Distributed-Representation Based Hybrid Recommender System with Short Item Descriptions

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Abstract

Collaborative filtering (CF) aims to build a model from users’ past behaviors and/or similar decisions made by other users, and use the model to recommend items for users. Despite of the success of previous collaborative filtering approaches, they are all based on the assumption that there are sufficient rating scores available for building high-quality recommendation models. In real world applications, however, it is often difficult to collect sufficient rating scores, especially when new items are introduced into the system, which makes the recommendation task challenging. We find that there are often “short” texts describing features of items, based on which we can approximate the similarity of items and make recommendation together with rating scores. In this paper we “borrow” the idea of vector representation of words to capture the information of short texts and embed it into a matrix factorization framework. We empirically show that our approach is effective by comparing it with state-of-the-art approaches.

1 Introduction

Recommender systems are a subclass of information filtering systems that seek to predict the rating or preference that a user would give to an item (Ricci et al., 2011). Recommender systems have been applied to a variety of applications, e.g., movies, music, news, books, research articles, search queries, social tags, financial services (Felfernig et al., 2007), and Twitter followers (Gupta et al., 2013). In general there are three ways to design recommender systems (Adomavicius and Tuzhilin, 2005), i.e., collaborative filtering (Breese et al., 1998), content-based filtering (Gopalan et al., 2014), and the hybrid filtering (Burke, 2002). Our work follows the strand of hybrid filtering systems.

There have been works on hybrid filtering systems. For example, Saveski and Mantrach (Saveski and Mantrach, 2014) propose to exploit information from item document, i.e., each item is assumed to be associated with a document, to help with recommendation based on the word frequency (or TF-IDF) in documents. Chen et al. present a topic-model based approach to utilize the context and item information (Chen et al., 2014) to help with recommendation. McAuley and Leskovec propose to build a hybrid recommender system by integrating information from review texts with rating scores (McAuley and Leskovec, 2013). Despite the success of the previous approaches, they are based on the assumption that the text information is abundant enough for frequency mining or topic models extraction. When the item description is limited or short, e.g., only a few phrases or tags available, they will not work well since “similar” items with limited descriptions can be very different based on frequency. For example, an item described by “a portable device” should be similar to the item described by “a light-weight and small equipment”, while they are very different based on frequency mining since they share very few words. There are indeed many applications, i.e., MovieLens as shown in Table 1 where item descriptions are often short.

In this paper, we aim to explore the similarity between short item descriptions by looking into the semantic relations between descriptions. Inspired by the vector representations of words (Mikolov et al., 2013c), which has been shown to be effective in capturing the semantic relations among words, we borrow the idea of vector representations to take advantage of short item descriptions to assist

1https://movielens.org
Table 1: Examples of item descriptions in MovieLens

| Item          | Description                     |
|---------------|---------------------------------|
| Toy Story     | animation, children’s, comedy   |
| Jumanji       | adventure, children’s, fantasy  |
| Heat          | action, crime, thriller         |
| Sabrina       | comedy, romance                 |
| Tom and Huck  | adventure, children’s           |
| Sudden Death  | action                          |
| GoldenEye     | action, adventure, thriller     |

recommendation. We first build a matrix based on the vector representations of words, and then integrate the matrix into the rating scores to build a matrix factorization objective function. Finally we solve the objective function using an expectation-maximization algorithm to make item recommendation. We call our algorithm RECF, which stands for hybrid RECommender system based on collaborative Filtering with short reviews.

