Intelligent recommendation of educational resources combining Neu-MF and T-S fuzzy control

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Abstract: The research uses Takagi-Sugeno (T-S) fuzzy control combined with neural matrix factorization (Neu MF) model to study the intelligent recommendation of educational resources. The recommendation performance of TS-Neu MF model is compared with other similar recommendation algorithm models under two test sets of E's dx and C er. The results of the experiments show that the TS-Neu MF model outperforms Deep FM by 56.6% in root mean square error (RMSE) metrics and 71.5% in mean absolute error (MAE) metrics, and outperforms the Neu MF model by 33.1% in RMSE metrics and 22.5% in MAE metrics under the E dx dataset. The training loss is about 0.04 lower than the Deep FM model, about 0.006 lower than the BPNN model, and about 0.02 lower than the Neu MF model.

Keywords: Neu MF; T-S fuzzy; educational resources; intelligent recommendation.

Biographical notes: Dan Li, Lecturer, Master's degree candidate, graduated from the ideological and political education major of Henan University of Technology, and worked in Henan Industry and Trade Vocational College. She has been a teacher of ideology and politics for eight years. She has devoted herself to ideological and political courses and higher vocational talent training. She has published more than 10 papers on education, teaching and learning, presided over and participated in seven projects, and won honorary titles such as excellent educator at the university level.

1   Introduction

With the continuous promotion of smart education in China, online educational resources are updated more and more rapidly, and the categories and subjects of online education are becoming more and more abundant (Lin, 2021). The increased curriculum diversity of educational resources means that the difficulty and complexity of selecting educational resources grows in parallel, and how to filter the suitable resources from the many online educational resources becomes a problem to be solved (O'Donoghue, 2020).

The effective sorting of data of educational resources and predicting users' needs to accurately select educational resources of interest to users is the core of educational resource recommendation research (Machado and Oliveira, 2021). Fuzzy prediction algorithms combined with neural network algorithms can well simulate the decision-making process of the human brain and are often used to study a wide variety of resource recommendation problems (Morales et al., 2021). This combination method can also be used to research the intelligent recommendation of educational resources. Compared with general recommendation algorithms, the combined algorithm model has improved accuracy and stability (Bhole et al., 2022). Therefore, the aim of this study is to combine Neu MF with T-S fuzzy control to explore the research on intelligent recommendation strategies for educational resources.

This research innovatively combines T-S fuzzy control with Neu MF neural network model, and applies it to educational resource recommendation. Taking advantage of their data processing characteristics, linear and nonlinear situations are optimized, which provides a reference for intelligent recommendation methods of educational resources. The research content mainly includes four parts. The second part is to conduct a review of the current research status of resource recommendation methods at home and abroad; the third part proposes an educational resource intelligent recommendation optimization method combining NeuMF and T-S fuzzy control, and establishes a fuzzy predictive control algorithm model in the first section of the third part, and constructs a fuzzy predictive control model based on Neu MF in the second section of the third part; the fourth part validates the TS-Neu MF educational resource The application effect of TS-Neu MF educational resource intelligent recommendation model is verified in Section 4. The results show that the intelligent recommendation method of educational resources combining Neu MF and T-S fuzzy control has a good application effect.

2 Related work

In order to promote educational resources to the intelligent era, the research of intelligent recommendation strategies for educational resources has become a focal issue nowadays, and researchers at home and abroad have also conducted in-depth research on this issue. Xiao et al. found that the existing learning resource recommendation systems have defects in adaptive range and large recommendation errors, and they designed a multimedia learning resource recommendation system by adding recursive neural systems to the system. that the newly designed system outperforms the original system under Gowalla dataset and Yelp dataset compared with the original system (Xiao et al., 2021).Wang and his experimental partners believe that as the user data index soars, the information data will be more diverse and complex, and we must spend a lot of time and effort when we want to get valuable information to filter the accuracy and adaptability of information, and they proposed an algorithm of collaborative filtering recommendation technology after analysing the current situation of college students' innovation and entrepreneurship resource recommendation (Wang, 2020). Jiang et al. summarised the current situation of personalised recommendation of educational teaching resources, combined with the current mainstream recommendation model, and constructed a .NET

platform-based recommendation model for international communication online teaching resources, and the experimental results show that under the application of their established recommendation model, mean absolute error (MAE) is lower, accuracy and recall are higher, and recommendation quality is higher compared with the recommendation model based on association rules and content (Jiang and He, 2021). Wang and Fu (2021) proposed a personalized learning resource recommendation method based on dynamic collaborative filtering algorithm recommendation method to solve the problems of sparse data and poor scalability in collaborative filtering algorithm, and used dynamic k-nearest neighbour and slope one algorithm to optimize it, and analysed the sparsity of learning resource data in the network based on the results of neighbour selection; used two-way self-balancing of stage evolution to improve personalized recommendation of resource push; used fuzzy adaptive binary particle swarm optimization algorithm based on evolutionary state judgement Chen and his team proposed an adaptive recommendation method based on learning style model to represent the characteristics of online learners, which achieves the adaptive recommendation of learning resources by mining the behavioural data of learners. of adaptive, and the experimental results show that this online learning style model facilitates data mining of learners and is significantly better than the traditional CF method (Chen et al., 2019).

