Continual Construction of Adaptive Learning Model for English Vocabulary Using Machine Learning and Virtual Reality

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Abstract: An adaptive learning model for English vocabulary through a machine learning is proposed in this paper. The four main types of user information, including basic student information, quiz information, course video viewing information, and forum interaction information, are processed through feature engineering, and a better model on sparse data is proposed through comparison on different models, and the prediction accuracy of the model is improved through natural language processing techniques, to achieve feedback on user learning efficiency through user data and provide teachers and students with the corresponding teaching and learning suggestions for teachers and students. It is found that the quiz information has more influence than the course video viewing information, and the accuracy is improved by about 3% compared with TF-IDF after introducing word embedding. The use of mobile for English learners to learn to read in a fragmented learning context enables targeted training in weak areas of English reading, thus improving different aspects of learners' reading skills.

Keywords: machine learning; English vocabulary; adaptive learning model, Virtual Reality
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1 INTRODUCTION

Compared with traditional learning methods, the biggest advantage of online learning is that it breaks through the limitations of time and space, allowing people to learn anytime and anywhere through Internet terminals, but there are still certain shortcomings in online education. Online education lacks the learning environment and teacher-student interaction of traditional education, and it is more through the active learning of students, which is not able to understand students' learning status and thus provide targeted guidance. Static teaching resources piled up online education approach and can not meet the development of modern education needs. Personalized learning means that through a comprehensive assessment of each learner, the strengths, and weaknesses, and even habits and preferences of the learner are discovered, and then the learning content and learning methods are customized for the learner to help the learner learn and expert knowledge better [20]. We focus on the differences of learners and truly tailor our teaching to their needs in a personalized way. Then a personalized online learning system needs to do two things, one is to discover the differences of students, and the other is to customize the learning process according to the differences.

Adaptive learning has been proposed for many years to improve the quality of education through data technology. At a micro level, Virtual Reality (VR) technology with adaptive learning is the process of assessing each student to identify strengths and weaknesses, and even habits and preferences, to provide each student with personalized learning content and methods to help them learn and master their knowledge. Due to the differences in learners' personalities, past educational backgrounds, study habits, and ages, each learner has his or her own learning pace, and a personalized learning system needs to provide instructional methods and content that meet the needs of the learners. Therefore, an online learning system equipped with adaptive learning should do two things: first, discover the differences among students, and second, develop different learning processes based on those differences. Based on everyone is learning style, a system with adaptive learning services usually continuously challenges learners with different levels of difficulty and gradually induces them to learn effectively at their own pace [14].

The problem of updating the speed of word resources has been solved with the help of crawlers and natural language processing technology. The remaining problems can be divided into two parts: how learners can choose the right application for themselves, and how platforms can solve the problem of catering to users' individual needs and reducing the number of choices they must make. The problem of difficult choices caused by the proliferation of resources does not only appear in the field of education, with the increasing speed of computer computing, as well as the continuous development of artificial intelligence, but we have also enjoyed the convenience of intelligent recommendations. For example, Pinterest image social sharing site, using a graph-based random walk algorithm, the user's behavior data into a point of the access network graph, filter, and recommend to the user is most likely to be interested in the image. The same is true for learning sites, where MU.com recommends courses taken by similar users and other similar courses based on learners' learning records, subjects of interest, and learners' social network connections.

2 CURRENT STATUS OF RESEARCH

Although corpus-based statistical methods are simple and feasible, the effective corpus so far is very limited, and in addition, the patterns of sentiment words appearing in the corpus are very difficult to be generalized [9]. Sentence-level sentiment analysis is mainly used to determine whether a sentence contains sentiment information and to determine the sentiment category contained [16]. Bykov et al. used a Bayesian classifier to discriminate whether a sentence contains sentiment information and then used unsupervised learning methods to classify the sentiment of text containing sentiment information and to obtain the sentiment polarity [3]. Agrawal proposed to use fuzzy set theory to level sentiments into three categories, i.e., positive, neutral, and negative [6]. Ma modeled sentences based on Sentiment Treebank using a deep recurrent neural network approach and achieved significant improvements in both dichotomous and quintuple classification of sentences, respectively [1]. In addition, some studies have been conducted by domestic researchers [12]. Klašnja-Milićević proposed a triple syntactic structure to determine the sentiment tendency of sentences [14]. Firstly, the inter-sentence element dependency modification relations were introduced based on the lexical method, and then these relations were classified at three levels according to the proximity, and the tree sentence representation structure was introduced, and finally, the tree representation structure and the triple syntactic structure were combined to determine the calculation order.

