Intelligent Recommendation of Open Educational Resources: Building a Recommendation Model Based on Deep Neural Networks

Zongkui Wang
Academic Affairs Division, Beijing Open University, Beijing 100081, China

***Abstract*—Information overload is a challenge for the development of online education. To address the problem of intelligent recommendation of educational resources, the study proposes an intelligent recommendation model of educational resources based on deep neural networks. First, a deep neural network-based custom recommendation model for educational resources is constructed after a multilayer perceptron-based prediction model is established. The results showed that the prediction model proposed in the study steadily reduced the average absolute error as the number of iterations increase, reaching an average of 0.704, with the loss value stabilising at around 0.6, which is lower than that of the deep neural network prediction model. Compared to the deep neural network prediction model, the normalised discounted cumulative gain is typically 0.01 higher and in terms of hit rate, 0.03 higher. The prediction time of the similarity algorithm is faster than that of the neural network. The mean squared error ranged from a high of 1.29 to a low of 1.19, both lower than other algorithms, and the mean absolute error ranged from a high of 0.56 to a low of 0.54, lower than all other algorithms except the support vector machine algorithm. The average absolute error of the deep neural network resource representation algorithm ranged from a high of 1.46 to a low of 1.45, lower than all other algorithms except the support vector machine algorithm, and the average squared error ranged from a high of 3.43 to a low of 3.24, better than all other algorithms. In conclusion, the model constructed by the study has a good application effect in recommending educational resources, and has a certain promoting effect on the development of online education.**

Keywords*—Intelligent recommendation; deep neural networks; multilayer perceptron; educational resources

I. Introduction

The development of online education (OE) has provided more convenience for learners, but with the abundance of educational resources (ER) there has also been an increase in knowledge redundancy, so how to reduce the cost of time for users to access the target content has become a key issue, and resource recommendation (RR) technology should also make more accurate, fast, timely and personalised changes. Machine Learning (ML) is ubiquitous in everyday life. Deep Neural Networks (DNN), a technique in the field of ML, is popular for its complex and deep structure with powerful predictive power and has appeared in many applications, such as face intelligence perception techniques [1-3]. Given the abundance of resources and the constrained storage space of mobile devices, providing users with individualised and accurate recommendations has become a crucial and urgent issue [4]. Intelligent recommendation of ER is an extremely complex process that focuses on both user and resource characteristics to personalise the recommended resources, as well as considering the accuracy and timeliness of the push. To date, there has been little research on personalised recommendations of learning resources combined with deep learning technology, and the models are relatively complex. In this context, this study constructs a DNN-based intelligent recommendation model for ER, consisting of a recommendation prediction model and a personalised recommendation model, and improves the recommendation prediction model using a Multilayer Perceptron (MLP). There are two main points of innovation in this study. The first point is to improve the scoring method of DNN prediction model using MLP. The second point is to optimize the recommendation effect by dividing the RR into three segments: resource filtering, RR and resource display. The core framework of the study is divided into four sections. The first section is a review of the current state of the art. The second is to construct a prediction model based on MLP-DNN and an intelligent recommendation model for ER based on DNN. The third part is an application effect analysis of the proposed model-based model. The last part concludes the whole study.

II. Related Works

DNNs are multilayer unsupervised neural networks capable of representing complex functions with fewer parameters, and are used in ML with the aim of allowing computers to simulate human learning. Samek et al. argue that with the widespread and highly successful use of ML in industry and science, there is a growing need for interpretable artificial intelligence, and therefore the problem of better understanding nonlinear ML, and in particular DNNs, interpretable and explainable methods for solving capabilities and strategies are receiving increasing attention [5]. Deep learning, according to Geirhos et al, is the foundation of today's machine intelligence and is what started the current wave of artificial intelligence, although its limitations have only recently come to light [6]. Jiang et al. demonstrate how DNNs designed as discriminative networks can operate as quick agent EM solvers and learn from training data. Additionally, they looked into how deep generative networks may be set up as reliable global optimizers and even learn geometric aspects from device distributions [7]. In order to better understand these learned representations, Bau et al. proposed network anatomy for methodically identifying the semantics of specific hidden units in image classification and image generation networks. They claimed that DNNs are effective at finding hierarchical representations for solving challenging tasks on large datasets [8]. Jeyakumar et al. compare the most cutting-edge explanation techniques to see which ones are best at explaining model decisions in their cross-analysis Amazon Mechanical Turkey study, which they use to support their claim that internal work on explaining DNN models has attracted a lot of interest recently [9]. Huang et al. argue that despite an initial understanding of adversarial DNN training, it remains unclear which configurations can lead to more robust DNNs, and propose to fill this gap by comprehensively investigating the effect of network width and depth on the robustness of adversarially trained DNNs [10]. In response to the problem that training DNNs typically requires large amounts of labelled data, Jing et al. introduced self-supervised learning methods as a subset of unsupervised learning methods to minimise the high cost of collecting and annotating large datasets [11]. According to the argument of Liang T et al., network compression and other optimisations can help DNNs overcome their complicated network design, which poses difficulties for effective real-time use and requires high computational and energy costs [12]. An xDNN has been proposed by Angelov et al. that solves the bottleneck of classical deep learning methods and provides an interpretable internal architecture that outperforms current approaches while consuming little CPU power and training time [13].

