Context-Aware Collaborative Topic Regression with Social Matrix Factorization for Recommender Systems

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Abstract

Online social networking sites have become popular platforms on which users can link with each other and share information, not only basic rating information but also information such as contexts, social relationships, and item contents. However, as far as we know, no existing works systematically combine diverse types of information to build more accurate recommender systems. In this paper, we propose a novel context-aware hierarchical Bayesian method. First, we propose the use of spectral clustering for user-item subgrouping, so that users and items in similar contexts are grouped. We then propose a novel hierarchical Bayesian model that can make predictions for each user-item subgroup, our model incorporate not only topic modeling to mine item content but also social matrix factorization to handle ratings and social relationships. Experiments on an Epinions dataset show that our method significantly improves recommendation performance compared with six categories of state-of-the-art recommendation methods in terms of both prediction accuracy and recall. We have also conducted experiments to study the extent to which ratings, contexts, social relationships, and item contents contribute to recommendation performance in terms of prediction accuracy and recall.

Introduction

Online social networking sites, such as Epinions, Twitter, and Last.fm, have become popular platforms on which users can link and share information with each other. These social networks contain not only large amounts of basic ratings information but also valuable information such as context, social relationships, and item content. The three types of information have proven to be valuable when combined with user-item rating information for building accurate recommender systems (RSs). However, as far as we know, no existing works incorporate diverse types of such information to further improve recommendation quality. Thus two questions arise:

- How can we combine the four types of information to improve recommendation performance?
- To what extent does each type of information contribute to recommendation performance?

This paper aims to provide useful insights about the answers to both of these questions.

Although collaborative filtering (CF) has been extensively studied in the literature (Mnih and Salakhutdinov, 2007; Su and Khoshgoftaar, 2009), it suffers from some inherent problems, such as data sparsity and imbalance of ratings, because it only uses user-item rating information. To alleviate the shortcomings of CF-based models, some additional information has been incorporated into RSs, such as context (Baltrunas, Ludwig, and Ricci, 2011), social relationships (Ma et al., 2008; Jamali and Ester, 2010; Chen et al., 2013), item content (Wang and Blei, 2011), a combination of item content and social relationships (Purushotham, Liu, and Kuo, 2012), a combination of item content and context (Agarwal and Chen, 2010), and a combination of context and social relationships (Liu, 2013; Liu and Aberer, 2013).

Although the four types of information have proven valuable for building accurate RSs, to the best of our knowledge, no existing work incorporates the diverse types of information to further improve recommendation quality. Incorporating more types of information into an RSs inevitably leads to greater challenges. One challenge is how to systematically incorporate each type of information into an RSs to improve the performance of predictions. Another challenge is how to make full use of each type of information, so that each plays the biggest possible role in improving recommendation accuracy.

Existing research incorporates context into RSs using a decision tree for subgrouping user-item ratings based on context (Zhong, Fan, and Yang, 2012; Liu and Aberer, 2013). Therefore, they can only handle categorical contexts. Existing work incorporates social relationships by putting a single prior on the whole social trust network (Ma et al., 2008; Jamali and Ester, 2010; Chen et al., 2013), thus neglecting the importance of individual trust among users.

In order to better address the above challenges and overcome the aforementioned problems, in this paper, we propose a novel context-aware hierarchical Bayesian method. The main contributions are summarized as follows:

- Our novel method can take rating, context (including user context, item context, and rating context), social relationships, and item content into consideration for prediction.

- We propose to use spectral clustering, rather than decision trees for matrix subgrouping, which allows our method to handle both categorical contexts (such as item categories) and continuous contexts (e.g. the number of trusters of a user).
- We propose a novel hierarchical Bayesian model that considers social relationship by putting different priors on users based on the trust values between users and their trustors, in order to can take full advantage of the social trust relationships.

Related Work

In this section, we present related work on RSs, including matrix factorization (MF) approaches, context-aware recommendation approaches, and topic-model-based recommendation approaches.

