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Design of Personalized Recommendation System for College Education Based on Multivariate Hybrid Criteria Fuzzy Algorithm

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Abstract: - The learner model's design is a most important aspect of a personalized college student education recommendation system. Currently, most learner models need more scientific focus, relying on a single method to collect dimensions and feature attributes with low computing costs. Hence, this paper introduced a Multivariate Hybrid Criteria Fuzzy Algorithm (MHCFA) for personalized college education recommendation. The MHCFA is trained by Social Feedback Artificial Tree (SFAT), where SFAT is the combination of Social Optimization Algorithm (SOA) and Feedback Artificial Tree (FAT). In addition, Deep Fuzzy Clustering (DFC) is utilized to group college education content. The RV-Coefficient is employed to select the best content. Moreover, the feature is extracted by All Caps and numerical for further personalized recommendations. In addition, the test results show that SFAT_MHCFA performs better in Precision, Recall, and F-Measure where the values gained 0.989, 0.878, and 0.859, respectively.

Keywords: Personalized Recommender System, Multivariate Hybrid Criteria Fuzzy Algorithm, College Education, Deep Fuzzy Clustering, Feedback Artificial Tree

1. Introduction

With an extensive improvement of educational information, college education is extremely valued by most of students [9][1]. Online college education blends traditional classroom instruction with Internet technology to overcome a restriction of the traditional classroom instruction in according to time, location, and the environment. It also allows distributing and reusing excellent instructional materials more widely. [10][1]. Personalized learning highlights that a learning process is the process that includes methods, techniques, content, and assessment methods by individual characteristics of the students and the potential of growth to encourage development all free and good students in all areas [11][1][9].

The rise of new educational information technology models has converted a traditional teacher-centered model into the learning model that focuses on students in a personalized and selective manner [10]. Recommendation systems (RSs) are dedicated to gathering relevant opinions about users. The user of this model is a college student, and the ideas are optional lessons. Collecting and integrating information from various sources to produce useful recommendations is the complex issue, many recommendation systems are trying to resolve [2]. RS is a software tool using information retrieval and the machine learning that can deliver suggestions on topics that are useful and interesting to people. RS is widely used for commercial purposes. [12][6].

For a personalized university education system, it is necessary to recommend the appropriate personalized learning materials for the current learning process, which still needs to be improved. Therefore, personalized learning RS has been widely researched. Knowledge acquisition (KT) is a powerful tool to implement artificial intelligence (AI) that supports education [13] It is about tracking the knowledge status of students (KS) based on their past performance and putting in place the necessary actions to improve the quality of learning. Despite a success in a KT field, one of the most popular KT models, the Bayesian KT model [5], suffers from serious problems. The combination of deep neural networks (DNN) and recommendation systems has developed rapidly in recent years. In [14], general linear and DNN models were trained to combine the benefits of memory and generalization of RSs [2].

A hybrid optimization model based on MHCFA is proposed to recommend personalized college education. This technology creates recommendations based on various content categories and user characteristics. Traditional methods focus only on lists; therefore, hybrid systems are modeled by considering the relationship between user interest in content and content usage. Here, DFC is used to group college education media content. In addition, pre-processing is the first step for sentiment classification, which is done by stemming and stop word removal, and All Caps and numerical extract the feature. Finally, SFAT_MHCFA is used for personalized recommendations.

The main contributions of this study are,

The MHCFA classifier is used for sentiment classification, and SFAT is used for MHCFA training. In addition, SFAT integrates SOA and FAT using the best features of both approaches. The SOA algorithm is inspired by human social behavior and aims to create a just society, by following two principles of justice: equal

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participation and social purpose. In contrast, FAT has two processes: an organic exchange process and a water reaction process, making it a useful search technology for solving optimization problems.

The paper format is as follows: Section 2 delivers the literature review of various personalized recommendations of college education; Section 3 describes a system model of personalized RS; Section 4 briefly describes SFAT_ MHCFA; Section 4 shows the results and details of project; and the Section 5 concludes a paper.

2. Literature survey

To address the issue of "information overload" caused by the abundance of educational resources, Chaohua Fang, and Qiuyun Lu *et al.* [1] analyze a requirements of an individualized recommendation system for the educational resources and suggest using the CB-Item CF-SVD + + algorithm in conjunction with it. A resource browsing capability is built into the personalized education resource suggestion system. It also provides functions for entering educational resource data and updating data. The method achieved more accurate recommendations but needed help to create a pre-study lesson plan based on the learners' attributes.

Yiu-Kai Ng and Jane Linn [2] created CrsRecs, which makes the process considerably simpler. CrsRecs rank potential course options according to the student's perceived preference using sentiment analysis, tag analysis, topic analysis, predicted professor/course ratings, and survey data revealing the priorities of students according to classes based on a hybrid technique. Since CrsRecs was not reliant on data from universities, any student enrolled in any institution may use it as long as the university's course details are included in the database, but does not include a hybrid optimization algorithm to further improve the system's performance.

