Volume : 4 | Issue : 5 | May 2015 • ISSN No 2277 - 8179

Research Paper

Cold Start Solving Recommender System With Social Contextual Information

Engineering

KEYWORDS : Social Recommendation, Individual Preference, Interpersonal Preference, Matrix Factorization.

Deepa Johny M.Tech CSE AWH Engineering College Calicut, India

ABSTRACT

Recommender systems made people easier to find recommendations like posts, products, information, and even other people. As the usage and popularity of social networking sites increases day by day, the recommender system also becomes more demandable. It is significant and challenging to bring together all the social contextual factors from users based on psychology and sociology studies like individual preference and interpersonal influence. The existing approaches consider these social contextual factors but not the new user problem and the new item problem effectively. This paper answers the problem of the new user problem and the new item problem in the probabilistic matrix factorization method so that it gives more effective recommendations.

Introduction

Recommender systems are extremely common in recent years, and are applied in a variety of applications. The most popular ones are probably used in applications for movies, music, news, books, research articles, search queries, social tags, and products in general. There are many applications where the recommender systems are used. As the usage and popularity of social networking sites increases day by day, the recommender system also becomes more demandable. It is significant and challenging to bring together the entire social contextual factor. Recently, in [11] proposed a method of social recommender systems that made use of social contextual factors from the contextual information and integrate them into a unified recommendation framework. However, in this work the new user problem and the new item problem was not fully solved. Fig.1 shows the social contextual information based on the social contextual factors on social networking sites. It is significant and challenging to bring together all the social contextual factors from users based on psychology and sociology studies like individual preference and interpersonal preference.

In recommendation systems, the user examines the content and the information about the user (sender). For example, in Facebook, when user receives a post by a friend, he views the post and read its content and sees whether it's interesting. In this user see two main things: (1) who sends the post and (2) content of post. If the same post has been sent by many friends then that seems to be more interesting. All these information can be taken from item content, user-item interaction, social relation and user-user interaction. These are the important factors to see whether the post should be recommended. This can be summarized as two factors: (1) individual preference and (2) interpersonal influence.

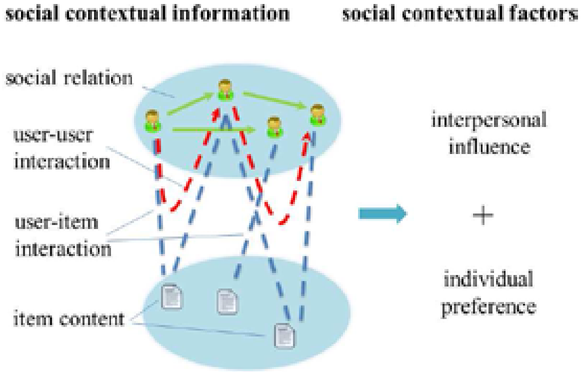

Fig.1. Social Contextual Information with social contextual factors

Only when both individual preference and interpersonal influence are properly incorporated into recommendation, can the uncertainty be reduced and quality improved. The work [11] is based on a probabilistic matrix factorization method to incorporate individual preference and interpersonal influence to improve the accuracy of social recommendation. More specifically, it uses: user data matrix, item data matrix, user-item preference matrix and user-user influence matrix. The new user problem and the new item problem is not fully considered in the previous works. Solving this problem makes the recommender systems easier and accurate.

To address this problem, this work provides a solution that incorporates the individual preferences manually by the user and giving recommendations considering the semantic meaning of the content. To be more precise, this work provides a solution for the new user problem and the new item problem in the recommendation system with the social contextual recommendation.

This paper is organized as follows. Section 1gives the introduction to relevant work. In Section 2, the related works are given. In Section 3, we illustrate the effectiveness of two contextual factors with studies on social data sets. In Section 4, we show the formulation on social contextual model. Section 6 comes to the conclusion.

Related Works

In this section, different types of recommender systems are viewed. There are mainly three types of recommender systems: (1) Content-based methods (2) Collaborative methods and the (3) Hybrid methods. The other methods widely used are trust-based, influence-based methods, matrix factorization methods. The content-based and collaborative methods are used to find out most valuable information. The trust-based and influence-based methods take advantage of the knowledge from user relationships. Matrix factorization methods are used for dealing with large data sets. There are also many mixture models of these methods.

