- Overview of multidomain recommender systems (Liang Hu, 25 mins)
- Multi-item domain recommender systems (Z. Y. Lai, 20 mins)
- **Multi-user domain recommender systems (Qi Zhang, 20 mins)**
- Multi-data domain recommender systems (Z. Y. Lai, 20 mins)
- Multi-spatial domain recommender systems (Qi Zhang 20 mins)
- Multi-temporal domain recommender systems (Z. Y. Lai, 20 mins)
- Multi-goal domain recommender systems (Liang Hu, 20 mins)
- Summary (Liang Hu, 5 mins)

Multi-user domain recommender systems

- Preliminary of multi-user domain recommender systems
- Multi-user domain modeling for groups recommendation
- Multi-user domain modeling for social network-based recommendation

Multi-user relations

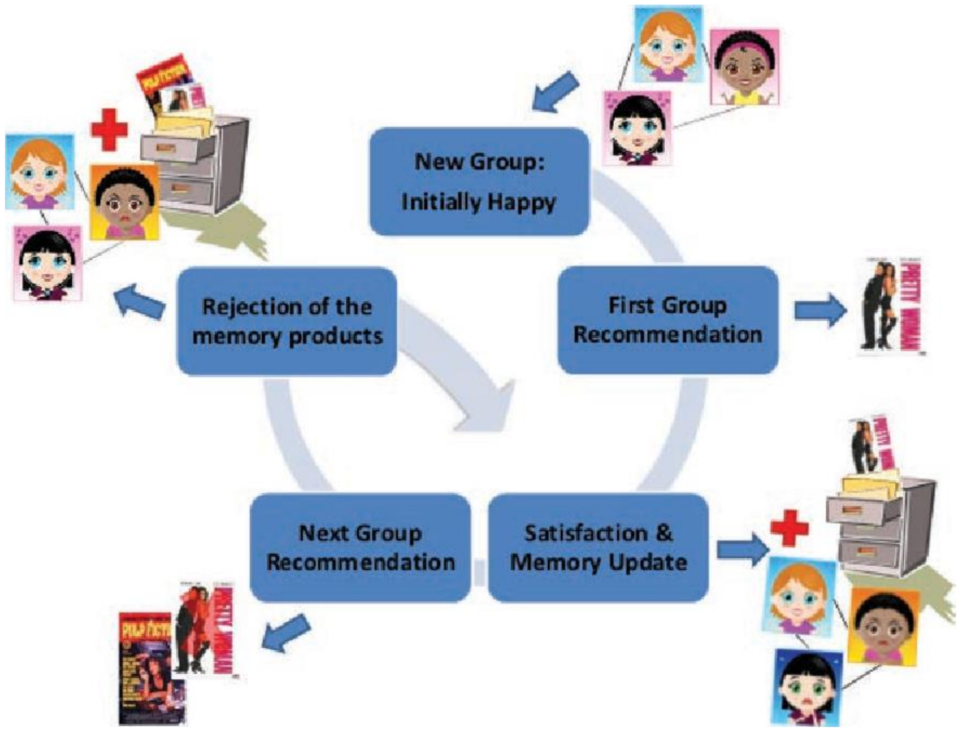
People' choices are often influenced by others in terms of group manners or social relations.

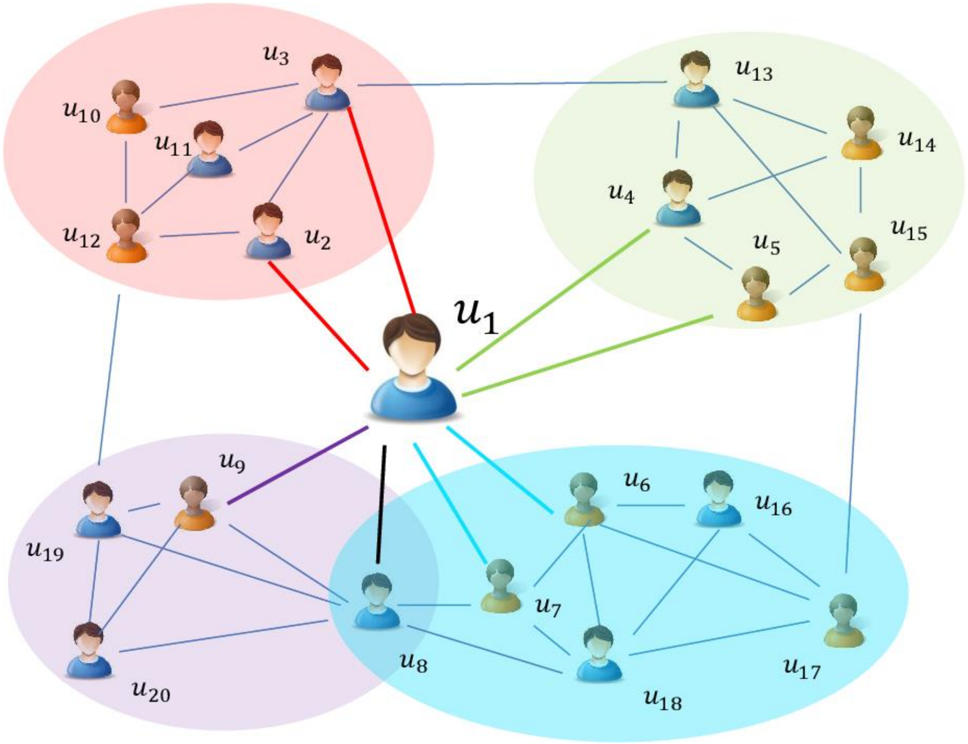
Member's choice should satisfy the meets of his group.

