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 semi-discrete socially embedded matrix factorization (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. 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 semi-discrete socially embedded matrix factorization (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 enforced 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 $R \in [0,1]^{m \times n}$, MF is to decompose $R$ into a user feature matrix $P = [p_1 \cdots p_m] \in \mathbb{R}^{f \times m}$ and an item feature matrix $Q = [q_1 \cdots q_n] \in \mathbb{R}^{f \times n}$. As such, an observed (or unobserved) rating of user $u$ on item $i$ is anticipated to be approximated (or predicted) by $\hat{r}_{ui} = p_u^T q_i$. A typical cost function of MF is defined as

$$\arg\min_{P,Q} \sum_{(u,i) \in \Omega} (r_{ui} - p_u^T q_i)^2, \quad (1)$$

where $\Omega$ is a set of the index of observed entries.

Given a social network among users, we employ DeepWalk (Perozzi, Alrhoufi, 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 $W$ and $V$ 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

$$\arg\min_{W,V} \sum_{u} \left[ \log \sigma(w_u^T h) + \log \sigma(-w_u^T \tilde{h}) \right], \quad (2)$$

where $h = \frac{1}{|\mathcal{N}_u^+|} \sum_{v \in \mathcal{N}_u^+} v_v$, $\tilde{h} = \frac{1}{|\mathcal{N}_u^-|} \sum_{v \in \mathcal{N}_u^-} v_v$, $w_u$ and $v_u$ are the $u$-th column of $W$ and the $u$-th row of $V$ respectively. Specifically, $w_u$ is taken as the social feature of user $u$ in our scheme.
To exploit the complementary properties between rating data and social data, we present a joint learning framework, termed socially embedded matrix factorization (SMF), by combining Eq. (1) with Eq. (2): 

$$ \arg \min_{P, Q, W, V} \sum_{(u, i) \in \Omega} (r_{ui} - p_u^T q_i)^2 + \alpha \|p_u - w_u\|^2 $$

$$ - \beta \sum_u [\log \sigma(w_u^T h) + \log \sigma(-w_u^T h)] $$

$$ + \frac{\lambda}{2} (\|P\|_F^2 + \|Q\|_F^2 + \|W\|_F^2 + \|V\|_F^2), $$

where $\|p_u - w_u\|^2$ aims to achieve a tight coupling of MF and NE model.

To speed up the online predictions, we further propose S2MF by partially discretizing the formulation of SMF. Denote $B = \{b_1 \cdots b_m\} \in \mathbb{B}^{f \times m}$ and $D = \{d_1 \cdots d_n\} \in \mathbb{B}^{f \times n}$ 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:

$$ \arg \min_{B, D, W, V} \sum_{(u, i) \in \Omega} (r_{ui} - s_H(b_u, d_i))^2 + \alpha \sum_u \|b_u - w_u\|^2 $$

$$ - \beta \sum_u [\log \sigma(w_u^T h) + \log \sigma(-w_u^T h)] $$

$$ + \frac{\lambda}{2} (\|W\|_F^2 + \|V\|_F^2) $$

$$ s.t. B \in \{\pm 1\}^{f \times m}, D \in \{\pm 1\}^{f \times n}, $$

$$ B1_m = 0, D1_n = 0, BB^T = mI_f, DD^T = nI_f, $$

where $s_H(b_u, d_i) = \frac{1}{2} \frac{1}{2f} b_u^T d_i$ is the Hamming similarity between $b_u$ and $d_i$.

We develop an efficient optimization algorithm to estimate the model parameters by alternately 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 achieved 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.

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

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.

### 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


