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Personalized Learning Resource Recommendation Based on Genetic Algorithm Optimized BP Neural Networks

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Abstract. Focusing on the issues of low accuracy and large error in the current research on learning resources recommendation, a personalized learning resources recommendation method on the ground of BP neural network enhanced by Genetic Algorithm (GA) is designed. Firstly, for the purpose of enhancing the convergence speed and global optimization ability of the BP algorithm, the GA is adopted to modify the original parameters of the neural network, optimize the network structure and performance, and then, relied on the optimized BP neural network, the personal information and behavioral information of the students on the learning platform combined with the attributes of the learning resources are taken as the input of the actual parameters, and the weights are adjusted by the damped least squares method during the training process, in order that the improved BP neural network is able to fully realize the global accuracy of the existing learning resources recommendation research. The fully optimized BP neural network can fully achieve the whole search function of the genetic algorithm and reduce the output error. Finally, the Singular Value Decomposition (SVD) is adopted to forecast the ratings of the above trained network, and the learning resources with low error and high ratings are recommended. Finally, the effectiveness of the suggested method is estimated using the MOOCCube dataset. The experimental outcome indicates that the personalized learning resource recommendation algorithm designed in this article has better performance according to accuracy, recall and F1-Score.
Keywords: Recommended learning resources; genetic algorithm; BP neural network; damped least square; singular value decomposition

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1. **Introduction.** As the Internet and information technology rapidly growing, people's demand for education continues to increase, prompting the diversification of modern education methods. Among them, online education, which is mainly based on Internet platforms, has been recognized and widely popularized by the public [1, 2]. Currently, many education platforms on the internet offer learning services by desegregating excellent quality courses and other course resources on the internet for users. However, in the face of massive learning resource data, the problem of information overload becomes more and more serious, and it is tough for users to discover suitable learning resources for themselves, and even problems such as cognitive load occur [3]. Information overload refers to the phenomenon that a large amount of information emerges in the process of information acquisition and processing, which makes it difficult for individuals to effectively process and use this information. Some users may choose to give up using the recommendation system because of information overload, or choose resources casually, which may reduce the accuracy and user satisfaction of the recommendation system. How to provide personalized recommendations for obtaining effective learning resources from massive learning resources in terms of the user's personal features and behavioral patterns in learning process has become the mainstream of current research [4, 5].

1.1. **Related work.** Recently, the research hotspot in the field of smart education is how to recommend high-quality personalized learning resources for students, so as to help smart education realize the concept of personalized teaching according to students' abilities. Brusilovsky and Peylo [6] offered a personalized studying recommendation path for students through adopting the scholarship level of the objected user and course. Shu et al. [7] offered a potentiality matrix putrefaction approach to address the issue of small data volume, and verified that the recommendation results are obtained by reducing the dimensions of the matrix. Carchiolo et al. [8] suggested a learning resource recommendation method that combines and fuses trust, but ignored the impact of trust propagation process. Wang and Fu [9] used collaborative filtering to recommend the method to autonomously choose proper studying resources for students. Chen et al. [10] conducted a collaborative filtering research of the studying resources of students in a vacant online course, and found that the studying resources of students were more suitable than those of other users. Machado et al. [11] proposed an adaptive recommendation method, which analyzes the resemblance between the objected user and closed users as a weighting value to predict the ratings of an item. Wang et al. [12] based on the similarity of the users and the attributes of the items to recommend users. Zhong and Ding [13] use collaborative filtering recommendation methods to combine the target's preference information and studying subjects to conduct the learners' knowledge points.

As deep learning techniques are becoming more and more flexible in utilizing various complex feature approaches, more researchers have begun to consider introducing deep learning as a powerful tool for recommender systems [14]. Cui et al. [15] suggested a recommendation method on the ground of temporal correlation and improved cuckoo search k-means, but it could not gain quick and precise recommendations. Chang et al. [16] suggested a two-stage collaborative filtering mechanism relied on user requirements to enhance the learning efficiency and precision. Shu et al. [17] used Convolutional Neural Network (CNN) to predict potential interest factors from textual information, but the recommendation efficiency is not high. Dias et al. [18] used Recurrent Neural Network (RNN) content recommendation algorithm, but it is not clear how the annotation technique can deal with the noisy text. Kong et al. [19] adopted BP neural network to forecast the ratings of the unrated items in the matrix, which improves the accuracy of the recommendation. Wu [20] proposed to use the integration algorithm of neural network to construct a structure of the user's interest preferences and populate the data predicted by the model into the user's ratings. Tao et al. [21] combined semantic annotation techniques and BP neural networks for extracting text from videos, but the accuracy of the recommendation is not high. Xuan et al. [22] proposed a dynamic information integration recommendation algorithm on the ground of content and BP neural networks, but the error of the recommended results is large.