2 Related Work

Our work is related to distributed representations of words. In earlier work, many models have been proposed to learn a distributed representation of words. Collobert and Weston (Collobert and Weston, 2008) propose a single convolutional neural network called SENNA, to output a host of language processing predictions. Mnih and Hinton (Mnih and Hinton, 2008) propose a fast hierarchical language model called HLBL, based on Log-Bilinear in (Mnih and Hinton, 2007) along with a simple feature-based algorithm, which outperforms non-hierarchical neural models in their evaluations. Mikolov (Mikolov, 2012) proposes a new statistical language model, RNNLM, based on RNN in (Mikolov et al., 2010). Huang et al. (Huang et al., 2012) propose a new model which increases the global context-aware to enrich the semantic information of words. And Mikolov et al. (Mikolov et al., 2013a) proposed two new models, CBOW and Skip-gram. Both models use a simple neural network architecture that aims to predict the neighbors of a word. CBOW predicts the current words based on the context and Skip-gram tries to maximize the classification accuracy of a word based on another word in the same sentence. Mikolov et al. (Mikolov et al., 2013a) also proposed a new tool for learning word vectors called word2vec (Mikolov et al., 2013c). To improve the accuracy of the word representation, Then in the following year, focusing on this technology of distributed representations. Frome et al. used it to make the language model pre-training of a new deep visual-semantic embedding model, as it has been shown to efficiently learn semantically-meaningful floating point representations of terms from unannotated text (Frome et al., 2013). Mikolov et al. (Mikolov et al., 2013b) developed a method that can automate the process of generating and extending dictionaries and phrase tables. Le and Mikolov (Le and Mikolov, 2014) proposed an unsupervised algorithm that learns fixed-length feature representations from variable-length texts. Qiu et al. (Qiu et al., 2015) explored distributed representations of words to detect analogies. In this paper, we exploit the distributed representation approach to transform item descriptions to vectors, and assist recommendation based on these vectors.

3 Problem Formulation

A rating matrix is denoted by $R \in \{1, 2, 3, 4, 5, ?\}^{N \times M}$, where $R_{uv}$ is a rating score given by user $u$ for item $v$, $N$ is the number of users, $M$ is the number of items, and the symbol “?” indicates no score is given by user $u$. An labeling matrix is denoted by $L \in \{0, 1, ?\}^{N \times M}$, where $L_{uv}$ is the label given by user $u$ for item $v$, with the meaning of “dislike”, “like” and “unknown label” for “0”, “1” and “?”, respectively. An item description vector is denoted by $Q$, where $Q_v$ is composed of a set of words describing the properties of item $v$. Note that $Q_v$ can be an empty set $\emptyset$ suggesting no item description given to item $v$. 
Our recommender system can be defined by: given as input a rating matrix $R$, a labeling matrix $L$ and an item description vector $Q$, it aims to estimate unknown rating scores "?" in $R$.

4 Our RECF Algorithm

In this section, we present our RECF algorithm in detail. We first build distributed representations of item descriptions, and then integrate the ratings, labelings and distributed representations of item descriptions to build a bayesian model and learn parameters of the model to build the recommender system. An overview of RECF is shown in Algorithm [1]. We will address each step of Algorithm [1] in detail in the subsequent sections.

Algorithm 1 The framework of our RECF algorithm

**input:** ratings $R$, labelings $L$, item descriptions $Q$

**output:** estimated ratings $\hat{R}$

1: build representations $C$ from descriptions $Q$

2: build hybrid model $M$ based on $R$, $L$ and $C$

3: learn the parameters of $M$ with EM approach

3.0: initiate $U$, $V$, $B_R$, $B_L$ and $W_C$

while the maximal iteration is not reached do

3.1: update $V$ using $U$, $B_R$, $B_L$ and $W_C$

3.2: update $U$ using $V$, $B_R$, $B_L$ and $W_C$

3.3: calculate $B_R$, $B_L$ and $W_C$ using $V$ and $U$

end while

4: compute $\hat{R} = U^TB_RV$

return $\hat{R}$

4.1 Distributed representations of descriptions

As the first step of Algorithm [1], we aim to build the distributed representations of item descriptions with $Q$ as input. We first learn the vector representations for words using the Skip-gram model with hierarchical softmax, which has been shown an efficient method for learning high-quality vector representations of words from unstructured corpora ([Mikolov et al., 2013c]). The objective of the Skip-gram model is to learn vector representations for predicting the surrounding words in a sentence or document. Given a corpus $C$, composed of a sequence of training words $(w_1, w_2, \ldots, w_T)$, where $T = |C|$, the Skip-gram model maximizes the average log probability

$$\frac{1}{T} \sum_{t=1}^{T} \sum_{-c \leq j \leq c, j \neq 0} \log p(w_{t+j}|w_t), \quad (1)$$

where $c$ is the size of the training window or context.

