Big Data-Assisted Recommendation of Personalized Learning Resources and Teaching Decision Support

https://doi.org/10.3991/ijet.v17i04.29585

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Abstract—The evaluation of personalized learning features can perceive the features of learning behaviors intelligently, and provide direct, reliable decision support for promoting personalized learning resources (PLRs). The current research has an urgent need to overcome several problems of PLR recommendation: the recommended PLRs fall short of demand, the learning behaviors are not analyzed dynamically, and the learning intentions are not predicted well. To solve these problems, this paper explores the big data-assisted recommendation of PLRs and teaching decision support. The education of spoken and written languages was taken as an example during the exploration. The authors detailed the flow of the proposed algorithm, and proved its effectiveness through experiments.

Keywords—big data analysis, recommendation of personalized learning resources (PLRs), teaching decision support

1 Introduction

With the rapid development of information technology (IT) and the Internet, online education platforms advance continuously, providing students with more diversified channels for knowledge acquisition [1-8]. The evaluation of personalized learning features can perceive the features of learning behaviors intelligently, and provide direct, reliable decision support for promoting personalized learning resources (PLRs) [9-13]. The effect of a PLR recommendation system hinges on the analysis of the historical data on personal learning behaviors. But a massive number of learning resource data is waiting to be screened [14-17]. Many researchers are striving to answer how to select the learning resources that interest learners out of massive learning data, and recommend them to learners.

Educational institutions regard online education as a successful technology that improves learning results, attention, and thus learning effects. Rahhali et al. [18] proposed a model for online education resource recommendation system, which suggest and encourage learners to choose courses according to their needs. The system relies on big data tools like Hadoop and Spark to better collect, store, analyze, process, optimize, and visualize data, and makes full use of cloud computing infrastructure, especially Google Cloud Services. Mobile learning provides a new experience for learners, enabling them to learn anything on portable or mobile devices anytime, anywhere. Radhakrishnan and Akila [19] highlighted the importance of guiding learners with learning interests, and developed a mobile learning system, which helps learners enter courses on different levels in different programs. To provide a personalized learning experience, the system finds learner preferences, selects the desired learning objects, and recommend learners some high-level majors, making it possible for them to achieve higher grades. Based on hybrid optimization algorithm, Vedavathi and Kumar [20] presented a user-oriented efficient learning resource recommendation system. Instead of helping learners looking for effective data, the system offers students the suggestions on the articles of interest, and caters to user preferences in undefined periods. Compared with traditional recommendation frameworks, the system is proved mature and accurate. Online learning environment promotes data-driven teaching processes. But the existing research is limited to data-driven decisions. Usher et al. [21] stressed the strong correlation between teachers' interest in learner data and their willingness to make data-driven decisions. Pan et al. [22] presented an enhanced solution to support teaching decision-making for each student: the tracking data of each student are synchronized with the middleware of local area network (LAN), such that the teacher client can distinguish between students, know the test progress of each student, and provide each student with targeted, interpretable teaching decision support.

To sum up, the current research has an urgent need to overcome several problems of PLR recommendation: the recommended PLRs fall short of demand, the learning behaviors are not analyzed dynamically, and the learning intentions are not predicted well. Currently, the application of big data is the research hotspot. More and more researchers pay attention to the role of teachers in teaching decisions, and introduce big data to the decision-making of education, and teaching, shedding light on domestic research of educational big data. However, few scholars have examined teaching decisions, in the light of the PLR recommendation for different types of students, failing to deeply integrate educational big data, or scientific teaching decisions. There is not yet a research system that systematically applies educational big data to teaching decisions. Taking the education of spoken and written languages as an example, this paper explores the big data-assisted recommendation of PLRs and teaching decision support, details the flow of the proposed algorithm, and proves its effectiveness through experiments.

