国际人工智能会议
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Who You Would Like to Share With? A Study of Share Recommendation in Social E-commerce

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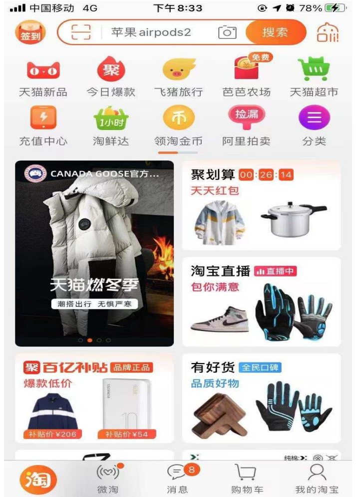
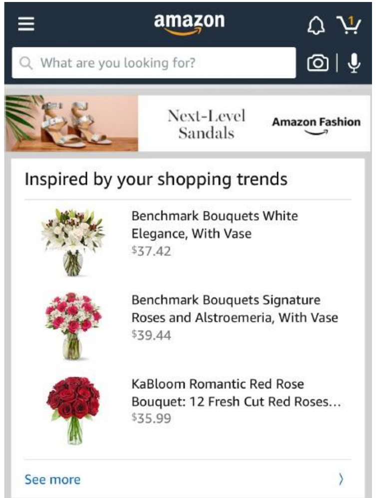
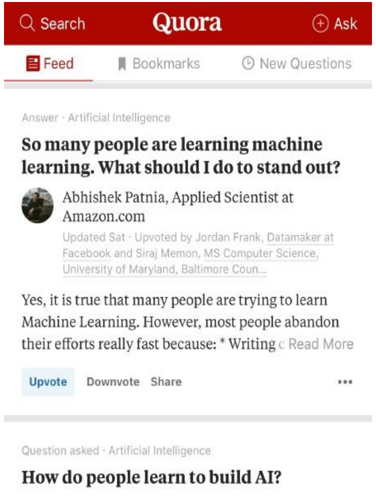
Introduction

- ❑ Recommender systems help users discover items of interest from a large resource collection
- ❑ Recommender systems are everywhere, e.g., Amazon, Quora, Douban
- ❑ Recommender systems play a pivotal role in various online

