ISSN : 0974 - 7435 Volume 10 Issue 20

2014

BioTechnology

An Indian Journal

FULL PAPER

BTAIJ, 10(20), 2014 [11940-11946]

Combining social network information with probabilistic matrix factorization to enhance recommendation performance

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ABSTRACT

This paper examines the problem of social collaborative filtering to recommend items of interest to users in a social network setting. Many social networks capture the relationships among the nodes by using trust scores to label the edges. The bias of a node denotes its propensity to trust/mistrust its neighbours and is closely related to truthfulness. It is based on the idea that the recommendation of a highly biased node should be removed. In this paper, we propose a model-based approach for recommendation employing matrix factorization after removing the bias nodes from each link, which naturally fuses the users' tastes and their trusted friends' favours together. The empirical analysis on real large datasets demonstrate that our approaches outperform other state-of-the-art methods.

KEYWORDS

Social network; Recommendation system; Matrix factorization; Trust-aware.

INTRODUCTION

With the advent of online social networks, the social network based approach to recommendation has emerged. This approach assumes a social network among users and makes recommendations for a user based on the ratings of the users that have direct or indirect social relations [1-3]. Due to their great commercial value, recommender systems [4-5] have also been successfully deployed in industry, such as product recommendation at Amazon, music recommendation at iTunes, movie recommendation at Netflix, etc.

Traditional collaborative filtering approaches predict users' interests by mining user rating history data[6-7]. The increasingly popular online social networks provide additional information to enhance pure rating-based recommender system. Several social-trust based recommendation system have recently been proposed to improve recommendation accuracy[8-11]. The common rationale behind all of them is that a user's taste is similar to and/or influenced by her trusted friends in social networks.

The first well known challenge is the data sparsity problem and cold start user. Cold start users are new users who have expressed only a few ratings. Using similarity based approaches, it is unlikely to find similar users since the cold start users only have a few ratings. Secondly, traditional recommender systems ignore the social connections or trust relations among users. But the fact is, in the real world, we always turn to friends we trust for book, music, or restaurant recommendations, and our favours can easily be affected by the friends we trust. Therefore, traditional recommender systems, which purely mine the user-item rating matrix for recommendations, do not provide realistic output[12-14].

A network based on trust is quite different from other networks. An explicit link in a network such as Facebook, Youtube signifies that two nodes are close. However, in a trust based network, two nodes may be close and may be connected but the link may show distrust. In a trust network, prestige of a node depends on the opinions of other nodes whereas trustworthiness of a node depends on how a node gives correct opinion about other nodes. We refer to truthfulness of a node as bias and prestige of a node as deserve. If a node is biased, then its opinion should not weigh significantly. Then, what another node deserves (prestige) relies more on nodes that are more truthful (i.e., have low bias). In this paper, we present a model that computes the prestige and trustworthiness of nodes in a trust-based network. It is based on the idea that the opinion of trustworthy nodes weigh more. We obtain the trustworthiness of a node by how well it computes the prestige of its neighbors.

We endow a novel under standing to all the ratings in the user-item matrix R . We interpret the rating $R_{i,j}$ in the user-item matrix as the representation mixed by both the user u_i 's taste and his/her trusted friend's tastes on the item v_j . This assumption naturally employs both the user-item matrix and the users' social trust network for the recommendations. In terms of the users' own tastes, we factorize the user-item matrix and learn two low-dimensional matrices, which are user-specific latent matrix and item-specific latent matrix. For the social trust graph, based on the intuition that users always prefer the items recommended by the friends they trust, we infer and formulate the recommendation problem purely based on their trusted friends' favors.

In this paper, by conducting latent factor analysis using probabilistic matrix factorization[15], we learn the user latent feature space and item latent feature space by employing a user social network and a user-item matrix simultaneously and seamlessly. Although recently, similar factor analysis methods have been employed in[16, 17] for document retrieval and document classification, our approach has three essential differences compared with these methods: (1) Our method can deal with missing value problem, while their methods cannot. (2) Our method is interpreted using a probabilistic factor analysis model after removing the biased nodes in the network. (3) Complexity analysis shows that our method is more efficient than their methods and can be applied to very large datasets.