Content-based methods have the basic idea of studying the item content for the ranking problems. The content-based approach in [4] rank candidate items by how well they match the topic interest of the user as their preference. These approaches works on individual patterns which are not able to learn user behavior patterns from user-item interaction data. Collaborative methods are two types: (1) memory-based and (2) model-based methods. The memory-based approach [5] calculates the similarity between all users based on their ratings of items. The model-based approach is based on pattern recognized in the rating of the users. Collaborative filtering only uses user-item interactions not the social relation data such user-user relation.

Volume : 4 | Issue : 5 | May 2015 • ISSN No 2277 - 8179

Matrix factorization methods [6], [7] represent the user-item rating matrix with low-dimensional latent vectors [8], [9]. Trust-based approaches recognize that influence governs the dynamics of social networks. The influence-based recommendation involves interpersonal influence into social recommendation cases [10]. SoRec [2] is a probabilistic factor analysis framework which fuses the users' tastes and their trusted friends' favors together.

To improve recommender systems, Ma et al. [3] propose a matrix factorization framework with social regularization by incorporating users' social network information into both friend network and trust network. This only utilizes users' individual features from interpersonal side but ignores users' individual side. This makes the framework lack of complete contextual information to further improve the performance. The approach [11] uses matrix factorization which utilizes both social contextual factors such as individual preference and interpersonal influence. These factors develop the structure of social behaviors and interactions. But the new user problem and the new item problem is not fully considered. This gives the motivation to add a functionality of the new user problem and the new item problem into the matrix factorization method [11]. This paper solves the issue of the new user problem and the new item problem effectively in probabilistic matrix factorization method.

Social Contextual Factors And Model

Let us consider an item a. The user adoption behavior depends on the individual preference to understand whether the user likes the item or not. Interpersonal influence determines whether the user has close relationship with the item sender(friend who sent a post). Based on these, LDA is applied to the content of the post. This extracts the topic level distribution of these items. How much a user like an item a is calculated by naïve preference measurement as

$$P_u(a) = T_a \cdot \left(\frac{1}{|A(u,a)|} \sum_{a' \in A(u,a)} T_{a'} \right)$$

where A(u,a) is the set of items adopted by user u excluding a and T_a is the topic distribution of item a.

For interpersonal influences, the recommended items adopted by u from u's friends or followees who send the item a is calculated by:

$$I_u(a) = \frac{1}{|V(u,a)|} \sum_{v \in V(u,a)} \frac{|S(u,v) \cap A(u)|}{|S(u,v)|} ,$$

where V(u, a) is the set of senders who send item a to user u, S(u, v) is the set of items sent from v to u, and A(u) is the set of items that u adopts.

Social contextual model is based on matrix factorization. Let us consider that there are M users and N items. The ith user is denoted by u_i and jth item is denoted as p_j. The information adoption matrix is denoted as $R \in \{0,1\}^{M \times N}$.

$$R = \begin{cases} 1 \ \text{if} \ u_i \ adopted \ p_j \\ 0 \ otherwise \end{cases}$$

The user preference prediction is based on three aspects : (1) content of the item, (2) the sender of item and (3) whether the user likes the item. The sender of item is taken from the user-user interaction. Whether the user likes an item is determined by the user-item interaction.

Let U be the user matrix, V be the item matrix, S be the interpersonal influence matrix, and G be the item sender matrix. From these information, the user-user preference similarity matrix W, item-item content similarity matrix C, and user-user interaction matrix F is computed.

$$W_{i,j} = \frac{\sum_{a \in A(u_i)} P_{u_i}(a)}{A(u_i)} \cdot \frac{\sum_{a' \in A(u_j)} P_{u_j}(a')}{A(u_j)}$$

$$C_{i,j} = T_{a_i} \cdot T_{a_j}$$

$$F_{i,j} = \frac{|S(u_i,u_j) \cap A(u_i)|}{|S(u_i,u_j)|}.$$

The users that are similar in hidden user space have similar preferences. The items that are similar in hidden item space have similar descriptive contents. High interpersonal influence in the hidden influence space generates frequent interpersonal interactions. The product of user hidden space and item hidden space corresponds to the users' individual preference on the items. The Hadamard product of interpersonal influence and individual preference is proportional to the probability of item adoptions.