1.2. **Contribution.** From the above analysis, it implies that there are two main difficulties in the field of learning resource recommendation: on the one hand, the error of learning resource recommendation is large; on the other hand, the learning intentions of students are diverse, so how to accurately capture the dynamic preferences of students has become another major problem.

Aiming at the above problems, this article designs a personalized studying resource recommendation method on the ground of BP neural network optimized by Genetic Algorithm (GA). The method first uses GA to modify the original parameters of the BP neural network, optimize the network structure and performance, and then on the ground of the optimized BP neural network, the personal information and behavioral information of the students on the learning platform combined with the attributes of the learning resources are used as the input of the actual parameters, and the weights are adjusted by the damped least squares method during the training process, in order that the comprehensively enhanced BP neural network is able to fully realize the global search operation of genetic algorithm and reduce the weight of the BP neural network. The fully enhanced BP neural network can both fully realize the global search operation of GA and reduce the output error. Subsequently, the Singular Value Decomposition (SVD) is adopted to forecast the ratings of the above trained network, and the learning resources with low error and high ratings are recommended. Finally, the experimental outcome indicates that the suggested algorithm can excellently enhance the precision, recall and F1-Score of the learning resources recommendation method.

2. Relevant theoretical analysis.

2.1. **Genetic algorithm.** GA is a heuristic universal seek algorithm [23], that simulates the selection, crossover and mutation phenomena in natural selection and population inheritance processes. The steps are indicated in detail as follows.

(1) Choose operation. Good individuals are chosen from the ancient population with some potentiality to develop a novel population. The probability that individual i is chosen is $p_i = \frac{G_i}{\sum_{j=1}^{N} G_j}$, where G_i is the pertinence value of single i; N is the singles' amount in the population.

(2) Intersection operation. Two individuals are randomly chosen in a population and the chromosomes are exchanged and combined to produce novel superior individuals. The intersection operation between the l-th chromosome b_{lj} and the k-th chromosome b_{kj} at place j is as follows.

$$\begin{cases} b_{lj} = b_{lj}(1-c) + b_{kj}\,c, \\ b_{kj} = b_{kj}(1-c) + b_{lj}\,c, \end{cases} \tag{1}$$

where b_{lj} and b_{kj} are segments of the l-th chromosome and the k-th chromosome at place j, respectively; c is an arbitrary number in the interval $[0,1]$.

(3) Mutation operation. An individual is randomly selected in the population and a single point of mutation in the single produces a new superior personality. The j-th gene b_{ij} of the i-th personality is mutated as follows.

$$\begin{cases} b_{ij} + (b_{ij} - b_{\max})\, g(f), & v \geq 0.5, \\ b_{ij} + (b_{\min} - b_{ij})\, g(f), & v < 0.5, \end{cases} \tag{2}$$

where $g(f) = R\big(1 - f/F_{\max}\big)^2$, $b_{\max}$ and $b_{\min}$ are the upper and lower bounds of b_{ij}; v is any number between $[0, 1]$; R is an arbitrary number; f and $F_{\max}$ are the amount of existing repetitions and the maximum amount of iterations, respectively.

For some complex problems, genetic algorithm can help BP neural network to better optimize the model structure and parameters, thus improving the ability to solve problems.

2.2. **BP neural network.** BP neural network makes up of stimulus level, implicit level and output level [24], in which the stimulus and output level is a single-layer framework, the implicit level is a single-level or multi-level framework, and the nodes in every level of the implicit level are disconnected from each other. The model is indicated in Figure 1.