Chen and other researchers studied the robust admissibility and state feedback stabilization of discrete-time T-S fuzzy singular systems with norm bounded uncertainties, and introduced a new approximation technique. The initial membership function can be conveniently expressed as a piecewise linear function considering the approximation error. The piecewise linear membership function, Lyapunov function based on fuzzy weighting and auxiliary matrix are used. Check the conditions of some sample points to determine the admissibility of the system. By selecting the special value of relaxation matrix, these conditions are simplified to normal parallel distribution compensation conditions (Chen and Yu, 2021). Yi and his team use T-S fuzzy model method to approximate nonlinear dynamics and design a filter for nonlinear systems. In order to ensure the asymptotic stability of the filtering error system and at the same time ensure the pre-specified criteria, they used the Lyapunov method in combination with the matrix analysis method. Based on the solvability of some linear matrix inequalities, the sufficient conditions for the existence of the expected filter parameters are established, and the validity and validity of the developed theoretical results are proved by numerical simulation results (Yi et al., 2021). Chen et al. efficiently learns from the entire data model parameters and proposed a general framework-ENMF (efficient neural matrix decomposition) based on a simple neural matrix decomposition architecture, and extensive experiments on three real public datasets showed that the proposed ENMF framework consistently outperformed the state-of-the-art methods significantly on Top-K recommendation tasks and showed significant advantages in terms of training efficiency (Chen et al., 2021). Wang et al. proposed a multi-attentive deep neural network recommendation model based on embedding and matrix decomposition, which can effectively alleviate the data sparsity and cold start problems by integrating user/item embedding representation and matrix decomposition representation. Experimental results on real datasets show that compared with other classical matrix decomposition

recommendation algorithms, the algorithm can produce higher prediction results and effectively improve recommendation quality and performance (Wang and Liu, 2020). Wang and his group proposed a deep neural attention matrix decomposition (IFDNAMF) recommendation model based on information fusion, which introduces attribute information and uses the product of elements between different information domains to learn cross features when performing information fusion. and uses the attention mechanism to distinguish the importance of different cross features on the prediction results. IFDNAMF employs deep neural networks to learn the higher-order interactions between users and items. Extensive experiments on two datasets, Movie Lens and Book crossing, proved the feasibility and effectiveness of the model team (Wang, 2021). Tang et al. proposed a backpropagation neural network recommendation algorithm based on cloud model, which can improve the accuracy of rating prediction by adding the cloud layer to the neural network, and experiments were conducted on real datasets and found that the method achieved better results in terms of completeness, accuracy and F1 compared with traditional recommendation methods (Tang et al., 2019).

As can be seen from the in-depth research of many domestic and foreign research scholars on aspects related to intelligent recommendation algorithms for educational resources, the core of the intelligent recommendation method for educational resources is a decision model based on data analysis, which can be carried out using the T-S fuzzy predictive control algorithm combined with neural networks. Therefore, this study combines Neu MF and T-S fuzzy control recommendation algorithm to promote the research of intelligent recommendation algorithm for educational resources.

3 Research on intelligent recommendation algorithm of educational resources combining Neu MF and T-S fuzzy control

3.1 Research on fuzzy predictive control algorithm in educational resource recommendation

Combining predictive information with rolling optimization is the core of fuzzy prediction, and the use of fuzzy predictive control in the recommendation of educational resources is beneficial to improve the fitness of resource recommendations (Wang et al., 2020; Liu et al., 2020). There are many fuzzy subspaces in the T-S fuzzy model, and the subspaces are partitioned by the input space, and there are several linear relational models in the subspaces that obey the IF-THEN rule. Let the input be $D = [d_1, d_2, ..., d_n]^T$, then d_i denotes a fuzzy variable, and let $T(d_i) = \{E_i^1, E_i^2, ..., E_i^{m_i}\} (i = 1, 2, ..., n)$, then $E_i^j (j = 1, 2, ..., m_i)$ denotes the jth linguistic variable of d_i. The affiliation function corresponding to this fuzzy set on the theoretical domain is denoted by $\mu_{E_i^j}(d_i)(i = 1, 2, ..., m_i)$, at which point the T-S fuzzy model is shown in equation (1).

$$R_j : y_j = p_{j0} + p_{j1}x_1 + ... + p_{jn}x_n, j = 1, 2, ..., m, m \leq \prod_{i=1}^{n} m_i \tag{1}$$

The satisfaction condition of equation (1) is $d_1 = E_1^j, ..., d_n = E_n^j$, and if expressed as a single-point fuzzy set, the fitness rule for the input D is shown in equation (2).

$$e_j = \mu_{E_1^j}(d_1) \wedge \mu_{E_2^j}(d_2) \wedge ... \wedge \mu_{E_n^j}(d_n) \tag{2}$$

The weighted calculation of the notational output quantity for equation (2), when the weighted average of the output quantity is shown in equation (3).

$$y = \frac{\sum_{j=1}^m e_j y_j}{\sum_{j=1}^m e_j y_j} = \sum_{j=1}^m \overline{e_j} y_j \tag{3}$$

In equation (3), $\overline{e_j} = e_j / \sum_{i=1}^m e_i$. If there are n fuzzy rules, then the i rule is shown in equation (4).

$$R_i : if \ x(\text{t}) \ is \ E_i \ then \ y_i(t+1) = e_{i0} + e_{i1}d_{t1} + e_{i2}d_{t2} + ... + e_{im}d_{tm}, i = 1, 2, ..., m \tag{4}$$

In equation (4), $x(t) = [x_{t1}x_{t2}...x_{ts}]$ is the regression vector of all the previous input and output data up to t, including t. The then statement is preceded by the If-Then rule antecedent, where E_i represents the fuzzy set, and the then statement is followed by the rule postcode, which consists of the linear relationship between input and output. Using the least squares method to identify the rule posterior pieces, let $\mu(t)$ be the affiliation of $x(t)$ to the ith rule, at which point the output is shown in equation (5).