By evaluating users' historical activity to determine their preferences and selecting content that matches their tastes for recommendation from a large amount of information, intelligent recommendation helps solve the information overload problem. Zhou et al. proposed an intelligent recommendation method to facilitate patients' healthcare decision-making process by providing automatic clinical guidance and pre-diagnostic advice to patients [14]. Zhou et al. designed and applied an intelligent recommendation mechanism to support user collaboration in an academic big data environment [15]. Traditional recommendation algorithms struggle to provide customers with quick and reliable recommendations in the IoT context, thus Cui et al. addressed this issue and suggested a new recommendation based on a time correlation coefficient model and an improved cuckoo search K-means [16]. According to Zhang et al., a lot of interpretable recommendation methods, particularly model-based methods, have been developed recently and applied to real-world systems to give not only high-quality recommendations but also understandable explanations [17]. To increase user trust and improve recommendation acceptance, Sardianos et al. contend that recommendation systems should be interpretable. They have created a clear and convincing recommendation mechanism that tailors recommendations based on user preferences and habits [18]. Logesh et al. argue that recommender systems are widely used to solve the problem of users suffering due to information overload problems in the Internet [19]. In line with Yin et al. [20], a new matrix decomposition model with deep feature learning was proposed in order to address the problem that the majority of current service recommendation methods have some significant flaws and cannot be directly used in edge computing contexts.

In conclusion, despite recent advances in ML and AI made possible by DNNs, the field of education has been slow to adopt these technologies, and there has been little research on how to integrate intelligent ER recommendations with deep learning technology. To address this shortcoming, the study constructs a DNN-based intelligent recommendation model (RM) for ER, which has important practical value and prospects for online education.

III. Construction of DNN-based Intelligent RM for ER

Online education is growing quickly as a result of the expansion of information technology in the field of education. However, the vast volume of ER also causes information overload, making it difficult for OE to make sensible recommendations of knowledge. In order to more accurately recommend appropriate contents for users and decrease the time cost of acquiring ER, the study builds an intelligent RM for ER based on DNN, including a recommendation prediction model of MLP-DNN and a DNN education resources personalised RM.

A. MLP-DNN-based Educational RR Prediction Model Construction

Developed from artificial neural networks, DNNs are the most fundamental model for deep learning techniques, allowing more efficient modelling of potential higher-order and non-linear interactions between multiple features through a multi-layer non-linear structure. DNNs add more hidden layers to artificial neural networks, with fully connected neurons between layers, and as the number of layers increases, DNNs have greater learning power. However, the more layers, the better. Fig. 1 shows the basic structure.

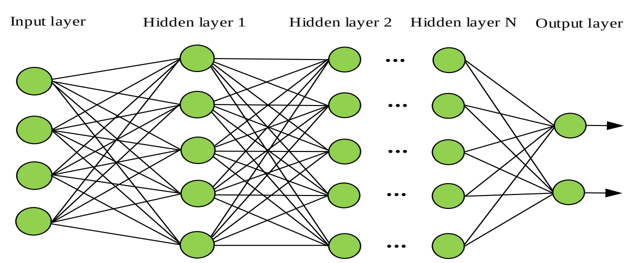

Fig. 1. Basic structure of deep neural networks.

Intelligent recommendation analyse the user's preferences and then recommend content for the user based on the preferences. Traditional RR methods mainly include hybrid recommendation methods, content-based recommendation, collaborative filtering recommendation methods and context-based recommendation methods. Intelligent recommendation of ER is not only about screening suitable content from a huge amount of ER and personalising it for users, but also about ensuring accuracy, efficiency, timeliness, diversity and initiative, in order to help users improve their learning efficiency. Fig. 2 revealed the system.