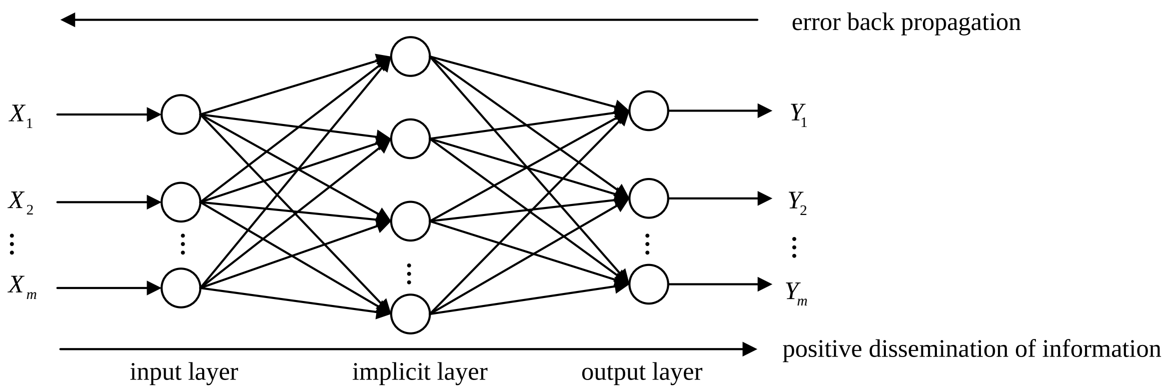

Figure 1. The model of BP neural network

The whole BP neural network is a mapping from an m-dimensional vector $X = (X_1, X_2, \ldots, X_m)^T$ to an m-dimensional transmitter $Y = (Y_1, Y_2, \ldots, Y_m)^T$. After obtaining the forecasting outcome, the weights and thresholds are adapted in terms of the error by back propagation, and so on until the error is small enough or the amount of loops arrives the maximum value to end the model training.

The output of a single neuron j is expressed in relation to the stimulus as follows.

$$O_i = \sum_{j=1}^{m} v_{ij} X_i \ - \ \delta_j \tag{3}$$

where v_{ij} is the weight of link neuron i and neuron j, and δ is the threshold.

The sigmoid operation $\mathrm{sigmoid}(X) = 1/(1 + e^{-X})$ is chosen for the excitation equation, and the final value Y_i of the forward propagation of the layer is obtained through

$$Y_i = \mathrm{sigmoid}(O_i) = \frac{1}{1 + e^{-O_i}} \tag{4}$$

where Y_i is the yield value of the system, T_i is the true value, and e is the mean square deviation among the yield value and the true value:

$$e = \frac{1}{2} \sum_{i=1}^{m} (Y_i - T_i)^2 \tag{5}$$

In terms of the error value of each iteration, the weights of each node are updated in the direction of gradient descent:

$$v_{ij} = v_{ij} + \Phi\, O_i\, (1 - O_i)\, X(i) \sum_{j=1}^{m} v_{ij} e_j \tag{6}$$

$$v_{jn} = v_{jn} + \Phi\, O_i\, e_j \tag{7}$$

where Φ is the training rate.

The threshold update equation is as follows.

$$\delta_j = \delta_j + \Phi\, O_i\, (1 - O_i) \sum_{j=1}^{n} v_{ij} e_j \tag{8}$$

3. **Genetic algorithm optimization of BP neural network model.** Using traditional BP neural networks for personalized recommendation of learning resources may cause the algorithm to fall into local optimum or converge slowly due to the issue of random initialization of parameters by the network. To improve the convergence speed of the BP algorithm and the ability of global search for optimal, the introduction of GA on weights of BP neural network, threshold optimization processing, specific steps are as follows:

(1) Real number coding. The original weights and thresholds of the BP neural network are encoded in real amount with faster operation speed, utilizing the linear transmutation as bellow.

$$X(j) = q(j) + b(j)\big(p(j) - q(j)\big) \quad (j = 1, 2, \ldots, m) \tag{9}$$

The j-th enhanced variable $X(j)$ in the $[q(j), p(j)]$ corresponds to a true number $b(j)$ in the $[0, 1]$. $b(j)$ represents a gene in genetic algorithms, and all the genes corresponding to the variables are sequentially linked together to form the coding form of the solution $(b_1, b_2, \ldots, b_l)$, which is called an individual or a chromosome.

