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Computer-Aided Design AND APPLICATIONS

Design of Individualized English Learning Path Recommendation Algorithm Based on Machine Learning and Internet of Things

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Abstract. Individualized English based on machine learning (ML) and Internet of Things (IoT) can play an important role in computer-aided instruction (CAI). This article introduces the problems existing when calculating the similarity of users and the importance of user comments to the recommendation system. Then, an emotion-based user similarity measurement method is proposed, which corrects the similarity between users by using the emotional comment information of users, thus improving the recommendation accuracy. In order to verify the effectiveness of this method, two methods are adopted to integrate user ratings and user comment information emotions, namely, the method based on opinion pre-filtering and the method based on user ratings embedding, and the recommendation results are evaluated. The experiment shows that the algorithm's functional index in collaborative filtering is higher than the same mean square error, and it is also verified that it is feasible to improve the recommendation effect by using auxiliary information such as user comments. This method improves the performance and accuracy of the recommendation model by integrating user ratings and user comments, and shows high stability in the face of different numbers of users evaluating projects together, thus ensuring the reliability of the recommendation system.

Keywords: Machine Learning; Internet of Things; English Learning; Individualized Recommendation; Computer-Assisted Instruction
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1 INTRODUCTION

The traditional English learning methods have the problems of low learning efficiency and unsatisfactory learning results. In order to solve these problems, researchers began to explore more individualized CAI methods. Individualized English learning path recommendation algorithm based on ML and IoT. By utilizing machine learning and deep learning technologies, automatic identity authentication can be performed on IoT devices. By analyzing the behavior patterns and access requests of the devices, the credibility of the devices can be determined, thereby controlling the access permissions of the devices. Al Garadi et al. [1] analyzed their advantages and disadvantages, and explored future application prospects. The survey mainly adopts the methods and case analysis. In the case analysis, we selected some successful attack cases and analyzed the technical means and defense methods of the attackers. The security issues of IoT will also become increasingly severe. The application of machine learning and deep learning in intrusion detection, malware defense, vulnerability mining, and other areas will become more mature and widespread. Meanwhile, with the continuous improvement and optimization of algorithms, the interpretability and robustness also be improved. First of all, the algorithm can automatically recommend individualized learning resources and learning paths for students to improve learning efficiency and learning results; Secondly, the algorithm can combine the personal information, learning history and learning objectives of learners to analyze, so as to provide the most suitable learning content and plan for each learner; Finally, the algorithm can also adjust and optimize the learning process in time by monitoring learners' learning behavior and effect in real time, and improve learning efficiency and learning results. With electronic learning management systems in the field of education is becoming increasingly widespread. Moodle, as a popular open-source e-learning management system, is widely adopted by many educational institutions and teachers. Chang et al. [2] explored the construction method. By analyzing learners' learning behavior and interests, recommend relevant learning materials and resources, such as courses, special lectures, e-books, etc. Through Moodle's course management function, personalized learning plans and progress tracking are customized for learners, so that they can keep track of their learning progress and completion status at any time. Based on learners' learning behavior and performance, diverse assessment methods are adopted, such as formative assessment, summative assessment, self-evaluation, etc., to provide personalized learning feedback and suggestions. By combining with CAI, the algorithm can provide more intelligent and individualized learning support for English learners, thus solving the problems of low learning efficiency and unsatisfactory learning results in traditional English learning and promoting the digital and individualized development of English education. With the continuous growth of online information and educational data, personalized online learning resource recommendation models have become increasingly important in improving learning effectiveness and educational quality. Chang and Liu [3] introduced how to build an adaptive personalized online learning resource recommendation model. In order to improve the accuracy and personalization of the recommendation model, we need to implement it through model training and evaluation. This process includes important steps such as data collection, data preprocessing, and feature extraction. Data collection mainly involves collecting user learning behavior data, learning resource description information, and other related data. These data can be obtained through online learning platforms, educational data mining, and other methods. Data preprocessing includes operations such as data cleaning, deduplication, and annotation to remove invalid and low-quality data and improve data quality and accuracy. Feature extraction involves extracting features related to user interests and behaviors from preprocessed data to train recommendation models. To meet the needs of large-scale connectivity and low power consumption, 5G wireless systems adopt multi antenna technology, high-frequency frequency band, and new modulation and demodulation technologies. These technologies not only improve system performance, Attackers may exploit the vulnerabilities of these devices for malicious attacks and data theft. Therefore, we need to pay more attention to the security issues of the Internet of Things and take effective measures to protect the security of IoT devices and data. These application scenarios have an urgent demand for 5G wireless systems, which will further promote the popularization of 5G wireless systems in the market. Through the Internet of Things technology, various devices and systems can connect and exchange data, thereby improving work efficiency and quality. At the same time, IoT technology has also brought positive impacts to local economic development, promoting the transformation and upgrading of the manufacturing industry, and enhancing industrial competitiveness. The Internet of Vehicles will promote the development of intelligent transportation and autonomous driving, improve travel experience, and reduce economic losses caused by traffic congestion [4].