IRT models are since the learning efficiency of learners remains constant over time, but logically the knowledge state of each learner is continuously changing because each learner increases knowledge due to online or offline learning, and has different rates of knowledge forgetting due to different levels of commitment to different content [10]. The TIRT (Temporal IRT) model extends the traditional IRT model by introducing a stochastic process in the temporal dimension [19]. Cameron et al. argue that fragmented learning is more applicable to the smaller granularity of knowledge and has weaker support for systematic learning, which can only be supplemented and augmented as systematic learning. From this, we can easily find that there are only a few studies on fragmented learning in China, and it is still in the stage of continuous research exploration. Most scholars only conduct theoretical discussions on the application of fragmented reading in university English teaching, and there are relatively few empirical studies [2]. The development dynamics, pros and cons, and positioning of fragmented research need to be improved, and the theoretical level needs to be solidified, and the application level needs to be combined with the characteristics of fragmented learning to do the corresponding software development [5]. Research on adaptive learning systems has evolved from a focus on learning content and adaptive navigation of learning content presented in the beginning, to later in-depth exploration of learner models while incorporating educational psychology factors such as learning styles into them and then to a gradual improvement to personalized learning support services such as tapping into learners' personalized learning needs [11].

Adaptive learning systems are different from traditional e-learning in that traditional e-learning systems do not pay attention to individual differences of learners and only provide the same learning resources and strategies, which can easily cause cognitive overload and network disorientation of learners; while adaptive learning systems dynamically present appropriate learning resources and learning activities based on learner characteristics and learning needs in the process of mobile fragmented learning. In contrast, adaptive learning systems present appropriate learning resources and learning activities based on learners' characteristics and learning needs in the process of mobile fragmented learning, thus stimulating learners' motivation, cultivating learning autonomy and improving learning efficiency. Although current adaptive learning systems have personalized features, many of them are mainly based on the judgment of learners' current knowledge level and then filter the learning resources suitable for the current level, without fully considering the different needs, learning preferences, and learning contexts of learners. Therefore, in the research of adaptive learning systems, the key lies in the establishment of learner models and the knowledge recommendation and service customization based on the established learner models. However, in the past, a single method was used to construct learner models, which often ignored the variability of feature terms and easily resulted in unsatisfactory recommendation effects.

3 ANALYSIS OF ADAPTIVE ENGLISH VOCABULARY LEARNING MODELS FOR MACHINE LEARNING

3.1 Improved Machine Learning Algorithm

Machine Learning is a discipline that studies how to use machines (computers) to simulate human learning activities and is a way for computers to use data rather than program instructions to acquire new knowledge and skills and to reorganize existing knowledge structures for computers to train through the processing of data. The purpose is to transform the process of human thinking and induction of experience into the process of computer training a model by processing and computing data [7]. Therefore, machine learning is like the process of human thinking experience, but the computer can consider more situations and perform more complex calculations. In a practical sense, machine learning is a method of using a data set to train a model and then applying the model to make predictions on an unknown data set.

Unlike some other statistical learning methods, the decision tree construction process does not rely on domain knowledge; it uses an attribute selection metric to select the attributes that best classify the data points into different classes. The construction of a decision tree is to determine the filtering attributes by the selection metric to construct the topology between the individual feature attributes. The most critical step in the construction of a decision tree is attribute splitting. Attribute splitting is the process of constructing different branches at a node according to the different divisions of a feature attribute, intending to make each split subset as pure as possible. High purity means that the items to be classified in a subset of splits belong to the same class as much as possible [6]. Plain Bayesian is a classification method based on Bayes' theorem and the assumption of conditional independence of features. In probability theory and statistics, Bayes' theorem expresses the probability of an event occurring, and the method for determining this probability is based on conditional prior knowledge associated with that event. And the process of probabilistic inference using the corresponding prior knowledge is Bayesian inference.

The conditional probability is the probability that event A will occur if event B occurs. It is usually denoted as P(A|B). It can be shown in Equation (1).

$$P(A|B)=\frac{P(A\cup B)}{P(A)} \tag{1}$$

Each node in the decision tree is considered as a candidate for pruning, and the subtree rooted at this node is removed to turn it into a leaf node, and then the node is removed or not based on the classification error rate to the validation set. In this method, the data set is divided into two data sets, one used as the training set to generate the decision tree and one used as the validation set to evaluate the classification accuracy of the pruned decision tree. REP is one of the simplest posts hoc pruning methods currently available, and its computational complexity is linear, which can improve the predictive classification ability of the decision tree for unknown new examples. However, the REP method is not suitable for use with a small amount of data, because branches with characteristics present in the training dataset are pruned, which can result in over-pruning. The pessimistic error pruning (PEP) method is one of the more accurate of the current decision tree post hoc pruning methods and it does not require a separate pruned dataset, which is advantageous for problems with small datasets and its time complexity is calculated linearly with the number of non-leaf nodes in the unpruned tree. PEP is the only post hoc pruning method that uses a top-down pruning strategy, which also leads to over-pruning problems.

