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PAPER

A Collaborative Filtering Recommendation Algorithm Model Based on User Feature Transfer

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ABSTRACT

The quality of teaching resources and recommended practices in flipped classrooms determine the advantages and disadvantages of this educational model. However, current teaching resource recommendation platforms suffer from issues such as cold startup and sparse data. In order to address these issues, a collaborative filtering recommendation algorithm based on user feature transfer was proposed and utilized to examine the correlation between students' preference behavior and the recommendation of teaching resources in flipped classes for tourism management. The aim was to enhance the quality of teaching in current classes. Using this algorithm, a transfer by user feature (TUF) model is constructed. In this model, a soft embedding method is employed to accurately extract user feature information in the auxiliary space. This method addresses the challenge of filling large-scale missing matrices in the auxiliary space. Additionally, singular value decomposition is performed to obtain more precise user features. Finally, an optimized Wiberg algorithm with rapid convergence is designed to solve the constructed model. The performance of this algorithm is measured and compared using two common datasets. Compared to other algorithms, the proposed algorithm demonstrates superior performance and a lower mean absolute error value. In summary, the recommendation algorithm can enhance the quality of resource organization and provide more suitable personalized recommendations for the recommendation platform. This is beneficial for improving the quality of students' learning.

KEYWORDS

transfer learning, flipped classroom, collaborative filtering, tourism management, arrangement of teaching resources

1 INTRODUCTION

With the rapid development of the Internet and web technology, the flipped classroom teaching mode has emerged as a new application of Internet technology and teaching resources, and its usage has become increasingly widespread [1]. The teaching mode of the flipped classroom is a transportation of the traditional teaching mode.

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Students learn through network technology and utilize online resources outside of class. They can then engage in class discussions, answer questions, and further explore the learning content. However, the current impact of students' autonomous learning after class is not ideal. The main reason is that autonomous online learning has somewhat changed students' learning habits. The recommendation system for online teaching platforms can accurately suggest teaching content based on the unique characteristics of individual students. The core of the recommendation system is the algorithm it uses to make recommendations. The performance of the algorithm directly affects the quality of the final recommendation results [2–3]. At present, collaborative filtering technology is one of the most mature technologies in recommendation systems. This algorithm utilizes the similarity of interests or features to identify the nearest neighbor and subsequently provides recommendations to the target users. Although the algorithm has a high recommendation quality, it still faces the problem of data sparsity. Users will have more comments on established fields and fewer comments on unfamiliar or new fields, resulting in a cold start. If we can learn users' preferences or characteristics from established fields and apply them to recommend new fields, it will significantly reduce the issue of data sparsity in those new fields [4–6].

Based on the concept of transfer learning, this research proposes a collaborative filtering recommendation model that utilizes user feature transfer. The objective of this model is to address the issues of data sparsity and low recommendation accuracy commonly found in traditional recommendation algorithms. By doing so, it aims to assist students in acquiring learning methods that are better suited to their individual characteristics within the new flipped classroom learning platform. At the same time, it can also help colleges and universities change the original learning mode and further improve the current teaching quality by utilizing the analyzed user characteristics.

The methodology of this research is divided into three parts. Firstly, in Section 3.1, a collaborative filtering recommendation algorithm model is constructed based on user feature migration. The objective of this model is to assist the target domain in learning the user evaluation model and subsequently enhance the recommendation quality of the target domain. The idea is utilized in flipped classroom education to enhance the quality of course recommendations through analysis of students' preferences. The role of the auxiliary space in the recommendation model is introduced in detail in Section 3.2. The SOFT-IMPUTE algorithm is utilized to address the issue of filling large-scale missing matrices, with the goal of optimizing the quality of feature extraction from the auxiliary space. Finally, the mathematical derivation process of the recommendation model is detailed in Section 3.3 of the method, and the model is optimized using the Wiberg algorithm in order to achieve an optimal solution. In the result analysis section, the performance of each algorithm is evaluated, and the recommendation model is applied to the flipped tourism management classroom to demonstrate its effectiveness in course recommendations. The recommendation results can not only help universities change their original learning model but also utilize the analyzed user characteristics to enhance the current teaching quality.

2 RELATED WORK

Transfer learning typically involves transferring knowledge from one domain to another target domain in order to improve the learning outcomes in the target domain. In practical applications, a common problem arises when the amount of data available is insufficient to effectively address practical problems. The introduction of transfer learning can help researchers uncover the relationship between large and small datasets, enabling them to apply knowledge transfer to complete practical applications. At present, the transfer learning algorithm has garnered attention and research from numerous researchers, both domestically and internationally. Hu J. et al. developed a transfer learning algorithm that utilizes the information from the target data to enhance the classification algorithm, ensuring the sensitivity of cell classification specific to the target data. The transfer learning algorithm significantly improves the accuracy of clustering and classification [7]. Scholars, such as Li, utilize transfer learning algorithms to address the issues of data scarcity and cold start when constructing recommendation system models using the support vector machine algorithm. The approach involves applying the characteristics and preferences of users in mature fields to the target field, ultimately enhancing recommendation accuracy and quality [8]. In order to enhance the accuracy of sepsis prediction in the emergency department, Wardi used the transfer learning algorithm to validate the feasibility of the machine learning algorithm and achieve improved algorithm performance. In the experimental results, the transfer learning algorithm improves the test performance of the machine learning algorithm and significantly enhances the external validity and generalization ability of the second site [9]. The Cai team combined the transfer learning algorithm with near-infrared spectroscopy technology. The transfer learning algorithm can help the model accurately extract soil nutrient information and improve the reliability of the feature extraction results. The transfer learning algorithm solves the problem of traditional models for extracting soil composition information. The problem of low precision [10]. Researchers, such as Chen, have introduced the transfer learning algorithm into evolutionary computing to create multi-task optimization. The migration algorithm is tested in the benchmark test problem, which verifies the efficiency and effectiveness of the algorithm. It also addresses the issue of slow convergence and low performance of the multi-objective EMTO algorithm when dealing with tasks with low correlation [11]. Lin and other scholars utilize a transfer learning algorithm to construct a stable reference signal with a limited number of training targets, thereby reducing the training cost of the SSVEP-BCI model. In the experimental results, the migration algorithm improves the accuracy of the model, reduces the training time of the model, and enhances the practicality of the model [12].

