Multimed Tools Appl (2018) 77:6425–6444
DOI 10.1007/s11042-017-4550-z

Rating prediction by exploring user's preference and sentiment

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Received: 1 September 2016 / Revised: 22 February 2017 / Accepted: 24 February 2017 /
Published online: 6 April 2017

Abstract With the development of e-commerce, shopping on-line is becoming more and more popular. The explosion of reviews have led to a serious problem, information overloading. How to mine user interest from these reviews and understand users' preference is crucial for us. Traditional recommender systems mainly use structured data to mine user interest preference, such as product category, user's tag, and the other social factors. In this paper, we firstly use LDA+Word2vec model to mine user interest. Then, we propose a social user sentimental measurement approach. At last, three factors, including user topic, user sentiment and interpersonal influence, are fused into a recommender system (RS) based on probabilistic matrix factorization. We conduct a series of experiments on Yelp dataset, and experimental results show the proposed approach outperforms the existing approaches.

Keywords Data mining · Recommender system · Reviews · User interest · User sentiment

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1 Introduction

There is much personal information in online textual reviews, which plays a very important role on user decision processes. Extracting user's interest with the content of reviews has received considerable attention in recent years. Especially, with the fast development of smart devices and cloud computing [7, 18, 31, 58, 67]. The smart phone allow us to access networks and generate personal reviews and ratings for the services he just involved. The cloud computing techniques and data storage approaches makes sure user a quick response to user's interaction [7, 8, 10, 18, 31, 58, 67]. Social media gathers much user generated content, including text, image, audio, music and video [74, 22, 23]. Especially, the social media meeting spatial technology [6, 80, 38, 44, 48, 41, 71], much online services can be shown on the map. Thus multi-modality or Multiview association for content understanding [76, 56, 75, 76, 77, 78, 79, 80] for recommendation is popular. Generally, user's long-term interest is stable in the short term, so the topics from user's reviews can be representative. For example, in the category of "smart phone", some users pay attention to the quality, some users focus on the price and others may evaluate comprehensively. Whatever, they all have their personal topics. Most topic models introduce reviewer's interests as topic distributions according to their reviews contents [16, 17, 26, 47, 59] and category tags [6, 55]. Topic distributions are widely applied in many areas, such as sentiment analysis [21, 64], collaborative filtering [9, 49, 61, 68], and social networks analysis [43, 66]. Sentiment analysis is the most fundamental and important work in user opinion mining. Existing works [52, 54, 65] mainly focus on positive-negative binary classification. However, it is more important to provide numerical ratings rather than binary decisions. For example, a customer could not make a purchase decision for several candidate products, because all of them reflect positive sentiment in a binary classification. Customers not only need to know whether the product is good or not, but also how good the product is. We also agree that different people may have different sentiment expression preferences. For example, someone likes to use "good" to describe an "excellent" product, while others may like to use "good" to describe a "just so so" product [24]. Both of the good reviews and bad reviews are valuable to be as references. For positive reviews, we can know the advantage of the product. For negative reviews, we can obtain the shortcoming in case of being cheated. However, user's sentiment is hard to predict and the unstructured data of reviews makes a great difficulty in exploring users.

In order to solve existing problems and understand users deeply, we use LDA + Word2vec model to mine user interest, and leverage user numerical sentiment for recommendation. LDA is one of the famous generative model [46], rather than the discriminative models, such as SVM and its enhancements [1, 11, 12, 28, 33, 70]. It has successful applications in textual analysis and recommendations systems [11, 16, 43]. In contrast to existing approaches [15, 21, 55, 60, 69], our rating prediction model takes three factors into consideration: user's topic distribution, user's sentiment on items, and user's interpersonal influence in a real friend circle. The differences between our model and our previous works [21] are given as follows. Previous work utilizes user sentiment similarity, interpersonal sentiment influence and item reputation similarity, whereas the proposed model contributes to leverage Word2vec model to enhance LDA model for user topic similarity. In addition, we directly utilize user sentiment to optimize the latent features according to the basic idea that user rates items with high sentiment scores may produce high ratings, whereas previous work leverage user sentiment to calculate interpersonal sentiment influence and item reputation similarity. The main contributions of our approach are summarized as follows:

1) We propose a recommendation model based on probabilistic matrix factorization with fully exploring the information of user reviews. We extract user interest topics, user

sentiment and user influence from reviews, and they are fused into our model for providing recommendations with more accuracy.

2) We propose to utilize LDA and Word2vec to represent user's interest distribution, and we leverage user sentiment according to the basic idea that user rates items with high sentiment scores may produce high ratings. User's interest shows what kind of items the user may be interested in. User's sentiment shows how much the user likes the item.
3) We fuse three factors, including user's interest distribution, user's sentiment, and user's interpersonal influence, into a probabilistic matrix factorization model to carry out an accurate recommendation.

The rest of paper is organized as follows. In Section 2, we present the related work on the rating prediction. In Section 3, the model we proposed is introduced in detail. Experiments and discussions are given in Section 4 and conclusions are drawn in Section 5.

2 Related work

We firstly review classical recommendation approaches in matrix factorization. Then, user interest mining and sentiment based approaches are reviewed.