Let c be the category of the corresponding sample and x be the feature vector of the corresponding sample. Based on Bayes' theorem, if we want to predict the label c of the sample based on the given feature vector x, it can be described as equation (2) and equation (3).

$$c=\arg\min P(\mathrm{c}|x) \tag{2}$$

$$P(\mathrm{c}|x)=\frac{P(P(\mathrm{c}|x)\cup P(\mathrm{c}))}{P(\mathrm{c}|x)} \tag{3}$$

So, a key problem for Bayesian classification to obtain P(c|x) translates into estimating the prior P(c) and the corresponding class conditional probabilities P(x|c). Estimating the category conditional probabilities generally establishes the shape of the probability distribution of the sample based on prior knowledge of the problem and then performs parameter estimation based on the training sample [20]. The common probabilistic model training refers to parameter estimation, which is generally performed using the great likelihood method. Since to estimate the category conditional probability P(x|c) it is essentially a more difficult problem to obtain its joint probability distribution, especially when the number of samples is insufficient. The plain Bayesian classifier simplifies the problem by assuming that the attribute conditions are mutually independent and can be represented by equation (4).

$$P(\mathrm{c}|x)=\frac{P(c)}{P(x)}\prod_{i=1}^{n}PP(\mathrm{c}|x) \tag{4}$$

In practical problems, often due to insufficient sample information, if the category conditional probabilities are estimated by frequencies, there will be some conditional probabilities of zero, which is usually also handled by smoothing (smoothing), as shown in Figure 1.
In the above convolutional operation, the model can learn local semantic information at the unit of every k-word directly in the utterance. Next, the model aggregates the locally significant information in the convolutional hidden sequence h using the p-dimensional maximum pooling operation, thus obtaining a global-level hidden sequence.

$$h_i^{cp}=\min\begin{bmatrix} h_{i+p-1}^{c} \\ \dots \\ h_{i,-1}^{c} \end{bmatrix} \tag{5}$$

During testing, the TACNN model can predict the inherent difficulty properties of an input reading comprehension problem based on its textual content. By quiz-dependent training objectives, the TACNN model learns difficulty differences from many question pairs, eliminating the error present in the computed difficulty so that the difficulty learned is based on the semantic level of the text, e.g., the complexity of the words, etc. Further, from a test evaluation perspective, the quality of the test papers can be assessed if the difficulty value of each of the questions is predicted in advance.

$$\partial_1\|c\|^2\leq\int_{t_0}^{t_0+T_0}\left|S^T(\tau)\mathrm{c}\right|^2 dv(\tau)\leq\partial_2\|c\|^2,\forall_{t_0}\geq 0,c\in R^n \tag{6}$$

This model applies to the working state in the network environment, and will not affect the solution of the whole problem due to the decision error or data anomaly of one or several individuals. Second, the group has self-organization. Everyone in the group can communicate with each other indirectly for information transfer and cooperation, so everyone can change the environment.

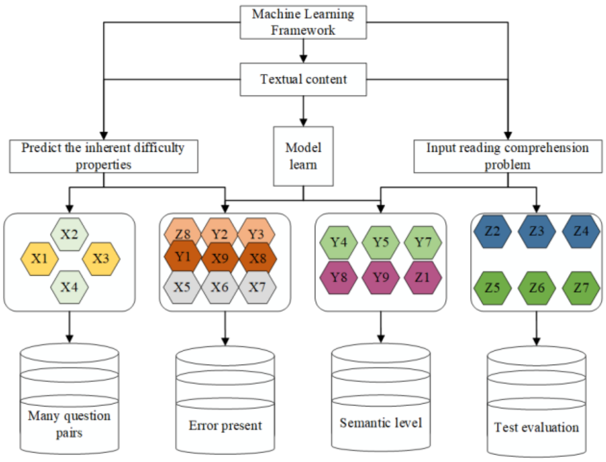

Figure 1: Improved machine learning algorithm framework.

The complex behaviors exhibited by the group are formally reflected through the intelligence of the individual interaction process, so the group has self-organization. Group intelligence is applied in educational settings, where individual learners learn specific points of knowledge with certain rules for their abilities and the behaviors they follow, and where indirect communication between individual learners is possible. Thus, groups present complex behaviors, or group intelligence as it is called, that have great reference and application value for new learners. The findings of group intelligence can be used in the teaching process to improve teaching methods, update teaching contents, and share learning strategies to achieve the purpose of helping learners optimize the learning process and improve teaching efficiency, as shown in Figure 2.

