Local and Global Information Fusion for Top-N Recommendation in Heterogeneous Information Network

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Background

Recommender System (RS)

- Discover items of interest from a large resource collection
- Basic recommendation method : Collaborative Filtering (e.g., matrix factorization)
- Suffer from cold-start problem
- Integrate more rich information (e.g., social network)

Heterogeneous Information Network (HIN)

- Include multiple types of nodes and links
- Model heterogeneous data and contain rich semantics
- Meta-path : Semantic paths between two objects in HIN

Local Information

- Direct interactions of users and items in HIN
- Breadth-first search (BFS)

Global Information

- Indirect interactions between users and items based on different meta-paths.
- Depth-first search (DFS)

Drawbacks of Traditional HIN based Recommendation

- Treat different local information equally
- seldom exploit and explore local information and global information simultaneously

Our idea

- Learn different weights for different neighbors
- An unified model to extensively exploit the local interaction information and fully explore the global interaction information

LGRec : The Proposed Method

Model Local Information

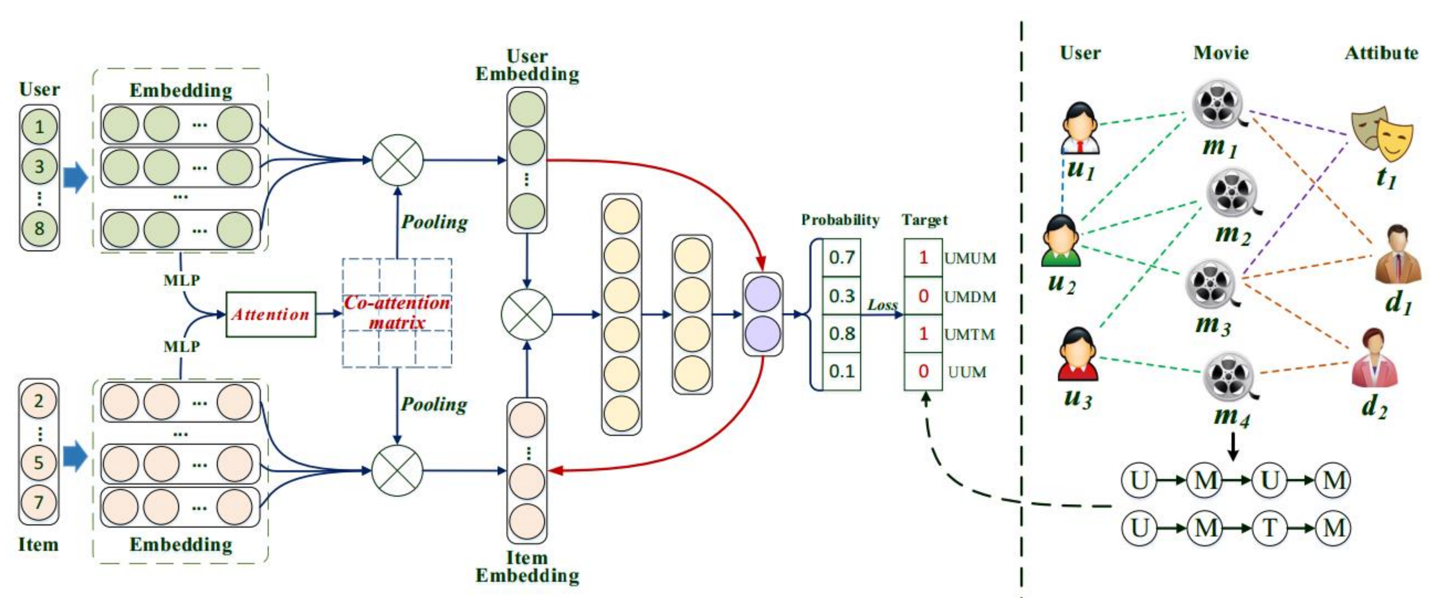
- Encoding user and item
- Co-attention mechanism

$$M_{i,j} = F(X_u^{(i)})AG(Y_v^{(j)})$$

- Generate embeddings

$$a_i^u = \mathrm{MP}(\{M_{ij}\}_{j=1}^{K_2}), \quad a_i^v = \mathrm{MP}(\{M_{ji}\}_{j=1}^{K_1}).$$

$$\boldsymbol{x}_u = \boldsymbol{X}_u \boldsymbol{a}^u, \quad \boldsymbol{y}_v = \boldsymbol{Y}_v \boldsymbol{a}^v.$$



