The Research of Intelligent Virtual Learning Community

Bo Song and Xiaomei Li

***Abstract*—At present, there are some problems in the way of research and training of primary school teachers, such as high cost, long cycle, limited number of research and training, slow updating of research contents and so on. Therefore, the virtual learning community for primary school teachers' research and training is constructed. In the process of implementation community core function, a hybrid recommendation algorithm based on content information label extraction and collaborative filtering is proposed for personalized recommendation system, which solves the problem of cold start of new users. Based on the NLP and the deep-learning algorithms, the two models of interest and behaviour are combined to update the interest model based on the behaviour of the learners in the intelligent teaching system. According to the user evaluation data, the intelligent teaching evaluation system has realized the intelligent evaluation of teachers' teaching activities. The insufficient in problem classification have been improved based on deep-learning algorithms for intelligent question answering system. The solution proposed in this paper has been applied to the research and training of primary school teachers in Liaoning province of China, which will play an important role in improving the level of teachers in primary education.**

***Index Terms*—VLC, teachers' research and training, NLP, deep learning.**

I. Introduction

As the participants and executors of educational work, teachers are the core and key factors that can not be ignored in the development of any type and level of education. The quality of the teachers' team directly affects the development of education. The most common ways to improve the quality of primary school teachers in China are two ways: training class and expert lecture. This traditional method of teaching research and training has many problems, such as high cost, long period, limited number of research and training, and slow updating of the content of research and training. It is difficult to meet the needs of the education development.

VLC(Virtual Learning Community) is a new network teaching support platform based on computer information processing technology, network resource sharing technology and multimedia information display technology. It will be applied to primary school teachers' research and training, which will have the advantages of low cost, fast speed and wide coverage. VLC has gradually become one of the most effective options for teachers in future research and training [1], [2]. The technical conditions for supporting VLC development have been mature enough, and the related theories in development and design are also very rich, but the research on VLC lacks the combination of specific subjects. Because the study in VLC ignores the learning characteristics of different courses, and the difference between community design and development caused by this feature, and the lack of effective knowledge processing and management of specific curriculum, the role of VLC in practical teaching is limited. Therefore, it is of great importance to improve the teaching effect by trying to build the VLC which combines class and extracurricular teaching, classroom teaching and self-study after class, which has very important practical and theoretical significance. The creation of VLC has very important practical promotion and theoretical reference [3]. NLP technology is an effective means to achieve interaction between human and machine through natural language, and has wide application space in the field of education. The early application of NLP technology in the field of education is to detect grammatical errors [4]. With the development of intelligent technology and the change of educational environment, the demand for NLP technology in the field of education is increasing. This paper will present the application of NLP technology in VLC, and build a model which is more consistent with learners' characteristics, so as to enhance the teaching efficiency of primary school teachers' research and training.

II. The Main Functions of VLC

In 1970s, the VLC research started and mainly focused on basic theory research [5]. The research on VLC mainly focuses on the functions, composition, research tasks, and the interaction and learning teams. VLC research in China is mainly focused on theoretical research, which is still in its infancy compared with foreign countries. At present, there are typical application cases in China, such as Capital Normal University VLC and South China Normal University online teaching. These successful application cases enable more and more educators begin to accept VLC, and schools are paying more attention to the construction of virtual campus. In general, the practice of combining the latest thinking with the construction of VLC is relatively infertile, and a part of the VLC that is trying to run has a variety of problems. For example, the structure of the home page is not clear enough, the model and the theory are disjointed, and VLC is not very different from the traditional network teaching support platform. These are the main problems to be faced in the construction of VLC in the future. According to the reality of the research and training of primary school teachers in China and the current research situation of VLC, this paper will build VLC for primary school teachers' training. According to the latest development of AI technology,

Manuscript received May 3, 2019; revised August 10, 2019.

Bo Song is with Software College of Shenyang Normal University, China (e-mail: songbo63@aliyun.com).

Xiaomei Li is with Liaoning Research and Training Centre for Basic Education, China (e-mail: 1715500576@qq.com).

doi: 10.18178/ijmlc.2019.9.5.849

intelligent technology such as Natural Language Processing is introduced into it. The core functions of VLC built in this paper include the following aspects: personalized recommendation system, intelligent teaching system, intelligent teaching evaluation system and intelligent question answering system.

There are some teaching resources recommendation systems in China, but there is still a gap compared with foreign countries in terms of the number of colleges and universities and the comprehensive evaluation of the teaching resources recommendation system [6]. In this paper, the traditional collaborative filtering algorithm is studied and improved. By introducing the concept of label extraction and similarity matrix, a hybrid recommendation algorithm based on content information label extraction and collaborative filtering is proposed [7]. This algorithm is applied to the recommendation of the teaching resources of the VLC, which aims to solve the new user cold start problem existing in the traditional recommendation algorithm, and provide the new user with the personalized resource service function.