$$\hat{y}(t) = \sum_{i=1}^m \partial_i(t)y_i(t) \tag{5}$$

In equation (5), $\partial_i(t) = \mu_i(t) / \sum_{i=1}^m \mu_i(t)$. There are two forms of applying the T-S model to educational resource recommendation, which are generalized predictive control and dynamic matrix control. Dynamic matrix control combined with the DMC (Dynamic matrix predictive control) algorithm is able to operate in complex environments to obtain the optimal amount of control for fuzzy systems. Applying the DMC algorithm to the real model requires adding adaptive elements to increase the robustness of the system. Otherwise, when the sample of the controlled object or the environmental parameters change, large errors will occur. Generalized predictive control has a similar principle to dynamic matrix control, in which linear elements also exist in generalized prediction. A fuzzy weighting method is used to obtain the parameters of the CARIMA (Controlled auto-regressive integrated moving average) model and to identify the rules in it. Combining the fuzzy generalized predictive control with the GPC algorithm enables the identification of the neural posterior by means of an online learning method. Considering the stability and learning mechanism, using generalized predictive control can maintain stronger learning. The T-S fuzzy neural network structure based on fuzzy generalized predictive control is used to design the intelligent recommendation model of educational resources, and the schematic diagram of the neural network structure is shown in Figure 1.

Figure 1 T-S fuzzy neural network structure diagram (see online version for colours)
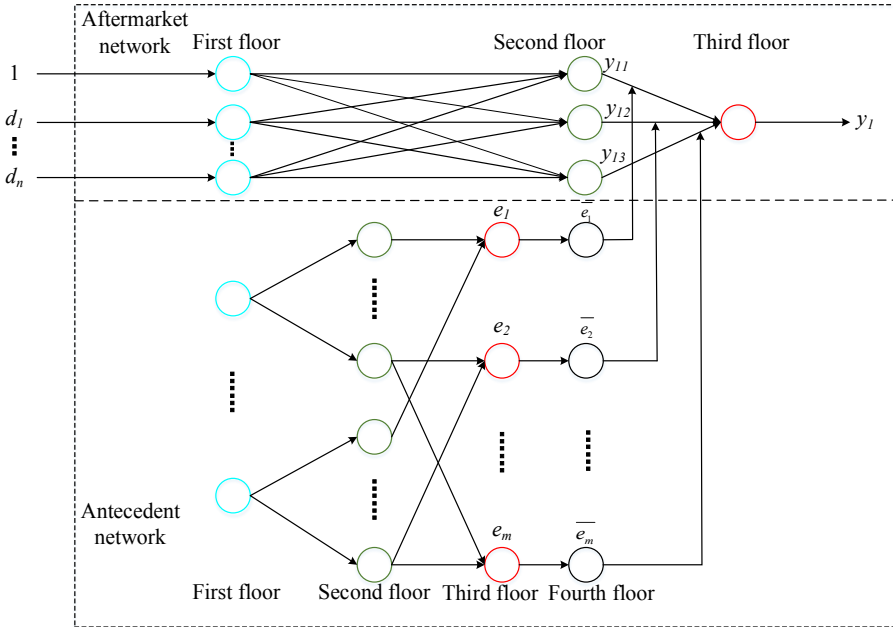
As shown in Figure 1, a four-layer structure exists in the pre-piece network: the input layer, the fuzzification layer, the rule layer and the normalization layer. The first layer belongs to the input layer and is connected to the component of D and is responsible for transporting it to the next layer. The second layer is the fuzzification layer, which will fuzzily the components transmitted from the input layer to obtain the affiliation function. The third layer is the rule layer, which is connected to the If-Then rule and matches the subordination function transmitted by the fuzzification layer with the antecedent of the If-Then rule to derive the adaptation degree (Li et al., 2019). The fourth layer is the normalization layer, which normalizes the adaptation degree and outputs it to the neural posterior as the connection weights (Liang and Yin, 2022; Wijaya, 2022). A three-layer structure exists for the posterior piece network; the first layer is also the input layer, which receives the input of data samples. The second layer is the rule layer, which is responsible for the connection with the posterior piece of If-Then rule, and the third layer is the computational layer, where the input results are combined with the weights in the anterior piece of the network to obtain the output results.

3.2 Research on Neu MF-based fuzzy predictive control model

T-S fuzzy prediction model has good ability to deal with linear relations, but there are not only linear relations but also many nonlinear relations exist in educational resources. The neural matrix decomposition model is introduced to process the nonlinear relations and combine both to construct a Neu MF-based fuzzy predictive control model to recommend educational resources (Yang et al., 2022; Ahmad and Ullah, 2019). The trans-matrix decomposition model is a combined model of GMF (Generalized matrix factorization) and MLP (Multi-Layer perceptron). The GMF model is responsible for processing the

matrix data information in educational resource recommendation (Gil et al., 2019; Parthasarathy and Kalivaradhan, 2021). The matrix of users' ratings of educational resource goals is an important component of the educational recommendation system, as shown in Table 1.

Table 1   User educational resource objective scoring matrix

	Resource objectives 1	*Resource objectives 2*	*Resource objectives 3*	*Resource objectives 4*	*Resource objectives 5*	*Resource objectives 6*
User 1	3	4	#	2	1	#
User 2	1	5	3	#	4	2
User 3	2	#	1	5	3	3
User 4	#	3	4	2	#	4

Table 1 is a simulated scoring matrix. Four users are simulated to score six educational resource goals. The score is 1–5. The # rating indicates that the rating of the educational resource target by the user is unknown. The intelligent recommendation of educational resources should predict the rating and recommend the educational resources to the users according to the rating, and this prediction process requires the participation of the GMF model in the Ner MF model, and the matrix decomposition is shown in equation (6).