(2) Calculate individual fitness. The sum of the absolute values of the errors between the desired and actual outputs of the neural network model is adopted as the fitness of the individual, which in this study is the difference between the real value of the user's preference and the forecasting value, and the smaller the error is, the better the individual's fitness is, and the closer it is to the optimum solution. The relevance value G is indicated below:

$$G = L\Big(\sum_{i=1}^{m} bct\big(T_i - O_i\big)\Big) \tag{10}$$

where m is the amount of network yield nodes; c denotes the chromosome; t denotes the fitness factor; O_i is the hoped yield of the i-th node of the BP neural network; and T_i is the actual yield of the i-th node; L is the coefficient.

(3) Choose operation. The roulette method is used, the purpose is to make the probability that the individual with smaller error is selected is greater. From the fitness function, it is known that the smaller the relevance, the smaller the error, so take the inverse of the relevance value:

$$g_i = \frac{L}{G_i}, \quad q_i = \frac{g_i}{\sum_{j=1}^{M} g_j} \tag{11}$$

where G_i is the relevance value of individual i; L is the constant; and M is the amount of individuals. Since the smaller the relevance value, the better, the inverse of the fitness is computed before individual selection.

(4) Intersection operation. Using the real amount intersection method, the intersection operation of the l-th chromosome b_l and the k-th chromosome b_k at place j is shown in Equation (1).

(5) Mutation operation. The j-th gene b_{ij} of the i-th individual is selected for mutation as indicated in Equation (2).

(6) Compute the individual fitness and determine whether the set end condition of the minimum error is met; if not, repeat steps (3) to (5); if the end condition is met, the optimized weights and thresholds of the BP neural network are assigned.

4. **Personalized learning resource recommendation based on genetic algorithm optimized BP neural network.**

4.1. **Student and learning resource relationship construction and entity embedding.**

In the Internet learning platform, the personal information and behavioral information of students on the network combined with the attributes of learning resources as the actual parameter inputs, the GA optimization BP neural network algorithm to enhance the original parameters, function fitting, and then optimize the weight adjustment in the neural network training process using the damped least squares method, the fully optimized BP neural network can fully achieve the global search function of the genetic algorithm but also reduce the output error. Finally, the singular value decomposition is used to predict the ratings of the above trained network, and the learning resources with low error and high ratings are recommended. The overall process is indicated in Figure 2.

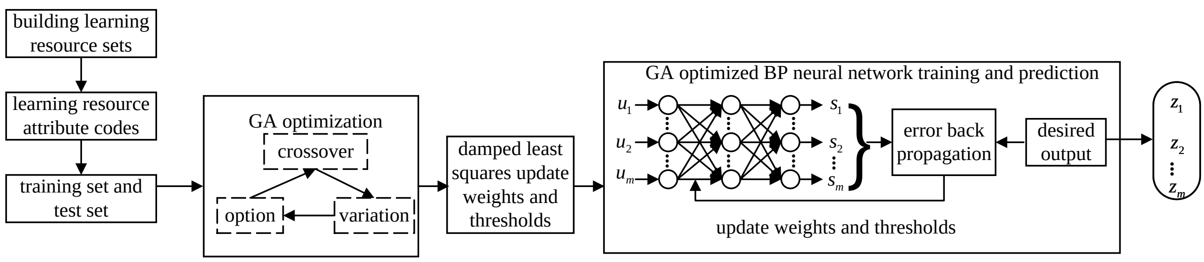

Figure 2. The flow of the designed method

Personalized learning resource sets are mainly constructed by self-built resource sets, locally uploaded resources and open e-learning resources. The attributes of studying resources chiefly contain knowledge points, authors, release time, duration, category, hardness level and other characteristics, of which the types of resources mainly include learning videos, code files, texts, slides and so on.