2.1 Matrix factorization based approaches

Some Matrix factorization[1, 2, 4, 6, 7, 77–81, 5, 46, 40]based social recommendations are proposed to solve the "cold start" problem, and they leverage friend information to predict user preferences. Jamali et al. [14] incorporated the mechanism of trust propagation into the recommendation model. Yang et al. [69] proposed the concept of "Trust Circles" in social network. It outperforms Basic MF [60] and Social MF [14] with respect to the accuracy of RS. The trust value between users is represented by the matrix S, and weighted social relationship of user u with user v is represented by a value $S_{u,v}^{c*}\in[0,1]$. The basic idea is that user latent feature should be similar to the average of his/her friends' latent features with weight of $S_{u,v}^{c*}$ in category c. Jiang et al. [15] demonstrated the significance of social contextual factors (including individual preference and interpersonal influence) in their model. Qian et al. [55] proposed a personalized recommender model (PRM) combining with several social factors. They made full use of categories of products and user personal interest. Zhao et al. [81] proposed the factor of interpersonal rating behavior diffusion to deep understand users' rating behaviors. They fused user personal interest, interpersonal interest similarity, interpersonal rating behavior similarity, and interpersonal rating behavior diffusion into a unified matrix-factorized framework.

2.2 User interest based approaches

There are many reviews based work for the task of user interest mining. Qu et al. [57] proposed a kind of bag-of-opinions model to predict user's numeric rating in a product review. And they developed a constrained ridge regression method for learning scores of opinions. Wang et al. [66] proposed a review rating prediction method by incorporating the character of reviewer's social relations. In addition, they classified the social relations of reviewers into strong social relation and ordinary social relation. Ling et al. [26] proposed a unified model that combines content-based collaborative filtering, and harnessing the information of both ratings and reviews. Moreover, they applied topic models to improve rating prediction accuracy. Luo et al. [47] defined and solved a new problem: aspect identification and rating, together with overall rating prediction in unrated reviews. They proposed a new LDA-style topic model which generates ratable aspects over sentiments and associates modifiers with ratings. Lu et al. [42] proposed a topic model to analyze users' interactive behaviors and measure the topic-specific relationship strength, and then they incorporated the relationship factor into the matrix factorization framework for recommendation.

2.3 Sentiment based applications

Many sentiment analysis works are proposed to extract user opinion. Sentiment analysis is mainly conducted on three different levels: review-level, sentence-level, and phrase-level. Review-level analysis [54, 65] and sentence-level analysis [52] attempt to classify the sentiment of a review to one of the predefined sentiment polarities, including positive, negative and neutral. While phrase-level analysis [20] attempts to extract the sentiment polarity of each product features. Pang et al. [54] proposed a context insensitive evaluative lexical method. Taboada et al. [63] presented a lexicon-based approach to extract sentiment. Their semantic orientation calculator uses dictionaries of words annotated with their semantic orientations (polarity and strength), and incorporates intensification and negation. Based on sentiment analysis, many works are proposed for personalized recommendation [20, 21, 73, 75]. Zhang et al. [73] proposed a self-supervised and lexicon-based (HowNet Sentiment Dictionary) sentiment classification approach to determine sentiment polarity of a review, and they used sentiment for recommendation. Zhang et al. [75] proposed an Explicit Factor Model (EFM) to generate explainable recommendations, and they extracted explicit product features and user opinions by phrase-level sentiment analysis on reviews. Delta TFIDF proposed by Martineau [50] outperforms raw term counts and TFIDF feature weights for documents of all sizes for sentiment polarity classification. Moreover, Lin [25] proposed to utilize an information theoretic approach on sentiment classification. They analyzed the relationships of terms with sentiment labels based on information theory, and the terms are weighted in vector space according to the sentiment scores and contribution to the document. Their experiments show the method has better performance than [50, 54].

Besides, there are some works on the topics of user context-awareness and intentions-awareness [30, 32, 34, 35, 45]. Some works also focus on the data fusion methods and fusion-based machine learning algorithms [4, 29, 36]. In addition, service quality evaluation in recommender systems has attracted attention [77, 78, 80]. Zhao et al. [78] proposed a model to conduct service quality evaluation by improving overall rating of services using an empirical methodology. They utilized the concept of user rating's confidence and explored spatial-temporal features and review sentimental features of user ratings to perform service quality evaluation. References [37, 79] mainly study how to utilize geographic information in recommender system.

3 The approach

We propose a rating prediction model based on user interest and sentiment, the model consists of three factors: user interest, user sentiment, and interpersonal influence [69]. In order to better understand the approach, we first give the overview of our model, and then introduce user interest and user sentiment respectively. At last, we fuse these factors into our model.