Intelligent Tutoring System is an important research field in educational technology [8]. With the help of artificial intelligence technology, it plays an important role in acquiring knowledge and skills without the guidance of human tutors. The ITS (Intelligent Tutoring System) in this article will use the research results of deep learning in the field of NLP and combine the two models based on interest and behaviour. When the learner is registered, the learner gives the initial interest, and the system gives the key words related to this interest so that the learner can operate the document of interest. The system can capture learners' behaviors and update learners' interest models according to learners' behaviors.

Teaching evaluation is an important part in education management. Intelligent evaluation system is a comprehensive management in the quality of education and teaching, and it is a major means of systematic and comprehensive evaluation of teachers' teaching quality. In the process of research on the evaluation of teaching quality, the United States started relatively early. It adopts the traditional pattern of students grading teachers. The focus of this evaluation method is to supervise teachers' teaching work and determine the quality of teachers' work. There are three typical methods of teaching quality evaluation: value added evaluation, peer evaluation and teaching according to their aptitude. Domestic schools basically have their own teaching quality evaluation system. However, most of it is simply based on the simple management information system, which is summarized on the basis of student scoring. It is a relatively simple algorithm used in the information system. In recent years, many universities begin to build digital campus and use the way of online teaching evaluation. In this paper, the intelligent teaching evaluation system can make a comprehensive analysis of the characteristics of teachers' teaching according to the data of students' evaluation, so that teachers can pay attention to their teaching shortcomings and correct them in time. Secondly, the function of teacher evaluation students is added in the evaluation system of teachers' teaching. In this system, students' comprehensive ability is regarded as an important indicator of teacher evaluation, so that students and parents can learn about their progress and deficiencies.

Now when people encounter problems, they always like to use search engines to find answers. As long as you input some keywords, the search engine will return many web pages that contain key words [9]. However, when using this method many web pages related to keywords will be returned, resulting in redundancy. People want to have a retrieval system that asks questions in natural language and can directly return answers. Intelligent Question-Answering System is an advanced information retrieval system in which users can ask questions in natural language and get the questions. Answering questions is an indispensable part in the teaching process [10]. However, traditional face-to-face questions and e-mail answering questions can not meet the needs of learners. In order to solve the above problems, this paper will design a Chinese question answering system for teachers' research and training based on the characteristics of knowledge in the field of education.

III. Implementation of VLC

A. Personalized Recommendation Algorithm

The personalized recommendation system of this system adopts the improved collaborative filtering recommendation algorithm in the literature [7], which solves the cold start problem of collaborative filtering and has used the Movie Lens data set to verify it [11]. Random recommendation, mean value method, iterative recommendation algorithm combining content and improved algorithm in literature [7] are used to conduct experiments respectively. The results of the experiment are shown in Fig. 1.

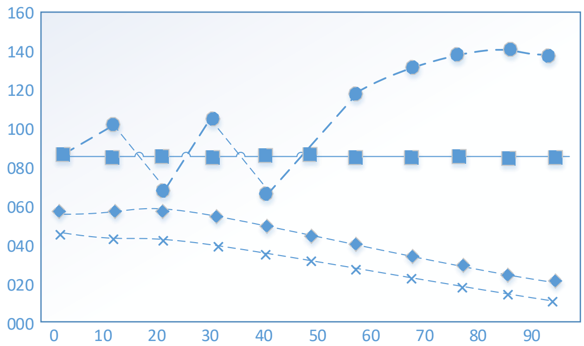

Fig. 1. MAE curves of four different methods.
Random recommendation method: —●—
Average method: —■—
Iterative algorithm combining content: —♦—
Algorithm in this paper: —×—

In Fig. 1, the MAE (average absolute error) calculated the average value of the difference between the prediction score and the user's true score, the lower the value of the MAE, the higher the accuracy of the algorithm [12]. Figure 1 shows the MAE curves of the four methods used in the experiment. It can be seen from the graph that the MAE curve is fluctuating, which is due to the arbitrary of random recommendation method. With the increasing number of grading, the MAE value of random recommendation methods is also increasing, and recommendation accuracy is getting worse.

The MAE of the average method is almost a fixed value, and it lacks individuation. The MAE values are close between the iterative recommendation algorithm combined with the content and the hybrid recommendation algorithm combined with the content information label proposed in this article. At first, they are a lower value. When the number of scores increases, the MAE value becomes lower, and the recommendation accuracy is also improved accordingly. The iterative algorithm combining content in experiments is usually used to solve the cold start problem [13], [14]. From the MAE value of the algorithm proposed in this paper, we can see that the accuracy of the hybrid recommendation algorithm combined with the content information label can reach the standard. And the iterative algorithm combined with content needs a lot of iterative computation, which is very large. However, the algorithm proposed in this paper is more convenient and flexible, and can reduce many unnecessary operations. It can improve the system's recommendation efficiency and enhance the user experience while ensuring the recommendation accuracy.