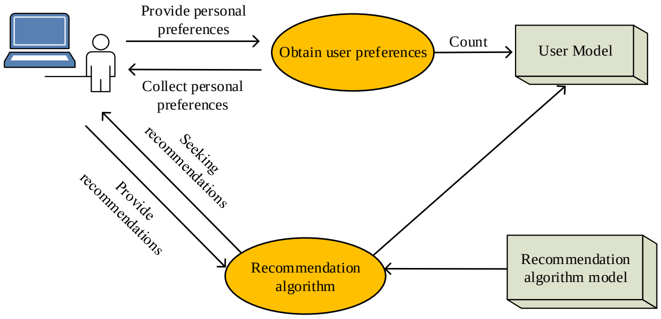

Fig. 2. General model for personalized recommendation systems.

To achieve personalised recommendations, the features of the user and ER need to be fully considered and the user's ratings need to be predicted. In order to obtain the attribute features of users and ER, the attributes of users and ER are first input into the DNN to obtain the vector of user and educational resource attribute features, as shown in Equation (1).

$$\begin{cases} \bar{x} = f(w_1 x + b_1) \\ \bar{y} = f(w_2 y + b_2) \end{cases} \tag{1}$$

In equation (1), x denotes the user attributes, y denotes the education resource attributes, w denotes the weights and b denotes the bias. The $concatenate(.)$ function is then used to fuse the individual attributes of the user and the educational resource to obtain the attribute features, as shown in equation (2).

$$\begin{cases} u_i = concatenate(\bar{x}) \\ s_j = concatenate(\bar{y}) \end{cases} \tag{2}$$

DNN models are constructed using the obtained user and educational resource features, including a DNN model for predicting user ratings of ER and a DNN model for predicting user learning intervals. The first DNN prediction model is based on real user context and learning resource context data, which can effectively predict users' ratings of relevant learning resources and ensure the personalisation and accuracy of educational RR. The user context includes characteristics such as age, gender and interests, and the educational resource context includes resource learning time interval, resource difficulty and user rating. The second DNN prediction model is based on real user context, educational resource context, and learning environment context, which can effectively predict users' learning interval and ensure the timeliness and proactivity of educational RR. After the model is constructed, it is trained by the existing real data, and the specific process is shown in Fig. 3.

However, the vector multiplication scoring approach used in the aforementioned DNN prediction model is computationally demanding and tends to consume a lot of resources, making the model less efficient and having a negative impact on the recommendation effect. The presence of numerous layers of neurons is the key feature of the multi-layer perceptron. By switching from a vector multiplication approach to one where the user and resource features obtained by the model are fed into the MLP and the final output is the predicted score, the DNN prediction model is improved by exploiting its processing of non-linear data. This is done by building a prediction model based on the MLP-DNNN. Fig. 4 illustrates the MLP-based rating prediction technique.

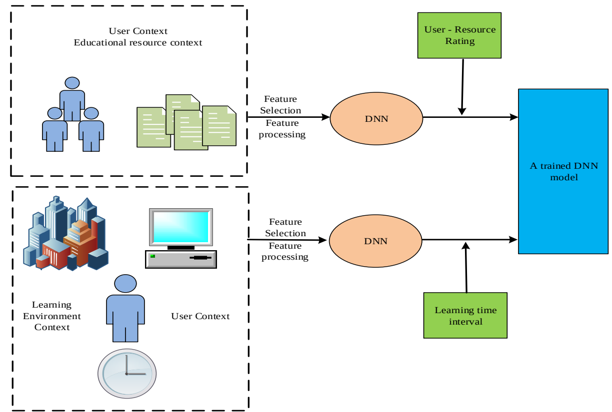

Fig. 3. DNN model training.

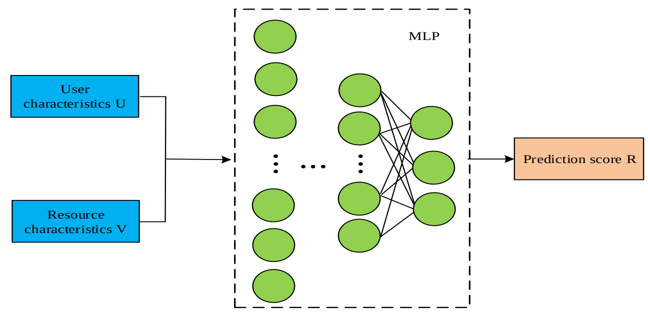

Fig. 4. MLP based scoring prediction method.