2 PLR recommendation algorithm

Figure 1 shows the architecture of our PLR recommendation and teaching decision support system. There are three layers of the system: an interactive interface layer, an algorithm logic layer, and a database layer. The core data mining functions of the system include the personalized recommendation and teaching decision support. The PLR recommendation algorithm is introduced as follows:

Collaborative filtering recommendation algorithm is one of the most common big data-based resource recommendation algorithms. The algorithm can make automatic recommendations from the perspective of learners. That is, the list of resources pushed to the learners are mostly determined based on their browsing history. Facing the education of spoken and written languages, the learning resource recommendation algorithms make recommendations based on learner interest or resource demand.

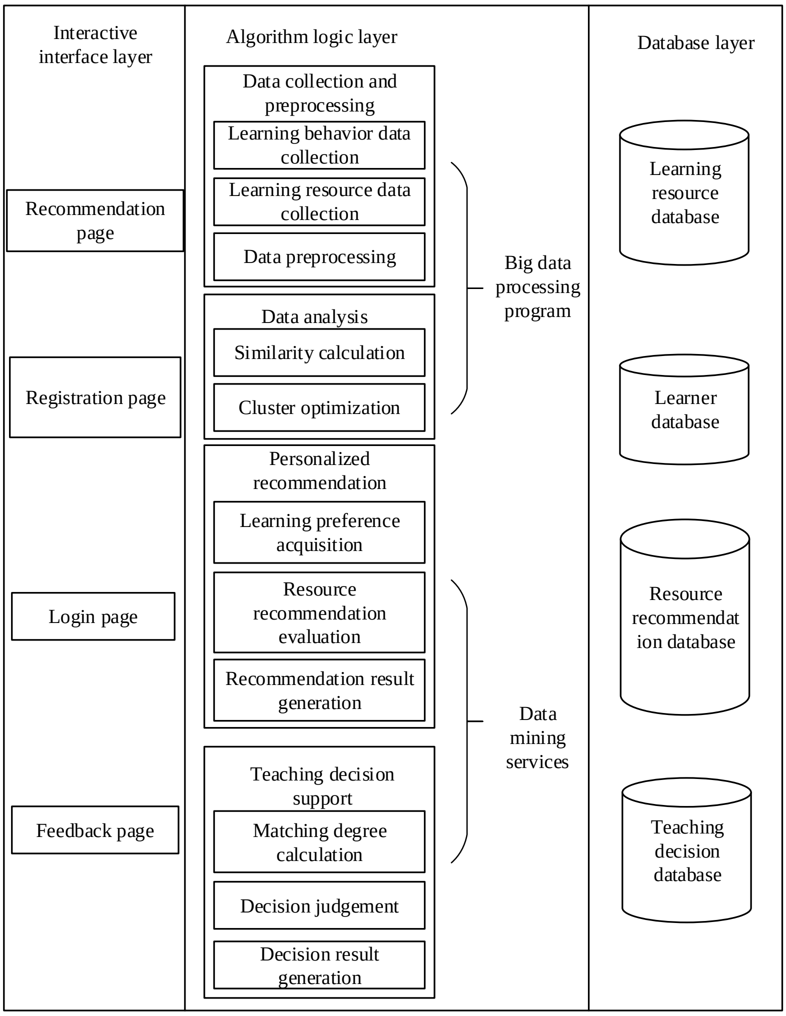

Fig. 1. System architecture

Learner interest-based recommendation algorithms perform calculation in three stages: learner interest modeling, learning similarity calculation, and generating recommended learning resources.

Firstly, the source data of the learning of spoken and written languages, including character learning, reading, writing, oral communication, and comprehensive language learning, are modeled. Then, similar learners are looked for based on similarity. After that, the learning resources without any historical learning record are found among learners, and used to compute the recommendation values. Finally, the learning resources are ranked to generate the recommendation results. Let $M(v)$ be the set of learning resources rated by learner v; $M(u)$ be the set of learning resources rated by learner u. Then, the learner similarity can be calculated by:

$$\theta_{vu} = \frac{\left|M(v) \cap M(u)\right|}{\sqrt{\left|M(v)\right|\left|M(u)\right|}} \tag{1}$$