With the continuous innovation and evolution of the educational model, the flipped classroom teaching method has gained widespread popularity. Various online and offline learning platforms also provide a plethora of teaching resources and personalized course recommendations for flipped classes. To demonstrate the improvement of students' writing skills under the flipped teaching model, scholars like Aldhafiri conducted experiments to study the effect of the flipped classroom teaching model on students' writing skills. They designed a series of comparative experiments. The results of the experiment found that the flipped teaching method could greatly help students improve their writing performance [13]. In order to enhance the academic performance of higher education students, the González-Velasco team implemented the flipped classroom teaching model and compared it to the traditional teaching model. The analysis of the results shows that the flipped classroom model can effectively help students improve their academic performance, and students have given positive evaluations of this teaching model [14]. Scholars like Yulian have enhanced the critical thinking skills of English learners through the implementation of the flipped classroom teaching model. They have also validated the effectiveness of this teaching model through careful design and experimentation. The results show that this model improves critical thinking in learning to speak in many ways. From the perspective of self-directed learning, students have a positive attitude towards this model [15]. Researchers, such as Byun, have implemented a personalized recommendation system for online exhibition activities. The system generates customer-related recommendations by analyzing customer characteristics and similarities in preferences. The system enhances the accuracy of product recommendations and improves customer satisfaction [16]. Lv proposed an interpretable recommendation model based on the existing recommendation system. This model aims to capture the hidden interactions between users and products in order to generate personalized recommendations. Experiments show that the algorithm can ensure the quality of recommendations, which is of great significance for a more personalized and intelligent recommendation system [17]. In order to address the issue of the neural network's inability to effectively expand the feature space and the lack of side information in the recommendation system, Yang and other scholars proposed a personalized recommendation system based on the dual auto-encoding indicator graph. The recommendation model was tested on a large number of real datasets. The recommendation model has high accuracy [18].

Through the above analysis, it is evident that the transfer learning algorithm has shown promising performance and application results. Considering the common limitations of personalized recommendation systems, this study aims to optimize the personalized recommendation system using the transfer learning algorithm. The optimized system will be applied to flipped classroom teaching in tourism management. The purpose is to ensure that students receive a learning method that is suitable for their individual characteristics in the flipped classroom teaching mode and to enhance students' ability to learn autonomously.

3 COLLABORATIVE FILTERING RECOMMENDATION ALGORITHM MODEL BASED ON USER FEATURE MIGRATION

3.1 Construction of collaborative filtering algorithm model for user feature migration

Domain-specific knowledge is not commonly shared, making it challenging to transfer non-shared knowledge through the construction of a transfer learning model. This type of knowledge is referred to as non-transferable knowledge. The other part of knowledge that is shared and can help the system accomplish the learning task in the target domain is called transferable knowledge [19–20]. Transfer learning, as a machine learning method, involves using a model developed for task A as a starting point to develop a model for task B.

In real life, the evaluation of goods by consumers or users can provide insights into the user's preferences for the goods. This valuable information reflects the user's behavior or habits. If user preferences and features can be transferred from the previously evaluated domain to the target domain, then this transfer learning is highly significant. This migration learning approach can assist the target domain in acquiring the user evaluation model, thereby enhancing the recommendation quality of the target domain. Based on this background, the study proposes the TUF model, and the specific process of TUF is shown in Figure 1.

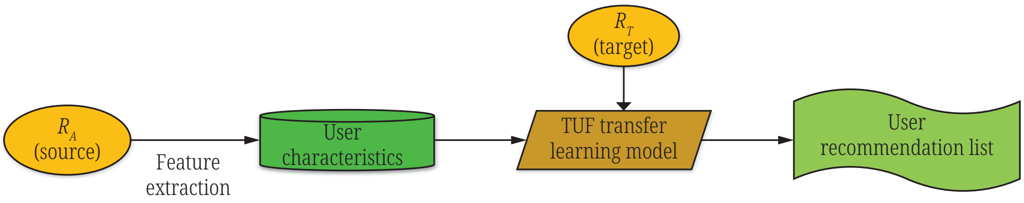

Fig. 1. Specific flowchart of TUF

In Figure 1, R_A represents the scoring matrix in the auxiliary space, while R_T represents the scoring matrix in the target space. The scoring matrix in the target space can be decomposed into two low-dimensional feature matrices U and V under the matrix decomposition technique. The basic model is shown in equation (1).

$$\Gamma(U,V) = \left\| W_T \odot (R_T - UV) \right\|_F^2 \rightarrow \min \tag{1}$$