FINDING THE BIAS AND PRESTIGE OF NODES

It is based on the idea that the opinion of trustworthy nodes weigh more. We obtain the trustworthiness of a node by how well it computes the prestige of its neighbors. We model the trust-based networks using graphs where the edge weight indicates the user opinion. If a user does not rate, then there is no edge.
Formally, let G = {V, E} be a graph, where an edge $e_{uv} \in E$ (directed from node u to node v) has weight $wt_{uv} \in [-1,1]$. We say that node u gives the trust-score of wt_{uv} to node v.

Let $d_{out}(u)$ denote the set of all outgoing links from node u and likewise, $d_{in}(u)$ denotes the set of all incoming links to node u. In this work, we measure two attributes of a node:

• Trustworthiness: This reflects the expected weight of an outgoing edge.
• Prestige: This reflects the expected weight of an inlink from an unbiased node.

Definitions

The trustworthiness of a node is its propensity to trust/mistrust other nodes. Thus, the propensity or trustworthiness of a node can be measured by the difference between the rating a node provides to another node (i.e., the edge weight) and the "ground" truth, i.e., what the second node truly deserves (this takes into account the trust by other nodes). The trustworthiness of a node u is given by

$$trustworthiness(u) = \frac{1}{2|d_{out}(u)|}\sum(wt_{uv} - prestige(v)) \quad (1)$$

Normalization is done to maintain the value of trustworthiness in the range of [−1, 1]. A node is truly truthful if it has a trustworthiness of 0.

A node has a positive bias if it has a propensity to give positive outlinks, and a negative trustworthiness otherwise. A node giving a positive rating to other nodes that do not deserve such ratings values would attract a high trustworthiness. Using trustworthiness, the inclination of a node toward trusting/mistrusting is measured. It can also be used to understand the true nature of a node. If a highly trustworthiness node (either positive or negative) gives a rating, then such score should be given less importance. We can do so by reducing the effect of trustworthiness from each outlink a node gives. However, if a node has an edge whose weight has an opposite sign of that of the bias, we do not make any changes. Intuitively, when a person known to give a negative feedback in general, actually gives a positive feedback, then her opinion should weigh significantly. Therefore, if a node has a positive (negative) trustworthiness and has an edge with negative (positive) weight, then we do not make any change to the edge weight.

We introduce an auxiliary variable X_{kv} to measure the effect of trustworthiness of node k on its outgoing edge to node v per-unit edge-weight:

$$X_{kv} = \begin{cases} 0 & \text{if}(trustworthiness(k) \times wt_{kv}) \le 0 \\ |trustworthiness(k)| & otherwise \end{cases} \quad (2)$$

From the above expression, we can see that when trustworthiness and edge weight are of opposite signs, X_{kv} becomes zero and there is no effect of the trustworthiness. Otherwise, X_{kv} becomes the absolute value of the trustworthiness.

We can now reduce the edge weight using the effect of trustworthiness, i.e., X_{kv}. The new weight wt'_{kv} is scaled from the old weight as follows:

$$wt'_{kv} = w_{kv}(1 - X_{kv}) \quad (3)$$

If edge-weight and bias are of opposite signs, the new weight remains the same, otherwise it is reduced.
The prestige value of a node represents the true trust a node deserves. We can use trustworthiness to define prestige. Prestige is the expected weight of an incoming link from an untrustworthiness node. For each inlink, we remove the effect of bias from the weight and then we compute the mean of all inlinks. The prestige of a node v is given by

$$prestige(v) = \frac{1}{d_{in}(v)}\sum_{k \in d_{in}(v)}(wt_{kv}(1 - X_{kv})) \quad (4)$$

Computing trustworthiness and prestige

In this section, we describe an algorithm to find the trustworthiness and prestige values of all nodes in the network. Note that the definitions as given in Eq. (1) and Eq. (4) are mutually recursive. Trustworthiness of a node depends on the prestige of its neighbours which in turn depends on the trustworthiness of their neighbours and so on. Thus, to solve this, we use the method of fixed-point iteration.