After obtaining the learning similarity, a record set is prepared based on the learning behavior records of l adjacent similar learners. On this basis, the recommendation value between each learner and each learning resource is calculated. Let *E(v,l)* be the item set of the l nearest neighbors of learner *v*; M(i) be the set of learners preferring learning resource *i*; θ_{vu} be the similarity between learners v and u; sui be the degree of preference of learner u for learning resource *i*. The recommendation value can be calculated by:

$$T(v,i) = \sum_{u=E(v,l)\cap M(i)} \theta_{vu} s_{ui} \tag{2}$$

where, s_{ui} is used to indicate whether a learner has rated a learning resource. Thus, the value of s_{ui} is set to 1. Through the above calculation, the rating of each learning resource by each learner is obtained. Then, the learning resource with the highest score is recommended to the other learners.

The resource demand-based recommendation algorithms essentially make recommendations according to the similarity between learning resources. Their calculation process also contains three steps: learning resource modeling, learning resource similarity calculation, and generation of recommended learning resources. Let $M(i)$ be the number of learners interested in learning resource i; θ_{ij} be the proportion of learners interested in resources i and j simultaneously. Then, the similarity of learning resources can be calculated by:

$$\theta_{ij} = \frac{\left|M(i) \cap M(j)\right|}{\sqrt{\left|M(i)\right|\left|M(j)\right|}} \tag{3}$$

After computing the similarity between learning resources, the learning resources similar to those in the learning records are pushed to the learners, marking the end of recommendation.

During the application, the above two algorithms must sort out the difficulty of each learning resource, and recognize the attributes of the corresponding knowledge point. Otherwise, it is impossible to complete analysis and modeling. But the sorting process brings an excessive burden to the algorithms. In addition, the learning resources must be assigned keywords or labels, so that proper learning resources can be discovered during the recommendation. Furthermore, the algorithms can only grasp attributes of learning resources, during the similarity calculation between learning resources, but cannot take account of the subjective initiative and real feelings of learners of spoken and written languages.

Therefore, this paper optimizes the above recommendation algorithm. In our algorithm, three steps are arranged: learning resource description, learning interest description, and generation of recommended learning resources. During the recommendation process, the features of the learning resources are illustrated by the vector space model. Let O be the eigenvector of a learning resource; *i* be the number of features of that learning resource; g_{ij} be the *j-th* eigenvalue of the *i-th* feature. Then, we have:

$$O=\left(g_{11},...,g_{1n},...,g_{i1},...,g_{ij}\right) \tag{4}$$

Based on the learning resources previously clicked or favored by a learner, the learning resource recommendation system judges his/her interested learning directions, and represents multiple interested learning resources altogether. Let P be the number of learning resources that interest the learner; $XQD(m)^{ij}$ be the degree of interest of learner m for the *j-th* eigenvalue of the *i-th* feature. The interest of the learner for each learning resource can be calculated by:

$$XQD_{(m)}^{ij}=\frac{\sum g_{ij}}{P} \tag{5}$$

Based on $XQD(m)^{ij}$, the following vector Dm can be constructed to illustrate learning interest:

$$D_m=\left(XQD_{(m)}^{11},...,XQD_{(m)}^{1j},...,XQD_{(m)}^{i1},...,XQD_{(m)}^{ij}\right) \tag{6}$$

Formula (6) shows that D_m characterizes the interest and preference of a learner for each dimension of learning resources. Finally, the learning resource recommendation system compares the interest description model and the candidate set of learning resources, and recommends the top-N most correlated learning resources to that learner.

3 Elman-based teaching decision reasoning

Neural networks are very suitable for intelligent teaching decision and reasoning, thanks to their strong ability of information processing, parallel storage, parallel computing, error tolerance, self-organization, and systematicity. Figure 2 explains the structure of teaching decision support.

As shown in Figure 2, the teaching decision support module consists of five parts: data collection, recommendation preference analysis, teaching plan revision, teaching decision reasoning, and teaching decision implementation.

The teaching decision support module collects the data outputted from the data processing module, and carries out a recommendation preference analysis. Based on the analysis results, the teaching plan is revised, the decision reasoning is implemented, and the control command is outputted and executed. The students' evaluation of teaching effect is fed back. This paper relies on Elman neural network to derive teaching decisions.

