Knowledge-Based Systems 109 (2016) 90–103

Contents lists available at ScienceDirect

Knowledge-Based Systems

journal homepage: www.elsevier.com/locate/knosys

Recurrent neural network based recommendation for time heterogeneous feedback

Caihua Wu [a], Junwei Wang [b], Juntao Liu [b,*], Wenyu Liu [c]

[a] Section of Automatic Command, Huang Pi NCO School, Air Force Early-warning Academy, Wuhan 430345, China
[b] 709th Research Institute, China Shipbuilding Industry Corporation, Wuhan, 430074, China
[c] Department of Electronics and Information Engineering, Huazhong University of Science and Technology, Wuhan, 430074, China

ARTICLE INFO

Article history:
Received 6 December 2015
Revised 17 June 2016
Accepted 22 June 2016
Available online 27 June 2016

Keywords:
Recommender system
Collaborative filtering
Time heterogeneous feedback
Recurrent neural network
Deep learning

ABSTRACT

In recommender systems, several kinds of user feedback with time stamps are collected and used for recommendation, which is called the time heterogeneous feedback recommendation problem. The existing recommendation methods can handle only one kind of feedback or ignore the time stamps of the feedback. To solve the time heterogeneous feedback recommendation problem, in this paper, we propose a recurrent neural network model to predict the probability that the user will access an item given the time heterogeneous feedback of this user. To our best knowledge, it is the first time to solve the time heterogeneous feedback recommendation problem by deep neural network model. The proposed model is learned by back propagation algorithm and back propagation through time algorithm. The comparison results on four real-life datasets indicate that the proposed method outperforms the compared state-of-the-art approaches.

1. Introduction

Nowadays recommendation systems are used in many different domains in online business systems [1], in which telecom products/services [2], government-to-business e-services [3], news [4], music [5] and so on are recommended to the users.

Because of the widely application, there are diverse kinds of user feedback in the recommendation systems, such as rating, transaction, browsing, reviewing, sharing and so on. Some kinds of feedback are explicit, such as rating and transaction, while some are implicit, such as click, browsing and so on. Some kinds of feedback are uncertain with respect to the user's preference, but some reflect the user preference certainly. For example, we cannot decide whether a user likes the product when he (or she) browsed it. However, we can infer a user likes the product when he (or she) rated it with high score. It is difficult to leverage all kinds of feedback effectively in the recommender systems because of the diversity. The existing recommendation methods can only handle one kind of explicit feedback, such as rating prediction methods [6,7], or one kind of implicit feedback, such as BPR [8] and its extensions [9]. Pan et al. [10] propose a method which can handle heterogeneous implicit feedback, but it cannot handle implicit and explicit feedback at the same time. On the other hand, the time stamps of the feedback are also useful for recommendation. The time sequence of user feedback reflects the change of the user preference. Using time stamps of feedback can make the recommendation results keep up with the trend of fashion or hot spots, which is very important in the time-sensitive fields, such as cloth, news and so on.

In this paper, we focus on the problem of time heterogeneous feedback recommendation. In this scenario, the recommender systems record different kinds of feedback activities and the corresponding time stamps. The feedback may be explicit or implicit, certain or uncertain. According to the recorded feedback and the time stamps, the recommender systems try to decide which items the users may be interested in, and recommend them to the users. For more details about the problem of time heterogeneous feedback recommendation, please see Section 3. In this paper we transform this problem to estimating the probability of a user prefers an item in the future given his (or her) historical feedback. The feedback activities are sorted by the time stamps as a sequence in order to reflect the trend of the user's preference. If each feedback activity is regarded as a symbol, the task of time heterogeneous feedback recommendation is very similar to that of N-gram language model, in which the probability of a symbol (word) appears after a sequence of symbols is estimated. This observation prompts that the idea of statistic language model can be used to solve the problem of time heterogeneous feedback recommendation.

* Corresponding author.
E-mail addresses: wucaihua2009@163.com (C. Wu), wjw.20012001@163.com (J. Wang), prolay@163.com (J. Liu), liuwy@hust.edu.cn (W. Liu).

http://dx.doi.org/10.1016/j.knosys.2016.06.028
0950-7051/

But the differences between these two problems are obvious. First, in recommender systems, because the preferences of users are different, a preference model should be learned for each user, while only one language model is needed for a particular language. Second, sentences of natural language are generated by the underlying grammar, while the feedback sequences are generated by the user preference which is more stochastic than nature language grammar. According to these characteristics, in this paper, we propose a recurrent neural network model to solve the time heterogeneous feedback recommendation problem. The proposed model has two advantages. First, different kinds of feedback are represented by vectors. This makes the model can treat diverse feedback in an uniform way. Second, the proposed model is a recurrent neural network, in which the influence of the previous feedback is remembered. This makes the model can handle time heterogeneous feedback in recommender systems.

