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Cross domain recommendation based on multi-type media fusion

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ABSTRACT

Due to the scarcity of user interest information in the target domain, recommender systems generally suffer from the sparsity problem. To alleviate this limitation, one natural way is to transfer user interests in other domains to the target domain. However, objects in different domains may be in different media types, which make it very difficult to find the correlations between them. In this paper, we propose a Bayesian hierarchical approach based on Latent Dirichlet Allocation (LDA) to transfer user interests cross domains or media. We model documents (corresponding to media objects) from different domains and user interests in a common topic space, and learn topic distributions for documents and user interests together. Specifically, to learn the model, we combine multi-type media information: media descriptions, user-generated text data and ratings. With this model, recommendation can be done in multiple ways, via predicting ratings, comparing topic distributions of documents and user interests directly and so on. Experiments on two real world datasets demonstrate that our proposed method is effective in addressing the sparsity problem by transferring user interests cross domains.

1. Introduction

Recommender systems attempt to suggest items that target users are likely to be interested in. The most representative recommendation method is Collaborative Filtering (CF) which predicts the preference of a user by combining feedbacks of other users with similar interests. Even though CF methods achieve great successes in practical applications, there are still some problems which limit their performance. One main limitation is the well-known sparsity problem [1,2]. That is, when some users access limited items or some items are used by limited users, it is difficult to predict user interests and overfitting may happen easily.

To alleviate the sparsity problem, auxiliary data, such as users' explicit and implicit feedbacks in other domains, can be used. Fig. 1 shows an example. Assuming the scenario that users leave less preference information (e.g., ratings and comments) in books but much more in movies. It is difficult to recommend books for these users only based on their feedbacks on books, since their interest data in books is limited (i.e., the data is sparse). Fortunately, we can transfer user interests from movies to books. Intuitively, if users like the movie *Harry Potter*, they may also like the book *Harry Potter*. In another more meaningful example, if users watched many science fiction films, they may be interested in books in similar styles.

The key is how to transfer user interests cross domains, even with different media types. Some researchers propose transfer learning methods to solve this problem [3,4]. They assume that the rating matrices in different domains share similar cluster-level rating patterns and consider these patterns as potential candidates to be transferred from the auxiliary domain. Although these methods can alleviate the sparsity problem to some extent, there are still two major limitations. Firstly, they require data in both the auxiliary domain and the target domain to be standardized and structured. It means that the data in both domains are in the form of rating matrices, while in practice this requirement cannot be met sometimes. Secondly, these methods are hard to extend for exploiting other kinds of information, such as media content and user-generated text data.

In practical applications, various kinds of information can be utilized to transfer user interests. For instance, in E-commerce websites such as Amazon, recommender system designers may be interested in transferring user interests cross commodity categories (e.g., electronic products to books). In this example, users' comments can be used to mine user interests, description text can be used to build correlations between commodities from different categories, and so on. In the example of Fig. 1, the useful information includes the content of the media itself, the media description text, some kinds of meta data and user-generated information. To transfer user interests based on these types of information, a nature solution is to build correlations or similarities between objects from different domains. However it is difficult to get these correlations which are consistent with user

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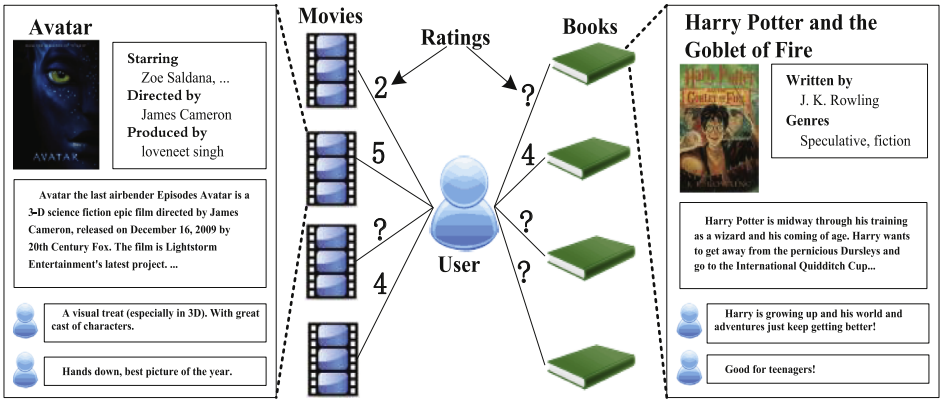

Fig. 1. An example for transferring user interests cross domains. We consider two domains here, movies and books.

interests, especially for objects in the form of different media types.