Word2vec [25] is adopted to encode textual information into low latitude and dense text vectors. Assuming that $X' = \{x_1, x_2, \ldots, x_m\}$ describes the student's personal attribute information, $Y' = \{y_1, y_2, \ldots, y_n\}$ describes the student's personal learning behavior attributes, x_i is the student's characteristics, such as school number, age, gender, etc., and the student's learning behavior characteristics are represented as y_i, for example learning mode, resource ID, etc. The equation is as bellow.

$$X = f(v_1 x + a_1) \tag{12}$$

$$Y = f(v_2 y + a_2) \tag{13}$$

where v_i is the corresponding feature weight and a_i is the bias. The obtained X' is fused with Y' to get the stimulus u_i of the BP neural network with the following equation.

$$u_i = \text{concatenate}(X \oplus Y) \tag{14}$$

4.2. **Personalized learning resource recommendation model based on genetic algorithm optimized BP neural network.** (1) Initialization. The BP network algorithm starts to run, set the amount of nodes in the stimulus, implicit and output levels as m, p, n, randomly initialize the weights w and thresholds δ to small random number between $[-1, 1]$, set the upper restriction of the amount of studying times, set the upper limit of the samples, set the upper limit of the error value as ξ, set the error E to 0, and set the learning rate as $\beta \in (0, 1)$. The BP network algorithm will be initialized as follows.

(2) Set the amount of populations, the amount of generations of genetic evolution, the intersection and the mutation probability, and compute the length of the individual code L in GA, and $X(j)$ is the initial real number code of the population construction.

$$L = m \times p + p \times n + n \tag{15}$$

(3) Input sample data. The characteristic attribute $U_l = [u_1, u_2, \ldots, u_m]$ representing the learning resource is input into the BP network as an input parameter of the recommender system, and the desired network output sample $S_l = [s_1, s_2, \ldots, s_m]$ is the desired evaluation of the learning resource, $Z_l = [z_1, z_2, ..., z_m]$ is the true output vector, and the network propagates forward.

(4) Forward computation. Output of the i-th neuron of the stimulus level is $Z_i = f(u_i)$. The w-th neuron of the implicit level's input I_j and output Z_w are as follows:

$$I_j = \sum_w v_{jw} Z_w + \delta_j \tag{16}$$

$$Z_w = f(I_w) \tag{17}$$

where v_{jw} denotes the junction weight from the w-th neuron in the implicit level to the j-th neuron in the output level, δ_j is the threshold of the w-th neuron in the implicit level, and I_w is the stimulus to the j-th neuron in the yield level.

(5) Compare the error between the output value and the desired value and compute the error operation $E = \frac{1}{2}\sum_{i=1}^{m} e^2(i)$, where e is the error vector. The training error is adopted as an individual fitness operation, and the relevance value of every individual in the population is computed as follows:

$$G = \sum_{i=1}^{m} |S_i - Z_i| \tag{18}$$

(6) Repeatedly iterate the choice, intersection and mutation genetic manipulation methods so that every current population can finish the genetic manipulation and produce the next generation. Determine whether the evolution has reached the maximum number of generations; if yes, go to (7), otherwise return to (3).

(7) Finish the genetics. The best individual is selected by comparing fitness values. Decode its chromosome to denote the network structure chosen, and assign its parameters to the BP network.

(8) The damped least squares Levenberg–Marquardt (LM) method [26] is utilized to solve the Jacobian matrix of the error with respect to the weights:

$$J(n \times m) = \begin{bmatrix} \dfrac{\partial e(1)}{\partial v_1} & \cdots & \dfrac{\partial e(1)}{\partial w_m} \\ \vdots & \ddots & \vdots \\ \dfrac{\partial e(n)}{\partial v_1} & \cdots & \dfrac{\partial e(n)}{\partial w_m} \end{bmatrix} \tag{19}$$

Calculate the error signals of the intermediate levels, and update the intermediate and output level weights and thresholds according to

$$\Delta v_{ij}(m) = \left(J^T(m)\, J(m) + \rho(m)\, I\right)^{-1} J^T(m)\, e(m), \tag{20}$$

where ρ is a scalar and I the identity matrix.

The error sum of squares is then updated iteratively by $v_{ij}(m+1) = v_{ij}(m) + \Delta v_{ij}(m)$. When $E(m+1) < E(m)$, the threshold δ ($\delta > 1$) is divided by ρ; conversely, when $E(m+1) > E(m)$, ρ is multiplied by δ. Convergence is accomplished when the error function decreases to the predefined target.