Matrix Factorization

MF (Mnih and Salakhutdinov, 2007; Koren, Bell, and Volinsky, 2009; Shan and Banerjee, 2010) is one of the most popular approaches to CF. It factorizes a user-item rating matrix into one user-specific matrix and one item-specific matrix. Then the common way is to minimize the sum-of-squared-errors objective function with quadratic regularization terms:

$$\begin{aligned} \arg\ min_{U,V} \textstyle\sum_{i=1}^{I} \sum_{j=1}^{J} I_{ij} \left(R_{ij} - U_i^T V_j\right)^2 \\ + \lambda_u \textstyle\sum_{i=1}^{I} \parallel U_i \parallel^2 + \lambda_v \sum_{j=1}^{J} \parallel V_j \parallel^2 \end{aligned} \tag{1}$$

Social matrix factorization (SMF) (Ma et al., 2008; Jamali and Ester, 2010; Chen et al., 2013) incorporates social relationship into MF to improve recommendation performance. The most common way is to add social regularization terms in Equation (1) to constrain the taste difference between one user and another. For example, Jamali and Ester (2010) use the average latent features of a user's direct neighbors as the user's only prior, based on the assumption that a user's taste is close to the average tastes of the user's friends. The social regularization term is shown in Equation (2). We refer to this term hereafter as MFTP.

$$\lambda_f \textstyle\sum_{i=1}^{I} \parallel U_i - \sum_{f \in N_i} T_{if} U_f \parallel^2 \tag{2}$$

However, MFTP doesn't treat users differently based on the trust values between users and their trustors. In our work, we assign different priors to users based on the trust values of users and those who they trust to take full advantage of the social trust relationships.

Context-aware Recommendation Approaches

Contextual information, such as age, time, and location, has proven to be useful for building more accurate RSs (Palmisano, Tuzhilin, and Gorgoglione, 2008).

Recent research focuses on the use of context for user-item subgrouping (Zhong, Fan, and Yang, 2012; Liu and Aberer, 2013). Subgrouping has proven to be a promising way to further improve the recommendation performance of many popular CF methods (Xu et al., 2012). However, the methods of both Zhong, Fan, and Yang (2012) and Liu and Aberer (2013) use decision tree to group users and items with similar contexts, thus they can only handle categorical contexts. To alleviate this problem, in our work, we propose the use of spectral clustering for user-item subgrouping, which can handle both categorical and continuous contexts.

Topic-model-based Recommendation Approaches

Topic models are used to discover sets of "topics" in a document based on a hierarchical Bayesian analysis of the original texts (Blei and Lafferty, 2009). As the simplest topic model, Latent Dirichlet Allocation (LDA) has been used for many applications, including for RSs (Blei, Ng, and Jordan, 2003).

Researchers have recently focused on the use of LDA to mine useful and rich-text content. Wang and Blei (2011) proposed collaborative topic regression (CTR), which combines the merits of MF and probabilistic topic modeling. To further improve recommendation performance, Purushotham, Liu, and Kuo (2012) combined CTR with SoRec (Ma et al., 2008) to obtain a consistent and compact feature representation called CTR-SMF. Because CTR-SMF uses SoRec to exploit social relationship, it doesn't treat all friends differently. In addition, CTR-SMF ignores another important source of information: context. In this paper, we will focus on overcoming these two drawbacks of CTR-SMF.

Proposed Method

In this section, we present our method: a context-aware hierarchical Bayesian model. First, we formalize the context-aware social recommendation problem and define notations. Then, we describe our motivation for creating our model. We then describe our context-based user-item subgrouping method based on spectral clustering and our proposed hierarchical Bayesian model. Finally, we provide our method of learning parameters using a variational expectation-maximization (EM) algorithm.

Preliminaries

Contextual information is available in many online social networks; thus on these networks, the traditional two-dimensional recommendation space $User \times Item$ becomes the three-dimensional recommendation space $User \times Item \times Context$. We classify contextual information in online social networks into three categories: (1) user context, which describes characteristics of a user, (2) item context, which describes characteristics of an item, (3) rating context, which represents the additional information provided by users when they rate items. For example, at *Epinions*, user context includes: (1) the number of visits, (2) the number of reviews provided, (3) the number of trusters, (4) the number of trustees, and (5) the user's average rating. Item context includes: (6) item categories, (7) the average rating for an item, and (8) the number of reviewers. Rating context includes: (9) hour-of-day, (10) day-of-week, and (11) review quality level[1].