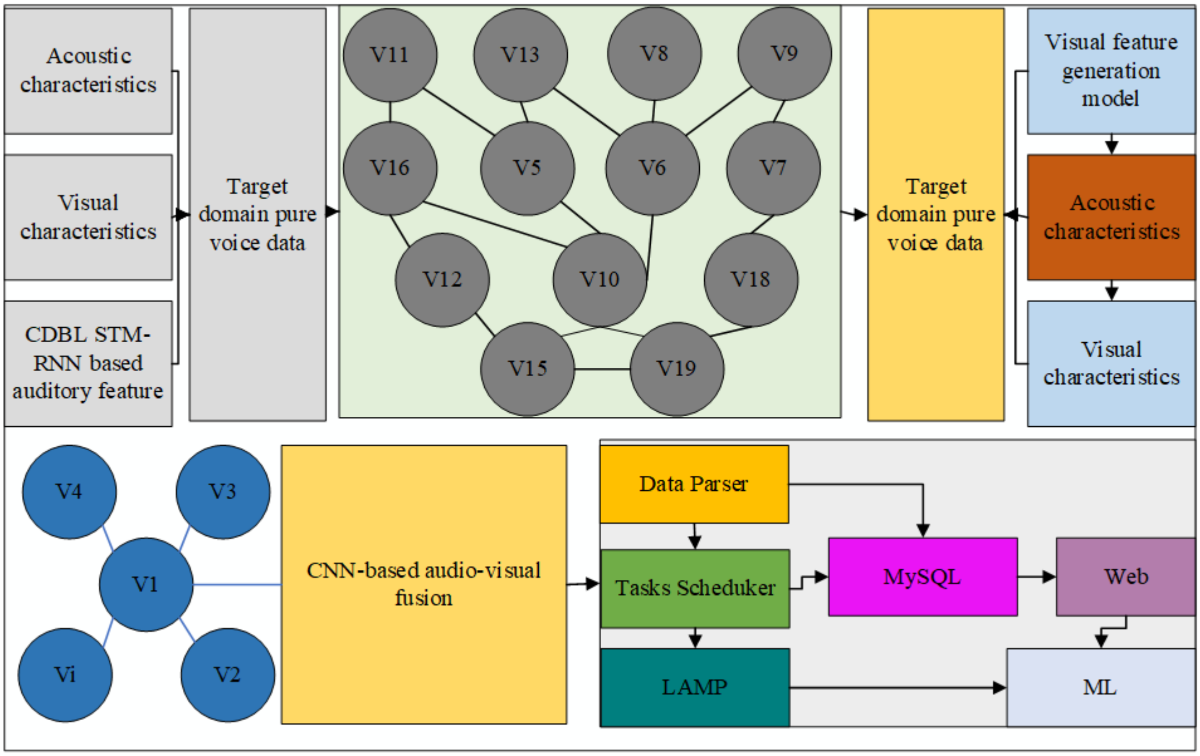

Figure 2: Two structures of formula graph network FGN.

We extracted from the raw data the last of those students who completed the entire course, i.e., learners with composite scores, and when combined with the previous distribution of students' composite scores, we labeled each valid learner as efficient, average, or inefficient accordingly. Raw records containing anomalous data will be discarded in our data filtering. For systemic reasons, there are also cases where some users have the same learning behavior but different composite scores, which are also removed in the data cleaning [16]. We assume that the final composite score can approximate the learning efficiency of the learners, because the composite score is a scoring system summarized by the MU platform based on a large number of course experiences, which can evaluate the learning efficiency of the learners in a more professional perspective, in addition, we know that the composite score is composed of several factors, including the performance of the quiz, the teacher's evaluation and the mutual evaluation of the learners. These factors also provide a good indication of the learner's learning status.

$$ {}_{a}^{G}D_{t}^{v}f(t)=\lim_{h\to 0}\frac{1}{h^{v}}\sum_{m=0}^{\left[\frac{t-a}{h}\right]}(-1)^{m}\frac{\Gamma(v+1)}{m!\Gamma(v-m+1)}f(t-mh) \tag{7} $$

$$ \frac{\partial L}{\partial a}=\sum_{i=1}^{n}[y_{i}-\frac{\exp(a+\sum_{j=1}^{m}x_{ij}\beta_{j})}{1+\exp(a+\sum_{j=1}^{m}x_{ij}\beta_{j})}]=0 \tag{8} $$

By mapping the original words to a low-dimensional space, not only the dimensionality of word representation is reduced, the similarity between words can be obtained based on the relationship between word embedding vectors. The reason the mathematical relationship between the mapped word embedding vectors can express the semantic relationship is that in the language model, the linguistic context Context(x) where the words are located is similar, similar words will have similar linguistic context in general.

3.2 English Vocabulary Adaptive Learning Model Design

There are many definitions of adaptive learning, and the broad definitions mainly classify learning into mechanical learning, demonstrative learning, and adaptive learning based on the different learning contents and ways. In contrast to the first two types, adaptive learning can give full play to the independent initiative of learning, and in the process of independent learning, learners discover, summarize, and reflect, and solve a series of problems in an autonomous way. With the development of technology, adaptive learning now usually refers to the use of digital learning platforms, which provide learning support services for learners and develop learning strategies according to the individual differences of learners, to push adaptive learning resources that are close to the individual needs of learners, which is a two-way interaction between learners and their surroundings. Adaptive learning refers to a personalized learning approach in which the system intelligently determines the current level of the learner by tracking the learner's behavior in the learning process to provide appropriate learning resources.

Independent students like to read independently and prefer reading contents related to natural science; in reading, they pay more attention to the contents related to the purpose of reading and like to grasp the main points of the article analytically; in terms of perception, they are often not easily influenced and disturbed by the surrounding environment and external factors; they are more independent, like to learn and think independently, are good at finding problems, and can reorganize the knowledge taught by teachers or learned from books into their knowledge. They can reorganize the knowledge taught by teachers or learned from books and turn it into their knowledge.

Field-dependent students prefer people- and society-related texts and group learning; they are easily influenced by the integrative thinking mode, and most of them are accustomed to identifying and examining texts word by word and sentence by sentence, reading more carefully and grasping the details of texts better; in terms of perception, they are often easily disturbed by the external environment. However, they are happy to learn in a collective situation, and in the collective, they are more submissive in terms of field dependence, can get along with others, and like to help others. They are also susceptible to cues from others, need more feedback, have homework goals and lessons explained in detail, and learn less actively. They prefer a non-analytical, generalized approach and therefore have difficulty in distinguishing the components and factors of things in complex situations, as shown in Figure 3.

