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A Hybrid Collaborative Filtering Model with Deep Structure for Recommender Systems

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Abstract

Collaborative filtering(CF) is a widely used approach in recommender systems to solve many real-world problems. Traditional CF-based methods employ the user-item matrix which encodes the individual preferences of users for items for learning to make recommendation. In real applications, the rating matrix is usually very sparse, causing CF-based methods to degrade significantly in recommendation performance. In this case, some improved CF methods utilize the increasing amount of side information to address the data sparsity problem as well as the cold start problem. However, the learned latent factors may not be effective due to the sparse nature of the user-item matrix and the side information. To address this problem, we utilize advances of learning effective representations in deep learning, and propose a hybrid model which jointly performs deep users and items' latent factors learning from side information and collaborative filtering from the rating matrix. Extensive experimental results on three real-world datasets show that our hybrid model outperforms other methods in effectively utilizing side information and achieves performance improvement.

Introduction

In recent years, with the growing number of choices available online, recommender systems are becoming more and more indispensable. The goal of recommender systems is to help users in identifying the items that best fit their personal tastes from a large repository of items. Besides, many commerce companies have been using recommender systems to target their customers by recommending items. Over the years, various algorithms for recommender systems have been developed. Such algorithms can roughly be categorized into two groups (Shi, Larson, and Hanjalic 2014): content-based and collaborative filtering(CF) based methods. Content-based methods (Lang 1995) utilize user profile or item content information for recommendation. CF-based methods (Salakhutdinov and Mnih 2011), on the other hand, ignore user or item content information and use the past activities or preferences, such as user buying/viewing history or user ratings on items, to recommendation. Nevertheless, CF-based methods are often preferred to content-based methods because of their impressive performance (Su and Khoshgoftaar 2009).

The most successful approach among CF-based methods is to learn effective latent factors directly by matrix factorization technique from the user-item rating matrix (Koren et al. 2009). However, the rating matrix is often very sparse in real world, causing CF-based methods to degrade significantly in learning the appropriate latent factors. In particular, this phenomenon occurs seriously in online travel agent(OTA) websites such as Ctrip.com, since user access these websites with lower frequency. Moreover, another limitation for CF-based methods is how to provide recommendations when a new item arrives in the system, which is also known as the cold start problem. The reason of the existence about cold start is that the systems cannot recommend new items which have not yet receive rating information from users.

In order to overcome the cold start and data sparsity problems, it is inevitable for CF-based methods to exploit additional sources of information about the users or items, also known as the side information, and hence hybrid CF methods have gained popularity in recent years (Shi, Larson, and Hanjalic 2014). The side information can be obtained from user profile and item content information, such as demographics of users, properties of items, etc. Some hybrid CF-based methods (Singh and Gordon 2008; Nickel, Tresp, and Kriegel 2011; Wang and Blei 2011) have integrated side information into matrix factorization to learn effective latent factors. However, these methods employ the side information as regularizations and the learned latent factors are often not effective especially when the rating matrix and side information are very spare (Agarwal, Chen, and Long 2011). Therefore, it is highly desirable to realize this latent factor learning problem from such datasets.

Recently, one of the powerful methods to learn effective representations is deep learning (Hinton and Salakhutdinov 2006; Hinton, Osindero, and Teh 2006). Thus, with large-scale ratings and rich additional side information, it is nature to integrate deep learning in recommender systems to learn latent factors. Thereby, some researches have made use of deep learning directly for the task of collaborative filtering. Work (Salakhutdinov, Mnih, and Hinton 2007) employs restricted Boltzmann machines to perform CF. Although this method combines deep learning and CF, it does not incorporate side information, which is crucial for accurate recommendation. Moreover, work (Van den Oord, Diele-