In equation (1), $\Gamma(U,V)$ represents the modeling of the feature matrices U and V. $\odot$ denotes the Hadamard product, which is a notation for matrix multiplication. It is similar to the multiplication sign in mathematical notation. W_T represents the marker matrix in the target space. The marker matrix is a matrix that contains values of 1 and 0, which are used to indicate the rated and unrated items in the rating matrix. 1 indicates that the item has been rated, and 0 indicates that the item has not been rated. The feature matrix U is used to represent the potential rating pattern of the user, while the feature matrix V is used to represent the potential rating pattern of the item. To prevent overfitting, the loss function of equation (1) can be mitigated by incorporating a regularization term, as illustrated in equation (2).

$$\Gamma(U,V) = \left\| W_T \odot (R_T - UV) \right\|_F^2 + \frac{P_u}{2}\left\| U \right\|_F^2 + \frac{P_u}{2}\left\| V \right\|_F^2 \rightarrow \min \tag{2}$$

Applied to matrix decomposition technique in the recommendation system, the matrix decomposition technique learns U and V as accurately as possible. If the same set of users exists in both the auxiliary space and the target space, and the evaluation data in the auxiliary space is more extensive than that in the target space, the optimization problem in equation (2) can be learned from U_A of the auxiliary space to optimize U of the target space. Theoretically, when the users and items in the auxiliary space are identical to those in the target space, the user characteristics of the two spaces are equally consistent, i.e., $U_A = \text{U}$. In practice, the user characteristics of the two spaces are similar, but not identical. Therefore, the study introduces the regular term $\left\| U - U_A \right\|_F^2$ to ensure similarity between the two, introduces the regular term $\left\| U - U_A \right\|_F^2$ into the constructed model equation (2), and introduces the regular term $\left\| V \right\|_F^2$ to prevent overfitting, and the study establishes a collaborative filtering recommendation model based on user feature migration, as shown in equation (3).

$$\Gamma(U,V) = \left\| W_T \odot (R_T - UV^r) \right\|_F^2 + \frac{P_u}{2}\left\| U - U_A \right\|_F^2 + \frac{P_v}{2}\left\| V \right\|_F^2 \rightarrow \min \tag{3}$$

In equation (3), both P_u and P_v are control parameters, and the larger P_u is, the closer the user feature matrix of the target space U is to the user feature matrix of the auxiliary space U_A. When P_u tends to infinity, then $U = U_A$; when P_u tends to 0, the model will not utilize the knowledge of the auxiliary space for the learning task in the target space, i.e., it degenerates to the traditional matrix decomposition model.

3.2 User feature extraction algorithm for auxiliary space

In the TUF model, the auxiliary space is responsible for assisting in learning the initial missing scoring matrix R_A to learn it to U_A. Due to the slow convergence of the matrix decomposition model, it is relatively ineffective for performing large-scale matrix decomposition. Therefore, to address the issue of filling large-scale missing matrices, the SOFT-IMPUTE algorithm is being investigated as a potential solution. For sparse low-rank matrices R_A, the problem of filling the matrix while minimizing the rank is highly challenging. Therefore, the basic matrix model is reconstructed using theories such as the Lagrange multiplier method to obtain an approximate form of the objective equation, as shown in equation (4).

$$f_\lambda(Z_A) = \frac{1}{2}\left\|W_A \odot (R_A - Z_A)\right\|_F^2 + \lambda\left\|Z_A\right\|_* \rightarrow \min \tag{4}$$

In equation (4) Z_A represents the filled matrix, λ denoting the decreasing factor of Z_A, and all singular values of matrix Z_A are synthetically represented by $\left\|Z_A\right\|_*$, which is the kernel parametrization of Z_A. In order to solve the optimization function of equation (4), the SOFT-IMPUTE algorithm is used to solve equation (4), which is described as shown below.

Input: missing scoring matrix R_A and convergence factor ε of the auxiliary space

Output: padding matrix Z_A

Step 1: Initialize $Z^{old} = 0$ and choose a set of decreasing factors from large to small as $\lambda = [\lambda_1, \lambda_2, \ldots, \lambda_n]$

Step 2: Iterate over each decreasing factor until it completes convergence. The iterative process is as follows:

a) Calculate the value of Z^{new} according to Equation $Z^{new} = W \cdot R_A + (1 - W) \cdot Z^{old}$

b) Perform singular value decomposition for Z^{new}. The decomposition formula is $Z^{new} = U \cdot S \cdot V^T$, where, $S = diag\,(\sigma_1, \sigma_2, \ldots, \sigma_n)$

c) Make the matrix $Z^{new} = U \cdot (S - \lambda) \times V^T$, with the minimum value being 0.

d) If $\dfrac{\left\|Z^{new} - Z^{old}\right\|^2}{\left\|Z^{new}\right\|} < \varepsilon$, then turn to (f).

e) Make $Z^{old} \leftarrow Z^{new}$ and transfer to (a).

f) Make $Z_\lambda \leftarrow Z^{new}$ and go to Step 2 and so on to get different padding matrices.

Step 3: Select the best padding matrix from all the options and assign it to Z_A.

The missing values of the SOFT-IMPUTE algorithm are filled with the predicted values computed during each iteration, without altering the existing or non-missing values. Ultimately, a matrix Z_A of the first rank and approximating R_A is obtained. The matrix Z_A is assigned so that $Z_A = U \times S \times V^T$, for the user feature dimension of the auxiliary space is consistent with the feature dimension of the target space. The study retains only the first few maximum singular values in the matrix Z_A. Thus, the user feature matrix learned in the auxiliary space can be represented as $U_A = U_d \cdot \sqrt{S_d}$. The choice of the SOFT-IMPUTE algorithm for extracting user features in the auxiliary space is advantageous for leveraging the richer data in the auxiliary space and for implementing the TUF collaborative filtering algorithm.

