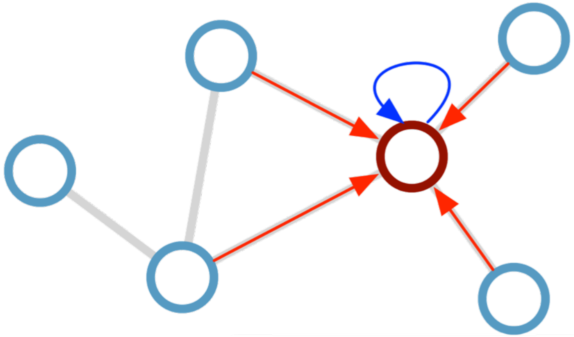


Relation-Aware GCNs for Agent-Initiated Social E-Commerce Recommendation

Fengli Xu, 17 August 2019

joint work with *Jianxun Lian, Xing Xie*; *Zhengyu Han, Yong Li*.

MSRA Tsinghua Univ.

Outline

What is social e-commerce?

GCN for RS

Model Design

Experiments

What is social e-commerce?

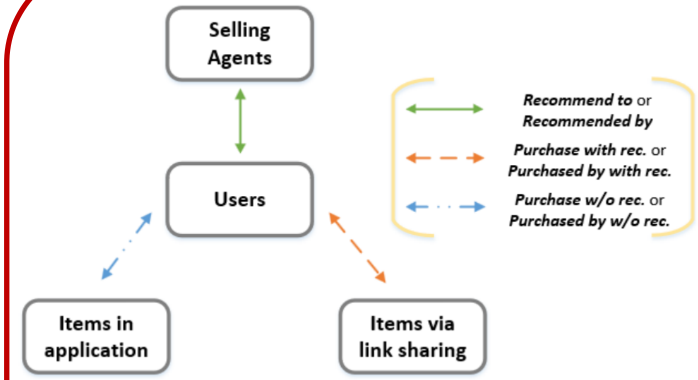
Social e-commerce

Review based:

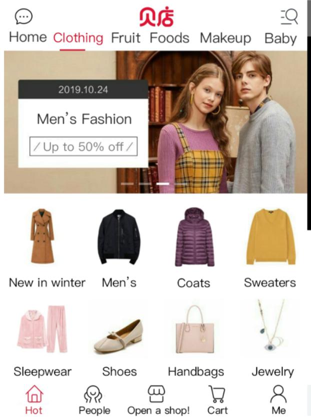
SNS based:

Group buying:

