

Tourism Recommendation Method Based on Tensor Decomposition and Its Application

Di Gao, Huili Yan*, Xinyi Xu

School of Tourism, Hainan University, Haikou 570228, China

*yhl_yanhuili@126.com

*Corresponding Author

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Abstract: Recommendation system is a popular Internet application system, which includes software tools and technologies that provide advice for users to choose products. When the user labels, this function can automatically provide some tag lists that the user may be interested in or related to for the user to choose to use. To solve the problems of complex and changeable user context and sparse data in tourism recommendation, a tensor decomposition recommendation algorithm based on mobile user context similarity is proposed. Combining the user's active interest tendency with the user's browsing behavior, the comprehensive interest is analyzed. According to the rating information of neighboring users with similar interests to the target users, the user's rating of the scenic spots to be recommended is predicted, and the scenic spots with the top n predicted scores are selected for recommendation.

1. Introduction

The massive growth of Internet information leads to the unsatisfactory efficiency of information use at present. In various online and offline applications of the Internet, there are various recommendation systems with different goals, such as online advertising recommendation that users are interested in, and small recommendation systems such as papers and songs. Personalized information recommendation is mainly to provide users with information that may be used in the future through their past marking behaviors [1]. At present, personalized information recommendation methods at home and abroad can be roughly classified into three categories: cluster-based, graph-based and matrix-based.

At present, there are some problems in tag recommendation system, such as vocabulary differences and semantic ambiguity. However, at present, the domestic tourism service websites basically stay on the simple information search, the service items are single, the introduction of tourist routes and scenic spots are almost fixed contents, and they are mostly described in the traditional ways such as words and pictures, which can not meet the individual user needs. It is a hot research topic to provide context-aware recommendation service for users by collecting user context information. Zhang Tianqi et al. [2] proposed some solutions to cold start, Liu Zhenjiao et al. [3] proposed a recommendation algorithm based on user trust and tensor decomposition, and Li et al. [4] proposed a recommendation application based on user clicks.

In this paper, a user-context-service tensor factorization (UCS-TF) algorithm based on mobile user's context similarity is proposed to construct a multi-dimensional user context similarity model. The tensor decomposition method is introduced into the tourism recommendation system, and the neighbor users of the target users are modeled to predict the user's preference value for accessing mobile services in a specific context, thus effectively processing high-dimensional sparse context data. Help users to make decisions, recommend services such as tourist attractions and tourism projects that meet their needs in massive tourism information, and avoid users' search behavior in numerous scenic spots as much as possible, which is more convenient for users.

2. Algorithm Description

2.1 Acquisition of Comprehensive Interest and Formation of Tourist Community

Explicit interest comes from the distribution of users' answers to specific questions, which requires users to consciously express their recognition of scenic spot information. The algorithm applies the core idea of web search and web ranking in social tag recommendation system. When an important user marks an important tag on an item, the item becomes an important item. Similarly, the tag follows the same idea and item as the user. Because the information recommended to each user can be regarded as an information arrangement, the problem of personalized information recommendation is transformed into the optimal solution of arrangement. Because this technology is based on products similar to users' favorite products, a large number of candidate products will be compared with users' favorite products in the database, and the most similar products will be recommended.

After classifying users according to their interest, we can quickly determine the community where the target users are located, and obtain k most similar users according to the similarity calculation results. Finally, we can make collaborative recommendation based on the scenic spot evaluation information of these similar users [5]. Only when users' implicit feedback is considered can a higher accuracy prediction method be given. When users provide operations reflecting users' preferences, such as collecting, loading shopping carts, paying for purchases, etc., the recommendation system can capture these users' implicit feedback information. Therefore, tensor decomposition can represent not only low-dimensional data, but also high-dimensional data. At present, tensor decomposition has been applied in various fields, such as chemical analysis and image analysis, mainly to decompose high-dimensional data.

Tensor decomposition is an extension of matrix decomposition. let X be a three-dimensional tensor (or a three-dimensional arrangement/array), its size is $I \times J \times K$ (as shown in figure 1), and the elements of each dimension come from the set S_1, S_2, S_3 . In the context tourism recommendation system, S_1 is the user configuration set, S_2 is the product configuration set, and S_3 is the personalized context variable set. For example, when context refers to time, the (i, j, k) -th element X_{ijk} represents the i -th user's score on the j -th product at time k .

