Paper Review

A Neural Influence and Interest Diffusion Network For Social Recommendation

(DiffNet++)

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Content

- ☐ Introduction
- ☐ Proposed Model
- ☐ Experiments
- ☐ Conclusions

Introduciton

Introduction to Social Recommendation

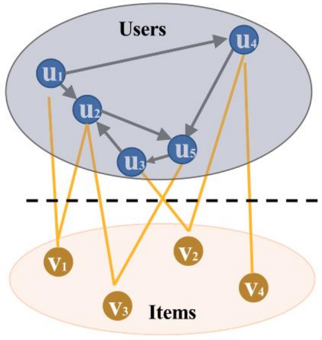
- **Collaborative Filtering (CF) based recommender systems (RecSys)**
  - Learn user and item embeddings by utilizing user-item interest behavior data
  - Performance is unsatisfactory due to the data sparsity issue
  - As most users have limited behavior data

- **Social Recommendation (SocialRec) plays an important role**
  - Users build social relationships and share their items preferences in social network
  - Social Influence Theory: user in a social network would influence each other, leading to similar interests among social connections
  - Focus on exploiting social relations among users to alleviate data sparsity

Introduction to SocialRec (Cont'd)

- **Key to SocialRec**
  - Learning user embeddings with two kinds of behaviors
  - **User-user social behavior** & **user-item interest behavior**

- **CF based models**
  - Treating user-item interest network to user-item matrix
  - Projecting both users and items into a low latent space



Social Recommendation

Social Matrix

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

Rating Matrix

	v_1	v_2	v_3	v_4
u_1	1	0	0	0
u_2	1	0	1	0
u_3	0	1	0	0
u_4	0	1	0	1
u_5	0	0	1	0

Social Recommender Systems (Socila RecSys)

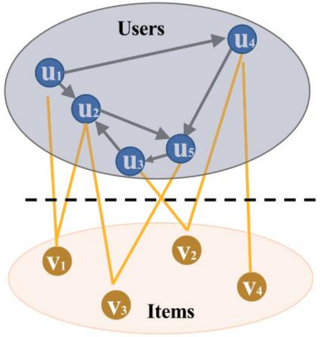
- **Most social based RecSys advance these CF models**
  - Leveraging the user-user matrix to enhance each user’s embedding
    - By learning with social neighbors’ records
  - Regularizing the user embedding learning process with social neighbors
    - e.g., SocialMF and SR, TurstSVD

- **Leverged the first-order social neighbors for Recommendation**

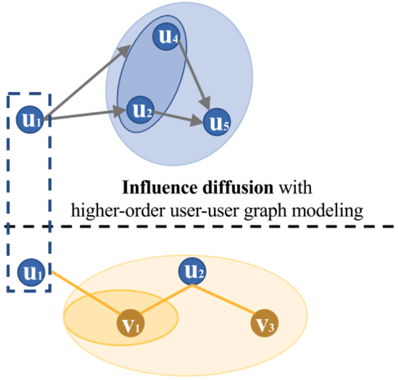
- **Paritally alleviated the data sparsity issue in CF**

Challenges

- **User play a central role in two kinds of behavior networks**
  - The user-user social network & the user-item interest network
- **Each user is influenced by**
  - The direct first-order social network structure
  - The higher-order ego-centric social network structure



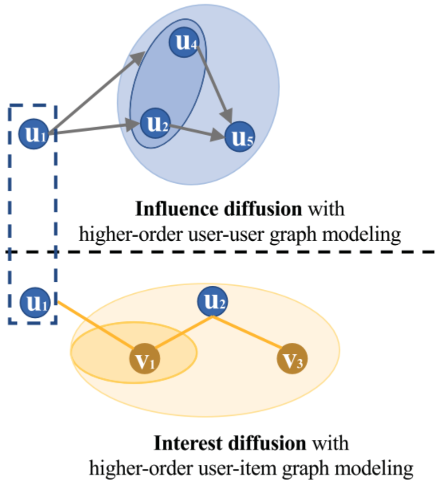
Social Recommendation



Interest diffusion with
higher-order user-item graph modeling

Challenges (Cont'd)

