



ELSEVIER

Contents lists available at ScienceDirect

## Neurocomputing

journal homepage: [www.elsevier.com/locate/neucom](http://www.elsevier.com/locate/neucom)

## Heterogeneous hypergraph embedding for document recommendation

Yu Zhu<sup>a</sup>, Ziyu Guan<sup>b</sup>, Shulong Tan<sup>c</sup>, Haifeng Liu<sup>d</sup>, Deng Cai<sup>a,\*</sup>, Xiaofei He<sup>a</sup><sup>a</sup> State Key Lab of CAD & CG, Zhejiang University, No. 388 Yuhangtang Road, Hangzhou 310058, China<sup>b</sup> College of Information and Technology, Northwest University of China, Xi'an, Shaanxi 710127, China<sup>c</sup> Baidu USA, Sunnyvale, CA, USA<sup>d</sup> College of Computer Science, Zhejiang University, No. 388 Yu Hang Tang Road, Hangzhou 310058, China

## ARTICLE INFO

## Article history:

Received 29 December 2015

Received in revised form

5 April 2016

Accepted 18 July 2016

Communicated by M. Wang

## Keywords:

Recommender systems

Hypergraph

Graph-based learning

## ABSTRACT

Nowadays, more and more users are using online tagging services to organize their resources, e.g. Web bookmarks and bibliographies. Tags not only facilitate organization and retrieval of resources, but also provide valuable semantic descriptions for both resources and users' interests. This work is focused on document recommendation using tagging data. Previous works either model the 3-order relation  $\langle user, tag, document \rangle$  in tagging data by an ordinary graph or model different types of relations by a homogeneous hypergraph. The former scheme would lead to serious information loss, and the latter one fails to discern the influence of different types of relations. In this paper, we propose a heterogeneous hypergraph model which fully exploits high-order relational information in tagging data and, meanwhile, customizes the influence of different types of relations. A novel heterogeneous hypergraph embedding framework is developed for document recommendation. The framework is general and can incorporate various relations among users, tags and resources. Experimental results on two real-world datasets show the superiority of the proposed method over traditional methods.

© 2016 Elsevier B.V. All rights reserved.

## 1. Introduction

With the explosive growth of Web2.0 applications, online tagging systems like Delicious, Last.fm and Flickr have become popular for users to annotate different types of web resources, i.e. documents, music tracks, and photos. Tags provide a convenient way for users to organize their own resources and help other users to retrieve relevant contents. Furthermore, tags also provide valuable semantic descriptions for both resources and users' interests. Hence, it is promising to exploit tagging data for recommendation [8,16,29].

Traditional recommendation methods can be roughly classified into two categories: content based recommendation and collaborative filtering (CF for short) based recommendation. The content based methods [40] usually analyze contents of resources associated with a user, and recommend similar resources accordingly. Instead of analyzing contents, the CF based methods utilize users' collaborative behaviors on resources (e.g. rating data [5]) to make recommendations, which have achieved great success in both industry and academia. The CF based methods can be further