The input vector of the input layer of the MLP is a fusion of the features of the user and the educational resource, as shown in equation (3).

$$x_0 = concatenate(u_i, v_j) \tag{3}$$

The output value of x_0 after the first layer is shown in equation (4).

$$x_1 = f(W_1 x_0 + b_1^{'}) \tag{4}$$

In equation (4), W_1 denotes the weight matrix, and $b_1^{'}$ denotes the bias vector. The final output layer is the prediction score, as shown in equation (5).

$$x_l = f(W_l x_l - 1 + b_l^{'}) \tag{5}$$

B. Building a Customised RM for ER using DNN

The RR model is closely interlinked with the prediction model and is an application of the prediction model, with the aim of improving the timeliness and accuracy of educational RRs after learning through big data. The RR model contains three core modules: resource filtering, RR and resource display, and the three modules are interrelated, as shown in Fig. 5.

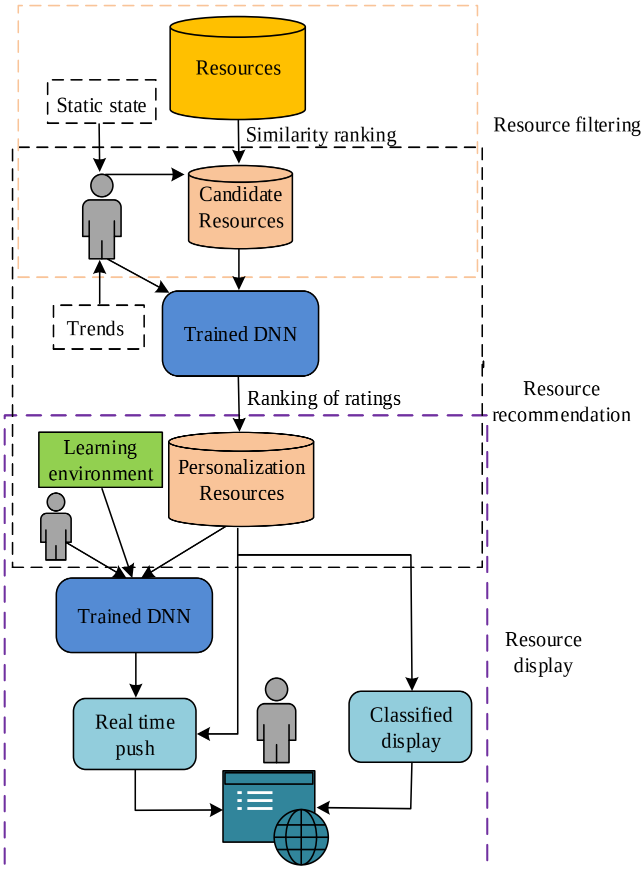

Fig. 5. A personalized RM for ER based on DNN.

In the resource filtering section, the research designs a similarity-based educational resource filtering algorithm. When ER are directly recommended by DNN intelligent RM, the large amount of information will increase the complexity of the model, increase the response time and reduce the recommendation efficiency, so ER should be filtered. The resource filtering method based on similarity ranking can filter out most of the ER that are not interesting or relevant to users before using the model to make recommendations. At the same time, in order to prioritise the latest resources, a similarity reduction method based on a time factor is designed to realise that the older the educational resource, the faster the similarity reduction. The similarity between ER and users' learning interests is calculated as shown in Equation (6).

$$S = \frac{A \times B}{\|A\| \times \|B\|} - at \tag{6}$$

In equation (6), t denotes the difference between the current time and the resource release time, A and B denote the learning interest vector and the educational resource vector respectively, and a denotes the acceleration of similarity decreasing with time, with the acceleration changing dynamically and calculated as shown in equation (7).

$$a = \frac{t}{\delta T^2} \tag{7}$$

In equation (7), T denotes the time duration of the educational resource desired by the user and δ denotes the variable parameter. Thus the final similarity between the educational resource and the user's learning interest is shown in equation (8).

$$S = \frac{A \times B}{\|A\| \times \|B\|} - \frac{t^2}{\delta T^2} \tag{8}$$

In the RR section, the research designs a DNN-based RR algorithm. The algorithm focuses on building and training a DNN, which predicts the user's rating of ER. User features are used as input with educational resource features such as user ratings, resource difficulty and resource learning time, and the output is the user's rating of the educational resource for RR. The main performance evaluation metrics often used in recommendation systems are Mean Squared Error (MSE), Mean Absolute Error (MAE), Standard Mean Error(SME), Recall and Accuracy. MSE is used to measure the accuracy of scoring, as shown in Equation (9).