Zhong Mingxia and Ding Rongtao [3] developed a RS self-learning resource using student behavior data from an online learning platform and a collaborative analysis algorithm with the knowledge index technology of the knowledge graph. The accuracy of the high recommendations of our system has been proven by tests. However, the diversity of users makes data collection and model development challenging.

A hybrid recommendation system developed by Hui Li *et al.* [4] improves the effectiveness of conventional recommendations. In addition to outlining user interest and teaching resource models, this research also describes the design and execution of a prototype system for tailored network teaching resources. The hybrid recommendation algorithm surpasses other algorithms regarding personalised, intelligent educational resource recommendations. The method improves the cold start aspect, leaving the new project problems unaddressed.

An Intelligent Recommender System (IRS) has been presented by D Kurniadi *et al.* [5] that uses intelligent agent of the students to support educational process in higher education. The article's discussion focuses on issues that students face about evaluating their academic performance, their chances of graduating on time, and advice on selecting courses that will best suit their needs and those of other students enrolled in the university. The method addresses student-related issues and makes suitable recommendations, but optimization algorithms should have been considered for effective performance.

Thoufeeq Ahmed Syed and Smitha Sunil Kumaran Nair [6] introduced a technique for discovering related references, which means, Most Recently Referred (MRR) and All Time Referred (ATR) titles by the students in Learning Management Systems (LMS). A customized dynamic sliding window is used to get the MRR references. This window can adjust its size based on the proportion of references/titles that students stated during the previous semester. The method addressed the challenge of disseminating educational resources, but the procedures must be fine-tuned to obtain more precise values.

Ziyu Liu *et al.* [7] devised a personalized learning route recommendation approach using in-depth mining of the online students' learning logs using students' learning styles. To begin, the method uses process mining method to mine the student's learning path, yielding an exceptional and generic learning path. The strategy improved pupils' learning outcomes, but the technique only recommends a path for one student, which is the major drawback.

Liang Zhang *et al.* [8] devised the Dijkstra-based Learning Resource Difficulty Prediction (Q-LRDP-D) algorithm to offer individualized learning materials that match teaching standards in higher education. Here, the learning resources were first modeled using Q matrix theory. After that, the difficulty of students' learning was identified using Long Short-Term Memory (LSTM). The method achieved better performance, but the Q matrix vector for new learning resources was not created automatically during resource bank development.

The following problems are identified in the related work:

The personalized RSs need help with problems, such as lack of understanding of content, student barriers, language barriers, confusing selection of learning materials, and lack of resources of structure and finance. Traditional methods may only partially reflect student progress, and it is difficult to identify areas where students are struggling or excelling. The challenges in implementing personalized education are the need to support the diverse needs of students based on knowledge, learning speed, needs, and educational characteristics. In addition, there are barriers related to data collection, classification, and access to individuals with different abilities, which are exacerbated by distance learning.

3. System model of Personalized Recommendation System

Recommendation systems seek to give correct recommendations to users by gathering and processing their data effectively. Every user has some personal information about her preferences and interests stored on their local device (such as smartphone). The produced recommendations are supplied or displayed to the users in several ways, including pop-up windows and messages. Figure 1 shows system paradigm for a personalized RS. This RS architecture has user, business, and data layers.

-User Layer

The user layer manages user-system interaction by responding to the user requests and showing content, like registration and login, resource browsing, and the information settings. This layer tracks user's access to website. The user's access records, which include viewing, buying, and commenting on resources. These users' behaviors are saved in a user behavior log database.

-Business Layer

This layer primarily implements the basic business logic of search suggestion, which includes two modules. The initial module is a recommendation module that executes the resource recommendation function and transmits results to user layer for display. This subsystem primarily analyses and evaluates user, user behavior and teaches resource information, allowing users to recommend resources based on various scenarios.

-Data Layer

It provides essential data storage services, backup recovery to assure data security and the reliability. Due to diverse application needs, storage layer is partitioned into three databases: user information, educational resource information, and user behavior. The user behavior log database is primarily employed to keep historical records of users' commenting, browsing, buying, collecting, and other activities. These records are then utilized later in research to construct user preference models.

