Semi-Discrete Social Recommendation (Student Abstract)*

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Abstract

Combining matrix factorization (MF) with network embedding (NE) has been a promising solution to social recommender systems. However, such a scheme suffers from the online predictive efficiency issue due to the ever-growing users and items. In this paper, we propose a novel hashing-based social recommendation model, called **s**emi-discrete **s**ocially embedded **m**atrix **f**actorization (S2MF), which leverages the dual advantages of social information for recommendation effectiveness and hashing trick for online predictive efficiency. Experimental results demonstrate the advantages of S2MF over state-of-the-art discrete recommendation models and its real-valued competitors.

Introduction

Social recommendation, aiming to improve the accuracy of traditional recommender systems by exploiting user-user connections to mitigate the sparsity of user-item interactions, has drawn substantial research attention. However, most existing social recommendation schemes suffer from the prediction efficiency issue, due to the ever-growing scales of users and items. A promising solution is to index users and items by hash codes, so that a user's preference on an item can be estimated in a Hamming space with very low computational cost (Zhang et al. 2016). Along this line, discrete social recommendation (DSR) model (Liu et al. 2019) or discrete trust-aware matrix factorization (DTMF) model (Guo et al. 2019) is proposed to leverage the dual advantages of social information for recommendation accuracy and hashing trick for prediction efficiency[1]. Despite enjoying many advantages, such a scheme has two critical limitations. First, DSR or DTMF only considers the local neighbors of each user, yet ignores the information propagation from each user to her multi-hop neighbors. Second, additional encoding loss might be generated in that DSR or DTMF imposes discrete constraints on both preference learning and social embedding, while the learned binary social features are actually not involved in predictions.

To this end, we propose a **s**emi-discrete **s**ocially embedded **m**atrix **f**actorization (S2MF) method, which combines matrix factorization (MF) (Koren, Bell, and Volinsky 2009) model for rating prediction with network embedding (NE) model for multi-hop structure analysis, *partially* under the discrete constraints. In this way, the *discrete* preference learning and *continuous* social embedding tasks can be reinforced each other in a joint optimization process, avoiding the *over-discretization* problem. Experimental results show that S2MF consistently outperforms state-of-the-art discrete recommendation models.

The Proposed Method

Given a user-item rating matrix $\mathbf{R} \in [0,1]^{m\times n}$, MF is to decompose $\mathbf{R}$ into a user feature matrix $\mathbf{P} = [\mathbf{p}_1 \cdots \mathbf{p}_m] \in \mathbb{R}^{f\times m}$ and an item feature matrix $\mathbf{Q} = [\mathbf{q}_1 \cdots \mathbf{q}_n] \in \mathbb{R}^{f\times n}$. As such, an observed (or unobserved) rating of user u on item i is anticipated to be approximated (or predicted) by $\hat{r}_{ui} = \mathbf{p}_u^T\mathbf{q}_i$. A typical cost function of MF is defined as

$$\arg\min_{\mathbf{P},\mathbf{Q}} \sum_{(u,i)\in\Omega} (r_{ui} - \mathbf{p}_u^T\mathbf{q}_i)^2, \tag{1}$$

where Ω is a set of the index of observed entries.

Given a social network among users, we employ DeepWalk (Perozzi, Alrfou, and Skiena 2014) to instantiate the NE model due to its simplicity. First, we perform the truncated random walk over the user-user network to collect a social corpus, in which each user u corresponds to a context user set $\mathcal{N}_u^+$ and a non-context user set $\mathcal{N}_u^-$. Second, we obtain users' social features by training a three-layer neural network using $\mathcal{N}_u^+$ and $\mathcal{N}_u^-$. Suppose $\mathbf{W}$ and $\mathbf{V}$ as two weight matrices linking input layer with hidden layer and linking hidden layer with output layer, the cost function of our NE model is

$$\arg\min_{\mathbf{W},\mathbf{V}} -\sum_u [\log\sigma(\mathbf{w}_u^T\mathbf{h}) + \log\sigma(-\mathbf{w}_u^T\bar{\mathbf{h}})], \tag{2}$$