$$MSE = \frac{1}{|T|} \sum_{i,j} (R_{i,j} - \hat{R}_{i,j})^2 \tag{9}$$

In equation (9), T represents the test set, $\hat{R}_{i,j}$ and $R_{i,j}$ represent the predicted and actual ratings respectively, and the smaller the difference between their values, the better the recommendation. The MAE measures the absolute error between the predicted and actual user ratings, as shown in equation (10).

$$M = \frac{1}{n} \sum_{a=1}^{n} |p_{ia} - r_{ia}| \tag{10}$$

In equation (10), n denotes the number of user i rated products, and p_{ia} and r_{ia} denote the predicted user ratings and actual user ratings respectively. The SME is described in equation (11) as follows.

$$N = \frac{M}{r_{max} - r_{min}} \tag{11}$$

r_{max} and r_{min} in equation (11), respectively, stand for the highest and lowest user rating numbers. In the equation (12), recall is the percentage of all products that the user is recommended by the system out of all items that the user likes, and accuracy is the percentage of items that the user is truly interested in.

$$\begin{cases} \mathrm{Re}\,call = \dfrac{N_{rs}}{N_r} \\ \mathrm{Pr}\,ecision = \dfrac{N_{rs}}{N_s} \end{cases} \tag{12}$$

In equation (12), N_s denotes the number of all recommended items, N_r denotes the number of all products that the user likes, and N_{rs} denotes the number of items that the user likes in the recommendation list. The paper suggests a DNN-based timely pushing of resource presentation method that can accurately forecast users' learning intervals and estimate the duration of their subsequent learning in order to carry out timely pushing of resources. The user's learning time on that day is shown in Equation (13).

$$T = \max(n_i) \rightarrow t_i (1 \le i \le 5) \tag{13}$$

IV. Analysis of the Effectiveness of DNN-based Intelligent RM for ER

The study constructs a DNN-based intelligent RM for ER, however, the effectiveness of the model has to be further verified. The research is analysed in two main aspects. The first part is an analysis of the effectiveness of the MLP-DNN-based RR prediction model. The efficiency of the algorithms created for the DNN-based customised RM for ER is examined in the second half.

A. Analysis of the Effectiveness of MLP-DNN-based Educational RR Prediction Model

The study collected and collated data from 400 users, 650 ER and 32,000 rating records from an online learning platform. As these data were both structured and unstructured, the data were pre-processed and classified and numbered. In Fig. 6, as the number of iterations increases, the MAE value gradually decreases to 0.704, indicating that the MLP-DNN prediction model combining both user characteristics and educational resource characteristics has more complete data and the error tends to decrease, which has some validity.

The network was trained with the DNN prediction model and the MLP-DNN prediction model. Fig. 7 shows that the loss value of the MLP-DNN prediction model is stable at about 0.82, while the loss value of the MLP-DN prediction model is stable at about 0.63.

After the rating prediction is completed, the top N learning resources are finally recommended. Normalize Discount Cumulative Gain (NDCG) and Hit Radio (HR), are two evaluation metrics based on the Top-N recommendation algorithm. The MLP-DNN prediction model and the DNN prediction model were analysed in terms of both NDCG and HR metrics respectively. Fig. 8 shows that as the number of Top-N rises, both models' NDCG and HR metrics continue to rise. However, the DNCG metric of the MLP-DNN prediction model was on average 0.01 higher than that of the DNN prediction model, and on average 0.03 higher in the HR metric.

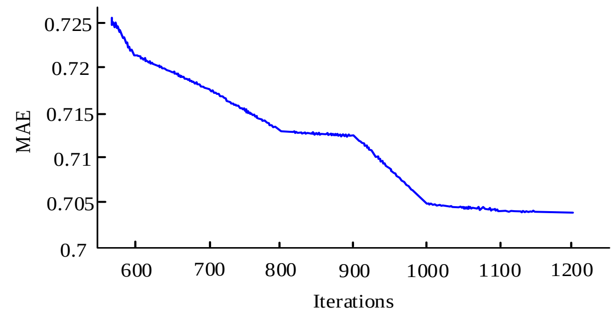

Fig. 6. The results of training MLP-DNN model using MAE function.