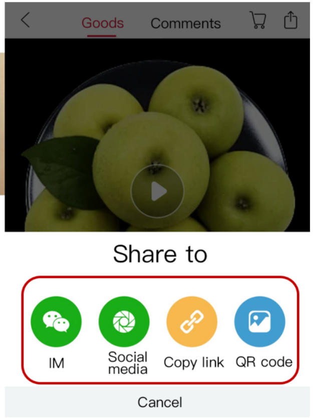
Agent-initiated Social e-commerce



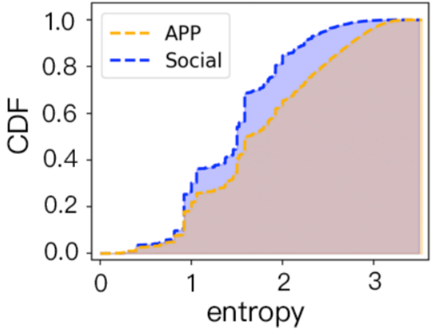
Characteristics

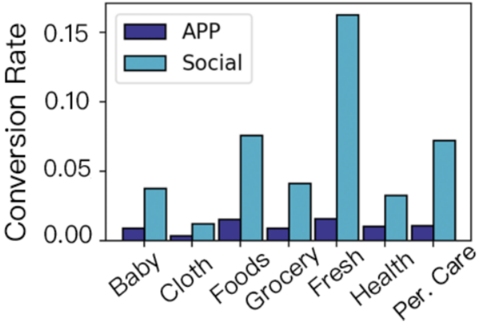


APP



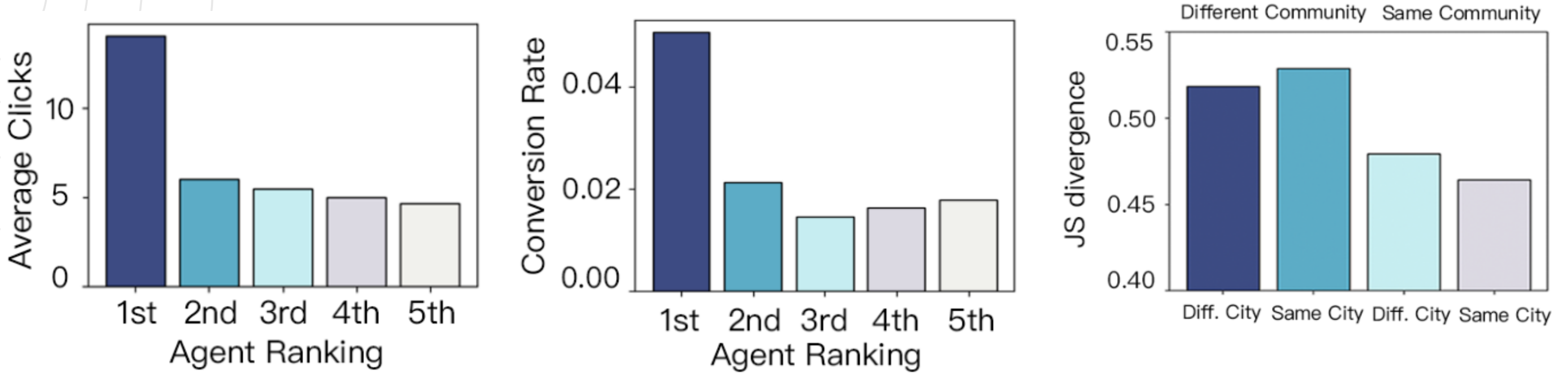
Social





	Item category distribution	Conversion rate
APP	Diverse	Higher
Social	Concentrated	Lower

Characteristics



(a) Average clicks per user (b) Average CVR per user (c) Purchase similarity

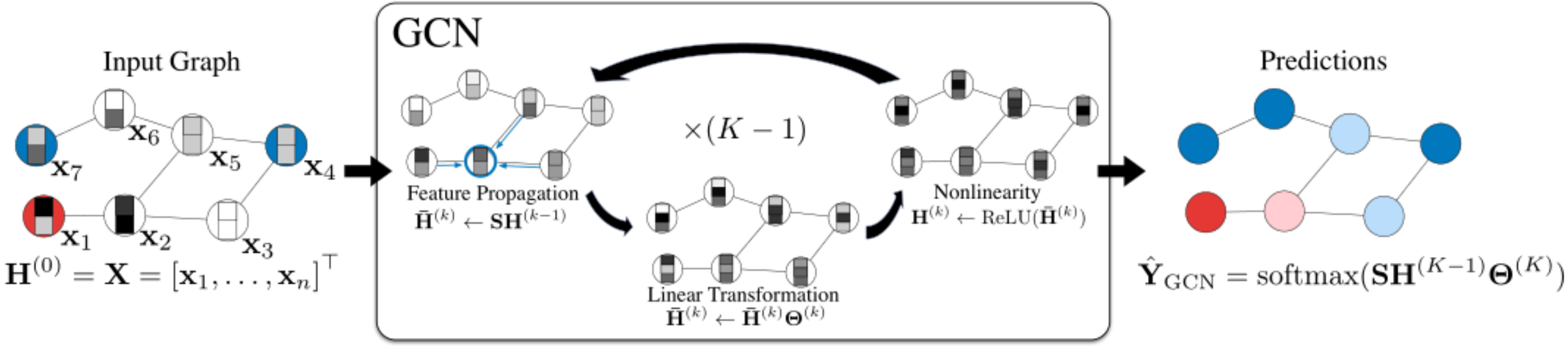
- Network structure matters.
- Node attribute matters.
- They are correlated with each other.

⇨ Can we use GCN?