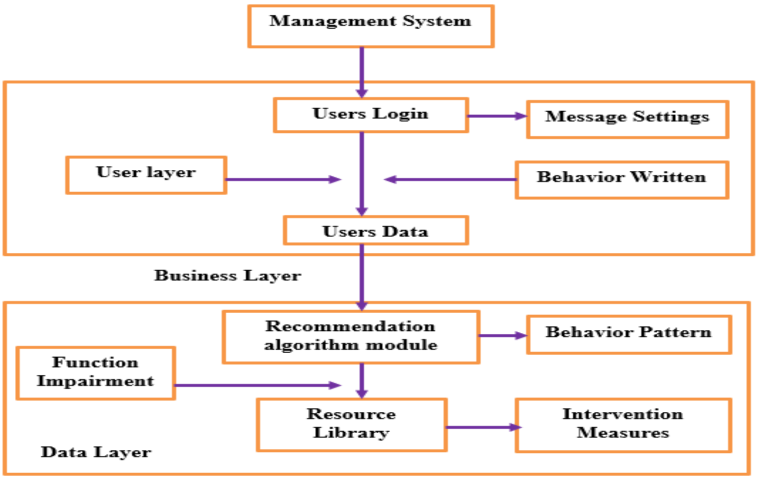


Figure 1. Personalized RS architecture

4. Proposed methodology

This section presents SFAT_MHCFA's recommendations for college education. This article recommends college education topics, including classification, matrix statistics, and reviews of the best college education options. The input data is given to a preference matrix, and then a binary preference matrix is created. After that, solve the binary matrix of college education content subscriptions and use DFC for grouping. After the DFC, the matching is made through the RV-Coefficient, which provides information on the academic programs of the best education. A good review is also sent to the classification system, which performs the stemming and stop word removal to process the data first. After pre-processing, capitalization and number features are extracted. In the best-case scenario, sentiment classification is performed by MHCFA, trained by SFAT, and recommended personalized college education. Figure 2 shows the SFAT_MHCFA block diagram.

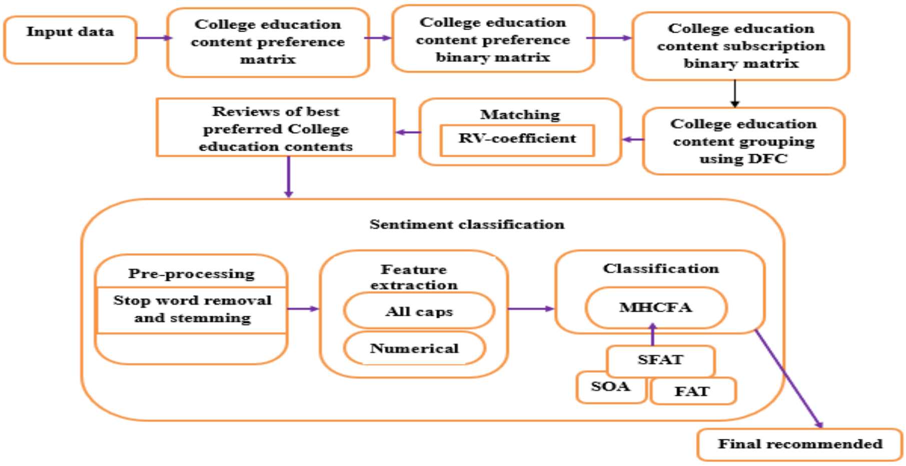


Figure 2. Schematic design of a college education recommendation using SFAT_MHCFA

List of college student's learner list,

$$I_h = \{h_g\} b < g \le t \tag{1}$$

where, t is the count of learners, and h_g is g^{th} learner.

Let's discuss the list of college student education content list:

$$I_q = \{R_g\} 1 < f \le s \tag{2}$$

where, s is education content count.

4.1 Education content preference matrix of college students

The input resource is taken from the college student education content dataset I_q and sent to the college student education content preference matrix, which contains the number of subscribed college student education content lists. Each education content list has a unique ID, described in the education content list ID, as well as the ID of the student taking that specific education content list, displayed in the education content list preference matrix.

4.2 Education content preference binary matrix

After creating the education content preference matrix, education content preference matrix is created based on subscribed education content list, which are indicated by 0 or 1. The specific education content list that the individual is looking for is written as 1; otherwise, it is written as 0.

4.3 Education subscription matrix

The output from the education content preference set is passed to the education content subscription matrix, which includes the subscribed education content list count. Hence, the learner's education content list is denoted as,

$$T_f = \{h_1^g, h_2^g, \ldots, h_v^g, \ldots, h_m^g\} \tag{3}$$

4.4 Education content subscription binary matrix

Following the creation of the education content subscription matrix, an education content subscription binary matrix based on the subscribed education content list is required, which is represented by 0 or 1. The relevant binary value of the entire education content list is represented as a binary sequence for each education content list. The specific education content list sought by the individual is denoted as 1, otherwise as 0.

4.5 Education content list grouping using DFC

DFC [17] groups visitors based on a binary matrix of knowledge content subscriptions to find exemplary visitors. The DFC input is a binary model of the education content preference matrix, resulting in a vector of visitor groups.