In formula 1, the root mean square error (RMSE) is another index to measure the accuracy of the recommendation system. Although the MAE has been widely used because of its simplicity and comprehensibility, there are still some limitations. Usually, low scores that are difficult to predict accurately tend to increase MAE value. RMSE squares every absolute error, and finally takes the square root of the mean error as the result. In Formula 1, N is the total number of experimental items in the experimental data.

$$RMSE = \sqrt{\frac{\sum_{(u,i)\hat{I}E^{P}} \left(r_{u,i} - p_{u,i}\right)^{2}}{N}} \qquad (1)$$

In Fig. 2, the RMSE curve of four cold start solutions is shown. The trend of RMSE curve is basically the same as that of MAE curve, but the error described by RMSE is more accurate. The experimental results show that the new improved algorithm proposed in this paper is feasible, and it is an effective recommendation algorithm to solve the cold start problem.

B. Deep Learning Algorithms

Deep-learning is a new branch of machine learning. It has great research value and practical value. Deep-learning has achieved amazing results in image and speech processing. At the same time, we hope to make further breakthroughs in Natural Language Processing by using it. The interest of a learner can be represented by a set of topics, which can be organized in a file or database. This article uses a database to organize the learner's interest model.

The definition of the learner's interest model is given, $U = \{(t_1, w_1), (t_2, w_2), \ldots, (t_n, w_n)\}$. In this formula, $t_i(i=1...n)$ is the topic item and $w_i(i=1...n)$ is the weight in the learner's interest model. A learner can be interested in a field and has a lot of interest in the field. For example, the learner is interested in the field of mathematics, in which he can be interested in many aspects such as numbers and comparisons. Define $S_i = \{Ip, In, Iq\}$, S_i is the aspect of interest, which is composed of Ip, In and Iq. In the aspect of interest, Ip is the model that learners interest in and In is the opposite model. Iq is the query vector, which describe the specific interest of learners. The vectors spaces of Ip, In and Iq are the same as those of U and all their characteristic items are derived from $t_i(i=1...n)$ of U, but $w_i(i=1...n)$ of Ip, In and Iq are different. The initial weights of Ip and In are obtained from the training text set, while those of Iq are input when the learners register and their weights are generally averaged.

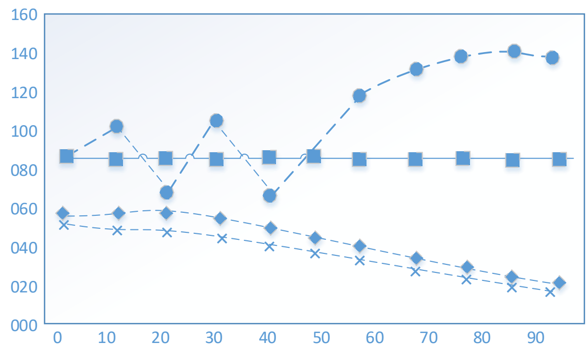

Fig. 2. MAE curves of four different methods.

Query expansion consists of two parts: the weight calculation of query keywords and the extension of new words. The study of Web Information Retrieval for individual learners involves changes in individual interests. Changes in personal interest include changes in the degree of interest, the emergence of new interests, and the disappearance of original interests. Therefore, learner-oriented query expansion includes the recalculation of query keyword weight, the expansion of new terms and the removal of the original query keyword. In this paper, a learner correlation feedback method based on vector model is used for query expansion, and a new correlation feedback algorithm is proposed. A typical relevance feedback method divides the search returned document into two categories: related and unrelated. According to the real situation of learners' information search, it is more reasonable to divide the result documents into three categories: highly relevant, generally relevant and unrelated. In the retrieval results by this way, the document that truly expresses the learner's query intention is defined as a much related class, some documents expressing partly learners' query intentions are defined as general related classes, while the others are unrelated classes. Therefore, a new relevance feedback algorithm based on vector model is proposed. The formula is as follows:

$$\bar{q}_m = \alpha\bar{q} + \beta\sum_{\forall \bar{d}_j \in D_r} \bar{d}_j 6 + \gamma\sum_{\forall \bar{d}_j \in D_c} \bar{d}_j + \lambda\sum_{\forall \bar{d}_j \in D_n} \bar{d}_j \qquad (2)$$

In the formula, D_r is a very relevant document set, which is fed back by learners. D_c is a set of general related document set, and D_n is an unrelated set of documents retrieved from the returned documents, $\bar{q}_m$ is the expanded query vector, and $\bar{q}$ is the initial query vector. The α, β, γ and λ are constants which are called adjusting factors. The query vector $\bar{q}$ initially entered by learners is the most important, and it is obtained through learner input. Therefore, α should be larger than the other three constants. The set of related documents expresses the learners' query intention, so the value of β and γ are greater than the value of λ.