Personalized recommendation systems are receiving increasing attention in intelligent product service systems. Unsupervised learning models, as a powerful machine learning algorithm, are playing an increasingly important role in recommendation systems. Chiu et al. [5] explored how to develop personalized recommendation systems for intelligent product service systems based on unsupervised learning models. In the past few years, unsupervised learning models have made significant progress in the application of personalized recommendations. However, existing research still has certain limitations. Firstly, most existing research focuses on a single unsupervised learning algorithm without fully exploring the combination and optimization of different algorithms. Secondly, further exploration is needed on how to integrate unsupervised learning models with other technologies to improve the performance of recommendation systems. Unsupervised learning models, the model is able to learn the features of the data and the relationship between the labels. Unsupervised learning is the process of encoding and decoding data by exploring its structures and associations. Reinforcement learning involves learning strategies through interaction with the environment to maximize rewards. Individualized English learning path recommendation algorithm combines ML and IoT technology, aiming at providing an optimal learning path for each learner, thus improving learning efficiency and learning results. In ML, through English learning data, the algorithm can learn the learning patterns and habits of different learners and provide them with individualized learning suggestions. In IoT technology, by monitoring learners' learning behavior and effect in real time, more accurate data support can be provided for the algorithm, so as to better adjust the learning path. The purpose of this article is to design a individualized English learning path recommendation algorithm based on ML and IoT. The algorithm can optimize and adjust the model according to the feedback data, and improve the accuracy and practicability of path recommendation.

Individualized English learning path recommendation algorithm can provide the best learning path for learners according to their personality characteristics and learning history, thus improving learning efficiency and learning results. The significance of this study lies in improving English learners' learning efficiency and achievements, promoting the digitalization and individualization of English education, promoting the further development of CAI, and cultivating learners' autonomous learning ability and individualized thinking ability through innovative technologies and methods. The research includes the following innovations:

(1) Combining ML and IoT technology, this article designs a individualized English learning path recommendation algorithm, which realizes the intelligent analysis and processing of a large quantity of English learning data and improves learning efficiency and learning results.

(2) ML algorithm is applied to English learning path recommendation. Through the learning and analysis of ML algorithm, learners' learning patterns and habits can be accurately identified, and the optimal learning path can be provided according to learners' personality characteristics.

(3) Based on these data, recommendation algorithms can analyze learners' learning preferences, ability levels, and interests, thereby recommending more suitable learning paths and resources for learners. This recommendation method can more accurately meet the needs of learners, improve learning effectiveness and experience.

The first section elaborates on the relevant background content of the Internet of Things. The second section conducted research on ideas and scholars' research viewpoints, summarizing different personalized achievements. Section 3 presents a recommendation application that combines ML algorithm with the Internet of Things. The fifth part is the conclusion and prospect, summarizing the research results, putting forward the future research direction and problems, and pointing out the shortcomings and limitations of this article.

2 RELATED WORKS

People's learning methods are also undergoing tremendous changes. In this era, personalized learning recommendation systems based on social tags have received widespread attention. Dong et al. [6] explore the background of personalized learning in the era of the Internet of Things, as well as the importance and methods of constructing personalized learning recommendation systems based on social tags. Content based recommendation algorithms mainly recommend based on learners' learning preferences, interests, and other characteristics, while collaborative filtering recommendation algorithms search for other learners who are similar to learners, and then recommend based on their learning habits. In addition, we also need to use data mining techniques to optimize system performance, such as sorting recommendation results, so that content that better meets learners' needs can be prioritized for recommendation. Computer assisted instruction (CAI), as an emerging educational method. Especially in vocational colleges, computer-aided teaching plays an important role in improving students' theoretical knowledge and practical skills. Traditional education often teaches according to fixed course schedules and content, which cannot fully consider individual differences among students. Ezenwa for et al. [7] analyzed students' weak knowledge points based on their learning data, and provided targeted supplementary teaching resources and practice questions to help students make up for their shortcomings. This personalized learning environment can improve students' learning outcomes, which are reflected in their academic performance. The results indicate that computer-aided teaching has important application value in technical colleges. It can not only improve students' theoretical and practical grades, but also enhance their mastery of professional skills. At the same time, the application of computer-aided teaching can also optimize teaching methods and content, improve teaching quality and effectiveness. Speech synthesis technology can convert text into speech, providing auditory information input for English hearing-impaired students. Especially for the plays an important role. Li and Ji [8] explored the application background and significance of computer-aided teaching in the analysis of English listening impairment. English listening impairment refers to the difficulties and challenges that people encounter in English listening comprehension. These difficulties and challenges may stem from various reasons, such as congenital hearing loss, acquired diseases, inadequate language environment, etc. English listening impairment not only affects students' academic performance, but may also have an impact on their future career development. Therefore, analyzing English listening barriers and taking effective measures to improve them is of great significance.

