A Survey on Personalized Recommendation Techniques

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Abstract: ***Recommendation systems are software agents that identify preferences of individual users and make recommendations accordingly. Personalized recommendation systems need to provide appropriate recommendations based on requirements and preferences. This article presents an overview of the personalized recommendation techniques and identifies the problems and describes different approaches for customization. The main techniques used for the survey are: 1) Circle-based recommendation, 2) Recommendation on Social Context and 3) Personalized Recommendation Model. The objective of this survey is to present a study on the main concepts, approaches and practices in the field of personalized recommendation systems. Accordingly, this document presents a number of possible directions of research.***

Keywords: Social networks, Personal Interest, Interpersonal influence, Recommender systems

1. Introduction

Recommendation systems are a subclass of information filtering system that seek to predict the "rating" or "preference" that a user would give to an item. Recommendation systems have become extremely common in recent years, and are used in a variety of areas: Some popular applications include movies, music, news, books, research articles, research queries, social tags and products in general. However, there are also Recommendation Systems for experts, collaborators, restaurants, financial services, life insurance and Twitter pages.

The main objective of the information retrieval system is to extract information from a large data set. The current system of information retrieval deals with the heterogeneous nature, high volume, constantly changing information. Personalization can be defined as any set of actions that can tailor the web experience to a particular user or set of users. Actions can range from a simple presentation to more pleasant to anticipate the needs of a user and provide the proper information. To achieve effective personalization, organizations needs the available data, including usage and click stream data, site content, site structure, knowledge of the field, as well as demographics and user profiles. Efficient and intelligent techniques for extracting useful knowledge and use the discovered knowledge to improve the user's web experience. In web customization challenges include scalability, heterogeneous data integration, recovery and filtering, knowledge representation, security and confidentiality of information, modeling. Recommendation systems represent a special class and Web applications, which focus particularly on filtering and selection of relevant information. Personalization in the web search engines can be achieved with the help of query's adaptation, matching result or combination of query and adaptation of results.

2. Recommendation Techniques

2.1 Circle-based Recommendation

Online social network information promises to increase recommendation accuracy beyond the capabilities of feedback-driven recommender systems. Recommender Systems (RS) deal with information overload by suggesting to users the items that are related to their interests. In traditional collaborative filtering approaches predict user's interests by mining user rating history data [4], [5] and [6]. As to better serve user's activities across different domains, many online social networks support a new feature of "Friends Circles", which select the domain oblivious "Friends" concept. Recommendation system should also benefit from domain-specific "Trust Circles". Intuitively, user may trust different subsets of friends regarding different domains. In most existing multi-category rating datasets, a user's social relations from all categories are mixed together. Here presents an effort to develop circle-based RS. The focus is on inferring category-specific social trust circles from available rating data combined with social network data. This outlines several variants of weighting friends within circles based on their inferred levels. The experiments on publicly available data demonstrated that the proposed circle-based recommendation models [1] can better utilize user's social trust information, resulting increased recommendation accuracy.

This technique infers the circles of friends from rating data concerning items that can be divided into different categories. The basic idea is that a user may trust each friend only concerning certain item categories but not regarding others. For instance, the circle of friends concerning cars may differ significantly from the circle regarding kid's TV shows.

To this end, divide the social network S of all trust relationships into several sub-networks $S^{(c)}$, each of which concerns a single category c of items.

Regarding each category c, a user v is in the inferred circle of user u, i.e., in the set $C_u^{(c)}$, if and only if the following two conditions hold:

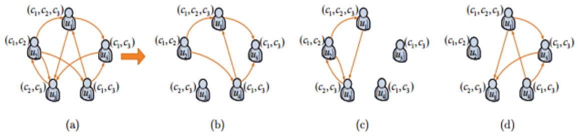

Figure 1: Illustration of inferred circles, where each user is labeled with the categories in which it has ratings.[1]

- $S_{u,v} > 0$ in the (original) social network,
- $N_u^{(c)} > 0$ and $N_v^{(c)} > 0$ in the rating data,

where $N_u^{(c)}$ denotes the number of ratings that user u has assigned to items in category c. Otherwise, the user v is not in the circle of u concerning category c, i.e., v doesnot belongs to $C_u^{(c)}$. This is illustrated for a toy example in Figure 1.

The trust values between friends in the same inferred circle are captured in a social network matrix $S^{(c)}$, such that $S_{u,v}^{(c)} = 0$ if v not belongs to $C_u^{(c)}$, $S_{u,v}^{(c)} > 0$ if v ∈ $C_u^{(c)}$. In the following, consider three variants of defining the positive values $S_{u,v}^{(c)} > 0$ when user v is in the inferred circle of user u regarding category c.

To illustrate this trust splitting, let us look at Figure 1: user u2 trusts user u1 and both of them have ratings in category c1 and c2. Assume the number of ratings u1 issued in category c1 and c2 are 9 and 1 respectively. The trust values in original social network is $S_{u2,u1} = 1$. Now after trust splitting, get $S_{u2,u1}^{(c1)} = 0.9$ and $S_{u2,u1}^{(c2)} = 0.1$.