The weights of the query keyword indicate the degree to which the learners are interested in things. The learners' queries can be expressed as the following vector $\bar{q} = \left(w_{1,q}, w_{2,q}, \ldots, w_{n,q}\right)$. Among the vector, n is the dimension, $w_{i,q}\left(i = 1 \cdots n\right)$ is the weight of query keyword and $w_{i,q} \in [0...n]$, weights higher the learner more interested in a thing. In a long period of time, the learners' interest in things will change, so the weight of the query key words that represent the interest of a certain degree of learners should also be changed accordingly. Formula 2 is used to recalculate the weight of query keyword. If the learner downloads the document, the corresponding result document is considered to be highly relevant by the learner. And if the learner navigates the document, the corresponding result document is considered generally relevant by the learner. However, a result document learner is neither downloading nor browsing, which is considered irrelevant by the learner. This hypothesis avoids the related and unrelated judgment of the learner's retrieval results in the feedback method, and also achieves the correlation and unrelated effect of the feedback method to the retrieval result area. A very relevant set of documents is recorded as D_r, a general relevant set of documents is recorded as D_c and the unrelated document collection is recorded as D_n. Using these three sets, we can recalculate the weight of query keywords. Query vectors and document vectors are represented by user model vector space. The vector of the document d_j is $\bar{d}_j = \left(w_{1,j}, w_{2,j}, \ldots, w_{n,j}\right)$. Among them, n is the dimension of the vector of the learner interest model, and $w_{i,j}\left(i = 1 \cdots n\right)$ is the weight of the t_i in the document d_j. The weight of the key words in the document does not use the TF-IDF calculation. Because the document is a web page document retrieved by the search engine, the IDF is difficult to determine. Therefore, the weight of the key words is calculated by TF, and the calculation formula is as follows:

$$w_{i,j} = \frac{tf_{i,j}}{\left|d_j\right|} \tag{3}$$

In the above formula, $tf_{i,j}$ is the word frequency of t_i in document d_j, and $\left|d_j\right|$ is the length of document d_j, that is the total number of entries in document d_j.

Using natural language processing (NLP) in deep learning to analyze the content that learners want to inquire, and give the best feedback. In the above process, how to give feedback content more in line with the interests of learners is the key problem to be solved in this section.

C. Intelligent Teaching Evaluation System

1) Building the weight model of PSO – AHP

The determination of weights is an important part of teaching evaluation, and the reasonable allocation of weights is the key to quantitative assessment. The common weight determination methods include Delphi method, analytic hierarchy process (AHP), entropy method and fuzzy cluster analysis method. Because the actual evaluation is often lack of sample data, and most of the index are qualitative index, so the commonly used weight method is AHP. In order to keep the original information of the decision maker to the maximum, and make the judgment matrix have better consistency and improve the weight value, the particle swarm optimization algorithm (PSO) is applied to the analytic hierarchy process. In this paper, we construct the PSO-AHP model, introduce the process of constructing the model, and apply it to the calculation and optimization of the weight value. In order to make the result of evaluation more scientific and reliable, PSO-AHP model is constructed. In this paper, we introduce the solution process of the model and apply it to the calculation and optimization of the weight value.

a) The establishment of a hierarchical structure model for teaching evaluation system

Suppose the teaching evaluation system has four levels from top to bottom, and it is sequentially recorded as A, B, C and D. The A level is the overall goal of system evaluation, and there is only one element. The number of elements of the A, B, C, and D levels are recorded as $n1, n2, n3, n4$.

b) Constructing judgment matrix

The elements of B, C and D are obtained by comparing the elements of the above level. In general, the 1-9 scale is used to describe the relative importance of each element and the judgment matrix of B level is $A_k = \left(a_{ij}\right)_{n_b \times n_b}$. The element a_{ij} indicates that the relative importance of element $\mathrm{B_i}$ to element $\mathrm{B_j}$ from the perspective of A level. Accordingly, the judgment matrix of the C level is $B_k = \left\{b_{ij}^k \left| i, j = 1...n_k; k = 1...n_b\right.\right\}_{n_c \times n_c}$ and D level is $C_k = \left\{c_{ij}^k \left| i, j = 1...n_d; k = 1...n_c\right.\right\}_{nd \times nd}$. Since there are many indicators used in general comprehensive evaluation, it is difficult to directly use the 1-9 scale method for the importance comparison of between elements. Therefore, the indirect judgment matrix of the three judgment scales from zero to two can be used first, and then converted into the judgment matrix of the judgment scale from one to nine, which can avoid logical errors.

c) Establishment of weight optimization model

The objective function is defined by the optimization process of the weight value corresponding to the judgment matrix $A_k = \left(a_{ij}\right)_{n_b \times n_b}$. The single ordering weight value for each element of the B layer is ω_k and $k \in (1, n_b)$. If the judgment matrix A_k satisfies $a_{ij} = \omega_i / \omega_j (i, j = 1\text{-}n_b)$, then A_k has complete consistency. So there is the following formula:

$$\sum_{i=1}^{n_b}\left|\sum_{k=1}^{n_b}(a_{ij}\omega_k - n_b\omega_i)\right| = 0 \tag{4}$$