[1]Review quality level refers to the level of the review given by the *Epinions* community

Assume a set of users $\mathbb{U} = \{u_1, ..., u_I\}$ and a set of items $\mathbb{V} = \{v_1, ..., v_J\}$. Let $U \in \mathbb{R}^{K \times I}$ and $V \in \mathbb{R}^{K \times J}$ be the latent user and item feature matrices, with column vectors U_i and V_j representing the *K*-dimensional user-specific and item-specific latent feature vectors of users *i* and item *j*, respectively. The ratings given by users on items are given in a rating matrix $R = [R_{ij}]_{I \times J \times C}$, in which R_{ij} denotes the rating of user *i* on item *j* in context *C*. The rating can be any real number, but often ratings are integers in the range [1, 5] (*Amazon*[2], *eBay*[3], etc.). Let N_i be the set of direct neighbors of user *i*, and $L = ||N_i||$. The trust values among users are given in a matrix $T = [T_{if}]_{I \times I}$, and every element T_{if} denotes the trust value of user *i* on user *f* as a real number in [0, 1].

Motivation

Our proposed method can handle rating, context, social relationships, and item content together. Our method first adopts spectral clustering to group those users and items that share similar contexts. Then in each user-item subgroup, we apply our proposed hierarchical Bayesian model to do prediction. Our model is a combination of LDA and SMF. We use LDA to mine the item content information, and we use SMF to handle rating and social trust relationships. However, unlike CTR-SMF (Purushotham, Liu, and Kuo, 2012) that only put a single prior on the whole social trust network, our model handles social relationship by putting one prior on each user based on the trust values between one user and the user's trustors, thus our method can treat all users differently and fit reality better than existing models.

In order to differentiate our method from CTR-SMF, we call it C-CTR-SMF2, where "C" stands for context-based user-item subgrouping, "CTR" stands for collaborative topic regression (Wang and Blei, 2011), and "SMF2" denotes our proposed social matrix factorization method, which is an extension of SoRec (Ma et al., 2008) and MFTP (Jamali and Ester, 2010).

Context-Based User-Item Subgrouping

Not all contexts equally affect recommendations. First, we apply statistical tests (Adomavicius et al., 2005; Odic et al., 2011) to investigate the interplay between contexts and ratings to select relevant contexts. Among the context in the preliminaries section above, we choose the following contexts for user-item subgrouping: (2) the number of reviews provided, (5) the users average rating, (6) item categories, and (7) the average rating for an item.

Next, we use spectral clustering (Ng et al., 2002) to do user-item subgrouping. The first step is to normalize all the selected contexts into the same range, such as [0, 5]. The second step is to compute the context-based rating similarity matrix. The last step is to use the rating similarity matrix and set a cluster number *l* to run spectral clustering. After clustering, we get *l* user-item rating sub-matrices, in which we can make predictions by applying our proposed hierarchical Bayesian model.

[2]http://www.amazon.com

[3]http://www.ebay.com

Our Proposed Model

Our proposed model, C-CTR-SMF2, is a hierarchical Bayesian model that jointly learns the user and item latent spaces. C-CTR-SMF2 is a combination of LDA and SMF, as shown in Figure 1. We use LDA to mine item content information, and we use SMF to handle ratings and social trust networks.

The content parameter λ_v balances the contribution of item content information to model performance, and C-CTR-SMF2 collapses to LDA when $\lambda_v = \infty$. The social parameter λ_f balances the contribution of social relationship to model performance, and C-CTR-SMF2 collapses to CTR when $\lambda_f = 0$. Thus, LDA and CTR are both special cases of our model. Moreover, unlike CTR-SMF, which assigns a single prior to all users, our model considers social information by assigning a different prior to each user based on the trust values between the user and the user's trustors. As the social regularization term in Equation (3) shows, these features allow our model to take full advantage of the social trust network.

$$\lambda_f \sum_{i=1}^{I} \sum_{f \in N_i} T_{if} \| \, U_i - U_f \, \|^{\,2} \tag{3}$$

The generative process in our model is as follows:

1. For all the users $u_1, ..., u_i, ..., u_I$,
   (a) Draw user latent vector set, $U \sim p\,(U)$, where $p(U) \propto N(0, \lambda_u^{-1}) \prod_{i=1}^{I} \prod_{f \in N_i} N(U_f, \lambda_f^{-1} {T_{if}}^{-1})$
2. For each item j,
   (a) Draw topic proportions $\theta_j \sim Dirichlet(\alpha)$
   (b) Draw item latent offset $\epsilon_j \sim N(0, \lambda_v^{-1})$, and set the item latent vector as $V_j = \epsilon_j + \theta_j$
   (c) For each word w_{jn},
      i. Draw topic assignment $z_{jn} \sim Mult(\theta)$
      ii. Draw word $w_{jn} \sim Mult(\beta_{z_{jn}})$
3. For each user-item pair (*i*, *j*), draw the rating
   (a) $$R_{ij} \sim N({U_i}^T V_j, c_{ij}^{-1})$$

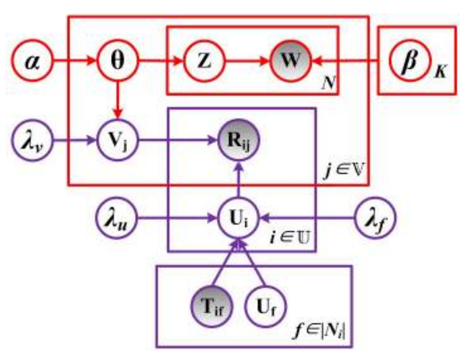

Figure 1: Graphic model of our proposed model C-CTR-SMF2. The LDA part is shown in red, and the SMF part is shown in purple.

The conditional distribution of observed ratings can be shown as

$$p\left(R|U, V, \sigma_R^2\right) = \prod_{i=1}^{I} \prod_{j=1}^{J} \left[N(R_{ij}|U_i^T V_j), \sigma_R^2)\right]^{I_{ij}^R}$$

where I_{ij}^R is an indicator function equal to 1 if user *i* rated item *j*, or 0 otherwise.

The user latent vector U_i has two parts of factors: the zero-mean Gaussian prior to avoid over-fitting, and the conditional distribution of user latent features given the latent features of the user's direct neighbors. Therefore,

$$p\left(U|U_f,T,\sigma_U^2,\sigma_T^2\right) \\ \propto p\left(U|\sigma_U^2\right) \times \prod_{i=1}^{I}\prod_{f\in N_i} p\left(U|U_f,{T_{if}}^{-1}\sigma_T^2\right)$$

The item latent vector V_j is generated by a key property due to CTR, which can be shown as

$$p\left(V|\sigma_V^2\right) \sim N(\theta_j,\lambda_v^{-1}I_k)$$

Using Bayesian inference, we can infer the following equation for the posterior probability of latent feature vectors given the user-item rating matrix and social trust matrix:

$$p\left(U,V|R,T,\sigma_R^2,\sigma_U^2,\sigma_V^2,\sigma_T^2\right) \\ \propto p\left(R|U,V,\sigma_R^2\right) \times p\left(U|U_f,T,\sigma_U^2,\sigma_T^2\right) \times p\left(V|\sigma_V^2\right)$$

Learning of Parameters

Directly compute the full posterior of U_i, V_j, and θ_j is intractable, we develop a variational EM algorithm to learn the maximum a posteriori estimates. Maximizing the posterior over the two latent features with fixed hyper-parameters is equivalent to maximum the following complete log likelihood of *U*, *V*, $\theta_{1:J}$, T, and R given λ_u, λ_v, λ_f, and β,

$$L = -\frac{\lambda_u}{2}\sum_i {U_i}^T U_i - \frac{\lambda_v}{2}\sum_j (V_j-\theta_j)^T(V_j-\theta_j) \\ +\sum_j\sum_n \log\left(\sum_k \theta_{jk}\beta_{k,w_{jn}}\right) \\ -\sum_{ij}\frac{c_{ij}}{2}\left(R_{ij}-{U_i}^T V_j\right)^2 \\ -\frac{\lambda_f}{2}\sum_i\sum_{f\in N_i} T_{if}(U_i-U_f)^T(U_i-U_f)$$