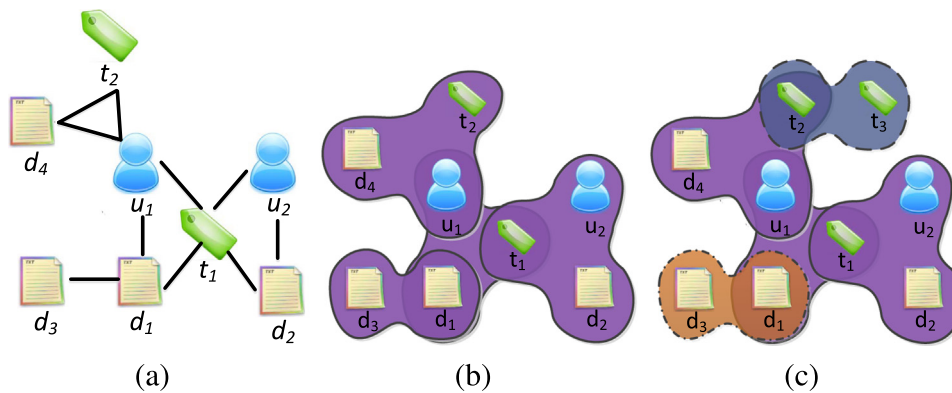
divided into memory-based CF methods and model-based CF methods. State-of-art CF models are model-based CF methods, and have demonstrated their superior performance in many recommendation competitions (e.g. Netflix Prize, KDD CUP and Music Hackathon) [15,30]. To overcome the drawbacks of both content based and CF based methods, hybrid solutions [12] are proposed utilizing both content and collaborative information. However, tagging data contains not only users and resources, but also tags. Users' tagging behavior forms the 3-order annotation-relation  $\langle user, tag, resource \rangle$ . Additionally, there exist other kinds of relations, such as the similarity relation between resources. Different types of relations make up a complex "heterogeneous" relational environment in tagging data. Traditional content based and CF based recommendation cannot effectively handle the complicated heterogeneity in social tagging services.

To exploit tagging data for recommendation, Guan et al. [8] propose a graph-based method *Multi-type interrelated objects embedding* (MIOE), which models annotation-relations and similarity relations between documents (doc-relations for short) by an ordinary graph as shown in Fig. 1(a). Documents are then recommended in a semantic space learned on the modeled ordinary graph. The ordinary graph model is also applied in [52,6]. However, the ordinary graph model leads to the information loss problem [4].

The hypergraph is a generalization of the ordinary graph where the edges, called hyperedges, can contain arbitrary number of vertices [2]. Thus it is a more appropriate tool to model complicated

\* Corresponding author.

E-mail addresses: [zy11120085@gmail.com](mailto:zy11120085@gmail.com) (Y. Zhu), [welbyhebei@gmail.com](mailto:welbyhebei@gmail.com) (Z. Guan), [laos1984@gmail.com](mailto:laos1984@gmail.com) (S. Tan), [haifengliu@zju.edu.cn](mailto:haifengliu@zju.edu.cn) (H. Liu), [dengcai@cad.zju.edu.cn](mailto:dengcai@cad.zju.edu.cn) (D. Cai), [xiaofeihe@gmail.com](mailto:xiaofeihe@gmail.com) (X. He).



**Fig. 1.** Models for annotation-relations  $\langle u_i, t_j, d_k \rangle$ ,  $\langle u_i, t_i, d_1 \rangle$ ,  $\langle u_2, t_1, d_2 \rangle$  and the doc-relation  $\langle d_3, d_4 \rangle$ , where  $\langle u_i, t_j, d_k \rangle$  represents that user  $u_i$  bookmarks  $d_k$  with  $t_j$  and  $\langle d_i, d_j \rangle$  represents that contents of documents  $d_i$  and  $d_j$  are similar. (a) is the ordinary graph model.  $\langle u_i, t_j, d_k \rangle$  is decomposed into pair-wise relations  $\langle u_i, t_j \rangle$ ,  $\langle t_j, d_k \rangle$  and  $\langle u_i, d_k \rangle$ , which, together with  $\langle d_i, d_j \rangle$ , are modeled as edges. (b) is the homogeneous hypergraph model.  $\langle u_i, t_j, d_k \rangle$  and  $\langle d_i, d_j \rangle$  are uniformly modeled as hyperedges, which are represented by the same purple color surrounded with the solid line. (c) is the heterogeneous hypergraph model. Different types of relations are treated differently, where  $\langle u_i, t_j, d_k \rangle$  is represented by the purple color surrounded with the solid line and  $\langle d_i, d_j \rangle$  is represented by the orange color surrounded with the dotted line. In this paper, we also incorporate tag-relations  $\langle t_i, t_j \rangle$  into our heterogeneous hypergraph model, which is represented by the green color surrounded with another type of dotted line. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

relations with arbitrary orders (annotation-relations are 3-order and doc-relations are 2-order). As shown in Fig. 1(b), objects ( $u_i$ ,  $t_j$  and  $d_k$ ) are modeled as vertices and relations ( $\langle u_i, t_j, d_k \rangle$  and  $\langle d_3, d_4 \rangle$ ) are modeled as hyperedges in a hypergraph. The hypergraph can better capture annotation-relations without information loss [4].