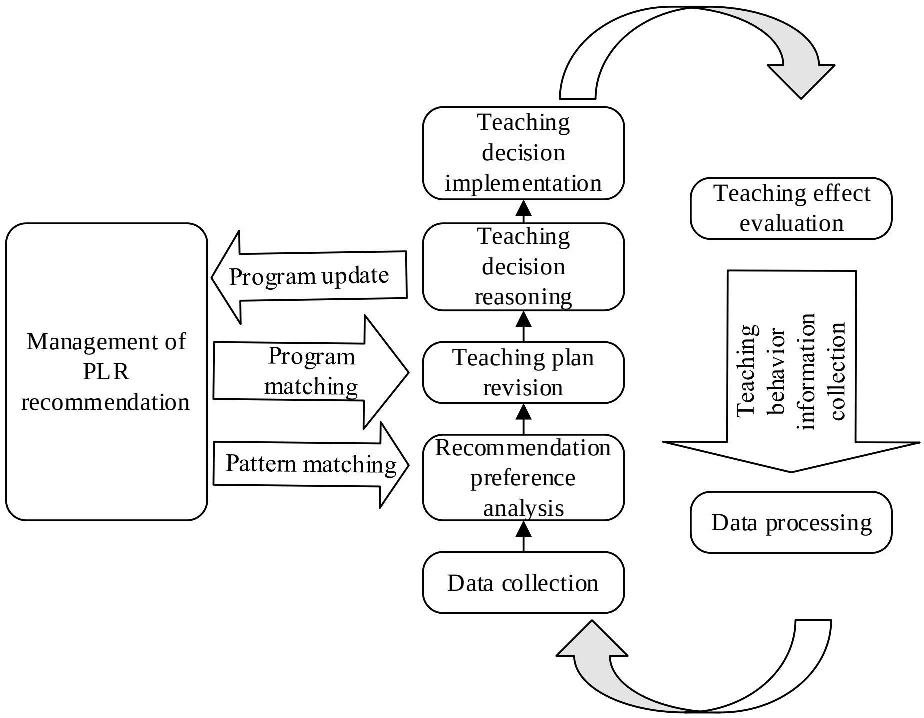

Fig. 2. Modules of teaching decision support

Elman neural network is a recurrent neural network (RNN), including an input layer, a hidden layer, an undertake layer, and an output layer. The structure of the network is shown in Figure 3. Let q^{j1}, q^{j2} and q^{j3} be the connection weight matrices between the undertake layer and the hidden layer, between the input layer and the hidden layer, and between the hidden layer and the output layer, respectively; $a_d(l)$ and $a(l)$ be the output of undertake layer and hidden layer, respectively; β be the self-connecting feedback gain factor; $g(a)$ be the activation function of sigmoid. Then, the state space of Elman neural network can be expressed as:

$$a(l) = g\left(q^{j1} a_d(l) + q^{j2} v(l-1)\right) \tag{7}$$

$$a_d(l) = \beta a_d(l-1) + a(l-1) \tag{8}$$

$$b(l) = h\left(q^{j3} a(l)\right) \tag{9}$$

Let $b_o(l)$ be the actual output of the entire neural network in step l. Then, the error function of Elman neural network can be expressed as:

$$R(l) = \frac{1}{2}\left(b_o(l) - b(l)\right)^T \left(b_o(l) - b(l)\right) \tag{10}$$

The partial derivative of weight is calculated by error function $R(l)$ through gradient descent. Let γ_1, γ_2 and γ_3 be the learning step lengths of q^{j1}, q^{j2} and q^{j3}, respectively. When the partial derivative is zero, the learning algorithm of Elman network can be expressed as:

$$\Delta q_{ij}^{j3} = \gamma_3 \xi_i^0 a_j(l)\left(i = 1,2,...,n; j = 1,2,...,m\right) \tag{11}$$

$$\Delta q w_{jw}^{j2} = \gamma_2 \xi_j^f v_w(l-1)\left(j = 1,2,...,m; w = 1,2,...,s\right) \tag{12}$$