The basic probability $p(w_{t+j}|w_t)$ is defined by the hierarchical softmax, which uses a binary tree representation of the output layer with the $K$ words as its leaves and for each node, explicitly represents the relative probabilities of its child nodes ([Mikolov et al., 2013c]). For each leaf node, there is an unique path from the root to the node, and this path is used to estimate the probability of the word represented by the leaf node. There are no explicit output vector representations for words. Instead, each inner node has an output vector $v'_{n(w,j)}$, and the probability of a word being the output word is defined by

$$p(w_{t+j}|w_t) = \prod_{i=1}^{L(w_{t+j})-1} \left\{ \sigma(\|n(w_{t+j}, i + 1) = \text{child}(n(w_{t+j}, i))\|) \cdot v_{n(w_{t+j}, i)} \cdot v_{w_t} \right\},$$

where $\sigma(x) = 1/(1 + \exp(-x))$. $L(w)$ is the length from the root to the word $w$ in the binary tree, e.g., $L(w) = 4$ if there are four nodes from the root to $w$. $n(w, i)$ is the $i$th node from the root to $w$, e.g., $n(w, 1) = \text{root}$ and $n(w, L(w)) = w$. $\text{child}(n)$ is a fixed child (e.g., left child) of node $n$. $v_{w_t}$ is the input vector representation of word $w_t$. The identity function $\|x\|$ is 1 if
Each user \( x \) is true; otherwise it is -1. We can thus build vector representations of words \( w \), denoted by \( \text{vec}(w) \), by maximizing Equation (1) with corpora.

With vector representations of words, we calculate the overall representations of item descriptions by “summarizing” all words in each item description. There could be many different ways to “summarize” all words. In this paper we consider a straightforward way of computing the overall representations of item descriptions, i.e., calculating an average representation over all words in each item description. We have \( C_v = \frac{1}{|Q_v|} \sum_{w \in Q_v} \text{vec}(w) \), where \( Q_v \) is the set of words describing the properties of item \( v \). If \( Q_v = \emptyset \), \( C_v \) is assigned with symbol “?” with the same meaning in \( R \). Note that we assume the importance of different words in \( Q_v \) is identical in describing item \( v \). It is possible to extend it to considering different importance of words by introducing weights to words when the prior knowledge is provided. We call the resulting matrix \( C = [C_1, C_2, \ldots, C_M]^T \) description matrix.

### 4.2 The hybrid model with item descriptions

In Step 2 of Algorithm 1, we aim to build a hybrid model \( \mathcal{M} \) to capture the underlying relations among ratings \( R \), labelings \( L \), and item descriptions \( C \). The framework of the hybrid model is shown in Figure 1.

![Figure 1: The hybrid model with ratings, labelings and item descriptions.](image)

The rationale of the hybrid model is based on the following four assumptions.

**Assumption 1**: Each user \( u \) and item \( v \) are characterized by an unknown feature vector \( U_u \) controlled by parameter \( \theta_u \) and \( V_v \) controlled by parameter \( \theta_v \), respectively. The rating \( R_{uv} \), which is controlled by parameter \( \alpha \), is assumed to be resulted from bridging \( U_u \) and \( V_v \) with unknown matrix \( B_R \) controlled by parameter \( \beta \). In other words, rating \( R_{uv} \) should be close to \( U_u B_R V_v^T \), i.e., \( R_{uv} \sim U_u B_R V_v^T \). The similar idea is exploited by (Pan and Yang, 2013). This idea can be formulated by maximizing the conditional distribution below, assuming it follows a Gaussian distribution:

\[
p(R_{uv}|U_u, B_R, V_v, \alpha) = \mathcal{N}(R_{uv}|U_u B_R V_v^T, \alpha^{-1}I) \quad \text{where} \quad \mathcal{N}(x|\mu, \alpha^{-1}I) = \frac{1}{\sqrt{2\pi\alpha}} \exp(-\alpha(x - \mu)^2).
\]

**Assumption 2**: Likewise, the labeling \( L_{uv} \), which is controlled by parameter \( \alpha \), is assumed to be resulted from bridging \( U_u \) and \( V_v \) with unknown matrix \( B_L \) controlled by the same parameter \( \beta \) of \( B_R \), i.e., \( L_{uv} \sim U_u B_L V_v^T \). We thus have \( p(L_{uv}|U_u, B_L, V_v, \alpha) = \mathcal{N}(L_{uv}|U_u B_L V_v^T, \alpha^{-1}I) \).