GCN for Recommendation

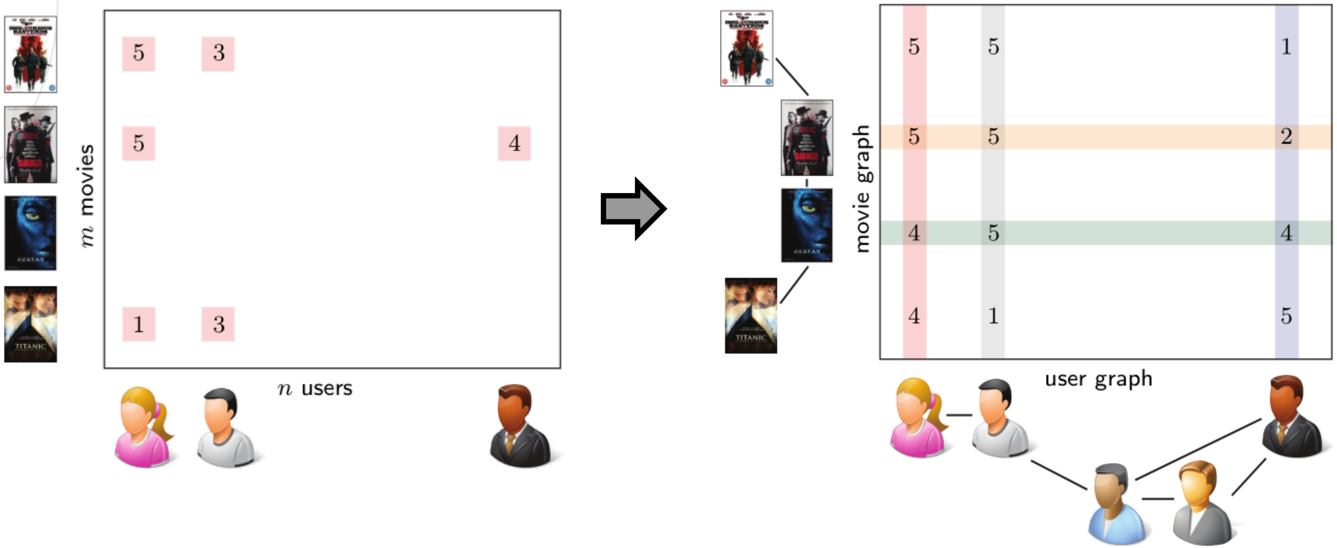
GCN 101

- Propagate node feature through network connection.
- Spatial invariant aggregator function.
- Stack *K* layer to aggregate from K-hops away.



(Courtesy to Felix Wu)

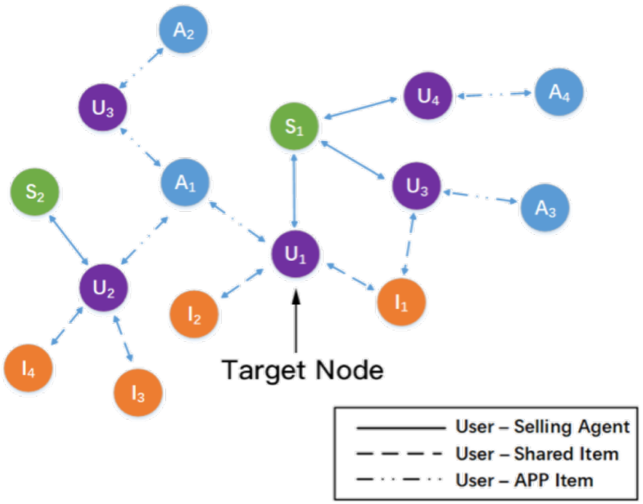
GCN for RS



Researchers widely consider GCNs are prime for RS, because interactions beyond user-item matters!