$$R \approx G^T \times H = \hat{R} \tag{6}$$

The rating data in Table I is constructed as a rating matrix of 4×6, and then decomposed into two rating matrices of G, H using equation (6), G^T as a matrix of $4 \times L$, and H as a matrix of $L \times 6$, with L denoting the number of topics and taking values ranging from 9 to 99. At this time, the values of the elements in the matrix are represented as shown in equation (7).

$$\hat{r}_{ij} = g_i^T h_j = \sum_{l=1}^{L} g_{il} h_{lj} \tag{7}$$

In equation (7), $\hat{r}_{ij}$ denotes the value of the element corresponding to the i row and j column of the matrix $\hat{R}$. $\hat{r}_{ij} = g_i^T h_j = \sum_{l=1}^{L} g_{il} h_{lj}$ represents the element in row i of matrix G^T, and h_j represents the element in column j of matrix H. The decomposition matrix is evaluated using the loss function in the way shown in equation (8).

$$e_{ij}^2 = (r_{ij} - \hat{r}_{ij})^2 = \left(r_{ij} - \sum_{l=1}^{L} g_{il} h_{lj} \right)^2 \tag{8}$$

Using the gradient descent method, the partial derivatives of g_{il} and h_{lj} are solved to determine their fastest direction of descent, at which point the negative gradient of the loss function is expressed as shown in equation (9).

$$\begin{cases} \dfrac{\partial}{\partial g_{il}} e_{ij}^2 = -2(r_{ij} - \hat{r}_{ij})^2 (h_{lj}) = -2e_{ij} h_{lj} \\[3mm] \dfrac{\partial}{\partial h_{lj}} e_{ij}^2 = -2(r_{ij} - \hat{r}_{ij})^2 (g_{il}) = -2e_{ij} g_{il} \end{cases} \tag{9}$$

The new values are obtained by updating the variables according to equation (9), as shown in equation (10).

$$\begin{cases} g_{il}' = g_{il} + \alpha \dfrac{\partial}{\partial g_{il}} e_{ij}^2 = g_{il} + 2\alpha e_{ij} h_{lj} \\[3mm] h_{il}' = h_{lj} + \alpha \dfrac{\partial}{\partial h_{lj}} e_{ij}^2 = h_{lj} + 2\alpha e_{ij} h_{lj} \end{cases} \tag{10}$$

In equation (10), α indicates the learning rate, and the smaller its value, the slower the iteration. The method shown in equations (9) and (10) is iterated until the algorithm converges, and to avoid overfitting errors, a regular term is set, as shown in equation (11).

$$e_{ij}^2 = (r_{ij} - \sum_{l=1}^{L} g_{il} h_{lj})^2 + \dfrac{\beta}{2} \sum_{l=1}^{L} (\|G\|^2 + \|H\|^2) \tag{11}$$

In equation (11), β denotes the regular parameter, which is taken according to the educational resource recommendation. After adding the canonical function, the elements are updated in combination with the negative gradient direction update variable as shown in equation (12).

$$\begin{cases} g_{il}' = g_{il} + \alpha \dfrac{\partial}{\partial g_{il}} e_{ij}^2 = g_{il} + \alpha(2e_{ij} h_{lj} - \beta g_{il}) \\[3mm] h_{il}' = h_{lj} + \alpha \dfrac{\partial}{\partial h_{lj}} e_{ij}^2 = h_{lj} + \alpha(2e_{ij} g_{il} - \beta h_{lj}) \end{cases} \tag{12}$$

Using equation (12) to parameterize the model avoids over-fitting. After deriving all matrix elements in G and H, the ratings of users i on the educational resource target j were calculated using equation (13).

$$g(i,1) \times q(1, j) + g(i,2) \times q(2, j) + \cdots + g(i,l) \times q(l, j) \tag{13}$$

Once the scores are obtained, recommendations are made to the users based on the size of the scores. In addition, the GMF model can be used to continue to derive and refine information about the user and the educational resource goals, the principle of which is shown in Figure 2.

The predicted values of S31, S61, S42, etc. in the scoring matrix can be derived from the operations of the GMF model, as shown in equation (14).

$$\hat{s}_{u,r} = f\left(u, r | g_u, h_r\right) = g_u^T h_r \tag{14}$$

In equation (14), g_u represents the potential characteristics of the user, h_r represents the potential characteristics of the educational resource, and $\hat{s}_{u,r}$ value represents the fit

between the educational resource and the user. The MLP model is responsible for supervised training, mapping the vectors of the multidimensional space into the hyperplane to do two-dimensional segmentation, and its model is shown in Figure 3.

Figure 2   Schematic diagram of GMF principle in educational resource prediction (see online version for colours)

Prediction value in transmission user education resource sparse matrix
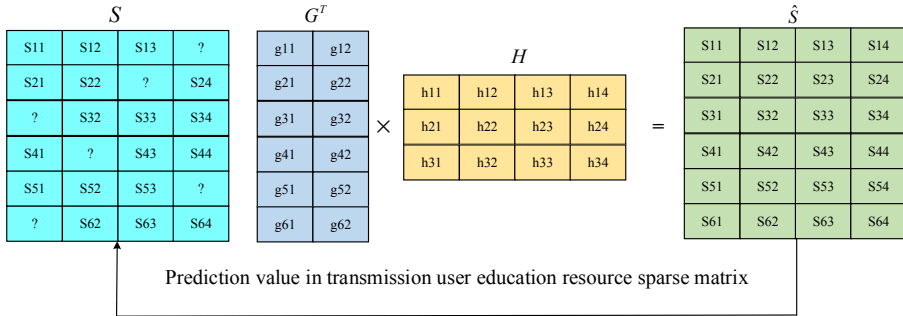
Figure 3   Schematic diagram of two-dimensional linear decision boundary (see online version for colours)
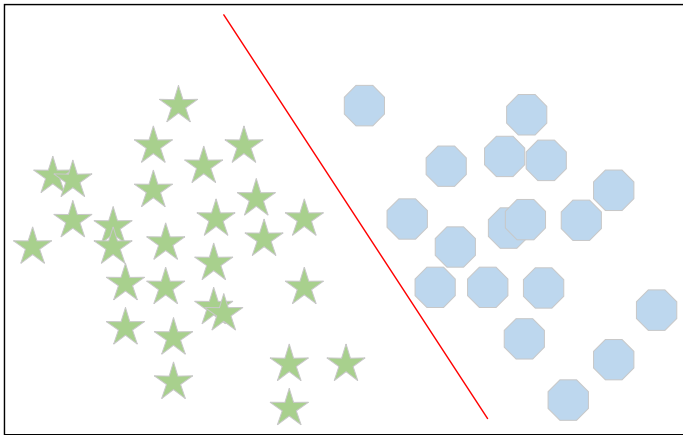