Friends' choices often have impact on our choices.

Multi-user domain recommender systems

Multi-user domain recommender systems aim to incorporate users' social behavior or group behavior to improve recommendation or provide group-base services.





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Group choices are joint decisions

- Group activities are observed throughout life
  - e.g., watching a family movie, planning family travel
- Each member of a group may have **different opinions** on the same items, so the main challenge in GRSs is to satisfy most group members with **diverse preferences**.

Profile Aggregation

- Group Preference Aggregation (GPA) (Pre-aggregation)
  - Regarding Groups as virtual individual users
  - Aggregating all members’ ratings into a group profile

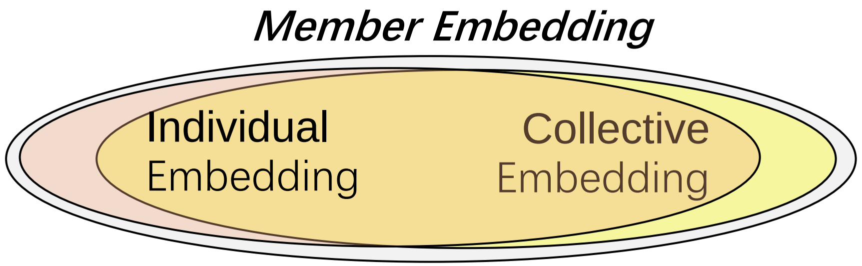
- Individual Preference Aggregation (IPA) (Post-aggregation)
  - Predicting the individual ratings over candidate items
  - Aggregating the predicted ratings of members via predefined strategies.

DLGR : Modeling Features in Group-based Decision

- ***Member Embedding***: which model the individual preference of a user when she/he makes choices as a group member, which can be regarded as **a mixture of *Collective Embedding* and *Individual Embedding*** .

- ***Collective Embedding***: which represent compromised preferences of a group, which are **shared among all members** and can be disentangled from the *Member Features*.

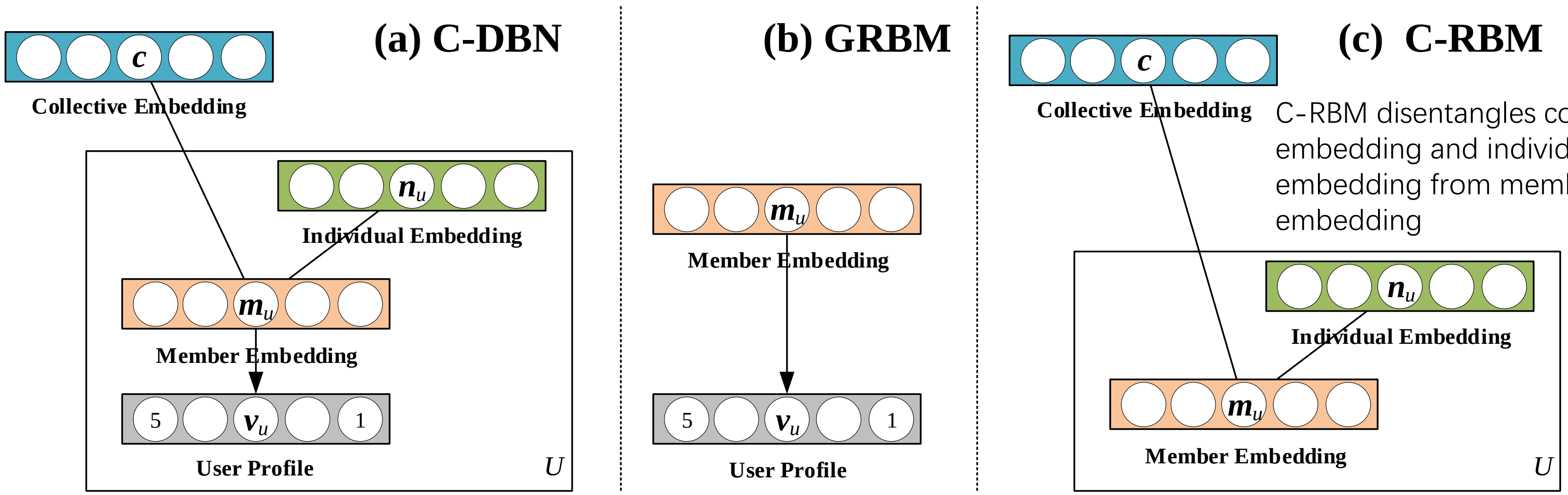
- ***Individual Embedding*** : these represent **independent individual-specific preference**, which can be disentangled from the *Member Features*.