$$\Delta q_{jl}^{k1} = \gamma_1 \sum_{i=1}^{n}\left(\xi_i^0 q_{ij}^{i3}\right)\frac{\partial a_j(l)}{\partial q_{jl}^{k1}}\left(j = 1,2,...,m; k = 1,2,...,m\right) \tag{13}$$

$$\xi_p^0 = \left(b_{o,p}(l) - b_p(l)\right) h_p^{'}(.) \tag{14}$$

$$\xi_p^f = \sum_{i=1}^{n}\left(\xi_i^o q_{ij}^{k3}\right) g_j^{'}(.) \tag{15}$$

$$\frac{\partial a_j(l)}{\partial q_{jk}^{k1}} = g_j^{'}(.)\, a_j(l-1) + \beta \frac{\partial a_j(l-1)}{\partial q_{jl}^{k1}}\left(j = 1,2,...,m; k = 1,2,...,m\right) \tag{16}$$

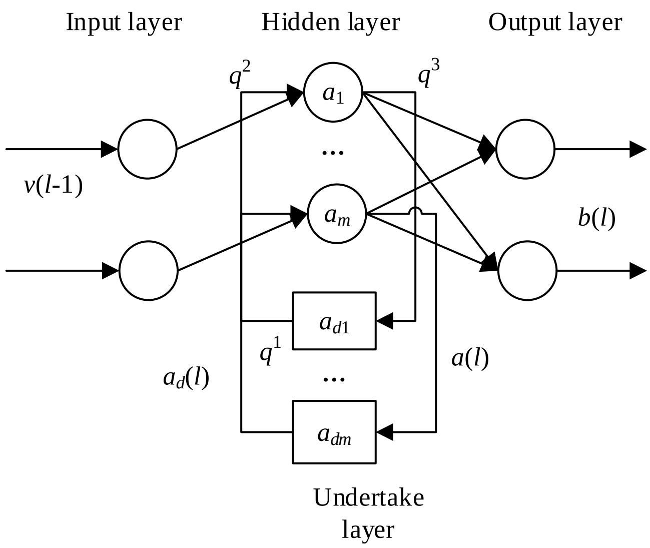

Fig. 3. Structure of Elman neural network

The Elman neural network is a typical dynamic feedback network. When the sum of squared errors (SSE) between the network output and expected output is smaller than the preset error threshold, the network weight is updated. Figure 4 explains the flow of Elman neural network algorithm.

Teaching is an open system. It is a process involving the interaction between various factors inside and outside the classroom. To realize the ideal teaching effect, the teacher must predict and integrate the various factors of teaching implementation carefully and comprehensively, and prepare, select, and apply the corresponding teaching plans, schemes, and measures. This paper carries out teaching decision-making, referring to the PLRs recommended for different types of students. Whether a teaching decision is suitable for most students is judged in five aspects: the matching degree of teaching goal, the matching degree of teaching objects, the matching degree of teaching contents, the matching degree of teaching method, and the matching degree of teaching evaluation. All these matching degrees can be calculated by the formulas for the similarity with learning interest and resource demand.

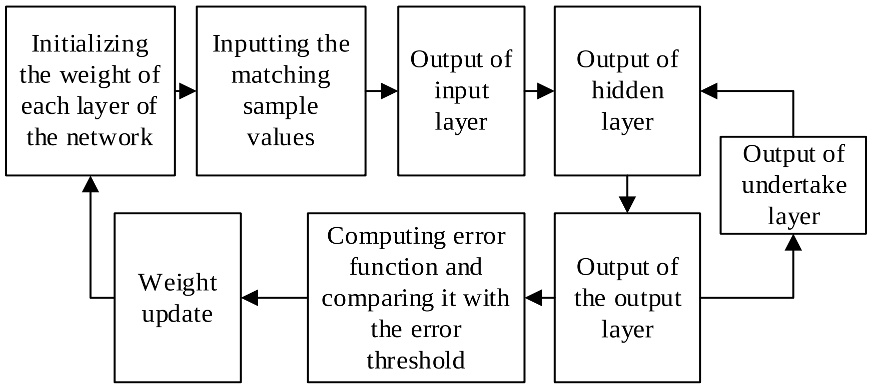

Fig. 4. Flow of Elman neural network algorithm

Based on the Elman neural network, an intelligent teaching decision model was established. Five parameters were imported: the matching degree of teaching goal a_1, the matching degree of teaching objects a_2, the matching degree of teaching contents a_3, the matching degree of teaching method a_4, and the matching degree of teaching evaluation a_5. To avoid data overflow of Elman neural network during the model construction, the input and output units of the network are normalized by:

$$a_{gui} = \frac{a - a_{min}}{a_{max} - a_{min}} \tag{17}$$

where, a_{max} and a_{min} are the maximum and minimum of a parameter, respectively.

According to the objective function (10) of our neural network, the network weights are updated at the minimum $R(l)$. Let $b_o(l)$ be the network output in the l-th iteration. Since the five parameters are normalized before being imported, the value of $b_o(l)$ falls in [0, k].

The value of $b_o(l)$ may be positive or negative. Let δ be the sensitivity coefficient, and Φ be the prediction result. Then, the teaching quality can be predicted by:

$$\Phi = \delta * b_o(l) \tag{18}$$

If Φ is a large positive number, the five parameters related to teaching decision are very likely to increase; if Φ is a small negative number, these parameters are very likely to decrease. If Φ belongs to [-δ, δ], then the teaching decision will lead to a good teaching quality, and the five parameters will remain unchanged in the future.

Based on the predicted teaching quality Φ, it is possible to implement decision reasoning and feedback control of the teaching goals, objects, contents, method, and evaluation, thereby achieving the ideal teaching quality. The conditions for teaching decision judgement can be expressed as:

$$\begin{cases} \Phi_l \geq \omega_1 \\ \omega_2 \leq \Phi_l < \omega_1 \\ \Phi_l < \omega_2 \end{cases} \tag{19}$$

For the l-th adjustment of the neural network, denoted as l, the thresholds ω_1 and ω_2 can be selected according to the actual conditions. To realize dynamic judgement of teaching decisions, and obtain a network with a fast speed and high training accuracy, this paper incorporates the feedback of output layer nodes to the Elman neural network, and connects it to the input layer. After the improvement, the input to the hidden layer covers both the input layer and the associative unit. Let q^{j1} and q^{j2} be the connection weight matrices between the associative unit and the hidden layer, and between the input layer and the hidden layer, respectively; β and λ be the self-connecting feedback factors; $g(a)$ be the activation function of sigmoid function. Then, the improved network can be expressed as:

$$a(l) = g\left(q^{j1}a_d(l) + q^{j2}v(l-1) + q^{j4}b_d(l)\right) \tag{20}$$

$$a_d(l) = \beta a_d(l-1) + a(l-1) \tag{21}$$

$$b_d(l) = \lambda b_d(l-1) + b(l-1) \tag{22}$$

$$b(l) = h\left(q^{j3}a(l)\right) \tag{23}$$

Taking the partial derivative of each connection weight function of the improved network, and setting the results to zeros, the learning algorithm of the improved network can be derived as:

$$\Delta q_{jl}^{k1} = \gamma_1 \sum_{i=1}^{n} \left(\xi_i^0 q_{ij}^{i3} \right) \frac{\partial a_j(l)}{\partial q_{jl}^{k1}} \left(j = 1,2,...,m; k = 1,2,...,m \right) \tag{24}$$

$$\Delta qw_{jw}^{j2} = \gamma_2 \xi_j^f v_w (l-1) \left(j = 1,2,...,m; w = 1,2,...,s \right) \tag{25}$$

$$\Delta qw_{ij}^{j3} = \gamma_3 \xi_i^0 a_j (l) \left(i = 1,2,...,n; j = 1,2,...,m \right) \tag{26}$$

$$\Delta q_{jk}^{j4} = \gamma_4 \sum_{i=1}^{n} \left(\xi_i^0 q_{ij}^{j3} \right) \frac{\partial a_j(p)}{\partial q_{je}^{j4}} \left(j = 1,2,...,m; e = 1,2,...,n \right) \tag{27}$$

$$\frac{\partial a_j(l)}{\partial q_{je}^{j4}} = g_j^{'}(.) b_e (l-1) + \lambda \frac{\partial a_j(p-1)}{\partial q_{je}^{j4}} \left(j = 1,2,...,m; e = 1,2,...,n \right) \tag{28}$$