It is difficult for learners to find the appropriate learning resources quickly and accurately from the huge number of resources, so the adaptive learning resource recommendation app described in this paper is mainly to solve this problem. By collecting the characteristics data of learners in the learning process and combining the three-dimensional characteristics of reading resources, we apply the decision tree ID3 algorithm to make adaptive resource recommendations. The back-end framework of the system's Web server is based on ASP.NET WebAPI, which provides a framework for HTTP services, using methods such as GET, POST to Request or Response requests, or return media types to provide Web services for the mobile side. The client uses the HTTP protocol to access the network, working principle: the client sends HTTP requests to the server, the server receives and parses the request information and returns the corresponding data content, then the client parses and processes the data and presents it [13]. The English fragmented reading resources adaptive recommendation App accesses the network with the method of HTTP URLConnection(), using a computer in the campus network (LAN) as the server, so it only needs to get an instance of HttpURLConnection, new out a URL with the IP of this computer and a specific port number, and pass it into the target network object. In the data interaction between the client and the server, the GSON open-source library provided by Google is used to parse the JSON data for formatted data transfer over the network.

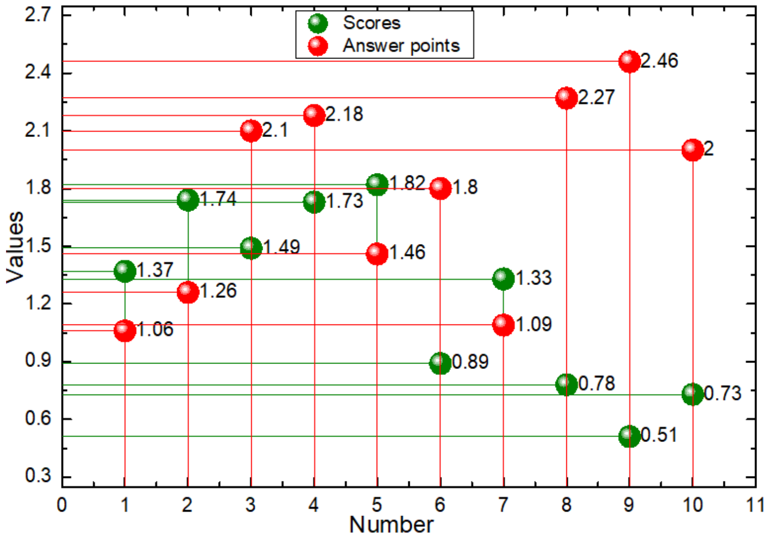

Figure 3: Cognitive style test scores.

The implementation of intelligent recommendations for adaptive learning platforms is an extremely complex achievement that requires unique learning solutions customized for learners and constantly revised to adapt to the individual needs of learners based on changes in the dynamic development factors inherent to users, such as the increase in the cognitive level of learners. Many e-commerce platforms and video sites have already achieved remarkable results through recommendation technology, which has served as a model for us. At present, common recommendation models include association rule-based recommendation, collaborative filtering recommendation, and hybrid recommendation. The first two algorithms are more similar. The first one looks for the similarity between users and users to find out the resources that similar learners have studied to recommend to the target learners, which can help learners with different professional backgrounds or even different abilities to personalize the recommended learning resources. The second algorithm calculates the similarity between different resources, predicts the ratings of similar resources with high similarity based on the target learners' ratings of existing resources, and recommends some similar resources with the highest ratings to users. However, it is obvious that this kind of recommendation is less diverse and is generally suitable for small recommendation systems. The third type, model-based collaborative filtering algorithm is the most mainstream type of collaborative filtering at present, using the idea of machine learning to model the problem of correlation between learner features and resource features, mainly using clustering algorithms, classification algorithms, matrix decomposition, neural networks, hidden semantic models, etc., as shown in Figure 4.

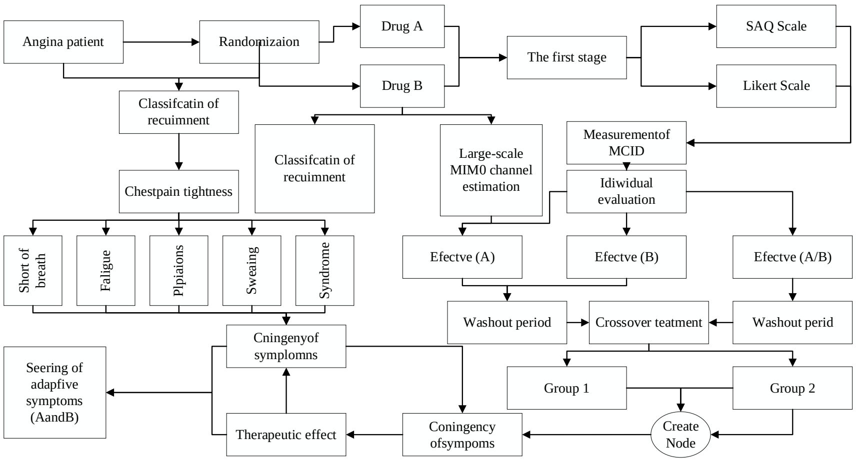

Figure 4: Flowchart.