Hu, L., Cao, J., Xu, G., Cao, L., Gu, Z., and Cao, W. Deep modeling of group preferences for group-based recommendation. In *Twenty-Eighth AAAI Conference on Artificial Intelligence*, 2014.

Disentangling Collective and Individual Features

- Each group choice can be regarded as a **joint decision** by all members



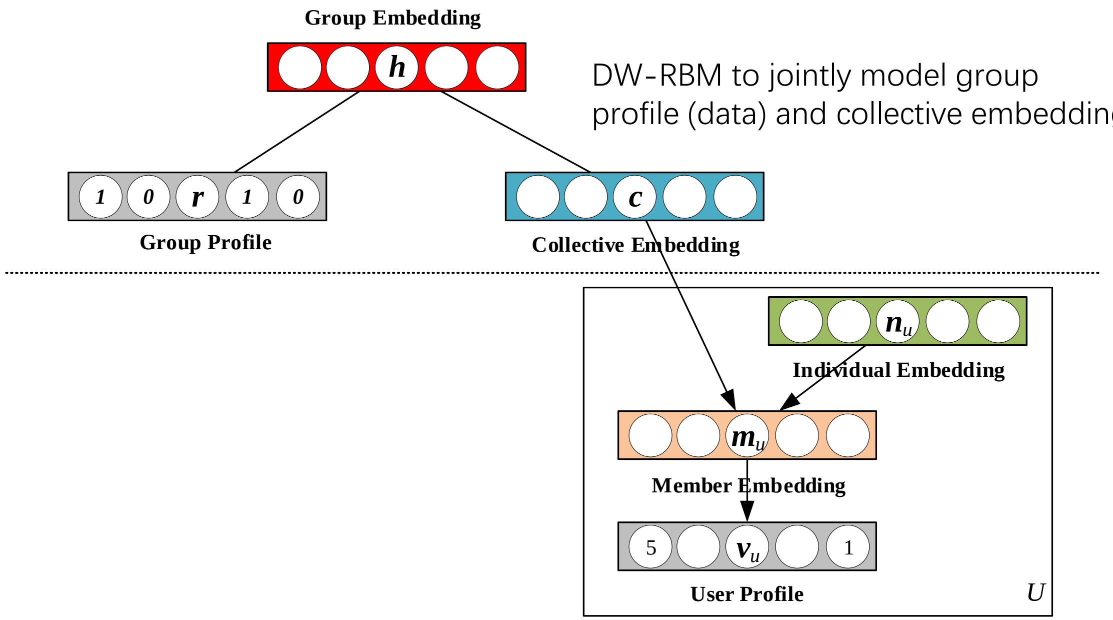
C-RBM disentangles collective embedding and individual embedding from member embedding

GRBM to learn member embedding

Hu, L., Cao, J., Xu, G., Cao, L., Gu, Z., and Cao, W. Deep modeling of group preferences for group-based recommendation. In *Twenty-Eighth AAAI Conference on Artificial Intelligence*, 2014.

Comprehensive Representation of Group Preferences

- A dual-wing RBM is placed on the top of DBN, which jointly models the group choices and collective features to learn the comprehensive features of group preference

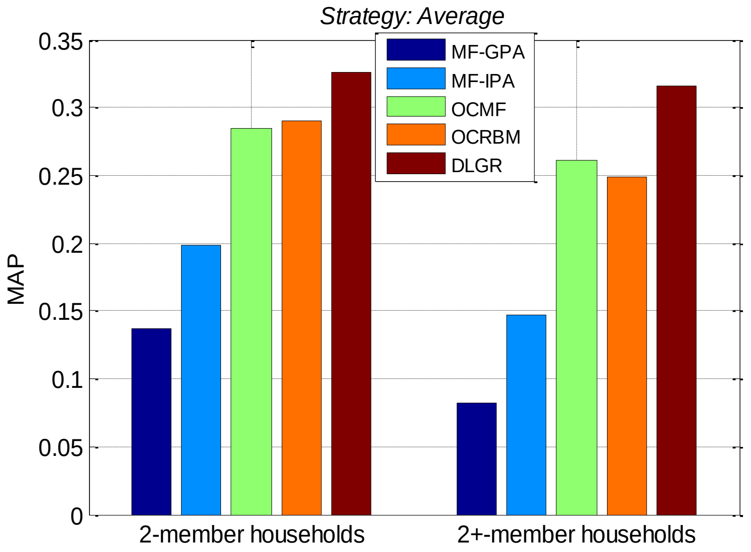


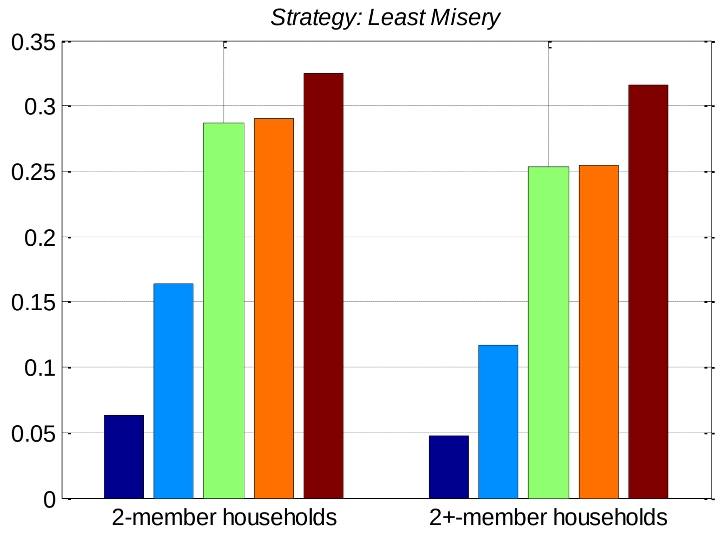
DW-RBM to jointly model group profile (data) and collective embedding