Obviously, if the value on the left is smaller, the degree of consistency of $\mathrm{A_k}$ is higher. When formula 4 sets up, there is complete consistency. Therefore, the weight calculation and optimization of each factor in the B layer can be summarized as the following objective function:

$$\text{MinCIF}(n_b)=\sum_{i=1}^{n_b}\text{-}\sum_{k=1}^{n_b}(a_{ik}\omega_k)\text{-}n_b\omega_i\text{-}/n_b \tag{5}$$

In the above objective function, the constraint conditions are as follows:

$$\begin{cases}\sum_{k=1}^{n_b}\omega_k=1\\ \omega_k>0(k=1\sim n_b)\end{cases}$$

In formula 5, the consistency index function is $\text{CIF}(n_b)$. It is a nonlinear optimization problem which is difficult to deal with by conventional methods. Therefore, when the minimum value of $\text{CIF}(n_b)$ is obtained, the corresponding weight value is the best value corresponding to matrix A. Even though A_k has been determined, the corresponding weight value can be optimized by solving the above optimization problem.

d) Using PSO to create the weight optimization model and carry out consistency check

PSO can solve hierarchy sorting and verify its consistency, which is to determine the ranking weights of the same level elements for the most high-level elements and verify the consistency of the matrix. This process is carried out layer by layer from the highest level to the lowest level. The ranking weight of the elements of the B layer is $\omega_k(k=1\text{-}n_b)$ and the consistency index function is $\text{CIF}(n_b)$.

The ranking weight of the elements of the C layer is: $\omega c_i^A=\sum_{k=1}^{n_b}\omega_k\omega c_i^k(i=1\text{-}n_c)$. And the consistency index function is $CIF^A(n_c)=\sum_{k=1}^{n_b}\omega_k CIF^K(n_c)$. The ranking weight of the elements of the D layer is $\omega d_i^A=\sum_{k=1}^{n_c}\omega c_k^A\omega d_i^k(i=1\text{-}n_d)$ and the consistency index function is $CIF^A(n_d)=\sum_{k=1}^{n_c}\omega c_k^A CIF^K(n_d)$.

When the $CIF^A(n_d)$ value is less than a certain standard, it is considered that the overall ranking results of the elements of the D layer have satisfactory consistency. And the total ranking weight value ωd_i^A of the elements calculated accordingly is acceptable. Otherwise, the maximum direction improvement method and interval number improvement method are used to adjust the judgment matrix [15] until the results meet the appropriate criteria.

When the judgment matrix is determined, the PSO-AHP model can optimize the weight value and obtain a relatively high degree of consistency. It overcomes the shortcoming of the AHP method that if the judgment matrix is given the weight value and consistency can not be improved. The PSO-AHP model maintains the original information of the judgment matrix to the greatest extent, so that the weight value can better reflect the real preference of decision makers.

D. Application of Machine Learning in Evaluation Model

In the construction of intelligent evaluation system model, we regard the teaching evaluation as a classification problem. The evaluation data collected by the intelligent evaluation system is a given set of training samples. It is easier to solve the rough classification rule (weak classifier) than to find the precise classification rule (strong classifier). Therefore, the method of lifting is to learn from the weak learning algorithm repeatedly, get a series of weak classifier (basic classifier), and then combine these weak classifiers to form a strong classifier.

The intelligent evaluation system collects a set of training data sets of two categories. The data-set T is $T=\{(x_1,y_1),(x_2,y_2),.....,(x_n,y_n)\}$. Among them, $x_i\in X\subseteq R^n$, $y_i\in Y=\{-1,+1\}$, X is an instance space, and Y is a set of mark-up. Using the following AdaBoost algorithm [16], a series of weak classifiers or basic classifiers are learned from the training data, and these weak classifiers are linearly combined into a strong classifier. The weight distribution of the initialization data is $D_1=(w_{11},..,w_{1i},..,w_{1N}),w_{1i}=\frac{1}{N},i=1,2,..,N$. It is assumed that the training data set has a uniform distribution of weights that is each training evaluation sample plays the same role in the learning of the basic classifier. This hypothesis ensures that the first step can be used to learn the basic classifier on the original data. The AdaBoost algorithm is used to learn the basic classifier repeatedly and perform the following operations sequentially in each round of m=1… M. Use D_m weighted training data-set to learn the basic classifier $G_m(x)$ and calculate the classification error rate $e_m=p(G_m(x_i)^1 y_i)=\sum_{G_m(x_i)^1 y_i}w_{mi}$. Here, w_{mi} represents the weight of the instance I in the m round and $\sum_{i=1}^{N}w_{mi}=1$. The formula for calculating the coefficient of $G_m(x)$ is as follows:

$$\alpha_m=\frac{1}{2}\log\frac{1-e_m}{e_m} \tag{6}$$

The logarithm here is the natural logarithm and α_m indicates the importance of $G_m(x)$ in the final classifier. Formula 6 shows that $\alpha_m\geq 0$ when $e_m\leq\frac{1}{2}$, and α_m increase with the decrease of e_m, so the smaller the classification error rate, the greater the role of the basic classifier in the final classifier. Update the weight distribution of training data-sets using the following formulas:

$$D_{m+1}=(w_{m+1,1},..,w_{m+1,i},..w_{m+1,N}) \tag{7}$$

$$w_{m+1,i}=\frac{w_{mi}}{Z_m}\exp(\text{-}\alpha_m y_i G_m(x_i)),i=1,2,...,N \tag{8}$$