With the continuous growth of online information and educational data, intelligent education recommendation systems have become increasingly important in improving teaching effectiveness and students' learning experience. However, traditional recommendation algorithms and clustering methods have certain limitations when dealing with complex multidimensional data. Therefore, Liu et al. [9] explored the application of multidimensional association. In recent years, incremental tensor decomposition has received widespread attention in recommendation systems. It can process multi-dimensional user behavior data and discover changes in users' interests in different fields and time spans. Multidimensional association recommendation recommends items of interest to different users by analyzing multidimensional data such as users, items, and time. Adaptive clustering is a method of clustering based on dynamic changes in data, which can better understand user behavior and needs. With the popularization of the Internet and the continuous development of technology, people's needs for learning are becoming increasingly diverse. Short video online learning resources, as a new learning method, have gradually been accepted and loved by a large number of users. Ouyang et al. [10] explored the significance, demand analysis, resource recommendation, and successful case analysis. In today's information society, people's demand for learning is constantly increasing. As a new type of learning method, short video online learning resources have the characteristics of brevity, refinement, and flexibility, which are very suitable for the learning needs of modern people. Through short videos, people can acquire a large amount of knowledge and skills in a short period of time, improving their overall quality. At the same time, short video online learning resources can also be quickly disseminated and shared through the Internet, allowing more people to benefit from this new learning method.

Oyebode et al. [11] will introduce the application of machine learning technology in adaptive and personalized systems. To learning from data through computer programs and utilizing the knowledge learned to complete specific tasks. Machine learning technology can automatically analyze, summarize, and summarize valuable information based on the characteristics and patterns of data. Adaptive and personalized systems refer to the ability to automatically adjust and optimize system parameters and services based on individual characteristics and needs, in order to provide more accurate and personalized services. This system can be widely applied in the fields of health and physical and mental health, such as by monitoring users' physiological data and behavioral habits. Automatically adjust health management and rehabilitation treatment plans. Rosali [12] found that CAI has a positive impact on high school physics academic performance. Specifically, students' acceptance and attitude towards CAI have a significant positive impact on their physics academic performance. In addition, we also found that the intelligent evaluation of CAI can effectively improve students' learning outcomes and reduce the burden on teachers. In comparison with traditional teaching, CAI can not only enhance students' interest and ability in learning, but also enhance their awareness and ability of self-directed learning. In the conclusion, we believe that CAI has great advantages in middle school physics teaching. By using CAI, teachers can better meet students' learning needs, improve teaching quality and efficiency. Therefore, education departments and schools should strengthen guidance and support for CAI, allocate educational resources reasonably, the Internet of Things technology can provide richer teaching resources and experimental equipment for physics teaching. Through the Internet of Things technology, teachers can monitor students' learning status and experimental operations in real time, and timely discover and solve problems encountered by students during learning. At the same time, IoT technology can also intelligently upgrade physics experimental equipment, allowing students to remotely operate and collect real-time data through intelligent terminals, improving the effectiveness and quality of experimental teaching. Sepasgozar et al. [13] will systematically review the applications of these two technologies in smart homes, with the aim of sorting out their development history, current status, and existing problems, and looking forward to future research directions and trends. In smart homes, the technology is mainly reflected in aspects such as home safety, energy management, and home entertainment. By utilizing artificial intelligence technology, real-time monitoring of the home environment can be achieved, improving the safety of the home. For example, using artificial intelligence cameras can perform facial recognition and behavior analysis to prevent the occurrence of family safety accidents. In addition, monitoring and analyzing household energy usage through artificial intelligence technology can help household users effectively manage energy consumption and reduce household energy costs. In terms of home entertainment, artificial intelligence technology can achieve speech recognition and natural language processing, providing more convenient entertainment experiences for home users.