- CF assumption: "Similar users show similar item interests"
- User latent collaborative interests are
  - Reflected by her rated items
  - Influenced by similar users' interests from items
- Previous CF and SocialRec models only considered the observed first-order structure of the two graphs, leaving the higher-order structures of users under explored



Heterogeneous Graph Structure

- **Graph Convolutional Networks (GCNs)**
  - Perform node feature propagation in the graph
  - The up to K-th order graph structure is captured with K iterations

- **Neural Graph Collaborative Filtering (NGCF)**
  - Directly encode the collaborative information of users
  - Explore the higher-order connectivity patterns with embedding propagation

- **Diffusion Neural Network (DiffNet)**
  - Model recursive social diffusion process in the social network
  - The higher order social structure is directly modeled in the recursive user embedding process

DiffNet (Previous Model)

- **Social diffusion** presents a dynamic recursive effect to influence each users's embedding

- As social influence propagation process begins,
  - Each user's first latent embedding is influenced by the initial embeddings of her trusted connections

- With the recursive influence diffuses over time,
  - Each user's latent embedding at k-th iteration is influenced by her trusted neighbors at the (k-1)-th iteration

DiffNet (Cont'd)

- User's interests change in recursive process
  - Preference from her historical behaviors: $\sum_{j \in R_a} \frac{v_j}{|R_a|}$
    - R_a : a's feedback
- Precising simulating recursive diffusion process in global social network
- It would better model each user's embedding
- Thus, improving the SocialRec performance

