Jointly Modeling Content, Social Network and Ratings for Explainable and Cold-start Recommendation

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Abstract

Model-based approach to collaborative filtering (CF), such as latent factor models, has improved both accuracy and efficiency of predictions on large and sparse dataset. However, most existing methods still face two major problems: (1) The recommendation results derived from user and item vectors of a set of unobserved factors are lack of explanation; (2) Cold start users and items out of user-item rating matrix cannot be handled accurately. In this paper, we propose a hybrid method for addressing the problems by incorporating content-based information (i.e., users' tags and items' keywords) and social information. The main idea behind our method is to build content association based on three factors-user interest in selected tags, tag-keyword relation and item correlation with extracted keywords, and then recommend the items with high similarity in content to users. Two novel methods-neighbor based approach and 3-factor matrix factorization are proposed for building tag-keyword relation matrix and learning user interest vector for selected tags and item correlation vector for extracted keywords. Besides, we introduce a social regularization term to help shape user interest vector. Analysis shows our method can generate explainable recommendation results with simple descriptions, and experiments on real dataset demonstrate our method improves recommendation accuracy of state-of-the-art CF models for previous users and items with few ratings, as well as cold start users and items with no rating.

Keywords: Collaborative Filtering, Recommender Systems, Explanation, Cold Start, Tag-Keyword

1. Introduction

Collaborative filtering (CF) has been proposed as a preferred technique for building recommender systems, which recommends items to users by information filtering on the past ratings of users on items. In the last few years, model-based CF methods, such as latent factor models [1, 2, 3], have become not only a hotspot in academic research, but also a focus concerned by industrial community due to their good accuracy and efficiency on large and sparse dataset. However, pure model-based methods face some crucial challenges (e.g., sparsity, cold start, prediction quality, scalability, etc). Despite that two recent attempts: context-aware [4, 5, 6, 7] and social-aware [8, 9, 10, 11, 12, 13, 14] have been conducted in the challenges, there are still two problems existing in most of the improved methods.

One important problem is explanation [15], which gets little attention of researchers in the past. The premise behind latent factor models is that user behaviour is determined by a small number of unobserved factors, and user's ratings on item are modeled by linearly combining user and item vectors of the factors. First, it is difficult to know what do the factors represent explicitly, which make it difficult for application providers to identify whether the recommended items match user interest. Second, making recommendation arbitrarily with the ratings is inefficient,

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Figure 1. User-item ratings establish the relationships between users' tags and items' keywords.

which make it difficult for users to accept the recommended items. Many times, the recommended items are quite to match user interest, but most users have an idle nature, cannot be proactive in clicking the links to take a closer look at the strange items, which make users missing the useful items. So an excellent recommender system needs not only to provide the items users really want, but also to help users understand the recommended items.

Another important problem is cold start (i.e., new users and new items) [16], viewed as a special case of the sparsity that happens in most of CF methods. From application providers perspective, the users and items newly added to the system contain a potential for huge new transactions. Meanwhile new items may get the special attention of users. Hence, efficiency of cold start recommendation is very important to providers' profit growth and users' satisfaction. Latent factor models that rely on user's and item's ratings cannot make recommendations for new users and new items since no rating is available to form their latent factor vectors. Some recent methods [17, 18, 11, 10, 19, 20, 21] are proposed to handle cold start users or items by incorporating additional information, such as content, context and social network. But no method is effective in the specific case of recommending new items to new users. Besides, in a practical application, the situations that context is difficult to get and social network is very sparse limit the use of the models. Therefore, cold start problem still needs further improvement.

Rather than complex context and social information, content-based information (i.e., user's tags and item's keywords) is not only more easily obtained, but also more direct to describe user interest and item features. User-item ratings establish the relationships between users' tags and items' keywords (Figure 1). A promising approach thus arises: we can build content association between user and item based on the tag-keyword relation (Figure 2), and then recommend the items with high similarity in content to users. This approach can not only give a good explanation of the recommendation results, but also use the previous tags and keywords to identify new users' interest and new items' features. However, there are three main challenges for designing this approach: (1) there are missing tag-keyword relations that is no related to user-item ratings; (2) every user has different interest in selected tags; (3) every item has different correlation with extracted keywords.

Based on the above discussion, we propose a hybrid method which generate explainable recommendation, meanwhile address cold start problem to some extent by incorporating content-based information and social information. We first propose a novel neighbor-based approach for helping to build the tag-keyword relation matrix, where partial missing entries are calculated based on the known relations between tags and keywords with the highest co-occurrence

Figure 2. We can make prediction based on the tag-keyword relation instead of the user-item rating matrix. But, there are missing tag-keyword relations that is no related to user-item ratings; every user has different interest in selected tags; every item has different correlation with extracted keywords.

frequency. Then, we propose a novel 3-factor matrix factorization model over the rating matrix for learning every user's interest vector for selected tags and every item's correlation vector for extracted keywords. In particular, we introduce a social regularization term to help shape user interest vectors by considering the influence of a user's friends. Finally, interest vectors, correlation vectors and tag-keyword relation matrix are integrated to make recommendations. Analysis shows our method can generate explainable recommendation results with simple descriptions attached to every recommended item that help users understand the item, and extensive experiments on real data show the accuracy improvement of our method over state-of-the-art CF models on making recommendations for previous users and items with few ratings, as well as cold start users and items with no rating.