Experimental Results

MAP and mean AUC of all comparative models with different strategies

	MAP			AUC		
Model/Strategy	No Strategy	Averag e	Least Misery	No Strategy	Averag e	Least Misery
kNN (k=5)	0.1595	N/A	N/A	0.9367	N/A	N/A
MF-GPA	N/A	0.1341	0.0628	N/A	0.9535	0.9297
MF-IPA	N/A	0.1952	0.1617	N/A	0.9635	0.9503
OCMF	0.2811	0.2858	0.2801	0.9811	0.9813	0.9810
OCRBM	0.2823	0.2922	0.2951	0.9761	0.9778	0.9782
DLGR	0.3236	0.3252	0.3258	0.9880	0.9892	0.9897





Attentive group recommendation: aggregate the preference of group members via learning

- Design a neural attention network to learn the weight of a member,
  - Assign different weights for a user when the group interacts with different items
  - Dynamically adjust the aggregation strategy for a group to capture the complicated process of group decision making

Cao, D., He, X. , et al. Attentive group recommendation. In *SIGIR 2018*, 2018.

User embedding aggregation and user-item and group-item interactions

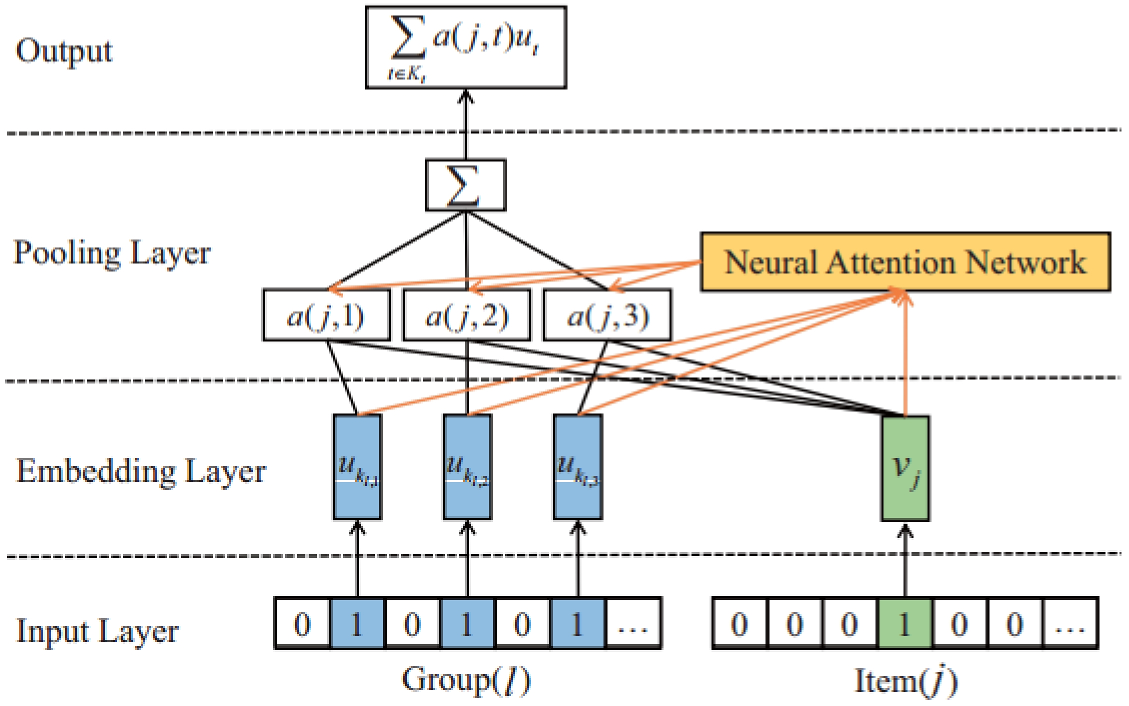


Figure 2: Illustration of the user embedding aggregation component based on neural attention network.