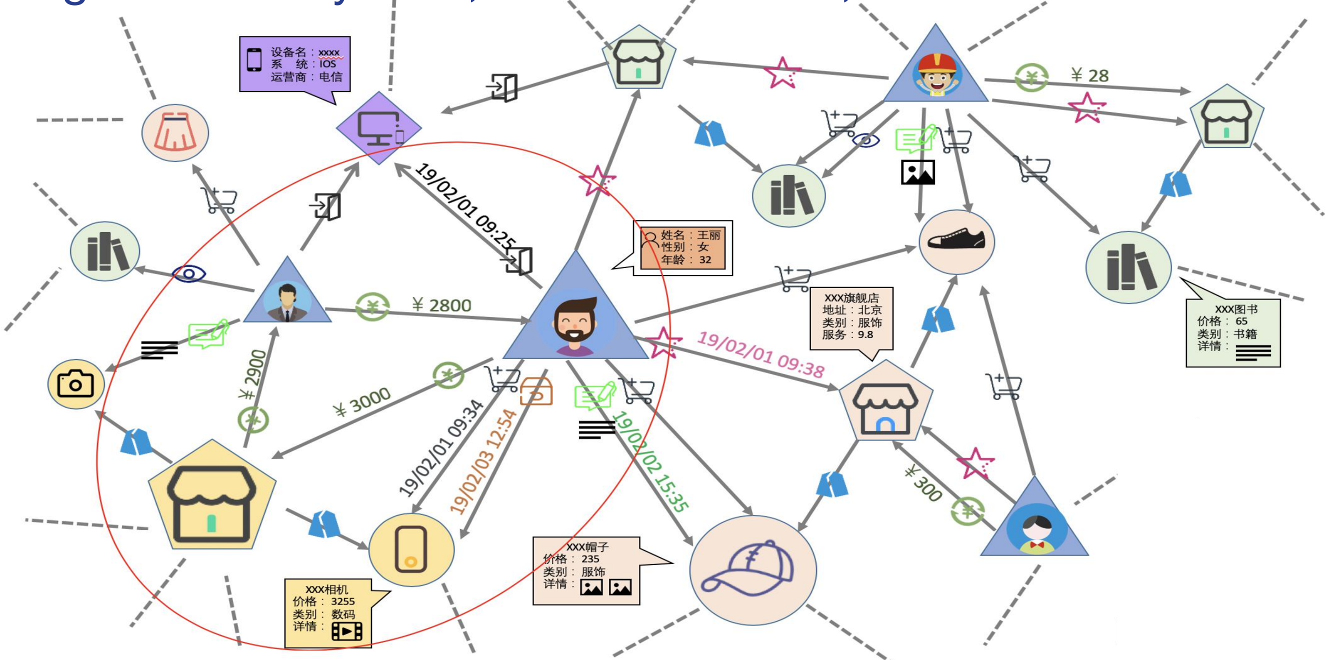






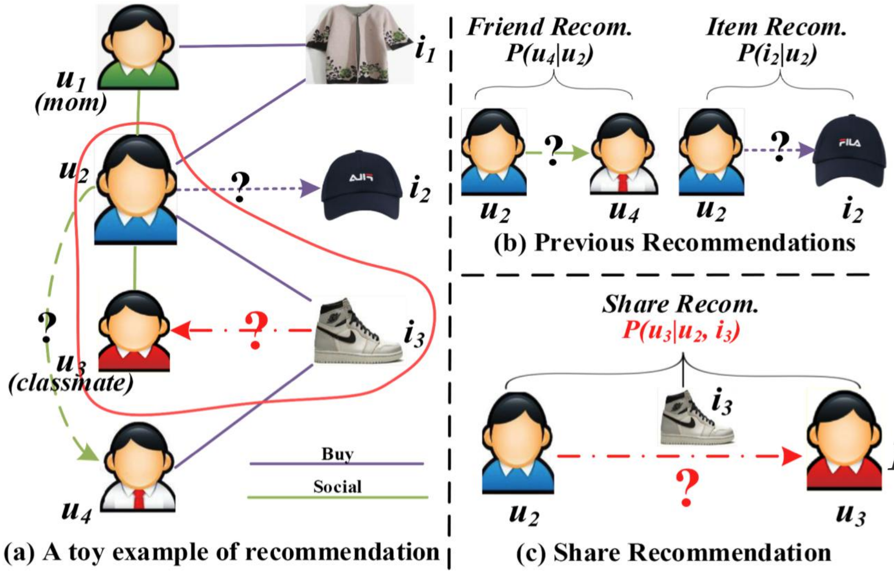
Introduction

- ❑ Real-world recommender system consists diverse nodes/edges, known as heterogeneous graph.
  - ❑Nodes: user, item, shop
  - ❑Edges: user-buy-item, user-social-user, user-share-friend



Introduction

- Share recommendation, which aims to predict whether a user will share an item with his friend P(Friend|User, Item).