The rest of this paper is organized as follows: In Section 2, we review the related work. In Section 3, we give the problem formulation. In Section 4, we present our method in detail. In Section 5, we report the experimental settings and results. In Section 6, we conclude this paper.

2. RELATED WORK

In this section, we review several major approaches to recommender systems [22] (content-based filtering, collaborative filtering and latent factor model) and the problems (explanation and cold start).

2.1. Content-based and Collaborative Filtering

Content-based filtering analyzes a set of descriptions of items previously rated by a user, and maintain a list of features for the user. The basic idea is to recommend the items based on how well the features of items match up the features of the user. Recently, some topic model-based methods [23, 24, 21] have been proposed to make recommendation based on semantic content. Content-based filtering has several advantages that not only provide good explanation on why the items occur in the recommended list, but also have the ability of recommending cold start items not yet rated to any user; nevertheless, the working on individual user needs specialized content-based technique and enough user ratings, which limit the application range of this method.

Collaborative filtering [25] relies on user-item ratings, which mainly contains two classes: memory-based and model-based. Memory-based [26, 27, 28, 29] use similarity comparison (e.g., *VSS* or *PCC* [27]) to build neighborhood relationship between users or items, and predict missing ratings based a weighted sum of ratings from similar users or items. Model-based [1, 2, 3], in contrast, use user-item ratings to train a model first, and then make recommendation via the model. Many experimental results and conclusions argue that model-based methods lead to somewhat more accurate results on large and sparse data, while memory-based methods have some practical advantages.

2.2. Latent Factor Model

Latent factor model, such as matrix factorization is a popular model-based approach, which decomposes $m \times n$ rating matrix R into two low-rank matrices: $U \in \mathbb{R}^{m \times d}$ and $V \in \mathbb{R}^{n \times d}$ ($d < \min(m, n)$), the product of which is used to construct a matrix approximation $R \approx UV^T$. One of the most popular methods by minimizing the sum-of-squared-errors objective function with quadratic regularization terms is

$$\mathcal{L} = \sum_{u=1}^m \sum_{v=1}^n I_{u,v} (R_{u,v} - U_u V_v^T)^2 + \lambda_1 \|U\|_F^2 + \lambda_2 \|V\|_F^2 \quad (1)$$

where λ_1 and λ_2 is the extent of regularization and $\|\cdot\|_{Fro}$ is the Frobenius norm. $I_{u,v}$ is the indicator function that is equal to 1 if user u rated item v and equal to 0 otherwise. The optimization problem in Equation 1 can be solved by performing gradient decent on U_u and V_v . Then, the missing rating can be predicted by $U_u V_v^T$.

Pure model-based methods have several challenges, such as data sparsity, scalability, cold start and poor prediction. Two recent attempts have been done to alleviate the above problems, one with contextual information [6, 7] and one with social information [12, 13, 14]. Context-aware recommendation [4, 5] take additional specific contexts (time, location emotion, review, etc) into account to give more accurate prediction. Social recommendation [8, 9, 10, 11] incorporating social networks information improve prediction quality and cold start user.

2.3. Explanation and Cold Start

In recommender systems, the accuracy metrics, such as MAE and RMSE are often used to evaluate the recommendation quality. However, the good prediction accuracy on benchmark datasets do not mean that we can make maximum use of recommender systems. In real world applications, lack of explanation may greatly reduce efficiency of the recommendation results. For example, poor explanation on how the system works reduces the reliability of recommender systems [30], and poor explanation on the recommended items reduces the acceptance of user on the items [31]. There is not much previous work on explanation [32, 33]. [32] proposed a unied framework, Personalized Semantic Ranking (PSR), to incorporate the user-generated content (UGC), and utilize the semantic information extracted from UGC to serve as proper explanations for recommendation. [33] proposed a Social-Relational Topic Model (SRTM), which jointly models UGC and social links into a unified generative process for alleviating the effect of topic-irrelevant links and obtaining reliable topics to explain the recommendation. But, they ignore the item-generated content, and cannot give the clear answer which item feature most attract the current user's interest to the given item.

Cold start is a common problem in recommender systems. Although latent factor model improves prediction accuracy when rating data is sparse, it does not work for cold-start recommendation where no rating data on users or items is available. There are some recent hybrid approaches on cold start: some with content information [17, 18], some with social information [11, 10] and some with context information [20, 19, 34]. But the problem is far from solved completely, especially recommending new items to new users. Recently, some cross-platform based methods [35, 36] are proposed to alleviating the data sparsity and cold-start problems. Based on the knowledge on different platforms, they explore the cross-platform collaborative relationship derived from content-based and network-based information to improve the recommendation. But, as to user privacy protection and industrial competition, the other platforms are often governed strictly on access for the related knowledge, which limit their scope of use.

In recent years, tag recommendation [37] and keyword extraction [38] techniques are largely applicable to the web. Tag and keyword both provide meaningful content descriptors of the objects, where tags selected by users have expressions of their interest and keywords extracted from items mean their features. That motivates us to attempt to improve explanation and cold start problems by combining content relationship between user and item with user-item ratings for the recommendation task.