2.2 Social Contextual Recommendation

Traditional techniques become unqualified because they ignore social relational data; existing social recommendation approaches consider social network structure, but no social context has been fully considered. With the emerge of social networks, researchers design trust-based [7,8] and influence-based [9, 10] methods to take use of the power coming from user relationships for recommendation. It is significant and challenging to fuse social contextual factors which are derived from user's motivation of social behaviors into social recommendation. Firstly present the particular importance of these two factors in online item adoption and recommendation. Then propose a novel probabilistic matrix factorization method to fuse them in latent spaces.

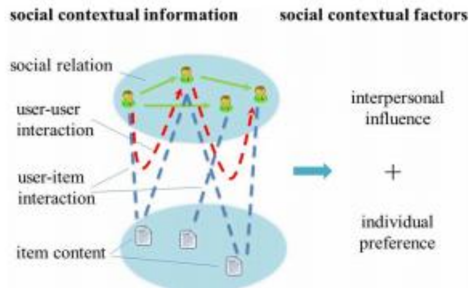

Figure 2: From Social Contextual Information to Social Contextual Factors [2]

The two contextual factors are: (1) individual preference and (2) interpersonal influence. Therefore, only when individual preference and interpersonal influence are properly incorporated into recommendation, the unpredictability can be reduced and the recommendation performance can be improved accordingly.

Here a social contextual recommendation framework (as shown in Figure 3) based on a probabilistic matrix factorization method is proposed to incorporate individual preference and interpersonal influence to improve the accuracy of social recommendation. More specifically, factorize the user-item interaction matrix into two intermediated latent matrices: user-item influence matrix and user-item preference matrix, which are generated from mainly three objective matrices: user latent feature matrix, item latent feature matrix, and user-user influence matrix. So we can partially observe individual preference and interpersonal influence based on historical user-item and user-user interaction data, the observed contextual factors are utilized compute the three objective latent matrices.

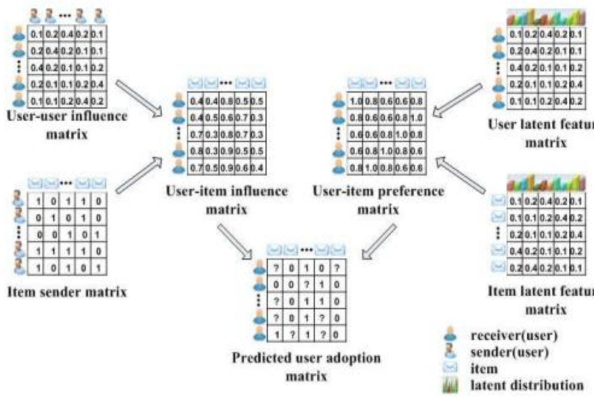

Figure 3: An illustrator on social contextual recommendation framework [2].

Figure 3 demonstrates the existence and significance of social contextual factors (including individual preference and interpersonal influence) for social recommendation on real large datasets.

The correlation is 1 or -1 in the case of perfect positive or negative linear relationship and zero if preference and influence are uncorrelated. In Figure 3, the absolute correlation values of more than 40 % users are less than 0.2 and the values of around 70% are less than 0.4. Thus conclude that individual preference and interpersonal influence can be applied as two complementary social contextual factors in recommendation.

2.3 Personalized Recommendation Model Combining User Interest and Social Circle

X. Qian, H. Feng, G. Zhao, and T. Mei, et. al. fuses three social factors: user personal interest, interpersonal influence and interpersonal interest similarity is to recommend user interested items [3]. The illustration of our approach is shown in Figure 4. Among the three factors, user personal interest and interpersonal interest similarity are the main contributions of the approach and all are related to user interest. Thus, introduce user interest factor firstly. And then, infer the objective function of the proposed personalized recommendation model. At last, give the training approach of the model.

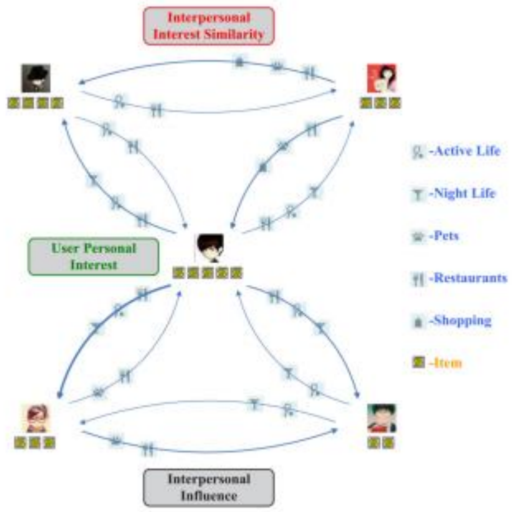

Figure 4: Three main social factors in our recommendation model [3].