3.1 Overview of our approach

Our recommendation algorithm is proposed by exploring social users in media-sharing sites. As illustrated in Fig. 1, the algorithm consists of three components: 1) Calculating interpersonal influence between the user and friends. 2) Calculating user interest similarity between the user and friends. 3) Calculating user sentiment. First, we leverage the CircleCon2b [69] model to get the interpersonal influences between the user and friends. Second, user interest is extracted by LDA [2] and word2vec [19] model. From Fig. 1, we can see that this step mainly contains two parts: extracting product features, calculating user interest distribution. After obtaining users' interest distribution, we calculate the similarities between the user and his/her friends. Third, we use a lexicon-based method to calculate user sentiment and extract user preference. Our sentiment dictionaries are Sentiment dictionary (SD), Sentiment degree

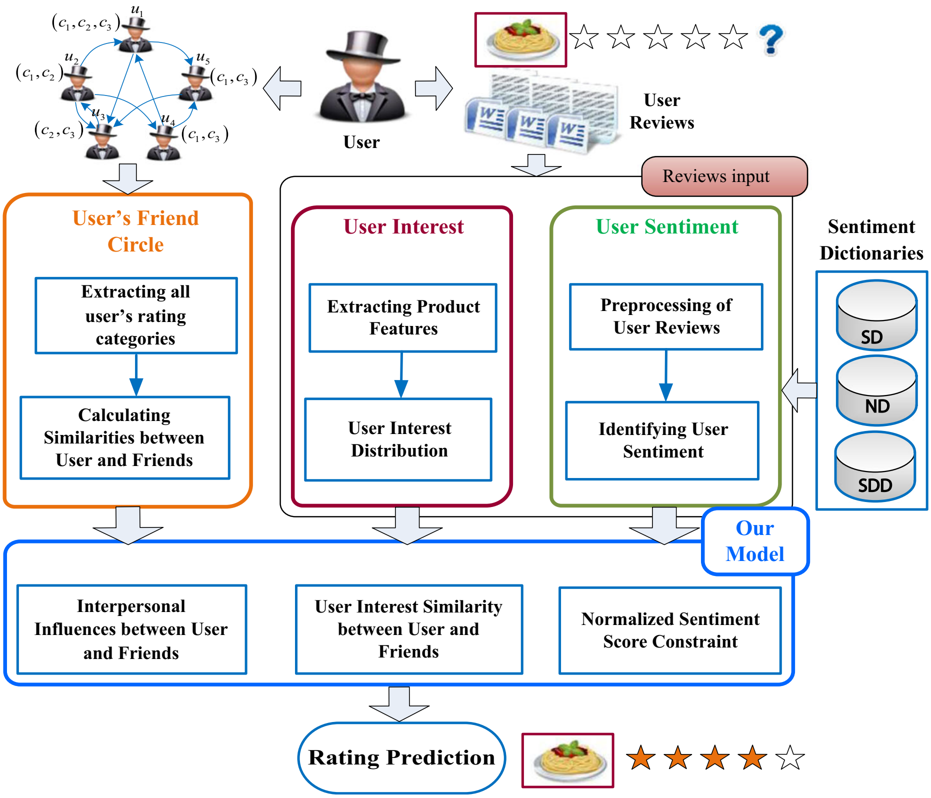


Fig. 1 System overview of our rating prediction model based on user interest and sentiment

dictionary (SDD) and negation dictionary (ND). Last, we fuse the three factors into our recommendation model to predict user's ratings.

3.2 User interest

User interest mainly focuses on the frequently talked product features. In this paper, we calculate user interest by leveraging LDA [2] and Word2vec model [19]. LDA model is used to extract product features. Word2vec model is used to train "N-gram" language model by using Neural Network machine learning algorithms. It can find corresponding vectors of words in the process of training. Here, we use Word2vec model to learn a specific user cared product features. The Word2vec code is available in the website: http://word2vec.googlecode.com/svn/trunk/.

3.2.1 Extracting product features

Product features mainly focus on the discussed issues of a product. In this paper, we extract product features from textual reviews using LDA [2]. LDA is a Bayesian model, which is utilized to model the relationship of reviews, topics and words. In Fig. 2, shaded variables indicate observed variables and unshaded variables indicate latent variables. The arrow indicates a conditional dependency between the variables and plates represented by the box. The definition of terminologies in LDA model is described in Table 1.

Data preprocessing for LDA To construct the vocabulary, we firstly collect all words in reviews without considering the order. Then we filter out "stop words", "noise words" and sentiment words, sentiment degree words, and negation words in the three sentiment

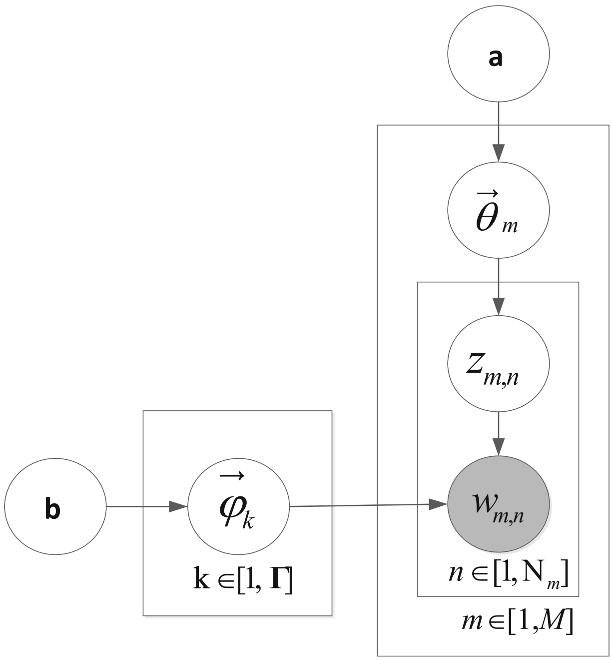


Fig. 2 Graphical model representation of LDA. The outer border represents user document, while the inner border represents the repeated choice of topics and words within a document