Challenges

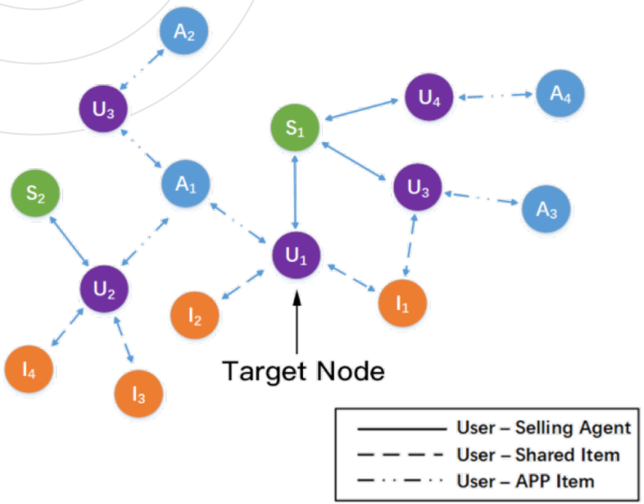
- GCN on heterogeneous graph.
- Going deeper, since important nodes are likely to be hops away (e.g. U-I-U-I).
- Complex and dynamic motivations in each purchase.



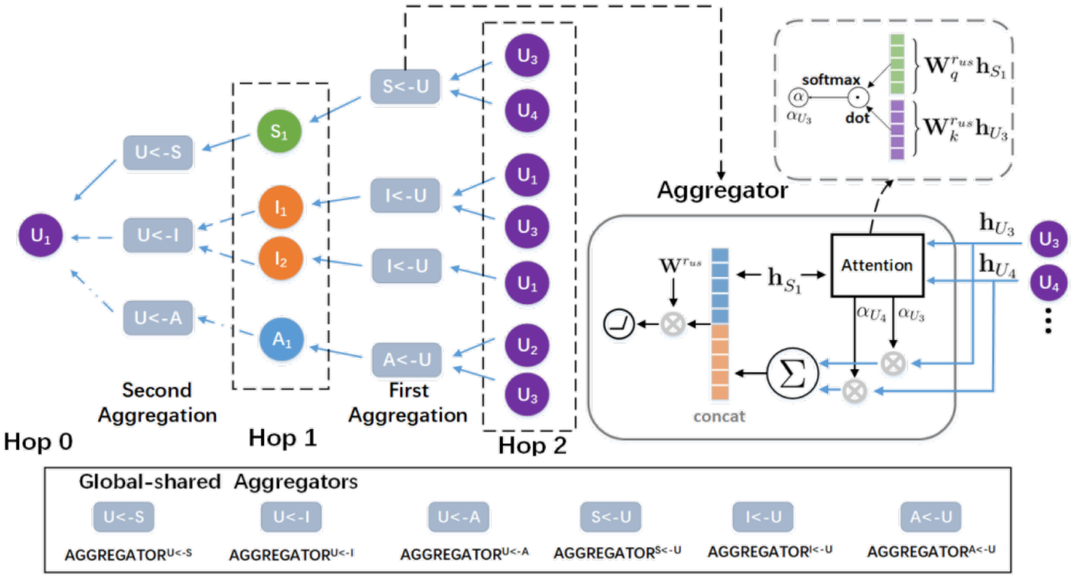
(a) An example of social e-commerce network

Model Design

Relation-aware aggregator



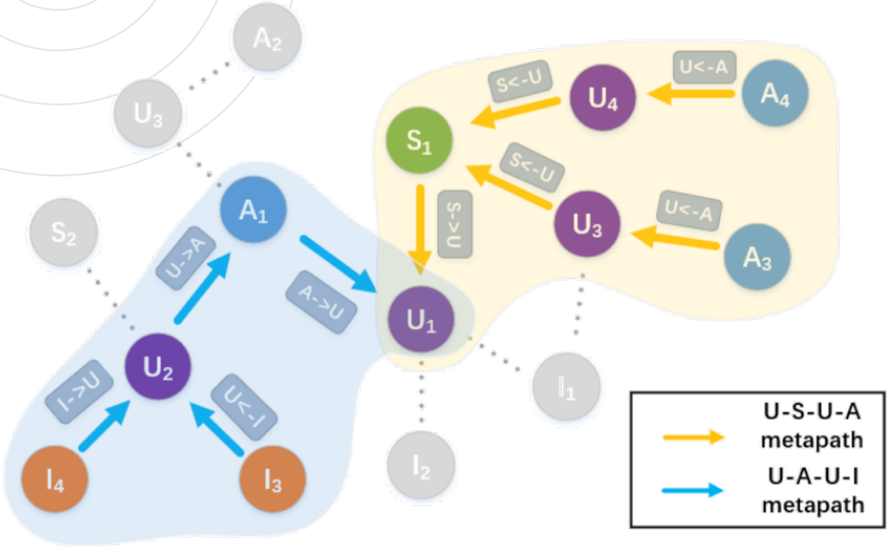
(a) An example of social e-commerce network