The personalized recommendation system for education has received widespread attention and research. The existing research mainly focuses on data collection and processing, selection and optimization of recommendation algorithms, and personalized recommendation strategies. Implement personalized recommendations based on user behavior and interests, including real-time and dynamic recommendations. Shi et al. [14] explored the design and analysis of personalized recommendation systems for education from the perspective of systems science communication. Through data collection, processing, selection of recommendation algorithms, and formulation of personalized recommendation strategies, the use of personalized recommendation based intelligent learning in web-based learning systems is an important trend in the current development of educational technology, which can improve learning effectiveness and efficiency, stimulate learning interest, and promote autonomous learning. However, attention needs to be paid to issues such as data privacy and security, recommendation accuracy and credibility, adaptability and availability, and feedback and adjustment. In the process of collecting and analyzing learner data, it is necessary to protect learners' privacy and data security. The accuracy and credibility of personalized recommendations are important factors that affect learning outcomes, so it is necessary to continuously improve the accuracy and credibility of recommendation algorithms. Artificial bee colony algorithm is a highly anticipated optimization algorithm in recent years, which has shown excellent performance in solving complex optimization problems, especially combinatorial optimization problems. Venkatesh et al. [15] explored how to apply artificial bee colony algorithm to personalized recommendation intelligent learning in network-based learning systems to improve learning performance. Specifically, each bee can be seen as a recommendation model, searching for the optimal solution in the search space, that is, finding the most suitable learning resources for learners. Through continuous iteration, the artificial bee colony algorithm can gradually optimize the recommendation model, improve recommendation accuracy and efficiency. Xu [16] uses clustering algorithms to group students according to their learning behavior and interests. Classify similar students into the same category and recommend the same learning resources and paths for the same category of students. By using association rule mining algorithms, identify the association relationships between student behavior and learning resources, and recommend other resources related to their chosen learning resources to students based on these association relationships. Utilizing deep learning algorithms, student features and learning resource features are taken as inputs, trained and learned through neural networks, and the final recommendation results are output. The traditional push mode mainly recommends based on learners' basic information, which lacks personalization and accuracy. Therefore, to analyze the needs of learners and push resources based on the analysis results. In today's information society, fragmented English reading has become a common way of learning. Learners learn at any time and place through various terminal devices, which provides convenience and challenges for learners. How to effectively promote learning resources suitable for learners. Zhang et al. [17] by pushing corresponding resources based on user needs, learning behavior, learning progress, and learning outcomes, users' needs can be better met and their learning outcomes improved. People are facing a massive amount of educational resource information. Facing the complex and ever-changing learning environment and user needs, designing an adaptive recommendation algorithm has become a key issue. Zhu [18] explored a personalized recommendation method. Generate new genes through crossover and mutation operations to increase the diversity of solutions. Strategies such as single point crossing and multi-point crossing can be adopted. In mutation operations, the robustness of the solution can be increased by randomly changing a portion of the gene. Dynamically adjust the parameters and strategies of genetic algorithms based on real-time user feedback and environmental changes. For example, the weight of the fitness function can be adjusted based on real-time feedback, or the probability of selection, crossover, and mutation operations can be adjusted based on environmental changes.

The above research has made remarkable progress in the design of individualized English learning path recommendation algorithm, but most researches only focus on the application of single ML algorithm or IoT technology, without considering the organic combination of the two. In this article, a individualized English learning path recommendation algorithm based on ML and IoT is proposed, which organically combines ML algorithm and IoT technology to realize more intelligent and individualized CAI support.

3 INDIVIDUALIZED ENGLISH LEARNING PATH RECOMMENDATION METHOD

The design of individualized English learning path recommendation algorithm needs to combine ML and IoT technology. ML can help the algorithm learn the learning patterns and habits of different learners from a large quantity of English learning data, and provide them with individualized learning suggestions. IoT technology can provide support for English learning path recommendation algorithm. Using IoT technology, learners' learning data can be collected in real time, including learning time, learning duration, learning content and grades. These data can provide strong support for English learning path recommendation algorithm. By analyzing and processing these data, we can more accurately understand learners' learning situation and needs, thus providing individualized learning path recommendation for them. The individualized English learning path recommendation method proposed in this article mainly combines ML algorithm and IoT technology to realize more intelligent and individualized learning support. By analyzing students' English learning behaviors and achievements, as well as students' learning data collected by using IoT technology, we can provide students with more accurate and practical English learning path recommendations.

Learning data collected by using IoT technology can be deeply analyzed and processed. For example, we can analyze learners' learning time, learning duration and learning content, so as to understand learners' preferences, difficulties and learning progress in English learning. Moreover, the natural language processing technology is used to preprocess the students' learning feedback text, including word segmentation, stop words removal, word stemming and other operations to remove noise and unnecessary information in the text. By sorting out and analyzing emotional words related to English learning, an emotional dictionary for English learning is constructed. This dictionary includes three categories: positive emotional vocabulary, negative emotional vocabulary and neutral emotional vocabulary. Through the emotion classifier, each student's learning feedback text can be classified into emotions. Combining the classification results with students' English learning path recommendation can provide students with more individualized learning resources and recommended paths according to their emotional state. See Figure 1 for the classification process of students' emotions.