where $\lambda_u=\sigma_R^2/\sigma_U^2,\ \lambda_v=\sigma_R^2/\sigma_V^2,\ \lambda_f=\sigma_R^2/\sigma_T^2,$ and Dirichlet prior (α) is set to 1. Note that c_{ij} is the confidence parameter for rating R_{ij}. For more details see (Wang and Blei, 2011). We optimize this function using coordinate descent, that is, by iteratively optimizing the MF variables $\{U_i, V_j\}$ and the topic proportions θ_j. For U_i and V_j, maximization follows in a similar fashion as MF (Hu, Koren, and Volinsky, 2008). Given the current estimate of θ_j, taking the gradient of *L* with respect to U_i and V_j and setting it to zero leads to,

$$U_i \leftarrow \left(VC_iV^T+\lambda_u I_K+\lambda_f T_i 1_I I_K\right)^{-1} \\ (\lambda_f U{T_i}^T + VC_iR_i) \tag{4}$$

$$V_j \leftarrow \left(UC_jU^T+\lambda_v I_K\right)^{-1}(UC_jR_j+\lambda_v\,\theta_j) \tag{5}$$

where C_i is a diagonal matrix with $c_{ij}, j = 1,...,J$ as its diagonal elements, $T_i = {T_{ij}}_{i=1}^{I}$ for user *i*, 1_I is a *I*-dimensional column vector with all elements equal to 1, and $R_i = {R_{ij}}_{j=1}^{J}$ for user *i*. For item *j*, C_j and R_j are similarly defined.

Equation (4) shows how social trust proportion T_i affects the user latent vector U_i, and how λ_f balances this effect. When $\lambda_f = 0$, our model collapses to the CTR, which uses item content and rating to make prediction. When $\lambda_f = \infty$, our model uses only social relationships to model user preferences. In all other cases, our model fuses information from item content, ratings and social relationships for prediction.

Equation (5) shows how topic proportion θ_j affects the item latent vector V_j, and how λ_v balances this effect. When $\lambda_v = 0$, our model uses only rating to make predictions. When $\lambda_v = \infty$, our model uses only item content to make predictions, and, consequently, our model behaves more like LDA. In all other cases, λ_v balances information from item content and rating.

Given U and V, we now learn the topic proportions θ_j. We first define $q\left(z_{jn}=k\right)=\Phi_{jnk}$, and then we separate the items that contain θ_j and apply Jensen's inequality,

$$L(\theta_j) \geq -\frac{\lambda_v}{2}(V_j-\theta_j)^T(V_j-\theta_j)+\sum_n\sum_k\Phi_{jnk} \\ (log\theta_{jk}\beta_{k,w_{jn}} - log\Phi_{jnk}) = L\left(\theta_j,\Phi_j\right)$$

where $\Phi_j = {\Phi_{jnk}}_{n=1,k=1}^{N\times K}$, *N* is the word number in the content of item *j*, and the optimal Φ_{jnk} satisfies $\Phi_{jnk} \propto \theta_{jk}\beta_{k,w_{jn}}$. Thus $L(\theta_j,\Phi_j)$ gives the tight lower bound of $L(\theta_j)$. Then projection gradient (Bertsekas, 1999) can be applied to optimize θ_j and coordinate descent can be applied to optimize other parameters *U*, *V*, $\theta_{1:J}$ and $\Phi_{1:J}$. Finally, after we have estimated *U*, *V* and Φ, we can optimize β,

$$\beta_{kw} \propto \sum_j\sum_n \Phi_{jnk}1[w_{jn}=w]$$

After the optimal parameters U^*, V^*, ${\theta_{1:J}}^*$ and β^* are learned, our model can be used to make predictions (recommendation).

$${R_{ij}}^* \approx U_i^{*T}V_j^*$$

Experiments and Analysis

In this section, we introduce the comprehensive experiments that we conducted to evaluate the performance of our method. Our experiments, which we conducted on a real-world *Epinions* dataset help us answer two key questions: (1) How does our model perform when compared with six state-of-the-art RSs? (2) To what extent do ratings, contexts, social relationships, and item contents contribute to recommendation performance?