We denote the trustworthiness and prestige of node v at iteration t by $trustworthiness'(v)$ and $prestige'(v)$ respectively. We use values obtained from iteration t to compute the values for iteration $t+1$. From the initial values of trustworthiness and prestige, prestige values at the next iteration are computed for all nodes. Then, using those values, the trustworthiness values are re-estimated. Thus, $prestige^{t+1}(u)$ depends on $trustworthiness^{t}(*)$, which in turn is computed using $prestige^{t}(*)$. Eq. (1) and Eq. (4) can be now re-written as:

$$prestige^{t+1}(v) = \frac{1}{|d_{in}(v)|}\sum_{k \in d_{in}(v)}(wt_{kv}(1 - X^{t}_{kv})) \quad (5)$$

$$trustworthiness^{t+1}(u) = \frac{1}{2|d_{out}(u)|}\sum_{v \in d_{out}(u)}(wt_{uv} - prestige^{t+1}(v)) \quad (6)$$

RECOMMENDATION WITH SOCIAL TRUST

Traditional recommender system techniques, like collaborative filtering, only utilize the information of the user-item rating matrix for recommendations while ignore the social trust relations among users. In this section, we describe a trust-aware recommendation problem based on matrix factorization technique.

Problem definition and preliminaries

In recommender systems we have a set of users $U = \{u_1, ..., u_N\}$ and a set of items $v = \{v_1, ..., v_M\}$. The ratings expressed by users on items are given in a rating matrix $R = [R_{u,v}]_{N \times M}$, in this matrix $R_{u,v}$ denotes the rating of user u on item v. $R_{u,v}$ can be any real number, but often ratings are integers in the range [1, 5]. In this paper, without loss of generality, we map the ratings 1, 5 to the interval [0,1] by normalizing the ratings. In a social rating network, each user u has a set N_u of direct neighbors and $wt_{u,v}$ denotes the value of social trust u has on v as a real number in [-1, 1]. Negative one means no trust and one means full trust. As above section described, if a highly trustworthiness node gives a rating, then such score should be given less importance, so we have removed the effect of bias nodes from the weight through computing the bias and prestige of nodes in the networks. In the following computation, we use the new edge-weight wt'_{kv} as the trust matrix (labeled w briefly).

The task of a recommender is as follows: Given a user u and an item v for which $R_{u,v}$ is unknown, predict the rating for u on item v using R and w.

In this paper, we employ matrix factorization techniques to learn the latent characteristics of users and items and predict the unknown ratings using these latent characteristics. Let $U \in R^{K \times N}$ and $V \in R^{K \times M}$ be latent user and item feature matrices, with column vectors U_u and V_i representing K-dimensional user-specific and item-specific latent feature vectors of user u and item v, respectively. The goal of matrix factorization is to learn these latent variables and exploit them for recommendation.

The social matrix factorization model

Following, we present our approach to incorporate trust propagation into a matrix factorization model for recommendation in social networks[18].

Due to social influence, the behavior of a user u is affected by his direct neighbors Nu. We formulate this influence as follows:

$$\overline{R}_{ik} = \sum_{j \in N_u} w_{i,j} R_{jk} \tag{7}$$

Where $\overline{R}_{ik}$ is the prediction of the rating that user u_i would give item v_j. R_{jk} is the score that user u_j give item v_k. Then the prediction of the ratings that user u gives to all the items can be inferred as:

$$\begin{pmatrix} \overline{R}_{i,1} \\ \overline{R}_{i,2} \\ \cdots \\ \overline{R}_{i,m} \end{pmatrix} = \begin{pmatrix} R_{1,1} & R_{2,1} & \cdots & R_{n,1} \\ R_{2,1} & R_{2,2} & \cdots & R_{n,2} \\ \cdots & \cdot\cdot & \cdots & \cdots \\ R_{1,K} & R_{2,K} & \cdots & R_{n,m} \end{pmatrix} \begin{pmatrix} w_{i,1} \\ w_{i,2} \\ \cdots \\ w_{i,n} \end{pmatrix} \tag{8}$$

We can then infer that for all the users to obtain

$$\overline{R} = wR \tag{9}$$

Where wR can be interpreted as the recommendations based on the trusted friends' tastes.