Table 1 The definition of terminologies in LDA model

Terminology	Description	Terminology	Description
V	The vocabulary, it has N_d unique words. Each word is presented by a label $\{1, 2, \cdots, N_d\}$.	d_m	The document/review of a user. All documents denotes as $D = \{d_1, d_{2,}\cdots, d_M\}$.
w_i	The word in a review.	Γ	The number of topics.
$\overrightarrow{\theta}_m$	The multinomial distribution of topics specific to the document m. One proportion for each document, $\Theta = \left\{\overrightarrow{\theta}_m\right\}_{m=1}^{M}$	$\overrightarrow{\varphi}_k$	component for each topic, $\Phi = \left\{\overrightarrow{\varphi}_k\right\}_{k=1}^{\Gamma}(\Gamma \times \mathrm{k\ matrix})$
$z_{m,n}$	The topic associated with the n-th token in the document m.	a,b	Dirrichlet priors to the multinomial distribution $\overrightarrow{\theta}_m$ and $\overrightarrow{\varphi}_k$.

dictionaries. The "stop words" could be some prepositions, articles, and pronouns etc. "Noise words" could be the advertisement link and digital gibberish. After words filtering, the input text is clear and without much interference for generating topics. All the unique words are constructed in the vocabulary V, each word has a label $w_i \in \{1, 2, \cdots, N_d\}$.

The generative process of LDA The input of LDA model is all users' document sets D, and we assign the number of topic Γ (we set 50 empirically). The output is the topic distribution for each user (each document) and the topic list, which contains $N_f = 10$ feature words under each topic. The generative process of LDA mainly consists of three steps:

- For each document $\boldsymbol{d}_j$, we choose a dimensional Dirichlet random variable $\theta_{\mathrm{m}} \sim$ Dirichlet (a);
- For each topic z_k, where $k \in [1, \Gamma]$, choose $\phi_k \sim$ Dirichlet (b). And For each topic $\mathrm{z_k}$, the inference scheme is based upon the observation that:

$$p\left(\Theta, \Phi \middle| D^{train}, \alpha, b\right) = \sum_z p\left(\Theta, \Phi \middle| z, D^{train}, \alpha, b\right) P\left(z, \middle| D^{train}, \alpha, b\right) \tag{1}$$

We obtain an approximate posterior on Θ and Φ by using a Gibbs sampler to compute the sum over z.

- Repeating the process above and eventually we get the output of LDA.

More details about the process of LDA could be found in [2].

Product features From LDA model, we obtain each user's topic preference distribution and the topic list. Under each topic, we have frequent product features (mainly some named entities and product attributes). We have given an example of topics (cluster center of a review) and product features in Table 2. From Table 2, we could see that users in each topic care about a different subset of features, and each subset mainly reveals a different kind of product features. The results indicate that users do comment on different features, which matches our assumption that users care about different aspects.

Table 2 Frequent product features of the top-5 topics on restaurant dataset of Yelp

Topics	Example of product features
Topic 1	prices, price, discount, worth, cash, card, queue, sell, pay, online
Topic 2	service, waiter, assistant, manager, waitress, servers, food, people, review, customer
Topic 3	attitude, kind, feeling, interior, feel, accessories, experience, environment, suit
Topic 4	wait, waiting, seat, location, hours, time, order, attitude, turn, minutes, phone
Topic 5	Seafood, lobster, dishes, shrimp, sauce, grouper, prawns, scallop, jellyfish, escargots, mussels

3.2.2 User interest distribution

After obtaining all users' topics, we can get $H = \Gamma \times N_f = 500$ product features in total. And we have each user's product feature distribution $\Omega_u = \{P_1, P_2, \cdots, P_H\}$ where P_i means the probability of user u belongs to the *i-th* product feature. Then we leverage Word2vec model [19] to extract each product feature's word vector. The dimension of the word vector we set is 100 as like in [19, 51]. Then we have each user's interest matrix $\mathbf{M}_u$ as follows:

$$\mathbf{M}_u = \Omega_u \times \mathbf{M}_p \tag{2}$$

where $\mathbf{M}_P$ is the product feature word vector matrix, the dimension is 500 × 100. Then we calculate the relevance of user u and user v as follows:

$$T_{u,v} = Sim(\mathbf{M}_u, \mathbf{M}_v) = \frac{1}{\sqrt{\sum_i \sum_j \left(M_u^{i,j} - M_v^{i,j}\right)^2}} \tag{3}$$

where $\mathbf{M}_u$, $\mathbf{M}_v$ are user u and user v*'s* word vector matrix respectively, $M_u^{i,j}$ $(i \in [1, 500], j \in [1, 100])$ denotes the element of user u's word vector matrix, and $M_v^{i,j}$ denotes the element of user v's word vector matrix. $T_{u,v}$ denotes that if each element in the two user feature matrixes are closer, then user u and user v have similar interest preferences.