Dataset

Epinions.com is a consumer opinion website for sharing knowledge about products. Members on *Epinions* can review items (e.g., food, books, and electronics) and assign numeric ratings from 1 to 5. Meanwhile, *Epinions* members can delimit their Web of Trust, a group of "reviewers whose reviews and ratings they have consistently found to be valuable." *Epinions* also provide user, item, and rating contexts. Thus *Epinions* is an ideal date source for experiments on social recommendation.

The dataset used in our experiments consists of 3,474 users who have rated at least one of a total of 26,850 items, with totally 77,267 reviews and 37,587 trust statements. The density of the user-item matrix is about 0.08%. For every item, we use all its pros, cons and the bottom line as its content, forming a total of 59,084 different terms.

Comparisons

We compare our proposed method C-CTR-SMF2 with six categories of recommendation methods, each of which is a promising method in its corresponding category.

PMF (Mnih and Salakhutdinov, 2007) is the basic MF method, which only considers ratings.

SoReg (Ma et al., 2011) is a method based on social trust that considers both ratings and social relationships.

fLDA (Agarwal and Chen, 2010) is a personalized sLDA (Blei and McAuliffe 2010) that considers both contexts and item contents.

CTR (Wang and Blei, 2011) is a topic-model-based recommendation model that incorporates both ratings and item contents.

CTR-SMF (Purushotham, Liu, and Kuo, 2012) is a combination of CTR and SoRec that incorporates ratings, item contents and social relationships, and it uses λ_q to balance the effectiveness of CTR and SoRec.

SoCo (Liu and Aberer, 2013) is a model that uses a random decision tree to perform context-based user-item subgrouping, and incorporates ratings, social relationships, and categorical contexts.

Metrics

In our experiments, we split the dataset into two parts — a training dataset (80%) and a testing dataset (20%). We use three metrics to measure the performance of various recommendation models: *Recall*, Mean Absolute Error (*MAE*), and Root Mean Square Error (*RMSE*). All three are commonly used metrics for evaluating the performance of predictions (Liu and Aberer, 2013; Purushotham, Liu, and Kuo, 2012), and they are defined as below:

$$Recall@300 = \frac{Number\ of\ items\ the\ user\ likes\ in\ Top\ 300}{Total\ number\ of\ items\ the\ user\ likes}$$

$$MAE = \frac{\sum_{r=1}^{N} |R_r - \hat{R}_r|}{N}$$

$$RMSE = \sqrt{\frac{1}{N}\sum\nolimits_{r=1}^{N} \left(R_r - \hat{R}_r\right)^2}$$

where *N* is the total number of predictions, R_r is the real rating of an item and $\hat{R}_r$ is its corresponding predicted rating. In the following paper, *Recall* is the abbreviation for *Recall*@300.

Parameters Selection and Analysis

We use fivefold cross validation to find that *K=6*, $\lambda_u = \lambda_v = 0.1$, $a = 1$, and $b = 0.01$ provides the best performance for MF methods. Note that a and b are tuning parameters ($a > b > 0$) for the confidence parameters c_{ij}; for more details see CTR (Wang and Blei, 2011). As for SoCo, we set both the number of the decision tree and tree height equal to 3 (Liu and Aberer, 2013). We also use fivefold cross validation to find that CTR delivers the best performance when $K = 20$, $\lambda_u = 0.1$, $a = 1$, and $b = 0.01$, and CTR-SMF delivers the best performance when $K = 15$, $\lambda_u = 0.1$, $a = 1$, and $b = 0.01$. Later in this section, we will vary the content parameter λ_v to study its effect on the performance of CTR. We will also vary both content parameter λ_v and social parameter λ_q to study their effect on the performance of CTR-SMF. For our method C-CTR-SMF2, just like CTR, we set $K = 20$, $\lambda_u = 0.1$, $a = 1$, and $b = 0.01$, and vary the spectral cluster number l, content parameter λ_v, and social parameter λ_f to study their effect on model performance.

