763	1.2479	1.6002	1.7726	1.4042
DCN	0.7909	0.7315	0.8073	1.1234	1.2210	1.2719
NARRE	0.7688	0.7266	0.7912	1.1120	1.1997	1.2675
CARL	0.7632	0.7193	0.8248	1.1308	1.2250	1.3199
DAML	0.7401	0.7164	0.7909	1.1086	1.2175	1.2700
NRCA	0.7658	0.7343	0.8100	1.1259	1.2034	1.2721
DSRLN	0.7538	0.7131	0.8141	1.1205	1.1951	1.1655
ANR	0.7825	0.7237	0.7974	1.1038	1.2021	1.2708
RGNN	0.7319	0.7125	**0.7786**	1.0996	1.1885	1.2645
APH	**0.6795***	**0.6884***	0.7859*	**1.0829**	**1.1757***	**1.1467***

NDCG@10 results

Dataset	Music	Office	Toys	Games	Beauty	Yelp
DCN	0.977	0.973	0.975	0.971	0.966	0.941
NARRE	0.978	0.976	0.981	0.968	0.971	0.957
CARL	0.980	0.978	0.978	0.969	0.966	0.943
DAML	0.982	0.978	0.979	**0.979**	0.967	0.958
DSRLN	0.781	0.974	0.977	**0.979**	0.967	0.948
MA-GNNs	0.979	0.973	0.975	0.966	0.965	0.933
RGNN	0.982	0.983	0.982	0.976	0.973	0.963
APH	**0.988***	**0.986***	**0.983***	0.977*	**0.974***	**0.965***

CTR@5 results

	Music		Office		Toys		Games		Beauty		Yelp	
	Pre@5	Rec@5	Pre@5	Rec@5	Pre@5	Rec@5	Pre@5	Rec@5	Pre@5	Rec@5	Pre@5	Rec@5
DCN	0.2327	0.6818	0.2555	0.5953	0.2408	0.6228	0.2561	0.6355	0.2876	0.7024	0.3238	0.5985
NARRE	0.2502	0.6603	0.3265	0.7361	0.0105	0.0341	0.2053	0.4984	0.1545	0.4094	0.3976	0.5907
DAML	0.2515	0.7019	0.3158	0.6796	0.2517	0.6638	0.2598	0.6622	0.2227	0.5911	0.3861	0.6138
RGNN	0.2690	0.7453	0.3229	0.6967	0.2874	0.7599	0.2809	0.7164	0.2985	0.7387	0.3824	0.6592
DSRLN	0.2721	0.7518	0.3386	0.7386	0.2873	0.7503	0.2673	0.7131	0.3044	0.7642	0.4278	**0.7248**
APH	**0.2730***	**0.7566‡**	**0.3461***	**0.7433‡**	**0.2985 ***	**0.7614***	**0.3263***	**0.7890***	**0.3158***	**0.7753***	**0.4407***	0.6996*

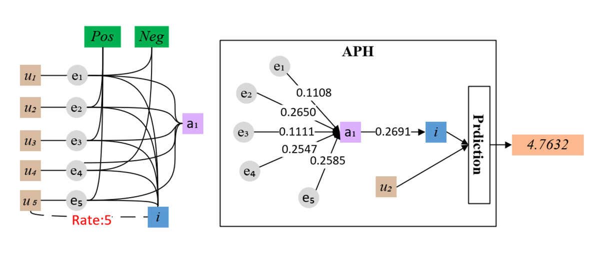
(2) Ablation study

Dataset	Music	Office	Toys	Games	Beauty	Yelp
APH(MAX)	0.7006	0.6951	0.7972	1.0879	1.1773	1.1913
APH(MEAN)	0.6933	0.7010	0.7918	1.0799	1.1820	1.1755
APH(-AF)	0.6873	0.7068	0.8040	1.0958	1.1899	1.1869
APH(-FM)	0.8173	0.7196	0.8228	1.1052	1.1999	1.1714
APH	**0.6795**	**0.6884**	**0.7859**	**1.0829**	**1.1757**	**1.1467**

(3) Case Study

Item: *B0000538AC*
Aspect: *pack*

	User	Sent. Polity	Attn. Score
e_1	*A2582KMXLK2P06*	*Neg*	*0.1108*
e_2	*A156P4FPL8OGXB*	*Pos*	*0.2585*
e_3	*A3S15YGZ6W6EV2*	*Pos*	*0.1111*
e_4	*A1S7BFT0HDF3HA*	*Neg*	*0.2547*
e_5	*A3QS4WWC1LCA6H*	*Pos*	*0.2650*



Code

WeChat