DFC

DFC [17] is a clustering approach that allocates data points to several clusters. The fuzzy clusters and borders can be built simply using the DFC. Furthermore, in an overlapping database, the DFC produces better results. DFC offers the advantage of requiring less processing time and providing more excellent performance. This method reduces computer complexity and eliminates the requirement for user input in the clustering process. In addition, the DFC method groups similar objects into clusters. Consider the following: number of iterations $Ite_{maximum}$, batch size a_p, number of clusters d, and input data $P' = \{L_1', L_2, \ldots, L_n', \ldots, L_d'\}$. The samples are divided into groups, and the training data of each group is considered $L_n, n = 1,2,\ldots,a / a_p$ .Therefore, the loss function of the autoencoder can be shown:

$$M(L\alpha)=\frac{1}{a}\sum_{n=1}^{a}\left\|l_{H,Q}(L_n)-L_n\right\|^2+\theta.Z(F) \tag{4}$$

where, $Z(F)$is regularization terms, $\|\ \|$ is Euclidean norm, and highlight reconstruction is $l_{H,Q}(d_N)$. The visitor grouping process that combines the number of visitors in a group can be
described as follows:

$$X_G=\{X_1,X_2,\ldots,X_m\} \tag{5}$$

where, X_G is the visiting group and m is the entire group.

4.6 Query

When a query is received, a query sequence is transformed to a binary according to preferred education content list.

4.7 Education content list mapping with RV-Coefficient

RV coefficients are used to align groups. The query binary sequence is compared with the grouped content binary sequence. The following provides the RV coefficient:

$$KZ(B^E,B^{G_e})=\frac{COV(B^E,B^{G_e})}{\sqrt{VAR(B^E)VAR(B^{G_e})}} \tag{6}$$

where, $COV(B^E,B^{G_e})$ represents the correlation between the group content and the query binary sequence, $VAR(B^E)$ represents the variance of the query binary, and $VAR(B^{G_e})$represents the variance of the group content binary. The best group is selected and sent into the relevant user retrieval system from group matching. Following the completion of group retrieval, the appropriate retrieval learner is done. This stage selects the optimal group from the obtained group in binary form. Furthermore, the learner ID is derived using binary values from the ideal group, and the learners determine the relevant education content list. The education content list is evaluated by number of visitors within optimal group. Following the retrieval of the suitable learner, the binary query sequence is matched against the previously seen binary sequence of the optimal group using angular distance.

4.8 Selection of Optimal Preferred Education Content

After comparing the query and best binary sequence groups, the angular distance is used to determine the optimal course. Following that, the best course is assessed using sentiment classification to determine whether the suggested education content is excellent.

4.9 Classification of Sentiments

At this point, the input is considered the best educational content, where sentiment classification uses the sentiment polarity of the opinion (negative or positive).

4.9.1 Pre-processing

Pre-processing helps describe the process a better way. The dataset contains unwanted words or phrases that make it difficult to work. Therefore, pre-processing is important in removing unnecessary words from the dataset. The stemming and stop-word removal are performed to filter the data. Stop words denote words that do not consider any data. It is a procedure of removing stop words from a large group of reviews. During this process, extraneous and nonsensical words are removed to diminish the noise in data. The stemming procedure is used to convert the words into stems. For example, agree, disagree, and agree – on a word level. It's easy to use, clean and precise and doesn't require a list of suffixes.

4.9.2 Significant Features Acquisition

At this time, essential features are created based on pre-processed data. The goal of feature extraction is to extract features that are relevant for improving sentiment classification. Next, an extraction process is used to extract relevant features such as all caps and numerical values. Words that use capital letters are called all-caps characters. Numerical count defines the term as having numerals.

4.9.3 Sentiment classification by SFAT_MHCFA

Here, feature vectors are considered for sentiment classification. The sentiment classification uses MHCFA, which is SFAT trains. The SFAT is the hybridization of SOA [19] and FAT [18] to classify the polarity of input information. Finally, SFAT_MHCFA creates lesson plans by providing relevant lessons to students. The structure of the MHCFA and its training process are explained as follows.

- MHCFA structure

A fuzzy model with multiple criteria was developed using the statistical theory MHCFA [15]. MHCFM can effectively handle sentiment classification for classifying the sentiments. Assume there is a sample $\{(y_g,z_g)\}$, where $g=(1,2,3,\ldots,s)$, s denotes sample size, y be the input vector (usually

multidimensional vector), and z represents output vector, which also serves as the vector to be classified. For any time node s, the equation is represented below,

$$z = u_0 + u_1 y_1 + u_2 y_2 + u_3 y_3 + ..u_m y_m \qquad \textbf{(7)}$$

where, y_m denotes each m vector dimension. The hyperplane of equation (1) is determined by the parameters u_m and u_0, which can be estimated through program training. To keep things simple, the formula can be written as,

$$z = c + \sum b_g z_g y(g).y \tag{8}$$

where, $y(g)$ is the training sample input, and z_g is the training sample output, "." is the point product. Entering the test model y corresponds to the support vector $y(g)$. Equation (2) indicates that fixing c and b_g solving the problem. This method is intuitively comparable to a linear problem. The MHCFM principle is to plot a support vector in high dimensions when dealing with complex issues that are not linearly separable. Linear classification identifies and captures patterns in nonlinear issues and then performs regression analysis as required. Equation (2) is re-written as,