In the previous paper, we have discussed the collaborative recommendation mechanism to mine learning partners to recommend raw words to users, but when new users use the system or when the interaction data between users and the platform has not accumulated to a certain amount, such a recommendation function cannot be realized or is of no practical value even if it is realized [18]. Therefore, to solve the problem of the "cold start" of the system, in addition to similar user recommendations, we also adopt the practice of mining the co-occurrence of words and similar words to achieve a mixture of word recommendations. The experimental corpus is trained by the word2vec model of the Gensim56 toolkit in python. Finally, the trained model is used to output similar words of words. It is easy to train word vectors in Gensim, save the trained model and load it, and call the most_similar () method to get similar words.

The above basic features describe the characteristics of individual words or symbols, but this paper considers the influence of the combination phrases of multiple words on the sentiment tendency of sentences, considering the contextual occurrence of negation words and degree adverbs. Therefore, based on the basic features of the text, according to the lexicality of the words before and after the sentiment words, which includes a total of 6 pattern combinations, and develop the corresponding formula for calculating the sentiment polarity value for each combination pattern. In this paper, we do not normalize the features of each category in the process of basic feature extraction, and the size of the features of each category may vary greatly, for example, the syntactic features of this paper may range from 0 to 100. But the corresponding word vector features are numbers between 0 and 1. Therefore, the fusion of these features without normalization may result in features with too small values not working.

4 ANALYSIS OF RESULTS

4.1 Machine Learning Algorithm Performance Results

The source of the test dataset in this paper is 120 texts selected from four other English textbooks that are different from the training dataset, including 40 texts at each of the three levels of difficulty: middle school (two difficulty levels), high school (two difficulty levels), and college (two difficulty levels), and 20 texts at each difficulty level of each level. The quantitative indicators of the test data set must be the same as those of the training data set, namely Total Words, Families, PETS 1, Baseword 1, PETS2, Average sentence length, and PETS 3, Number of Clauses, and 6 levels of difficulty: Junior-middle, Junior-high, Junior-middle, Senior-high, College-1, and College-2. Some of the data are shown in Figure 5.

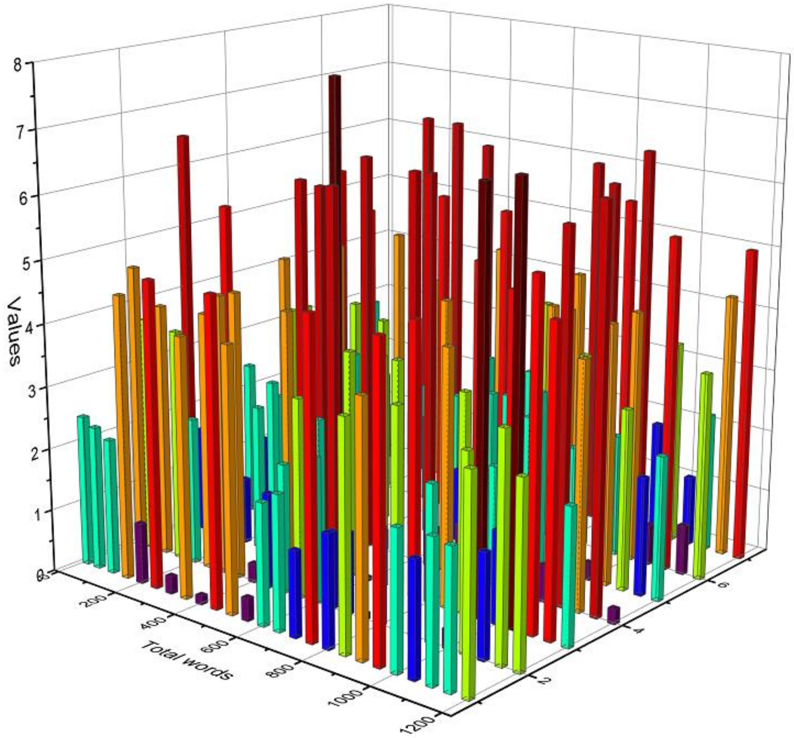

Figure 5: Test data.

In the experiments discussed in the previous section, we manually examined most of the misclassified examples of both models. We found that most of the misclassified learners were difficult to classify manually even in a manual manner. For example, in our processed dataset, one learner had a final score of 92, which is already in the better part of the group with an overall score of 100, yet this learner had only one test participation record and a recorded score of 75. The model ended up misclassifying the learner as an average learner. However, due to the limited scope of the data available on the online education platform, it appears that the learner's data retention on the platform is like that of other learners with similar learning behaviors (learners with low test participation but average test scores). However, most of the learners in this situation usually have a relatively average overall rating performance. Therefore, we attribute the misidentification of such learners to specific learners that the system cannot capture. This is because we know from the course leaders that there are still some special cases of learners who are retaking the course or have a solid foundation in the subject, who do not actively participate in the whole learning program but still achieve a good overall score due to their good foundation.