4 Experiments and results analysis

The recommendation performance of learning interest-based recommendation algorithm, resource demand-based recommendation algorithm, and our algorithm were measured by precision, recall, and F-score. Figure 5 compares the recommendation accuracies of the three algorithms. Tables 1 and 2 compare the recalls and F-scores of the three algorithms, respectively.

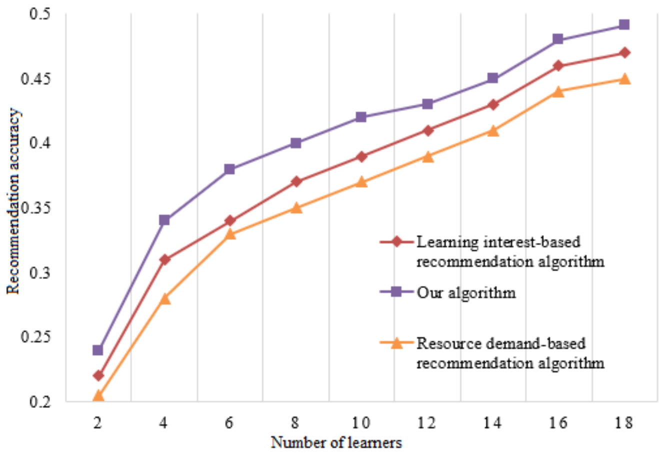

Fig. 5. Comparison of recommendation accuracies

The experimental results show that our algorithm achieved an obvious advantage in performance over learning interest-based recommendation algorithm, and resource demand-based recommendation algorithm. This is because our algorithm combines the recommendation principles of the two algorithms. Facing the same number of learners, our algorithm realized 5% more accurate recommendation results than the two contrastive algorithms.

The decision quality is greatly affected by the number of hidden layer nodes, which is determined in this research through multiple comparisons. The hidden layer was assigned 14, 18, 22, 26, and 30 nodes, in turn. Figure 6 compares the decision errors under different number of hidden layer nodes. It can be observed that proper addition of hidden layer nodes improved network performance. The best setting for our neural network is 22 hidden layer nodes. Next, the connection weights of our neural network were initialized, the relevant parameters were configured (decision error threshold = 0.02; maximum number of iterations = 1,000; learning rate = 0.03), and the neural network was trained.

The teaching decision support module aims to generate commands through teaching decision reasoning, and achieve feedback control of the teaching effect under the specific teaching decision. The proposed neural network merely outputs a numerical value. To convert the value into a command, it is necessary to set the values of ω_1 and ω_2 in the decision judgement conditions. Table 3 compares the decision accuracies at different ω_1 and ω_2. It can be seen that, the teaching decision accuracy first increased and then decreased, with the expansion of the interval of [ω_1, ω_2]. Through comprehensive consideration of actual factors, ω_1 and ω_2 should both be set to 0.3, which lead to the highest teaching decision accuracy.

