Personalized Recommendation Combining User Interest and Social Circle

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Abstract: With the advent and popularity of social network, more and more users like to share their experiences, such as ratings, reviews, and blogs. The new factors of social network like interpersonal influence and interest based on circles of friends bring opportunities and challenges for recommender system (RS) to solve the cold start and sparsity problem of datasets. Some of the social factors have been used in RS, but have not been fully considered. In this paper, three social factors, personal interest, interpersonal interest similarity, and interpersonal influence, fuse into a unified personalized recommendation model based on probabilistic matrix factorization. The factor of personal interest can make the RS recommend items to meet users' individualities, especially for experienced users. Moreover, for cold start users, the interpersonal interest similarity and interpersonal influence can enhance the intrinsic link among features in the latent space. We conduct a series of experiments on three rating datasets: Yelp ,MovieLens, and Douban Movie. Experimental results show the proposed approach outperforms the existing RS approaches

Keywords: Interpersonal influence, personal interest, recommender system, social networks

I. Introduction

Recommender framework (RS) has been effectively misused to fathom data over-burden. In E-Commerce, similar to Amazon, it is imperative to taking care of mass size of data, for example, suggesting client favored things and items. Luckily, the presence of web2.0 enormously enhances client's drive on the Internet, and after that brings volume of interpersonal organizations, for example, Facebook,Twitter,Yelp, Douban, Epinions, and so on. The interpersonal relationship, particularly the friend networks, of informal communities makes it conceivable to unravel the frosty begin and sparsity problem."Moves as one longings, chooses as you like."Just like the logo says, client's decision is dependably firmly identified with his/her own advantage. It is extremely prevalent for clients to share, transfer, and remark their most loved substance. This paper, three social components, individual interest, interpersonal interest likeness, and interpersonal impact, wire into a bound together customized suggestion model in view of probabilistic lattice factorization. The identity is meant by client thing importance of client enthusiasm to the theme of thing. To epitomize the impact of client's identity, we mine the point of thing in view of the regular thing classification labels of rating datasets. In this way, every thing is meant by a classification circulation or theme appropriation vector, which can mirror the normal for the rating datasets. In addition, we get client interest taking into account his/her rating conduct. We then allocate to the impact of client's identity in our customized suggestion model relative to their aptitude levels. Then again, the client relationship of informal organization contains two components: interpersonal impact and interpersonal interest comparability.

II Related Work

In this paper, we concentrate on probabilistic grid factorization with thought of elements of informal community. In the accompanying, we quickly survey some significant attempts to this paper, including the fundamental network factorization model [4] with no social variables, the CircleCon model [1] with the component of interpersonal trust values and the Social Contextual (ContextMF) model [2] with interpersonal impact and individual inclination.

III Implementation

Basic Matrix Factorization

To introduce various sophisticated approaches [1], [2], [3], [5], we first briefly review the basic probabilistic matrix factorization (BaseMF) approach [4], which does not take any social factors into consideration. The task of RS is to decrease the error of predicted value using R to the real rating value. Thus, the BaseMF model is trained on the observed rating data by minimizing the objective function

$$\Psi(\boldsymbol{R}, \boldsymbol{U}, \boldsymbol{P}) = \frac{1}{2}\sum_{u,i}(R_{u,i} - \hat{R}_{u,i})^2 + \frac{\lambda}{2}(\|\boldsymbol{U}\|_F^2 + \|\boldsymbol{P}\|_F^2) \qquad (1)$$

ContextMF Model

Jiang et al. [2] demonstrate the significance of social contextual factors (including interpersonal influence and individual preference) for item adopting on real Facebook and Twitter style datasets. The task of ContextMF model in [2] is to recommend acceptable items from sender u to receiver v.Here, the factor of interpersonal influence is similar to the trust values in CircleCon model [1].Moreover, individual preference is mined from receiver's historical adopted items. And the interpersonal preference similarity values are represented by the matrix W. Each of the rows is normalized to unity .

The objective function of this model is

$$\begin{aligned}&\Psi(R,U,P,S^*,W^*)\\&=\frac{1}{2}\sum_{u,i}(R_{u,i}-\hat{R}_{u,i})^2+\frac{\lambda}{2}(\|U\|_F^2+\|P\|_F^2)\\&\quad+\frac{\beta}{2}\sum_u((U_u-\sum_v S^*_{u,v}U_v)(U_u-\sum_v S^*_{u,v}U_v)^T)\\&\quad+\frac{\gamma}{2}\sum_{u,v}(W^*_{u,v}-U_uU_v^T)^2\end{aligned} \tag{5}$$