In the sparse data set of this thesis, the experimental results show that statistical processing of the fine-grained features or dimensionality reduction by other means can significantly improve the prediction effect of the model. The statistical analysis of the fine-grained data shows that the covariance matrix is generated from the test scores of some of the tests under the fine-grained features, as shown in Figure 6, and the covariance matrix shows a strong correlation between a series of tests, which can be interpreted as a clear series affiliation of the tests. This is because the tests scheduled for each semester do not necessarily follow the same set of tests used previously, i.e., the sets of tests in different semesters may be identical, intersecting, or completely mutually exclusive.

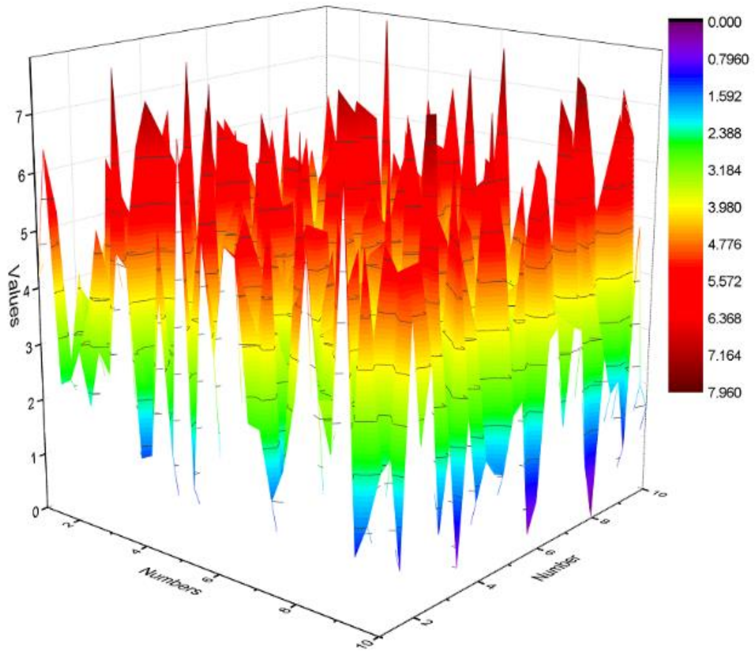

Figure 6: Partial test score covariance.

In addition, the diversity of learners also increases the complexity of the problem, for example, some learners will choose to participate in the same course in different semesters, but for most learners, this situation is relatively rare, if we use fine-grained data, the model will easily fall into overfitting because the feature vector has fewer effective dimensions but higher total dimensionality. Ideally, if we have the knowledge map between the quizzes, we can easily correct the quiz-related features, but the actual data is more difficult to obtain the knowledge map due to historical reasons. We find that more than 91.5% of the learners have taken the test less than or equal to 14 times.

4.2 Adaptive Learning Model Results

From Figure 7, we can see that learners in category 1 have higher reading ability levels and set learning goals, and the system recommends more difficult resources, indicating that these learners have higher English reading ability levels and stronger motivation to learn, and the system recommends resources that meet the learners' needs in terms of difficulty. The cognitive style of learners in category 2 is field-independent and they often learn in a relatively quiet environment, so the recommended resources are moderate in topic and difficulty. Based on the characteristics of the field-independent learners, it shows that the learning effect of these learners is easily affected by the topic and the type of topic, and is not easily affected by the noise level of the environment. The learners in category 3 have set learning goals and do questions with more difficult resources, and often study in a relatively quiet environment, indicating that these learners are more motivated to learn and prefer to study in a low-volume environment, and the difficulty of the system-recommended resources in the process of doing questions indicates that the English reading ability level of these learners is relatively high.

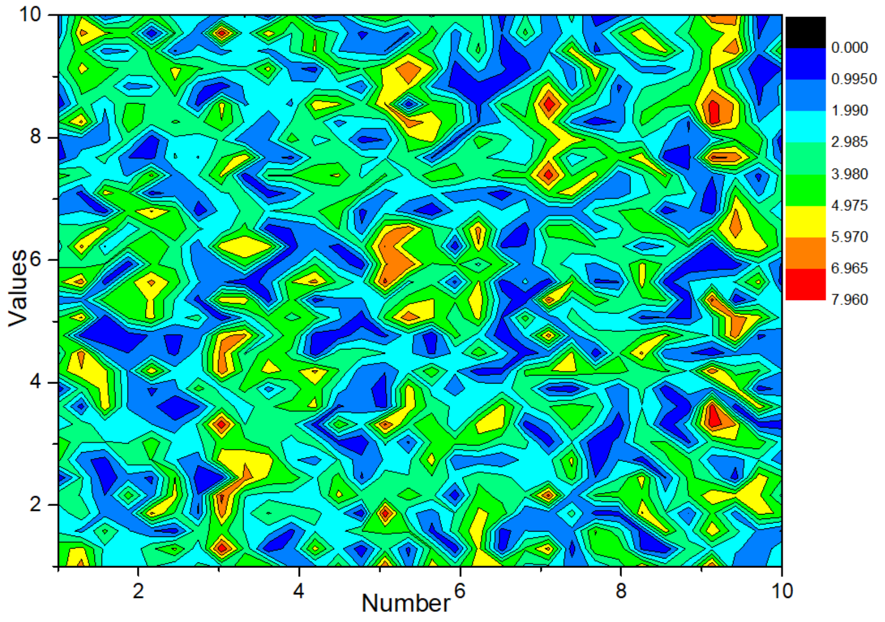

Figure 7: Radar map of the distribution of the characteristics of the three types of learners.