From the social trust network aspect, we define the conditional distribution over the observed ratings as:

$$p(R \mid w, U, V, \sigma_R^2) = \prod_{i=1}^{n} \prod_{j=1}^{m} \left[N\left(R_{ij} \,\middle|\, g\left(\sum_{k \in N_u} w_{ik} U_k^T V_j\right), \sigma_w^2\right) \right]^{I_{ij}^R} \tag{10}$$

Where I_{ij}^R is the indicator function that is equal to 1 if user i rated item j and equal to 0 otherwise.

Hence, through a Bayesian inference, we have

$$p(U,V \mid R, w, \sigma_w^2, \sigma_U^2, \sigma_V^2) \propto p(R \mid w, U, V, \sigma_w^2) p(U \mid w, \sigma_U^2) p(V \mid w, \sigma_V^2)$$

We can assume that w is independent with the low-dimensional matrices U and V, then this equation can be changed to

$$p(U,V\left|R,w,\sigma_w^2,\sigma_U^2,\sigma_V^2\right.) \propto p(R\left|w,U,V,\sigma_w^2\right.)p(U\left|\sigma_U^2\right.)p(V\left|\sigma_V^2\right.)$$
$$=\prod_{i=1}^{n}\prod_{j=1}^{m}\left[N(R_{ij}\left|g(\sum_{k\in N_u}w_{ik}U_k^TV_j),\sigma_w^2\right.)\right]^{I_{ij}^R}$$
$$\times\prod_{i=1}^{n}N(U_i\left|0,\sigma_U^2\mathrm{I}\right.)\times\prod_{J=1}^{m}N(U_j\left|0,\sigma_V^2\mathrm{I}\right.) \tag{11}$$

Where $p(U\left|\sigma_U^2\right.)$ and $p(V\left|\sigma_V^2\right.)$ are zero-mean spherical Gaussian priors on user and item feature vectors. This equation specifies the method to recommend based on users' trusted friends tastes.

RESULT AND DISSCUSS

Dateset and evaluation

We choose Epinions as the data source for our experiments on recommendation with social trust ensemble. Epinions. com is a well known knowledge sharing site and review site, which was established in 1999. Every member of Epinions maintains a "trust" list which presents a social network of trust relationships between users. Epinions is thus an ideal source for experiments on social trust recommendation. The dataset used in our experiments is collected by crawling the Epinions. com site on Jan 2009. It consists of 51,670 users who have rated a total of 83,509 different items. The total number of ratings is 631,064. The density of the user-item rating matrix is less than 0.015%. We can observe that the user-item rating matrix of Epinion is very sparse, since the densities for the two most famous collaborative filtering datasets Movielens and Eachmovie are 4.25% and 2.29%, respectively. Moreover, an important factor that we choose the Epinons dataset is that user social trust network information is not included in the Movielens and Eachmovie datasets. The statistics of the Epinions user-item rating matrix is summarized in TABLE 1. As to the user social trust network, the total number of issued trust statements is 511,799. The statistics of this data source is summarized in TABLE 2.