(a) A toy example of recommendation

(b) Previous Recommendations

(c) Share Recommendation

Binary Interaction

$Pr(Item|User)$

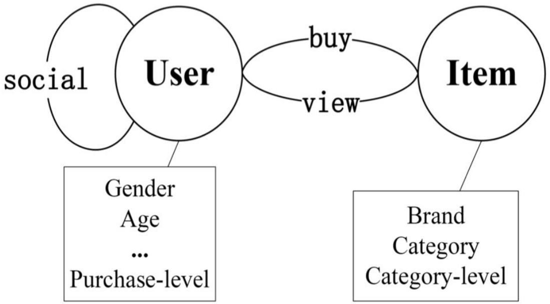
$Pr(User|User)$

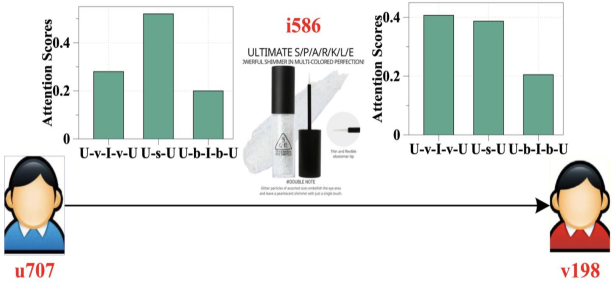
Ternary Interaction

$Pr(Friend|User, Item)$

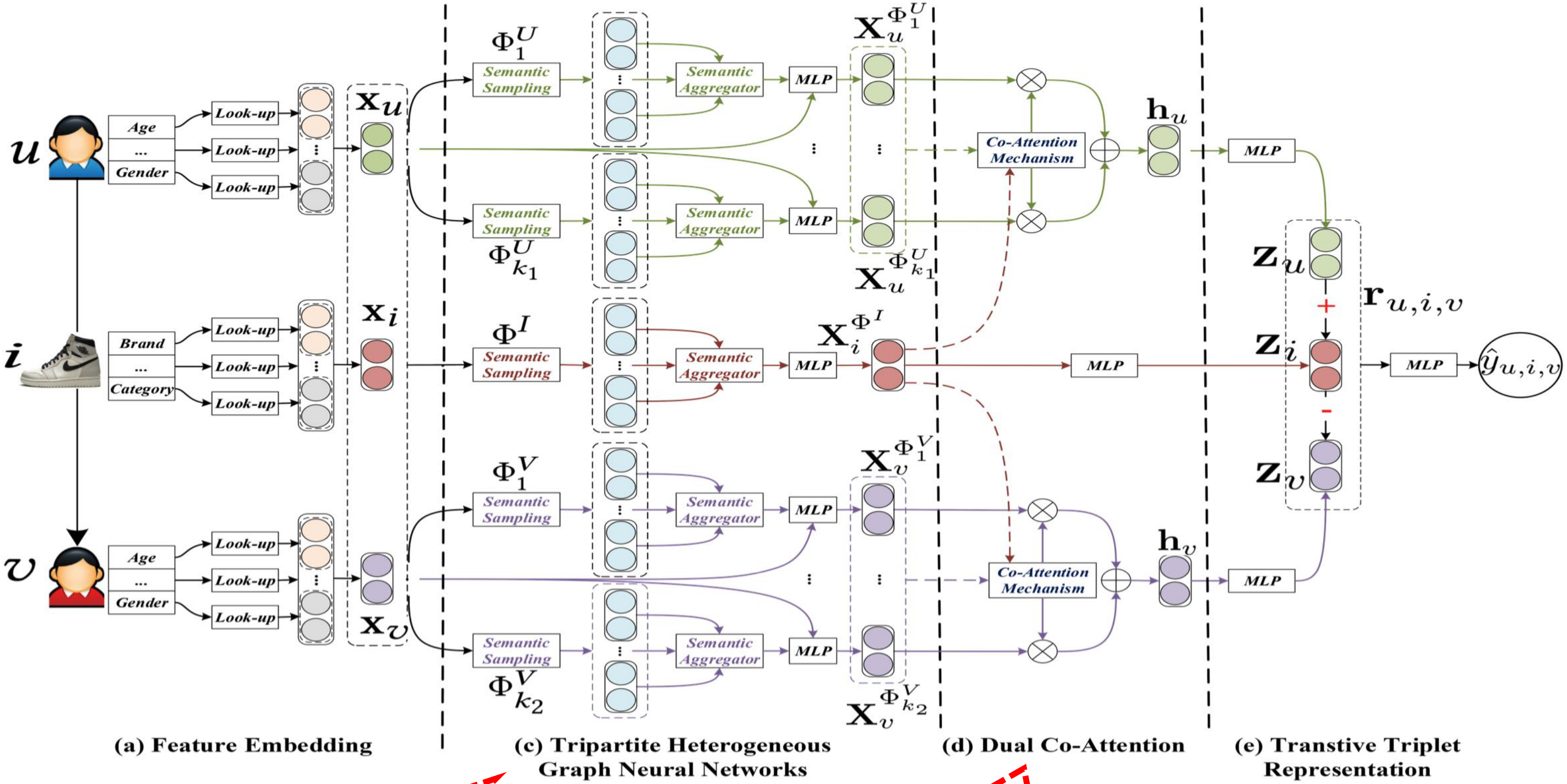
Introduction

- Challenges in share recommendation
  - Rich Heterogeneous Information
    - Handle the complex interaction information and utilize the diverse feature information simultaneously
  - Complex ternary interaction
    - The suitability of a share action, which evaluates the matching degree of <u, i, v>