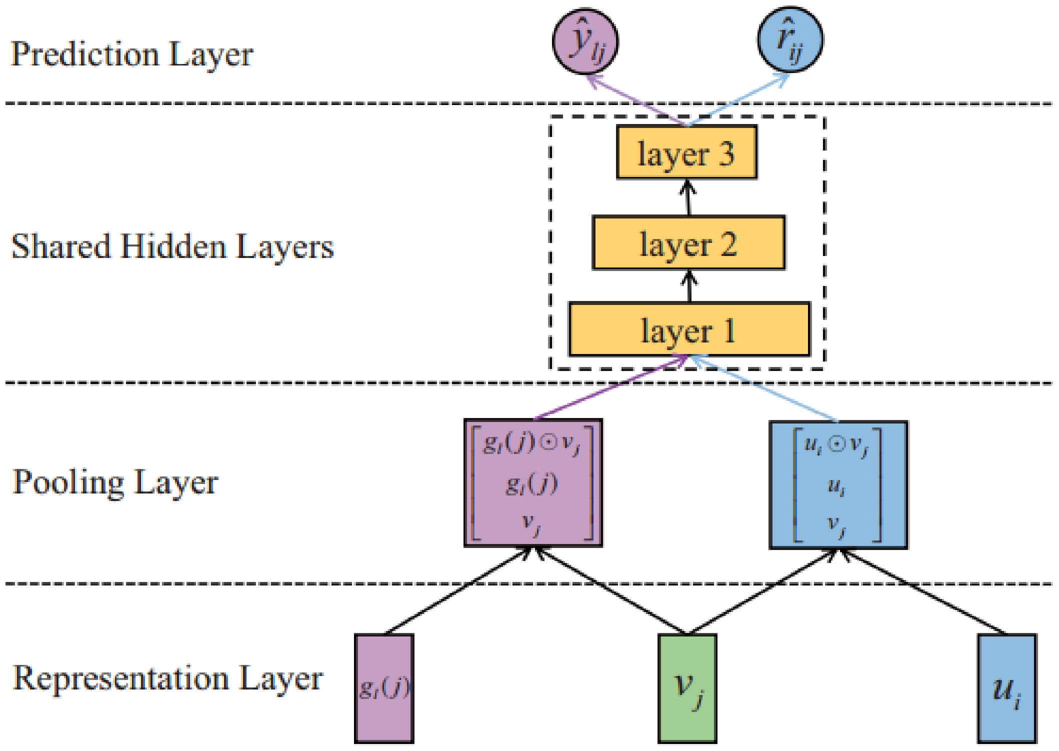
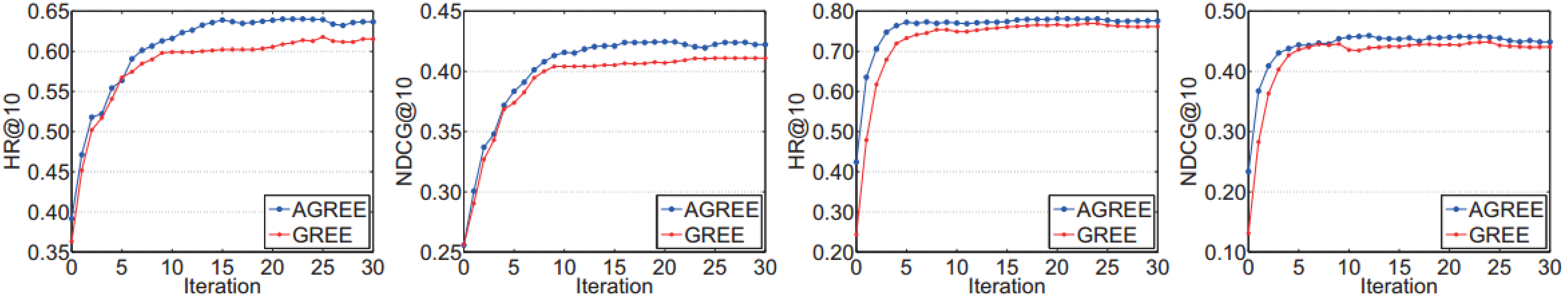


Figure 3: Illustration of interaction learning based on NCF.

Performance comparisons

- Attentive group recommendation model obviously outperforms baselines in both single user recommendations and group recommendations.
- Attention mechanism contributed greatly to the improvement of group recommendation performance.

Overall Performance Comparison (Mafengwo)				
	K=5		K=10	



(a) Mafengwo — HR@10 **(b) Mafengwo — NDCG@10** **(c) CAMRa2011 — HR@10** **(d) CAMRa2011 — NDCG@10**

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Social Recommendation

- The growth of social media usage

https://www.smartinsights.com/social-media-marketing/social-media-strategy/new-global-social-media-research/

Traditional Social Recommendation

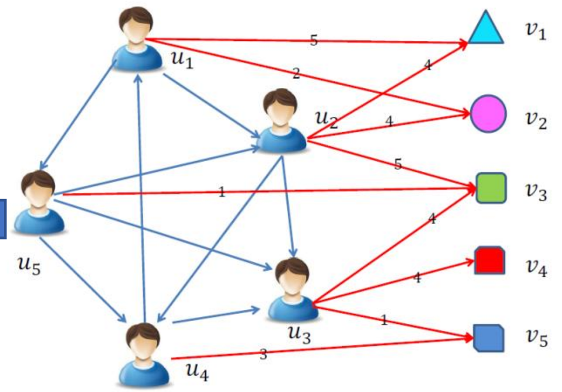
- Recommendation + social relations
  - Latent factor model:
    - Co-factorization
    - Regularization methods

