Leveraging Meta-path based Context for Top-N Recommendation with A Neural Co-attention Model

Binbin Hu[1], Chuan Shi[1], Wayne Xin Zhao[2], Philip S. Yu[3]

[1]Beijing University of Posts and Telecommunications

[2]Renming University of China [3]University of Illinois at Chicago

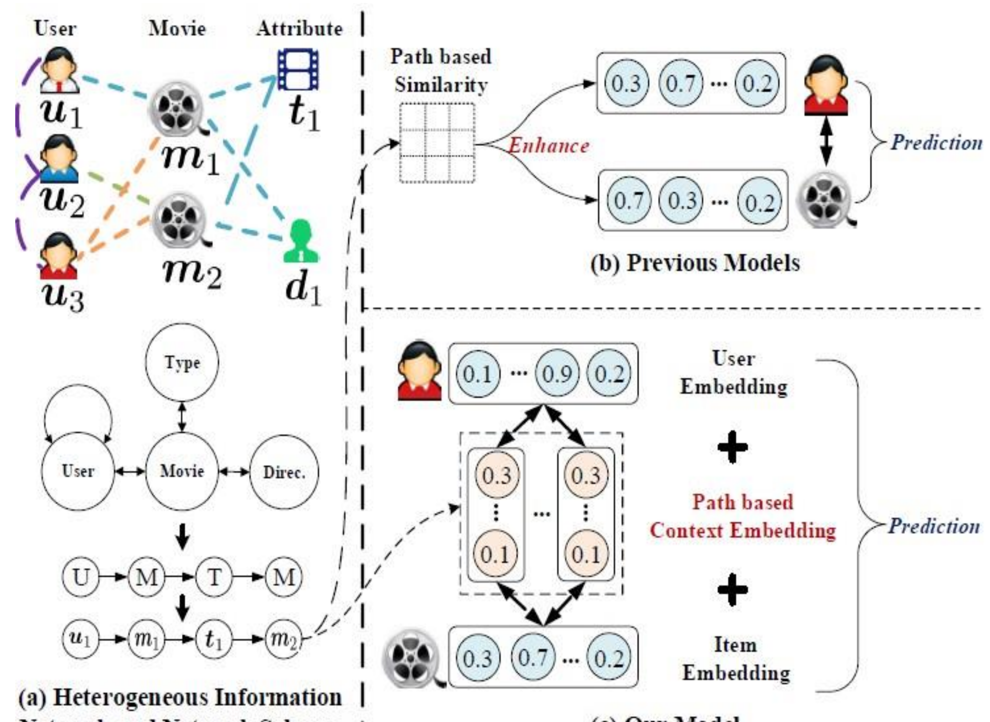
Background

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



(a) Heterogeneous Information Network and Network Schema (b) Previous Models (c) Our Model

Traditional HIN based Recommendation

- Path based relatedness as direct features
- Path based similarities for enhancing user/item representations

Drawbacks

- Representations aren't tailored for recommendation
- Without explicit representation for path/meta-path
- Only capture two way user-item interactions

Our idea

- Learn explicit representations for meta-path based context tailored for the recommendation task
- Model a three-way interaction: ⟨user, meta-path, item⟩

