WEB-based Collaborative Platform for College English Teaching

Yuwan Zhang
Henan Polytechnic Institute, School of Culture, Tourism and International Education, Nanyang, 473000, China

***Abstract*—At present, colleges and universities are trying to apply online education. The online college English course teaching cooperation platform is an important part of college English teaching. At present, teachers' scoring method for students' online examination on this kind of platform is mainly human scoring, which has a low efficiency. In view of this, based on the characteristics of web, this paper constructs an English test paper scoring algorithm based on text matching degree algorithm and improved KNN algorithm. The data analysis type of the algorithm is mainly prescriptive analysis that is, judging whether to give points according to the characteristics of the data. The automation and high efficiency of the algorithm can save a lot of human costs in the field of online education. The experimental results show that the recall rate of the improved KNN scoring algorithm for specific semantic topics is up to 0.9, and only 7.3% of students report that the algorithm misjudges their grades. The results indicate that the algorithm has the potential to be applied to the Web-based college English course teaching collaboration platform and reduce the workload of teachers and improve their efficiency.**

Keywords—Web; text similarity; KNN algorithm; vocabulary matching; network teaching

I Introduction

With the development of network and information technology, online teaching mode is gradually adopted by major universities. This mode is different from traditional teaching, and teaching methods are more diversified and convenient for students [1]. English is a required course for most majors in colleges and universities, and the number of users of its web-based teaching collaboration platform has been very large. Therefore, it often takes more time for English teachers to correct students' test papers online, which increases labor costs and reduces efficiency [2]. The reason why the English test paper correction of the web network teaching collaboration platform cannot be fully automated is that it is difficult to judge the compliance of students' answers with the standard answers through algorithms [3]. Among related technologies, text similarity detection is a technology to calculate the same degree of two texts, and k-nearest neighbor (KNN) algorithm is a mature classification algorithm [4]. In order to solve the automation problem of online English test paper marking, this paper studies the scoring algorithm of English test paper on the WEB online teaching platform based on these two technologies. The goal of the algorithm is to provide an automatic marking method, which can complete the marking of objective and subjective questions with high accuracy.

The article is divided into five parts. The second part is related works, which describes the latest progress in research related fields and shows the basis of research. The third part is the method, which describes the construction and related settings of the algorithm. The fourth part is the experiment, which describes the performance test of the algorithm. The fifth part is conclusion, which summarizes the whole research and proposes the future direction of the research.

II Related Works

In recent years, relevant literature and research results have been sorted out. The fields involved are mainly the latest development of online education research, as well as the application of KNN and text similarity technology. Some studies have explored the web-based online teaching platform and related technologies. Poultsakis led his team to study the application of digital learning and related tools in Greece and found that the popularity of digital learning is very low [5]. This is largely due to the backwardness of digital learning-related technologies in the region, which leads teachers to believe that the teaching effect of digital learning is poor and do not trust digital learning. Stamatios Papadakis et al. studied the situation of students using mobile phones to access a learning management system [6]. According to the survey results, there are differences in the use of the learning management system by students through mobile phones. Due to the limitations of reliability and practicality, the system is more used by students as a document library than a learning tool. Panagiotakopoulos and his team proposed a structured approach to develop an outreach plan aimed at improving the coding ability of pre-service and in-service teachers [7]. The project is a successful online teaching plan, with the actual number of classroom logins and completion rate of 70.84%. Researchers believe that this is because the design of the project is easy to use. Christianson designed a remote online voting system to help students enhance their sense of participation. The students said they had a positive experience in this way of participation [8]. Karakose and his partners studied the psychological state and Internet addiction of school administrators and teachers under the background of the epidemic, and the results showed that Internet addiction indirectly affected teachers' loneliness and happiness [9]. The research expenditure on teachers' mental health also needs attention, and it is one of the feasible schemes to reduce teachers' workload through innovative algorithms. Lavidas K et al. studied the online teaching of preschool teachers during the epidemic, and pointed out that preschool teachers use less online teaching, and they prefer real communication framework and teaching process [10]. Katsaris and his partner analyzed 42 papers related to online teaching from 2015 to 2020, introduced the theoretical and technical background of adaptive e-learning system, and emphasized the importance and efficiency of using learning style in adaptive learning process [11]. From the conclusion of this article, we can see that there is little research on automatic algorithms for marking test papers in online English teaching. From the research in the field of online education, we can see that the research of auxiliary technology for teacher's examination paper marking has received little attention and there is still a lot of research space.

Some researchers have also made corresponding explorations in KNN and text similarity detection. Zardari Za et al. have developed a detection and prevention algorithm to deal with network attacks. The algorithm is based on KNN and can distinguish abnormal nodes from normal nodes according to their behavior differences. Experiments show that the algorithm can effectively reduce latency and increase network throughput [12]. Wang and his team proposed a weighted KNN algorithm, which is calculated based on signal similarity and spatial location. They applied it to fingerprint location. The evaluation results show that the algorithm can improve the accuracy of fingerprint location [13]. In order to solve the problem of abnormal bridge health monitoring data, Lei Z and his research team proposed a KNN based bridge health monitoring algorithm. The algorithm measures the pattern distance between time subsequences according to the similarity of time series, and then selects abnormal patterns. The experimental results show that the model has certain reference value [14]. Pang and his collaborators put forward a Chinese text similarity detection method based on the semantics of feature phrases, which obtains feature phrases by replacing concepts and calculates text similarity. Experiments show that the output results are reliable [15]. Yang et al. proposed a news topic text detection method based on capsule semantic graph, which has lower time complexity than traditional detection, and the experimental data show that it has high accuracy and recall [16]. Franclinton and his research team proposed an extensible code similarity detection model with online architecture rather than local spikes. The experimental results show that the model can better maintain the academic integrity in programming [17].

Through combing the research trends in related fields, it is found that the web-based online teaching platform has been widely practiced and applied, but there is a lack of research on automatic scoring of English test papers. On the other hand, KNN and text similarity detection technology have also been applied in many fields. The research combines these two technologies in order to make contributions to the research of automatic scoring technology in the web online teaching platform.

