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An item orientated recommendation algorithm from the multi-view perspective

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ABSTRACT

In the traditional recommendation algorithms, items are recommended to users on the basis of users' preferences to improve selling efficiency, which however cannot always raise revenues for manufacturers of particular items. Assume that, a manufacturer has a limited budget for an item's advertisement, with this budget, it is only possible for him to market this item to limited users. How to select the most suitable users that will increase advertisement revenue? It seems to be an insurmountable problem to the existing recommendation algorithms. To address this issue, a new item orientated recommendation algorithm from the multi-view perspective is proposed in this paper. Different from the existing recommendation algorithms, this model provides the target items with the users that are the most possible to purchase them. The basic idea is to simultaneously calculate the relationships between items and the rating differences between users from a multi-view model in which the purchasing records of each user are regarded as a view and each record is seen as a node in a view. The experimental results show that our proposed method outperforms the state-of-the-art methods in the scenario of item orientated recommendation.

1. Introduction

In the era of information explosion, there spring up a great amount of data in Internet. So it is difficult for us to select useful information before we make a decision on a large number of choices in a short time and people have troubles choosing suitable items. To deal with this problem, recommendation algorithm emerges as the times require. It has been widely used in a number of famous e-commerce platforms like Amazon [1], Netflix [2], YouTube [3], Yahoo [4], etc. In recommender system, appropriate items are recommended to users based on users' preferences or purchasing records, increasing their urge to shop. Generally speaking, the traditional recommendation algorithms can be classified into three types: collaborative filtering (CF), content-based recommendation (CB) and hybrid recommendation [5]. Moreover, some other recommendation algorithms integrating the knowledge transferred from other information like social network [6], item's tag [7] or the context [8] have also been developed to meet the needs of different application tasks. In addition, many techniques can be incorporated into recommendation algorithms, like matrix factorization [9], graph model [10], random walk [11] and Bayesian approach [12].

However, all the existing algorithms only take the users' benefits into consideration, and there are no algorithms designed to perform recommendation on the basis of items to raise revenues for manufacturers of particular items. Assume that, a manufacturer has a limited budget for an item's advertisement. With this budget, it is only possible for him to advertise to a limited number of users. How to select the most suitable users that can increase advertisement revenue? It is clear that it seems to be an insurmountable problem to the existing recommendation algorithms. To our best knowledge, all the existing algorithms are designed to recommend items to users and there are no algorithms recommending users to items. To address the above issue, we present an approach based on the multi-view learning and perform item orientated recommendation.

Nowadays a multitude of heterogeneous but related views of data have arisen in many fields, and been widely investigated in social network mining [13], clustering [14], classification [15], computer vision [16], domain adaption [17] and transfer learning [18], etc. Combining information on these related views will improve

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the learning performance because we use more information to describe objects. It leads to the emergence of a challenging machine learning problem termed multi-view learning [19,20]. In the multi-view learning, different views admit the same underlying class structure and the generated model can not only better capture the data within individual views but also be consistent across different views [14,21]. However, up to now there are no recommendation algorithms investigating multi-view learning.

In this paper, we propose a novel item orientated recommendation algorithm from the multi-view perspective (MVIR) which can recommend users to an item to raise advertisement revenue for the manufacturer. A multi-view model is firstly established where the purchasing records of each user are represented by a view and items purchased by this user correspond to the nodes in the view. The relationships between items and the differences between users will be learned from the multi-view model by the gradient descent algorithm. Both of them will be used to predict the potential customers to items.

To evaluate the effectiveness of the proposed approach, extensive experiments have been conducted on four real-world rating datasets. Experimental results show that the proposed MVIR algorithm can recommend users to items well, which means that a manufacturer of a particular item can advertise to those recommended users to increase the revenue because they are the most likely to buy the item. We compare our algorithm with some state-of-the-art recommendation algorithms and the results show that the MVIR is the most suitable one for the problem of recommending users to items.

The contributions are summarized as follows:

1. A novel item orientated recommendation algorithm is proposed to increase advertisement revenues of manufacturers of particular items. It is the first time to incorporate multi-view learning to perform recommendation.
2. The proposed model utilizes multi-view to learn the items' relationships and users' rating differences to provide the target items with the users that are the most possible to purchase them so that manufacturers can make the best of the advertising budget.
3. Extensive experiments conducted on several real-world rating datasets show that our model outperforms other state-of-the-art recommendation algorithms and can predict users who will buy target items accurately.