  - Asymmetric Share Action
    - P(u3|u2, i3)(√) P(u2|u3, i3)(×)





Model



Handle rich information.

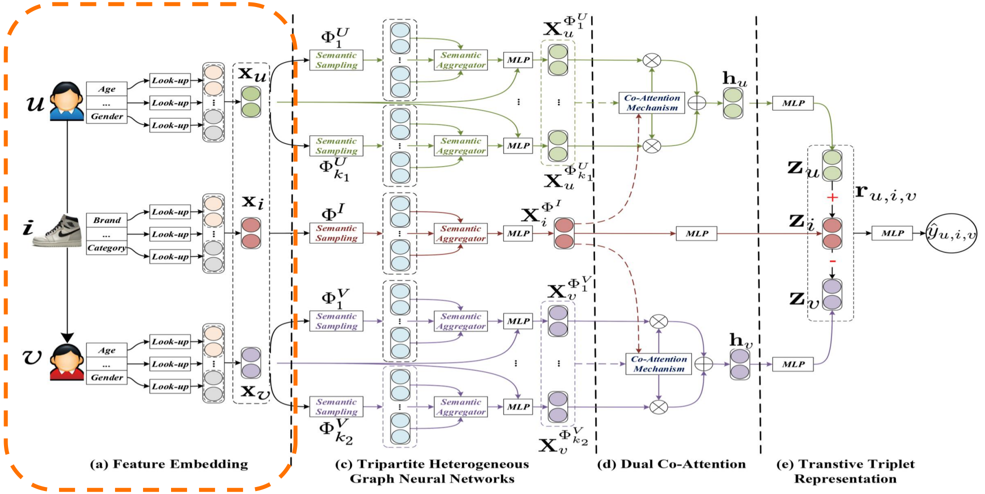
Improve ternary suitability.

Depict asymmetry.

Model

- ❑ Feature Embedding
  - ❑Dynamic/inductive embedding
  - ❑Reduce parameter complexity

$$\mathbf{x}_u = \sigma\left(\mathbf{W}_U \cdot \left(\Big\Vert_{k=1}^{|f^U|} \mathbf{e}_u^{f_k^U}\right) + \mathbf{b}_U\right)$$



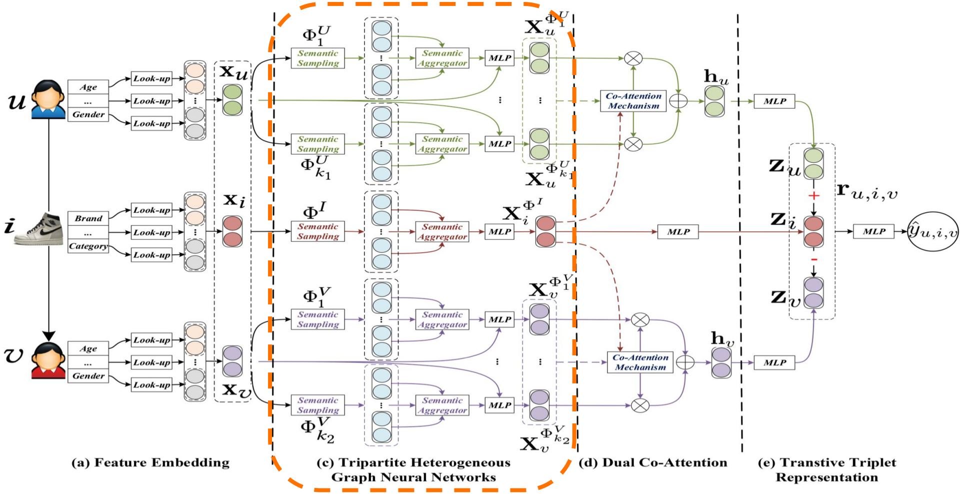
Model

- Tripartite Heterogeneous Graph Neural Networks
  - Unify structural and attribute information
  - Diverse interaction -> multiple representations
  - Real-time prediction