3.3 User sentiment

The purpose of extracting user sentiment from reviews is to help predict social users' ratings. The basic idea is that user rates items with high sentiment scores may produce high ratings. We extend HowNet Sentiment Dictionary [20] to identify user sentiment. More details could be found in [21].

We firstly remove some "stop words" and "noise words" as Section 3.2.1. Then each textual review will be divided into several clauses by the punctuation mark. For each clause, we look up the dictionary SD to find the sentiment words before the product features, and take the sentiment degree words into consideration to strengthen the sentiment. Then we check the negative prefix words based on the dictionary ND and add a negation check coefficient. The more details could be found in [21]. For a review r that user u posts for the item i, we get the sentiment score as follows:

$$S(r) = \frac{1}{N_c} \sum_{c \in r} \sum_{w \in c} Q \cdot D_w \cdot R_w \tag{4}$$

where c denotes the clause. N_c denotes the number of clauses. Q denotes the negation check coefficient. D_w is determined by an empirical rule [21]. R_w denotes the initial score of the sentiment word w.

After obtaining the review r's basic sentiment score and improving the sentiment mapping by conjunctive rules [21], we normalize the score as follows:

$$E_{u,i} = \frac{10}{1+e^{-S(r)}} - 5 \tag{5}$$

3.4 Recommendation model based on user interest and sentiment

Our model contains the following three aspects: 1) Interpersonal influence $S^{c*}_{u,v}$ [69], which means whom you trust more. 2) User interest similarity $T^{c*}_{u,v}$, (hereinafter "$*$" denotes a normalized symbol), 3) User normalized sentiment $E^{*}_{u,i}$, which decides how much you are interested in the item. We fuse the three factors into the objective function as follows:

$$\begin{aligned}\Psi(\boldsymbol{R}^c, \boldsymbol{U}^c, \boldsymbol{P}^c) &= \frac{1}{2}\sum_{u,i}\left(R^c_{u,i} - \hat{R}^c_{u,i}\right)^2 + \frac{\lambda}{2}\left(\|\boldsymbol{U}\|^2_F + \|\boldsymbol{P}\|^2_F\right) \\ &+ \frac{\alpha}{2}\sum_u\left(\left(U^c_u - \sum_v S^{c^*}_{u,v}U^c_v\right)\left(U^c_u - \sum_v S^{c^*}_{u,v}U^c_v\right)^T\right) \\ &+ \frac{\beta}{2}\sum_u\left(\left(U^c_u - \sum_v T^{c^*}_{u,v}U^c_v\right)\left(U^c_u - \sum_v T^{c^*}_{u,v}U^c_v\right)^T\right) + \frac{\gamma}{2}\sum_{u,i}\left(E^{*}_{u,i} - U^c_u P^{cT}_i\right)^2\end{aligned} \tag{6}$$

where $\hat{R}^c_{u,i}$ is the predicted rating given by user u to item i in category c. It can be calculated according to Eq. (7). $S^{c^*}_{u,v}$ is the interpersonal influence friend v to user u according to the method proposed in [69]. It means that user latent feature U^c_u should be similar to the average of his/her friends' latent features with weight of $S^{c^*}_{u,v}$. Note that $*$ indicates the normalized value in our model. $T^{c^*}_{u,v}$ is the topic similarity between users. The basic idea is that if two users have the similar topics on items, they may have the similar latent features with the weight $T^{c^*}_{u,v}$. $E^{*}_{u,i}$ is the sentiment score user u to item i. According to Eq. (7), predicted rating is proportional to $U^c_u P^{cT}_i$. Therefore, sentiment score $E^{*}_{u,i}$ is also proportional to $U^c_u P^{cT}_i$. It is the basic idea of the last term of our model. The target of fusing the three part is to optimize the latent features U_u and P_i with more conditions. The inference of our model is similar to [14, 15, 55].

$$\hat{R}_{u,i} = \overline{R} + U_u P^T_i \tag{7}$$

where $\overline{R}$ is the average rating, U_u and P_i are the latent features of user u and item i.

The differences between our model and our previous works [21] are given as follows. Previous work [21] utilizes user sentiment similarity, interpersonal sentiment influence and item reputation similarity, whereas the proposed model contributes to leverage Word2vec model to enhance LDA model for user topic similarity. In addition, we directly utilize user sentiment to optimize the latent features according to the basic idea that user rates items with high sentiment scores may produce high ratings, whereas previous work [21] leverages user sentiment to calculate interpersonal sentiment influence and item reputation similarity. That is to say, the terms of applying $T^{c^*}_{u,v}$ and $E^{*}_{u,i}$ are our contributions.