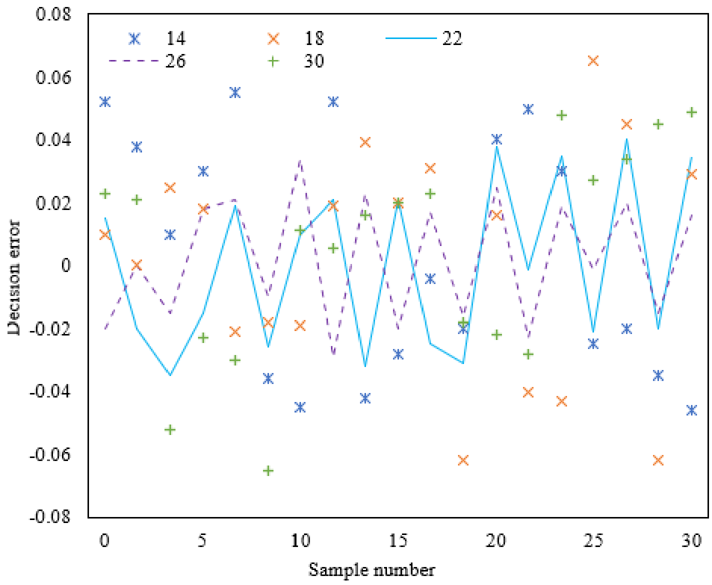

Fig. 6. Comparison of decision errors under different number of hidden layer nodes

Table 1. Recalls of three algorithms

Number of learners	2	4	6	8	10	12	14	16
Learning interest-based recommendation algorithm	0.251	0.235	0.214	0.263	0.315	0.326	0.412	0.435
Resource demand-based recommendation algorithm	0.274	0.285	0.291	0.316	0.335	0.374	0.415	0.438
Our algorithm	0.287	0.259	0.234	0.325	0.328	0.367	0.384	0.395

Table 2. F-scores of three algorithms

Number of learners	2	4	6	8	10	12	14	16
Learning interest-based recommendation algorithm	0.227	0.237	0.284	0.311	0.325	0.347	0.425	0.473
Resource demand-based recommendation algorithm	0.225	0.239	0.247	0.326	0.338	0.349	0.425	0.458
Our algorithm	0.215	0.226	0.253	0.315	0.329	0.349	0.369	0.394

Table 4 provides the statistics on teaching decision accuracy. It can be observed that the teaching decision support module achieved ideal decision results on each parameter: the matching degree of teaching goal, the matching degree of teaching objects, the matching degree of teaching contents, the matching degree of teaching method, and the matching degree of teaching evaluation. The mean decision accuracy was as high as 92.7%. In addition, each parameter became more regular, and easier to be learned by the teaching decision support module. Hence, our neural network is applicable to intelligent teaching decision-making, and our model performs excellent in the decision process.

Table 3. Comparison of decision accuracies at different ω_1 and ω_2

ω_1	ω_2	Accuracy (100%)
0	0	0.758
0.04	-0.08	0.825
0.2	-0.2	0.887
0.27	-0.28	0.869
0.3	-0.3	0.935
0.39	-0.37	0.924
0.4	-0.4	0.985
0.45	-0.48	0.874

Table 4. Statistics on teaching decision accuracy

Item / System	General decision	*Elman*	Our model
Teaching goal	0.625	0.852	0.924
Teaching objects	0.824	0.934	0.927
Teaching contents	0.785	0.928	0.958
Teaching method	0.834	0.829	0.935

Teaching evaluation	0.734	0.925	0.962
Mean	0.764	0.917	0.927

5 Conclusions

Taking the learning of spoken and written languages as an example, this paper explores the big data-assisted PLR recommendation, and teaching decision support, and details the flow of the relevant algorithm. The recommendation performance of learning interest-based recommendation algorithm, resource demand-based recommendation algorithm, and our algorithm were measured by precision, recall, and F-score. The comparison shows that our algorithm far outperforms the other two methods. In addition, the decision errors were compared at different number of hidden layer nodes, and the decision accuracies were contrasted at different ω_1 and ω_2. In this way, the neural network structure was optimized, and the feedback control of teaching effect was realized under the implementation of the specific teaching decision. Finally, the statistics on teaching decision accuracy were provided, which demonstrates the superiority of our model in the decision process.

6 Acknowledgment

1. General research project of ideological and political theory teachers in colleges and universities in 2021(21JDSZK099). Project Name: Research on teaching Mode reform of Ideological and Political Course in Higher Vocational Colleges.
2. Major project of basic research of Philosophy and Social Sciences in Colleges and universities of Henan Province in 2022(2022-JCZD-09). Project Name: Research on the Cultivation System of Vocational College Students' core literacy from the perspective of Type education.

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Article submitted 2021-12-15. Resubmitted 2022-01-10. Final acceptance 2022-01-12. Final version published as submitted by the author.