TABLE 1:Statistics of User-Item Rating Matrix

Statistics	User	Item
Max. Num. of Ratings	1960	7082
Avg. Num. of Ratings	12.21	7.56

TABLE 2 : Statistics of Social Trust Network

Statistics	Trust per User	Be trusted per User
Max. Num.	1763	2443
Avg. Num.	9.91	9.91

We use two metrics, the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE), to measure the prediction quality of our proposed approach in comparison with other collaborative filtering and trust-aware recommendation methods. The metrics MAE is defined as:

$$MAE=\frac{\sum_{i,j}\left|r_{i,j}-\bar{r}_{i,j}\right|}{N}$$

where $r_{i,j}$ denotes the rating user *i* gave to item *j*, $\bar{r}_{i,j}$ denotes the rating user *i* gave to item *j* as predicted by a method, and *N* denotes the number of tested ratings. The metrics RMSE is defined as:

$$RMAE=\sqrt{\frac{\sum_{i,j}\left(r_{i,j}-\bar{r}_{i,j}\right)^2}{N}}$$

Experiment result

One challenge of the recommender systems is that it is difficult to recommend items to users who have very few ratings. Hence, in order to compare our approach with the other methods thoroughly, we first group all the users based on the number of observed ratings in the training data, and then evaluate prediction accuracies of different user groups. We compare our method with the following approaches: 1) PMF: this method is proposed by Salakhutdinov and Minh in [19]. It only uses user-item matrix for the recommendations, and it is based on probabilistic matrix factorization. 2) Trust: this is the method purely uses trusted friends' tastes making recommendations. It is proposed in Section 3.2 in this paper. The experimental results are shown in Figure 1. Users are grouped into 6 classes: "1−10", "11−20", "21−40", "41−80", "81 − 160" and "> 160", denoting how many ratings users have rated.

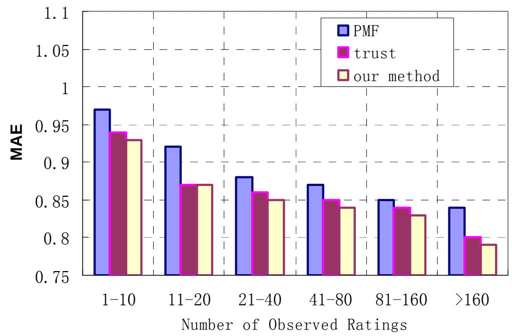

Figure 1 : MAE comparison on different user rating scales

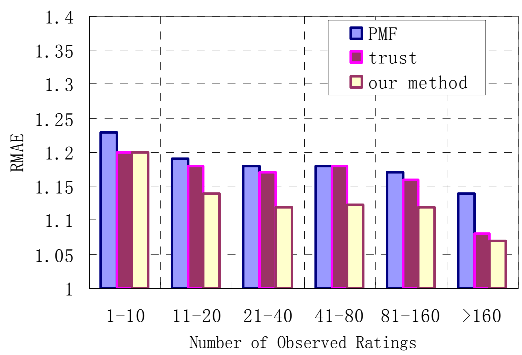

Figure 2: RMSE comparision on different user rating scales

In Figure 1 and Figure 2, we observe that our algorithm consistently performs better than other methods, especially when few user ratings are given. When users' rating records are ranging from 1 to 80, our method performs much better than the Trust, PMF approaches.

CONCLUSION

With the advent of online social networks, exploiting the information hidden in the social network to predict the behaviour of users has become very important. In this paper, we presented a novel approach to improve recommendation accuracy by introducing the social network information. Based on the intuition that a user's social network will affect this user's behaviour on the Web, we present a novel social recommendation framework removing the biased node before probabilistic matrix factorization. The experimental results show that our approach outperforms the other state-of-the-art collaborative filtering algorithms, our method can be applied to other popular research topics, such as social search and many other tasks in information retrieval and data mining. In our experiments on publicly available data, we showed significant improvements over existing approaches that use mixed social network information.

ACKNOWLEDGMENTS

The research is supported by the key project of science and technology plan from Lianyungang City, No.CG1214, No.CG1315. The research is supported by the Natural Science Foundation of Jiangsu Province Nos. 13KJB520002, 14KJB520005. A Project Funded by the Priority Academic Program Development of Jiangsu Higher Education Institutions, jiangsu province college students' innovative entrepreneurial training projects. National Natural Science Funds of China (Grant No. 61403156, No.61403155)

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