III CONSTRUCTION OF SCORING ALGORITHM FOR TEST PAPER OF WEB-BASED COLLABORATIVE TEACHING PLATFORM FOR COLLEGE ENGLISH COURSE

A. *Web Architecture Selection and Vocabulary Matching Algorithm Construction*

The WEB-based College English course network teaching cooperation platform uses B/S architecture to send documents. The structural diagram of B/S architecture is shown in Fig. 1. This architecture has very low requirements on the equipment of the client layer. Only a normal WEB browser is required to participate in College Online English courses. Due to the great differences in the electronic equipment used by college students, it is inevitable to make mistakes when using the client mode. Therefore, the B/S architecture is the most secure [18]. In addition, the architecture has good reusability and scalability, which is conducive to the long-term use and version update of the English course online education collaboration platform [19].

After the framework of the platform is determined, the corresponding algorithm can be built. The test paper questions adopted by the WEB-based College English course network teaching and writing platform can be divided into objective questions and subjective questions. Due to the existence of standard answers to objective questions, students need to be completely consistent with the standard answers to score. Therefore, the idea of complete vocabulary matching can be used to build an objective question scoring algorithm. The judgment formula is shown in formula (1).

$$S = \frac{S_t N}{N_t} \tag{1}$$

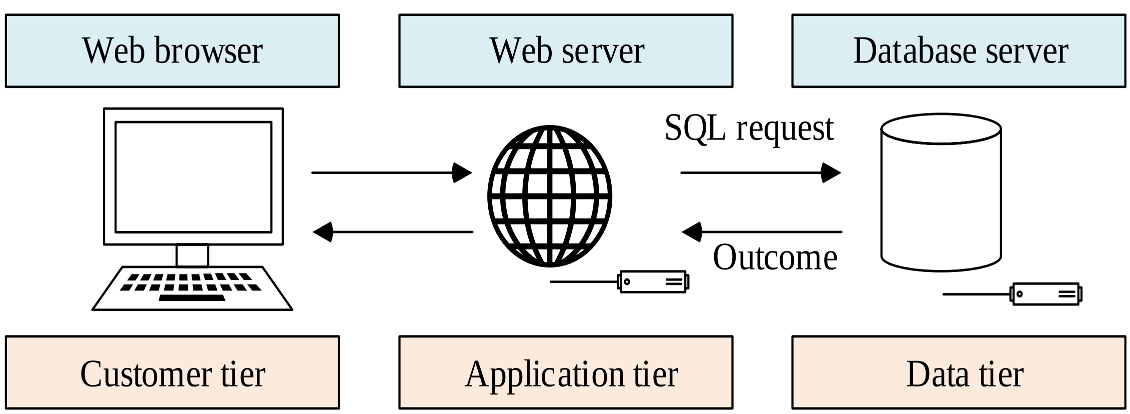

Fig. 1. B/S framework principle.

In formula (1), S represents the student's score on the question, and N represents the number of matching keywords with the standard answer, while S_t and N_t respectively represent the total score of the question and the number of all keywords. Compared with the scoring of objective questions, the algorithm of subjective questions is more complex. The reason is that both the reference answers of subjective questions and the answers of students are presented in the form of paragraphs. At the same time, the logic adopted by the two texts is not necessarily the same. There will also be differences in the keywords used by the two. It is common for the reference answers and the keywords used by students to be synonyms or superior and subordinate words (Liu M et al. 2021) [20]. The method that teachers use for manual marking of subjective questions is usually judged according to the coincidence degree of key words and reference answers in students' texts, as well as their writing logic and the purity of the overall content (Khan I u et al. 2021) [21]. The scoring algorithm design of English subjective questions on the web online teaching platform refers to the logical design of teachers' scoring, and it uses the method of prescriptive analysis to evaluate the score. Its process is shown in Fig. 2.

According to Fig. 1, the scoring logic of the algorithm is an imitation of the teacher's human scoring. On the one hand, the evaluation matches the keyword of the standard answer with the text of the student's answer, and gives the score according to the proportion of the number of successful matches in the total number. On the other hand, the text similarity between the standard answer and the student's answer is calculated, and the score is given according to the degree of fit between the two texts, and then the two scores are combined according to a certain weight to obtain the final score. In this model, the word matching algorithm adopts a two-way matching algorithm. This algorithm is an optimization of the ordinary single item matching algorithm. It can distinguish keywords from the forward and reverse directions. In this algorithm, the matching degree between a keyword and the keyword in the student's answer is calculated by the common formula (2).

$$\alpha(K_i, D_i) = {Max(K_i, K_j)} / {m_i} \tag{2}$$

In equation (2), $\alpha(K_i, D_i)$ is the ratio of a keyword to the number of characters of the current keyword. When the value is greater than the given threshold, the keyword matching is considered successful, otherwise, the matching is considered failed. K_i and K_j are respectively the number of characters of keywords in the student text when the forward matching and reverse matching are successful, while m_i is the number of characters of keywords in the reference answer. This algorithm effectively avoids the recognition failure due to the difference between the students' words and the reference answer. After the keyword matching condition is obtained, the keyword score of the question can be calculated. The calculation logic of the score of the subjective question is similar to that of the objective question. It is judged by the ratio of the total number of identified successful keywords to the total number of keywords in the reference answer. The calculation process is shown in formula (3).