3.5 Model training

For each category c, we get the corresponding matrix factorization model as Eq. (6) to obtain a separate user latent profile U_u and item latent profile P_i. And the objective function can be minimized by the gradient decent approach as [69]. More formally, the gradients of the objective function with respect to the variables U_u and P_i in category c are shown as (8) and (9) respectively:

$$\begin{aligned}\frac{\partial\Psi}{\partial U_u^c} = &\sum\nolimits_{i\in H_u^c} I_{u,i}^{R^c}\left(\overset{c}{\hat{R}}_{u,i} - R_{u,i}^c\right)P_i^c + \alpha\left(U_u^c - \sum_{v\in F_u^c} S_{u,v}^{c^*} U_v^c\right)\\ &-\alpha\sum\nolimits_{u\in F_v^c} S_{v,u}^{c^*}\left(U_v^c - \sum\nolimits_{w\in F_v^c} S_{v,w}^{c^*} U_w^c\right) + \beta\left(U_u^c - \sum_{v\in F_u^c} T_{u,v}^{c^*} U_v^c\right)\\ &-\beta\sum\nolimits_{u\in F_v^c} T_{v,u}^{c^*}\left(U_v^c - \sum\nolimits_{w\in F_v^c} T_{v,w}^{c^*} U_w^c\right) + \gamma\sum\nolimits_i\left(U_u^c P_i^{cT} - E_{u,i}^{c^*}\right)P_i^c + \lambda U_u^c\end{aligned} \quad (8)$$

$$\frac{\partial\Psi}{\partial P_i^c} = \sum\nolimits_u\left(\overset{c}{\hat{R}}_{u,i} - R_{u,i}^c\right)U_u^c + \gamma\sum\nolimits_u\left(U_u^c P_i^{cT} - E_{u,i}^*\right)U_u^c + \lambda P_i^c \quad (9)$$

where F_v^c denotes user v's friends in category c. The initial values of U^c and P^c are sampled from the normal distribution with zero mean. The user and item latent feature vectors U^c and P^c are updated based on the previous values to insure the fastest decreases of the objective function at each iteration. We set the iteration number $\tau = 500$, and step size $\ell = 0.0002$ to insure the decrease of the objective function in training. The whole procedure of our algorithm is summarized in Algorithm 1.

4 Experiment

We conduct a series of experiments to evaluate the performance of proposed recommendation model based on user interest and sentiment. We choose Yelp as the our dataset, which contains eight categories: *Active Life*, *Beauty&Spa*, *HomeServices*, *Hotel&Travel*, *Nightlife*, *Restaurants*, *Shopping*, and *Pets*. In the following experiments, we firstly evaluate our sentiment algorithm, and then evaluate our rating prediction model. The compared approaches are Base MF [60], CircleCon2b [69], Context MF [15], PRM [55] and EFM [75].

4.1 Sentiment evaluation

We evaluate the sentiment by transforming each sentiment value $E_{u,i}$ into a binary value, namely, $E_{u,i} > 0$, review will be regarded as positive; $E_{u,i} \leq 0$, review will be regarded as negative. When testing in a positive dataset, $E_{u,i} \leq 0$, this case is misclassification; When testing in a negative dataset, $E_{u,i} > 0$, this case is also the misclassification. We firstly label all 5-star Yelp reviews as positive reviews and label all 1-star Yelp reviews as negative reviews, and there are 57,193 positive reviews and 9799 negative reviews in total. The statistics and evaluation results of our sentiment algorithm are shown in Table 3. From Table 3, we can see that the average precision on Yelp is 87.1%. And the precision on positive review corpus and negative review corpus is 91.75% and 60.16% respectively. We also test our sentiment algorithm on the other two public datasets [53, 62], the average precision is 72.7% and 73.5% respectively.

Algorithm 1. The proposed rating prediction model

Input: The rating matrix R in training dataset.
User's interest similarity T calculated by Eq. (3).
User's sentiment E calculated by Eq. (5).
User's interpersonal influence S calculated by [69].
Setting parameters, including iteration count τ, learning rate ℓ, tradeoff parameters λ, α, β and γ.
Output: The performance evaluation results RMSE and MAE.
1: Initialize latent feature matrices U and P.
2: for $t = 1 : \tau$ do
3: for each user u and item i parallel do
4: Calculate $\frac{\partial \Psi}{\partial U_u^c}$ and $\frac{\partial \Psi}{\partial P_i^c}$ by Eq. (8) and (9).
5: Update U_u^c and P_i^c by
6: $U_u^c = U_u^c - \ell \frac{\partial \Psi}{\partial U_u^c}$
7: $P_i^c = P_i^c - \ell \frac{\partial \Psi}{\partial P_i^c}$
8: end for
9: end for
10: for each test user u do
11: for each test item i do
12: Predict the rating user u to item i by Eq. (7).
13: end for
14: end for
15: Output RMSE and MAE calculated by Eq. (10) and (11).