As shown in Figure 3, if the samples present in the plane are distinguished by pentagons and octagons, as the sample set keeps getting larger, the new samples will be continuously labelled and expanded using the neighbouring samples as references, so that the classification method will have a large bias. Therefore, it is necessary to divide new interval straight lines for the expanded new sample set, re-label all samples, and bring all input data in the form of vector $k = (k1, k2)$, at which time the transfer function is shown in equation (15).

$$f(k) = c \cdot k + z \tag{15}$$

In equation (15), c denotes the weight vector and z denotes the vertical offset. After the training of the perceptron, the weights c evolve and are adjusted to the optimum. Combining the perceptron gives a multilayer perceptual neural network that has three

layers, the input layer, the hidden layer and the output layer. Each neuron is an individual perceptron with a weight. The MLP model is essentially an approximate classification model that accomplishes the job of matching educational resources with users, and its structure is schematically shown in Figure 4.

Figure 4 MLP educational resources recommendation structure chart (see online version for colours)
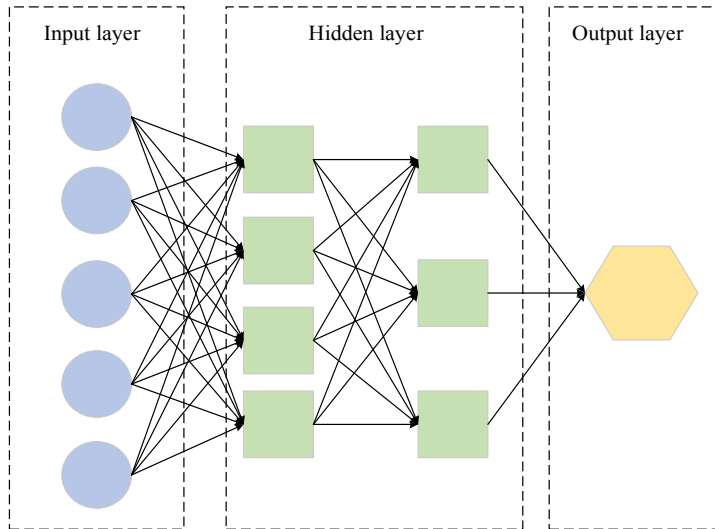

In Figure 4, the output layer is responsible for receiving inputs of parameters such as user feature values and educational resource feature values. The implicit layer is responsible for optimizing the correlation between users and educational resources and deriving the predicted values. The output layer is responsible for outputting the predicted values between users and educational resources. The Re LU function is used to activate the input layer, and the user eigenvalue and educational resource eigenvalue are mapped to the hidden layer. Since the number of layers is not specified in the hidden layer, the appropriate number of layers can be selected according to their needs. The hidden layer optimizes the user education resource association layer by layer, uses the two classification characteristics in the chain derivation rule to obtain the nonlinear prediction value of the user education resource, and outputs it through the output layer. The Neu MF model is obtained by combining the GMF model and the MLP model, and the flow of the Neu MF model applied to the intelligent recommendation of educational resources is shown in Figure 5.

As shown in Figure 5, the personal information and professional demand information of users and the category information of educational resources are input into the input layer of the model as user characteristic information and educational resource characteristic information respectively, and then the results are matched to the *Sigmoid* function after the calculation of each of the two models to derive the predicted value of educational resources by the method shown in equation (16).

$$y_{u,r} = f_{out}\left(W_{out}\begin{bmatrix} y^{GMF} \\ y^{MLP} \end{bmatrix}\right) \qquad (16)$$

The educational resources are data tagged, well categorized and labelled combined with T-S fuzzy prediction and Neu MF model to build the final TS-Neu MF model for intelligent recommendation of educational resources, and the recommendation framework of TS-Neu MF model is shown in Figure 6.