$$S = S_t \frac{\sum_{i=1}^{N_t} \alpha(K_i, D_i)}{N_t} \tag{3}$$

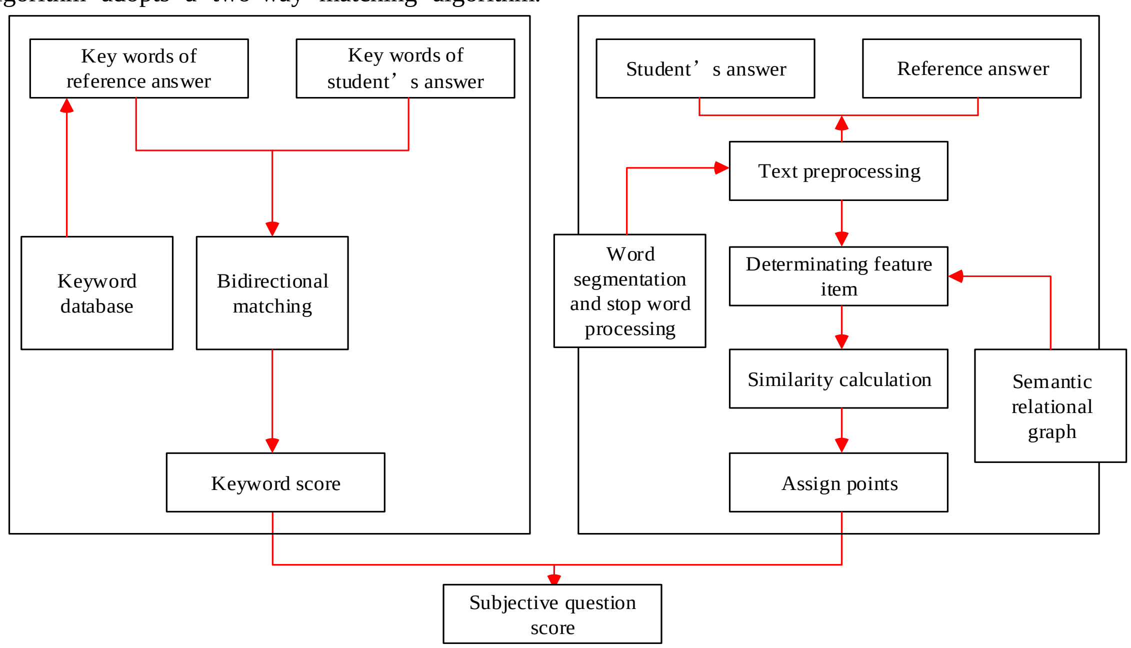

Fig. 2. Flow chart of subjective question scoring algorithm.

B. Text Similarity Detection Algorithm

According to the flow chart of subjective question scoring algorithm, the flow of text similarity detection algorithm is to preprocess student answers and reference answers, match feature vectors by combining semantic association, then calculate similarity, and finally calculate scores according to the closeness of answers. Text preprocessing mainly includes two steps: word segmentation and stop word filtering. The word segmentation tool uses THULAC as the word separator. The tool has high word segmentation accuracy and good recognition ability for professional terms. At the same time, it has good adaptability to the web [22]. Stop word filtering is the operation of filtering words such as "very" and "do" that have little effect on the actual meaning of the text, which can effectively reduce the workload of subsequent recognition and matching, save computing resources and improve speed [23]. In the subsequent feature item determination steps, the traditional feature item weight calculation does not consider the semantic problem, but the proposed vector space model takes the semantics into account when selecting feature items, so it is necessary to build a semantic association diagram. In this study, the semantic association diagram is made based on the How Net semantic knowledge dictionary, and its principle is shown in Fig. 3.

In Fig. 2, T_1, T_2, T_3 and other items are semantic topic nodes. These items are a large number of semantic hypernyms, but these items do not have hypernyms. "Sports", "biology" and other words can be used as semantic topics, while t_4, t_5, t_6 and other items are called non semantic topic nodes. These nodes belong to the hyponymy of one or more semantic topics, and may have their own hypernymic or hyponymic words, "Basketball" is the non-semantic topic node of "Sports". Based on the upper and lower semantic relations of the semantic association graph, the upper semantic relations of the semantic association graph can be expressed in mathematical form, and the expression is shown in formula (4).

$$\begin{cases} L_U(t_i) = L(t_i), U = 1 \\ L_U(t_i) =_{\cup t_k \in L_{u-1}(t_i)} L(t_k), U > 1 \end{cases} \tag{4}$$

In formula (4), $L_U(t_i)$ represents the set of semantics starting from t_i and going up the U layer, besides t_k and t_i respectively represent different semantic nodes. Based on this formula, the union of all the superscript nodes of any node can be obtained, that is, the set of the node. The expression for finding the set is shown in formula (5).

$$L_U(t_i) = L1(t_i) \cup L_2(t_i) \cup L_3(t_i) \cup \cdots \tag{5}$$

After the definition of semantic association graph is completed, it is necessary to build a semantic space vector model. The model is set as R, its dimension is set as D, and the feature vector is $\vec{t}$. Then the expression of the model and semantic feature vector is shown in equation (6).

$$\begin{cases} R = T_{\geq 0}{}^{D} \\ \vec{t} = (t_1, t_2, \cdots, t_n) \end{cases} \tag{6}$$

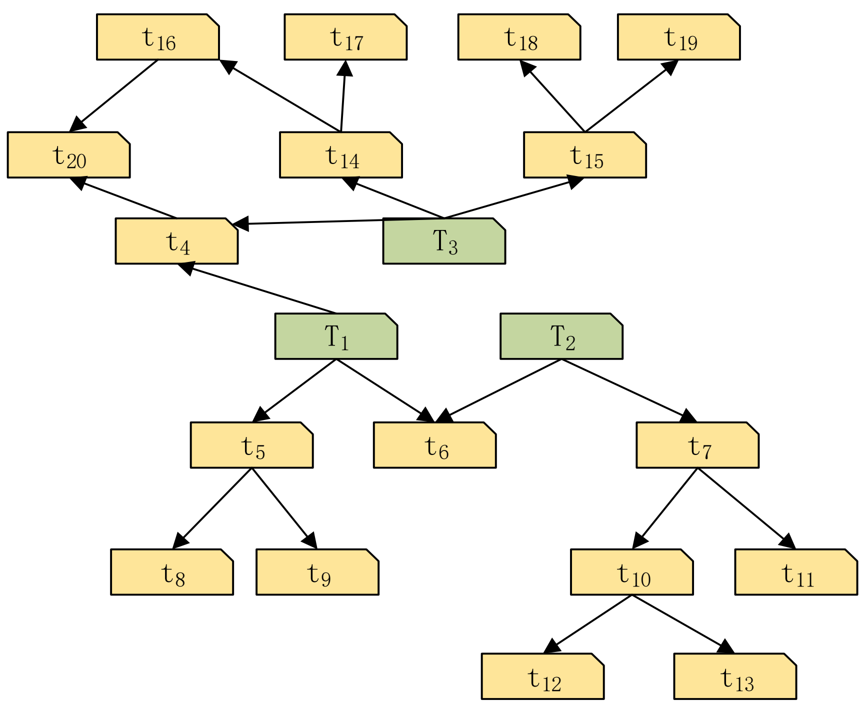

Fig. 3. Schematic diagram of semantic association.