3.3 Operational procedure of the TUF model solving algorithm

Solving the user characteristic matrix and the item characteristic matrix of the target space of the TUF model is the main task of the iterative algorithm. The goal of this algorithm is to achieve or complete the optimal solution of the model [11–22]. There are multiple methods to solve the TUF model, and out of these algorithms, the Wiberg algorithm demonstrates superior performance. The Wiberg algorithm is less sensitive to the initial values, converges faster in the global range, and exhibits good numerical performance. However, the algorithm does not solve the matrix decomposition model with regular terms. Therefore, the study re-discusses the method of solving the TUF model and incorporates the fundamental concept of Wiberg's algorithm to make necessary adjustments to the TUF model.

Let the vectors of the rows of the matrix u be reconstituted to form a new vector, then $u = vec(U) = [u_1^T, u_2^T, \cdots, u_m^T]^T$, and similarly vector U_A and V to obtain $u_l = vec(U_L) = [u_{l1}^T, u_{l2}^T, \cdots, u_{lm}^T]^T$ and $v = vec(V) = [v_1^T, v_2^T, \cdots, v_m^T]$. Therefore, the model is reproduced as shown in equation (5).

$$\Gamma(u,v) = \left\|P_u - r\right\|_F^2 + \frac{P_u \left\|u - u_A\right\|_F^2 + P_v \left\|v\right\|_F^2}{2} = \left\|Qv - r\right\|_F^2 + \frac{P_u \left\|u - u_A\right\|_F^2 + P_v \left\|v\right\|_F^2}{2} \tag{5}$$

In equation (5) in Q denotes a matrix consisting of the elements in the matrix u, P denotes a matrix consisting of the elements in the matrix V, the elements in the matrix r are scored vectors, and $r = [r_{i,j}]$. The above form's basic structure is solely for descriptive convenience, as it is necessary to address missing terms. Therefore, the matrix P and the matrix Q keep the rows corresponding to the known items. The model proposed in the study has two parameter variables to be determined: the matrix u and the matrix v. Once v is determined, the matrix u can be calculated using equation (6).

$$\begin{cases} \partial\Gamma/\partial u = (P^T P + p_u I)u - (P^T r + p_u u_l) = 0 \\ u = (P^T r + p_u u_l)/(P^T P + p_u I) \end{cases} \tag{6}$$

Equation (6) determines the variable parameter u, while the determination of the parameter variable v is also solved using the Wiberg algorithm. By treating the variable parameter u as a function of the variable parameter v, i.e., $u = \tilde{u}(v)$, the optimization problem in the TUF model is transformed into a solution problem with only one parameter variable. Then, the loss function of the variable parameter v is given by equation (7).

$$\varphi(v) = \frac{f^T f + p_u g_u^T g_u + p_v g_v^T g_v}{2} \tag{7}$$

In equation (7), $\varphi(v)$ is the expression of the loss function and $f = P\tilde{u}(v) - r$, $g_u = \tilde{u}(v) - u_l$, $g_v = v$. In order to minimize the loss function, the variable parameter v is updated at each layer iteration as well as satisfying the requirements as in equation (8).

$$\begin{cases} v(iter+1) = v(iter) + \Delta v \\ \dfrac{d\varphi}{dv} + \dfrac{d^2\varphi}{dv^2}\Delta v = 0 \end{cases} \tag{8}$$

In equation (8), *iter* denotes the number of iterations and Δv denotes the direction vector. The first-order derivative as well as the second-order derivative of the loss function are solved as shown in Equation (9).

$$\begin{cases} \dfrac{d\varphi}{dv} = \left(\dfrac{df}{dv}\right)^T f + p_u \left(\dfrac{dg_u}{dv}\right)^T g_u + p_v v \\ \dfrac{d^2\varphi}{dv^2} = \left[\left(\dfrac{df}{dv}\right)^T \dfrac{df}{dv} + \left(\dfrac{d^2 f}{dv^2}\right)^T f\right] + p_u \left[\left(\dfrac{dg_u}{dv}\right)^T \dfrac{dg_u}{dv} + \left(\dfrac{d^2 g_u}{dv^2}\right)^T g_u\right] + p_v I \end{cases} \tag{9}$$

In equation (9) $I = dg_v/dv$, the research proposed method in which the higher order terms can be neglected, and further derivative of $f(v)$ and $g_u(v)$, and through the complex function derivative rule to obtain the equation (10).

$$\begin{cases} \dfrac{df}{dv} = \dfrac{\partial f}{\partial u}\dfrac{d\tilde{u}}{dv} + \dfrac{\partial f}{\partial v} \\ \dfrac{dg_u}{dv} = \dfrac{d\tilde{u}}{dv} \end{cases} \tag{10}$$

f The partial derivative of the matrix u and the matrix v gives equation (11).

$$\frac{\partial f}{\partial u} = P, \frac{\partial f}{\partial v} = Q \tag{11}$$

Differentiating equation (6) to obtain equation (12).

$$\frac{d(P^T f + p_u g_u)}{dv} \approx P^T \frac{df}{dv} + \frac{dg_u}{dv} = P^T \left(\frac{\partial f d\tilde{u}}{\partial u dv} + \frac{\partial f}{\partial v}\right) + p_u \frac{d\tilde{u}}{dv} = 0 \tag{12}$$