DiffNet Model Architecture

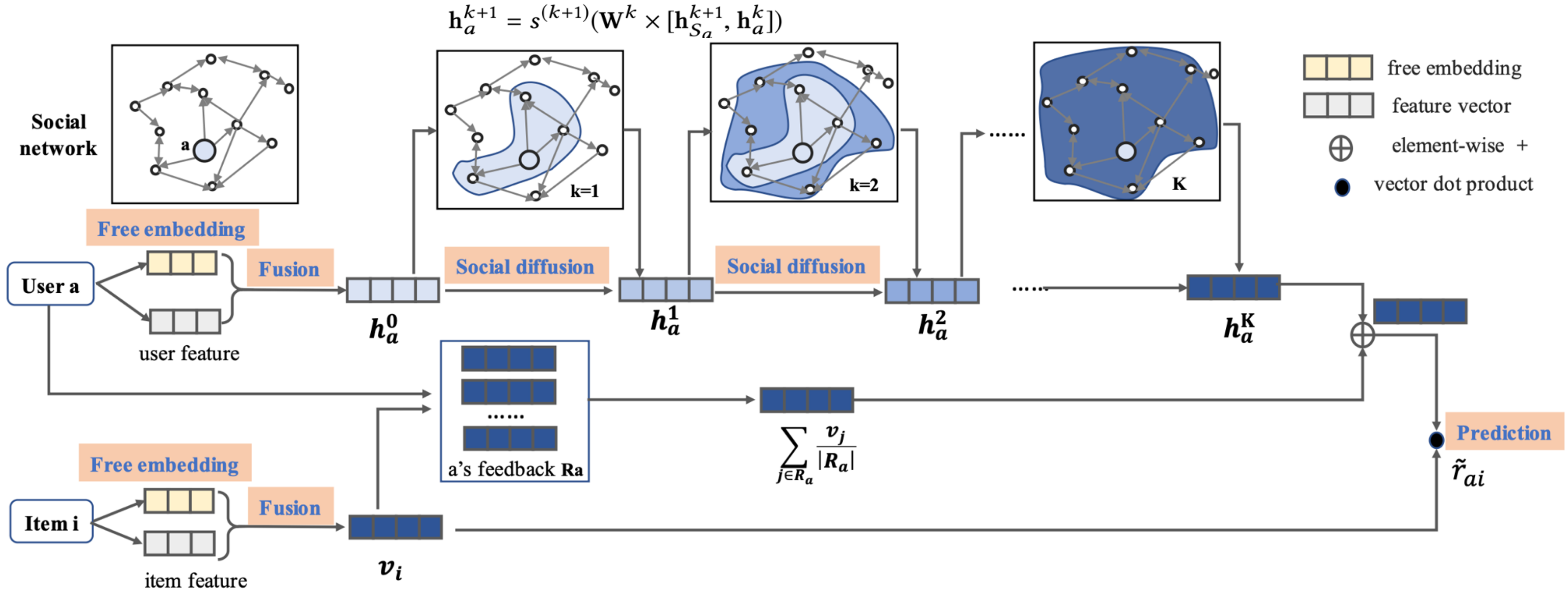


Figure 1: The overall architecture of our proposed model. The four parts of DiffNet are shown with orange background.

Proposed Method

- **Advance DiffNet structure and jointly model the two graph structure**
  - User-user graph and user-item graph

- **DiffNet is not well designed in practice**
  - Seem to perform message passing on both user’s social and interest networks
  - Two graphs serve as different sources to reflect each user’s latent preferences

- Different users may have different preferences in **balancing** in two graphs
  - Some users are likely to be swayed by social neighbors
  - Others prefer to remain their own tastes

DiffNet++

- **An Improved algorithm of DiffNet with higher-ordered**
  - SocialRec problem as predicting the missiong edges in the user-item interest graph
  - Taking both user-user social graph and user-item interest graph as input

- **Model both higher-order social influence and interest diffusions in a unified model**

- **Multi-level attention network structure**
  - Learns how to attentively aggregate user embeddings
  - From different nodes in the graph, and from different graphs