**Assumption 3**: The item description \( C_v \), which is controlled by parameter \( \xi \), is assumed to be resulted from the item features \( V_v \) and unknown matrix \( W_C \) controlled by parameter \( \delta \), i.e., \( C_v \sim V_v^T W_C \). We thus have \( p(C_v|V_v, W_C, \xi) = \mathcal{N}(C_v|V_v^T W_C, \xi^{-1}I) \).

**Assumption 4**: Furthermore, we assume the distributions of \( U_u, V_v, B_R, B_L \) and \( W_C \) are \( p(U_u|\theta_u) = \mathcal{N}(U_u|0, \theta_u^{-1}I) \), \( p(V_v|\theta_v) = \mathcal{N}(V_v|0, \theta_v^{-1}I) \), \( p(B_R|\beta) = \mathcal{N}(B_R|0, (\beta/q_R)^{-1}I) \), \( p(B_L|\beta) = \mathcal{N}(B_L|0, (\beta/q_L)^{-1}I) \), \( p(W_C|\delta) = \mathcal{N}(W_C|0, (\delta/q_C)^{-1}I) \), where \( q_R, q_L, q_C \) are numbers of not “?” elements in \( R, L \) and \( C \), respectively.
Based on the hybrid model shown in Figure 1, our objective is to maximize the function as below:

$$\max_{U, V, R_B, L_B, W_C} \log F_R + \lambda_L \log F_L + \lambda_C \log F_C$$

(2)

where $\lambda_L > 0$ and $\lambda_C > 0$ are tradeoff parameters to balance the ratings, labelings, and item descriptions. $U \in \mathbb{R}^{n \times d}$ and $V \in \mathbb{R}^{m \times d}$ satisfy $U^T U = I$ and $V^T V = I$, respectively. $F_R$, $F_L$ and $F_C$ are defined by

$$F_R = \prod_{u,v} \left[p(R_{uv} | U_u, B_R, V_v, \alpha) p(U_u | \theta_U) p(V_v | \theta_V) p(B_R | \beta)\right]^{x_{uv}}.$$

$F_L = \prod_{u,v} \left[p(L_{uv} | U_u, B_L, V_v, \alpha) p(U_u | \theta_U) p(V_v | \theta_V) p(B_L | \beta)\right]^{y_{uv}}$ and

$$F_C = \prod_{v} \left[p(C_v | W_C, V_v, \xi) p(V_v | \theta_V) p(W_C | \delta)\right]^{z_v},$$

where $x_{uv}$, $y_{uv}$ and $z_v$ are indicator variables for $R_{uv}$, $L_{uv}$ and $C_v$, respectively. If $R_{uv} = \text{"m"}$ (or $L_{uv} = \text{"m"}$ or $C_v = \emptyset$), then $x_{uv} = 0$ (or $y_{uv} = 0$ or $z_v = 0$); otherwise $x_{uv} = 1$ (or $y_{uv} = 1$ or $z_v = 1$).

Specifically, based on the Gaussian distributions given above, the log-posterior function of the ratings is shown below:

$$\log F_R = - \sum_{u,v} x_{uv} \left[\frac{\alpha}{2} (R_{uv} - U_u B_R V_v^T)^2 + \frac{\theta_U}{2} \|U_u\|^2 + \frac{\theta_V}{2} \|V_v\|^2 + \frac{\beta}{2} \|B_R\|^2 + K_R\right],$$

(3)

where $K_R = ln \sqrt{2\pi} + ln (\theta_U/2) + ln (\theta_V/2) + ln (\beta/2)$ is a constant. Likewise, we can compute the log-posterior functions of the labelings $\log F_L$ and descriptions $\log F_C$. We can see the objective function Equation (2) can be reduced to a polynomial function. We will solve the optimization problem using an EM-style algorithm in the next subsection.