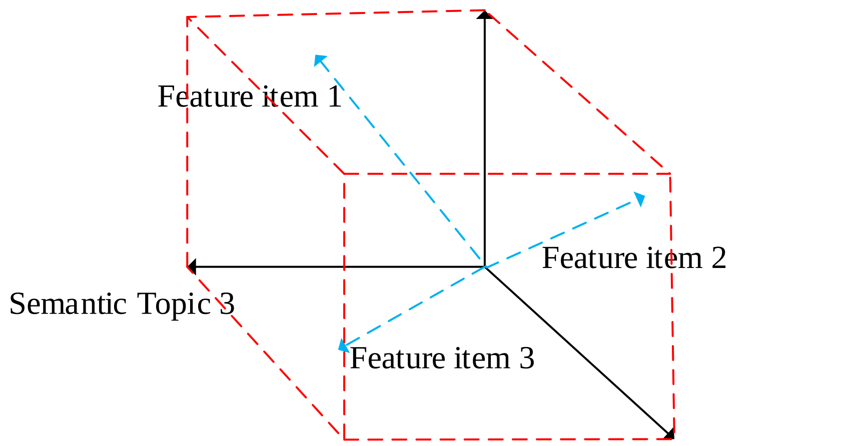

Fig. 4. Schematic diagram of feature item and semantic topic space.

The number of t_i in equation (6) is determined by the dimension, that is, $i \in \{1, 2, \cdots, D\}$, and $t_i \in [0,1]$. According to this formula, the schematic diagram of the semantic space vector model is shown in Fig. 4. Each coordinate axis in the figure represents a semantic topic. The more a feature item matches a semantic topic, the greater its value on the coordinate axis of the topic. If a feature item is related to a plurality of semantic topics, its vector will be between the two fields. The correlation between each feature item and each semantic topic depends on the weight of each vector. The higher the correlation with a topic, the higher the weight of its corresponding component.

After defining the semantic space vector model, it is necessary to quantify and express the semantic feature vector in an appropriate way. Quantification is to meet the needs of text similarity calculation, and the appropriate expression can simplify the calculation and improve the efficiency of the algorithm. In terms of quantification, the following rules are designed. First, the weight of the feature item ranges from 0 to 1. The larger the value, the better the feature item reflects the semantics. When the weight is close to 1, the feature item is considered to be basically equivalent to the semantic topic. When the weight is close to 0, the feature item is considered to be basically irrelevant to the semantic topic. Secondly, in terms of the angle of feature items, it is stipulated that the angle between synonyms and feature items not in any semantic field is 0, the angle between synonyms and hyponyms should be close to 0, and the vector angle between feature items in different fields is 90 degrees. In the aspect of feature vector representation, the occurrence times of feature items in the text and their weights in the semantic space vector model are used as variables to represent the feature vector, and the expression is shown in formula (7).

$$|\alpha| = \left|\sum_{i=1}^{n} F(t_i)\vec{t_i}\right| \tag{7}$$

In formula (7), $|\alpha|$ is the feature item vector after normalization, $F(t_i)$ is the number of times the feature item appears in the text, and $\vec{t_i}$ is its corresponding vector in the semantic space. After the feature vector is properly expressed, the text similarity between the student answer and the reference answer can be detected. Here, the vector cosine method is used for detection, and its expression is shown in formula (8).

$$SIM = \frac{\sum_{t=1}^{N} \omega_{it} \bullet \omega_{kt}}{\sqrt{(\sum_{t=1}^{N} \omega_{it}{}^2) \bullet (\sum_{t=1}^{N} \omega_{kt}{}^2)}} \tag{8}$$

In formula (8), SIM refers to the text similarity of student answers and reference answers. ω_{it} and ω_{kt} respectively represent the weight of student answers and reference answers in the t feature item. N is the total number of feature items. It can be seen that the smaller SIM, the smaller the text similarity, and vice versa. Finally, after the keyword matching degree and text similarity are obtained, the subjective questions can be scored according to their respective weights. The scoring calculation process is shown in formula (9).

$$S = (A \times S_k + B \times SIM) \times S_t,\ A + B = 1 \tag{9}$$

In formula (9), S is the final score of students, S_k refers to the score of students in keyword matching, A and B are the weights of keyword matching and text matching respectively, and S_t is the total score of the topic.

C. Subjective Item Scoring Algorithm Based on Nonlinear Classifier KNN

As a compulsory course for most majors, College English courses attract a large number of students every year, which leads to a large number of examination papers on the WEB English teaching platform [24]. In order to further improve the efficiency of subjective question marking, KNN algorithm is introduced into the test paper scoring algorithm. The data scored by word matching and text similarity algorithm is used as the training set to train the KNN algorithm. The successfully trained KNN algorithm will be able to evaluate other test papers with high efficiency. The judgment principle of KNN Algorithm in subjective question scoring situation is shown in Fig. 5. For the red circular judgment object in the figure, KNN algorithm will calculate the samples of orange Pentagram and black triangle, that is, the distance between the training sample and the judgment object, take the first k distances with the shortest distance, and then analyze the category of the corresponding K samples. The category with the largest number of samples is considered as the category of the judgment object.