In this paper, we propose a Bayesian hierarchical approach based on Latent Dirichlet Allocation (LDA) for cross domain recommendation. We model documents (we consider all types of objects, such as movies and books, as documents) from different domains and user interests in a common topic space. The topic distributions for documents and user interests are learned simultaneously and the topic distribution of a particular document is built on document content as well as user interests. Then the correlations among different types of media can be constructed based on the topic distributions. Since we incorporate user interests in topic modeling, the correlations are forced to agree with user tastes. Specifically, a document corresponds to a media object and includes three parts of information: media content (or its description text), user-generated text data and ratings. We model media content in a similar way as the basic LDA model. But for the user-generated text, we choose topics either from the document topic or the user interest topic, because user generated text, such as tags, is related to both the document and the user interests. Finally, we model ratings based on the assumption: a user will like a document if there are common topics between the user interests and the document. Given two topics chosen from the document and the user respectively, a rating is drawn from a rating distribution. Different from the word distribution in basic LDA model which is in the form of a two order matrix, the rating distribution here is a three order tensor. Based on this model, we can suggest documents to users based on predicting ratings or by comparing topic distributions between documents and user interests directly. Experiments on two real world datasets demonstrate that our proposed method outperforms baseline methods in cross domain recommendation.

The rest of this paper is organized as follows. Section 2 reviews the related work. In Section 3, we represent the data used in our method and define notations. In Section 4, we introduce our proposed method on cross domain recommendation. Extensive experimental results are presented in Section 5. We conclude our paper in Section 6.

2. Related work

In this paper, we propose to transfer user interests for cross media recommendation based on LDA model. Our work is related to recommendation by transfer learning, cross media retrieval and recommendation by LDA model. In this section we provide a brief review of these works.

2.1. Cross domain recommendation

Recently, some researchers introduce transfer learning methods for cross domain recommendation. Phuong et al. propose to apply multi-task learning (a kind of transfer learning methods [5]) to collaborative filtering [6]. This work treats each user rating prediction as a classification problem and solves multiple classification problems together. It does not consider any auxiliary data and is very different from the problem we focus on. To utilize information in related relations or networks, [7,8] consider heterogeneous relations as auxiliary information sources and introduce methods based on the Collective Matrix Factorization framework. However, all the information used in their methods, either the target relation or auxiliary relations, is from a common domain, which is different from our purpose of transferring user interests cross media. As mentioned in Section 1, Li et al. consider the cluster-level rating patterns as potential candidates to be transferred from the auxiliary domain [3,4]. These methods require that the rating matrix in auxiliary data is dense which is often impossible in practice. Besides, Pan et al. try to discover the principle coordinates of both users and items in the auxiliary data matrices, then use these coordinates to adapt to the target data [2]. Zhang et al. propose to use probabilistic matrix factorization to model the ratings in each domain simultaneously. In this way, knowledge can be transferred cross domains adaptively [9]. Cao et al. introduce a nonparametric Bayesian framework to transfer knowledge for cross domain recommendation [10]. Recently, Pan et al. proposed to utilize unstandardized rating information in auxiliary domains: such as binary ratings, rating ranges and rating distributions [11,12]. These methods focus on similar problems as ours, but they only involve ratings and ignore other kinds of useful information. Our proposed method is a more flexible one which can exploit various types of information, ratings, media content, user-generated text and so on.

Besides, Tang et al. propose a novel generative model to recommend research collaborators in different domains to facilitate cross domain collaborations [13]. This work is similar to the friend recommendation task in social networks but for “friends” in different research domains, which is very different from our task. We focus on resource recommendation in this paper.

2.2. Cross media retrieval

Cross media retrieval is committed to searching and processing documents containing different types of media in an integrated way. The key problem of cross media retrieval is to find correlations between the considered media types. There are already some outstanding papers in this direction. Jeon et al. propose to