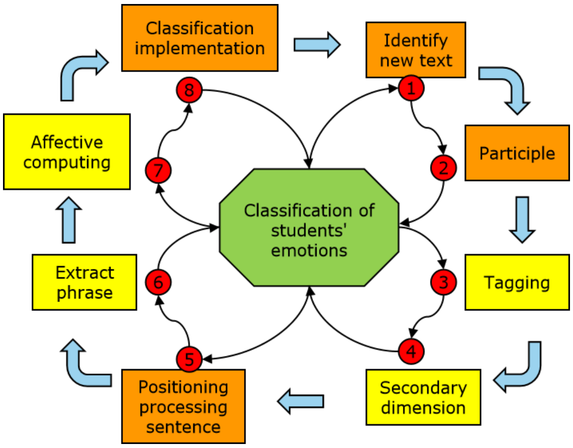

Figure 1: Classification of student emotions.

According to students' feedback data and practical application effect, the emotion classifier and English learning path recommendation algorithm can be continuously optimized and adjusted to improve the accuracy and practicability of the algorithm. Through the above process, students' emotion classification in individualized English learning path recommendation algorithm based on ML and IoT technology can be realized. This helps to better understand students' emotional state and learning needs.

According to the learning data collected and analyzed based on ML and IoT technology, we can find the characteristics of students' learning preferences, learning difficulties and learning habits. Therefore, according to these characteristics, we can make English learning paths that meet their needs and levels, and push relevant learning resources and information in real time through IoT technology. The ML model of student preference analysis is shown in Figure 2.

Naive Bayesian classification model can be used for emotional analysis of user comments. By training a naive Bayesian classification model based on emotional tags, we can predict the emotional tendency of user comments, so as to understand the evaluation and feedback of users on courses or resources. The user similarity measurement method based on emotion can analyze and learn the user comment information through naive Bayesian classification model, and then calculate the similarity between different users according to their emotional tendencies and characteristics. By analyzing users' emotions and similarities, we can get users' interests and preferences, so as to recommend suitable English courses and learning resources for them. In the naive Bayesian classification model, the following deduction can be made:

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

Since the denominator is a constant value, there is no need to calculate it, so you only need to calculate the value of the numerator and compare the largest one.

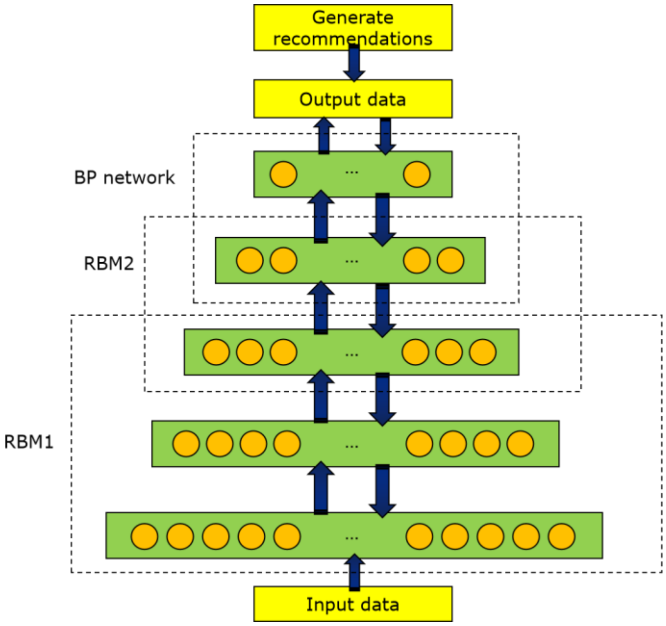

Figure 2: ML model of student preference analysis.

The training sample data are discrete values:

$$P(a_k|C_i) = \frac{S_{ik}}{S_i} \tag{2}$$

Where S_{ik} is the quantity of samples with the attribute value of a_k and class C_i.

Using TF-IDF method to extract keywords related to English learning from students' text feedback. These keywords can help us understand students' English learning interests and preferences. For other types of data, such as learning behavior and learning time, we transform them into numerical eigenvectors. Through feature extraction, the data of each student is represented as a feature vector. This feature vector is composed of keywords and behavioral characteristics related to English learning, which represents students' interests and habits in English learning.