$$\mathbf{x}_u^{\Phi_1^U}, \mathbf{x}_u^{\Phi_2^U}, \cdots, \mathbf{x}_u^{\Phi_{k_1}^U} = HeteGNN^U(u; \Phi_1^U, \Phi_2^U, \cdots, \Phi_{k_1}^U).$$

$$\mathbf{x}_u^{\Phi^U} = \sigma(\mathbf{W}^{\Phi^U} \cdot (\mathbf{x}_u || \mathbf{x}_u^{\mathcal{N}_u^{\Phi^U}}) + \mathbf{b}^{\Phi^U}),$$

$$\mathbf{x}_u^{\mathcal{N}_u^{\Phi^U}} = MeanPooling(\{\mathbf{x}_n | \forall n \in \mathcal{N}_u^{\Phi^U}\}).$$



Model

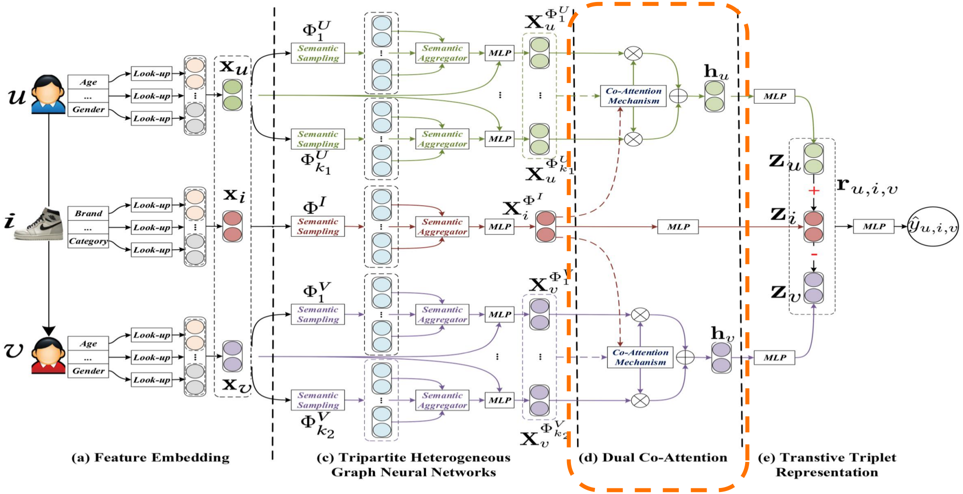
- ❑ Dual Co-Attention Mechanism
  - ❑Interaction-aware attention weights
  - ❑Discover diverse share motivations

$$w_{u,i}^{\Phi_1^U}, w_{u,i}^{\Phi_2^U}, \cdots, w_{u,i}^{\Phi_{k_1}^U} = \mathrm{CoAtt}_{U,I}(\mathbf{x}_u^{\Phi_1^U}, \cdots, \mathbf{x}_u^{\Phi_{k1}^U}, \mathbf{x}_i^{\Phi^I})$$

$$\alpha_{u,i}^{\Phi_m^U} = \mathbf{q}_{U,I}^T \cdot \sigma(\mathbf{W}^{U,I} \cdot (\mathbf{x}_u^{\Phi_m^U} \| \mathbf{x}_i^{\Phi^I}) + \mathbf{b}^{U,I}),$$

$$w_{u,i}^{\Phi_m^U} = \frac{\exp(\alpha_{u,i}^{\Phi_m^U})}{\sum_{m=1}^{k_1} \exp(\alpha_{u,i}^{\Phi_m^U})},$$