3. PROBLEM FORMULATION

Suppose that we have a set of users $\mathcal{U} = \{u_1, \dots, u_m\}$ and a set of items $\mathcal{V} = \{v_1, \dots, v_n\}$, and the ratings are expressed by a matrix $R \in \mathbb{R}^{m \times n}$. Let $\mathcal{K}_U = \{k_1^U, \dots, k_M^U\}$ be a set of tags and $\mathcal{K}_V = \{k_1^V, \dots, k_N^V\}$ be a set of keywords. $K_U(u)$ denotes the tags selected by user u and $K_V(v)$ denotes the keywords extracted from item v (an example is shown

User	Tags	Item	Keywords
u_1	{sport, iFans, action}	v_1	{durable, practical}
u_2	{iFans, shopping}	v_2	{iphone, high-tech, novel}
u_3	{sport, action, young}	v_3	{Nike, durable, practical}
u_4	{vegetarian, fantasy}	v_4	{practical, high-tech, durable}
u_5	{sport, shopping, young}	v_5	{Nike, novel, durable}

(a) Users' tags
(b) Items' keywords

Figure 3. Example users' tags and items' keywords datasets

in Figure 3). We define the tag-keyword relation matrix $S \in R^{M \times N}$, where $S_{i,j}$ denotes the similarity between tag i and keyword j . To consider user's different interest in selected tags, we define an interest vector $P_u = (p_u^{(1)}, \dots, p_u^{(|K_U(u)|)})$ for every user, the z -th element $p_u^{(z)}$ of which defines user u 's interest in the z -th tag of $K_U(u)$. Likewise, to consider item's different correlation with extracted keywords, we define correlation vector $Q_v = (q_v^{(1)}, \dots, q_v^{(|K_V(v)|)})$ for every item, the z -th element $q_v^{(z)}$ of which defines item v 's correlation with the z -th keyword of $K_V(v)$.

Our goal is to build content association between user and item based on the three factors-tag-keyword relation matrix S , user interest vector P_u and item correlation vector Q_v , and then recommend the items with high similarity in content to users.

4. OUR METHOD

As mentioned before, our method relies on having: (1) tag-keyword relation matrix S ; (2) user interest vector P_u for selected tags; (3) item correlation vector Q_v for extracted keywords. In this section, we will systematically describe our solutions for parameters estimation and prediction.

4.1. Building the Tag-Keyword Relation Matrix

User-item ratings establish the relationships between users' tags and items' keywords. Let the tuple $\langle k_i^U, k_j^V, R_{z^*} \rangle$ denote a set of ratings R_{z^*} , where z^* is a user-item pair (u, v) that contain tag k_i^U and keyword k_j^V respectively. We first initialize partial entries of the relation matrix S that is related to the observed tuples. Then, we exploit the known entries for filling in the missing entries.

Initialization. Generally, a tag is selected by multiple users and a keyword is shared by multiple items, leading to multiple instances of the same tag-keyword pair with different rating values. Assume that we have a list of tuples related to tag i and keyword j

$$\Phi_{i,j} = \{ \langle k_i^U, k_j^V, R_{1^*} \rangle, \langle k_i^U, k_j^V, R_{2^*} \rangle, \dots, \langle k_i^U, k_j^V, R_{N^*} \rangle \}$$

and $\vec{n}_{i,j} = \{n_{i,j}^{(1)}, \dots, n_{i,j}^{(r)}\}$ count the occurrences of rating scale $\{1, \dots, r\}$ with N^* total ratings. We then compute $S_{i,j}$ as

$$S_{i,j} = \sum_{z=1}^r \frac{n_{i,j}^{(z)} z}{N^*} \quad (2)$$

which ensures $S_{i,j}$ is a weighted sum of the ratings in $\Phi_{i,j}$. A simple example of the calculation is shown in Figure 4(a).

Fill in the missing entries. This task can be done by any typical CF approach, such as memory-based or model-based methods that suffer from the sparsity of the rating matrix. However, what it different from general case about the rating matrix is that some tags or keywords frequently appear together in users' $K_U(u)$ or items' $K_V(v)$ (e.g.,

Figure 4. A example of initializing one entry $S_{i,j}$ of the relation matrix based on the ratings $\{R_1^*, R_2^*, \dots, R_{N^*}^*\}$ in the tuples $\Phi_{i,j}$, and a example of filling one missing entry $S_{sport,durable}$ based on the neighborhood points generated by $C_2^T(sport)$ and $C_2^K(durable)$. The users and items are the examples in Figure 3. Note that $\vec{n}_{i,j} = \{n_{i,j}^{(1)}, \dots, n_{i,j}^{(r)}\}$ count the occurrences of rating scale $\{1, \dots, r\}$ with N^* total ratings.

tags $\{sport, yong\}$ and keywords $\{durable, practical\}$ in Figure 3). We therefore propose a neighbor-based approach for calculating partial missing entries based on the known relations between tags and keywords with the highest co-occurrence frequency, meaning a preprocessing for improving CF approach against the sparsity of S . Let $C_k^T(i)$ denote a set of tags that have $Top - k$ co-occurrence frequency with tag i and $C_k^K(j)$ denote a set of keywords that have $Top - k$ co-occurrence frequency with keyword j . We compute the missing $S_{i,j}$ using a weighted sum of the neighbor entries related to $C_k^T(i)$ and $C_k^K(j)$.