Find the union of users who have scored item i and item j respectively:

$$U = U_i \cup U_j \tag{3}$$

$$U = \{X_{u1}, X_{u2}, \cdots, X_{un}\} \tag{4}$$

$$V = \{X_{v1}, X_{v2}, \cdots, X_{vn}\} \tag{5}$$

The U,V characteristic distance of students is as follows:

$$d_{uv} = \sqrt{\sum_k^n |x_{uk} - x_{vk}|^2} \tag{6}$$

$$Sim_{uv} = \frac{1}{1+d_{uv}} = \frac{1}{1+\sum_k^n |x_{uk} - x_{vk}|^2} \tag{7}$$

These resources can be English learning related materials, learning courses, and even learning experience sharing of other users. When users evaluate N items emotionally, the calculation of preference matrix is defined as:

$$Q_N = \frac{1}{N}\sum_{k=1}^{N} a_k Y_k \tag{8}$$

Let the user i belong to the p -class k_p, and the ratio of the quantity of users h_p to the total quantity of users s is included in the class k_p, which is called the confidence factor of users' emotion on this topic, and is represented by T :

$$T_i = \frac{h_p}{s} \tag{9}$$

Each feature is given a certain weight, and then it is multiplied by the feature vector to get the numerical representation of the user interest vector. These weights can be calculated by ML algorithm or set manually according to domain knowledge and experience. According to the similarity of users' interests and the recommendation results of ML algorithm, individualized English learning path recommendation can be provided for users. Specifically, the most suitable learning resources can be recommended to users according to the similarity of users' interests and the recommendation results of ML algorithm. Moreover, it can also provide users with individualized learning suggestions and learning plans to help them better achieve their English learning goals.

According to the extracted points of interest, the user's historical preference data is divided into different groups. For users in each group, a historical preference similarity set is established according to their historical preference data and similarity of interest points. This similarity set can include user's historical preference data, similarity of interest points and some other useful information, such as user's behavior pattern, preference change trend and so on. With the passage of time and the change of users' behaviors, the similar sets of users' interests and historical preferences also need to be constantly updated and maintained. This can be achieved by collecting user behavior data regularly and updating the historical preference similarity set. The user's interest preference is processed by grouping fusion method, and the historical preference similarity set s_i is established according to the similarity criterion of interest points:

$$sim(i, j) = \frac{\sum_{u\in U}\left(R_{ui} - \overline{R}_i\right)\left(R_{uj} - \overline{R}_j\right)}{\sqrt{\sum_{u\in U}\left(R_{ui} - \overline{R}_i\right)^2}\sqrt{\sum_{u\in U}\left(R_{uj} - \overline{R}_j\right)^2}} \tag{10}$$

The calculation of course popularity characteristics will comprehensively consider the quantity of students, the quantity of users' ratings and the quantity of ratings. Therefore, the courses under each secondary classification are sorted separately. After getting the sorted list, calculate the final course popularity characteristic value:

$$pref_{HOT}(u,i) = 1 - \frac{R_i}{N} \tag{11}$$

In the above formula, N represents the total quantity of courses under the corresponding classification, and R_i represents the ranking of course i, that is, the relatively hottest course under this classification.

4 ALGORITHM TESTING AND ANALYSIS

Collect user rating data and user comment information from an English learning platform. User rating data includes users' ratings of different courses or resources, and user comment information includes users' comments and feedback on courses or resources. Preprocessing the collected raw data, including data cleaning, deduplication, normalization and other operations, to ensure the quality and effectiveness of the data. The purpose of the experiment is to verify the advantages and effectiveness of the user similarity measurement method based on emotion in the English learning path recommendation system, and further illustrate the effectiveness and reliability of this method by comparing it with the traditional collaborative filtering recommendation algorithm. Generally speaking, the length of recommendation list will affect the acceptance and satisfaction of users. If the recommendation list is too short, some resources that users may be interested in may be missed; If it is too long, users may need to spend more time and energy browsing and evaluating these resources. From Figure 3, we can see that our algorithm is obviously superior to the traditional collaborative filtering recommendation algorithms (User_CF and Item_CF) in the accuracy of recommendation results.

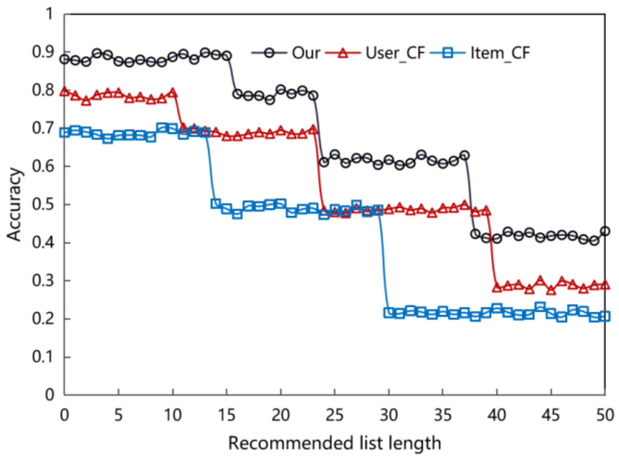

Figure 3: Comparison of accuracy of algorithm recommendation results.