Proposed Model

DiffNet++

Model Architecture

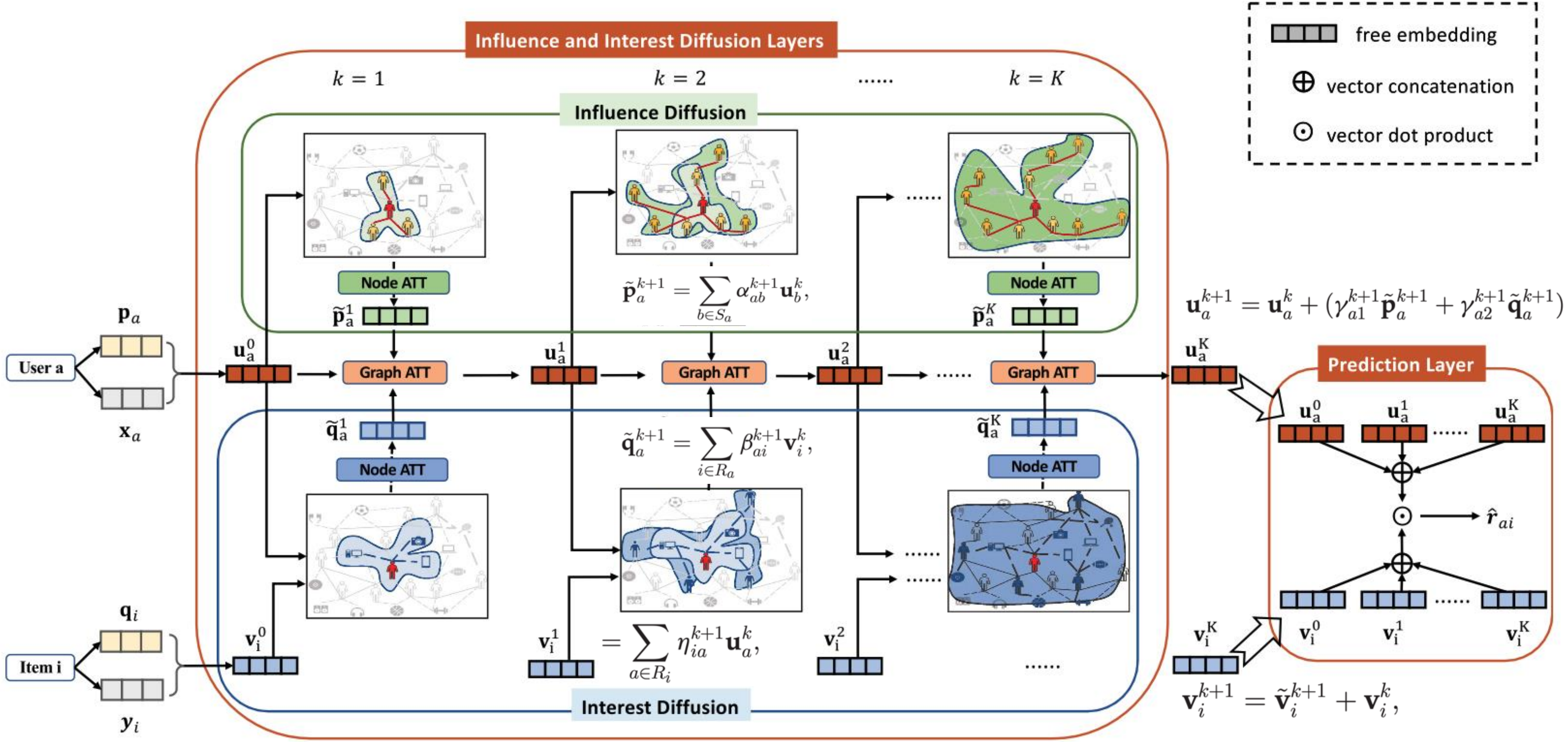


Fig. 2. The overall structure of the DiffNet++ model. As shown in the graph, we use *Node ATT* to denote the node level attention layer in each graph, and *Graph ATT* to denote the graph attention layer when fusing the interest graph representation and social graph representation.

Experiments

Dataset and Baselines

Overall Performance Comparison

Performance Under Different Sparsity

Detailed Model Analysis

Datasets

- Yelp: a well-known online location vased social network
  - Where user can make friends with others and review restaurants
  - Rating [0,5] => larger than 3 = liked
  - Rich reviews => using Word2vec => feature vector
- Flickr: an online image based social sharing platform
  - For users to follow others and share image preferences
  - Feature representation: avg of img feature representations she liked in the training data

TABLE 1
The Statistics of the Four Datasets After Preprocessing

Dataset	Yelp	Flickr	Epinions	Dianping
Users	17,237	8,358	18,202	59,426
Items	38,342	82,120	47,449	10,224
Ratings	204,448	327,815	298,173	934,334
Links	143,765	187,273	381,559	813,331
Rating Density	0.03%	0.05%	0.03%	0.12%
Link Density	0.05%	0.27%	0.15%	0.02%
Attributes	✓	✓	×	×

Baselines

TABLE 2
Comparison of the Baselines, With "F" Represents Feature Input and "S" Denotes the Social Network Input

Model		Model Input		User Embedding Ability			
		F	S	OI	OS	HI	HS
Classical CF	BPR [37]	×	×	×	×	×	×
	FM [36]	√	×	×	×	×	×
Social recom-mendation	SocialMF [19]	×	√	×	√	×	×
	TrustSVD [14]	×	√	√	√	×	×
	ContextMF [21]	√	√	×	√	×	×
	CNSR [44]	×	√	×	√	×	√
Graph neural network based recom-mendation	GraphRec [10]	×	√	√	√	×	×
	PinSage [48]	√	×	√	×	√	×
	NGCF [41]	×	×	√	×	√	×
	DiffNet-nf [43]	×	√	×	√	×	√
	DiffNet [43]	√	√	×	√	×	√
	DiffNet++-nf	×	√	√	√	√	√
	DiffNet++	√	√	√	√	√	√

For the modeling process, we use OI and OS to denote the observed first-order interest network and social network for user embedding learning. We use "HS" to denote the higher-order social information for embedding learning, and "HI" to denote higher-order interest information for embedding learning.