4.2 Rating prediction

4.2.1 Performance measures

In each category of Yelp, we use 80% of data as the training set and the remaining 20% as the test set. The evaluation metrics we use in our experiments are Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). They are the most popular accuracy measures in the literature of recommendation systems [14, 15, 55, 60, 69]. RMSE and MAE are defined as

$$\mathrm{RMSE} = \sqrt{\sum_{(u,i) \in R_{\mathrm{test}}} \left| R_{u,i} - \hat{R}_{u,i} \right|^2 / |R_{\mathrm{test}}|} \tag{10}$$

Table 3 The statistics and evaluation results of our sentiment algorithm

Test dataset		Precision of positive	Precision of negative	Average precision
Movie [53]	2000 reviews	863/1000	592/1000	72.7%
SFU [62]	400 reviews	184/200	110/200	73.5%
Yelp [55]	66,992 reviews	52,474/57,193 (91.75%)	5895/9799 (60.16%)	87.1%

where R_{test} is the set of all user-item pairs (u, i) in the test set. MAE is defined as

$$MAE = \sum_{(u,i)\in R_{\text{test}}} \left| R_{u,i} - \hat{R}_{u,i} \right| / |R_{\text{test}}| \tag{11}$$

4.2.2 Performance comparison

We compare the performance of our algorithm with existing models including BaseMF [60], CircleCon2b [69], Context MF [15], PRM [55] and EFM [75] on Yelp dataset. The brief introduction of the compared algorithms are given as follows.

- **Base MF:** This method is the basic matrix factorization approach proposed in [60], which does not consider any social factors.
- **CircleCon2b:** This method is proposed in [69], which focuses on the factor of interpersonal trust in the social network and infers the trust circle based on matrix factorization.
- **Context MF:** This method [15] improves the accuracy of traditional item-based collaborative filtering in [61], and SoRec in [14]. It takes both interpersonal influence and individual preference into consideration.
- **PRM:** This method is proposed in [55], which considers three social factors, including interpersonal influence, interpersonal interest similarity and personal interest. It is also based on matrix factorization to predict users' ratings.
- **EFM:** This method is proposed in [75]. It builds two characteristic matrixes (i.e. user-feature attention matrix and item-feature quality matrix) in its framework. Each element in the user-feature attention matrix measures to what an extent a user cares about the corresponding product feature/aspect. Each element in the item-feature quality matrix measures the quality of an item for the corresponding product feature/aspect.

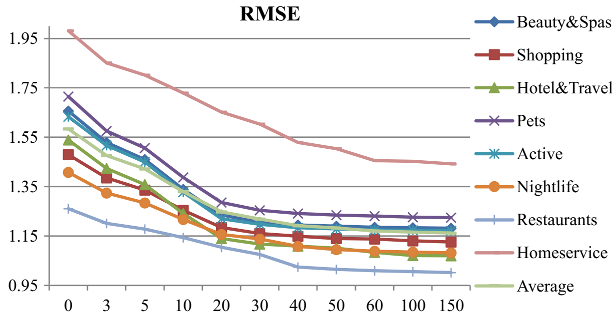
λ is a coefficient for preventing over-fitting, α, β and γ are trade-off parameters. In all compared algorithms, we keep the same initialization input and same parameters in all compared methods. In our model, we set $k = 10$, $\lambda = 1$, $\alpha = \beta = \gamma = 5$. Note that whatever these parameters are, it is fair for all compared algorithms. In order to implement the compared methods, we extract different features in the matrix factorization framework, and build the corresponding feature matrices (i.e. user-feature attention matrix and item-feature quality matrix in EFM [12]). In Table 4, we show the performance of all compared methods based on the Yelp dataset. Note that we enforce the interpersonal influence in other methods as CircleCon2b in our model. We can see that *HomeServices* category and *Pets* category of Yelp have less rating information than other categories [55]. Comparing with the dataset in [55], we find

Table 4 Performance comparisons for eight categories on Yelp

Category	Base MF		CircleCon2b		Context MF		PRM		EFM		OURS	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
Active Life	1.633	1.238	1.477	1.126	1.285	1.002	1.265	0.984	1.215	0.941	1.146	0.893
	29.82%	*27.87%*	*22.41%*	*20.69%*	*10.81%*	*10.88%*	*9.41%*	*9.25%*	*5.68%*	*5.10%*		
Beauty&Spa	1.813	1.390	1.656	1.272	1.454	1.147	1.431	1.128	1.385	1.086	1.315	1.037
	27.47%	*25.4%*	*20.59%*	*18.47%*	*9.56%*	*9.59%*	*8.11%*	*8.07%*	*5.05%*	*4.51%*		
HomeService	1.981	1.558	1.844	1.454	1.624	1.294	1.611	1.284	1.583	1.273	1.533	1.234
	22.61%	*20.80%*	*16.87%*	*15.13%*	*5.60%*	*4.64%*	*4.84%*	*3.89%*	*3.16%*	*3.06%*		
HotelTravel	1.683	1.318	1.539	1.201	1.337	1.055	1.321	1.042	1.267	1.024	1.219	0.961
	27.57%	*27.09%*	*20.79%*	*19.98%*	*8.83%*	*8.91%*	*7.72%*	*7.77%*	*3.79%*	*6.15%*		
Night Life	1.408	1.099	1.311	1.026	1.176	0.93	1.150	0.913	1.134	0.899	1.083	0.874
	23.08%	*20.47%*	*17.39%*	*14.81%*	*7.91%*	*6.02%*	*5.83%*	*4.27%*	*4.50%*	*2.78%*		
Pets	1.873	1.440	1.715	1.329	1.499	1.195	1.481	1.181	1.436	1.146	1.380	1.083
	26.32%	*24.79%*	*19.53%*	*18.51%*	*7.94%*	*9.37%*	*6.82%*	*8.30%*	*3.90%*	*5.50%*		
Restaurants	1.261	0.983	1.202	0.944	1.149	0.909	1.094	0.873	1.113	0.886	1.105	0.882
	12.37%	*10.27%*	*8.07%*	*6.57%*	*3.83%*	*2.97%*	*−1.01%*	*−1.03%*	*0.72%*	*0.45%*		
Shopping	1.600	1.228	1.479	1.138	1.321	1.032	1.302	1.016	1.278	0.999	1.225	0.956
	23.44%	*22.15%*	*17.17%*	*15.99%*	*7.27%*	*7.36%*	*5.91%*	*5.91%*	*4.15%*	*4.30%*		
Average	1.657	1.282	1.528	1.186	1.356	1.071	1.332	1.053	1.301	1.032	1.251	0.990
	24.5%	*22.78%*	*18.13%*	*16.53%*	*7.74%*	*8.1%*	*6.08%*	*5.98%*	*3.84%*	*4.08%*		