(b) Illustration of the mechanisms in AGGREGATOR^r

Share aggregators *relation-wise* instead of *layer-wise*.

Meta-path defined receptive field



Algorithm 2 : Embedding generation algorithm

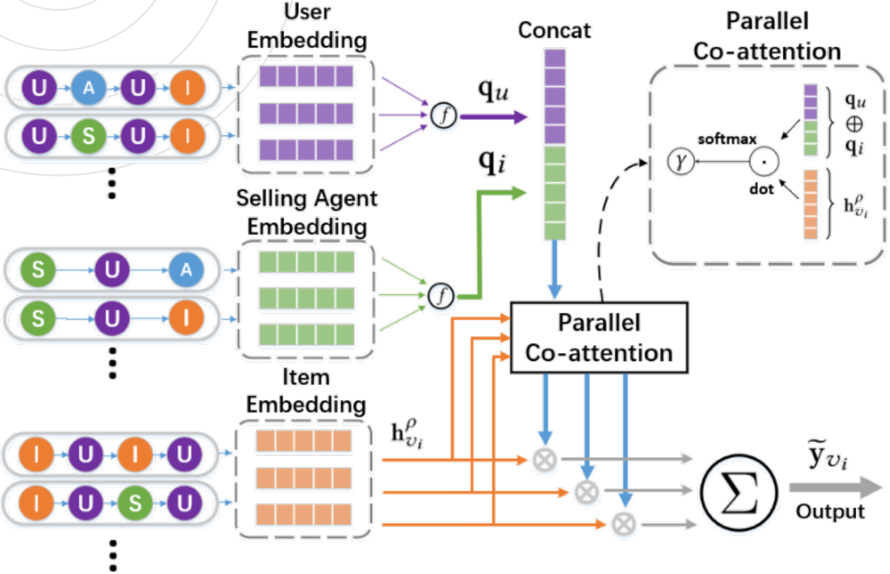
Input: social e-commerce graph $G_{SE} = (V, E)$, target node w, node features $\{\mathbf{x}_v, \forall v \in V\}$, meta-path $\rho = (r_1, r_2, \cdots, r_l)$, relation-based aggregator function AGGREGATOR$^{\mathrm{r}}$

Output: vector representation $\mathbf{h}_w^\rho$ for node w

/*Sampling meta-path defined receptive field */
$f_w^\rho(0) \leftarrow w$
for $i = 1$ to l **do**
  $f_w^\rho(i) \leftarrow \bigcup \{\mathcal{N}_{r_i}(v) |\ \forall\ v \in f_w^\rho(i-1)\}$
end for
/*Generating embeddings */
$\mathbf{h}_v \leftarrow \mathbf{x}_v, \forall v \in f_w^\rho(l)$
for $i = l$ to 1 **do**
  for $v \in f_w^\rho(i-1)$ **do**
    $\mathbf{h}_v \leftarrow \mathrm{AGGREGATOR}^{\mathrm{r}_i}(\mathbf{x}_v, \{\mathbf{h}_j |\ \forall j\ \in \mathcal{N}_{r_i}(v)\})$
  end for
end for
$\mathbf{h}_w^\rho \leftarrow \mathbf{h}_w$

Carve out *relevant receptive field* with *semantic-aware meta-paths*.

Co-attentive embedding fusing



Example of fusing item embedding from different Metapaths.

Dynamically assign attention weights by co-attending to other elements in each purchase.