Here it is based on a probabilistic linear model with Gaussian observation noise as in [12]. The conditional distribution [11] over the observed entries in R as:

Incorporating social contextual factors and maximizing the pos-

$$P(R \mid S,U,V,\sigma_R^2) = \prod_{i=1}^{M} \prod_{j=1}^{N} N(R_j \mid S_i G_j^T \circ U_i^T V_j, \sigma_R^2)$$

terior distributions[11] which is equal to the minimizing the sum-of-squared errors function with hybrid quadratic regularization terms

$$\begin{aligned} J = & \|R - SG^T \circ U^T V\|_F^2 + \alpha \|W - U^T U\|_F^2 \\ & + \beta \|C - V^T V\|_F^2 + \gamma \|F - S\|_F^2 + \delta \|S\|_F^2 \\ & + \eta \|U\|_F^2 + \lambda \|V\|_F^2 \end{aligned}$$

where and

$$\alpha = \frac{\sigma_R^2}{\sigma_W^2}, \beta = \frac{\sigma_R^2}{\sigma_C^2}, \gamma = \frac{\sigma_R^2}{\sigma_F^2}, \delta = \frac{\sigma_R^2}{\sigma_S^2}, \eta = \frac{\sigma_R^2}{\sigma_U^2}, \lambda = \frac{\sigma_R^2}{\sigma_V^2}$$

||.||F is the Frobenius norm.

Starting is from random initialization on S, U, V. Two matrices are kept fixed and solve each of the given matrices alternatively. Proceed step by step until convergence. The objective is obviously lower bounded by 0. The alternating gradient search procedure will reduce it in order. In this paper, the gradient search method[11] is used to solve the problem. The gradients of the objective with respect to the variables are

$$\begin{aligned} \frac{\partial J}{\partial S} = & -2(R - SG^T \circ U^T V)G \\ & - 2\gamma(F - S) + 2\delta S, \end{aligned}$$

$$\begin{aligned} \frac{\partial J}{\partial U} = & -2V(R - SG^T \circ U^T V)^T G \\ & - 4\alpha U(W - U^T U) + 2\eta U, \end{aligned}$$

$$\frac{\partial J}{\partial V} = -2U(R - \mathcal{S}G^{T} \circ U^{T}V) - 4\beta V(C - V^{T}V) + 2\lambda S$$

Gradient-based approach to social contextual model is based on Algorithm 1[11]. J decreases the fastest in the direction of gradients during each iteration and the sequence ($J^{(t)}$) converges to the desired minimum.

New User Problem And New Item Problem

The new user problem and the new item problem consists of mainly two important factors: (1) If a new user comes, how do we recommend an item without having any idea about his preferences?, (2)When a new item is added how does we recommend it to the user without having any rating for the item?

Here it updates the user-item matrix by adding more preferences to it. The users are given choice for expressing their interest for the items given by the system just immediately after the user registration and at any time of its use. The users get their own of choice of updating their preferences. These preferences are taken stored and added with the user-item preference to perform the rest. Now the system use this inbuilt preference with three matrices: user matrix, item matrix, and user-user influence matrix.

A(u,a) is the set of items adopted by user u. Let D(u,b) be set of preferred items b manually by user u. Then the new set of items adopted by user u becomes

$$A(u,a) \cup D(u,a)$$

Let A(u,a) be updated as a new set of items obtained. How much a user like an item a is calculated by naïve preference measurement which becomes

$$P_u(a) = T_a \cdot \left(\frac{1}{A(u,a)} \sum_{a' \in A(u,a)} T_{a'} \right)$$

For interpersonal influences, the recommended items adopted by u from u's friends or followees who send the item a is calculated by:

$$I_u(a) = \frac{1}{|V(u,a)|} \sum_{v \in V(u,a)} \frac{|S(u,v) \cap A(u)|}{|S(u,v)|}$$

Semantic meaning is considered for each item of the user. If the user has the preference of related items , the semantic meaning of the content is searched and recommendations are given considering the meanings.

