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Gated recurrent units based neural network for time heterogeneous feedback recommendation

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A B S T R A C T

Nowadays, recommender systems face the problem of time heterogeneous feedback recommendation, in which items are recommended according to several kinds of user feedback with time stamps. Previously proposed recurrent neural network based recommendation method (RNNRec) cannot analyze feedback sequences on multiple time scales, and gradient vanishing may occur when the model is trained through back propagation through time (BPTT) algorithm. To address these issues, we propose a gated recurrent units (GRU) based neural network to predict which items users will access in the future. The GRU layer in the model can analyze feedback sequences on multiple time scales and can avoid gradient vanishing during training. The proposed approach is verified on three large-scale real-life datasets, and the comparison indicates that the proposed approach outperforms several state-of-the-art methods.

1. Introduction

Nowadays recommendation systems are widely deployed in different kinds of online business systems [16,17,45]. In these systems, there are diverse kinds of user feedback, such as rating, transaction, browsing, reviewing, sharing and so on. The feedback may be explicit or implicit, certain or uncertain. Time stamps of the feedback are also recorded to reflect the change of the user preference. According to the historical feedback with time stamps, recommender systems try to decide which items the users may prefer in the future, and recommend these items to the users. This problem is called time heterogeneous feedback recommendation, which was introduced for the first time in [43]. This paper will also give a brief introduction to this problem in Section 3.1. In this circumstance, it is difficult to leverage all kinds of feedback effectively because of the diversity. Traditional recommendation methods can only handle one kind of explicit feedback, such as rating prediction methods [28,29], or one kind of implicit feedback, such as BPR [8] and its extensions [27]. AdaptiveBPR [25] can handle heterogeneous implicit feedback, but it cannot deal with implicit and explicit feedback simultaneously. Additionally, the time stamps of the feedback are also valuable for recommendation. It is necessary to use this information to catch up with the fashion trend or the hot spots, which is very important in time-sensitive fields, such as clothes, news, etc.

In our previous work [43], a recurrent neural network based recommendation approach (RNNRec) is proposed to address the problem of time heterogeneous feedback recommendation. In RNNRec, historical feedback activities of the users

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with time stamps are treated as sequences, and a recurrent neural network is trained using these feedback sequences. It is reported that the recommendation results generated by RNNRec are more accurate than those generated by traditional recommendation methods. However, RNNRec has two main drawbacks. First, training the recurrent neural network by back propagation through time (BPTT) algorithm may cause the gradient vanishing problem [5], although it is not observed when the number of unfolded time steps is relatively small in [43]. Second, in RNNRec, the feedback activities are sorted by the time stamps. Only the order information of the time stamps are used, and the time interval between two feedback activities are ignored. This makes RNNRec unable to analyze feedback sequences on multiple time scales. For example, in RNNRec, two neighboring feedback activities occurring in a single day are treated identically to those occurring within a week. Obviously, it is unreasonable. So multiple time scale analysis is needed for the time heterogeneous feedback recommendation problem.

To address these problems, in this paper, we modify the model of RNNRec, and design a neural network with gated recurrent units (GRU) according to the characteristic of time heterogeneous feedback recommendation. It is reported that GRU can prevent gradient vanishing when the neural network is trained through BPTT [5]. And the GRU layer, including the reset gate and the update gate, can learn both long-term and short-term dependencies from sequences [4]. In this way, the users' historical feedback sequences can be analyzed on multiple time scales.

The main contribution of this paper is that we propose a gated recurrent units neural network based recommendation method (GRURec) to address the problem of time heterogeneous feedback for recommendation. In GRURec, feedback sequences are analyzed on multiple time scales, and gradient vanishing is avoided during training. Because of these two advantages, GRURec gets more accurate results than the state-of-the-art methods on three large-scale real-life datasets.

The rest of this paper is organized as follows. In Section 2, the related work about recommendation methods and deep learning based recommendation methods is provided. After a brief introduction to the problem of time heterogeneous feedback for recommendation and RNNRec [43] in Section 3, the proposed recommendation method is introduced in details in Section 4. The experimental results on three large-scale real-life datasets are presented and discussed in Section 5, followed by the conclusions and future work in Section 6.

2. Related work

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

Recommendation approaches have become an important research area in the past decade. Recommendation approaches are generally divided into collaborative filtering (CF) approaches, content-based (CB) approaches and hybrid approaches [1]. Content-based recommendation approaches recommend the items which are similar to the favorite items of the user according to the item properties. Collaborative filtering approaches 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. Hybrid approaches combine content-based approaches and collaborative filtering approaches to avoid their limitations.

Matrix factorization based approaches are the most popular collaborative filtering approaches, in which users and items are represented by latent feature vectors. The ratings are predicted by the inner product of the user latent feature vector and the item latent feature vector. Matrix factorization based approaches gain great success, such as Variational Bayesian Matrix Factorization (VBMF) [15], Probabilistic Matrix Factorization (PMF) [29], Bayesian Probabilistic Matrix Factorization (BPMF) [28], General Probabilistic Matrix Factorization (GPMF) [33] and so on. But the data sparsity problem and the cold-start problem [14] are also challenges. To alleviate these problems, side information, such as social relation and tag information, is integrated into the framework of matrix factorization. These approaches can be divided into factorization based approaches [23,35,46,47] and regularization based approaches [13,22,44,46,50]. In factorization based approaches, the relation matrix representing social relation or other relations is factorized 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 approaches, regularization terms, which measure the difference of the related users or items, are added to the loss function. Some approaches [3,19,49] are also proposed to use the side information in other ways.

Traditional matrix factorization based recommendation approaches are point-wise approaches, in which the objective function is the sum-of-squares of factorization errors. Recently, pair-wise approaches and list-wise approaches are also proposed. In pair-wise approaches, such as BPRMF [8] and Weighted BPRMF (WBPMF) [27], the objective function is the pair-wise comparison error. In list-wise methods, such as ListPMF [20] and QMF [21], the recommended item list is regarded as a whole instance, and the log-posterior over the recommended item list with respect to the observed preference orders is maximized.

Instead of exploiting explicit feedback, some approaches, such as BPRMF [8], Weighted BPRMF (WBPMF) [27], CLiMF [34] and AdaBPR [25], take implicit feedback as training samples.

How to represent user preferences in recommender systems is also an important issue. Traditional matrix factorization based approaches use linear functions to represent the user preferences. In [31,32], user preferences are defined through fuzzy logic. In recent years, some researchers propose to use quadric function [21] and regression tree [18] to represent the user's preference.