$$S_{i,j} = \sum_{z \in C_k^T(i)} \sum_{w \in C_k^K(j)} \frac{N_{i,z}^T + N_{j,w}^K}{N(i,j)} I_{z,w} S_{z,w} \quad (3)$$

where $N_{i,z}^T$ denote the co-occurrence number of tags i and z , and $N_{j,w}^K$ denote the co-occurrence number of keywords j and w . $N(i,j)$ is the normalization

$$N(i,j) = \sum_{z \in C_k^T(i)} \sum_{w \in C_k^K(j)} I_{z,w} (N_{i,z}^T + N_{j,w}^K) \quad (4)$$

where $I_{z,w}$ is the indicator function that is equal to 1 if $S_{z,w}$ is known and equal to 0 otherwise, ensuring that $S_{i,j}$ only weights across the known $S_{z,w}$. A simple example of calculating $S_{i,j}$ using the $Top - 2$ $C_2^T(i)$ and $C_2^K(j)$ is shown in Figure 4(b). After the preprocessing stage, we apply a CF approach on S to fill in all the rest missing entries. Note that our preprocessing, at best, can fill in all the missing entries, which eliminates the need to apply CF approach; at worst, do not fill in any entry, which maintains CF approach on the original S .

4.2. Learning User Interest vector and Item Correlation Vector

Although we build the full relation matrix S , a user has different interest in selected tags and an item have different correlation with extracted keywords. In order to provide personalized and accurate recommendation, we propose a 3-factor matrix factorization model for learning interest vector P_u and correlation vector Q_v . Let $S'_{u,v}$ denote a sub-matrix of S only corresponding to the relations between user u 's tags $K_U(u)$ and item v 's keywords $K_V(v)$.

We define the prediction $\hat{R}_{u,v}$ of user u ' rating on item v as a bilinear function of P_u and Q_v in the following:

$$\hat{R}_{u,v} = \sum_{a=1}^{|K_U(u)|} \sum_{b=1}^{|K_V(v)|} P_{u,a} (S'_{u,v})_{a,b} Q_{v,b} \quad (5)$$

where the known $(S'_{u,v})_{a,b}$ measures the affinity of the two factors $P_{u,a}$ and $Q_{v,b}$. The equation is rewritten as a simple form (an example is shown in Figure 5):

$$\hat{R}_{u,v} = P_u S'_{u,v} Q_v^T \quad (6)$$

Furthermore, we formulate the optimization problem for finding the best P_u and Q_v as

$$\mathcal{L} = \sum_{u=1}^m \sum_{v=1}^n I_{u,v} (R_{u,v} - P_u S'_{u,v} Q_v^T)^2 + \frac{\lambda_1}{2} \sum_{u=1}^m \|P_u\|_F^2 + \frac{\lambda_2}{2} \sum_{v=1}^n \|Q_v\|_F^2 \quad (7)$$

which transforms traditional 2-factor factorization in Equation 1 into a 3-factor factorization in Equation 7. The advantage of our method is that the dimensions of the vectors P_u and Q_v are equal to the number of $K_U(u)$ and $K_V(v)$, which relax the low-rank assumption in traditional matrix factorization. A local minimum of the objective function can be found by performing gradient descent on P_u and Q_v for all users and items.

$$\frac{\partial \mathcal{L}}{\partial P_u} = \sum_{v=1}^n I_{u,v} (P_u S'_{u,v} Q_v^T - R_{u,v}) Q_v (S'_{u,v})^T + \lambda_1 P_u \quad (8)$$

$$\frac{\partial \mathcal{L}}{\partial Q_v} = \sum_{u=1}^m I_{u,v} (P_u S'_{u,v} Q_v^T - R_{u,v}) P_u S'_{u,v} + \lambda_2 Q_v \quad (9)$$

4.3. An Enhanced Model by Social Regularization

On the basic of our 3-factor matrix factorization model presented in the previous section, we propose an enhanced model taking into account social information to better shape user interest. Inspired by *SoReg* [11], we make an assumption: if user i has a friend f , there is a similarity between their interest. But, unlike user latent factor vectors with the same dimension in *SoReg*, the dimensions of user interest vectors in our method are equal to the number of every user's tags, different from each other. Hence, we cannot use *SoReg* directly to impose constraints on user interest vectors. Even so, every user's interest on all keywords can be calculated as $P_u S'_u$, where S'_u is a sub-matrix of S corresponding to the relations between user u 's tags $K_U(u)$ and all keywords $\mathcal{K}_V$. All users' $P_u S'_u$ are in the same dimension (an example is shown in Figure 6), and we propose a social regularization term

$$\frac{\alpha}{2} \sum_{u=1}^m \sum_{f \in \mathcal{F}(u)} \text{sim}(u, f) \|P_u S'_u - P_f S'_f\|_F^2 \quad (10)$$

to constrain interest on all keywords between one user and their friends, where α is a constant controlling the extent of social regularization and $\text{sim}(u, f)$ is the similarity function. In this paper, we apply Pearson Correlation Coefficient (*PCC*) to measure the similarity.