4.3 The EM algorithm

In Step 3 of Algorithm 1 we aim to learn the parameters $B_R$, $B_L$, $W_C$, $U$ and $V$ using the EM approach. As the beginning of the EM approach, we initialize $U$ and $V$ using the SVD result of labelings $L$, since the labeling data $L$ describes users’ “high-level” or general interest in items. After that we initialize $B_R$, $B_L$ and $W_C$ with Equations (5) and (6) using $U$ and $V$, which will be introduced in Section 4.3.2.

4.3.1 Learning $V$ and $U$

In Steps 3.1 and 3.2 of Algorithm 1 we aim to learn $V$ and $U$. Given $U$ and $B_R$, $B_L$, $W_C$, we can update $V$ using gradient descent approach. We first simplify the optimization function from Equation (2), as shown below:

$$\min_{U, V} f = \min_{U, V} \frac{1}{2} \|X \odot (R - U B_R V^T)\|_F^2 + \frac{\lambda_R}{2} \|Y \odot (L - U B_L V^T)\|_F^2 + \frac{\lambda_C}{2} \|Z \odot (C - V W_C)\|_F^2,$$

s.t. $U^T U = I, V^T V = I,$

(4)

where $X = [x_{uv}]$, $Y = [y_{uv}]$, $Z = [z_v]$. We then iteratively update $V$ and $U$ by $V = V - \gamma_1 \frac{\partial f}{\partial V}$ and $U = U - \gamma_2 \frac{\partial f}{\partial U}$, where $\gamma_1$ and $\gamma_2$ are two learning constants.

4.3.2 Calculating $B_R$, $B_L$ and $W_C$

In Step 3.3 of Algorithm 1 we compute $B_R$, $B_L$ and $W_C$ using $U$ and $V$. For $B_R$, we have the optimal function shown below, $\min_{B_R} \frac{1}{2} \|X \odot (R - U B_R V^T)\|_F^2 + \frac{\lambda_R}{2} \|B_R\|_F^2$. Letting $B_R = vec(B_R) = [B_{R1}, \ldots, B_{Rd}]$, $m_{ui} = vec(U_u V_i \cdot)$, $R = vec(R)$, where vec($Y$) indicates a vector built by concatenating columns of the matrix $Y$, we have the following equivalent problem, $\min_{B_R} \frac{1}{2} \|R - M \cdot B_R\|_F^2 + \frac{\lambda_R}{2} \|B_R\|_F^2$, where $M = [...m_{ui}...]^T$. Letting $\nabla B_R = 0$, we have

$$vec(B_R) = B_R = (M^T M + \beta I)^{-1} M^T R.$$

(5)

Likewise, we have $vec(B_L) = (M^T M + \beta I)^{-1} M^T L$, where $L = vec(L)$. Finally, we can easily compute $B_R$ and $B_L$ from $vec(B_R)$ and $vec(B_L)$, respectively.
Given $V$, we can estimate the parameter $W_C$ by optimizing the subject function from Equation (2). We have $\min_{W_C} \frac{1}{2} \| Z \odot (C - VW_C) \|^2_F + \frac{\lambda}{2} \| W_C \|^2_F$. We calculate the gradient $\nabla W_C = -V^T C + V^T VW_C + \beta W_C$, and set $\nabla W_C = 0$. As a result, we have

$$W_C = (V^T V + \delta I)^{-1} V^T C. \quad (6)$$

### 4.3.3 Tradeoff between $\lambda_L$ and $\lambda_C$

The initial values of the tradeoff parameters $\lambda_L$ and $\lambda_C$ are set before running the program, which are determined through repeated experiments. During execution, $\lambda_L$ will remain the same while $C$ will change. The reason is that, the labeling data includes accurate information while item description matrix $C$ is obtained based on distributed representations of descriptions. When the labeling data is sparse, the noise issue with item descriptions may be worsened. Thus, the positive influence of $C$ only plays in a macroscopic level but not in a microcosmic one. At the later period of convergence, continuing using $C$ may reduce the accuracy. In other words, the influence of $C$ should be gradually decreased as running the algorithm. We thus propose three options to adjust the value of $\lambda_C$, as shown below.