$$\min_{\mathbf{U},\mathbf{V},\mathbf{Z}} \|\mathbf{W}\odot\overset{\text{rating factorization}}{\boxed{(\mathbf{R}-\mathbf{U}^\top\mathbf{V})\|_F^2}} + \alpha \sum_{i=1}^{n} \sum_{u_k\in\mathcal{N}_i} \overset{\text{social factorization}}{\boxed{(\mathbf{S}_{ik}-\mathbf{u}_i^\top\mathbf{z}_k)^2}}$$

$$+ \lambda(\|\mathbf{U}\|_F^2+\|\mathbf{V}\|_F^2+\|\mathbf{Z}\|_F^2)$$

	v_1	v_2	v_3	v_4	v_5
u_1	5	?	2	?	?
u_2	4	4	5	?	?
u_3	?	?	4	4	1
u_4	?	?	?	?	3
u_5	?	?	1	?	?

(b) Traditional Recommender Systems



(a) Connected Users

rating matrix

	v_1	v_2	v_3	v_4	v_5
u_1	5	?	2	?	?
u_2	4	4	5	?	?
u_3	?	?	4	4	1
u_4	?	?	?	?	3
u_5	?	?	1	?	?

social matrix

	u_1	u_2	u_3	u_4	u_5
u_1	0	1	0	0	1
u_2	0	0	1	1	0
u_3	0	0	0	0	0
u_4	1	0	1	0	0
u_5	0	1	1	1	0

(c) Social Recommender Systems

Tang, J., Hu, X., & Liu, H. (2013). Social recommendation: a review. *Social Network Analysis and Mining*, *3*(4), 1113-1133.

ESRF: Enhanced Social Recommendation Framework

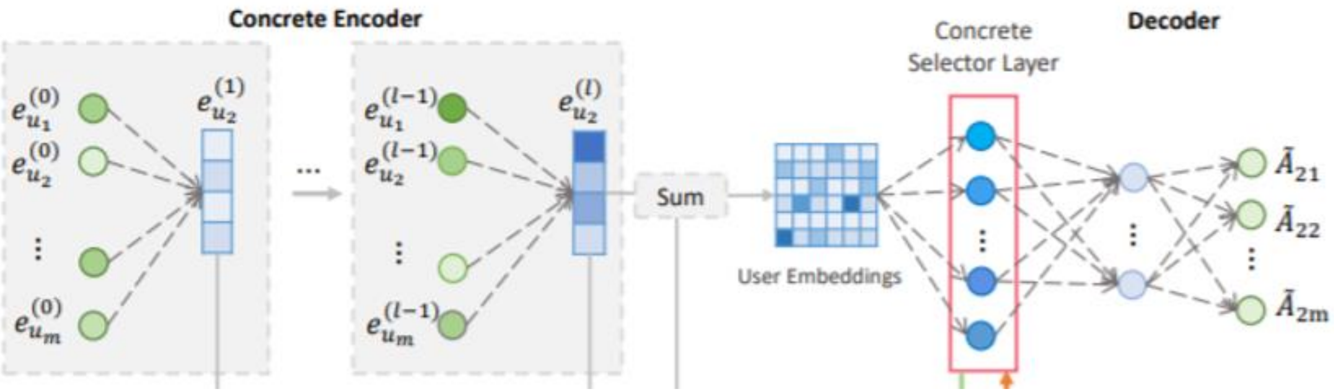
Recent reports from industry show that social recommender systems consistently fail in practice, attributing to the following issues:

- Data sparsity;
- Social noisy
- Multi-facet Social relations

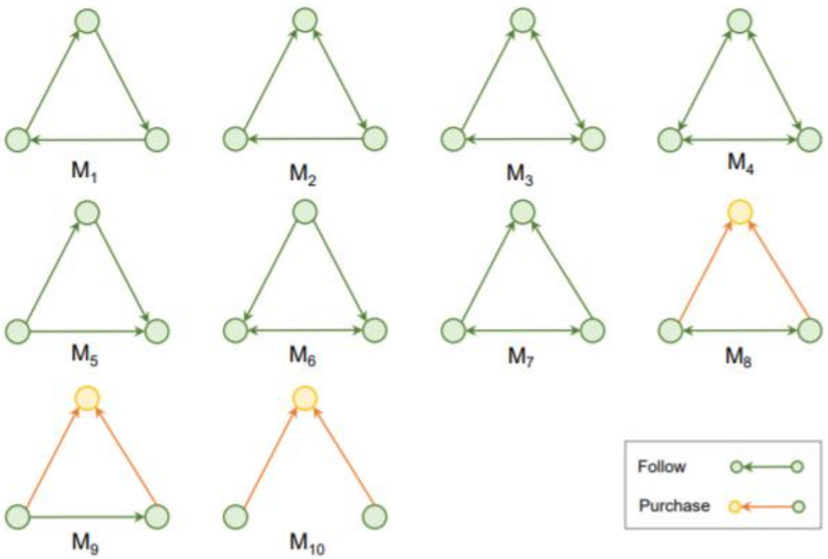
Junliang Yu, Hongzhi Yin, Jundong Li, Min Gao, Zi Huang, and Lizhen Cui. Enhancing Social Recommendation with Adversarial Graph Convolutional Networks. 2020, TKDE,