In formula 8, Z_m is a normalization factor and $Z_m = \sum_{i=1}^{N} w_{mi}\exp(-\alpha_m y_i G_m(x_i))$. Formula 8 can also be written as follows:

$$w_{m+1,i} = \begin{cases} \dfrac{w_{mi}}{Z_m} e^{-\alpha_m}, G_m(x_i) = y_i \\ \dfrac{w_{mi}}{Z_m} e^{\alpha_m}, G_m(x_i)^1 y_i \end{cases} \tag{9}$$

It can be seen from the above formula that the weights of the samples classified by the basic classifier are enlarged, but the weights of the samples correctly classified are reduced. Therefore, miscalculation samples play a greater role in the next round of learning. The linear combination of basic classifiers is constructed to get the following final classifier $G(x)$.

$$G(x) = sign(f(x)) = sign\left(\sum_{m=1}^{M} \alpha_m G_m(x)\right) \tag{10}$$

The linear combination $f(x) = \sum_{m=1}^{M} \alpha_m G_m(x)$ implements the weighted voting of basic classifier from 1 to M. The coefficient α_m represents the importance of the basic classifier $G_m(x)$, where the sum of all α_m is not 1. The symbol of $f(x)$ determines the classification of instance x, and the absolute value of $f(x)$ represents the certainty factor of classification.

The intelligent evaluation system uses the supervised learning in machine learning and uses the Ada-boost algorithm to reduce the error rate. The constructs of final classifier by using the linear combination of the basic classifier achieve the best prediction model. How to distribute weight values reasonably and build prediction models reasonably is the key technical problem to be solved at this stage. The learning model constructed by intelligent evaluation system has certain guiding significance for the development of teaching management. At the same time, in the face of different school groups, the emphasis of teaching evaluation is also different.

E. Intelligent Question Answering System

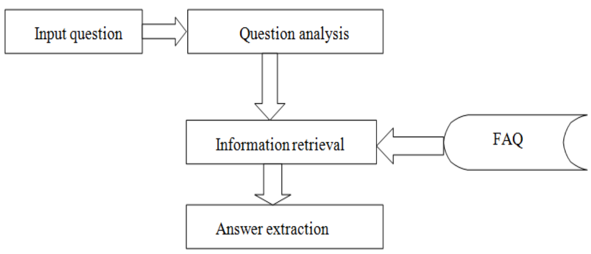

Fig. 3. The structure of intelligent question answering system.

As shown in Fig. 3, intelligent question answering system generally consists of three parts, question analysis, information retrieval and answer extraction. The task of question analysis is to determine the type and classification of question, the type of expected answer and the key content of the question [17]. The main task of the information retrieval section is to locate the document information associated with the user question. The answer extraction part is to filter the most accurate answer from the result set.

Question classification is an important part of the question analysis. Determining the type of the question can not only reduce the search space, but the question classification can sort the candidate answers [18]. Therefore, the performance of the question classification model directly affects the accuracy of the answer extraction [19] and the overall performance of the system [20].

In recent years, machine learning based question classification has become the main research method of question classification. Machine learning based classification models include support vector machine (SVM), Bias and K-nearest neighbour algorithm. These classification methods have certain subjectivity in question feature extraction and can not express the implicit syntactic meaning of the question. Deep learning can learn the intrinsic syntactic and semantic features of sentences by self learning, thus making them more accurate and objective. Long short term memory (LSTM) is a kind of time recurrent neural network and it is a special type of RNN.

In this paper, feature extraction method and LSTM model are combined to improve classification performance. Unlike LSTM, the uni-gram feature, POS and word weight feature are used in the corpus prepossessing module. In the generation module of word embedding, the method of word embedding prepossessing and word embedding fusion can be used to replace the original word embedding method. In addition, the Term Weight method is added to the LSTM network model to adjust the influence of each output result on sentence features.

a) Corpus prepossessing module

In the classification model, the corpus prepossessing module is the most basic module in the system, and the quality of data directly affects the performance of the system. The corpus prepossessing module first analyzes the word information in the corpus, then digitizes the words and obtains the digital representation of the sentence with uni-gram features. Secondly, we carry out POS on sentences and digitally convert POS. Finally, a Term Weight feature is added to each word to represent the weighted features of the word. In this process, words and category information are encoded, and the categories of sentences and sentences are represented by encoding values. The encoding method is shown below.