where $\mathbf{h} = \frac{1}{|\mathcal{N}_u^+|}\sum_{v\in\mathcal{N}_u^+}\mathbf{v}_v$, $\bar{\mathbf{h}} = \frac{1}{|\mathcal{N}_u^-|}\sum_{v'\in\mathcal{N}_u^-}\mathbf{v}_{v'}$, $\mathbf{w}_u$ and $\mathbf{v}_u$ are the u-th column of $\mathbf{W}$ and the u-th row of $\mathbf{V}$ respectively. Specifically, $\mathbf{w}_u$ is taken as the social feature of user u in our scheme.

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[1]DSR and DTMF models are independently proposed by (Liu et al. 2019) and (Guo et al. 2019), but they are with the same idea in essence.

		CiaoDVD				Epinions			
Methods	Metric	8 Bits	16 Bits	32 Bits	64 Bits	8 Bits	16 Bits	32 Bits	64 Bits
SMF	NDCG@10	<u>0.82807</u>	<u>0.83035</u>	<u>0.82818</u>	<u>0.83171</u>	<u>0.84666</u>	<u>0.84680</u>	<u>0.84639</u>	<u>0.84801</u>
	Improve	-1.61%	-1.28%	-1.48%	-1.27%	-3.50%	-2.26%	-1.87%	-1.77%
MF	NDCG@10	0.75201	0.76588	0.76055	0.76881	0.79658	0.80503	0.80629	0.80686
	Improve	+8.34%	+7.03%	+7.28%	+6.81%	+2.57%	+2.81%	+3.01%	+3.24%
DSR/DTMF	NDCG@10	0.74898	0.75168	0.75942	0.76142	0.78722	0.78880	0.79586	0.79665
	Improve	+8.78%	+9.05%	+7.44%	+7.84%	+3.79%	+4.93%	+4.36%	+4.57%
DCF	NDCG@10	0.72930	0.73269	0.74305	0.74921	0.77929	0.78257	0.78837	0.79123
	Improve	+11.72%	+11.87%	+9.81%	+9.60%	+4.84%	+5.77%	+5.35%	+5.28%
S2MF	NDCG@10	**0.81475**	**0.81969**	**0.81595**	**0.82114**	**0.81702**	**0.82769**	**0.83053**	**0.83302**

Table 1: Performance of S2MF compared with state of the arts on CiaoDVD and Epinions datasets.

To exploit the complementary properties between rating data and social data, we present a joint learning framework, termed **s**ocially embedded **m**atrix **f**actorization (SMF), by combining Eq.(1) with Eq.(2):

$$\begin{aligned}\arg\min_{\mathbf{P},\mathbf{Q},\mathbf{W},\mathbf{V}} &\sum_{(u,i)\in\Omega}(r_{ui}-\mathbf{p}_u^T\mathbf{q}_i)^2+\alpha||\mathbf{p}_u-\mathbf{w}_u||^2\\ &-\beta\sum_u[\log\sigma(\mathbf{w}_u^T\mathbf{h})+\log\sigma(-\mathbf{w}_u^T\bar{\mathbf{h}})]\\ &+\frac{\lambda}{2}(||\mathbf{P}||_F^2+||\mathbf{Q}||_F^2+||\mathbf{W}||_F^2+||\mathbf{V}||_F^2),\end{aligned}\tag{3}$$

where $||\mathbf{p}_u-\mathbf{w}_u||^2$ aims to achieve a tight coupling of MF model and NE model.