Model Global Information

- Meta-path based interaction
- Generate latent relation based on MLP

$$\boldsymbol{h}_{u,v} = \boldsymbol{x}_u \oplus \boldsymbol{y}_v,$$
$$\boldsymbol{z} = \mathrm{MLP}(\boldsymbol{h}_{u,v}),$$

- Multi-label classification

$$\boldsymbol{p}_z = \boldsymbol{W}_o \boldsymbol{z} + \boldsymbol{b}_o,$$

$$\ell_{mc}(\boldsymbol{y}) = -\boldsymbol{y} * \log(\sigma(\boldsymbol{p}_z)) - (1-\boldsymbol{y}) * \log(1-\sigma(\boldsymbol{p}_z)) = \boldsymbol{p}_z - \boldsymbol{p}_z * \boldsymbol{y} + \log(1 + exp(-\boldsymbol{p}_z)).$$

Unified Model

$$s(u, v, z) = ||\boldsymbol{x}_u + \boldsymbol{z} - \boldsymbol{y}_v||_2^2.$$

$$\ell_{trans} = max(0, \lambda + s(u^+, v^+, z^+) - s(u^-, v^-, z^-)),$$

$$\ell = \ell_{trans} + \alpha[\ell_{mc}(\boldsymbol{y}^+) + \ell_{mc}(\boldsymbol{y}^-)] + \beta\ell_{reg}.$$

Performance

Datasets

Datasets	Relations (A-B)	#A	#B	#A-B	Meta-paths
Movielens	*User-Movie*	943	1,682	100,000	*UMUM*
	User-Age	943	8	943	*UMGM*
	User-Occupation	943	21	943	*UAUM*
	Movie-Genre	1,682	18	2,861	*UOUM*
LastFM	*User-Artist*	1,892	17,632	92,834	*UATA*
	User-User	1,892	1,892	18,802	*UAUA*
	Artist-Artist	17,632	17,632	153,399	*UUUA*
	Artist-Tag	17,632	11,945	184,941	*UUA*
Yelp	*User-Business*	16,239	14,284	198,397	*UBUB*
	User-User	16,239	16,239	158,590	*UBCaB*
	Business-City (Ci)	14,267	47	14,267	*UUB*
	Business-Category (Ca)	14,180	511	40,009	*UBCiB*
Amazon	*User-Item*	3,584	2,753	50,903	*UIUI*
	Item-View	2,753	3857	5,694	*UIVI*
	Item-Brand	2,753	334	2,753	*UIBI*
	Item-Category	2,753	22	5,508	*UICI*

Effectiveness Experiments

Models	Movielens		LastFM		Yelp		Amazon	
	HR@10	NDCG@10	HR@10	NDCG@10	HR@10	NDCG@10	HR@10	NDCG@10
ItemKNN	0.5854	0.3368	0.6327	0.5176	0.1480	0.0944	0.3153	0.1864
BRP	0.6766*	0.3860	0.7690	0.6061	0.5162	0.3186	0.3890	0.2195
MF	0.6702	0.3869*	0.7611	0.6051	0.5139	0.3176	0.3379	0.1893
NeuMF	0.6723	0.3816	0.7579	0.6070*	0.6660*	0.4218*	0.3619	0.2023
LRML	0.6140	0.3500	0.7204	0.5411	0.5934	0.3608	0.3304	0.1788
SVDFeature$_{hete}$	0.6033	0.3366	0.7848*	0.5813	0.6586	0.4117	0.3111	0.1575
FMG$_{rank}$	0.6267	0.3519	0.7758	0.5905	0.6080	0.3418	0.4154*	0.2244*
LGRec$_{noAtt}$	0.4836	0.2446	0.7104	0.5531	0.1372	0.0756	0.2720	0.1380
LGRec$_{noGlo}$	0.6564	0.3824	0.7717	0.6060	0.5894	0.3353	0.3820	0.2151
LGRec	**0.6914**	**0.3989**	**0.7865**	**0.6228**	**0.6902**	**0.4396**	**0.4235**	**0.2383**

