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Latent space regularization for recommender systems

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ABSTRACT

The primary latent factor model cannot effectively optimize the user-item latent spaces because of the sparsity and imbalance of the rating data. Although existing studies have focused on exploring auxiliary information for users or items, few researchers have considered users and items jointly. For instance, social information is incorporated into models without considering the item side. In this paper, we introduce latent space regularization (LSR) and provide a general method to improve recommender systems (RSs) by incorporating LSR. We take the assumption that users prefer items that cover one or several topics that they are interested in, instead of all the topics, which reflects real-world situations. For instance, a user may focus on the humorous part of an item when he or she is at leisure time, regardless of the relevance of the item to his research topics. LSR operates from this assumption to account for both the user and item sides simultaneously. From another point of view, LSR is likely to improve the Tanimoto similarity of observed user-item pairs. As a result, LSR utilizes the number of ratings in a manner similar to weighted matrix factorization. We incorporate LSR into both the traditional collaborative filtering models that use only rating information and the collaborative filtering model that uses auxiliary content information as two examples. Experimental results from on two real-world datasets show not only the superiority of our model over other regularization models, but also its effectiveness and the possibility of incorporating it into various existing latent factor models.

1. Introduction

With the development of online businesses, users are faced with the problem of information overload, which is caused by a large variety of products. RSs solve this problem to a certain extent, and have become a core component of online businesses, given that they are changing the way users discover items.

The most popular approach of RS is collaborative filtering (CF), which makes recommendations based on a user's previous behaviors in relation to a particular items. The most successful CF algorithms, as demonstrated by the Netflix Prize competition [5], are the *latent factor models* [19,24,33]. In these models, both users and items are transformed into the same latent space, and the original user-item rating matrix is then factorized into a low-rank user feature matrix and a low-rank item feature matrix. However, the primary latent factor model cannot optimize latent spaces effectively because of the sparsity and imbalance of the rating data [31].

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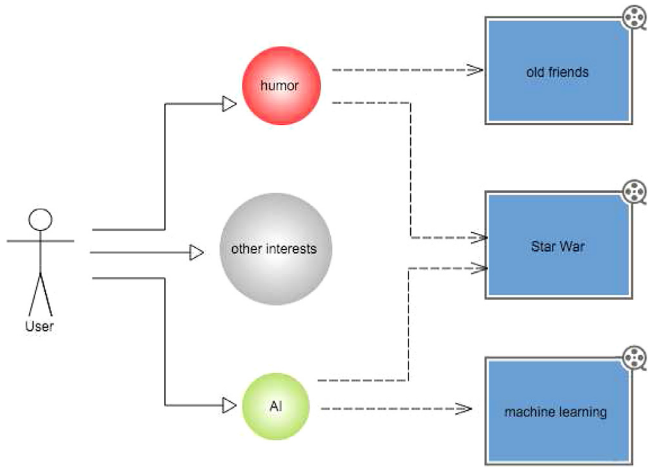

Fig. 1. Illustration of latent space regularization. The user is interested in many topics, including "humor", "AI" (artificial intelligence), and so on (indicated as "other interests"). Three videos are available: "old friends" is the most humorous one, "machine learning" is the most relevant to AI topic, and "Star Wars" is relevant to both topics. Though the user is interested in many topics, but he prefers to watch "old friends" to have fun regardless of the AI topic.

To overcome the main disadvantage of the primary latent factor model, a few studies have explored auxiliary information, such as user review information on items [28,35–37] and user social networks [11,17,24,27,31]. Factorization and spatial information in the computer vision field have been combined in some instances [40,41]. The idea behind the corpus regularizer and social regularizer is to impose constraints on users or items to learn a reasonable latent space. Auxiliary information can be seen as a way to filter latent spaces that satisfy observed ratings but are unreasonable according to auxiliary information. However, their disadvantages are as follows: (1) to some extent, social relations and user tastes are inconsistent. (2) User reviews reflect only the explicit parts of properties (i.e., those appearing in the reviews) and therefore may be incomplete. (3) Social relations and text information are not always available. (4) Auxiliary information may limit the diversity of the recommendations. For instance, social relations tend to result in recommending almost the same items for a user community, given the similarity of their preferences; corpus information limits the implicit interests that are not reflected in reviews.

Recently, many studies have focused on the trade-off between predictive accuracy and diversity, which includes individual diversity and aggregate diversity [8,12,18,25]. Instead of several similar items, personalized items should be recommended to improve the quality of the recommendation. Individual diversity reflects this consideration to some extent, but aggregate diversity seems more reasonable because RSs can recommend the best-selling items to all users to improve individual diversity [1]. Awareness of the importance of diversity has increased in the last few years. We also look into how regularization methods affect aggregation diversity given the improvement of predictive accuracy, because most previous models focus on predictive accuracy but ignore recommendation diversity.

Inspired by the restricted Boltzmann machine in deep learning [14], we filter unreasonable latent spaces by introducing LSR. Rating behavior indicates not only a rating but also the kind of items a user is interested in. That is to say, the observed user-item pairs should have high similarities. LSR utilizes the implicit feedback and user-item joint confidential functions to optimize the latent spaces rather than explore auxiliary information.

Motivation. We present a motivating example. As illustrated in Fig. 1, the user is a humorous person and has interest in artificial intelligence. Three candidate videos are available for recommendation to him. We may recommend "old friends" to him according to the humor topic and "machine learning" course according to the AI topic. Given that these two topics are reflected in "Star Wars", traditional RSs may recommend "Star Wars" and other videos that are relevant to *both* topics. But we may give another solution according to the assumption that users like items that cover one or several topics that they are interested in, instead of all the topics. The user may prefer to take the "machine learning" course when he wants to learn something, but prefers to watch "old friends" for entertainment when he feels upset. By emphasizing the specified topics, we recommend more diversity and personal items, instead of the most popular items, which are always related to many topics.

Instead of exploring the relationships between users or items[1], our proposed LSR utilizes rating information to explore relationships between users and items, which model the real-world recommendation process more directly.

This paper is organized as follows: Section 2 introduces related studies. Section 3 presents a latent space confidential function and two novel models. Section 4 presents the empirical results. Finally, Section 5 presents our conclusions and suggestions for future work.

[1] User relations are used to choose user-specified latent vectors and textual information is used to choose item-specified latent vectors. Both reveal relations between users or items and ignore the interaction of the other side.