- DiffNet++-nf and DiffNet++ are the only two models that consider the higher-order social influence and higher-order interest network for SocialRec

Overall Comparison with Dimension Size (d)

- Graph neural models beat matrix baselines by a large margin
  - GraphRec, PinSage, NGCF, DiffNet, DiffNet++

TABLE 3
Overall Comparison With Different Dimension Size D on Yelp and Flickr (Attributes are Available)

Model	Yelp						Flickr					
	HR			NDCG			HR			NDCG		
	D=16	D=32	D=64	D=16	D=32	D=64	D=16	D=32	D=64	D=16	D=32	D=64
BPR	0.2435	0.2616	0.2632	0.1468	0.1573	0.1554	0.0773	0.0812	0.0795	0.0611	0.0652	0.0628
FM	0.2768	0.2835	0.2825	0.1698	0.1720	0.1717	0.1115	0.1212	0.1233	0.0872	0.0968	0.0954
SocialMF	0.2571	0.2709	0.2785	0.1655	0.1695	0.1677	0.1001	0.1056	0.1174	0.0862	0.0910	0.0964
TrustSVD	0.2826	0.2854	0.2939	0.1683	0.1710	0.1749	0.1352	0.1341	0.1404	0.1056	0.1039	0.1083
ContextMF	0.2985	0.3011	0.3043	0.1758	0.1808	0.1818	0.1405	0.1382	0.1433	0.1085	0.1079	0.1102
CNSR	0.2702	0.2817	0.2904	0.1723	0.1745	0.1746	0.1146	0.1198	0.1229	0.0913	0.0942	0.0978
GraphRec	0.2873	0.2910	0.2912	0.1663	0.1677	0.1812	0.1195	0.1211	0.1231	0.0910	0.0924	0.0930
PinSage	0.2944	0.2966	0.3049	0.1753	0.1786	0.1855	0.1192	0.1234	0.1257	0.0937	0.0986	0.0998
NGCF	0.3050	0.3068	0.3042	0.1826	0.1844	0.1828	0.1110	0.1150	0.1189	0.0880	0.0895	0.0945
DiffNet-nf	0.3126	0.3156	0.3195	0.1854	0.1882	0.1928	0.1342	0.1317	0.1408	0.1040	0.1034	0.1089
DiffNet	0.3293	0.3437	0.3461	0.1982	0.2095	0.2118	0.1476	0.1588	0.1657	0.1121	0.1242	0.1271
DiffNet++-nf	0.3194	0.3199	0.3230	0.1914	0.1944	0.1942	0.1410	0.1480	0.1503	0.1100	0.1132	0.1169
DiffNet++	**0.3406**	**0.3552**	**0.3694**	**0.2070**	**0.2158**	**0.2263**	**0.1562**	**0.1678**	**0.1832**	**0.1213**	**0.1286**	**0.1420**

Overall Comparison with D

- **DiffNet++ model always performs the best under any dimension D**
  - Effectiveness of modeling the recursive diffusion process in social interest network
  - Although they do not model the user and item features

TABLE 4
Overall Comparison With Different Dimension Size D on Epinions and Dianping (Attributes are not Available)