Substitute equation (11) into equation (12) to obtain equation (13).

$$\frac{d\tilde{u}}{dv} = \frac{P^T Q}{-(P^T P + p_u I)} \tag{13}$$

Equation (13) is substituted into equation (10) to obtain equation (14).

$$\begin{cases} \dfrac{df}{dv} = \left(I - \dfrac{PP^T}{PP^T + p_u I}\right) Q \\ \dfrac{dg_u}{dv} = \dfrac{P^T Q}{-(PP^T + p_u I)} \end{cases} \tag{14}$$

The first-order derivative and second-order derivative in equation (9) are assigned separately. The first-order derivative is set to z and the second-order derivative is set to H, then the direction variable of the variable parameter is Δv as shown in equation (15).

$$\Delta v = \frac{z}{H} \tag{15}$$

Through the derivation of the aforementioned equation, the solution method for the TUF model is obtained. Firstly, the SOFT-IMPUTE algorithm is used to predict the filling of R_A; secondly, the singular value decomposition is performed on the filled R_A to obtain the user characteristic matrix in the auxiliary space, which is then converted into vector form. Thirdly, random initialization is performed. Fourthly, the constructed matrix is calculated using the formula P u. Fifthly, the convergence is checked to determine if the stop condition is met. If the stop condition is met, the variable parameters are reduced. If the stop condition is not met, the constructed matrix Q is linearly computed as the direction vector using the formula. Sixth, the model is solved. The computation in the fourth step ensures that the solution of the current iteration is the optimal solution for the target loss function. The specific flowchart of Wiberg's algorithm is shown in Figure 2.

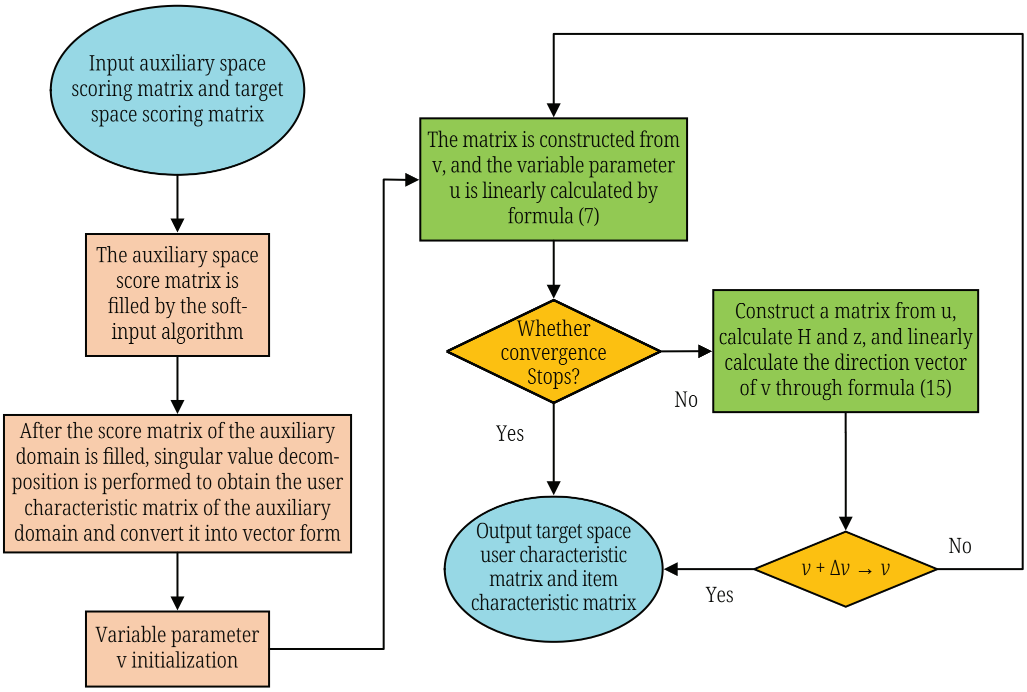

Fig. 2. Specific flow chart of Wiberg algorithm

Figure 2 illustrates the flow of the Wiberg algorithm executed in the TUF model. The inputs of the model are the scoring matrix of the auxiliary domain R_A and the scoring matrix of the target domain R_T. The outputs are the user feature matrix of the target domain U and the item feature matrix V. First, the SOFT-IMPUTE algorithm is used to fill in the predictions of R_A, perform the singular value decomposition step is performed to obtain the user feature matrix of the auxiliary domain, which is then converted to vector form. Initialize the variable parameter v so that the matrix is composed of v and the variable parameter u is calculated from Equation (7). Check if the algorithm converges at this point. If it does, output the target space user feature matrix and the item feature matrix to end the operation.

A complexity analysis is performed in addition to this. The complexity analysis is performed by updating the time complexity of the two linear equations u and v for each level of iteration. It is expressed as $u\ O\,(mnd^2)$ and is expressed as $v\ O\,(sn^2d^2)$. The current assumption is that the algorithm converges after *iter* iterations, and the overall time complexity of the algorithm is expressed as $O\,((iter \times sn^2 + mn)d^2)$. In large-scale datasets, attention still needs to be paid to the time required for computing the linear system of equations due to the complexity of the structure. In this case, the ALS method of updating v is used in this paper instead of the Wilberg algorithm for updating the v step. Although the ALS method requires more iterations to achieve convergence the TUF model, the overall computational effort may still be relatively small for large-scale problems.