Solutions to the three questions

validity issue

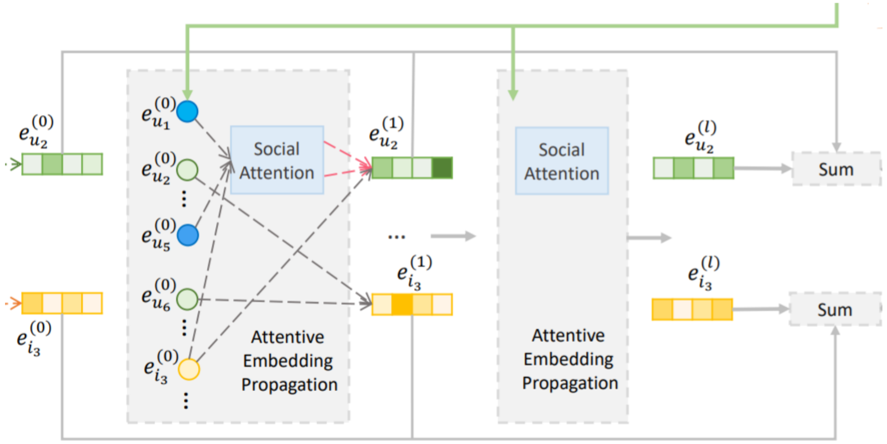


Use neighborhood in graph to reconstruct the explicit social profiles



Motifs used in the work. The green circles denote users, and the yellow circles denote items.

relation sparsity

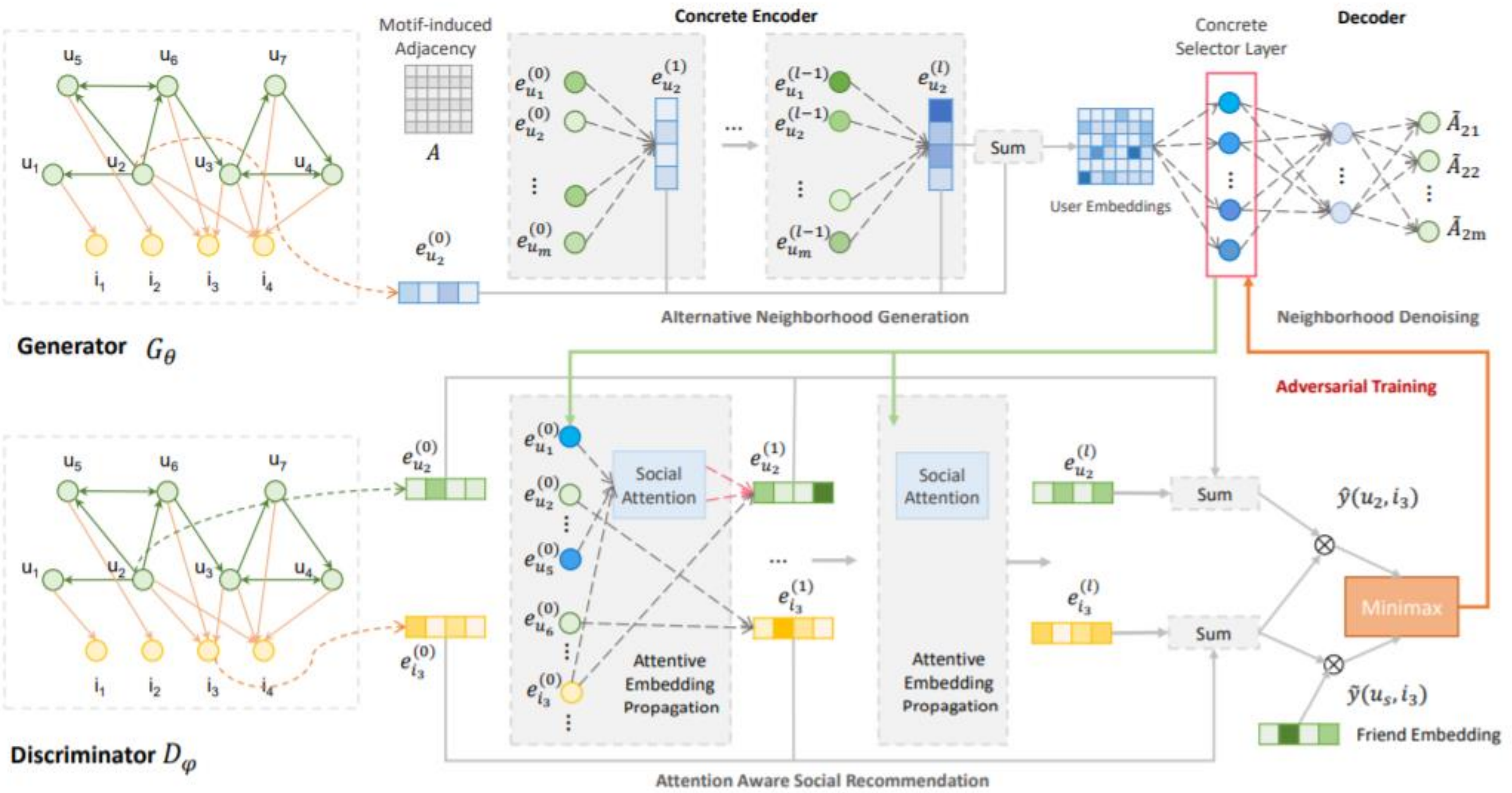


Attention Aware Social Recommendation

multifacets problem

a social attention mechanism is employed to weigh the contribution of the new neighbors and selectively aggregate information