$$\text{sim}(u, f) = \frac{\sum_{j \in I(u) \cap I(f)} (R_{u,j} - \bar{R}_u) (R_{f,j} - \bar{R}_f)}{\sqrt{\sum_{j \in I(u) \cap I(f)} (R_{u,j} - \bar{R}_u)^2} \sqrt{\sum_{j \in I(u) \cap I(f)} (R_{f,j} - \bar{R}_f)^2}} \quad (11)$$

With the social regularization, our model is redefined as

$$\mathcal{L} = \sum_{u=1}^m \sum_{v=1}^n I_{u,v} (R_{u,v} - P_u S'_{u,v} Q_v^T)^2 + \frac{\alpha}{2} \sum_{u=1}^m \sum_{f \in \mathcal{F}^+(u)} \text{sim}(u, f) \|P_u S'_u - P_f S'_f\|_F^2 + \frac{\lambda_1}{2} \sum_{u=1}^m \|P_u\|_F^2 + \frac{\lambda_2}{2} \sum_{v=1}^n \|Q_v\|_F^2 \quad (12)$$

Figure 5. With an extra factor: sub-relation matrix $S'_{u,v}$, we transform the traditional 2-factor matrix factorization $U_u V_v^T$ in Equation 1 into a 3-factor matrix factorization $P_u S'_{u,v} Q_v^T$ in Equation 7.

Figure 6. $P_u S'_u$ with the same dimension represents every user u 's interest on all keywords $\mathcal{K}_V$. Based on the concept of “social recommendation” that users may share similar interest with their friends, there is similar interest on all keywords between one user and their friends.

The new gradient descents on P_u and Q_v are

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial P_u} = & \sum_{v=1}^n I_{u,v} (P_u S'_{u,v} Q_v^T - R_{u,v}) Q_v (S'_{u,v})^T + \sum_{f \in \mathcal{F}^+(u)} \text{sim}(u, f) (P_u S'_u - P_f S'_f) (S'_u)^T \\ & + \sum_{g \in \mathcal{F}^-(u)} \text{sim}(u, g) (P_u S'_u - P_g S'_g) (S'_u)^T + \lambda_1 P_u \end{aligned} \quad (13)$$

$$\frac{\partial \mathcal{L}}{\partial Q_v} = \sum_{u=1}^m I_{u,v} (P_u S'_{u,v} Q_v^T - R_{u,v}) P_u S'_{u,v} + \lambda_2 Q_v \quad (14)$$

where $\mathcal{F}^+(u)$ denote user u 's outlink friends and $\mathcal{F}^-(u)$ denote user u 's inlink friends.

4.4. Training and Prediction

Our method consists of the following two steps: on the first step, we propose a novel neighbor-based approach for building the relation matrix S ; on the second step, we propose a novel 3-factor matrix factorization model for learning interest vector P_u and correlation vector Q_v . The whole training algorithm is shown in Algorithm 1.

Algorithm 1 The whole training algorithm

Input: List of tuples $\Omega = \langle \text{tags}, \text{keywords}, \text{ratings} \rangle$; $\mathcal{K}_U = \{k_1^U, \dots, k_M^U\}$; $\mathcal{K}_V = \{k_1^V, \dots, k_N^V\}$; $K_U(u)$; $K_V(v)$.

Output: The relation matrices S ; user interest vectors P_u ; item correlation vector Q_v .

From Ω , $K_U(u)$ and $K_V(v)$, construct the tuples $\Phi_{i,j}$ corresponding to every tag-keyword pair.

1: Building the Tag-Keyword Relation Matrix

Initialization:

```
for  $i \leftarrow 1, \dots, M$  do
  for  $j \leftarrow 1, \dots, N$  do
    if  $\Phi_{i,j} \notin \emptyset$ , then calculate  $S_{i,j}$  using Equation 2.
  end for
end for
```

Fill in the missing entries:

```
for  $i \leftarrow 1, \dots, M$  do
  for  $j \leftarrow 1, \dots, N$  do
    if  $\Phi_{i,j} \in \emptyset$  then
      From  $K_U(u)$  and  $K_V(v)$ , construct the  $C_k^T(i)$  and  $C_k^K(j)$  corresponding to tag  $i$  and keyword  $j$ .
      Estimate  $S_{i,j}$  using Equation 3.
    end for
  end for
  if there are missing entries in  $S$ , run CF method on  $S$  to fill in them.
```

2: Learning user interest vectors and item correlation vectors

```
for  $t \leftarrow 1, 2, \dots$  do
  Calculate  $\frac{\partial \mathcal{L}}{\partial P_u}^{(t-1)}$  and  $\frac{\partial \mathcal{L}}{\partial Q_v}^{(t-1)}$  using Equation 8 and 9 (or 13 and 14).
   $P_u^{(t)} = P_u^{(t-1)} - \lambda_1 \frac{\partial \mathcal{L}}{\partial P_u}^{(t-1)}$ 
   $Q_v^{(t)} = Q_v^{(t-1)} - \lambda_2 \frac{\partial \mathcal{L}}{\partial Q_v}^{(t-1)}$ 
  Repeat the iterative computation until convergence.
end for
```

