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Event Recommendation in Event-Based Social Networks

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Abstract

With the rapid growth of event-based social networks, the demand of event recommendation becomes increasingly important. Different from classic recommendation problems, event recommendation generally faces the problems of heterogenous online and offline social relationships among users and implicit feedback data. In this paper, we present a baysian probability model that can fully unleash the power of heterogenous social relations and efficiently tackle with implicit feedback characteristic for event recommendation. Experimental results on several real-world datasets demonstrate the utility of our method.

Introduction

Recent years have witnessed the popularity of Event-based Social Networks (EBSNs), such as *Meetup*. In EBSNs, event recommendation, as an essential topic in recommender systems, plays an important role in recommending the most relative events to users who are likely to participate. The services allow users to organize, participate, comment and share offline events such as cocktail parties, seminars and concerts. The work (Liu and et al. 2012) studied the heterogeneous property of EBSN on community and information. The work (Zhang and et al. 2013) studied the new group recommendation method based on event-based social network.

Different from traditional recommendation problems(Qiao and et al. 2014), event recommendation encounters new characteristics: (1)Heterogeneous online+offline social relation, which is described in (Liu and et al. 2012). Apparently, online social relationship is presented by online social group or social network. Meanwhile, shared offline events present offline social relationship, where link relations exist when users will meet each other while they participate in the same events. Fig 1 depicts the characteristic from Meetup. (2)Implicit feedback data from users. Such as in *Meetup*, the feedback data are reflected by the RSVP choice (”yes”, ”no”).

Therefore, in this paper, we propose a method which can comprehensively take the heterogenous social impact and implicit feedback characteristic into consideration. Experiments carried out on several real data sets verify the effectiveness of our proposed model.

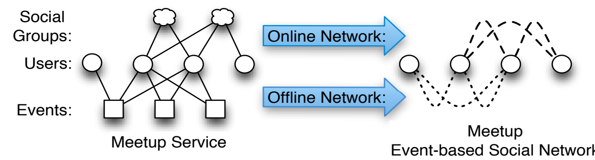

Figure 1: Heterogeneous social characteristic in EBSNs (Liu and et al. 2012)

Heterogenous Social Relation

Heterogenous social relations are special characteristic for event-based social networks, which are constituted with online social relation and offline social relation.

Online social relation. In most event-based social services, social group is a main representative style to describe social relation among users. In Meetup, users may share comments, photos and event plans in the same online social groups. For social group, we define the edge weight w_{ij}^{on} representing online social relation between user i and j.

$$w_{ij}^{on} = \frac{|G(u_i) \cap G(u_j)|}{|G(u_i) \cup G(u_j)|} \tag{1}$$

where $G(u_i)$ is the set of social groups user i joined, $|G(u_i) \cap G(u_j)|$ is the number of members of the intersection set $G(u_i) \cap G(u_j)$, and $|G(u_i) \cup G(u_j)|$ is the number of members of the union set $|G(u_i) \cup G(u_j)|$.

Offline social relation. The offline social network of the EBSN, is constructed in a similar way based on the co-participation of social events: user u_i and u_j are connected if they co-participated in the same event. Let w_{ij}^{off} represent offline social relation between user i and j. Hence, the offline social relation can be obtained by:

$$w_{ij}^{off} = \frac{|E(u_i) \cap E(u_j)|}{|E(u_i) \cup E(u_j)|} \tag{2}$$

where $E(u_i)$ is the set of events user i has participated, $|E(u_i) \cap E(u_j)|$ is the number of members of the intersection set $E(u_i) \cap E(u_j)$, and $|E(u_i) \cup E(u_j)|$ is the number of members of the union set $|E(u_i) \cup E(u_j)|$.

Table 1: AUC of test sets

Method	MF	BMF	BMFon	BMFoff	Our
NYC	0.801	0.851	0.862	0.867	**0.875**
LA	0.798	0.845	0.856	0.861	**0.869**
Houston	0.811	0.863	0.871	0.878	**0.885**
Chicago	0.803	0.844	0.851	0.862	**0.871**
SF	0.792	0.838	0.846	0.852	**0.866**

Methodology

We apply matrix factorization latent factor model, which has spawned a large body of researches and been proved efficiently. In the setting of matrix factorization, the fundamental idea is to embody user i and item j with low-dimension latent factors U_i and V_j. Then the dyadic rating $r(u_i, v_j)$ of user i to item j is usually approximated according to inner product $U_i^T V_j$.