Figure 5   Neu MF educational resource recommendation model flow chart (see online version for colours)
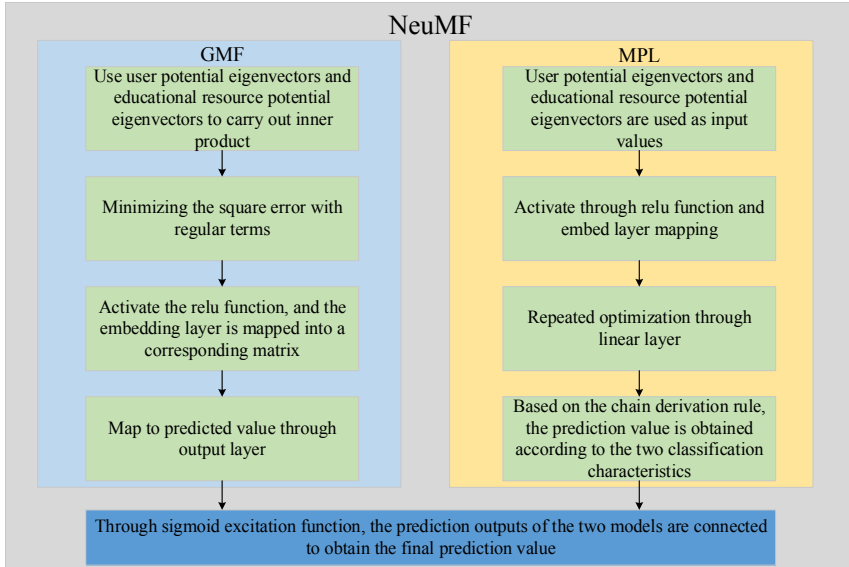
Figure 6   Educational resource feature matching model framework based on TS-Neu MF model (see online version for colours)
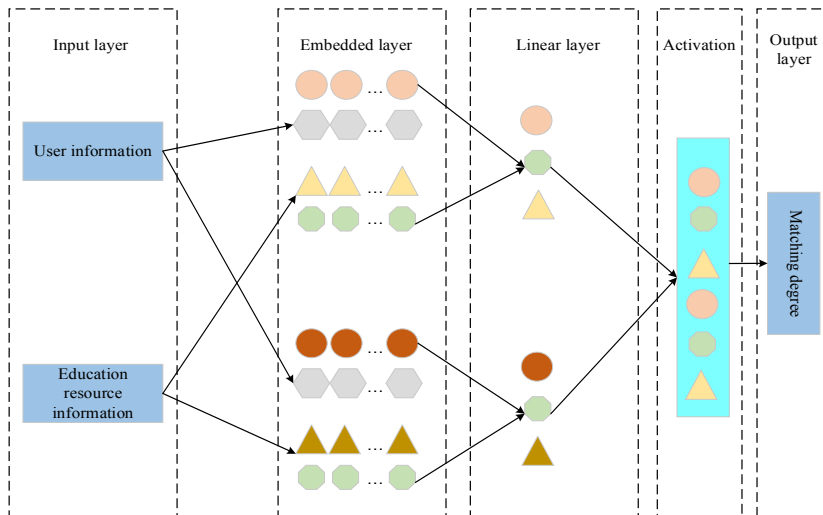
As shown in Figure 6, the structure of the TS-Neu MF model has five parts, and the graphs of different shapes and colours in the figure represent different information, including the information of user identity in the linear relationship, the information of educational resources in the linear relationship, the information of user identity in the nonlinear relationship, the information of educational resources in the nonlinear relationship, the additional information of educational resources in the linear relationship, and the additional information of educational resources (Gihes et al., 2021; Abbas et al., 2022). This information is transmitted through the input layer to the embedding layer for processing, and then the linear relationship information is extracted and processed again, and finally the processing results are transmitted to the activation, and then the matching degree results are output. the output results of the Neu MF model are not only related to the above relationships, but also related to the general information of users and educational resources, and similarly the T-S model is also affected by the general information, and the output results are shown in equation (17) The output is shown in equation (17).

$$\hat{y}_{u,r} = f_{out}\left(W_{out}\begin{bmatrix} y^{Ne} \\ y^{TS} \end{bmatrix}\right) \tag{17}$$

In equation (17), W_{out} is the connection weight, y^{Ne} indicates the Neu MF model output which is calculated as shown in equation (18), and y^{TS} indicates the T-S model output which is calculated as shown in equation (18).

$$\begin{cases} y^{Ne} = (u_0^{Ne} \oplus u_1^{Ne} \oplus ... \oplus u_n^{Ne})(r_0^{Ne} \oplus r_1^{Ne} \oplus ... \oplus r_n^{Ne}) \\ y^{TS} = f_{TS}(W_n(...f_1(W_1\begin{bmatrix} u_0^{TS} \oplus u_1^{TS} \oplus ... \oplus u_n^{TS} \\ r_0^{TS} \oplus r_1^{TS} \oplus ... \oplus r_n^{TS} \end{bmatrix} + b_1)) + b_n) \end{cases} \tag{18}$$

In equation (18), u denotes the user feature vector, u_n^{Ne} refers to the Neu MF model, u_n^{TS} refers to the T-S model, denotes the educational resource feature vector, r r_n^{Ne} refers to the Neu MF model, and r_n^{TS} refers to the T-S model. $\oplus$ denotes the linking role, which connects the user's feature vector with the user's attribute vector and the educational resource's feature vector with the educational resource's attribute vector in series. For example, vector $(1,1,j)$ becomes vector $(1,i,j)$ after connecting, i indicates the input length, and j indicates the potential length of the vector. The TS-Neu MF model of educational resource recommendation first extracts information related to users and educational resources, such as users' personal information, professional information and demand information, and information about educational resource content base, bias and extension, etc. in the input layer, and then transmits this information to the embedding layer after coding (Cai et al., 2022). The resources are trained and computed in the form of vectors in the embedding layer, and the training results are derived. Finally, the training results of the two modules Neu MF and T-S in the TS-Neu MF model are activated by the corresponding functions and the connection is completed to obtain a final prediction value, which exists in the interval $[0,1]$.

4   Experiment and analysis of TS-Neu MF educational resources intelligent recommendation model

The experiment was completed under Windows operating system, and the model was debugged and evaluated using a python language editor. A public dataset of online courses, E dx, and a comprehensive dataset, comprehensive educational resources (CER), which crawled several public educational resource websites, were chosen as the evaluation dataset. In the experiments, each hyperparameter setting is kept consistent with the initial settings of the benchmark model, and the performance of each recommended model is analysed by observing the results of several experiments and recording the average results (Al-Kfairy et al., 2019). The test results of the TS-Neu MF educational resource intelligent recommendation model proposed in the study were compared and analysed with those of Neu MF, Deep FM, and BPNN. The initial learning rate was set to 0.01% and the number of iterations was set to 120, and the root mean square error (RMSE) and MAE of each algorithm were compared under two data sets, and the experimental results are shown in Figure 7.