Model	Epinions						Dianping					
	HR			NDCG			HR			NDCG		
	D=16	D=32	D=64	D=16	D=32	D=64	D=16	D=32	D=64	D=16	D=32	D=64
BPR	0.2620	0.2732	0.2822	0.1702	0.1788	0.1812	0.2160	0.2302	0.2299	0.1286	0.1326	0.1319
SocialMF	0.2720	0.2842	0.2893	0.1732	0.1824	0.1857	0.2325	0.2345	0.2410	0.1360	0.1377	0.1416
TrustSVD	0.2726	0.2854	0.2884	0.1773	0.1839	0.1848	0.2364	0.2371	0.2341	0.1381	0.1401	0.1390
CNSR	0.2757	0.2874	0.2898	0.1748	0.1856	0.1876	0.2356	0.2377	0.2418	0.1394	0.1413	0.1435
GraphRec	0.3093	0.3117	0.3156	0.1994	0.2016	0.2051	0.2408	0.2541	0.2622	0.1412	0.1503	0.1556
PinSage	0.2980	0.3003	0.3073	0.1911	0.1933	0.1928	0.2353	0.2452	0.2552	0.1390	0.1434	0.1489
NGCF	0.3029	0.3065	0.3192	0.1977	0.2008	0.1958	0.2489	0.2586	0.2584	0.1470	0.1503	0.1534
DiffNet	0.3242	0.3281	0.3407	0.2007	0.2054	0.2191	0.2522	0.2600	0.2645	0.1483	0.1521	0.1555
DiffNet++	**0.3367**	**0.3434**	**0.3503**	**0.2158**	**0.2217**	**0.2288**	**0.2676**	**0.2682**	**0.2713**	**0.1593**	**0.1589**	**0.1605**

Overall Comparison

DMAIS

- With different Top-N values (Available Attributes)

TABLE 5
Overall Comparison With Different Top-N Values (D=64) on Yelp and Flickr (Attributes are Available)

Model	Yelp						Flickr					
	HR			NDCG			HR			NDCG		
	N=5	N=10	N=15	N=5	N=10	N=15	N=5	N=10	N=15	N=5	N=10	N=15
BPR	0.1695	0.2632	0.3252	0.1231	0.1554	0.1758	0.0651	0.0795	0.1037	0.0603	0.0628	0.0732
FM	0.1855	0.2825	0.3440	0.1341	0.1717	0.1876	0.0989	0.1233	0.1473	0.0866	0.0954	0.1062
SocialMF	0.1739	0.2785	0.3365	0.1324	0.1677	0.1841	0.0813	0.1174	0.1300	0.0723	0.0964	0.1061
TrustSVD	0.1882	0.2939	0.3688	0.1368	0.1749	0.1981	0.1089	0.1404	0.1738	0.0978	0.1083	0.1203
ContextMF	0.2045	0.3043	0.3832	0.1484	0.1818	0.2081	0.1095	0.1433	0.1768	0.0920	0.1102	0.1131
CNSR	0.1877	0.2904	0.3458	0.1389	0.1746	0.1912	0.0920	0.1229	0.1445	0.0791	0.0978	0.1057
GraphRec	0.1915	0.2912	0.3623	0.1279	0.1812	0.1956	0.0931	0.1231	0.1482	0.0784	0.0930	0.0992
PinSage	0.2105	0.3049	0.3863	0.1539	0.1855	0.2137	0.0934	0.1257	0.1502	0.0844	0.0998	0.1046
NGCF	0.1992	0.3042	0.3753	0.1450	0.1828	0.2041	0.0891	0.1189	0.1399	0.0819	0.0945	0.0998
DiffNet-nf	0.2101	0.3195	0.3982	0.1535	0.1928	0.2164	0.1087	0.1408	0.1709	0.0979	0.1089	0.1192
DiffNet	0.2276	0.3461	0.4217	0.1679	0.2118	0.2307	0.1178	0.1657	0.1855	0.1072	0.1271	0.1301
DiffNet++-nf	0.2112	0.3230	0.3989	0.1551	0.1942	0.2176	0.1140	0.1503	0.1799	0.1021	0.1169	0.1256
DiffNet++	**0.2503**	**0.3694**	**0.4493**	**0.1841**	**0.2263**	**0.2497**	**0.1412**	**0.1832**	**0.2203**	**0.1269**	**0.1420**	**0.1544**