4 EXPERIMENTAL RESULTS AND ANALYSIS OF COLLABORATIVE FILTERING RECOMMENDATION ALGORITHM MODEL BASED ON USER FEATURE MIGRATION

In order to verify the effectiveness of the collaborative filtering recommendation algorithm model proposed in the study, two open data sets were used for the experiment: the AIMedia data center and the dysprosium data aggregation data set. In the AIMedia data center, the user's rating range for the flipped classroom approach in tourism management is set as [1, 5]. Select 500 users randomly from the database to evaluate the flipped class of tourism management. At the same time, the 500 users need to meet the requirement of having been evaluated at least 30 times in the previous class evaluation. Different types of data sets in tourism management are divided into auxiliary space and target space. It is assumed that the score data of 500 users in the flipped class of humanistic tourism management will be used as the score data of the target space, and the score data of other types of flipped classes in tourism management will be used as the score data of the auxiliary space. The data in the target space is divided into training sets and test sets. The training sets account for 80% of the data, while the remaining 20% is used as the test set data. The division of this dataset is shown in Table 1.

Table 1. Division of data sets in AI media data center

Data Set	AI Media Data Center				
Tourism management category	Humanity	History	Delicious food	Scenery	Politics
Number of users	500				
Number of auxiliary space items	1542	1658	1288	1068	1546
Number of target space items	362	246	616	836	358
Sparsity of auxiliary space training	6.4%	6.9%	8.4%	8.0%	7.0%
Sparsity of target space training	10.6%	10.9%	5.8%	5.1%	7.8%

In the dysprosium data set, users' ratings for different types of flipped classrooms in tourism management range from [1–6]. To ensure the consistency of rating data, the study replaces the initial rating of 6 with a rating of 5. Additionally, 500 users are randomly selected for the dataset. Different types of flipped classrooms for tourism management are also randomly assigned, with 1000 evaluation items used as auxiliary space items and 500 evaluation items used as target space items. Each user is placed in the auxiliary space. Both the space and the target space have evaluated at least 25 or more flipped classrooms on tourism management. Similarly, the target space is further divided into the training set and the test set. The training set is divided into four groups based on the number of user evaluations in the target space. The number of user evaluations in the four groups is 10, 15, 20, and 25, respectively. The test set consists of the remaining scoring data. All scoring data in the auxiliary space is used as the training set. The partition description of this dataset is shown in Table 2.

Table 2. Description of dysprosium data set division

Data Set	Dysprosium Polymerization			
Group	Data 1 = 10	Data 2 = 15	Data 3 = 20	Data 4 = 25
Number of users	500			
Number of auxiliary space items	1000			
Number of target space items	500			
Sparsity of auxiliary space training	11.7%			
Sparsity of target space training	2.1%	2.9%	4.3%	5.2%

Three non-migratory learning algorithms and two migratory learning algorithms are used for comparison. The non-migratory learning algorithms include the Pearson correlation similarity-based nearest neighbor collaborative filtering algorithm for a single target domain (referred to as PCC), the SOFT-IMPUTE on single domain algorithm (referred to as SOFT-IMPUTE, SD), and the traditional matrix decomposition collaborative filtering algorithm for a single target domain with regular terms (denoted as RMF). The two migration learning algorithms are SOFT-IMPUTE on multi-domain (referred to as SOFT-IMPUTE, MD) and collaborative filtering with joint matrix decomposition (referred to as CMF).

For other migration learning algorithms, specific conditions are necessary for user feature migration. However, these conditions are not applicable to this dataset, so no relevant comparison can be made. On the parameter setting of the model, refer to previous relevant studies and select various user profiles for migration. In the PCC algorithm, the parameter for the number of nearest neighbors is set to 120. In the RMF model, the regularization parameter is adjusted to its optimal value. In the CMF model, the test functions used in the target space and auxiliary space are the most suitable for the model. The regularization term parameters of the TUF model are also adjusted to their optimal state. All other parameters are set to the same state. The experimental results use the mean absolute error (MAE) as the standard for evaluating the algorithm. The experimental results of each algorithm represent the optimal solutions within the specified parameter range. In order to mitigate the uncertainty of the experimental results, each algorithm conducts five random experiments and calculates the mean value as the final result of the experiment. Figure 3 shows the effects of five different algorithms tested on the data.

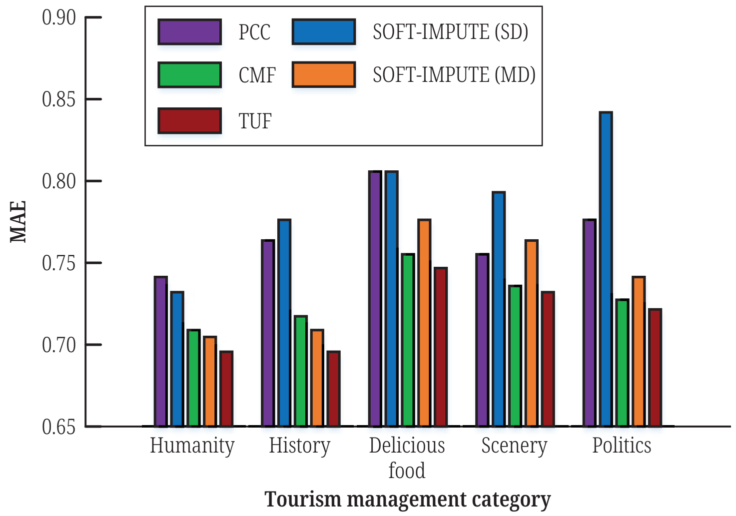

Fig. 3. Effects of five different algorithms in data testing

From the results in Figure 3, it can be seen that for flipped classrooms with various types of tourism management in the target space, the performance of CMF, SOFT-IMPUTE (MD), and TUF transfer learning algorithms is better than that of PCC and SOFT-IMPUTE (SD) algorithms for non-transfer learning. Therefore, it shows that transfer learning can effectively improve the quality of recommendations in the target space by utilizing the features from the auxiliary space. The transfer learning algorithm is illustrated in Figure 4.