1. **Linear decline**: Linear decline is the simplest model to specify the declining, in which we compute $\lambda_C$ as follows:

$$\lambda_C = \begin{cases} m - (\text{iter} - 1) \cdot k & \text{if } \text{iter} < \frac{m}{k} + 1 \\ 0 & \text{else} \end{cases} \quad (7)$$

where $m$ is the initial value of $\lambda_C$, $\text{iter}$ is the iteration and $k$ is the step size.

2. **Nonlinear decline**: To emphasize the strong influence of $C$ in the early period, in nonlinear decline, the decreasing speed of $\lambda_C$ also decreases in the execution. We propose a simple model as follows:

$$\lambda_C = m/\text{iter} \quad (8)$$

3. **Mutation**: While the two methods mentioned above are easy to implement, the problem is that it is difficult to determine the step size. Intuitively, if the number of iterations before convergence is large, we should adjust the value of $m$ to decrease the step size, thus extending the time of influence by $C$. Hence, we propose a method of mutating $C$ according to the convergence situation:

$$\lambda_C = \begin{cases} m & \text{if before the first convergence} \\ 0 & \text{else} \end{cases} \quad (9)$$

The advantage of this method is that we do not need to consider the convergence speed.

Finally, in Step 4 of Algorithm 1 we estimate values of “?” in $R$ for recommendations by calculating $UB_R V^T$.

### 5 Experiments

In this section, we evaluate our RECF algorithm using two datasets MovieLens and Douban by comparing it against other four algorithms, SVD (Pan and Yang, 2013), CSVD (Pan and Yang, 2013), CSVD+Binary (Saveski and Mantrach, 2014) and CSVD+TFIDF (Saveski and Mantrach, 2014). SVD is an approach that exploits just ratings for building models for item recommendations. CSVD is an approach that exploits both ratings and labelings information for building models for item recommendations. CSVD+Binary and CSVD+TFIDF are two state-of-the-art approaches that exploit item description information for improving recommendation accuracy. They convert the item descriptions to Binary matrix and tf-idf representations, respectively, and combine them with ratings together to build recommender systems (Saveski and Mantrach, 2014). To make the comparison fair, we fed the labelings to the

[http://www.datatang.com/data/42832](http://www.datatang.com/data/42832) and [http://www.datatang.com/data/44858](http://www.datatang.com/data/44858)
approaches by (Saveski and Mantrach, 2014), resulting in CSVD+Binary and CSVD+TFIDF. For both datasets MovieLens and Douban, we randomly split the data into $n$ ($n=3, 5, 10, 15, 20$) subsets. We randomly selected one for training, one for building labeling data $L$ by setting $L_{ui}$ be 1 if $R_{ui} > 3$ and $L_{ui}$ be 0 otherwise (as done by (Pan and Yang, 2013)). The other $n-2$ subsets are used for testing.

We exploit two metrics to measure the performance, i.e., Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), as shown below,

$$ MAE = \frac{1}{|T_E|} \sum_{(u,i) \in T_E} |r_{ui} - \hat{r}_{ui}| $$

$$ RMSE = \sqrt{\frac{1}{|T_E|} \sum_{(u,i) \in T_E} (r_{ui} - \hat{r}_{ui})^2} $$

where $r_{ui}$ is the ground-truth rating, $\hat{r}_{ui}$ is the predicted rating and $|T_E|$ is the number of testing ratings.

Figure 2: Performance of our RECF algorithm and w.r.t. sparsity of rating scores in dataset Douban.

Figure 3: Performance of our RECF algorithm and w.r.t. sparsity of rating scores in dataset MovieLens.

5.1 Performance w.r.t. sparsity

We first would like to see the performance with respect to different sparsities, by varying the percentage of available ratings (i.e., the rating scores given by users). We ran our RECF algorithm and SVD, CSVD, CSVD+Binary, CSVD+TFIDF five times with different training and testing subsets and computed an average of accuracies. In our RECF algorithm we set $\lambda_L$ to be 0.2 and $\lambda_C$ to be 2.5 in Equation (2).

The results are shown in Figures 2 and 3 where we varied the sparsity from 1.4% to 0.21% in dataset Douban, and from 0.16% to 0.02% in dataset MovieLens, respectively.