Firstly, the sentence is segmented and the category label is extracted from the category field to count the frequency of words and category labels. The words and categories are sorted according to the frequency, and the ordered word list and category table are generated. For each word, use its label in the ordered word list as its encoding. Then the questions are encoded according to the coding values of the words, and the method of category coding is the same. The encoded corpus, generated word list and category table are passed to the next module as the processioning results.

b) The generation module of word embedding

The module consists of two sub modules: feature vector per training and feature vector fusion. On the basis of the traditional NNLM, Molotov [11] proposed a language model based on the recurrent neural network model. The model solves the limitation of the history length of the NNLM model, and reduces the computation of the hidden layer to the output layer, so that the training efficiency is greatly improved. Through the network training process of RNNLM, the word embedding vector with good performance can be obtained. The RNNLM network structure, as shown in Fig. 4, is composed of the three layers of the input layer, the hidden layer and the output layer, and the nonlinear hidden layer in the RNNLM model is the key to improve the performance of the system.

In the input layer of RNNLM, the input data of the network are two items, which are the words vector at the current time and the state information of the hidden layer at the last time and the word vectors are expressed in the one-hot method. In the hidden layer, the current hidden layer state is updated by inputting information, and the update method is shown in formula 11.

$$s(t) = f(Uw(t) + Ws(t - 1)) \tag{11}$$

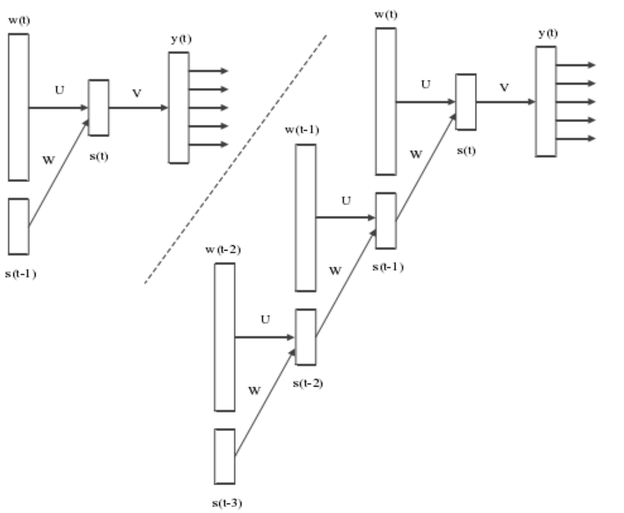

Fig. 4. The network structure of RNNLM.

Among them, $s(t)$ represents the state information of the hidden layer at t time, $s(t-1)$ represents the hidden layer state at the last moment, and W and U represent the network parameters. In the process of network computing, the current hidden layer state is passed into the input layer at the next time, and the update of the state is circulated by this method until the end of the sentence. F is the activation function, and the calculation method is shown in formula 12.

$$f(x) = \frac{1}{1 + e^{-x}} \tag{12}$$

In the output layer, the output value of the sentence is calculated according to the hidden layer state of the last word. The calculation method is shown in formula 13.

$$y(t) = g(Vs(t)) \tag{13}$$

Among them, V is the network parameter matrix of the hidden layer to the output layer, the $s(t)$ represents the state information of the hidden layer in the t moment, and the calculation method of the function g is shown in formula 14.

$$g(x_k) = \frac{e^{x_k}}{\sum_m e^{x_m}} \tag{14}$$

In the output layer, we apply the Term weight to the output of the hidden layer, and then extract the sentence features through the pooling layer. Finally, the softmax function is used to classify the sentence feature vectors and complete the sentence classification task.

IV. Conclusion

Through the construction of VLC, the system solves the problem of primary school teachers' research and training, and provides learners with the learning content that meets the learners' own background, so that the learners' learning is more effective and personalized.

Firstly, the recommendation algorithm based on Collaborative Virtual Learning Community solves the problems of user behavior information overload, sparse score matrix and cold start. The personalized recommendation system is implemented by establishing the more effective recommendation algorithm so that the learners can quickly select the personalized knowledge resources that meet the needs of the learners and create a better user experience. In the intelligent teaching system, NLP technology is applied in the teaching process of VLC. When learners register, learners input the initial interests. According to the initial interests, the system gives the query keywords related to the interests, so that learners can operate on the documents they are interested in. At the same time, the system can capture learners' behaviors and update learners' interest models according to learners' behaviors. In the intelligent teaching evaluation system, we integrate the theory of comprehensive evaluation and the theory of intelligence to complete the comprehensive evaluation. Based on the analysis of intelligent methods in comprehensive evaluation, this paper studies the problem of subjective and objective weight selection, selection and integration of models and synthesis of evaluation. The machine learning is used in the intelligent evaluation system, the completed evaluation data is taken as the training set and the error can be reduced as much as possible. The successful construction of the model can predict the teachers' problems and shortcomings in the future teaching. At the same time, the reasonable application of machine learning makes the system more plasticity and plays a guiding role in the future development of teaching management. In view of the existing problems in AHP, this paper studies and improves the PSO. Maintaining the advantages of the AHP, a weight index model of PSO-AHP is proposed for the current evaluation needs. The problems such as fixed matrix can not be changed and the characteristics of matrix are lost are solved in the PSO-AHP model. Finally, this paper studies the intelligent question answering system for the training of primary and secondary school teachers, using deep learning technology to solve the problems existing in the classification.