One possible strategy when considering the characteristics of users and items is to use feature engineering techniques. We can extract useful features from user behavior data, such as user purchase history, browsing history, etc., and use these features to train machine learning models. Similarly, we can also extract useful features from the attributes of the project, such as the type and theme of the project. Then, we can combine the characteristics of users and projects and use collaborative filtering or content-based recommendation methods for recommendation. In Figure 4, the performance of the recommendation algorithm in this article is better than the traditional collaborative filtering recommendation algorithm in Recall index, and its performance is relatively stable under different K values.

The algorithm can consider more user behavior patterns and interest similarity, thus improving the Recall index. The performance of the algorithm in this article is relatively stable under different K values. In contrast, the traditional collaborative filtering recommendation algorithm performs poorly when the k value is small, but its performance gradually improves with the increase of the k value. By analyzing the results of Figure 4, Stability under different K values. Therefore, it is considered that the recommendation algorithm has great potential in practical application.

According to the results of Figure 5, it can be clearly seen that the user's emotional evaluation of the recommended courses is constantly improving during the iterative process of the recommendation algorithm.

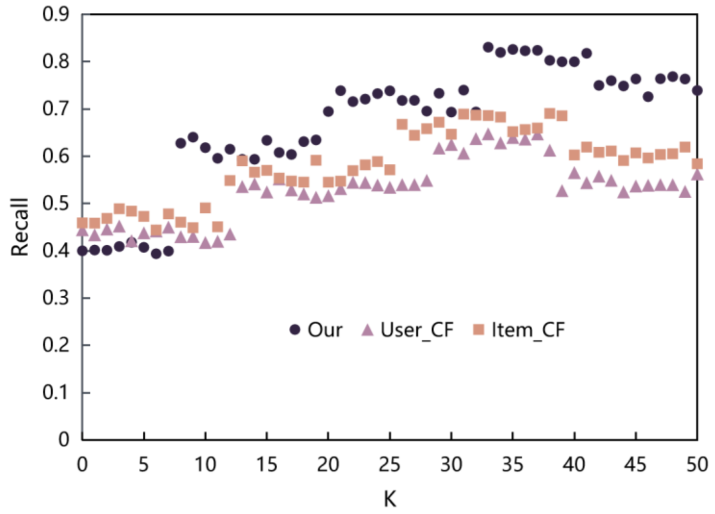

Figure 4: Recall index of the algorithm under different quantity of neighboring users.

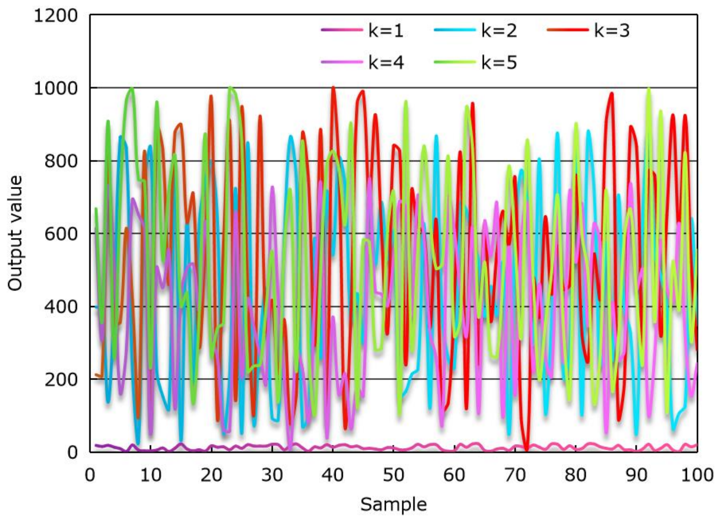

Figure 5: Results of English learning path recommendation algorithm.

According to the user's emotional evaluation and feedback, the user preference matrix can be corrected in time. This dynamic correction enables the algorithm to better capture users' interests and preferences, thus improving the accuracy of recommending courses. By collecting users' emotional evaluation of the recommended courses online and dynamically modifying the user preference matrix, the English learning path recommendation algorithm in this article can continuously improve and improve the recommendation quality.

By combining users' ratings with users' comments, the performance of the recommendation model can be effectively improved. This combination can make the model better understand users' needs and preferences, thus providing users with more accurate recommendations. By using the historical data and comments of users, this algorithm can better capture users' interests and preferences, thus achieving better results in the recommendation process. The MSE index obtained on the test set is shown in Figure 6.