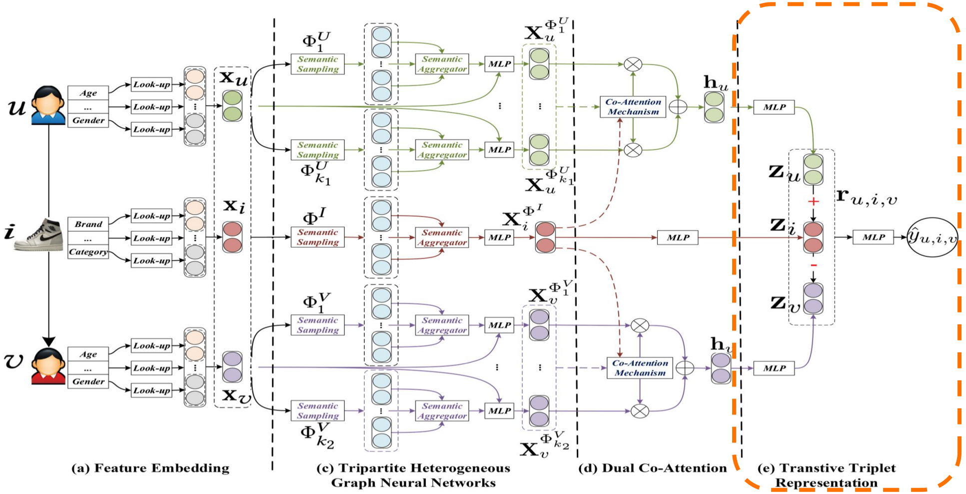
$$\mathbf{h}_u = \sum_{m=1}^{k_1} w_{u,i}^{\Phi_m^U} \cdot \mathbf{x}_u^{\Phi_m^U}$$



Model

- ❑ Transitive Triplet Representation
  - ❑Asymmetry of share action
  - ❑Item translating

$$\mathbf{r}_{u,i,v} = |\mathbf{z}_u + \mathbf{z}_i - \mathbf{z}_v|$$



- ❑ Loss Function

$$\hat{y}_{u,i,v} = \sigma(\mathbf{W} \cdot \mathbf{r}_{u,i,v} + b)$$

$$L = \sum_{u,i,v \in \mathcal{Y}^+ \cup \mathcal{Y}^-} (y_{u,i,v} \log \hat{y}_{u,i,v} + (1 - y_{u,i,v}) \log (1 - \hat{y}_{u,i,v}))$$

Experiment

❑Comparison Methods

❑Baselines

- LR/DNN/XGBoost
- GraphSAGE (NIPS17)
- IntentGC/IntentGC+ (KDD19)
- MEIRec/MEIRec+ (KDD19)

❑Variants

- HGSRec \ :
- HGSRec \

❑Dataset

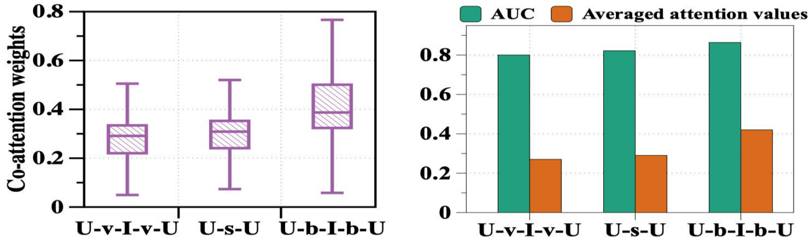
Dataset	3-days	4-days	5-days
#$\langle u, i, v\rangle$ in Training	3,324,367	4,443,996	5,611,531
#$\langle u, i, v\rangle$ in Validation	1,401,395	1,401,395	1,401,395
#*User* in Training	1,064,426	1,315,126	1,546,017
#*Item* in Training	537,048	679,784	818,290
#*User* in Validation	539,959	539,959	539,959
#*Item* in Validation	247,907	247,907	247,907
#Instances of *U-s-U*	13,419,250	16,622,210	19,596,190
#Instances of *U-v-I-v-U*	26,838,500	33,244,420	39,192,380
#Instances of *U-b-I-b-U*	5,367,700	6,648,884	7,838,476
#Instances of *U-b-I*	26,852,400	33,989,200	40,914,500