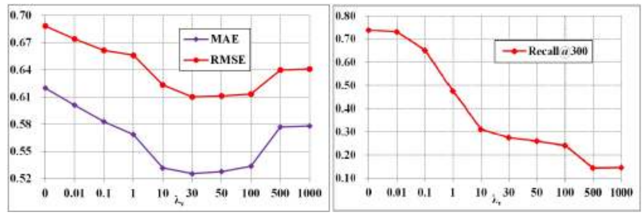

Figure 2: Comparison of predictive performance for CTR by varying λ_v. Left plot: *MAE* and *RMSE*, Right plot: *Recall*

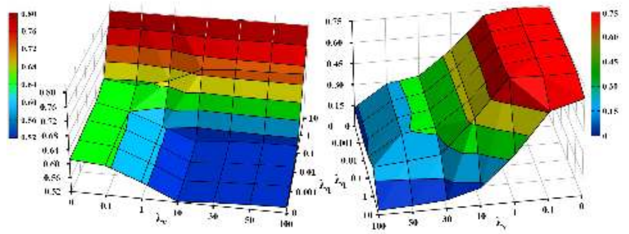

Figure 3: Plots of predictive performance for CTR-SMF by varying content parameter λ_v and social parameter λ_q. Left plot: *MAE*, Right plot: *Recall*

First, we need to determine the best parameters for CTR and CTR-SMF. We can see from Figure 2 that CTR achieves the best predictive accuracy and recall when $\lambda_v = 30$ and $\lambda_v = 0$, respectively. Figure 3 shows 3D-plots of the predictive performance of CTR-SMF. From the plots, we can see that CTR-SMF achieves the best predictive accuracy when $\lambda_v = 10$ and $\lambda_q = 0.01$, and achieves the best prediction recall when $\lambda_v = 0.1$ and $\lambda_q = 0$.

Next, we study the effect of λ_v and λ_f on our proposed model C-CTR-SMF2. Figure 4 shows 3D-plots of predictive performance for C-CTR-SMF2. The content parameter λ_v balances the information from item content and rating: the bigger λ_v is, the more we use item content to make predictions. The social parameter λ_f balances the effect of social trust relationships, and the bigger λ_f is, the more we use social trust relationships to make predictions. We can see from Figure 4 that C-CTR-SMF2 achieves the best predictive accuracy when $\lambda_v = 30$ and $\lambda_f = 0.0001$, and achieves the best prediction recall when $\lambda_v = 0$ and $\lambda_f = 0.0001$. This indicates that ratings, social relationships, and item content all contribute to model performance.

Finally, we study the effect of cluster number l on our model. Figure 5 indicates that our method achieves the best predictive accuracy and recall when l=3. This is because when l first increases, a user-item subgroup with similar contexts can better capture users' preferences and thus provide better performance. However, when l exceeds a certain threshold (l=3 in our dataset), the recommendation performance decreases, because the density of the rating matrix gets sparse. This result shows the effectiveness of context-based user-item subgrouping.

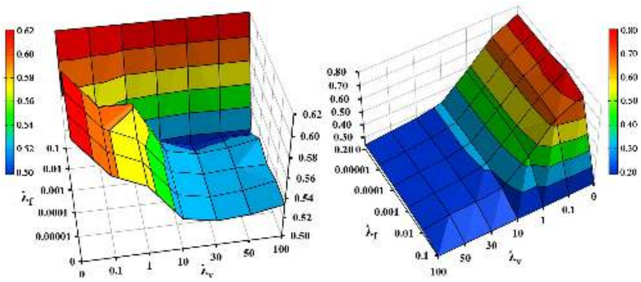

Figure 4: Plots of prediction performance for C-CTR-SMF2 by varying content parameter λ_v and social parameter λ_f, and fixing l=1. Left plot: *MAE*, Right plot: *Recall*

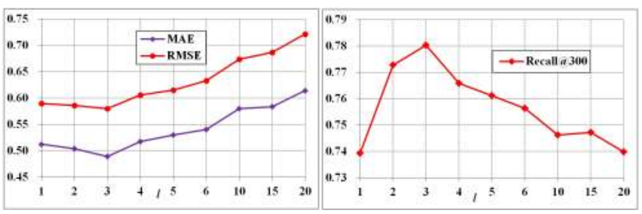

Figure 5: Comparison of prediction performance for C-CTR-SMF2 by varying cluster number l. Left plot: *MAE* and *RMSE*, Right plot: *Recall*