Metrics

HR@10, NDCG@10

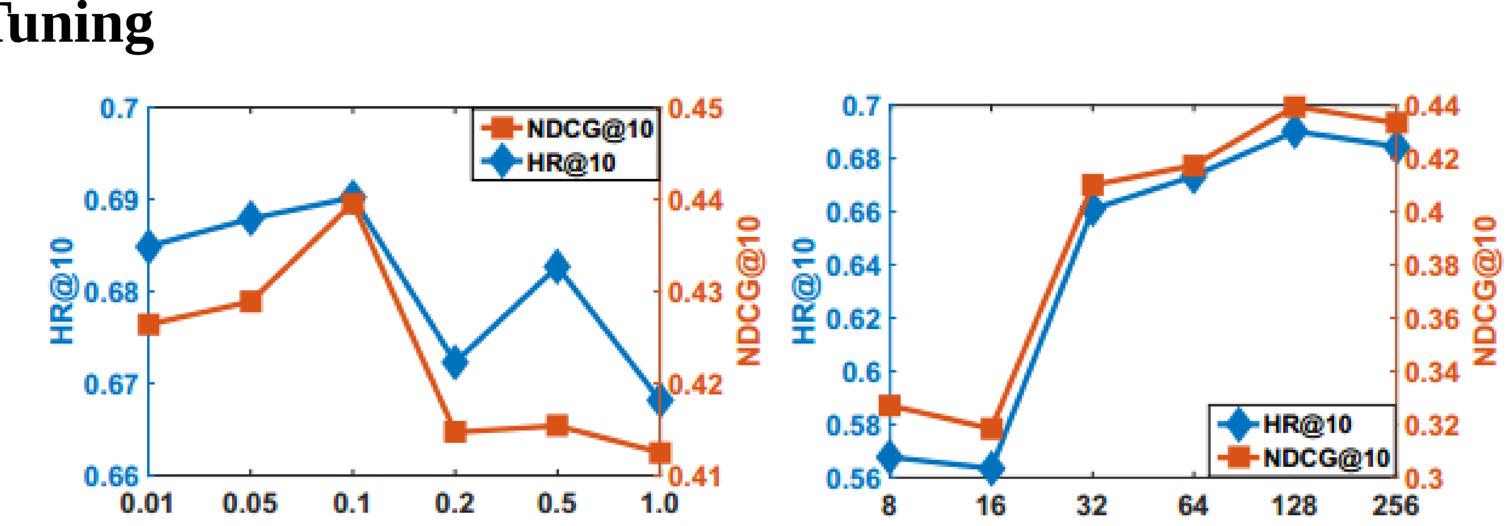
Compared Methods

CF based
- ItemKNN
- BPR
- MF
- NeuMF
- LRML

HIN based
- SVDFeature$_{hete}$
- FMG$_{rank}$

Ours
- LGRec$_{noAtt}$
- LGRec$_{noGlo}$
- LGRec

Parameters Tuning



(a) Varying α (b) Varying d

Conclusions

- We proposed a unified deep model to fully utilize local and global information for top-N recommendation.
- We learns importance of neighbors by the co-attention mechanism and optimize a multi-label classification problem to capture meta-path based interactions.
- Extensive experimental results show the effectiveness of LGRec.
- More materials in webpage : www.shichuan.org

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