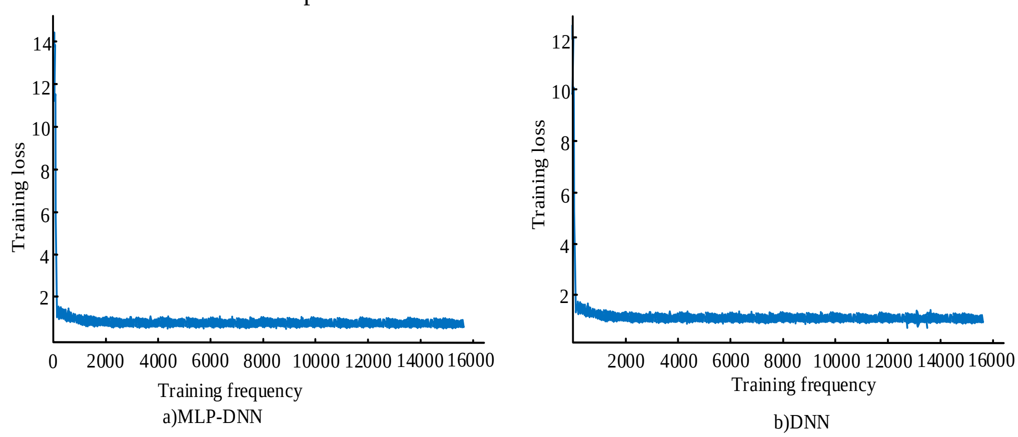

Fig. 7. Results of training networks using DNN model and MLP-DNN model.

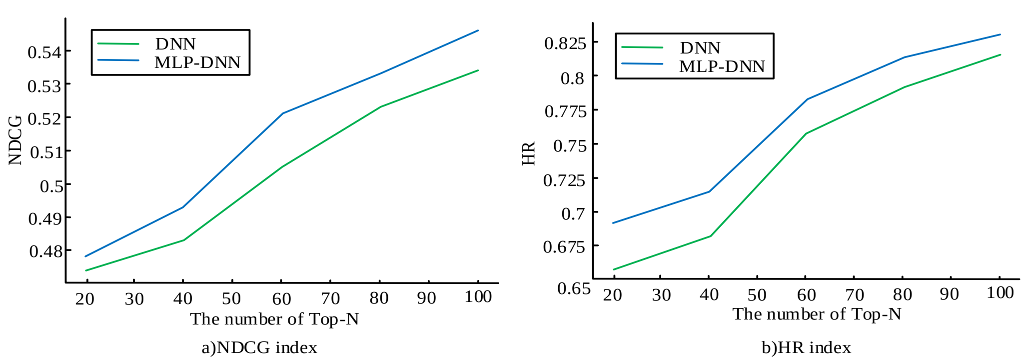

Fig. 8. The influence of top N number on recommendation performance.

In summary, the MLP-DNN prediction model constructed in the study has some validity and is better for rating prediction, faster scoring, simpler methods and better recommendations than the DNN prediction model.

B. Analysis of the Effectiveness of DNN-based Personalized RM Algorithm for ER

The study analyses the rationality and effectiveness of the three algorithms developed in the DNNER personalised RM. The first is the similarity-based ER filtering algorithm, where the most important step is to process the user's learning interests and the relevant text of the ER, convert the text into a vector, calculate the cosine similarity through the vector, and add a decrementing time factor to the final similarity calculation. To more accurately convert the text into vectors, the study uses a Chinese BERT pre-training model based on the full word coverage technique on top of BERT. The study briefly compares the resource filtering algorithm based on similarity ranking with the time required for neural network prediction. Fig. 9 shows that the time needed for prediction by the similarity algorithm is less than the time needed for prediction by the neural network, demonstrating that the resource filtering algorithm based on similarity ranking developed in this study can speed up the efficiency of recommendations and decrease response times, and its use can also speed up the feature processing process of resources.

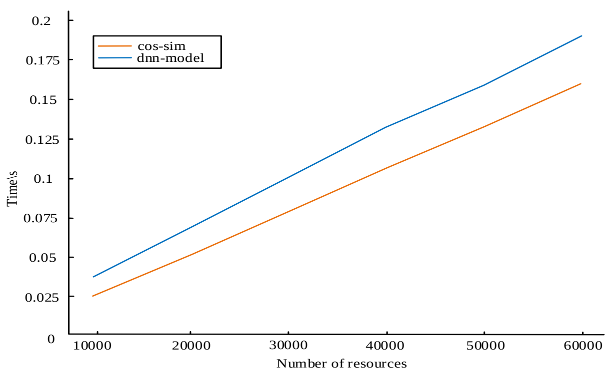

Fig. 9. Comparison of the time required for similarity algorithm and neural network prediction.