Explainable recommendation: Given a user-item pair (u, v) , $P_u S'_{u,v}$ is a $1 \times |K_V(v)|$ vector whose elements represent user u 's interest in item v 's keywords. By integrating with Q_v correlation on every keyword, we have a set

$$\Upsilon(u, v) = \left\{ \left[P_u S'_{u,v} \right]_1 Q_{v,1}, \left[P_u S'_{u,v} \right]_2 Q_{v,2}, \dots \right\} \quad (15)$$

which correspond with user interest on item v 's keywords. Note that the sum of elements in $\Upsilon(u, v)$ is the prediction (i.e., $P_u S'_{u,v} Q_v^T$) for user u 's rating on item v . Based on the values of $\Upsilon(u, v)$, we can select some of the best keywords from $K_V(v)$ to design a simple description attached to the recommended item. For instance, for a “sport” user, the keywords “practical” and “durable” may draw more user’s attention rather than other keywords in $K_V(v)$ do. So we take the two keywords as an identifier to help recommending the shoes to the “sport” user, even can form a message prompt

*The Nike shoes are **practical and durable**, which you may need right now.*

Obviously, users prefer to the products understood intuitively rather than the strange products lacking of description information. And, compared to previous work [32, 33], the method can explicitly declare which item feature may attract the current user's interest.

Cold start recommendation: In addition to making recommendations for present users and items, our method can perform the following cold start recommendation for new users and new items:

- **New user.** If the new user u_{new} 's tags are known and included in $\mathcal{K}_U$, we can compute user u_{new} 's rating on any item v using $P_{u_{new}} S'_{u_{new},v} Q_v^T$. However, we cannot learn $P_{u_{new}}$ because there is no user u_{new} 's historical rating data. In this case, every tag in $\mathcal{K}_U(u_{new})$ is treated fairly:

$$P_{u_{new}} = \left(\frac{1}{|\mathcal{K}_U(u_{new})|}, \dots, \frac{1}{|\mathcal{K}_U(u_{new})|} \right) \quad (16)$$

- **New item.** If the new item v_{new} 's keywords are known and included in $\mathcal{K}_V$, we can compute any user u 's rating on item v_{new} using $P_u S'_{u,v_{new}} Q_{v_{new}}^T$. However, we cannot learn $Q_{v_{new}}$ because there is no item v_{new} 's historical rating data. In this case, every keyword in $\mathcal{K}_V(v_{new})$ is treated fairly:

$$Q_{v_{new}} = \left(\frac{1}{|\mathcal{K}_V(v_{new})|}, \dots, \frac{1}{|\mathcal{K}_V(v_{new})|} \right) \quad (17)$$

- **New users and new items.** In this extreme case, our model can still make recommendations as long as the new user u_{new} 's tags and new item v_{new} 's keywords are known. The prediction formula is $P_{u_{new}} S'_{u_{new},v_{new}} Q_{v_{new}}^T$, where $P_{u_{new}}$ and $Q_{v_{new}}$ are Equation 16 and 17.

5. EXPERIMENTS

5.1. Datasets

Tencent Weibo¹ is one of the largest Chinese online social websites. As a micro-blogging, it has become a major online communication platform for following some items' trend, building friendship and sharing interest. In our experiments, we choose the real Tencent Weibo data published by KDD Cup 2012². This dataset is much bigger and richer than before (Netflix, Movielens, Epinions and so on), sampling from 425 million weibo users for 50 days and containing 2 million active users, more than 6000 items, 300 million recommendation records and 3 million following actions. Meanwhile, the dataset contains social network information and much description information such as user's tags, item's keywords, item's category, timestamps and so on. We will predict user's action to items, where 1 represents the user accepts the recommendation of item, and 0 represents the user rejects the recommended item.

We extract a small dataset over a period of time randomly. The basic statistics of the dataset are summarized in Figure 7 (a). The density of the user-item rating matrix is

$$\frac{379598}{12518 \times 3610} = 0.83\%$$

The average user has 30 following/not following actions. We divide the rating data into five parts (Figure 7 (b)). The biggest part is used as the training set R_{train} and the test set R_{test} . Only the users of dataset R_{new}^U do not exist in the training data. Only the items of dataset R_{new}^I do not exist in the training data. Both the users and items of dataset R_{new}^{UI} do not exist in the training data. Different proportions of R_{train} and R_{test} will be applied to the performance comparison experiments. We use R_{new}^U , R_{new}^I and R_{new}^{UI} to test the performance of our model for cold start recommendation in Section 5.6.

¹<http://t.qq.com/>

²<http://www.kddcup2012.org/>

Figure 7. The extracted dataset

5.2. Metrics

In our experiments, we use two kinds of popular metrics to evaluate the performance: one with rating, *MAE*; one with ranking, *Recall*.

MAE, short for Mean Absolute Error, is defined as

$$MAE = \frac{1}{|R_{test}|} \sum_{R_{u,v} \in R_{test}} |R_{u,v} - \hat{R}_{u,v}| \quad (18)$$

where $R_{u,v}$ in R_{test} denotes the information adoption value given to item v by user u . The smaller *MAE* value means better performance.

Recall is defined as the ratio of accepted items N_{rs} to total number of relevant items N_r

$$Recall = \frac{N_{rs}}{N_r} \quad (19)$$

The bigger *Recall* value means better performance.

5.3. Comparisons and Implementation

In order to show the performance improvement, we compare our method with traditional memory-based algorithms, matrix factorization, social recommendation and other state-of-the-art methods.