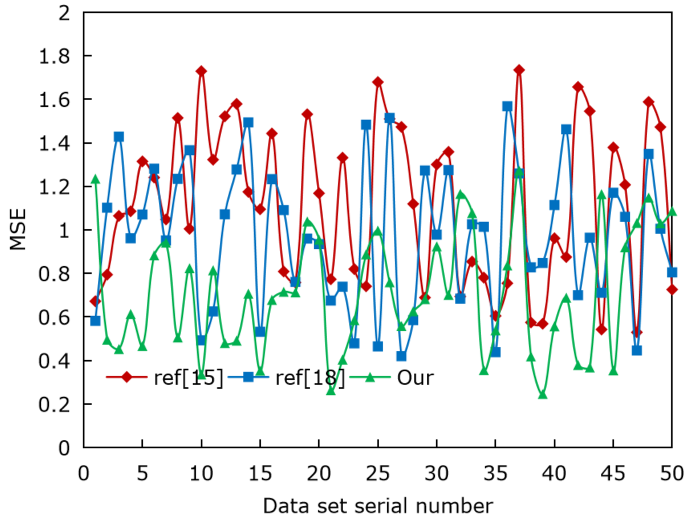

Figure 6: Scoring prediction results of recommendation model.

The results show that the proposed algorithm is obviously superior to the traditional collaborative filtering recommendation algorithm in MSE evaluation index. This shows that this fusion method can effectively improve the performance of the recommendation model, and also verifies the feasibility of improving the recommendation effect by using auxiliary information such as user comments.

When calculating the similarity of users, the traditional similarity measurement method is unstable when the common items of users are sparse, and the similarity tends to be stable with the increase of common items of users. The user similarity measurement method based on emotion proposed in this article corrects the similarity between users through user emotional comment information, and it is basically stable when the quantity of users' common items is sparse. Figure 7 shows the variation law of similarity value with the quantity of co-evaluation courses.

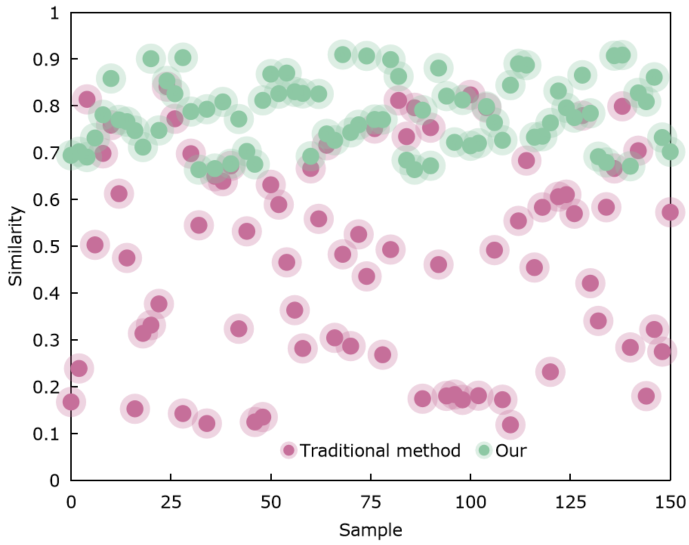

Figure 7: Variation of similarity value with the quantity of co-evaluation courses.

When the quantity of courses jointly evaluated by users is small, the traditional similarity measurement method fluctuates greatly, which means that the similarity between users may be difficult to calculate accurately because there are too few items jointly evaluated. The user similarity measurement method based on emotion proposed in this article corrects the similarity between users by using the user's emotional comment information, so that it can still maintain high stability when the quantity of users' common items is sparse. By comparing the results of two different similarity measurement methods, we can see that the user similarity measurement method based on emotion proposed in this article has certain advantages in stability. This advantage can make this method keep stable results in the face of different numbers of users evaluating projects together, thus ensuring the reliability of the recommendation system.

5 CONCLUSION

Individualized English learning path recommendation algorithm based on ML and IoT can play an important role in CAI. By combining with CAI, ML and IoT can provide more intelligent and individualized learning support for English learners and promote the digital and individualized development of English education. Individualized English learning path recommendation algorithm combines ML and IoT technology, aiming at providing an optimal learning path for each learner, thus improving learning efficiency and learning results. Combining ML and IoT technology, this article designs a individualized English learning path recommendation algorithm, which realizes the intelligent analysis and processing of a large quantity of English learning data. The research results show the advantages and effectiveness of user similarity measurement method based on emotion in English learning path recommendation system. This method improves the performance and accuracy by integrating user ratings and user comments. In the face of different users evaluating projects together, this method shows high stability, thus providing a guarantee for the reliability of the recommendation system.

Although the user similarity measurement method based on emotion proposed in this article has improved the recommendation effect to a certain extent, the recommendation algorithm still has some limitations, such as unable to predict user interests completely and accurately, unable to overcome the problem of data sparsity, and so on. Future research can explore more advanced recommendation algorithms and technologies, such as deep learning and reinforcement learning, to further improve the recommendation effect.

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