To speed up the online predictions, we further propose S2MF by *partially* discretizing the formulation of SMF. Denote $\mathbf{B}=[\mathbf{b}_1\cdots\mathbf{b}_m]\in\mathbb{B}^{f\times m}$ and $\mathbf{D}=[\mathbf{d}_1\cdots\mathbf{d}_n]\in\mathbb{B}^{f\times n}$ as the matrices composed of users' and items' hash codes, we use Hamming similarity to reconstruct the observed user-item ratings, reserving other components in Eq.(3). In addition, we impose balance and de-correlated constraints on hash codes. The objective of our S2MF model is defined as:

$$\begin{aligned}\arg\min_{\mathbf{B},\mathbf{D},\mathbf{W},\mathbf{V}} &\sum_{(u,i)\in\Omega}(r_{ui}-s_H(\mathbf{b}_u,\mathbf{d}_i))^2+\alpha\sum_u||\mathbf{b}_u-\mathbf{w}_u||^2\\ &-\beta\sum_u[\log\sigma(\mathbf{w}_u^T\mathbf{h})+\log\sigma(-\mathbf{w}_u^T\bar{\mathbf{h}})]\\ &+\frac{\lambda}{2}(||\mathbf{W}||_F^2+||\mathbf{V}||_F^2)\end{aligned}\tag{4}$$

$$\begin{aligned}s.t.\quad &\mathbf{B}\in\{\pm1\}^{f\times m},\mathbf{D}\in\{\pm1\}^{f\times n},\\ &\mathbf{B}\mathbf{1}_m=0,\mathbf{D}\mathbf{1}_n=0,\mathbf{B}\mathbf{B}^T=m\mathbf{I}_f,\mathbf{D}\mathbf{D}^T=n\mathbf{I}_f.\end{aligned}$$

where $s_H(\mathbf{b}_u,\mathbf{d}_i)=\frac{1}{2}+\frac{1}{2f}\mathbf{b}_u^T\mathbf{d}_i$ is the Hamming similarity between $\mathbf{b}_u$ and $\mathbf{d}_i$.

We develop an efficient optimization algorithm to estimate the model parameters by alternatively solving a series of mixed-integer programming subproblems. More details can be found in the Appendix.

Empirical Study

We evaluate our S2MF model on Ciao and Epinions datasets, comparing to DCF (Zhang et al. 2016), DSR (or DTMF), MF and SMF. The quantitative results are shown in Table 1, where the best results performed by real-valued models are underlined while the best results achieved by discrete models are boldfaced, and the 'Improve' indicates the relative improvements of S2MF over other methods.

By comparing three discrete models, we observe that S2MF and DSR/DTMF outperform the social-free model DCF, and S2MF achieves much better performance than DSR/DTMF on two datasets, which demonstrates the desirability of applying social information to hash codes learning and the superiority of our solution to social information processing over that used by DSR/DTMF. Furthermore, comparing discrete models with real-valued models, we find that two existing discrete models DSR/DTMF and DCF perform worse than MF, while S2MF considerably outperforms MF and shows very competitive performance compared to SMF. This observation again verifies the effectiveness of the proposed semi-discrete social recommendation model.

Conclusion

In this paper, we presented a S2MF model that combines MF with NE *partially* under the discrete constraints to model the influence propagation process of users' interest over social network, as well as to avoid the additional encoding loss caused by the over-discretization. As moving forward, we are going to extend our S2MF by designing more delicate objective towards NDCG metric.

References

Guo, G.; Yang, E.; Shen, L.; Yang, X.; and He, X. 2019. Discrete Trust-aware Matrix Factorization for Fast Social Recommendation. In *IJCAI*.

Koren, Y.; Bell, R.; and Volinsky, C. 2009. Matrix Factorization Techniques for Recommender Systems. *Computer* 42(8): 30–37.

Liu, C.; Wang, X.; Lu, T.; Zhu, W.; Sun, J.; and Hoi, S. 2019. Discrete Social Recommendation. In *AAAI*.

Perozzi, B.; Alrfou, R.; and Skiena, S. 2014. DeepWalk: online learning of social representations. In *KDD*, 701–710.

Zhang, H.; Shen, F.; Liu, W.; He, X.; Luan, H.; and Chua, T. S. 2016. Discrete Collaborative Filtering. In *SIGIR*, 325–334.