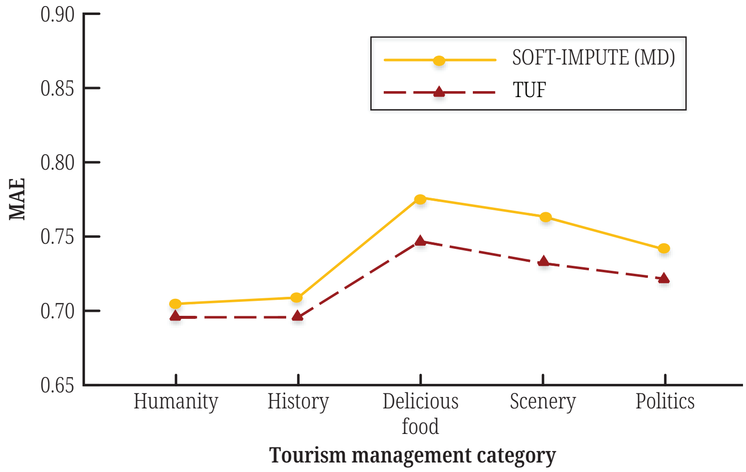

Fig. 4. Neutral energy comparison of migration algorithms

Figure 4 reveals that the recommendation accuracy of the TUF collaborative filtering recommendation algorithm in the flipped classroom of various types for tourism management in the target space is higher than that of the CMF and SOFT-IMPUTE (MD) transfer learning algorithms. The TUF model has higher accuracy in extracting user features from the auxiliary space and effectively migrates these features to the target space. This helps in learning the user features in the target space and significantly improves the recommendation effect in the target space. Figure 5 shows a comparison of the experimental results between the traditional matrix factorization model (RMF) and the TUF model after implementing transfer learning in the AI media research data center.

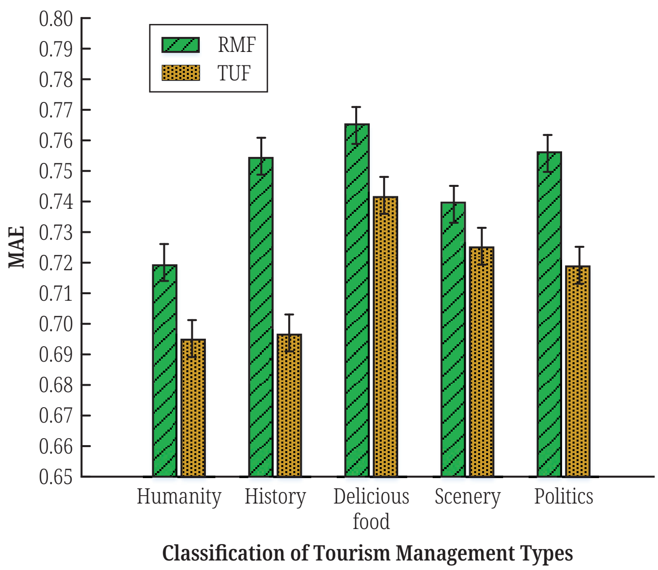

Fig. 5. Comparison of experimental results between traditional matrix decomposition model RMF and TUF model in AI media data center

The recommendation effect of the two models can be seen in Figure 5. When comparing the recommendation effect across different types, the TUF model performs better than the RMF model. The validity of the model proposed by the research has been verified, and the feasibility of using the transfer learning algorithm in the collaborative filtering algorithm has been demonstrated. Additionally, it effectively solved the problem of data sparsity. Figure 6 shows a comparison of the performance results of different algorithms in dysprosium number aggregation.

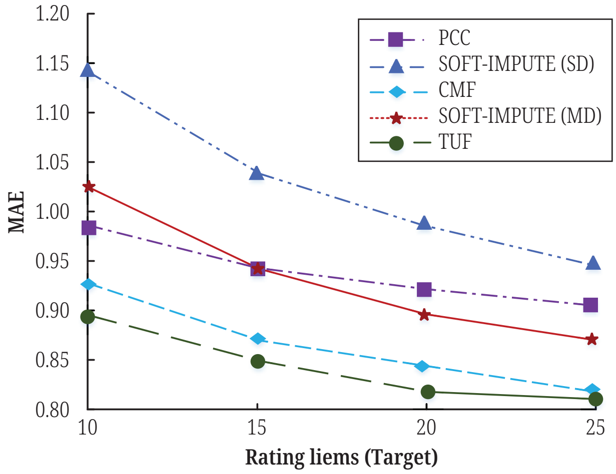

Fig. 6. Comparison of performance results of different algorithms in dysprosium aggregation

As shown in Figure 6, the number of user evaluations on the project is increasing, and the recommendation accuracy of various algorithms is also improving. In the mature auxiliary space, the SOFT-IMPUTE algorithm accurately fills in the matrix with missing data, thereby effectively extracting the user characteristics of the auxiliary space. In an environment with lower sparsity, the TUF algorithm demonstrates a more effective recommendation effect compared to several other algorithms. This indicates that the user features learned and extracted from the auxiliary space can effectively assist in the learning task of the target space. It aims to predict unknown scoring items and effectively alleviate the problem of data sparsity. Figure 7 presents a comparison of the experimental results between the traditional matrix factorization model (RMF) and the TUF model after the implementation of transfer learning in dysprosium number aggregation.