The effect of the DNN constructed and trained by the RR algorithm was then further validated. By using Python programming technology to process user data and course rating data collected from an online learning platform, we obtained 65783 rating records for 790 courses from 24244 users. The pre-processed dataset was split and 80% was classified as the training set for training the DNN, while the remaining dataset was used to test and validate the DNN. Select Adagrad optimiser, Huber loss function, relu activation function. Divide all the data into four samples of increasing quantity, 40%, 60%, 80% and 100% of the total quantity. The sample distribution is shown in Fig. 10, where the number of users in samples 1 to 4 is 12444, 16801, 20735, and 24244, respectively. The number of courses is 761, 777, 785, and 790, respectively. The evaluation scores are 26313, 39470, 52626, and 65783, respectively.

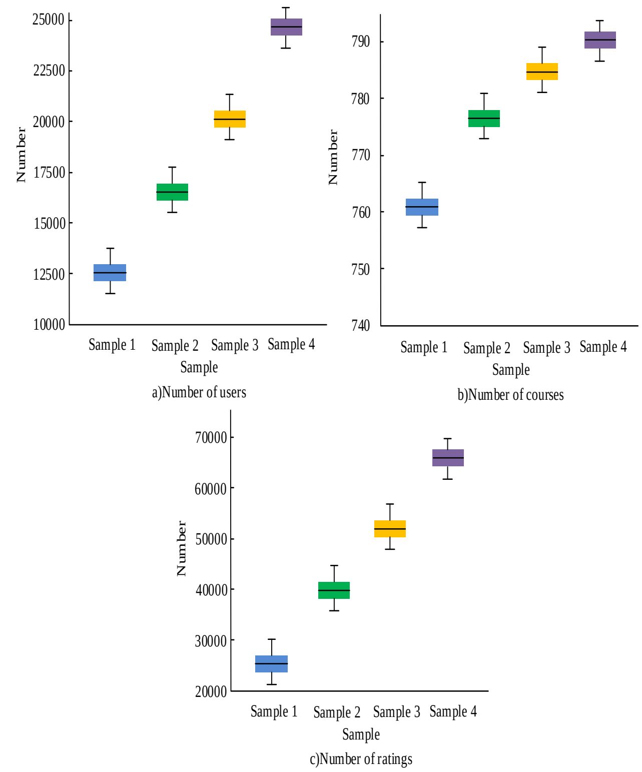

Fig. 10. Data distribution of resource recommendation algorithm experiments.

Decision Tree (DT), Support Vector Machine (SVM), k-Nearest Neighbor (KNN) and Convolutional Neural Networks (CNN) were selected to compare with the algorithm designed in this study. DNNRR algorithm designed in this study. In Fig. 11, in the comparative trials of the four samples, the MAE value of the DNNRR method designed in the study was the highest at 0.56 and the lowest at 0.54; it was lower than all the other algorithms except the SVM algorithm which was slightly higher; the MSE value was the highest at 1.29 and the lowest at 1.19, which were lower than the other algorithms. There is no difference between the MAE values of the CNN algorithm and the DNNRR algorithm, except for the obvious difference in the first sample, but the MSE values of the DNNRR algorithm are both lower than those of the CNN algorithm.

To verify the feasibility of the DNN-based resource display algorithm, using 70413 learning records from 13891 users collected and preprocessed on an online learning platform as experimental data. The Adam optimiser was chosen, the tanh activation function was picked, δ was set to 2.5, and the initial learning rate was set to 0.001. Following the calculation of the time interval, 80% of the data set was divided into the training set and 20% into the test set. The data was divided into four samples in the same way as in the experiments to validate the DNNRR algorithm, as shown in Fig. 12.

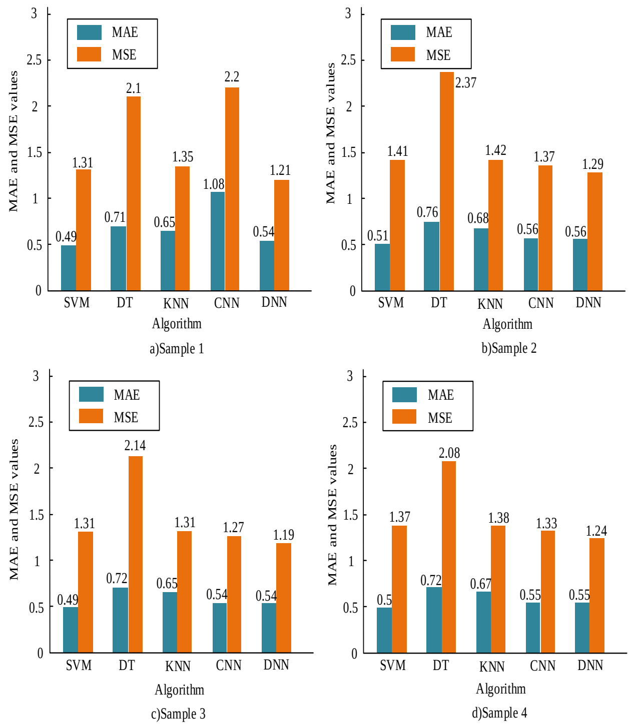

Fig. 11. Comparison results of MAE and MSE values for different recommendation algorithms.