Figure 7   RMSE and MAE test results under different data sets (see online version for colours)
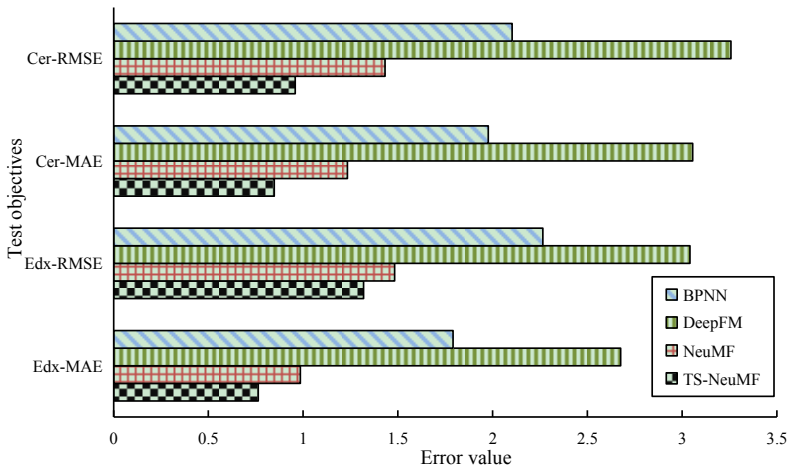
In Figure 7, the abscissa is the error value. The larger the value, the more errors of the algorithm model, and the worse the situation. From the comprehensive view of the experimental results, all algorithmic models outperform the self-crawled constructed integrated dataset CER on the EDX dataset, indicating that the self-constructed dataset needs more optimization, and also indicating that the sample size of this dataset is large enough. TS-Neu MF has the most excellent performance in both datasets (Johnston, 2019). This shows that the research on the optimization of educational resource recommendation has achieved remarkable results, which is better than other recommendation algorithms, with 56.6% performance improvement in RMSE metrics and 71.5% performance improvement in MAE metrics than Deep FM under the EDX dataset. with 56.6% performance improvement in the RMSE metric and 71.5% performance improvement in the MAE metric, and 33.1% performance improvement in the RMSE metric and 22.5% performance improvement in the MAE metric than the

unoptimized Neu MF. Similar results are presented under the CER data, where TS-Neu MF outperforms Neu MF, Deep FM and BPNN in both RMSE and MAE metrics. Continuing to compare the training loss and convergence of each algorithm during training, the obtained experimental results are shown in Figure 8.

Figure 8   Loss function under two data experiments: (a) experimental results of Cer dataset and (b) experimental results of Edx dataset (see online version for colours)

(a)   (b)
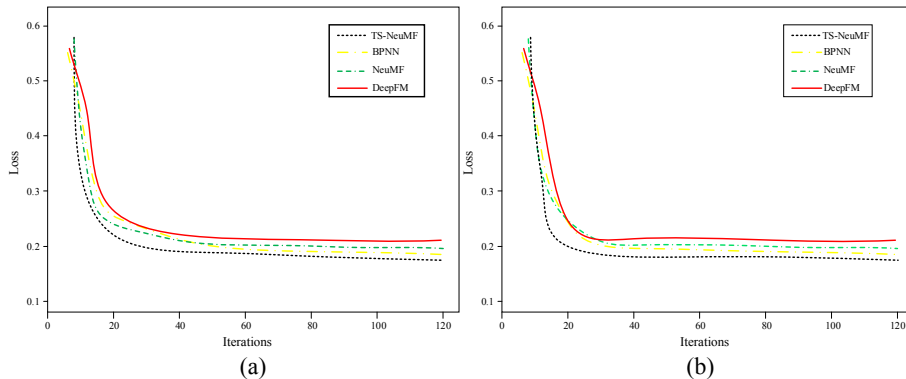
In Figure 8, the abscissa is the number of model iterations, and the ordinate is the training loss. The lower the training loss, the more stable the model operation, and the better the performance. As can be seen from Figure 8, the training losses of all four recommendation algorithm models keep decreasing with the increasing number of iterations (Byk and Tan, 2020). In the CER data set, the training loss of the TS-Neu MF algorithm model decreases rapidly when the number of iterations is lower than 18, and the decreasing trend becomes flat and starts to converge as the number of iterations increases; the TS-Neu MF algorithm model performs better in the EDX data set, and starts to converge at about 16 iterations, which is significantly better than the other algorithms. The other three algorithm models gradually converge at about 21 iterations. After 120 iterations, the training loss of the TS-Neu MF model is reduced to 0.19238, the training impairment of the BPNN model is reduced to 0.19897, the training impairment of the Neu MF model is reduced to 0.21238, and the training impairment of the Deep FM model is reduced to 0.23164. Thanks to the TS fuzzy predictive control module, the TS-Neu MF model is able to The BPNN model performs relatively better than the Neu MF model, but not better than the TS-Neu MF model, indicating that the study has a better effect on the optimization of the Neu MF model. HR (Hit Rate) and NDCG (Normalize Discounted Cumulative Gain) are important indicators for the accuracy investigation of the recommendation algorithm, and HR@5, HR@10, NDCG@5 and NDCG@10 are used as evaluation indicators, and the performance of the four algorithmic models under the two data sets is shown in Figure 9.