However, feedback of a user to an event is implicit, where presence or absence is represented by binary value 1 or 0. Bayesian Personalized Ranking (BPR)(Rendle and et al. 2009) emphases on predicting the dyadic rating $r(u, v)$ and make the items with higher ratings rank higher, which is efficient for the implicit feedback recommendation problem. Hence we choose the BPR optimization criterion and adapt it to our event recommendation problem. We regard the events which user u have participated as the positive event set, denoted by P_u^I, while the other events as the negative event set, expressed as N_u^I. Then the best ranking result for user u is that all events participated by him should rank higher than other events that he didn't participate, which approximately can be expressed by the below optimization problem,

$$\max_{\Theta} \prod_{(u_i,v_j,v_k)\in(U,P_u^I,N_u^I)} P(r(u_i,v_j) > r(u_i,v_k)|\Theta) \tag{3}$$

where $\Theta = (U, V)$ is the parameter set in the model.

Social relation is usually applied to improve recommendation. In the paper, we use social regularization term, which is based on the assumption that the preference of a user is close to the weighted average preference of his friends. Thus, we denote W^{on} representing social relation among users. In order to satisfy baysian model, we place zero-mean spherical Gaussian priors for regularization term as below.

$$P(U_i|W^{on}, \sigma) \propto N(U_i - \sum_{j=1}^{n} \frac{w_{ij}}{\sum_{k=1}^{n} w_{ik}} U_j : \mathbf{0}, \sigma^2 I) \tag{4}$$

For our problem, we simple apply both online and offline social relations into social regularization term separately.

Additionally, in order to avoid over-fitting in the learning process, we also enforce Gaussian priors on the latent factor vectors U_i, V_j. Now let $\Phi = (\sigma, \sigma_u, \sigma_v)$ be the Gaussian prior parameters for social regularization, latent factor vectors U_i and V_j separately. Thus, given the user-event feedback matrix R, the online social relation W^{on} and the offline social relation W^{off}, $P(\Theta|R, W^{on}, W^{off}, \Phi)$ is proportional to:

$$\prod_{(u_i,v_j,v_k)\in(U,P_u^I,N_u^I)} P(r(u,v_j) > r(u,v_k)|\Theta)$$
$$\prod_i P(U_i|W^{on}, \sigma) P(U_i|W^{off}, \sigma) \prod_i P(U_i|\sigma_u) P(V_i|\sigma_v) \tag{5}$$

where $P(r(u, v_j) > r(u, v_k)|\Theta) := l(r(u, v_j) - r(u, v_k))$ and function l represents the logistic function.

Then, we can get the target optimization function, commonly represented as a log-likelihood function. The parameters are learned by maximizing the objective function by using stochastic gradient descent.

Experiments

We got the five data sets as in Table 1 for the five American cities in Meetup by extracting them from the data sets published by (Zhang and et al. 2013). In order to avoid a very slow training scheme, we randomly sample 10 events users have not joined for each negative events and and 1 event joined by the users for each positive event to constitute the training pairs. (Zhang and et al. 2014) For all the data sets, we randomly split them with 80% into the training sets and 20% into the test sets .

To test the effectiveness of our method, we compare our method with Collaborative Filter based on pure Matrix Factorization(short for **MF**), Baysian MF considering implicit feedback(short for **BMF**), BMF with online social regularization(short for **BMFon**), BMF with offline social regularization(short for **BMFoff**). Table 1 demonstrates the experimental results under standard evaluation metrics **AUC**. From the results, we can find that the performance of the model under implicit feedback can be improved. Social information can be applied to improve performance of the model by comparing BMFon, BMDoff with BMF. Overall, our proposed model combining heterogenous social information into matrix factorization outperforms others.

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