Experiment

❑Offline Results

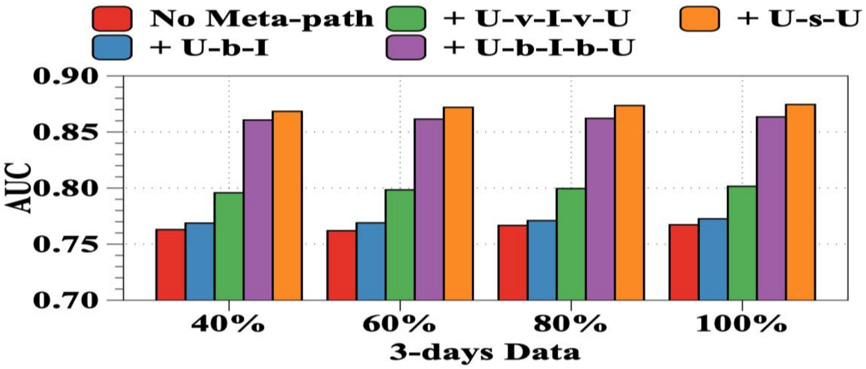
Methods	3-days				4-days				5-days			
	40%	60%	80%	100%	40%	60%	80%	100%	40%	60%	80%	100%
LR	0.6756	0.6762	0.6726	0.6769	0.6758	0.6765	0.6768	0.6772	0.6762	0.6767	0.6772	0.6774
XGBoost	0.7204	0.7214	0.7213	0.7218	0.7208	0.7211	0.7215	0.7249	0.7272	0.7254	0.7178	0.7214
DNN	0.7130	0.7120	0.7167	0.7203	0.7104	0.7133	0.7148	0.7180	0.7096	0.7112	0.7146	0.7151
GraphSAGE	0.7055	0.7097	0.7086	0.7089	0.6982	0.6969	0.7046	0.7103	0.6911	0.6966	0.7125	0.7106
IntentGC	0.6223	0.6178	0.6220	0.6225	0.6187	0.6230	0.6311	0.6317	0.6260	0.6291	0.6311	0.6315
IntentGC+	0.7315	0.7337	0.7392	0.7434	0.7387	0.7399	0.7422	0.7451	0.7414	0.7422	0.7453	0.7479
MEIRec	0.6494	0.6510	0.6530	0.6553	0.6545	0.6555	0.6566	0.6572	0.6519	0.6558	0.6620	0.6563
MEIRec+	0.7682*	0.7740*	0.7706*	0.7829*	0.7697*	0.7775*	0.7687*	0.7636*	0.7658*	0.7729*	0.7663*	0.7766*
HGSRec$_{\backslash att}$	0.8663	0.8695	0.8716	0.8726	0.8700	0.8727	0.8731	0.8751	0.8711	0.8723	0.8734	0.8759
HGSRec$_{\backslash tra}$	0.7817	0.7910	0.7950	0.7995	0.7640	0.7912	0.7709	0.7963	0.7822	0.7889	0.7883	0.8137
HGSRec	**0.8684**	**0.8720**	**0.8736**	**0.8745**	**0.8705**	**0.8739**	**0.8743**	**0.8769**	**0.8727**	**0.8753**	**0.8772**	**0.8792**
Improvements	13.0%	12.7%	13.4%	11.7%	13.1%	12.4%	13.7%	14.8%	14.0%	13.2%	14.5%	13.2%