Experiments

Dataset &Settings

- Collect a dataset that consists of the interactions between 87,105 users, 77,982 items and 13,057 selling agents.
- Also a social scenario only dataset (-).
- 80% training, 10% validation, 10% test.
- We handcraft 11 metapaths for users, selling agents and items.

Table 2: The basic statistics of evalution dataset.

Node types	#Node	Avg. Inter. (Social)	Avg. Inter. (APP)
User	87105	6.36	26.15
Item	77982	7.10	29.21
Selling Agent	13057	40.99	-

Table 3: The selected meta-paths for each type of node.

	Meta-paths
Users	U-I, U-A, U-S-U-I, U-A-U-I, U-I-U-I
Selling Agents	S-U, S-U-I, S-U-A
Items	I-U, I-U-I-U, I-U-S-U, I-U-A-U

Baselines

- BMF: Classic biased matrix factorization model.
- DNN: Content-boosted deep learning recommendation model.
- Metapath MF: Perform matrix factorization on extended interaction matrices based on metapaths.

- ReGCN: A degraded variant of RecoGCN, which only employs the r-Aggregators.
- ReGCN$_{MP}$: Integrates metapath defined receptive field sampler into ReGCN.

- PinSage: The state-of-the-art GCN recommender system.
- GAT: The state-of-the-art attention-based GCN model.
- HAN: The state-of-the-art GCN-based network embedding model for HINs.
- DiffNet: The state-of-the-art GCN model that considers the social influence diffusion in recommendation problem.

Performance

- GCN models achieve superior performance in general.
- All variants of our model achieve superior performance.
- Each component results in significant performance gain.

Table 4: Performance comparison with baseline models, where (**) indicates p<0.01 significance over best baseline.

Method	MRR@30	NDCG@30	HR@1	HR@3
BMF(-)	0.2326	0.3795	0.1454	0.2305
BMF	0.2105	0.3621	0.1181	0.2106
DNN(-)	0.2348	0.3814	0.1472	0.2336
DNN	0.1895	0.3445	0.0991	0.1863
Metapath MF(-)	0.2226	0.3710	0.1394	0.2152
Metapath MF	0.2207	0.3691	0.1390	0.2118
PinSage(-)	0.2533	0.4015	0.1448	0.2611
PinSage	0.2493	0.3988	0.1348	0.2637
GAT(-)	0.2536	0.4020	0.1439	0.2637
GAT	0.2339	0.3867	0.1191	0.2429
DiffNet	0.2254	0.3721	0.1449	0.2204
HAN	0.2571	0.4037	0.1542	0.2621
ReGCN	0.2553	0.4033	0.1463	0.2628
$ReGCN_{MP}$	0.2593	0.4061	0.1526	0.2663
RecoGCN(-)	0.2619	0.4073	0.1596	0.2675
RecoGCN	**0.2632****	**0.4086****	**0.1592****	**0.2708****

Performance

- Combining APP interactions surprisingly result in performance degeneration in most baselines.
- RecoGCN is able to leverage APP interactions.

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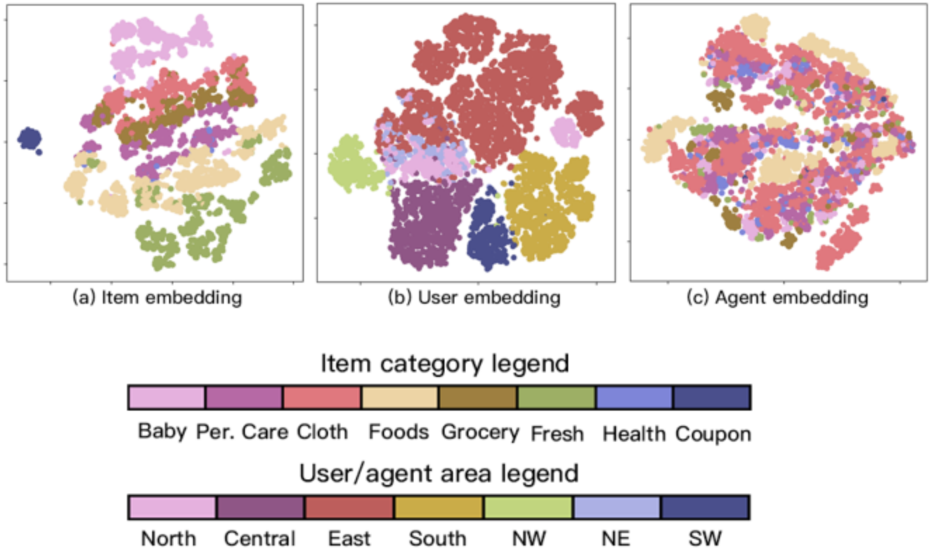
RecoGCN	**0.2632****	**0.4086****	**0.1592****	**0.2708****