Overall Comparison

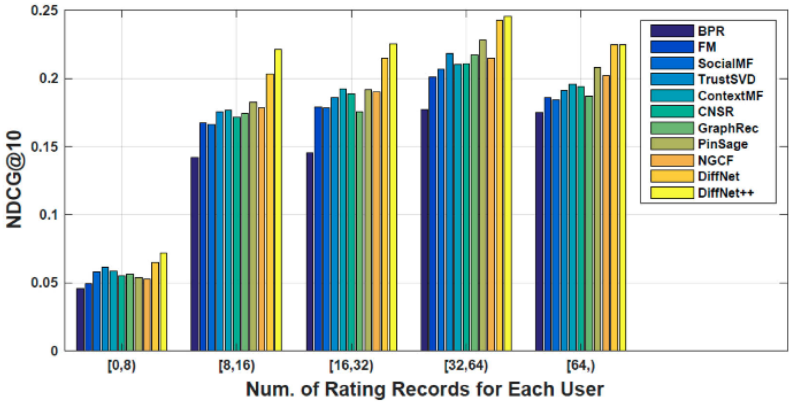
- With different Top-N values (NOT available Attributes)

TABLE 6
Overall Comparison With Different Top-N Values (D=64)on Epinions and Dianping (Attributes is not Available)

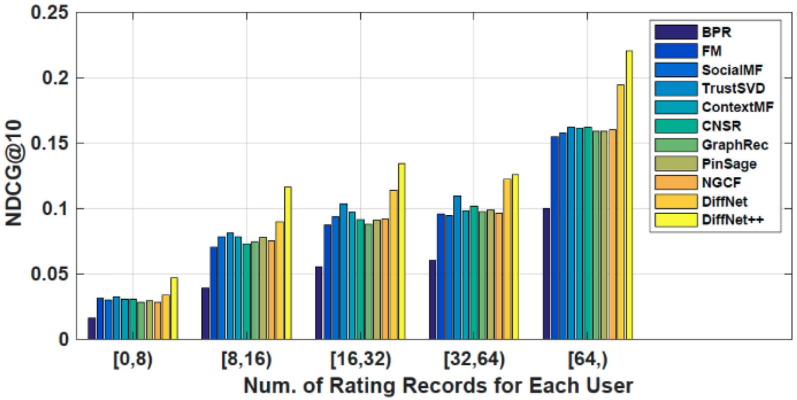
Model	Epinions						Dianping					
	HR			NDCG			HR			NDCG		
	N=5	N=10	N=15	N=5	N=10	N=15	N=5	N=10	N=15	N=5	N=10	N=15
BPR	0.2005	0.2822	0.3256	0.1526	0.1812	0.1917	0.1412	0.2299	0.2864	0.1024	0.1319	0.1482
SocialMF	0.2098	0.2893	0.3431	0.1575	0.1857	0.2016	0.1546	0.2410	0.3063	0.1111	0.1416	0.1608
TrustSVD	0.2102	0.2884	0.3396	0.1574	0.1848	0.2001	0.1521	0.2341	0.2966	0.1100	0.1390	0.1574
CNSR	0.2151	0.2898	0.3444	0.1592	0.1876	0.2035	0.1564	0.2418	0.3077	0.1132	0.1435	0.1621
GraphRec	0.2335	0.3156	0.3620	0.1764	0.2051	0.2199	0.1725	0.2622	0.3300	0.1240	0.1556	0.1755
PinSage	0.2207	0.3073	0.3073	0.1589	0.1908	0.2008	0.1631	0.2552	0.3177	0.1141	0.1489	0.1664
NGCF	0.2308	0.3192	0.3777	0.1706	0.1958	0.2131	0.1695	0.2584	0.3263	0.1220	0.1534	0.1733
DiffNet	0.2457	0.3407	0.3967	0.1857	0.2191	0.2357	0.1734	0.2645	0.3302	0.1235	0.1555	0.1748
DiffNet++	**0.2602**	**0.3503**	**0.4051**	**0.1973**	**0.2288**	**0.2450**	**0.1798**	**0.2713**	**0.3375**	**0.1281**	**0.1605**	**0.1802**

Performance Under Different Sparsity

- Grouping users into different interest groups based on # of observed ratings of each user
- As users have more ratings, the overall performance increases among all models
- Especially, **DiffNet++ model shows larger improvements on sparser dataset**
  - e.g., users have less than 8 rating records



(a) Yelp dataset.