Although KNN algorithm has the advantages of fast operation and no need to retrain when adding new samples, when there is difference in the number of samples or uneven density distribution, it will also lead to great error in the output results [25]. Fig. 6(a) is a schematic diagram of the output error of the algorithm result caused by the error of the sample number. As shown in the figure, when the value of K is large, although the object to be determined is closer to Y, it may still be determined as X, because the number of X is much higher than Y. Fig. 6(b) is a schematic diagram of misjudgment caused by too large difference in sample density. It can be seen that under this condition, the object to be judged is closer to Y, but the X distribution in a K finger is too dense, resulting in the number of X greater than Y.

In view of this situation, the KNN local weight correction algorithm is used to improve. The principle of the algorithm is to give a lower weight to the samples with too many and too large density compared with other training samples within the range of K value. On the contrary, a higher weight is given to smooth out the error. To describe the correction algorithm, a weight correction parameter needs to be defined, and its expression is shown in equation (10).

$$\begin{cases} \omega(c) = \dfrac{\log\left(\dfrac{AvgNum}{Num(c)} + \beta\right)}{\log(\beta + 1)} \\ \beta = \left\lfloor \dfrac{MaxNum}{AvgNum} \right\rfloor \end{cases} \tag{10}$$

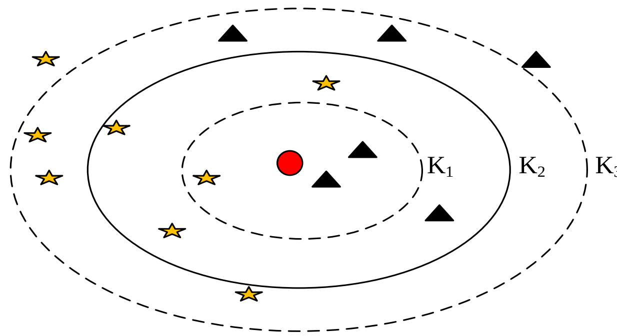

Fig. 5. Principle of KNN algorithm applied to test paper scoring.

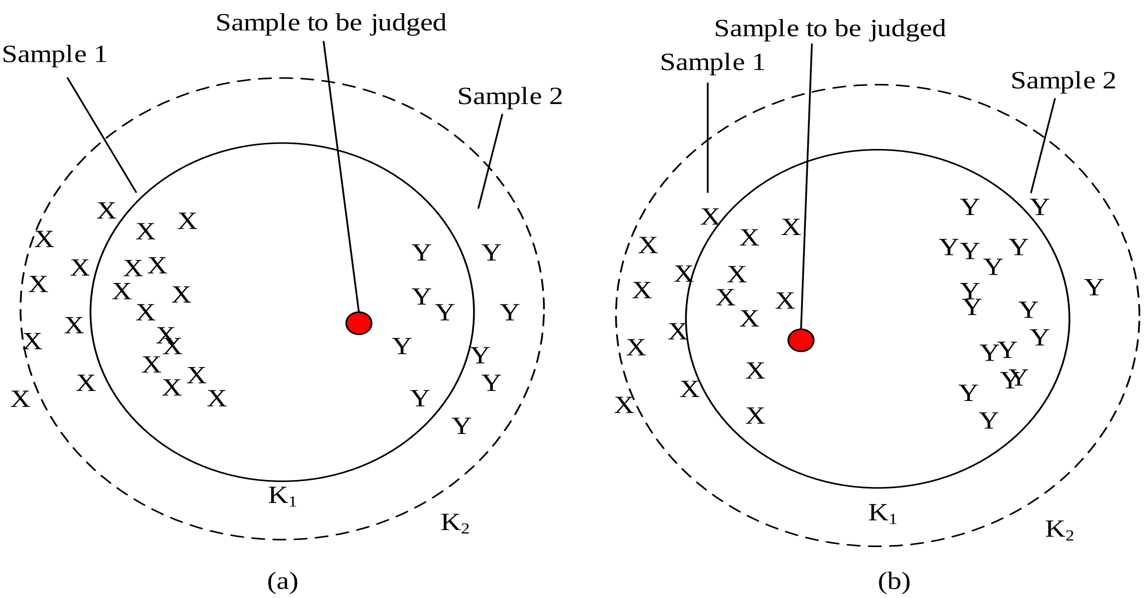

Fig. 6. Misjudgment principle of KNN Algorithm in subjective question scoring.

In equation (10), $\omega(c)$ is the weight correction parameter of the object category, β is the adjustable parameter, $MaxNum$ and $avgNum$ are the maximum number of samples and the average number of samples of each category respectively, and $Num(c)$ is the number of samples of the object category. The weight correction parameter can give different values according to the number and density of the actual training sets to smooth out this difference. The training samples with large differences in the number of samples can also enable KNN to output correct results. Finally, score one by one based on the weight correction parameters, and the expression of the final score is shown in equation (11).

$$S = \frac{\sum_{i=1}^{k} \omega(c) \bullet SIM}{k} \tag{11}$$

In equation (11), k is the nearest number, SIM represents the text similarity between the student's answer and the nearest sample, and S is the final score of the student's answer. Due to the existence of weight correction parameters, the weight of each type of sample is no longer unified as 1. Therefore, theoretically, the probability of outputting wrong results due to the difference in the number and density of samples will be greatly reduced.

IV Performance Analysis of Test Paper Scoring Algorithm for Web-based English Teaching Platform

The performance analysis of the test paper scoring algorithm of the web network teaching platform mainly includes the judgment ability of the improved KNN algorithm, the differences between the scoring algorithm and manual scoring, and the scoring time. For KNN algorithm, the selection of K value has a great impact on its performance. Therefore, the algorithm is tested under different K values. The results are shown in Fig. 7.