Embeddings Visualization

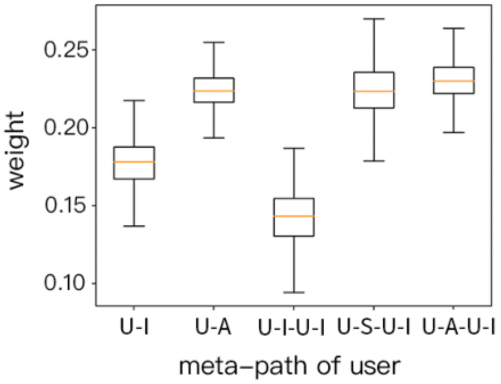
- Users are well distinguished based on categories and regions.
- Semantic-aware. Coupon is isolated, Fresh foods close to Foods, etc.

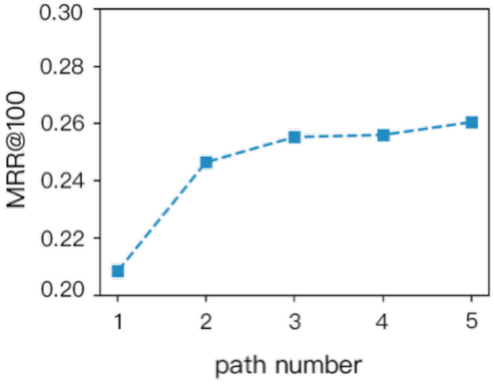


2D t-SNE plot of Embeddings from $ReGCN_{MP}$.

Meta-paths Importance

- High importance in *U–S–U–I* indicates strong *social regularization.*
- Importance on *U–I–U–I* is surprisingly low. Could be *U–A–U–I* better capture *CF* effect.
- Adding in high quality meta-paths result in constantly performance boost.





Summary

- An exploratory study to analyze the behavior characteristics in the newly-emergent agent-initiated social e-commerce.
- A relation-aware GCN framework for heterogeneous graph.
- A method to leverage metapath to reduce receptive field size and makes it semantic-aware.
- A co-attentive mechanism to dynamically reason the motivation of each purchase.
- Experiments and model analysis to evaluate and understand the performance of the proposed model.

Related Projects

Accepted:

- **When E-Commerce Meets Intimacy: An Empirical Study of Social Commerce Site Beidian.** Hancheng Cao, Zhilong Chen, ***Fengli Xu***, Yong Li, Tao Wang. In ICWSM, 2020.

- **Relation-Aware Graph Convolutional Networks for Agent-Initiated Social E-Commerce Recommendation.** ***Fengli Xu***, Jianxun Lian, Zhenyu Han, Yong Li, Yujian Xu, Xing Xie. In CIKM, 2019.

- **"I Think You'll Like It": Modelling the Online Purchase Behavior in Social E-commerce.** ***Fengli Xu***, Zhenyu Han, Jinhua Piao, Yong Li. In ACM CSCW, 2019.

In submission:

- **Growth Via Referral: Understanding the Invitation Acceptance in Agent-initiated Social E-commerce.** ***Fengli Xu***, Guozhen Zhang, Yuan Yuan, Diyi Yang, Yong Li. In submission to ACM CHI, 2020.

Thanks!

Any questions?

You can find me at

- Email: xfl15@mails.tsinghua.edu.cn
- Homepage: http://fenglixu.com
- Code: anonymous0522/RecoGCN @ Github