Besides the trust values between friends in the same category [1], user's interest is another significant factor to affect user's decision-making process, which has been proved by the psychology and sociology studies[6]. Jiang et al. [2] demonstrated the effect of ContextMF model with consideration of both individual preference and interpersonal influence. There are two main differences of the user interest factor in this model to individual preference in ContextMF: 1) The independence of user interest. It means who can recommend items based on user interest at certain extent. In other words, utilizes user's connection with the items to train the latent feature vectors, especially for experienced users. 2) Interest circle inference. In CircleCon model [1], divide the tested social network into several sub-networks, and each of them correspond to a single category of items. Thus considering the cold start users who has a few rating records, uses friend's interest in the same category to link user latent feature vector.

The personalized recommendation model contains the following three aspects: 1) Interpersonal influence $S^{c*}_{u,v}$ [1], which means whom you would trust. 2) Interest circle inference $W^{c*}_{u,v}$, which means whose interest is similar to yours.3) User personal interest $Q^{c*}_{u,i}$, which has effect on what items you would be interested in. Here combine interpersonal influence S, interpersonal interest similarity W and user personal interest Q with the rating matrix R to decrease the predicted error. Thus, for each category c, through Bayesian inference, the posterior probability of latent features giving the rating and social context factors are defined.

For each category c, get the corresponding matrix factorization model as [11] to obtain a separate user latent profile Uc and item latent profile Pc. And the objective function can be minimized by the gradient decent approach.

Where $I^{R^c}_{u,i}$ is the indicator function that is equal to 1 if user u has rated item i in c, and equal to 0 otherwise. $\hat{R}^c_{u,i}$ is the predicted rating value in c . $|H^{c*}_u|$ is the normalized number of items that user u has rated in category c, which is the factor of a user depends on his/her personal interest to rate an item.

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

Figure 5: Personalized Recommendation Algorithm.

The initial values of Uc and Pc are sampled from the normal distribution with mean zero. It epidemically has little effect on the latent feature matrix learning. The item and user latent feature vectors Pc and Uc are updated based on the previous values to ensure the fastest decrease of the objective function in each iteration. Here the step size is a considerable issue. Adjust it to insure the decreases of the objective function in training.

3. Performance Measures

A number of experiments were conducted to compare the personalized recommendation model (PRM) [3] with the following existing models.

- CircleCon[1] : In this method including four variants: CircleCon 1, CircleCon 2a, Circle Con 2b, and CircleCon 3. It improves the accuracy of BaseMF and SocialMF [3] by introducing the inferred trust circle of social network. And Yang et al. have demonstrated CircleCon 2a, CircleCon 2b, and CircleCon 3 have much better performance. Thus, we just exclude CircleCon1.

- ContextMF [2] : This method improves the accuracy of traditional item-based collaborative filtering model in [12], influence-based model in [13], and SoRec in [14] by taking both interpersonal influence and individual preference into consideration.
- PRM [3]: Analogous, $Q_{u,i}$ in which the item topic distribution vector is calculated from the second level of the category tree. And also the similarity is measured by cosine similarity.

The evaluation metrics used in the experiments are Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), as these are the most popular accuracy measures in the literature of recommender systems. RMSE and MAE are defined as

$$RMSE = \sqrt{\frac{\sum_{(u,i)\in \Re test}(R_{u,i} - \hat{R}_{u,i})^2}{|\Re test|}} \quad (1)$$

$$MAE = \frac{\sum_{(u,i)\in \Re test}|R_{u,i} - \hat{R}_{u,i}|}{|\Re test|} \quad (2)$$

Where $R_{u,i}$ is the real rating value of user u on item i, $\hat{R}_{u,i}$ is the corresponding predicted rating value, and test is the set of all user-item pairs in the test set.

Table 1: Comparison Results of Algorithms for Recommendation[3]

Category	Circle Con		Context MF		PRM	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
Active Life	1.779	1.380	1.360	1.026	1.278	1.007
Beauty and Spas	1.950	1.533	1.567	1.203	1.432	1.131
Home Services	2.16	1.676	1.723	1.340	1.638	1.311
Hotels & Travel	1.862	1.459	1.409	1.085	1.310	1.037
Night Life	1.497	1.159	1.320	1.023	1.147	0.914
Pets	2.190	1.724	1.715	1.289	1.551	1.219
Restaurants	1.340	1.035	1.280	0.995	1.083	0.867
Shopping	1.727	1.337	1.413	1.087	1.318	1.029
Average	1.810	1.413	1.473	1.131	1.351	1.070

In Table 1, shows the performance based on the Yelp dataset. From Table 1, can see that the accuracy of our personalized recommendation model is much better than the BaseMF for the social factors. For the social recommendation models, decrease the prediction error by 34% and 6% on MAE, by 45% and 12% on RMSE over CircleCon and ContextMF. The results demonstrate the significant of user's individuality in recommendation system.

4. Conclusion

In the circle based recommendation system [1] with the factor of interpersonal trust values, the Social Contextual model [2] with interpersonal influence and individual preference and the Personalized Recommendation Model [3] with personal interest, interpersonal interest similarity and interpersonal influence. By comparing the three recomendation algorithms it can be concluded that Personalized Recommendation Model [3] is better than that of other algorithm. Personalized Recommendation Model has higher accuracy, less error rate and higher performance. It will make an efficient recommendation , avoid cold start and sparsity problem of data set.

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