The learning effect is mainly evaluated from the learners' correctness rate of doing the questions, but since the recommended resources in this system are recommended differently based on different learning data of different learners, the length of learning and the size of the resources are different, thus, the different learning processes and different learning results of different learners cannot be evaluated uniformly with only a single evaluation. In this study, the evaluation of learning effectiveness was conducted by analyzing only those learners in the system who were able to learn continuously.

As can be seen in Figure 8, the learners were able to use the App to assist in the learning of English fragmented reading continuously, and the learning effect was generally on the rise, indicating that the use of the App to assist in the learning of the English 4 close reading module could improve the learners' learning ability, and the learning effect was also increasing with time, and the correct rate of doing questions was also increasing. Due to the short duration of the learners' study and the complex learning environment of mobile fragmentation during the learning process, which also influences more factors than just the decibel value of the volume noise level, it is obvious that the correct rate of doing the questions in the line graph also occasionally decreases.

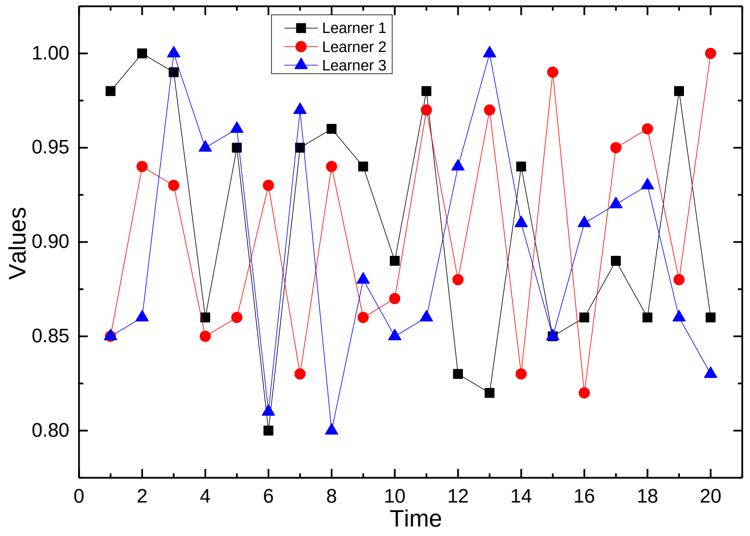

Figure 8: Typical learner's daily correct learning rate.

Learner 1's learning effectiveness fluctuated and rose significantly, but there were two declines in between. Further examination of the background data shows that learner 1's current reading ability is level 6, and his cognitive style is field-dependent. Learner 2's current reading ability is level five, and the cognitive style is field independent, and the learning effect is relatively stable showing an upward trend; while for the field-independent learners, they are not easily influenced by the environment, but the rise is not very large, which is related to the learners' current reading ability, the level five reading ability in this study which is comparable to the level of English level four, and the reading resources are comparable to the level of college English level four reading materials equivalent, so it is difficult for learners 3 to do level 4 topics.

The above analysis shows that the learning effect can be improved by the analysis of the learning process of typical learners in a month of English fragmented reading learning through the recommended resources of this system, and the weaknesses of the learning process can be identified in time and improved in the intensive training. Combined with the regression equation, learner 1 verifies that learners with a field-dependent cognitive style in equation (5) have a poorer learning effect and are easily influenced by the environment; learner 2 verifies that learners with a lower reading ability in equation (6) have a more obvious learning effect; learner 3 verifies that learners with a field-dependent cognitive style and lower resource difficulty in equation (7) have a more obvious learning effect. The continuous increase in learning effect reflects that the selection of learner characteristics and resource characteristics in the push model and the setting of values are reasonable and can reflect the changes in the learner model more sensitively, and in the next stage of system improvement, we can make quick responses in the push learning resources accordingly.

5 CONCLUSION

The scope, status, and characteristics of research in the field of adaptive learning and adaptive learning system are analyzed and sorted out, and then the definition and characteristics of fragmented learning, the concept of English fragmented reading, the definition and characteristics of adaptive learning and adaptive learning system are described. The ID3 algorithm is suitable for processing discrete-valued sample data and introduces the concept of entropy in information theory so that the algorithm can obtain a decision tree with the lowest number of nodes to generate resource recommendation strategies. We also find that the same model has better learning efficiency predictions on tight feature datasets than on fine-grained feature datasets. In addition, we experimented with different combinations of features, i.e., basic features, quiz features, course video viewing features, and forum interaction features. The experimental results show that learner learning efficiency is strongly correlated with basic learner information, quiz scores, quiz submission behavior information, and forum interaction information, while course video viewing information is less correlated, and we analyze the possible reasons for this. In addition, we introduced a word embedding model to process the textual information generated by the learners' forum interactions. It was found that the introduction of word embedding significantly improved the learning efficiency prediction model compared to the statistical features of text generated by forum interaction information.

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