When the value of K is 39, the accuracy of both the improved KNN algorithm and the original KNN algorithm reaches the maximum, and then the accuracy of both algorithms begins to decline slowly. However, when K is 39, the accuracy of the improved KNN algorithm is 13% higher than that of the traditional algorithm, which shows that the weight correction parameters can significantly improve the accuracy of the KNN algorithm under the appropriate K value. Therefore, the value of K in this experiment is 39. The experiment was conducted on a WEB teaching platform based on Windows 10, which uses MySQL 5.1 database and Tomcat 6.0.33 server. In the process of correcting the actual test paper, different semantic topics may have an impact on the accuracy of the algorithm. Therefore, the common semantic topic data sets in six English tests are used to test the performance of the algorithm under different semantic topics. The performance is shown in Fig. 8.

Fig. 8(a) shows the test results of algorithm accuracy, Fig. 8(b) shows the test results of recall, and Fig. 8(c) shows the test results of F value. Under different semantic topics, the performance of the improved KNN algorithm and the original KNN algorithm shows obvious fluctuations. The improved KNN algorithm can achieve a recognition accuracy of 100% at most, while the lowest is only 34%. The highest recall rate is 0.90, and the lowest is only 0.50. However, compared with the two algorithms, the accuracy of the improved KNN algorithm is always higher than the original KNN algorithm, and the maximum difference between the two is 0.50. Except for the sixth semantic topic, the recall rate of the improved KNN algorithm is also higher than the original KNN algorithm. The results show that different semantic topics may have a significant impact on the performance of the algorithm. The web-based test paper scoring algorithm is constructed by imitating the mechanism of teacher manpower scoring. Therefore, comparing the scoring results with the teacher manpower scoring results can better evaluate its performance. The comparison results are shown in Fig. 9.

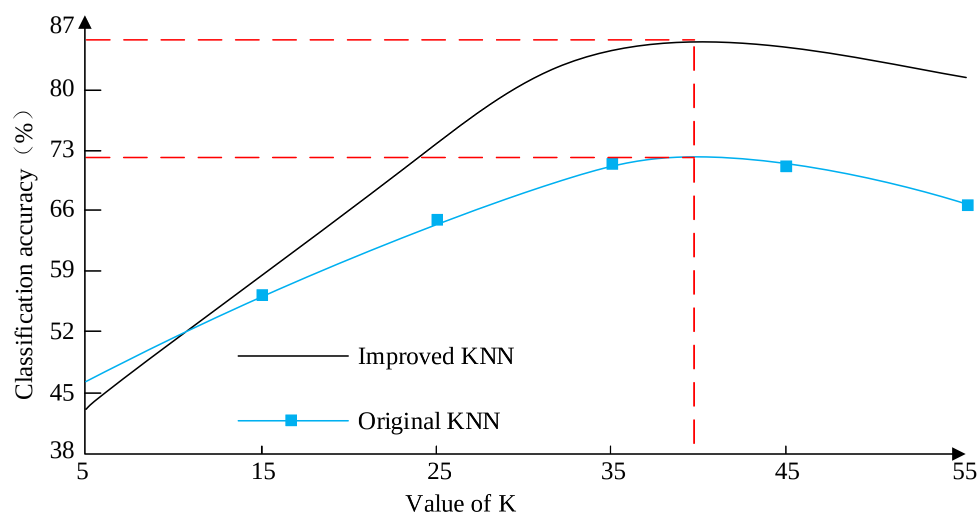

Fig. 7. Algorithm performance under different K values.

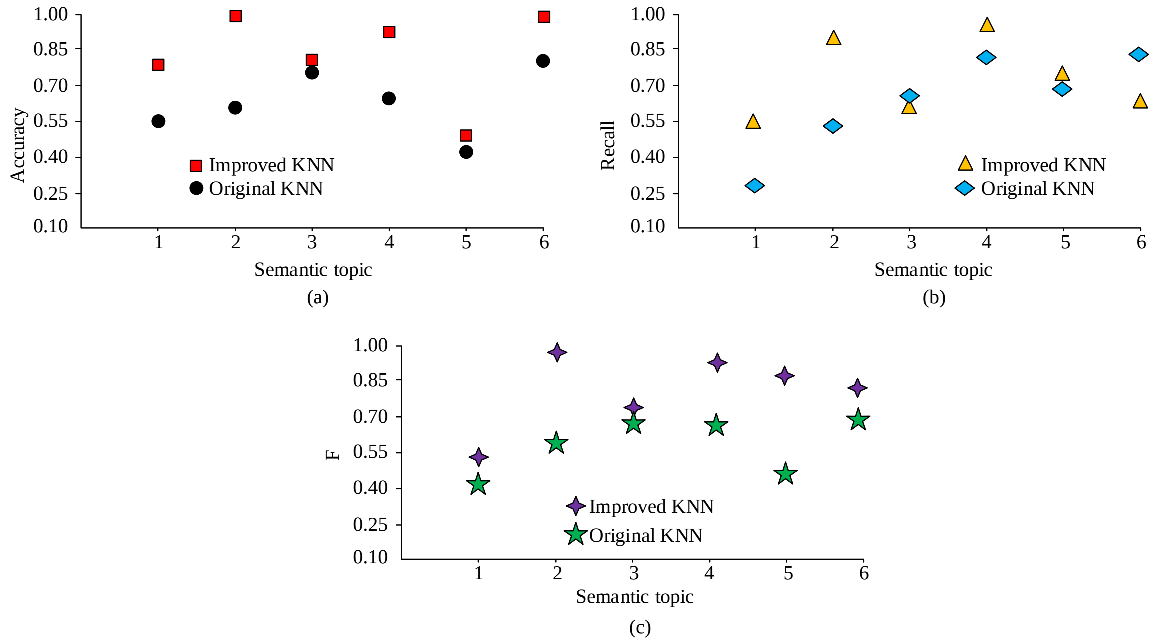

Fig. 8. Performance of the algorithm under different semantic topics.