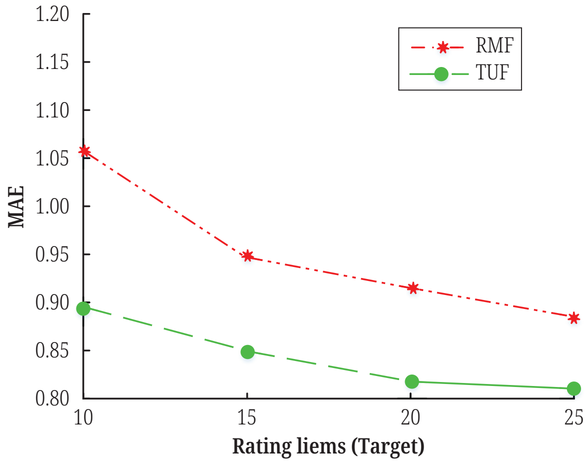

Fig. 7. Comparison of experimental results between traditional matrix decomposition model RMF and TUF model with transfer learning in dysprosium number aggregation

As shown in Figure 7, the TUF model demonstrates better recommendation performance compared to the RMF model on the dysprosium number aggregation dataset. This finding further confirms the viability of applying transfer learning algorithms to collaborative filtering recommendation systems. After conducting multiple rounds of comparison, it is worth noting that the SOFT-IMPUTE algorithm performs better in multiple fields on both datasets compared to the SOFT-IMPUTE algorithm used in a single field. This indicates that when the same algorithm is applied across different fields, the learned algorithm demonstrates improved recommendation quality and accuracy compared to uncited transfer learning.

5 CONCLUSION

The core of the flipped classroom lies in the online independent learning component for students, and the effectiveness of online learning recommendations directly impacts the quality of students' learning. However, the current recommendation system faces challenges in obtaining high-quality recommendations due to sparse data. This study proposes a collaborative filtering recommendation model (TUF) based on a migration learning algorithm and the traditional matrix decomposition model. The aim is to address or mitigate the issue of data scarcity in recommendation systems. The study investigates the migration of user features from the TUF model in the auxiliary space to the target space, which effectively aids in task learning. Additionally, the study employs the Wiberg algorithm to iteratively solve the model, which enables rapid convergence and the attainment of the optimal solution. The experimental results show that the TUF algorithm, evaluated in the AI media data center, has the smallest mean absolute error (MAE) results. The average MAE of the algorithm is approximately 0.71. Compared with other models, the results of the TUF model tested in dysprosium aggregation are still at optimal performance, with MAE values of 0.89 for TUF in 10 data sets, 0.86 in 15 data sets, and in 20 data sets TUF's MAE value is 0.83 in 10 datasets, 0.86 in 15 datasets, 0.83 in 20 datasets, and 0.82 in 25 datasets. In summary, the algorithm model proposed in the study can effectively organize the resources of the teaching platform and provide personalized course recommendations based on students' individual learning methods. This approach is beneficial for increasing students' interest in the flipped classroom and enhancing the quality of learning.

6 FUTURE WORKS

Aiming to address several issues in the current teaching resource recommendation platform, this article examines the collaborative filtering algorithm from the perspective of transfer learning. It proposes a collaborative filtering recommendation model that is based on user feature migration. The model is then applied to the flipped tourism management classroom in order to analyze the correlation between students' preferred behavior and teaching resource recommendations. The ultimate goal is to enhance the overall teaching quality. The research has made the following contributions:

1. A collaborative filtering algorithm model is constructed that is based on user feature migration. This model can assist in learning user evaluation models by considering user characteristics in the target space. As a result, it further enhances

the recommendation quality of the target space. Applying this model to the flipped classroom in university tourism management can recommend teaching resources to each student based on their individual characteristics, thereby enhancing teaching quality.

2. The SOFT-IMPUTE algorithm is utilized to address the slow convergence rate of matrix decomposition models in recommendation systems. It aims to enhance the decomposition performance of large-scale matrix decomposition models. Experimental results show that the SOFT-IMPUTE algorithm can effectively solve the aforementioned problems and optimize the recommendation quality of the recommendation model.
3. Finally, the Wiberg algorithm is used to solve the user characteristic matrix and the project characteristic matrix of the target space in the TUF model. This allows the model to successfully obtain the optimal solution in the final iteration process. The research results show that the Wiberg algorithm used has good iterative performance and can optimize the TUF model to achieve the optimal solution.

The algorithms mentioned above are utilized in the collaborative filtering recommendation model, and each of them can effectively enhance the recommendation performance of the model. When applied to actual teaching, the proposed model can effectively organize the resources of the teaching platform and provide personalized course recommendations based on students' individual learning methods. This can help students enhance their interest in the flipped classroom and improve the quality of their learning.

Furthermore, there are still numerous shortcomings in the study. The proposed algorithm assumes that the auxiliary space and the target space have the same set. However, the algorithm has not been tested for practicality when a common set is not available. Timely recommendation is one of the essential requirements for recommendation systems in practical applications. With the growing number of project books and users, the recommendation algorithm needs to handle larger-scale data. Therefore, more advanced machine learning methods are necessary to classify the data and reduce the running time of the recommendation algorithm.

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