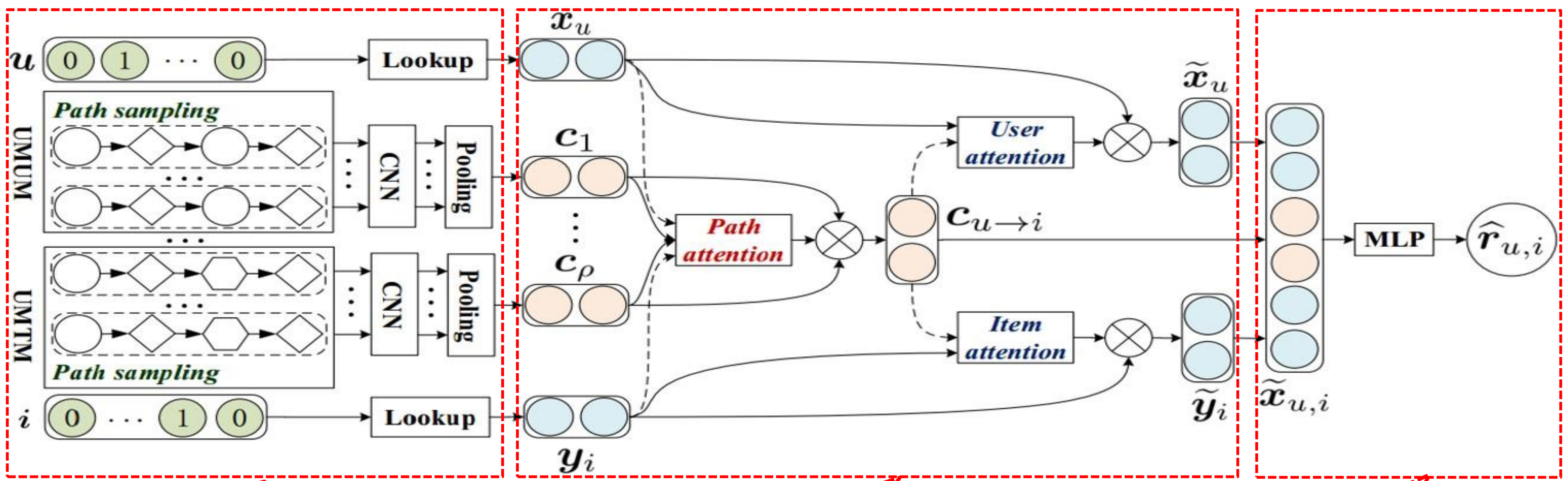
MCRec : The Proposed Model

Challenges	Solutions
? Heterogeneity	✓ A flexible deep NN based framework
? Interpretability	✓ Meta-path based context embedding
? Mutual Effect	✓ A neural co-attention model
? Rank	✓ A ranking predication model

Benefits

- Comprehensively and flexibly utilize heterogeneous information
- Utilize context semantics for interpretable recommendation
- Utilize the mutual effect between user-item pair and meta-path based context
- A more useful ranking model for HIN based recommendation

Meta-path based Context for RECommendation (MCRec)



Embedding Model

- User/item embedding with lookup
- Sampling path instances via priority based random walk
- Meta-path based context embedding with CNN

Co-attention Improving Model

- Path attention

$$\boldsymbol{\alpha}^{(1)}_{u,i,\rho} = f(\mathbf{W}^{(1)}_u \mathbf{x}_u + \mathbf{W}^{(1)}_i \mathbf{y}_i + \mathbf{W}^{(1)}_\rho \mathbf{c}_\rho + \mathbf{b}^{(1)}),$$
$$\alpha^{(2)}_{u,i,\rho} = f(\mathbf{w}^{(2)\top} \boldsymbol{\alpha}^{(1)}_{u,i,\rho} + b^{(2)}),$$

- User and item attention part

$$\boldsymbol{\beta}_u = f(\mathbf{W}_u \mathbf{x}_u + \mathbf{W}_{u\to i} \mathbf{c}_{u\to i} + \mathbf{b}_u),$$
$$\boldsymbol{\beta}_i = f(\mathbf{W}'_i \mathbf{y}_i + \mathbf{W}'_{u\to i} \mathbf{c}_{u\to i} + \mathbf{b}'_i),$$

Ranking Model

- Concatenate
- Multi-layer perceptron
- Optimization with negative sampling

Performance

Datasets

Datasets	Relations (A-B)	#A	#B	#A-B	Meta-paths
Movielens	*User-Movie*	943	1,682	100,000	UMUM
	User-User	943	943	47,150	UMGM
	Movie-Movie	1,682	1,682	82,798	UUUM
	Movie-Genre	1,682	18	2861	UMMM
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

Metrics

Prec@10, Recall@10, NDCG@10

Compared Methods

CF based
- ItemKNN
- BPR
- MF
- NeuMF

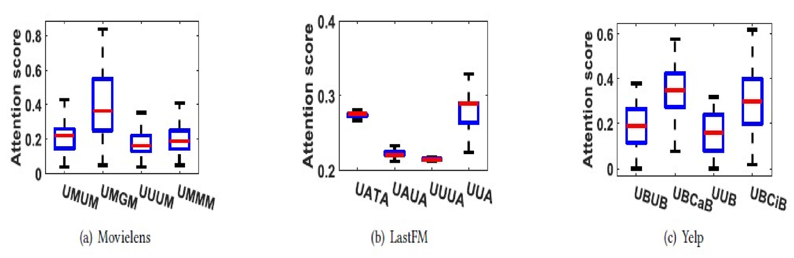
HIN based
- $\mathrm{SVDFeature}_{hete}$
- $\mathrm{SVDFeature}_{mp}$
- HeteRS
- FMG_{rank}