$$z = c + \sum b_g z_g J(y(g).y) \tag{9}$$

where, $J(y(g).y)$ referred to as kernel function, it is a significant component of the MHCFM that has a direct impact on calculation results. There are numerous types of the kernel functions, like polynomial kernel:

$$J(y, z) = (yz + 1)^f \tag{10}$$

Gaussian nuclear Radial Basic Function (RBF) is expressed by,

$$J(y, z) = \exp(-\|y - z\|22\alpha 2) \tag{11}$$

In the actual testing and usage, β is frequently used to substitute $\beta = -12\alpha 2$, thus α. After the experimental Gaussian kernel, the sentiment classification is improved.

- Training of MHCFA

This section describes the MHCFA training process, performed using the SFAT algorithm. Here, the classifier weights are trained using the SFAT algorithm to gain optimal solution. The social characteristics of people drive the SOA approach [19] in an ideal society. The algorithm is based on the principle of opportunity and community. The FAT [18] is based on organic material transport and moisture feedback method. The advantage of the FAT algorithm is that it achieves excellent classification performance. Therefore, the SFAT algorithm was created by combining the advantages of the FAT algorithm and the SOA algorithm, achieving best performance with low computational complexity and the high processing speed. The various algorithm components involved in the SFAT training process are explained as follows:

-Initialization

The solution initialization is the main step, denoted by G, and m is a solution, where $1 \le \sigma \le m$.

$$G = \{G_1, G_2, \ldots, G_\sigma, \ldots, G_m\} \tag{12}$$

In them, the entire solution is shown as m and G_σ shows the solution σ.

-Fitness calculation

The fitness function uses an error function to calculate the optimal solution, which is the following equation:

$$Fit = \frac{1}{\tau} \sum_{u=1}^{\tau} [\mathrm{M} - \mathrm{O}_u]^2 \tag{13}$$

where, the objective output is determined as M, τ determines the total training samples, and O_u is the classification output.

- Equality of opportunity Evaluation

According to SOA, equal opportunities are defined as the following location for each individual:

$$G_t^{new} = G_t^{old} + rand(\mathrm{H} - \mathrm{K} \times G_t^{old}) \tag{14}$$

Among them, $rand$ determines the random number, H determines the optimal position, and K determines the self-selection coefficient, G_t^{old} is the old position of individual. Here, the best positions H are represented by:

$$\mathrm{H} = rand\{\mathrm{T}, J\} \tag{15}$$

Here, T represents an optimal solution, and J represents optimal solution of entire community. The density point is given by,

$$U = \frac{G_1 p_1 + G_2 p_2 + \ldots + G_m p_m}{p_1 + p_2 + \ldots + p_m} \tag{16}$$

Among them, U represents a density point, p_1 is the individual's objective function, and $G_1 \ldots G_m$ represents the individual's social status.

- Community Principle Evaluation

As society moves forward, partnerships must exist to improve open spaces. Therefore, reviewing the principles of society:

$$G_t^{new} = G_t^{old} + rand\left(\mathrm{T} - Q\right) \tag{17}$$

$$G_t^{new} = G_t^{old} + rand\mathrm{T} - randQ \tag{18}$$

where, Q is Empty Point. In addition, the standard parameters of the SOA algorithm [19] are combined with the standard parameters of the FAT [18] to gain algorithm performance by reducing optimization problem. The FAT standard equation is given by,

$$G_t^{new} = G_t^{old} + \left(rand\left(0,1\right) \times G^* - rand\left(0,1\right) \times G_t^{old}\right) \times n \tag{19}$$

$$G_t^{new} = G_t^{old} + rand\left(0,1\right) \times G^* \times n - rand\left(0,1\right) \times G_t^{old} \times n \tag{20}$$

$$G_t^{new} = G_t^{old}\left(1 - rand\left(0,1\right) \times m\right) + rand\left(0,1\right) \times G^* \times n \tag{21}$$

$$G_t^{old} = \frac{G_t^{new} - rand\left(0,1\right) \times G^* \times n}{1 - rand\left(0,1\right) \times m} \tag{22}$$

where, G_t^{new} is the new solution, $n = 0.382$ is constant, G^* is the best solution.