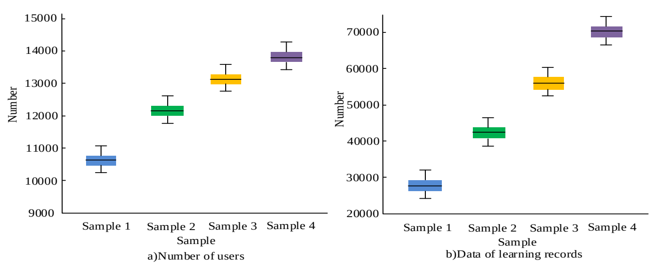

Fig. 12. Data distribution of resource display algorithm experiments.

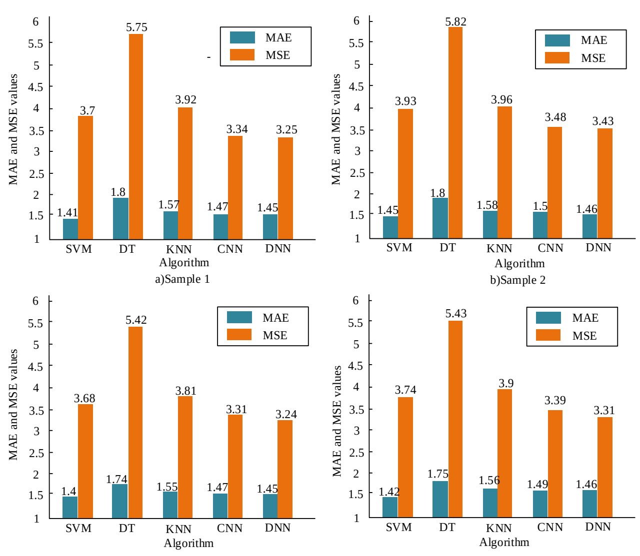

Fig. 13. Comparison of MAE and MSE values of 5 algorithms.

The same comparison was made with four classical algorithms, DT, SVM, KNN and CNN. In Fig. 13, in the comparison experiment for the four samples of different algorithms, the highest MAE value of the DNN resource display algorithm designed in this study is 1.46 and the lowest is 1.45, which are lower than the other algorithms except that it is higher than the SVM algorithm. The highest MSE value is 3.43 and the lowest is 3.24, which are better than the other algorithms. The study shows that the designed DNN-based resource presentation algorithm is reasonable and effective.

V. Conclusion

Online learning platforms are steadily getting better thanks to the Internet's quick development. This convenience is accompanied with information overload, which adds to the time required for users to obtain knowledge. Intelligent recommendation technology can help solve this problem by providing personalised, intelligent, accurate and timely information recommendations. To address the problem of rational exploitation of OE resources, the study proposes a recommendation prediction model based on MLP-DNN and a personalised RM based on DNN. The outcomes revealed that the Loss value of the MLP-DNN prediction model was stable at about 0.6, which was about 0.2 lower than the Loss of the DNN prediction model. The DNCG metric was on average 0.01 higher than the DNN prediction model, and the HR metric was on average 0.03 higher than the DNN prediction model. The similarity algorithm took less time to predict than the neural network algorithm. The MAE value of the DNNRR algorithm was the highest at 0.56 and the lowest at 0.54, and the MSE value was the highest at 1.29 and the lowest at 1.19. The MAE values were lower than the other algorithms except for the SVM algorithm. The highest MAE value of the DNN resource display algorithm is 1.46 and the lowest is 1.45, and the highest MSE value is 3.43 and the lowest is 3.24. The MAE values are lower than other algorithms except for the higher than SVM algorithm, and the MSE values are lower than other algorithms. In conclusion, the model constructed by the research institute has a certain promoting effect on the development of the online education industry. However, the data collected in this study is still not rich enough for DNN learning, and the user evaluation experiments are not exhaustive enough. Therefore, in the future research work, it is necessary to further improve the system, collect more data, combine specific scenarios to collect more user evaluations, and establish corresponding answer banks to achieve automatic question answering function, so as to better apply to the intelligent recommendation of educational resources.

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