From the figures, we can see that both MAE and RMSE become larger when the percentage of ratings decreases in both datasets. This is consistent with our intuition since the fewer the ratings are, the larger the MAE and RMSE are. Comparing different curves, CSVD+Binary, CSVD+TFIDF and RECF algorithms generally perform better than SVD and CSVD in terms of MAE and RMSE, especially when the rating message is very sparse. This indicates item descriptions can indeed help improve the recommendation accuracy. However, in Douban field, we find that CSVD-TFIDF performs almost the same as CSVD while CSVD-Binary even makes a negative effect on the result. The main reason is that the item descriptions we can use are only tags instead of long text descriptions. The item description information cannot be captured correctly by Binary or tf-idf matrix, which harms the recommendation accuracy. In contrast, our RECF algorithm can better leverage these item description information based on distributed representations of words.

Furthermore, in both datasets, we can also observe that MAE (or RMSE) of SVD (or CSVD, CSVD+Binary, CSVD+TFIDF) increases faster than our RECF algorithm as the percentage of rating scores decreases, i.e., the sparsity increases, which suggests that our RECF algorithm functions even better, compared to the other four approaches, when the rating data is much sparser. This is because the impact of item descriptions relatively becomes larger when rating data decreases, resulting larger improvement of accuracies by item descriptions.
5.2 Tradeoff between $\lambda_C$ and $\lambda_L$

Next, we would like to see the impact of $\lambda_C$ in Equation (2). We tuned the tradeoff between $\lambda_L$ and $\lambda_C$ by varying the value of $\lambda_C$ with respect to the number of iterations in RECF, as presented by Equation (9). As we can see from Equation (9), the value of $\lambda_C$ is fixed to be $m$ before the first convergence and 0 once our RECF algorithm converging, where $m$ is the preset initial value of $\lambda_C$. We fixed $m$ to be 2.5 and $\lambda_L$ to be 0.2 as done in the last subsection. We present the results in Figures 4 and 5.

![Figure 4: Impact of $\lambda_C$ and $\lambda_L$ in our RECF algorithm in dataset Douban.](image)

![Figure 5: Impact of $\lambda_C$ and $\lambda_L$ in our RECF algorithm in dataset MovieLens.](image)

We find that the changes of performance (i.e., curves) can be divided into two stages, which indicate two phases of convergence. The first phase is for the tradeoff parameter of description matrix $C$, namely $\lambda_C$. At the beginning of convergence, $C$ weights more than $L$ and dominates the convergence. In this period, the curve declines as expected. However, as we can see from the figures, the curve may prematurely converge with a relatively low accuracy. The reason is that, due to the characteristics of $C$ – capturing the similarity information in short descriptions with noise generated by word embedding, it may have a negative effect in a microcosmic level to get more accurate results. When we change $\lambda_C$ to 0, i.e., $C$ no longer has any impact on the recommendation result, the curves go to another convergence stage, which verifies that $C$ mainly help improve the accuracy in the early stage by estimating values of “?” in $R$. Once the information from item descriptions $C$ has been encoded in $R$ and $L$ after the first convergence, the impact of item descriptions should be reduced (letting $\lambda_C$ be 0) and as a result, the impact of rating scores $R$ and labelings $L$ is relatively magnified to improve the recommendation accuracy. The rationale is that when the number of iterations reaches a threshold reducing the impact of description matrix $C$ could help avoiding overfitting when continuing running our RECF algorithm. Note that setting $\lambda_C$ to be 0 indicates we do not need to update parameters $W_C$ in the objective function of Equation (2) and as a result the size of parameters to be learnt is reduced. In summary, $C$ should be weighed larger than $L$ in the early stage for quickly injecting it’s impact on the learning process, and then reduced to zero to increase the impact of $R$ and $L$.

6 Conclusion

In this paper, we propose a novel algorithm RECF to explore item descriptions to help improve the recommendation accuracy using distributed representations of item descriptions. Using this vector representation, we transform the item descriptions into vector representations, and combine them with rating and labeling data to build a hybrid recommender system. We exhibit that our RECF approach is effective by comparing with the state-of-the-art approaches that exploit item descriptions. In the future, we would like to explore more information in our algorithm framework, such as user profiles or reviews, to further improve recommendation accuracies.
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