Let M(u, a) be set of preferred items when considering with the semantic meaning of the set of items A(u,a). M(u,a) is obtained by getting the items from A(u,a) and searching the meaning of the content in a dictionary and this M(u,a) is used to update the set of items A(u,a).

```
Algorithm:
Data :  Content of the post by user
Initialization : Manual preferences by user
Result:   Recommendations using manual preferences and
semantic meaning of the preferences
      while Preferences are not empty do
         Get meaning of all the preferences
         Add the semantic meaning to the preferences
        if  Preferences match the content of post then
          Recommends the item
        else
          No Recommendations
        end
      end
```

Maintaining this user preference and semantic meaning provides the system to calculate the recommendation more precisely. So this cold start problem will not occur as new user will already have some preferences inbuilt. If a new item comes, users will have preferences when the semantic is also considered. This increases the recommendations of the proposed recommender system.

Conclusion

In this paper, the cold start problem finds the solution by giving preferences manually by the user at the time of registration and later on. The semantic meaning of the content are also obtained to get more recommendation based on the similar meaningful items. So the new user problem and the new item problem does not occur. i.e. When a new user comes, he/she will have the preferences updated by them. So the relevant recommendations are obtained by the system using these preferences and semantic meaning of the content. A major advantage of the proposed method is that the cold start problem does not occur.

REFERENCE

[1] G. Adomavicius and A. Tuzhilin, "Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions," IEEE Trans. Knowledge and Data Eng., vol. 17, no. 6, pp. 734-749, June 2005. | [2] H. Ma, H. Yang, M.R. Lyu, and I. King, "SoRec: Social Recommendation Using Probabilistic Matrix Factorization," Proc. 17th ACM Conf. Information and Knowledge Management (CIKM '08), pp. 931-940, 2008. | [3] H. Ma, D. Zhou, C. Liu, M.R. Lyu, and I. King, "Recommender System with Social Regularization," Proc. Fourth ACM Int'l Conf. Web Search and Data Mining (WSDM '11), pp. 287-296, 2011 | [4] M. Balabanovi_c and Y. Shoham, "FAB: Content-Based, Collaborative Recommendation," Comm. ACM, vol. 40, no. 3, pp. 66-72, 1997 | [5] B. Sarwar, G. Karypis, J. Konstan, and J. Reidl, "Item-Based Collaborative Filtering Recommendation Algorithms," Proc. 10th Int'l Conf. World Wide Web (WWW '01), 2001. | [6] Y. Koren, "Matrix Factorization Techniques for Recommender Systems," Computer, vol. 42, no. 8, pp. 30-37, 2009. | [7] M. Jiang, P. Cui, R. Liu, Q. Yang, F. Wang, W. Zhu, and S. Yang, "Social Contextual Recommendation," Proc. 21st ACM Int'l Conf. Information and Knowledge Management (CIKM '12), pp. 45-54, 2012. | [8] X. Liu and K. Aberer, "SoCo: A Social Network Aided Context-Aware Recommender System," Proc. 22nd Int'l Conf. World Wide Web (WWW '13), pp. 781-802, 2013. | [9] J. Huang, X. Cheng, J. Guo, H. Shen, and K. Yang, "Social Recommendation with Interpersonal Influence," Proc. 19th European Conf. Artificial Intelligence (ECAI '10), 2010. | [10] P. Massa and P. Avesani, "Trust-Aware Recommender Systems," Proc. ACM Conf. Recommender Systems (RecSys '07), pp. 17-24, 2007. | [11] Meng Jiang, Peng Cui, Fei Wang, Wenwu Zhu and Shiqiang Yang, " Scalable Recommendation with social contextual information," IEEE Transactions On Knowledge and Data Engineering, Vol. 26, No. 11, November 2014 | [12] R. Salakhutdinov and A. Mnih. Probabilistic matrix factorization. Neural Information Processing Systems (NIPS), 2007 |