The rest of this paper is organized as follows. Section 2 introduces the related works on recommendation algorithm and multi-view. In Section 3, we describe the proposed MVIR algorithm in detail. In Section 4, extensive experiments will be conducted to illustrate the performance of the proposed algorithm. Section 5 concludes this paper.

2. Related work

In this section, we review several major approaches for recommender systems and multi-view learning.

The collaborative filtering (CF) algorithm is one of the most successful methods in e-commerce [22–24]. The CF algorithm utilizes scores of users' rating records to predict items the target user will like. There are two kinds of CF algorithms, one of which is item-based collaborative filtering (IBCF) [25] and the other is user-based collaborative filtering (UBCF) [26]. The IBCF algorithm computes the items' similarities according to the users' rating records and recommends items to a user which are similar to what the user have purchased. On the contrary, the UBCF algorithm measures the similarities between users and provides target users with the items that the similar users have purchased [27]. The most widely used similarities include cosine-based similarity, correlation-based similarity and adjust-cosine similarity [28]. Apart from the CF algorithm, the content-based (CB) algorithm [29] also plays a significant role in the industry. It finds some features to represent an item and utilizes the profile of a user to learn the user's preference, then the recommendation is made by mapping the result of profile learning and the features of an item. The most common way to learn users' preferences is to use the key words with high weight as features generated by TF-IDF [30] from users' documents. Hybrid recommendation algorithm can combine the advantages of different recommendation algorithms to make a better recommendation result. The simplest approach is to combine the results calculated from the CF and CB algorithms directly [31] while the more comprehensive method is to integrate different algorithms into a single model, e.g. [32].

Some other recommendation algorithms have been developed. Matrix factorizations, like probabilistic matrix factorization (PMF) [9], maximum-margin matrix factorization (MMMF) [33], non-negative matrix factorization (NMF) [34] and tensor decomposition (TD) [35], are commonly used in recommendation. In [9], PMF was proposed to obtain the latent feature matrices of users and items respectively by decomposing the user-item rating matrix and get the final rating matrix by the product of the two feature matrices. Another perspective of the matrix factorization is tensor decomposition (TD), for it is viewed as a high-order extension of the matrix factorization [35]. The algorithm discovers three latent feature matrices of user, item and the other element like time information [36] or tag [37] respectively by decomposing the tensor.

More information is combined with the existing CF algorithm or matrix factorization [6,38–41]. For instance, SocialMF [6] incorporating PMF with social network can form the user-user trust matrix and the user-item rating matrix, after that the latent feature matrices of user and item can be acquired by trust propagation and PMF, making better recommendation and solving the cold-start problem. In [38], a generalized stochastic block model (GSBM) supposes that the relation between users and items is governed by the relation between their groups, respectively. All users and items are grouped according to the links between users and the rating to the items. In [40], a tag system U-CF-TR inferring users' similarities according to items' tags and users' rating records, is combined with the CF algorithm to improve recommendation quality. Moreover, in [41], it proposed a model named FUSE which utilizes the PARAFAC to extract the knowledge from the auxiliary domains and makes use of the knowledge in target domain.

In addition, several techniques can be added into recommendation algorithms [11,12,42]. In [11], the items will be recommended to users by performing query centered random walk on the K-partite graph. It utilizes multi-way clustering to group together the highly related nodes and the recommendation is made by traversing the subgraph induced by clusters on the basis of a user's preference. The model proposed in [12] uses Bayesian treatment on matrix factorization to place Gaussian-Wishart priors on the user and item hyperparameters of their corresponding feature vectors obtained by PMF and is trained by Markov chain Monte Carlo methods to implement recommendation. Restricted Boltzmann Machines (RBM) [42], one of the most important network structures in deep learning, is utilized to make a movie recommendation on the Netflix dataset.

For multi-view, there are many applications in different fields, such as networks, clustering, classification, computer vision, domain adaption, transfer learning, etc. [13,16,43–46]. A generalized framework PICA [13] is developed to find the relation between users from multislice networks. In [16], it developed a model based on multi-view and deep convolutional neural networks to do face detection, which does not require annotation and is able to detect faces in a wide range of orientations. Multi-view

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