Ours
- MCRec_{rand}
- MCRec_{avg}
- MCRec_{mp}
- MCRec

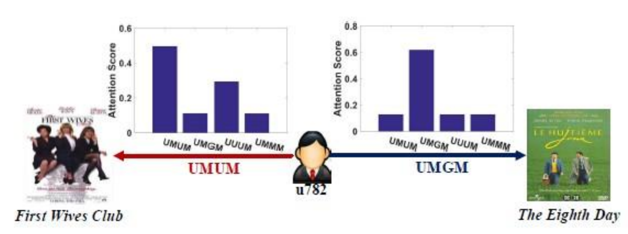
Effectiveness Experiments

Model	Movielens			LastFM			Yelp		
	Prec@10	Recall@10	NDCG@10	Prec@10	Recall@10	NDCG@10	Prec@10	Recall@10	NDCG@10
ItemKNN	0.2578	0.1536	0.5692	0.4160	0.4513	0.7981	0.1386	0.5421	0.5378
BRP	0.3010	0.1946	0.6459	0.4129	0.4492	0.8099	0.1474	0.5504	0.5549
MF	0.3247	0.2053	0.6511	0.4364	0.4634	0.7921	0.1503	0.5350	0.5322
NeuMF	0.3293*	0.2090	0.6587	0.4540	0.4678	0.8104	0.1504	0.5857	0.5713
$\mathrm{SVDFeature}_{hete}$	0.3171	0.2021	0.6445	0.4576	0.4841	0.8290*	0.1404	0.5613	0.5289
$\mathrm{SVDFeature}_{mp}$	0.3109	0.1929	0.6536	0.4391	0.4651	0.8116	0.1524	0.5932	0.5974*
HeteRS	0.2485	0.1674	0.5967	0.4276	0.4489	0.8026	0.1423	0.5613	0.5600
FMG_{rank}	0.3256	0.2165*	0.6682*	0.4630*	0.4916*	0.8263	0.1538*	0.5951*	0.5861
MCRec_{rand}	0.3223	0.2104	0.6650	0.4540	0.4795	0.8002	0.1510	0.5842	0.5718
MCRec_{avg}	0.3270	0.2111	0.6631	0.4645	0.4914	0.8311	0.1595	0.5933	0.6021
MCRec_{mp}	0.3401	0.2200	0.6828	0.4662	0.4924	0.8428	0.1655	0.6303	0.6228
MCRec	**0.3451#**	**0.2256#**	**0.6900#**	**0.4807#**	**0.5068#**	**0.8526#**	**0.1686#**	**0.6326#**	**0.6301#**

Qualitative Analysis for the Recommendation Interpretability

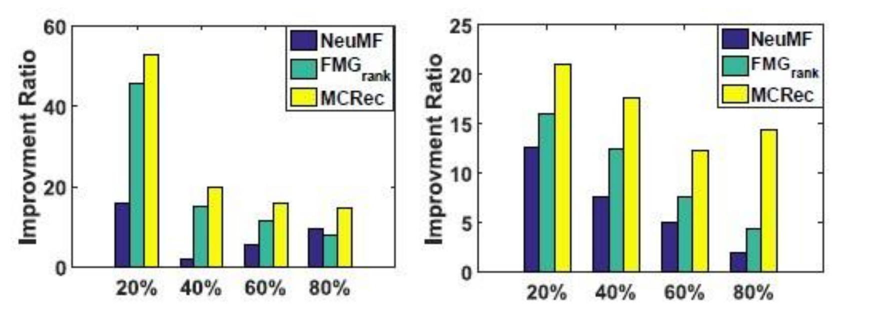


Distribution of Attention Weights



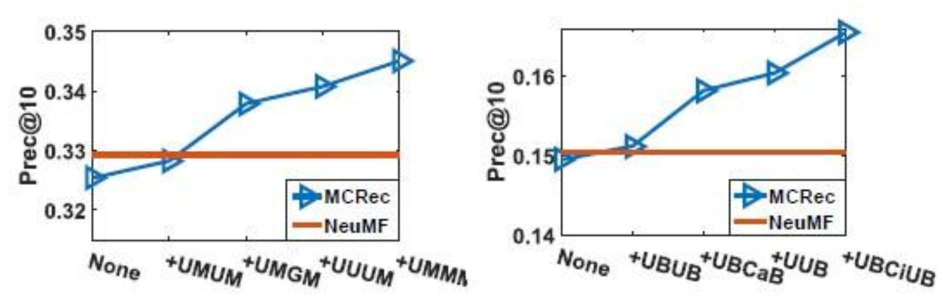
Case Study on Movielens Dataset

Cold-start Recommendation



(a) Movielens (b) Yelp

Impact of Different Meta-paths



(a) Movielens (b) Yelp

Conclusions

- We designed a three-way neural interaction model by explicitly incorporating meta-path based context
- The co-attention model mutually improved the representations
- Extensive experimental results show the effectiveness of MCRec
- More materials in webpage : www.shichuan.org

Acknowledgements

This work is supported in part by the National Natural Science Foundation of China (No. 61772082, 61502502, 61320106006, 61375058), the National Key Research and Development Program of China (2017YFB0803304), and the Beijing Municipal Natural Science Foundation (4182043, 4162032). This work is also supported in part by NSF through grants IIS-1526499, IIS-1763325, and CNS-1626432, and NSFC 61672313.

Contact

- hubinbin@bupt.edu.cn
- shichuan@bupt.edu.cn
- batmanfly@gmail.com
- psyu@cs.uic.edu