where the element of individual inclination is authorized by the last term in (5), which implies that client idle element Uu ought to be like his/her companions' idle element with weight of their inclination likeness in informal organization, and the rating qualities is anticipated by (1).Once the model is trained,the rating qualities can be anticipated by for any client thing sets. Other than the interpersonal impact (like the trust values in CircleCon model [1]),individual inclination is a novel element in ContextMF demonstrate, and is implemented by the last term in (5). Note that despite everything we execute the interpersonal impact as CircleCon model [1] and preclude the theme importance of things, as we additionally anticipate evaluations of things in Epinions style datasets and utilize the circle based thought in our analyses. Albeit singular inclination is proposed in this model, client inert component is still associated with his/her companions as opposed to his/her trademark. Actually, the variable of individual inclination of this model is upheld by interpersonal inclination similarity.Comparing ContextMF model, the proposed customized suggestion model has three distinctions: 1) the errand of our model is to prescribe user,regardless of sender or beneficiary, intrigued and obscure things. 2) client individual hobby is straightforwardly identified with his/her appraised things rather than join with his/her companions. 3) the variable of client enthusiasm for our model mined from client evaluated things has more impact than individual inclination in ContextMF model, on the grounds that it less demanding for the prescribed things of our model to be changed ContextMF model, because it easier for the recommended items of our model to be transformed into purchase rate than the adopted items in Facebook style social networks.

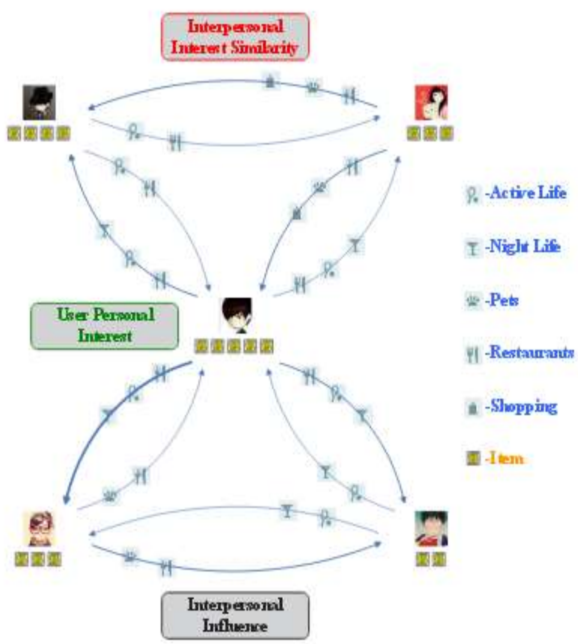

Figure 1. Three main social factors in our recommendation model, including user personal interest, interpersonal interest similarity, and interpersonal influence. The items under users are historical rating records, which can be used to mine users' personal interest. The category icon on line between two users denotes their interest similarity. And the boldness of the line between users indicates the strength of interpersonal influence.

TABEL 2
ALGORITHM OF PERSONALIZED RECOMMEN-DATION

Algorithm of Personalized Recommendation Model (PRM)
Initialization: $\Psi^c(0) = \Psi^c(\boldsymbol{U}^c(0), \boldsymbol{P}^c(0))$.
Require: $0<l<1$, $t=0$.
while($t<1000$)
calculate $\frac{\partial \Psi^c(t)}{\partial \boldsymbol{U}^c}, \frac{\partial \Psi^c(t)}{\partial \boldsymbol{P}^c}$
search optimal l
$\boldsymbol{U}^c(t)=\boldsymbol{U}^c(t)-l\frac{\partial \Psi^c(t)}{\partial \boldsymbol{U}^c}$, $\boldsymbol{P}^c(t)=\boldsymbol{P}^c(t)-l\frac{\partial \Psi^c(t)}{\partial \boldsymbol{P}^c}$
If ($\Psi^c(t) < \varepsilon$)
break;
t++;
end

Comparative Algorithms

We conducted series of experiments to compare our personalized recommendation model (PRM) with the following existing models.
BaseMF: This model is the basic matrix factorization
approach proposed in [4] without consideration of any social factors.
CircleCon: This method is proposed in [1], including
Four variants:CircleCon1,CircleCon2a, CircleCon2b, and CircleCon3. It improves the accuracy of BaseMF and SocialMF [3] byintroducing the inferred trust circle of social network. And Yangetal. have demonstratedCircleCon2a,CircleCon2b,andCircleCon3 have much better performance. Thus, we just omit CircleCon1.
ContextMF: This method [2] improves the accuracy of traditional item-based collaborative filtering model in [9], influence-based model in [16], and Sorec in [17] by taking both interpersonal influence and individual preference into consideration. As stated in Section III, we train the model as (5).

IV. CONCLUSION

In this paper, a personalized recommendation approach was proposed by combining social network factors: personal interest, interpersonal interest similarity, and interpersonal influence. In particular, the personal interest denotes user's individuality of rating items, especially for the experienced users, and these factors were fused together to improve the accuracy and applicability of recommender system. We conducted extensive experiments on three large real-world social rating datasets, and showed significant improvements over existing approaches that use mixed social network information. At present, the personalized recommendation model only takes user historical rating records and interpersonal relationship of social network into consideration. In our future works, we will take user location informationto recommend more personalized and real-time items.

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