Substitute equation (22) to equation (18),

$$G_t^{new} = \left[\frac{G_t^{new} - rand\left(0,1\right) \times G^* \times n}{1 - rand\left(0,1\right) \times m}\right] + rand\mathrm{T} - randQ \tag{23}$$

$$G_t^{new} - \frac{G_t^{new}}{1 - rand\left(0,1\right) \times m} = \left[\frac{- rand\left(0,1\right) \times G^* \times n}{1 - rand\left(0,1\right) \times m}\right] + rand\mathrm{T} - randQ \tag{24}$$

$$G_t^{new}\left[\frac{\left(1 - rand\left(0,1\right) \times m\right) - 1}{1 - rand\left(0,1\right) \times m}\right] = \left[\frac{- rand\left(0,1\right) \times G^* \times n}{1 - rand\left(0,1\right) \times m}\right] + rand\mathrm{T} - randQ \tag{25}$$

$$G_t^{new} == \left[\frac{- rand\left(0,1\right) \times G^* \times n}{1 - rand\left(0,1\right) \times m}\right] + rand\mathrm{T} - randQ\left[\frac{1 - rand\left(0,1\right) \times m}{\left(1 - rand\left(0,1\right) \times m\right) - 1}\right] \tag{26}$$

- Density and empty point computation

Use the equation below to evaluate the density points and void points shown below,

For non-positive p_t, the point density is expressed as,

$$U = \sum_{t=1}^{H} \frac{p_t}{\sum_{x=1}^{H} p_x} G_t \tag{27}$$

For non-positive p_t, the empty point is expressed by,

$$Q = \sum_{t=1}^{H} \frac{\frac{1}{p_t}}{\sum_{x=1}^{H} \frac{1}{p_x}} G_t \tag{28}$$

where, $\frac{p_t}{\sum_{x=1}^{H} p_x}$ is relative fitness.

- *Computation of feasibility*: To determine the optimal option, re-evaluate the fit using equation (13).

-*End:* Repeat all the steps above until the best solution is found. Table 1 shows SFAT algorithm pseudo code.

Table 1. Pseudo code for SFAT algorithm

Input: G
Output: G_t^{new}
Start
Initialize set of population G
Population is determined
$\mathrm{T} \leftarrow$ Best solution
For $x = 1\ to\ x_{\max}$ do
$Q \leftarrow$ Evaluate empty point
For $t = 1\ to\ H$ do
$\mathrm{H} = rand(\mathrm{T}, Q)$;
$\mathrm{K} = rand\{0,1,2\}$;
Evaluate G_t^{new} using 18th equation
end
If G_t^{new} improved than G_t^{old} then
$G_t \leftarrow G_t^{new}$
end
Estimate original population
$\mathrm{T} \leftarrow$ Optimal solution
$U \leftarrow$ Compute Density point;
For $t = 1\ to\ H$ do
Compute G_t^{new} SFAT algorithm using 26th equation
end
If G_t^{new} best than G_t^{old} then
$G_t \leftarrow G_t^{new}$
end
Evaluate novel population
$\mathrm{T} \leftarrow$ Top solution;
end
Print Top solution

As a result, MHCFA is used to train the weights of SFAT, which is produced by combining the advantages of SOA and FAT. Furthermore, SFAT_MHCFA is used to help determine the optimum solution to recommend education content of college students.

4. Results and discussion

The outcomes and the discussion of the SFAT_MHCFA for education content recommendation are analyzed in the section.

4.1 Experimental setup

SFAT_MHCFA is tested with the PYTHON tool running the Windows 10 operating system.

4.2 Dataset description

The E-Khool dataset [20] is used for the experiments of SFAT_MHCFA. This dataset contains 100,000 rows and employs 25 education content and his 1,000 learners. The dataset includes a variety of contents, including accounting, engineering, language, and business. A dataset consists of various attributes, such as: Subscription date, ID, rating (1-5), learner ID, date of rating and review. The SFAT_MHCFA system is evaluated using four measures:

-*Precision:* It defines the mutual proximity of two or more dimensions and is expressed as:

$$\Pr e = \frac{w_i}{w_i + r_i} \tag{29}$$

where, w_i and r_i is true and false positive.

-*Recall:* It estimates the complete true positives that the system collects based on the true positive labels and is given by,

$$\mathrm{Re} = \frac{w_i}{w_i + r_j} \tag{30}$$

where, r_j is false negative.

-*F-measure:* The F value is calculated based on the harmonic mean recall and precision and is displayed as:

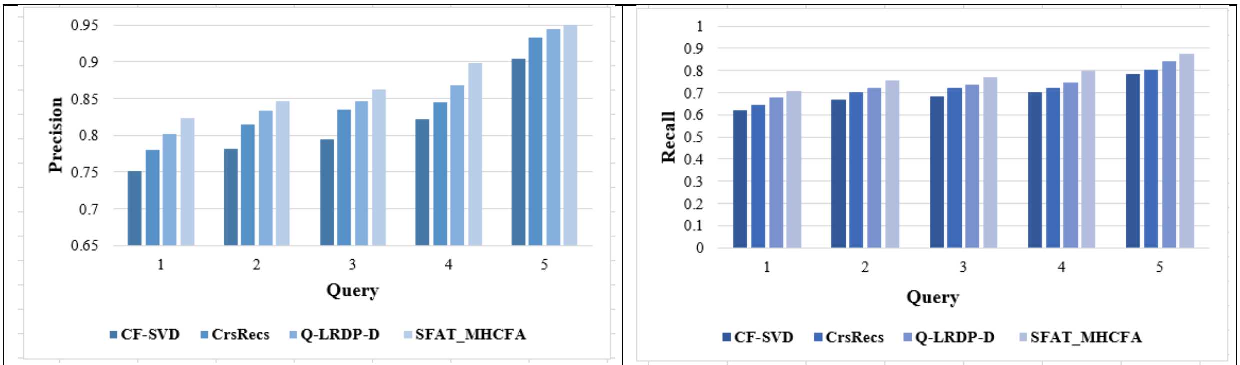
$$F_m = 2 \times \left(\frac{\Pr e * \mathrm{Re}}{\Pr e + \mathrm{Re}} \right) \tag{31}$$