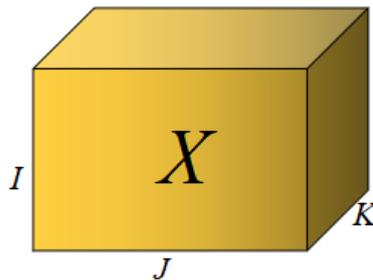


Fig.1 Three-Dimensional Tensor Direct Graph

Because of the multi-dimensional characteristics of tensor, we usually consider to reduce the dimension of tensor. The most commonly used decomposition methods are CP- decomposition (Candecomp/Parafac) and HOSVD decomposition (High Order Singular Value Decomposition).

In personalized information recommendation, you can recommend resources, tags, etc. to users. In this paper, taking tag recommendation as an example, all the historical labeling information of users is represented by set P_s , which is the two-dimensional projection of S on users and resources [6]:

$$P_s = \{(u, i) | \exists t \in T : (u, i, t) \in S\} \quad (1)$$

Users mark resources freely, and their interaction with the system enables them to contact the tags marked by other users. In order to identify users' requirements quickly and accurately, a method is needed to transform users' query requirements into effective information for

recommendation. The disadvantage of applying content-based filtering recommendation system is that the establishment of user model relies too much on the specific products that users have selected and clicked. The method of obtaining implicit interest degree is relatively simple, and it can be obtained from users' browsing records. Therefore, the relationship among the three can be regarded as a three-part graph, and the three nodes located at the vertex of the three-part graph (representing the user set, the item set and the tag set, respectively) strengthen their own weights by transmitting weights to each other.

2.2 Tensor Decomposition Model Based on User Context Similarity

Tensor can completely represent high-dimensional data and maintain the intrinsic structure information of high-dimensional spatial data, so tensor decomposition method is widely used in context-aware recommendation systems. Regularization is the method of modifying learning algorithm to reduce generalization error instead of training error. For example, a user's favorite sport type is "climbing mountains", which means that those tourism resources with this concept in ontology description meet the user's preference. In contrast, the method proposed in this paper refers to a three-dimensional tensor model which can describe three dimensions at the same time, and the three dimensions represent users, items and labels respectively. Among them, the core tensor is the most important, which retains the main information of the original tensor and has certain stability.

The order of tensor is the number of modes (directions) [7]. A one-dimensional tensor is a vector in the conventional sense (directed or undirected), a two-dimensional tensor is a matrix, and a tensor decomposition with three or more dimensions is called a high-order tensor. However, because there is a three-dimensional relationship among users, items and tags in the social tag recommendation system, CF algorithm cannot be directly applied. In order to apply CF algorithm, reference [8] reduced the three-dimensional relationship to two-dimensional relationship, and proposed a two-dimensional model to describe the relationship among users, items and tags.

Regularization can not only extract effective features, but also reduce the generalization error of the model. In this paper, $L^{2,1}$ and L^1 regular terms are added to punish. The formula is

$$\Omega(\theta)_{2,1} = \sum_{i=1}^d \sqrt{\sum_{j=1}^m \theta_{ij}^2} \quad (2)$$

The L^1 formula is

$$\Omega(\theta)_1 = \sum_{ij} \|\theta_{ij}\| \quad (3)$$

The regular term in this paper is obtained by combining the above $L^{2,1}$ and L^1 .

$$\Omega(\theta) = \lambda \Omega(\theta_{2,1}) + \beta \Omega(\theta)_1 \quad (4)$$

Among them, $L^{2,1}$ can realize feature selection by compressing the parameters corresponding to unimportant features to zero, and L^1 can realize sparseness at the same time, which improves the expressive ability and generalization effect of the model.

The rapid increase in the number of Internet applications and users has greatly increased the scale of input data in the recommendation system. The recommendation algorithm needs to process more than one million pieces of data. Moreover, when users share the same tags or resource objects and mark shared resource objects, they will have an indirect contact with others. According to the user's query (direct demand), lock the demand category, and then according to the specific requirements, get the retrieval conditions. Specifically, because scalar has no direction and no basis vector, it can be said that the scalar component is composed of 0 basis vectors, so scalar also becomes zero-order tensor; The core idea is to assume that every potential pattern in one individual object can acquire the same pattern in another individual object, and these patterns can be measured under different conditions.

In order to control the gap between the estimated value \bar{Y} and the observed value Y and minimize the distance between the estimated value and the observed value, we introduce the loss function $L(\bar{Y}, Y)$ of the following form:

$$L(\bar{Y}, Y) = \frac{1}{\|G\|_1} \sum_{i,j,k} B_{i,j,k} l(\bar{y}_{i,j,k}, y_{ijk}) \quad (5)$$

In which $l: y \times R \rightarrow R$ is a point-by-point loss function to punish the difference between the estimated value and the observed value, $\|\cdot\|_1$ is l_1 norm [9], B_{ijk} is the element of binary tensor B , \bar{y}_{ijk} is defined by formula (5), y_{ijk} is the observed value, and the selectable loss functions are as follows.