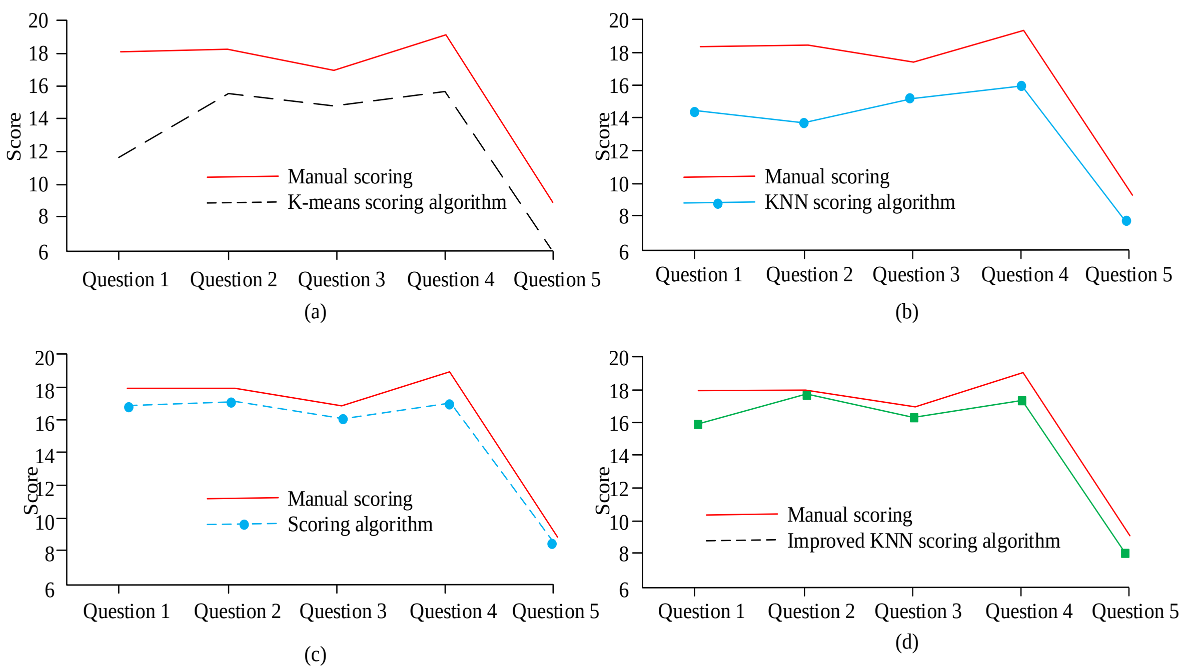

Fig. 9. Comparison of different algorithms and manpower scoring.

Fig. 9(a), Fig. 9(b), Fig. 9(c) and Fig. 9(d) are the comparison results of human scoring and K-means clustering algorithm, original KNN algorithm, test paper scoring algorithm without KNN and improved KNN algorithm respectively. Three machine learning algorithms are trained based on test paper scoring algorithm. It can be seen that the change trend of the scores of the four algorithms is basically consistent with the human scoring, which means that the four algorithms have successfully imitated the mechanism of teachers' human scoring to a certain extent, but the distance between the broken line of K-means clustering algorithm and the original KNN algorithm and the broken line of human scoring is significantly greater than that of the test paper scoring algorithm and the improved KNN algorithm, which means that the test paper scoring algorithm and the improved KNN algorithm have a better effect on the imitation of human scoring. In order to further study the performance differences of several algorithms, the difference between them and the human score is described with pictures, as shown in Fig. 9.

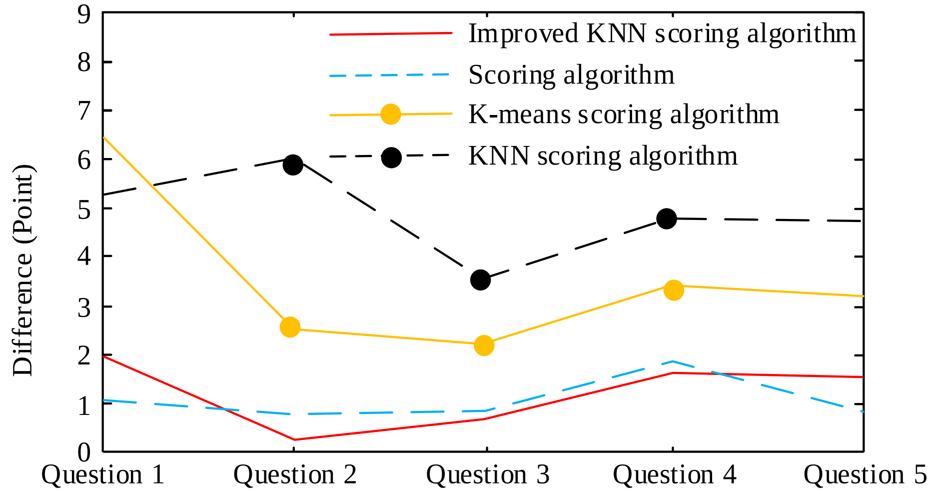

Fig. 10. Difference between different algorithms and manpower scores.

It can be seen from Fig. 10 that the difference between the scoring algorithm and the improved KNN algorithm and the manpower score is very low, ranging from 0 to 2 points, and the difference between the two is also small, less than 1 point. The difference between the other two algorithms is significantly greater, and the difference with the manpower score fluctuates between 2 and 6.5 points, which indicates that the scoring algorithm has a good imitation effect on the manpower score, while the improved KNN algorithm has a good learning effect on the scoring algorithm, and the learning effect of the original KNN and K-means clustering algorithm is inferior to the improved KNN algorithm. In addition to teachers, students often evaluate the fairness and accuracy of the automatic scoring algorithm. With the student feedback system of the Web English teaching platform, we studied and collected the proportion of misjudgments reported by students in multiple test papers through the platform under several scoring algorithms, and evaluated the performance of the algorithm from this angle. The results are shown in Fig. 11.