(b) Flickr dataset.

Detailed Model Analysis

- Diffusion Depth K
  - # of layer K determines the diffusion depth of different graphs (Best setting: K = 2)
  - Adding more layers may introduce unnecessary neighbors in the process

TABLE 7
HR@10 and NDCG@10 Performance With Different Diffusion Depth K ($D = 64$)

Depth K	Yelp				Flickr			
	HR	Improve	NDCG	Improve	HR	Improve	NDCG	Improve
$K = 2$	0.3694	-	0.2263	-	0.1832	-	0.1420	-
$K = 0$	0.2632	-28.32%	0.1554	-30.81%	0.0795	-55.21%	0.0628	-53.86%
$K = 1$	0.3566	-2.89%	0.2159	-3.87%	0.1676	-5.58%	0.1283	-5.73%
$K = 3$	0.3626	-1.25%	0.2215	-1.38%	0.1743	-1.80%	0.1347	-1.03%

Detailed Model Analysis (Cont'd)

☐ The Effects of Multi-Level Attention

- Either/both node level or/and graph level attention modeling could improve Rec results
- Improvement of attention modeling varies in different datasets
- Usefulness of considering the important strength of different elements in the modeling process varies
- Multi-level attention modeling could adapt to different datasets' requirements

TABLE 8
HR@10 and NDCG@10 Performance With Different Attentional Variants ($D = 64$)

Graph Attention	Node Attention	Yelp				Flickr			
		HR	Improve	NDCG	Improve	HR	Improve	NDCG	Improve
AVG	AVG	0.3631	-	0.2224	-	0.1733	-	0.1329	-
AVG	ATT	0.3657	+0.72%	0.2235	+0.49%	0.1792	+3.40%	0.1368	+2.93%
ATT	AVG	0.3662	+0.85%	0.2249	+1.12%	0.1814	+4.67%	0.1387	+4.36%
ATT	ATT	0.3694	+1.74%	0.2263	+1.75%	0.1832	+5.71%	0.1420	+6.85%

Detailed Model Analysis (Cont'd)

Attention Value Analysis

- A larger value of γ_{a1}^{k} indicates the social influence diffusion process is more important
  - To capture the user embedding learning with less influence from the interest network
- First diffusion layer k = 1 for both datasets; Social influence strength are very high
  - First-order social neighbors play a very important role in user representation
- When k = 2; social influence strength varies among two datasets
  - Larger in Yelp, Smaller in Flickr
  - Flickr data sets shows denser social links => a considerable amt of directed links at first layer

TABLE 9
Mean Statistics of the Graph Level Attention Values ($K = 2$), With γ_{a1}^{k} is the Social Influence Weight and γ_{a2}^{k} is the Interest Weight

Layer k	Yelp		Flickr	
	Social γ_{a1}^{k}	Interest γ_{a2}^{k}	Social γ_{a1}^{k}	Interest γ_{a1}^{k}
$k = 1$	0.7309	0.2691	0.8381	0.1619
$k = 2$	0.6888	0.3112	0.0727	0.9273

Conclusion

Conclusions

- **Users play a central role in social network and interest network**
  - Jointly modling higher-order structure of these two networks mutually enhance each other

- **Learned user embedding from convolutions on user social neighbors and interest neighbors**
  - Both the higher-order social structure and interest network are directly injected

- **Deisgned a multi-level attention network to attentively aggregate the graph and node level representations for better user modeling**

- **Future work:** To explore the graph reasoning models to explain the paths for users behaviors

Thank You!

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