- **Item-based** CF algorithm [28] finds the relationships between items and then predicts the rating for the target item based on the weighted averaging of the ratings which have been rated by the target user.
- **PMF** is a matrix factorization model, proposed by Salakhutdinov et al. in [2], which outperforms traditional memory-based algorithms on the large, sparse and imbalanced rating matrix. Given the rank, it can build a matrix approximation which minimize the sum-of-squared instance to the rating matrix.
- **SocialMF** is a model-based approach in social networks, proposed by Jamali et al. in [10], which incorporates the mechanism of trust propagation. It makes the features of every user dependent on the feature vectors of the his direct neighbors. The model can improve accuracy for cold start users.
- **SoReg** is a matrix factorization model with social regularization, proposed by Ma et al. in [11]. It makes a distinction between “social friendships” and “trust relationships. In order to represent the various social friendships, the model treats dissimilar tastes of friends in the different social regularization.

Figure 8. Impact of parameters (Neighbor Number and Iteration Number)

- **LLR** is a two-phase layered learning framework, proposed by Ji et al. in [17], which incorporates the category, item content and social networks information. It can utilize the item's content similarity in the same category to overcome the difficulties of large amount and dynamic update of items.

We call our method proposed in Section 4 **CSR**. Meanwhile, we implement different configurations of our method to demonstrate the effectiveness of our neighbor-based approach and social regularization.

- **CSR_{CF}^S** . This method uses *Item-based* to fill in S without our preprocessing, and uses 3-factor matrix factorization model with social regularization in Equation 12.
- **CSR_{MF}^S** . This method uses *PMF* to fill in S without our preprocessing, and uses 3-factor matrix factorization model with social regularization in Equation 12.
- **CSR_{MF+}^{-S}** . This method adds our preprocessing to *PMF*, and uses our basic 3-factor matrix factorization model in Equation 7.
- **CSR_{MF+}^S** . This method adds our preprocessing to *PMF*, and uses 3-factor matrix factorization model with social regularization in Equation 12.

If no indicator is specifically stated, **CSR** means **CSR_{MF+}^S** .

JAMA³ is an open matrix package for Java, developed at NIST and the University of Maryland. It provides the fundamental operations of numerical linear algebra, such as matrix addition and multiplication, matrix norms and selected element-by-element array operations, etc. All models in our experiments are implemented using this library.

5.4. Parameter Settings

In this section, we analyze how the changes of the parameters affect the performance of our method. We aim to find the best settings by applying different parameter configurations.

Number of neighbors: On the first step, we use the neighbor entries related to tags and keywords with *Top-k* co-occurrence frequency to fill in the missing entries. If k is too small, the neighbor entries will be too unique, and there may even be no observed neighbor entries for the missing entry. If k is too big, the complexity of searching neighbor entries and calculating weight coefficient will considerably increase. We conduct experiments with k from 5 to 20. Figure 8(a) shows that with k increasing, *MAE* decreases and *Recall* increases gradually, but when k goes over 10, the values change rather slow. So we choose *Top-10* nearest neighbors.

Number of iterations: On the second step, the gradient descent method based on iteration computation is time-consuming because each iteration needs to calculate gradient and update parameters. Too many times of iterations cannot necessarily get good results, and might even appear overfitting problem with high probability. We conduct experiments on different iterations. In Figure 8(b), we observe that *MAE* decreases and *Recall* increases gradually with the number of iterations increasing. It is better to run 60 iterations because more than 60 iterations incur higher computational overhead without the big performance improvement in return.

Figure 9. Impact of Parameter α

5.5. Impact of Parameter α

In our 3-factor matrix factorization model, the parameter α controls the influence of social information on the objective function (Equation 12), balancing user interest from the rating data (Equation 7) and the user social network (Equation 10). A large value of α indicates that we are more inclined to mine the rating data for user interest. A small value of α indicates that we are more inclined to have user interest close to the interest of the user's friends. Figure 9 shows the impacts of α in our method. We observe that α has a significant effect on recommendation results: as α increases, MAE decreases and Recall increases at first, but when α surpasses a certain threshold (0.01), MAE begins to increase and Recall begins to decrease. This phenomenon shows fusing the two aspects generates more accurate user interest than only considering rating data or social information does.

5.6. Performance Comparison

In this section, we use different training data R_{train} (25%, 50% and 75%) to evaluate the performance.

Different training data. Table 1 shows comparison results. We observe that in all experiments, our four methods (CSR_{CF}^S , CSR_{MF}^S , CSR_{MF+}^{-S} and CSR_{MF+}^S) are more accurate than other methods. Traditional memory-based algorithms, i.e., *Item-based* has the worst performance. *PMF* performs much better than *item-based* algorithm, proving the advantage of latent factor model. *SocialMF* and *SoReg* have almost the same accuracy, both superior to *PMF*, proving the effectiveness of incorporating social information, but *SoReg* is a bit lower because it uses better social regularization term. *LLR* outperforms *SoReg*, proving that better than social information, category and keyword contribute more to moding user personalized behavior. Note that CSR_{MF}^S performs better than CSR_{CF}^S , which shows *PMF* is more efficient than *item-based* in filling in S ; CSR_{MF+}^S performs better than CSR_{MF}^S , which shows the effectiveness of our neighbor-based approach in improving the sparsity of S ; CSR_{MF+}^S performs better than CSR_{MF+}^{-S} , which shows the effectiveness of the user social network in shaping user interest vector. On 25% R_{train} , our method decreases the prediction error (MAE/Recall) as high as 6.99%/6.04% in contrast to *LLR*. On 50% R_{train} , the corresponding improvements are 9.64%/8.98%. On 75% R_{train} , the corresponding improvements are 11.9%/10.48%.