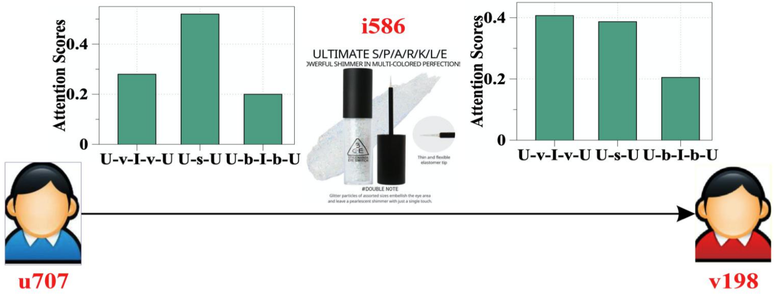
Experiment

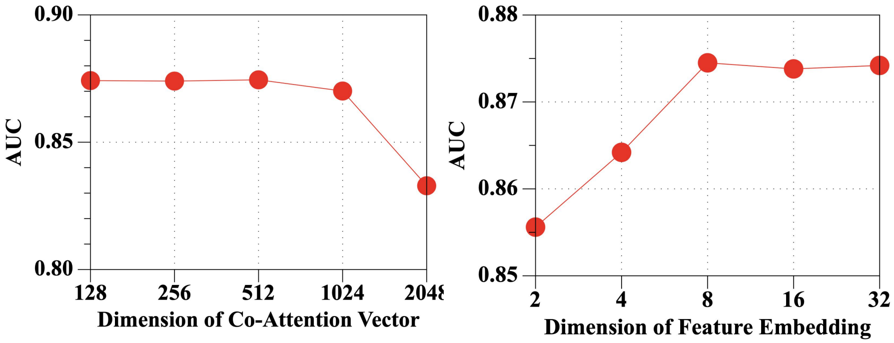


(a) Attention distributions of meta-paths

(b) Performance of meta-paths and corresponding averaged attention values

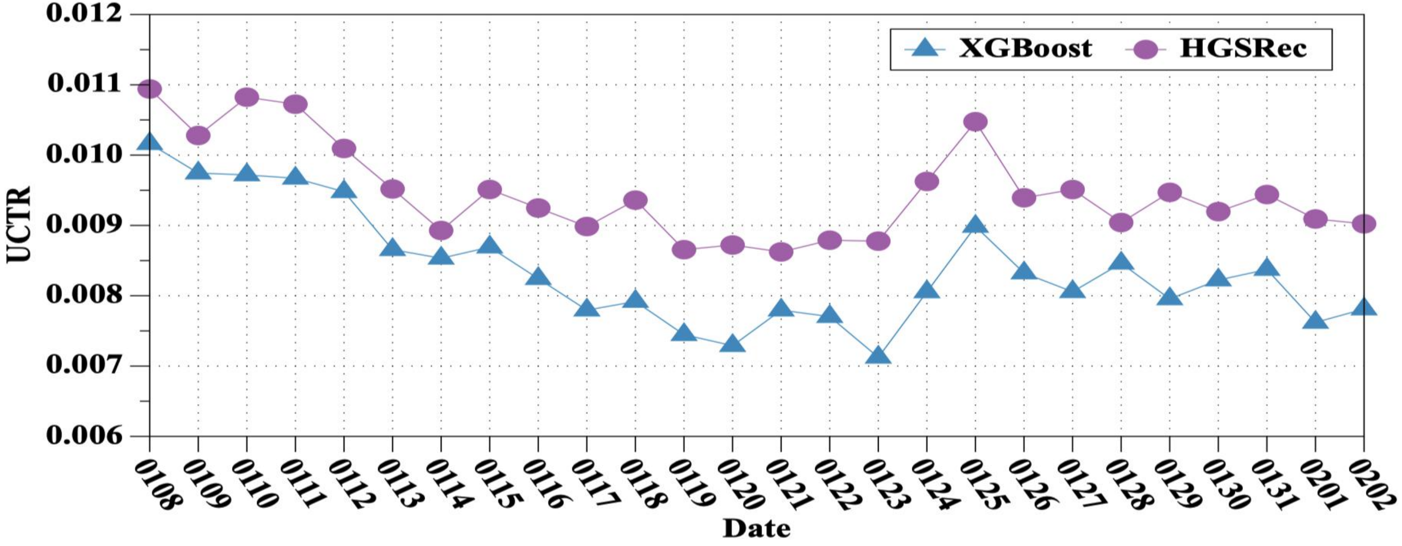






Experiment

❑Online Results



Conclusion

- ❑Discover interesting problems from the real-world scenario.
- ❑A simple yet effective model is welcome in the industry.

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THANKS

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