Schematic overview of framework



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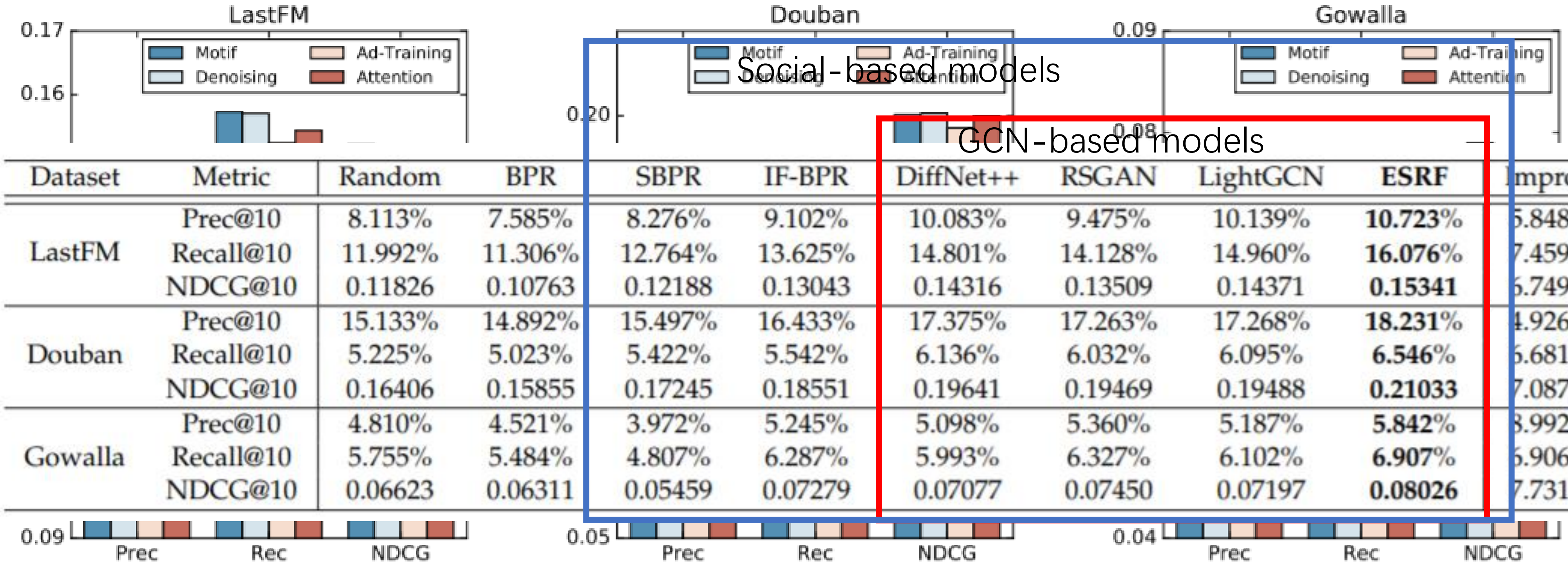
Results



Social-based models

GCN-based models

Dataset	Metric	Random	BPR	SBPR	IF-BPR	DiffNet++	RSGAN	LightGCN	ESRF	Improv.
LastFM	Prec@10	8.113%	7.585%	8.276%	9.102%	10.083%	9.475%	10.139%	**10.723%**	5.848%
	Recall@10	11.992%	11.306%	12.764%	13.625%	14.801%	14.128%	14.960%	**16.076%**	7.459%
	NDCG@10	0.11826	0.10763	0.12188	0.13043	0.14316	0.13509	0.14371	**0.15341**	6.749%
Douban	Prec@10	15.133%	14.892%	15.497%	16.433%	17.375%	17.263%	17.268%	**18.231%**	4.926%
	Recall@10	5.225%	5.023%	5.422%	5.542%	6.136%	6.032%	6.095%	**6.546%**	6.681%
	NDCG@10	0.16406	0.15855	0.17245	0.18551	0.19641	0.19469	0.19488	**0.21033**	7.087%
Gowalla	Prec@10	4.810%	4.521%	3.972%	5.245%	5.098%	5.360%	5.187%	**5.842%**	8.992%
	Recall@10	5.755%	5.484%	4.807%	6.287%	5.993%	6.327%	6.102%	**6.907%**	6.906%
	NDCG@10	0.06623	0.06311	0.05459	0.07279	0.07077	0.07450	0.07197	**0.08026**	7.731%

Ablation study on the three datasets.

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