4.3 Comparative methods

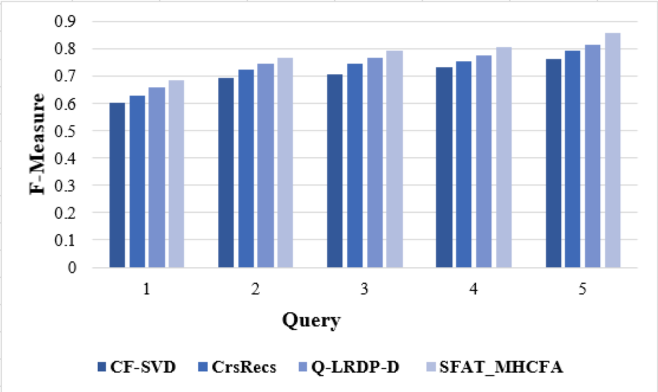
The performance gain of SFAT_MHCFA is evaluated by comparing it to conventional techniques, like CF-SVD [1], CrsRecs[2], and Q-LRDP-D [8].

4.4 Comparative assessment

Figure 3 shows SFAT_MHCFA evaluation using performance metrics. The query is modified to determine precision, recall, and F-value. Figure 3a) shows the accuracy-based evaluation after modifying the query. The precision value of SFAT_MHCFA for query=1 is 0.823, while the precision values of standard techniques such as CF-SVD, CrsRecs, and Q-LRDP-D are 0.751, 0.78, and 0.802, respectively. The precision of SFAT_MHCFA increases as the queries increase, but the performance appears to remain consistent. Figure 3b) shows the recall after the queries are reversed. Although, SFAT_MHCFA increases by 0.756 in the second query, the recall values of CF-SVD, CrsRecs, and Q-LRDP-D are 0.671, 0.704, and 0.723. The higher value indicates better performance. Compared to SFAT_MHCFA, CrsRecs has the highest Recall and ranks second in student learning recommendations. Figure 3c) shows the evaluation results based on the F measure. In this study, SFAT_MHCFA outperformed three other classical methods in recommending knowledge to students. Thus, when the query is 4, the F-measures for the various algorithms are 0.731, 0.754, 0.777, and 0.807. Therefore, the SFAT_MHCFA performs the correct recommendations by combining the two optimization cycles.



(i)	(ii)



(iii)

Figure 3. Evaluation of SFAT_MHCFA i) Precision, ii) Recall, and iii) F-Measure

4.5 Comparative Discussion

Table 1 compares SFAT_MHCFA by evaluation measure. The recall, precision, and the F-measure values of SFAT_MHCFA are 0.989, 0.878 and 0.859, respectively. Similarly, established methods such as CF-SVD, CrsRecs, and Q-LRDP-D achieve parameters of 0.905, 0.935, and 0.947, recall rates of 0.784, 0.806, and 0.849, and F measures of 0.765, 0.797, and 0.815. The following table illustrates how the SFAT_MHCFA has greater precision than CF-SVD, CrsRecs, and Q-LRDP-D. The hybrid optimized model outperformed other classifiers in most cases on the basis of F-Measure, recall, and precision. CF-SVD and CrsRecs did not achieve perfect precision, indicating that more malicious programs were missed. Current methods cannot take into account the changes in consumers' attention to the types of content they access. Acting according to each method is not enough to accurately understand user preferences. Therefore, SFAT_MHCFA can effectively solve this problem.

Table 1. Comparative discussion

Metrics	CF-SVD	CrsRecs	Q-LRDP-D	SFAT_MHCFA
Precision	0.905	0.935	0.947	**0.989**
Recall	0.784	0.806	0.849	**0.878**
F-Measure	0.765	0.797	0.815	**0.859**

5. Conclusion

This paper describes how the SFAT_MHCFA is used by the personalized recommender system to facilitate the recommendation of college education content. Furthermore, DFC is utilized to content grouping, whereas RV-Coefficient is used for matching and choose the best match contents. Then, the sentiment classification is done by following steps: Pre-processing, Feature Extraction, and Sentiment classification. Here, the sentiment is classified by MHCFA in which MHCFA is trained by SFAT. The SFAT is the integration of two optimization algorithms, like SOA and FAT. In addition, the test results show that SFAT_MHCFA performs better in terms of Recall, precision, and the F-Measure with the values of 0.989, 0.878, and 0.859, respectively. In the future, other parameters will be integrated into optimization algorithms for better recommendations.