Different users and items. In order to make a more detailed analysis, we evaluate how our method performs for different users and items. Users are grouped into 5 classes: "1-20", "20-40", "40-80", "80-160" and " ≥ 160 ", denoting how many ratings a user has in the training data. Items are grouped into 5 classes: "1-20", "20-40", "40-80", "80-160", "160-320" and " ≥ 320 ", denoting how many ratings every item has in the training data. From Figure 10 and 11, we observe that the performance of all the methods is improved gradually with the number of users' and items' observed ratings increasing. We also observe our method outperforms other methods in all the user and item groups, especially when few user ratings or few item ratings are given. Actually, when few ratings are observed, our method can find the accurate tag-keyword relation matrix since tags are selected by multiple users and keywords are shared by multiple items, proving the outstanding ability of our method to handle sparse data.

³<http://math.nist.gov/javanumerics/jama/>

Table 1. Performance comparison on Different Training Data

Training Data	Metrics	Item-based	PMF	SocialMF	SoReg	LLR	CSR_{CF}^S	CSR_{MF}^S	CSR_{MF+}^S	CSR_{MF+}^S
25%	MAE	0.2477	0.2269	0.2184	0.2163	0.2131	0.2074	0.2031	0.2009	0.1982
	Improve	19.98%	12.65%	9.24%	8.37%	6.99%				
	Recall@10	0.2604	0.2757	0.282	0.2842	0.2896	0.2956	0.3003	0.3022	0.3071
	Improve	17.93%	11.39%	8.9%	8.06%	6.04%				
50%	MAE	0.2035	0.1930	0.1914	0.1906	0.1795	0.1708	0.1663	0.1641	0.1622
	Improve	20.29%	15.96%	15.25%	14.9%	9.64%				
	Recall@10	0.2867	0.2963	0.2986	0.3035	0.3118	0.3284	0.3312	0.3347	0.3398
	Improve	18.52%	14.68%	13.8%	11.96%	8.98%				
75%	MAE	0.1919	0.1891	0.1823	0.1803	0.1580	0.1511	0.1475	0.1450	0.1412
	Improve	26.42%	25.33%	22.55%	21.69%	11.9%				
	Recall@10	0.2968	0.2998	0.3063	0.312	0.3281	0.352	0.3541	0.3689	0.3625
	Improve	22.13%	20.91%	18.35%	16.18%	10.48%

(a) MAE on Different User Rating scales

(b) Recall on Different User Rating scales

(c) Distribution of Testing Data (User)

Figure 10. Performance Comparison on Different Users (75% Training Data)

(a) MAE on Different Item Rating scales

(b) Recall on Different Item Rating scales

(c) Distribution of Testing Data (Item)

Figure 11. Performance Comparison on Different Items (75% Training Data)

Figure 12. Cold Start Recommendation

5.7. Cold Start Recommendation

In this section we analyze the capability of our method on cold start recommendations for new users and new items.

New users. Out of the baselines, *SocialMF* can deal with new users by incorporating the connections in social network. Figure 12 (a) compare the accuracy of our method and *SocialMF* on R_{new}^U . Results show that our method performs better on both metrics, which shows that our method handles new users better than *SocialMF*.

New items. Similar to our method, *LLR* can make recommendation for new items by incorporating item's keywords. Figure 12(b) compare the accuracy of our method and *LLR* on R_{new}^U . We observe that our method outperforms *LLR* in all the experiments, which shows that our method handles new items better than *LLR*.

New users and new items. One special case is that the user and item both do not exist in the previous rating matrix. All the baselines cannot deal with this situation. But our method can still make recommendations by considering the relations between user's tags and item's keywords. When using 25% R_{train} , *MAE* and *Recall* on R_{new}^{UI} are 0.2121 and 0.2795. When using 50% R_{train} , the corresponding values are 0.1826 and 0.3066; when using 75% R_{train} , the corresponding values are 0.1631 and 0.3408.

The comparison experiments in this section verify that our method achieves good performance on cold start recommendation for new users and new items.

6. CONCLUSION

In this paper, we study the explanation and cold start problems in recommender systems based on collaborative filtering. By incorporating content-based information and social information, we proposed a hybrid method which uses user-item ratings to build content association between users and items based on three factors-user interest in selected tags, tag-keyword relation and item correlation with extracted keywords, and then recommends the items

with high similarity in content to users. In order to perform the content association, two novel methods (neighbor-based approach and 3-factor matrix factorization) and a social regularization are proposed. Analysis shows our method can generate explainable recommendation results with simple descriptions, and experiments demonstrate our method improves recommendation accuracy of state-of-the-art CF models for previous users and items with few ratings, as well as cold start users and items with no rating.

In the future, we may conduct online A/B-tests based experiments to investigate the effect of description information on recommending the items when a user is browsing a website, since our analysis is a simple discussion and our present offline experiments cannot quantify exactly how much effect the explanation has on users' acceptance of the recommended items.

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