However, as far as we know, previously proposed hypergraph models [4,51,46,14] are all homogeneous. That is, all relations are uniformly modeled by hyperedges as shown in Fig. 1(b). In tagging data, various types of relations can be used for recommendation (e.g. other than the annotation-relations, we can also incorporate doc-relations to cope with the cold-start issue). Differentiating them allows us to customize the influence of different relations so as to improve recommendation performance [8]. For example, according to [1], collaborative information (e.g. annotation-relations) generally has a greater contribution over content information (e.g. doc-relations) to recommendation. This is easy to be understood since similar documents may be the repeated report, which are out of our interests. Thus we may assign a smaller weight to the doc-relations compared to the annotation-relations.

In this paper, we advocate using a heterogeneous hypergraph to model relations in tagging data as shown in Fig. 1(c), where different types of relations are explicitly distinguished. A heterogeneous hypergraph in this paper refers to a hypergraph with different types of vertices and hyperedges, corresponding to different types of objects and relations in tagging data. A heterogeneous hypergraph embedding (HHE) framework is proposed for document recommendation in tagging services. HHE integrates different types of relations to construct a heterogeneous hypergraph, such as annotation-relations, doc-relations, tag-relations (short for tag correlations) and user-relations (short for user social relations in social network applications). Specifically, for tag-relations, co-occurrence information [10] and topic models [13] are exploited to measure correlations among tags in previous works. However, they still make use of tagging data, which will result in information redundancy in our HHE framework. In this work, we advocate measuring tag-relations by utilizing the information in external resources, e.g. Wikipedia, Google News, with the *word2vec* tool,<sup>1</sup> which can learn vector representations of tags. Correlations can be measured based on the learned vectors. By exploiting heterogeneous relations in the constructed hypergraph, HHE maps all objects (users, tags and documents) to a common semantic space

which preserves the original connectivity among objects. That is, strongly connected objects will stay close to each other in the learned semantic space. Then latent relations between different objects can be mined by the distance metric in the space. For document recommendation, given a user, the closest documents which have not been bookmarked by this user can be recommended to him/her.

The contributions of this paper can be outlined as follows:

- We model different types of relations by a heterogeneous hypergraph. Compared to previous methods, our model can better utilize tagging data in that (1) there is no information loss and, meanwhile, (2) different types of relations are treated differently (i.e. influence customization). We develop a novel subspace embedding algorithm HHE on the heterogeneous hypergraph for document recommendation. HHE is general and various high-order relations can be incorporated. A high-order relation refers to a relation involving two or more objects.
- We exploit external resources to capture a well measured tag-relation by *word2vec* tool. This type of relations is utilized to drag correlated tags to be closer in the learned semantic space, which can improve the recommendation performance.
- Our method is evaluated on two real-world datasets. HHE is proved highly effective compared against two state-of-art algorithms [8,4] and four traditional recommendation methods. We also analyze how the heterogeneous hypergraph model and tag-relations affect the recommendation performance with carefully designed comparison experiments.

## 2. Related work

Our work is related to resource recommendation in tagging services, hypergraph modeling and graph-based subspace learning. In the following three subsections, we will briefly introduce these works.

### 2.1. Resource recommendation in tagging services

There are many works [41,45] integrating tagging information into traditional recommendation approaches. They treat tags as resources or treat tags as users and thus lose the information of tag-resource relations or tag-user relations. Studies in [8,6,19,52] construct bipartite and affinity graphs to model tagging data, then

<sup>1</sup> <https://code.google.com/p/word2vec/>

Download English Version:

<https://daneshyari.com/en/article/4948331>

Download Persian Version:

<https://daneshyari.com/article/4948331>

[Daneshyari.com](https://daneshyari.com)