(9) At the end of training, the test dataset utilizes SVD [27] to forecast the scores of the above trained network, and the simulation predicts the learning resources with small errors and high scores to make recommendations. The SVD equation is indicated below.

$$R_{m\times n} = Q_{m\times m}\, \Sigma_{m\times n}\, P^T_{n\times n} \tag{21}$$

where m is the number of students, n is the number of learning resources, $Q_{m\times m}$ is an $m \times m$ orthogonal matrix, $P^T_{n\times n}$ is an $n \times n$ orthogonal matrix, and $\Sigma_{m\times n}$ is an $m \times n$ diagonal matrix.

Meanwhile, $Q_{m\times m}$ and $P^T_{n\times n}$ are dimensionality-reduced, from which the first t left and right singular vectors are extracted and recombined into the novel $Q_{m\times t}$ and $P^T_{t\times n}$. After dimensionality reduction, the new scoring matrix is obtained as

$$R_t = Q_{m\times t}\, P^T_{t\times n}.$$

5. **Algorithm performance testing and analysis.**

5.1. **Comparison of algorithm performance.** To estimate the performance of the algorithm designed in this article, this model is compared with other existing models for experiments. All the experiments are carried out under Linux operating system and Python 3.8 programming environment. For the convenience of analysis, the literature [10] is denoted as ELSRB, the literature [19] as FSABP, the literature [21] as DNNBP, and the algorithm in this article is denoted as GAOBP.

The experimental data adopted in this article comes from the open dataset MOOC-Cube [28] published by ACL2020, which integrates data on courses, concepts, and student behaviors. In this paper, we select learners' historical behavioral data and personal attributes, and the data preprocessing cascades the data tables and cleanses invalid data. The final outcome is a database with 7290 learners and a resource pool with 32957 learning resource interactions. The training set, validation set and test set are divided in the ratio of 8:1:1. The partitioned data is indicated in Table 1.

To estimate the performance of GAOBP designed in this article, the experiments set the length of the recommendation list to 10, the threshold to 6, the weighting factor to 0.5, the initial value of l to l, the step size to 1, and the maximum value of l to 100.

Table 1. Online education platform user dataset

Dataset	Number of students	Number of student–resource interactions
Train set	5800	254010
Valid set	745	30491
Test set	745	32158

The comparisons of the four methods on the Normalized Discounted Cumulative Gain (NDCG) [29] for various values of l are indicated in Figure 3.