By comparing several algorithms, it is found that the proportion of students' reported misjudgment under the original KNN algorithm is the highest in each test paper, the highest is 12.5%, and the lowest is 7.8%. The student report misjudgment ratio of the scoring algorithm and the improved KNN algorithm is always lower than that of the original KNN algorithm, of which the highest is 10.8% and the lowest is 7.3%. According to the data statistics of the web platform, the average student report misjudgment ratio of teachers' manual correction is 5.7%. The algorithm is very close to this standard, which means that the evaluation accuracy of the algorithm is also high from the perspective of the evaluated students. Finally, the time consumed by different algorithms for the same test set is studied and counted. Since the original intention of the scoring algorithm is to improve the efficiency of the Web English teaching platform, the algorithm time is an important evaluation item. The results of time-consuming evaluation are shown in Table I.

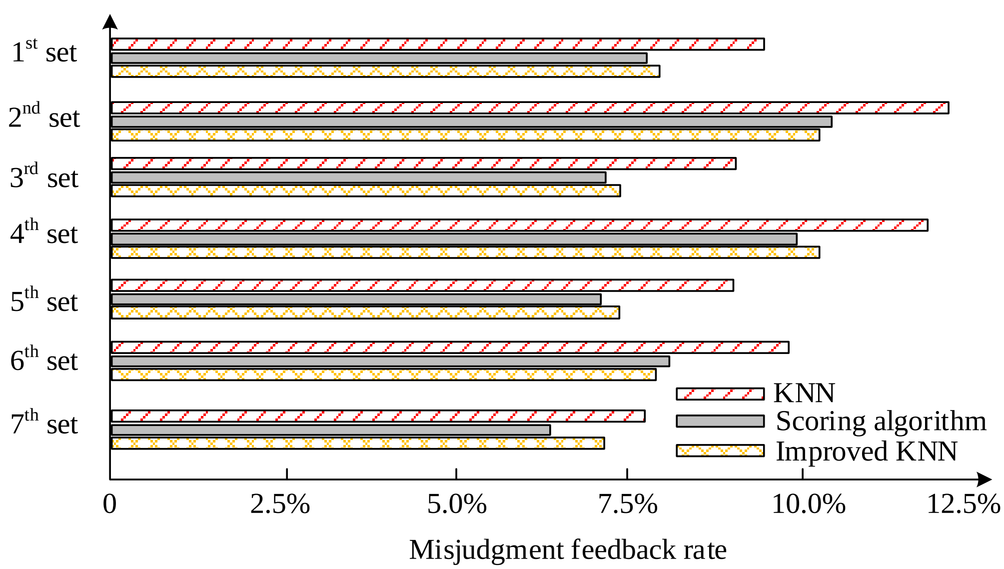

Fig. 11. Proportion of students' report misjudgment under different algorithm.

TABLE I. ALGORITHM TIME-CONSUMING DETECTION

\		Scoring algorithm	Improved KNN	KNN
Time consuming (s)	Set 1	177	124	137
	Set 2	130	105	100
	Set 3	212	108	114
	Set 4	97	63	59
	Set 5	133	93	91

Table I describes the time-consuming of scoring three algorithms in five different sets of test papers. The time-consuming of the original KNN algorithm and the improved KNN algorithm is always less than that of the scoring algorithm for each set of test papers. The difference between the time-consuming of the improved KNN algorithm and the scoring algorithm is up to 104 seconds, indicating that the machine learning algorithm is stable in judging speed than the scoring algorithm without machine learning. Comparing the original KNN algorithm with the improved KNN algorithm, it is found that the time-consuming of the two algorithms is relatively close, and they have their own advantages and disadvantages in different test papers, which shows that the improved KNN algorithm is similar to the original KNN Algorithm in terms of calculation speed.

V DISCUSSION

The English grading algorithm based on KNN and text similarity is constructed. The algorithm is divided into two parts: objective question scoring and subjective question scoring. Due to the inconsistency between students' answers and reference answers, it has been difficult to use automatic algorithms to completely replace teachers' manual scoring in the subjective scoring of English test papers. The algorithm's ability to judge the text similarity of different semantic topics has been tested. The results show that the proposed algorithm can achieve the highest recognition accuracy of 100%, and the highest recall rate is 0.90. Even for the performance of the method itself, the improved KNN structure in the algorithm is obviously superior to the ordinary KNN model. In the test of actual English test paper data, the algorithm is used to compare with the teacher's manual grading. Compared with other similar algorithms, the score given by the proposed algorithm is significantly closer to the score of the teacher's manual score, and the maximum difference between the scores is no more than two points. Further research on the misjudgment rate reported by students, shows that the proposed algorithm has the lowest misjudgment rate, which is the closest to the misjudgment rate of teachers' manual grading. In the current subjective question scoring algorithm applied in the online learning platform, the collected data of false judgment rate is often more than 13%. Therefore, the research believes that the proposed algorithm has higher scoring performance in comparison, and can be applied to the English test paper scoring on the WEB online learning platform.

VI CONCLUSION

The WEB-based College English course network teaching cooperation platform has broadened the channels of College English teaching, so that students and teachers can carry out English teaching activities more conveniently and efficiently. In the online examination of the WEB College English teaching platform, the scores of test papers, especially the subjective questions, are often scored by teachers' manpower, which is no different from the efficiency of traditional offline teaching. Therefore, this research designs a test paper scoring algorithm based on the College English teaching platform combined with the improved KNN algorithm. The performance test results show that the algorithm performs well in the similarity between the scores and the scores of teachers' manpower, The lowest score difference between it and the teacher manpower score is only 0.4 points, and the highest is only 2 points. In addition, the algorithm has outstanding performance in the classification accuracy of different semantic topics. The accuracy of some semantic topics reaches 100%, and the accuracy of all semantic topics is higher than the traditional KNN algorithm. In terms of the time-consuming of the algorithm, the minimum time-consuming of the algorithm in the experiment is only 63 seconds, which is significantly faster than the human scoring speed. According to the test results, the algorithm can correct the objective and subjective questions of the online English teaching test paper with the accuracy close to that of human marking. Its application can effectively reduce the workload of teachers and improve efficiency. At the same time, the algorithm has the potential to be applied to other subjects. The imperfection of this study lies in the calculation speed. The improved KNN algorithm is not much different from the traditional algorithm. Therefore, on the basis of this study, how to improve the speed is the next research direction.

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