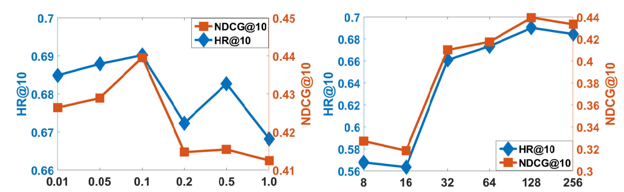
Table 2: Results of effectiveness experiments on four datasets. We use "*" to mark the best performance from the baselines.

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**

To examine the effectiveness of the co-attention mechanism and the global information modeling method, we consider two variants as compared baselines, namely LGRec$_{noAtt}$ (our model without co-attention mechanism) and LGRec$_{noGlo}$ (our model without global information). And LGRec is our complete model.

Results and analysis. We report the comparison results of our proposed model and baselines on four datasets in Table 2. The major findings from the experimental results are summarized as follows: (1) LGRec is consistently better than all the baselines on the four datasets. This observation demonstrates the effectiveness of our model on the task of top-N recommendation, which is more capable of utilizing local neighborhood information and global heterogenous information. (2) Considering the two variants of LGRec, we can find that the overall performance order is as follows: LGRec > LGRec$_{noGlo}$ > LGRec$_{noAtt}$. The result indicates that the gobal information and co-attention mechanism really work in our model and the global information play a critical role for the performance improvement in most cases. (3) Among these baselines, HIN based methods (SVDFeature$_{hete}$ and FMG$_{rank}$) outperform CF methods (ItemKNN, BPR and MF) in most cases, which indicates the usefulness of heterogeneous information. In addition, NeuMF also achieves competitive performance due to the adoption of neural network, while its performance is still worse than LGRec because of the absence of heterogeneous information.

Parameter tuning. We examine the effect of balance parameter α and the dimension of embeddings d on the performance for our model. As shown in Fig 2, we can see that (1) when $\alpha = 0.1$, our model achieves the best performance, indicating that the balance parameter should be set to a small number; and (2) our model achieves the best performance when $d = 128$, which indicates that the dimension of embeddings cannot be set too small or too large.



(a) Varying α (b) Varying d

Figure 2: Performance tuning with the varying of the parameter α and the dimension of embeddings d on Yelp dataset.

4 CONCLUSION

In this paper, we proposed a novel deep neural network model to fully utilize local and global information for top-N recommendation in HIN. The model firstly learns user (item) embeddings according to the neighbor items (users) with a co-attention mechanism. In addition, our model learns relation representations between users and items to capture meta-path based interactions by optimizing a multi-label classification problem. Considering these two factors, an unified optimization objective is learned for top-N recommendation. Extensive experimental results have demonstrated the recommendation effectiveness of our model.

5 ACKNOWLEDGEMENT

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REFERENCES

[1] Tianqi Chen, Weinan Zhang, Qiuxia Lu, Kailong Chen, Zhao Zheng, and Yong Yu. 2012. SVDFeature: a toolkit for feature-based collaborative filtering. *JMLR* 13, Dec (2012), 3619–3622.
[2] Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. 2017. Neural collaborative filtering. In *WWW*. 173–182.
[3] Binbin Hu, Chuan Shi, Wayne Xin Zhao, and Philip S Yu. 2018. Leveraging Meta-path based Context for Top-N Recommendation with A Neural Co-attention Model. In *SIGKDD*. 1531–1540.
[4] Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, and Lars Schmidt-Thieme. 2009. BPR: Bayesian personalized ranking from implicit feedback. In *UAI*. 452–461.
[5] Badrul Sarwar, George Karypis, Joseph Konstan, and John Riedl. 2001. Item-based collaborative filtering recommendation algorithms. In *WWW*. 285–295.
[6] Chuan Shi, Binbin Hu, Wayne Xin Zhao, and Philip S Yu. 2018. Heterogeneous Information Network Embedding for Recommendation. *TKDE* (2018).
[7] Chuan Shi, Yitong Li, Jiawei Zhang, Yizhou Sun, and S Yu Philip. 2017. A survey of heterogeneous information network analysis. *TKDE* 29, 1 (2017), 17–37.
[8] Yi Tay, Luu Anh Tuan, and Siu Cheung Hui. 2018. Latent Relational Metric Learning via Memory-based A ention for Collaborative Ranking. In *WWW*. 729–739.
[9] Huan Zhao, Quanming Yao, Jianda Li, Yangqiu Song, and Dik Lun Lee. 2017. Meta-graph based recommendation fusion over heterogeneous information networks. In *SIGKDD*. 635–644.