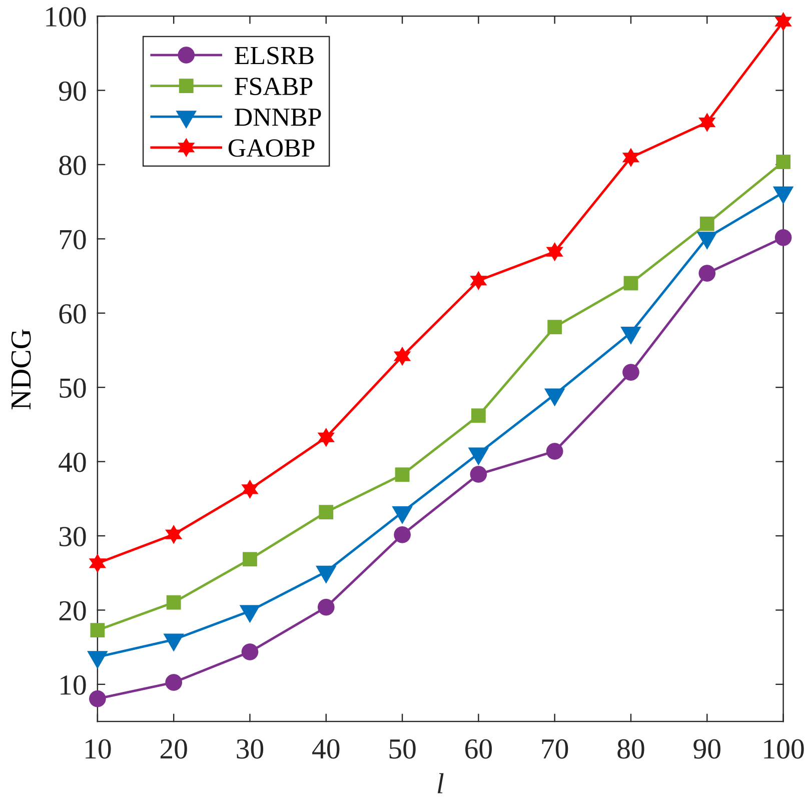

Figure 3. Comparison of NDCG with various algorithms

As can be seen from Figure 3, the ELSRB only recommends the most popular course resources and does not take into account the students' attribute features and interests, resulting in inaccurate recommendation outcome, and the outcome is far worse than the other recommendation models. Both the FSABP model and the DNNBP model use the user's interests embedded in the user's behavioral sequences as a multivariate interest for recommendation, and the multidimensional embedding vectors that express the students' interests are extracted and adopted for the recommendation.

We can conclude from the experiments that the multidimensional embedding vectors have better performance than the unidimensional embedding vectors, and the use of multidimensional embedding vectors to model the multiple interests of the learners in the e-learning platforms is conducive to enhancing the precision of the sequence recommendation. The performance of the DNNBP model is lower than that of the FSABP model, and the reason for this result is that the DNNBP requires a large amount of data for training to get a better recommendation effect, while the FSABP needs a great amount of data for training to get a better recommendation effect. The fuzzy clustering and BP neural network are used in FSABP to get better results with less data, but the BP neural network is not optimized, which leads to the recommendation effect still needing improvement. The GAOBP model outperforms the other three recommendation models, and the weights are adjusted and the final outcome is better than the other three recommendation models. Through optimization of the BP neural network by GA and adjustment of the weights, the performance of the recommended final outcome is higher than the other models.

Table 2 lists the average values of precision, recall and F1-Score of the four algorithms relied on the experimental outcome, and it can be analyzed that the GAOBP algorithm has an average increase of 14.3%, 6.4% and 8.9% in accuracy, 13.9%, 6.1% and 8.3% in recall, and 14.1%, 6.2% and 8.6% in F1-Score, compared with the ELSRB, the FSABP and the DNNBP algorithm. Recall is improved by 13.9%, 6.1% and 8.3% on average, and F1-Score is improved by 14.1%, 6.2% and 8.6% on average. On the ground of the above analysis, it implies that the GAOBP algorithm suggested in this article has better recommendation performance and stability, and is an effective and feasible recommendation algorithm.

Table 2. Average of the evaluation indicators for the four algorithms

Method	Precision	Recall	F1-score
ELSRB	0.772	0.793	0.782
FSABP	0.851	0.871	0.861
DNNBP	0.826	0.849	0.837
GAOBP	0.915	0.932	0.923

5.2. **Results and analysis of ablation experiments.** To better estimate the effect of the optimization part of the GA and the weight adjustment of the LM algorithm in the GAOBP model, ablation experiments are carried out on the dataset respectively, and two comparative models are designed for the analysis, and the evaluation indexes are MAE, top-l recommendation and click prediction rate (CTR).

(1) Remove the genetic algorithm optimization module. Directly use the traditional BP neural network for predictive analysis of learning resources, denoted as GAOBP-GA.

(2) Remove the damping algorithm adjustment weight module. Use the GA to enhance the BP neural network, and the weights are not adjusted throughout the process, noted as GAOBP-LM.

The outcome of the ablation experiment are indicated in Figure **??**. The MAE values of the three models first decrease gradually with the increase of the amount of neighboring users l and then stabilize, and the GAOBP model always has a smaller MAE value. Meanwhile, comparing the traditional BP neural network recommendation model GAOBP-GA and the recommendation model GAOBP-LM, which only optimizes the BP neural network without adjusting the weights, it implies that there is not a big gap between the two in the MAE value when the value of l is relatively small; however, as l increases, the speed of MAE decline of the GAOBP model is higher than that of GAOBP-GA and GAOBP-LM, which indicates that the optimization of the BP neural network model through GA and the adjustment of the weights with the use of the damping least squares method makes the prediction of the scoring error smaller, which proves that the GAOBP has better performance.