The percentage numbers in each cell are the relative improvements of our model over the various baseline models

Fig. 3 RMSE line chart of impact of user interest similarity factor on eight categories of Yelp



that the more ratings in a category, the higher accuracy the RS achieves. It is clearly shown in Table 4 that our model performs much better than the PRM and EFM. For EFM model, we decrease the average prediction error by 3.84% and 4.08% in RMSE and MAE. The result demonstrates that user sentiment and user interest can improve the performance of RS. From Table 4, we can also see that the interpersonal influence in social networks (CircleCon2b model) has a great impact on the accuracy of RS, which agrees well with the findings of [69].

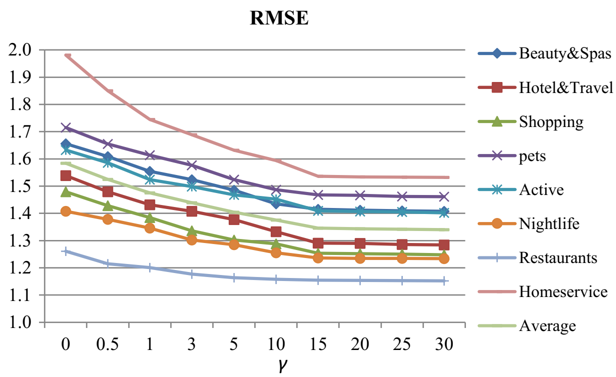
4.3 Discussion

Besides the performance comparison in Table 4, here we discuss two aspects in our experiments based on Yelp dataset: the impact of user interest factor, the impact of user sentiment factor.

4.3.1 The impact of user interest factor

To discuss the impact of user interest factor, we conducted a series of experiments on Yelp dataset. In our model, we set $\alpha = 5$, $\gamma = 0$, and let β range from 0 to 150 for the purpose of testing the importance of user interest factor. The performance is shown in Fig. 3. From Fig.3, we can see that the RMSE drops in all testing categories when β ranges from 0 to 50. The performances are stable when β is in the range [50,150]. The average RMSE under $\beta = 50$ ($\alpha = 5$, $\gamma = 0$) is 1.182 on Yelp dataset. Compared to the Base-MF model, we can see that the

Fig. 4 RMSE line chart of impact of user sentiment factor on eight categories of Yelp



average RMSE decreases about 25.38%. The experiment result suggests that user interest factor makes great contributions to the accuracy of rating prediction.

4.3.2 The impact of user sentiment factor

To discuss the importance of reviews sentiment, we set $\alpha = 5$, $\beta = 0$, and let γ range from 0 to 30. And we only use user's sentiment to estimate user's ratings to the new items. From the result of experiment as shown in Fig. 4, we can see that the RMSE drops in all testing dataset when β ranges from 0 to 15. The performances are stable when β is in the range [18, 64]. The average RMSE under $\gamma = 15$ ($\alpha = 5$, $\beta = 0$) is 1.346 on Yelp dataset. By comparing with Base-MF, we can see that the average RMSE decreases about 15.03%. Here we make Base-MF model as a baseline. The experiments demonstrate that the review sentiment factor has an effective impact on rating prediction in recommendation systems.

5 Conclusions and future work

In this paper, a rating prediction model is proposed by combing three factors: user sentiment, user topic similarity, and interpersonal influence. We used LDA + word2vec model to mine user interest, which is effective to improve the performance. Besides, we designed the method of identifying user sentiment, which is crucial to reflect user's interest. We conducted extensive experiments on a real-world social rating dataset, and it shows significant improvements over existing approaches. Recently, deep learning is proofed to be an effective solution to learn salient features [56, 72, 13, 27, 3, 39] for multimedia content understanding, retrieval, mining and recommendation. Thus, in our future we will fuse the deep features from multiple aspects of social media to perform personalized recommendation.

Acknowledgements This work is partly supported by the NSFC under 61572083, the China Fundamental Research Funds for the Central Universities under Grant 310824153508 and 310824173401 (Chang'an University).

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