Performance Comparison and Analysis

After choosing parameters, we compare the performance of various recommendation models on *Epinions* dataset. Table 1 demonstrates that our method, C-CTR-SMF2, improves the recommendation performance of PMF, SoReg, fLDA, CTR, CTR-SMF, and SoCo by as high as 13.1%/11.7%/114.0%, 9.4%/6.6%/114.0%, 26.1%/36.0%/4072.0%, 6.9%/4.9%/5.5%, 6.1%/3.1%/4.2%, and 7.4%/3.1%/37.7% in terms of MAE/RMSE/Recall, respectively.

Table 1: Performance comparison on *Epinions* dataset

	PMF	SoReg	fLDA	CTR	CTR-SMF	SoCo	C-CTR-SMF2
MAE	0.5629	0.5398	0.6620	0.5255	0.5212	0.5283	**0.4893**
RSME	0.6568	0.6211	0.9070	0.6102	0.5984	0.5988	**0.5801**
Recall	0.3641	0.3641	0.0187	0.7396	0.7440	0.5666	**0.7803**

Analysis: In all the cases in the experiment, our proposed method C-CTR-SMF2 performs the best. This is because our model takes ratings, contexts, social relationships, and item contents into consideration. In particular, we adopt spectral clustering to do context-based user-item subgrouping and thus can handle both categorical and continuous contexts. Meanwhile, we put different priors on users based on the trust values between uesrs and their trustors. In this way, we can take full advantage of individual trust among users, which reflects reality better.

Model Performance Discussion

To see the contribution of each type of information to model performance, we've conducted the following experiments:

(1) Compare C-CTR-SMF2 with C-C-SMF2 (set $\lambda_v = 0$ in C-CTR-SMF2) to test the effect of item content on prediction performance.

(2) Compare C-CTR-SMF2 with C-R-SMF2 (set $\lambda_v = \infty$ in C-CTR-SMF2) to test the effect of ratings on prediction performance.

(3) Compare C-CTR-SMF2 with C-CTR (set $\lambda_f = 0$ in C-CTR-SMF2) to test the effect of social relationships on prediction performance.

(4) Compare C-CTR-SMF2 with CTR-SMF2 (set l=1 in C-CTR-SMF2) to test the effect of contexts on recommend prediction.

Figure 6 shows the predictive performance of C-CTR-SMF2 compared with other four approaches, each of which excludes one type of information. Figure 6 shows that C-C-SMF2 has the worst prediction accuracy, which indicates that item content has the most significant impact on prediction accuracy. Similarly, C-R-SMF2 has the worst recall, which indicates that ratings have the most obvious influence on recall. Specifically, the contributions of the four types of information to prediction accuracy in descending order are item contents, social relationships, contexts, and ratings. The contributions of the four types of information to recall in descending order are ratings, social relationships, item contents, and contexts. This experiment provides valuable insight about how to construct high-quality RSs with the four types of information.

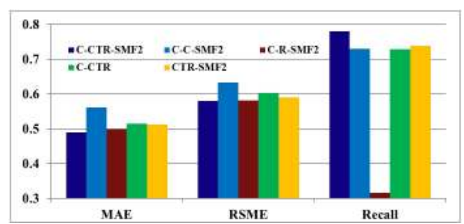

Figure 6: Prediction performance of C-CTR-SMF2 compared with other fours approaches

Conclusions and Future Work

In this paper, we have proposed a novel context-aware hierarchical Bayesian method, which systematically combines ratings, contexts, social relationships, and item content to improve quality of recommendation. We proposed to use spectral clustering for user-item subgrouping, in order to handle both categorical and continuous contexts. We also applied different priors to users based on the trust values between users and their trustors, in order to take full advantage of the social trust relationships. Experiments conducted on *Epinions* dataset illustrate that our approach outperforms six categories of the state-of-the-art recommendation approaches. Experiments also indicate that item contents and ratings have the most important influence on prediction accuracy and recall, respectively.

Our future work will be channeled in two directions. One direction is to take the dynamics of evolving user preference into account. Another direction is to examine parallel implementations of our algorithms, in order to make them scalable to large-scale datasets.

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