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References

[1] Chaohua Fang and Qiuyun Lu,"Personalized Recommendation Model of High-Quality Education Resources for College Students Based on Data Mining", Complexity, pp.1-11, 2021.

[2] Yiu-Kai Ng, and Jane Linn,"CrsRecs: A Personalized Course Recommendation System for College Students", In 2017 8th International Conference on Information, Intelligence, Systems & Applications (IISA), pp. 1-6, IEEE, August 2017.

[3] Mingxia Zhong, and Rongtao Ding,"Design of a Personalized Recommendation System for Learning Resources based on Collaborative Filtering",Journal of Circuits, Systems and Signal Processing, vol.16, pp.122-31, 2022.

[4] Hui Li, Haining Li, Shu Zhang, Zhaoman Zhong, and Jiang Cheng,"Intelligent learning system based on personalized recommendation technology", Neural Computing and Applications, vol.31, pp.4455-4462, 2019.

[5] D Kurniadi, E Abdurachman, H L H S Warnars and W Suparta,"A proposed framework in an intelligent recommender system for the college student", In Journal of Physics: Conference Series, IOP Publishing, vol. 1402, no. 6, pp. 066100, December 2019.

[6] Thoufeeq Ahmed Syed, and Smitha Sunil Kumaran Nair,"Personalized Recommendation System for Advanced Learning Management Systems", In Proceedings of the 8th International Conference on Information Communication and Management, pp. 90-95, August 2018.

[7] Ziyu Liu, Liye Dong, Changli Wu,"Research on Personalized Recommendations for Students' Learning Paths Based on Big Data",International Journal of Emerging Technologies in Learning (iJET), vol.15, no.8, pp.40-56, 2020.

[8] Liang Zhang, Xiao Zeng and Ping Lv,"Higher Education-Oriented Recommendation Algorithm for Personalized Learning Resource", International Journal of Emerging Technologies in Learning (Online), vol.17, no.16, pp.4, 2022.

[9] Hongyu Shi, Ling Chen, Zhenxing Xu, Dandan Lyu,"Personalized location recommendation using mobile phone usage information", Applied Intelligence, vol.49, pp.3694-3707, 2019.

[10] Xiaoyan Zhang, Haihua Luo, Bowei Chen, Guibing Guo," Multi-view visual Bayesian personalized ranking for restaurant recommendation",Applied Intelligence, vol.50, no.9, pp.2901-2915, 2020.

[11] Mukul Gupta , Pradeep Kumar,"Recommendation generation using personalized weight of meta-paths in heterogeneous information networks", European Journal of Operational Research, vol.284, no.2, pp.660-674, 2020.

[12] Adrian Kirkwood and Linda Price," Technology-enhanced learning and teaching in higher education: what is 'enhanced' and how do we know? A critical literature review", Learning, Media and Technology, vol.39, no.1, pp.6-36, 2013.

[13] Heonseok Ha, Uiwon Hwang, Yongjun Hong, Jahee Jang, and Sungroh Yoon,"Deep Trustworthy Knowledge Tracing",arXiv preprint arXiv:1805.10768, 2018.

[14] Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishi Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ispir, Rohan Anil, Zakaria Haque, Lichan Hong, Vihan Jain, Xiaobing Liu, Hemal Shah,"Wide & Deep Learning for Recommender Systems", In Proceedings of the 1st workshop on deep learning for recommender systems, pp. 7-10, September 2016.

[15] Zhang Xiao-Wen and Zeng Min, "An empirical study on big data stock volatility forecasting algorithm based on multivariate hybrid criterion fuzzy model", International Journal of Electrical Engineering & Education, 60(1_suppl), pp.2877-2889, 2023.

[16] Cong Wanga,b,⇑, Yifeng Zheng a,b, Jinghua Jiang a,c, Kui Ren," Toward Privacy-Preserving Personalized Recommendation Services", Engineering, vol.4, no.1, pp.21-28, 2018.

[17] Feng, Q., Chen, L., Chen, C.P. and Guo, L., "Deep Fuzzy Clustering—A Representation Learning Approach", IEEE Transactions on Fuzzy Systems, vol.28, no.7, pp.1420-1433, January 2020.

[18] Li, Q.Q., He, Z.C. and Li, E., "The feedback artificial tree (FAT) algorithm", Soft Computing, pp.1-28, 2020.

[19] Karimi, N. and Khandani, K., "Social optimization algorithm with application to economic dispatch problem", International Transactions on Electrical Energy Systems, vol.30, no.11, p.e12593, 2020.