Square error, conditional mean loss function and corresponding derivative are given as follows,

$$l(\bar{y}, y) = -\frac{1}{2}(\bar{y} - y)^2 \quad (6)$$

$$\delta_{\bar{y}} l = \bar{y} - y \quad (7)$$

Absolute error: the conditional median loss function and the corresponding derivative are given

$$l(\bar{y}, y) = |\bar{y} - y| \quad (8)$$

$$\delta_{\bar{y}} l = \sin[\bar{y} - y] \quad (9)$$

In the field of personalized web search, with the increasingly fierce competition of web search, the Internet has higher and higher requirements for personalized web search. With the accumulation of time, the number of visits by users to a certain scenic spot will gradually accumulate, but the accumulation of these histories may not accurately reflect the current interests of users. Because of the sparsity of data, there is no intersection between most users and current target users, which leads to low prediction accuracy. However, in many cases, the user's preferences only depend on the user's own desire to buy or the attractiveness of the goods themselves, and then collaborative filtering will produce great errors.

2.3 Model Integration

Combining the prediction results of multiple models to generate the final prediction result is called model integration. Integrated models often get better results than single models. The hidden interest score of a scenic spot can be expressed by the proportion of the number of times a user browses the scenic spot in a certain period of time in his whole browsing record. It is necessary to carry out matrix expansion on tensors, that is, rearrange tensors into a matrix according to different dimensions (n - modules). We call this process n - module matrix expansion of tensors.

After specifying the base vector, the vector has three components, and each component A_x (or A_y, A_z) has only one subscript, so the vector is called the first-order tensor; After the specified basis vector, each component of the two-dimensional tensor in three-dimensional space has two subscripts, and the two groups of basis vectors are combined into nine basis vectors, which constitute nine components of the two-dimensional tensor.

The social label problem is usually described as an undirected tripartite hypergraph, which is referred to as tripartite graph [10]. Figure 2 is a three part graph model, where *item* is a class of nodes described by index i , *tag* is a class of nodes described by index j , and *user* is a class of nodes described by index k . The relationship between nodes *item* and *tag* is represented by matrix U_{ij} , which is marked by subscripts i and j . the relationship between nodes *item* and *user* is represented by matrix V_{ik} , which is marked by subscripts i and k . The relationship between node *tag* and node *user* is represented by matrix W_{jk} , which is marked by indexes j and k . By observing Figure 1, we can see that the traditional algorithm of Tripartite Graph does not consider the association between nodes of the same type in the data set.

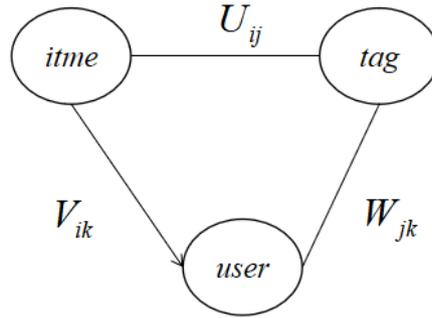


Fig.2 Tri-Graph Model

Tri-graph model can clearly explain the relationship in social label system by using this relationship matrix in $\{item, tag, user\}$. However, it is difficult for the Tri-Graph algorithm to calculate according to the relation hyperedge. It must first transform one hypergraph into three bipartite graphs with regular edges, so that the Tri-Graph calculation can be easier.

Y^0, Y^1, Y^2, \dots , is calculated iteratively in turn by filling the missing values with specified values and decomposing them according to the standard tensor, as shown in Formula (10).

$$\min_{Y^{t+1}} \|(X_{\Omega} + Y_m^t) - Y^{t+1}\|^2 \quad (10)$$

In which Y^t is the solution of the t -th iteration, Y_m^t is the missing value part in Y^t , and X_{Ω} is the set of non-zero value elements in the input tensor X with missing values

Social tag recommendation system is an application system for recommending a set of tags to a user, and the tags in the set may be used by the user to mark a resource item. The designed user ontology should be conducive to the use of reasoning rules. In the process of building, especially in the description of user preferences, the concepts that may be associated with the hotel ontology are considered. Then, matrix decomposition is carried out by iterative method, so that the missing scoring values in the original scoring matrix can be obtained by the decomposed matrix. Target users use the predicted values of mobile services in different contexts, and recommend suitable mobile services to users according to the order of predicted values from high to low.