As can be seen from Figure 9, the TS-Neu MF model still performs the best, thanks to the model's comprehensive optimization consideration combining both linear and nonlinear relationships, and its performance meets expectations. the BPNN model outperforms the Neu MF model under the EDX dataset, and under the CER dataset, it does not perform as well as the Neu MF model. The difference in performance between the two is related to the dataset adaptation. (Kalali and Heidari, 2021) The Neu MF model is more comprehensive in considering the processing of self-built educational

resources dataset, but it is not as good as BPNN in general curriculum resources dataset, indicating that the study has better results in optimizing the processing for educational resources, and the recommendation processing for general resources needs to be strengthened. The changes of HR@10 and NDCG@10 metrics with the number of iterations for each algorithm model were observed for the CER dataset, and the experimental results are shown in Figure 10.

Figure 9	Experimental results of HR and NDCG evaluation indicators (see online version for colours)
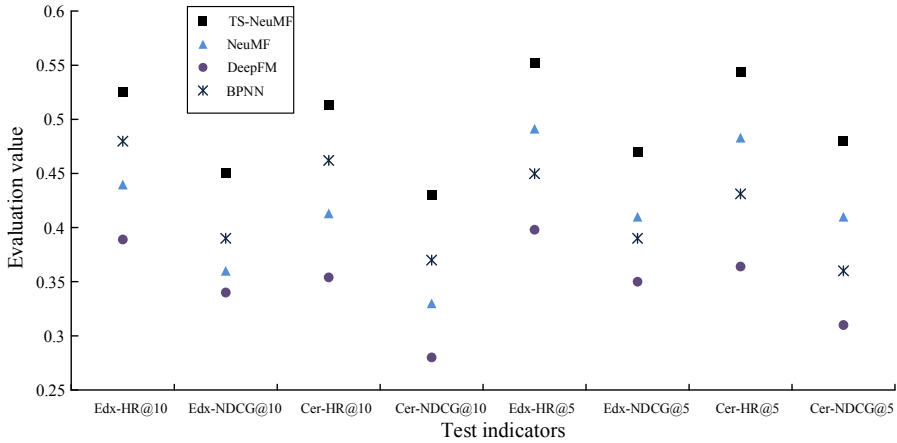
Figure 10	Iterative change relationship between HR and NDCG indicators (see online version for colours)
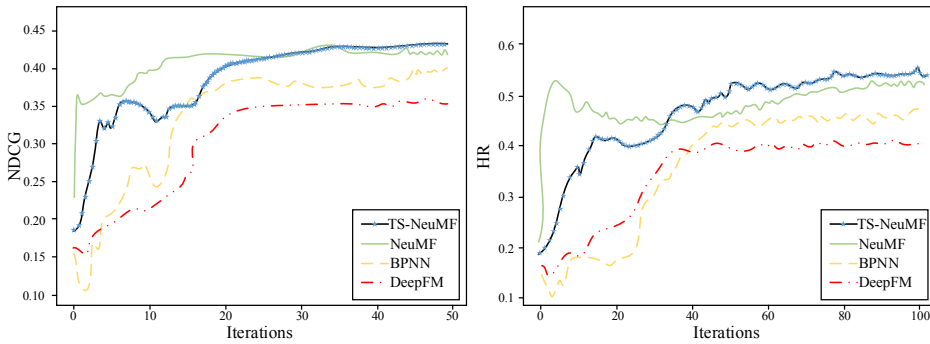
It can be seen from Figure 10 that, excluding the interference of normal performance fluctuations, the performance of the four models is improved with the increasing number of iterations. At the beginning of the model run, Neu MF performed the best, but as the number of iterations increased, the Neu MF model performance peaked and then stopped changing, and the TS-Neu MF model came later and gradually overtook as the best performing model. Since the TS-Neu MF model combines T-S fuzzy prediction and Neu MF, it can reach learning enhancement in both nonlinear and linear relationships between users and educational resources, so its learning ability is stronger and the upper limit of algorithm efficiency is higher. The performance of BPNN model and Deep FM model also improves with the increase of iterations, but the overall level is lower than that of

TS-Neu MF model. The experimental results show that the study addresses the problem of intelligent recommendation of educational resources, and the proposed TS-Neu MF model has a better recommendation effect as expected. From the results, we can see that the method proposed in this paper still has some limitations in learning function, and cannot maintain high learning ability. When the accuracy reaches a certain level, it will reach the boundary, which is difficult to continue to improve. It is expected to continue to improve in the subsequent research.

5 Conclusion

The study addresses the problem of intelligent recommendation methods for educational resources and proposes the TS-Neu MF educational resource intelligent recommendation model by combining Neu MF and T-S fuzzy control. The research results show that the experimental performance of TS-Neu MF model outperforms similar recommendation algorithms under both EDX and CER test sets. Under the EDX dataset, the TS-Neu MF model outperforms Deep FM by 56.6% in RMSE metrics and 71.5% in MAE metrics, and outperforms the Neu MF model by 33.1% in RMSE metrics and 22.5% in MAE metrics. The TS-Neu MF model also performs best in training loss under both test sets, with training loss about 0.04 lower than that of the Deep FM model, 0.006 lower than that of the BPNN model, and 0.02 lower than that of the Neu MF model. In the evaluation of HR and NDCG metrics, TS-Neu MF model performs consistently better than similar evaluation algorithms, and the performance of each evaluation data is higher than that of BPNN model and Deep FM model by more than 20%. The stability and learning ability of TS NeuMF model are better than other algorithms, and the experimental results are in line with expectations. There are also some deficiencies in the research, such as the insufficient number of samples in the experimental data set and the incomplete processing of the self-built Cer data set. It is expected that in the follow-up research, more teaching resource data sets can be experimented, more teaching resource information can be adapted, and the research will become more comprehensive and accurate.

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