From Table 2, it implies that when l takes the value of 20, the recommendation success rate of GAOBP-GA is 27.64%, that of GAOBP-LM is 30.16%, and that of GAOBP is 34.91%. In addition, the AUC of GAOBP is improved by 5.98% and 3.23% compared with that of GAOBP-GA and GAOBP-LM, and the accuracy is improved by 6.05% and 2.84%, respectively. The recommendation success rate of GAOBP is significantly better than that of GAOBP-GA and GAOBP-LM. Secondly, it can be observed that there is a substantial decrease in the recommendation performance of GAOBP after the removal of GA, which proves the importance of the GA-optimized BP neural network model. If the weights of the BP network are not adjusted by the damping least squares method, the recommendation performance will also be degraded. Since different students pay different attention to different features of learning resources, assigning different weights to different features by LM can capture students' personalized preferences, and thus the weight adjustment is also essential in the dynamic preference modeling part.

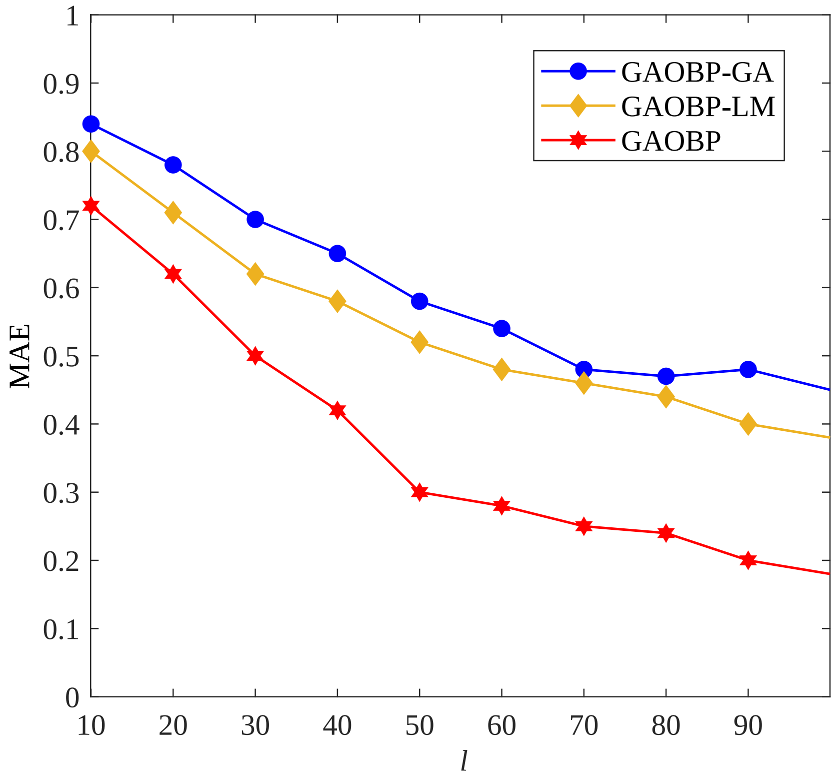

Figure 4. Comparison of MAE for different models

Table 3. Results of ablation experiments for each component

Method	Top-l		CTR	
	l@20	l@40	AUC	Accuracy
GAOBP-GA	0.2764	0.4029	0.8637	0.8418
GAOBP-LM	0.3016	0.4364	0.8912	0.8739
GAOBP	0.3491	0.4536	0.9235	0.9023

6. **Conclusion.** Intending to the issues of low accuracy and large error in current learning resource recommendation study, this article designs a personalized learning resource recommendation method on the ground of GA optimization BP neural network. The method first adopts the global optimal seek capability of GA to enhance the weakness of BP network sensitive to the initial weights, and then the personal information and behavioral information retained by the students on the learning platform combined with the attributes of learning resources are adopted as the actual parameter inputs, and the weights are adjusted with the damped least squares method during the training process

to reduce the output error. Finally, the SVD is adopted to forecast the ratings of the above trained network, and the learning resources with low error and high ratings are recommended. The algorithm performance comparison experiments are conducted on the MOOCCube dataset, and the experimental outcome indicates that the proposed algorithm has better accuracy, recall and F1-Score, which verifies the effectiveness of the designed algorithm.

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