3. Experimental Analysis

The most important thing is to get the user behavior data (preference coefficient). Users can't tell the system their personal preferences by themselves. In the face of massive music and various tags, the data we can get is only some operation data of users. And set up an interest level queue for these objects according to the degree of interest of users, and recommend the objects at the front of the queue to users. According to these conditions, we search in the hotel ontology, get qualified hotel examples, and take these hotels as the data source of the second recommendation.

Firstly, the performance of UCS-TF algorithm is compared with Cosine Similarity (COS), Pearson correlation coefficient collaborative filtering method and Cosine algorithm under the condition of different neighbor user numbers (K), and the results are shown in Table 1.

Table 1 Comparison of Mae Values of Similarity Algorithms under Different Values

Algorithm	Number of neighbor users (k value)		
	15	25	35
COS)	0.923	0.851	0.882
Pearson	0.805	0.911	0.837
Cosinel	0.843	0.896	0.850
UCS-TF	0.87	0.825	0.916

It can be seen from Table 1 that with the increase of the value, the overall trend of the average absolute error of each similarity algorithm is decreasing, and the prediction accuracy is improved.

Among different numbers of nearest neighbors, UCS-TF algorithm has higher prediction accuracy than other similarity calculation methods. Compared with cosine similarity method, Pearson correlation coefficient and Cosine algorithm, the average absolute error of the best performance is reduced by 11.2%, 10.1% and 4.2% ($k = 25$).

In addition, the foreign data sets referenced and compared in this paper include MovieLens, a movie recommendation network, and Last.fm, a social music platform. The specific application data sets are listed in Table 2 below.

Table 2 Scale of Experimental Data Set

Data set	Number of users	Number of products	Number of context variables
Last.fm	2712	1809	3
MovieLens	457	1552	7

The 3d CCTF model with added context variables and the traditional 2d model MF algorithm are tested on the Last.fm data set. the abscissa indicates the use ratio of training set, and the ordinate indicates the hit rate of users. the results are shown in fig. 3. the hit rate of the 3d tensor model is increased by 21.9% compared with that of the 2d matrix model through 10 tests.

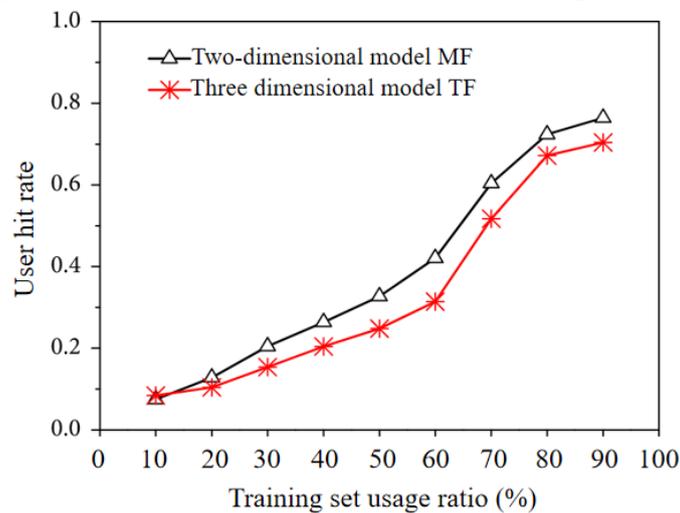


Fig.3 Comparison of Hit Rate between Two-Dimensional and Three-Dimensional Model Algorithms

The core part of collaborative recommendation algorithm is to find the nearest neighbor user for the target user. Compared with the traditional direct global traversal search method, the search range of this algorithm is limited to the community where the target user is located, and the search space is well reduced.

Tourism resources are recommended content. This paper introduces the key technology of semantic web-ontology to describe tourism resources. Ontology is a basic means to describe concepts and the relationship between concepts, which provides good data integration and interoperability. Users will click and browse the interesting scenic spots with high frequency. If a user visits a certain scenic spot, he can be considered interested in the scenic spot. For the integrated model, the lower the correlation of prediction error of baseline model, the better the effect of integrated model. The more models there are, the better the integration effect will be, but the model training time and memory resource consumption will be increased accordingly.

4. Conclusion

Collaborative tag recommendation algorithm recommends tags to users based on collecting which tags other users put on the same item, aiming at mining which tags can better describe the item. By analyzing the comprehensive interest of tourists, this paper predicts their preferences and recommends scenic spots that they are really interested in. A three-dimensional tensor

decomposition model of mobile user-context-mobile service is established by using neighbor users, and the predicted value of mobile service of target users is obtained. The experimental results show that the fusion of mobile users' context similarity and context similarity confidence can improve the recommendation performance and alleviate the sparsity of data. Provide personalized service to help enterprises promote the sales of tourism products and improve the loyalty of tourists in the fierce e-commerce competitive environment.

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