We summarize the contributions of this paper here.

1. In this paper, we propose the problem of time heterogeneous feedback recommendation and the model of this problem. We transform this problem to estimating the probability of a user prefers a item in the future given the historical feedback.
2. According to the model of time heterogeneous feedback recommendation problem, we propose a recurrent neural network to solve this problem. To our best knowledge, it is the first time to use recurrent neural network to solve this problem. The proposed neural network is composed of two parts: the recurrent part and non-recurrent part. The recurrent part remembers the influence of the historical feedback. And the non-recurrent part represents the underly user preference. Further more, the proposed neural network can handle different kinds of feedback in a uniform way.
3. We propose two algorithms to learn the proposed neural network recommendation model using back propagation and back propagation through time, respectively.
4. We compare the proposed recommendation method with the state-of-the-art recommendation methods, and the proposed method gets more satisfied results.

The rest of this paper is organized as follows. In Section 2, the related work about the recommendation methods and deep neural network is provided. In Section 3, the problem of time heterogeneous feedback recommendation is discussed. In Section 4, the proposed neural network recommendation model is introduced in details. The experimental results on four large real life datasets are presented and analyzed in Section 5 followed by the conclusions and future work in Section 6.

2. Background and related work

In this section, the related research fields of recommendation and deep neural network are introduced briefly.

2.1. Recommendation

Recommender systems have become an important research area in the past decade. Recommender systems try to predict the items that the users may be interested in by collecting the feedback activities of the users, such as rating, transaction, browsing, reviewing, sharing and so on. Recommendation methods are generally divided into collaborative filtering (CF) methods and content-based (CB) methods [11]. Content-based recommendation methods recommend the items which are similar to the favorite items according to the property of the item. Collaborative filtering methods always build a model for each user from the historical activities, and the model is used to predict the items that the user may be interested in.

Matrix factorization based recommendation methods, such as Variational Bayesian Matrix Factorization (VBMF) [12], Probabilistic Matrix Factorization (PMF) [6], Bayesian Probabilistic Matrix Factorization (BPMF) [7], General Probabilistic Matrix Factorization (GPMF)[13] and so on, are the most popular collaborative filtering methods. Each user and item is represented by the latent feature vector. The ratings are predicted by the inner product of the user latent feature vector and the item latent feature vector. Matrix factorization based recommendation methods gain great success, but they also face the challenge of the data sparsity problem and the cold-start problem [14]. To address these problems, side information, such as social relation and tag information, is integrated into matrix factorization by factorization manner [15–20] or regularization manner [19,21–25]. In factorization-based methods, relation matrix representing social relation or other relation is factored as well as the rating matrix. The weighted sum of the relation matrix factorization error and the rating matrix factorization error is minimized. In regularization-based methods, regularization terms, which measure the difference of the related users or items, are added to the loss function. Except for this two kinds of methods, there are some recommendation methods using side information in other ways [26–28].

Traditional matrix factorization based recommendation methods take the sum-of-squares of factorization errors as the objective function, which can be regarded as point-wise methods. Recently, some pair-wise methods, such as BPRMF [8] and Weighted BPRMF (WBPMF) [9], are proposed, in which the pair-wise comparison error is minimized. List-wise methods are also proposed, such as ListPMF [29] and QMF [30]. In these methods, the recommended item list is regarded as a whole instance, and the log-posterior over the recommended item list with the observed preference orders is maximized. Conditional preference is considered in QMF as well as TreeMF [31].

Recently, some methods, such as BPRMF [8], Weighted BPRMF (WBPMF) [9] and CLiMF [32], are proposed for implicit feedback recommendation. Pan et al. [10] propose a method for heterogeneous implicit feedback recommendation.

2.2. Deep neural network

2.2.1. Neural network language model

Neural networks are widely used for natural language processing. The first neural network language model is proposed by Bengio et al. [33], which is a feed forward neural network based language model. The input of the model is the historical $n-1$ words. Each of the input word is encoded by a real value vector. There is only one hidden layer in the model. The output is the probability distribution of the words in the vocabulary given the historical $n-1$ words. The model is trained by stochastic gradient descent using back propagation algorithm. And the training process is time-consuming. A single training epoch takes almost one week using 40 CPUs.

To reduce the training time, the model is trained through parallel technology [34]. Mikolov et al. [35] train the model by 2 stages. In the first stage, a bigram model, which uses only one historical word, is trained. And then, an n-gram model is trained based on the already trained bigram model.

Different kinds of neural networks, such as recursive neural networks [36–38], recurrent neural networks [39,40] and convolution neural networks [41,42], are also proposed for natural language processing.

In recurrent neural networks, the hidden layers are connected recurrently to the input layers. A recurrent neural network language model is proposed by Mikolov et al. [43,44]. The previous history is represented by the recurrent hidden layer in this model.