ACKNOWLEDGMENTS

The authors acknowledge: (1) The Basic Research Foundation of Universities in Liaoning (Grant: 2017L317); (2) The 17th Five-Year Plan of Education Science in Liaoning Province. (Grant: JG18DB451).

REFERENCES

[1] X. F. Ma and X. F. Li, "Virtual Learning Community-A new platform for teachers' professional development," *E-education Research*, vol. 4, pp. 35-38, 2009.
[2] L. Wang, *Virtual Learning Community Principles and Applications*, Higher Education Press, 2004.
[3] D. Q. Wu and W. Yang, "Construction of Java virtual learning community based on knowledge management," *Computer Education*, vol. 7, pp. 69-72, 2015.
[4] M. Wang, S. W. Yu, and X. F. Zhu, "Natural Language Processing technology and its educational application," *Mathematics in Practice and Theory*, vol. 20, pp. 151-156, 2015.
[5] L. H. Zhang, *Design and Implementation of Virtual Learning Community*, Beijing Jiaotong University, 2014.
[6] H. H. Wu and B. Song, "The teaching resources recommendation system research based on Java EE," *Software Engineering*, vol. 4, no. 21, pp. 19-25, 2016.
[7] B. Song and J. Gao, "Improvement and application of collaborative filtering recommendation algorithm in e-learning system," *Journal of Shanxi University*, vol. 4, 2015.
[8] B. Song and X. Yan, "Intelligent tutoring system of primary mathematics based on EGL and Web 2.0," *Software Engineering*, vol. 4, no. 2, pp. 34-40, 2016.
[9] W. Zhang, *Technology and Application of Chinese Question Answering System*, Electronic Industry Press, 2016.
[10] T. Jiang, *Research and Implementation of Intelligent Question Answering System for Educational Technology Discipline*, Huazhong Normal University, 2012.
[11] T. Mikolov, M. Karafiát *et al*, "Recurrent neural network based language model," in *Proc. INTERSPEECH*, 2010, vol. 2, no. 3, pp. 1045-1048.
[12] Y. X. Zhu and L. Y. Lu, "Review of recommendation system evaluation indicators," *Journal of University of Electronic Science and Technology of China*, vol. 41, no. 2, pp. 163-175, 2012.
[13] N. Lam, T. Vu, and D. Le, "Addressing cold-start problem in recommendation systems," in *Proc. ICUIMC'08*, New York, USA, 2008, pp. 208-211.
[14] W. Chu and T. Park, "Personalized recommendation on dynamic contents using predictive bi-linear models," in *Proc. 18th International Conference on World Wide Web*, 2009, pp. 691-700.
[15] J. J. Zhu, *Research and Application of Several Problems in Analytic Hierarchy Process*, Northeastern University, 2005.
[16] H. Li, *Statistical Learning Method*, Beijing, Tsinghua University Press, 2012, vol. 3, pp. 138-153.
[17] A. B. Abacha and Z. P. Means, "A medical question-answering system combining NLP techniques and semantic web technologies," *Information Processing & Management*, 2015, vol. 51, no. 5, pp. 570-594.
[18] B. Loni, G. V. Tulder, P. Wiggers *et al.*, *Question Classification by Weighted Combination of Lexical, Syntactic and Semantic Features Text, Speech and Dialogue*, Springer Berlin Heidelberg, 2011, pp. 243-250.
[19] R. Mudgal, R. Madaan, A. K. Sharma *et al.*, "A novel architecture for question classification based indexing scheme for efficient question answering," *Computer Science*, 2013.
[20] M. Dan, M. Paşca, S. Harabagiu *et al.*, "Performance issues and error analysis in an open-domain question answering system,". in *Proc. Meeting of the Association for Computational Linguistics*, Philadelphia, 2002, pp. 33-40.

Bo Song obtained the master degree of technology of education from Fukuoka Education University in Japan in 1999. Since 2003, he has been a teacher in Software College of Shenyang Normal University in China and was a professor in 2011. His research interests include software engineering, NLP and deep-learning.

Xiao-Mei Li obtained the master degree of education from Shenyang Normal University in China in 2017. Since 2000, she has been a teacher in Liaoning Research and Training Centre for Basic Education in China and was a professor in 2011. She won the second-class and third-class of natural science achievements in Liaoning Province in China in 2014 and 2017 respectively. Her research interests include mathematics education in primary schools and intelligent education information.