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Online Learning Resource Recommendation Based on Attention Convolutional Neural Network

Wei-Li Wang*

Zhengzhou Shengda University, Zhengzhou 14333, P. R. China
wangweili202311@163.com

Ning Zhang

Proximity Learning Co., Ltd, OH 43537, Maumee, United States
nw0295@163.com

*Corresponding author: Wei-Li Wang
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Abstract. *As emerging computer technology advances and the number of online learning platforms grows, the diversity of learning resources continues to expand. However, the exponential growth in the scale of educational resources has created a challenge for learners to navigate and select suitable resources from the vast array of options available. The challenge lies in effectively screening valuable learning resources from the abundant pool of options and providing personalized learning resource recommendation services for learners. Online learning platforms accumulate extensive historical learning data, while online learning resources possess abundant potential information. Hence, it is possible to develop personalized online learning resource recommendation methods tailored to individual learners. Compared to traditional recommendation algorithms, attention convolutional neural networks have stronger expressive power and can more accurately capture hidden relationships between learners and learning resources, improving the accuracy and personalization of recommendations. Moreover, attention convolutional neural networks have the capability to handle multimodal data, efficiently fuse various types of data for recommendation, and enhance both the diversity and accuracy of the results. Building upon the aforementioned benefits, this paper presents a novel online learning resource recommendation model (DE) that leverages attention convolutional neural networks. Experimental results demonstrate the superior performance of the proposed algorithm across various datasets compared to the baseline. This model provides excellent performance for personalized learning resource recommendation services in the education big data environment, further enhancing learners' online learning experience.*
Keywords: Attention convolutional neural network; Learning Resource; Personalized recommendation; Deep learning; Smart education

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1. **Introduction.** Personalized learning plays a crucial role in facilitating students' individualized growth, serving as a significant objective in school development, and representing a pivotal direction for educational advancement [1].As information technology continues to be extensively applied and rapidly develops within the education sector, coupled with the swift implementation of the "Internet plus+ Education" strategy, online learning resources have witnessed a remarkable surge in their growth and availability. We can obtain interested learning resources through online terminals anytime, anywhere. Nevertheless, the proliferation of online learning resources presents us with both opportunities and challenges in the realm of personalized learning. The abundance of learning

resources can potentially lead to resource saturation, making it challenging to swiftly locate the most suitable learning materials amidst the vast array of options available [2,3]. Emerging technologies like deep learning, speech recognition, facial recognition, and other intelligent technologies have been widely adopted across different fields. These advancements have significantly improved productivity and convenience in our everyday lives, earning positive evaluations as a result [4]. As an emerging deep learning model, attention convolutional neural networks have strong expressive power and sensitivity to hidden relationships between learners and learning resources. Therefore, online learning resource recommendation based on attention convolutional neural networks has become a highly focused research field [5].

Personalized learning resource recommendation technology, as an intelligent information filtering technology, constructs learners' feature models by analyzing their interest preferences and historical behavior data, then conducts feature mining on learning resources or information, and finally automatically recommends resources or information that meet their needs to learners [6]. Compared to the standardized and unified services provided by traditional online learning platforms, Personalized learning resource recommendation services enable learners to search for learning resources without having to operate independently, which is beneficial for improving their learning experience and efficiency. Consequently, the exploration of personalized learning resource recommendation technology has emerged as a critical research area within the realms of educational informatization and intelligent information processing. Moreover, the advancement of artificial intelligence can potentially contribute to facilitating intelligent learning practices [7,8].

The objective of constructing a personalized recommendation approach utilizing attention convolutional neural networks is to effectively harness the wealth of data derived from educational big data and online learning platforms. By integrating the individual circumstances of learners and learning resources, this methodology aims to accomplish personalized learning resource recommendations, yielding favorable recommendation outcomes [9,10,11]. The fusion of attention convolutional neural network technology and personalized learning resource recommendation can demonstrate efficient performance in feature extraction, classification prediction, regression analysis, solving the optimal value function of functions, image recognition, and other aspects. It can effectively solve problems such as sparsity of large-scale data and inability to represent feature attributes of high-dimensional data, and it can maximize the mining of learners' potential interest preference information during the learning process using online learning platforms, so more accurate personalized learning resource recommendation methods can be planned or designed [12]. Hence, this article applies attention convolutional neural network technology within the realm of deep learning, blending recommendation algorithms with the extraction of latent feature information. This integration aims to enhance the precision of recommendation algorithms significantly.

1.1. **Related Work.** Deep learning, a vital subdivision of machine learning, stands out as one of the most remarkable technologies within the realm of contemporary machine learning. In the domain of recommendation systems, attention convolutional neural network-based models can be categorized into two primary stages: the training phase and the recommendation phase [13]. The training process includes the processing of learning platform data and algorithm design, while the recommendation process involves the generation of resource recommendation sequences and the evaluation of recommendation effectiveness. The attention convolutional neural network, as a variation of deep neural networks, comprises an input layer, multiple hidden layers, and an output layer [14]. The neurons between each layer are fully connected. With an increase in the number of layers, attention convolutional neural networks exhibit enhanced learning capabilities, although it is important to note that more layers do not necessarily translate to better performance. Furthermore, a suitable number of layers can effectively enhance the network's performance.

Wu et al. [15] put forward a novel context-aware recommendation model called the convolutional matrix decomposition model, which integrates convolutional neural networks with probability matrix decomposition to address the issue of sparse ratings. Alshmrany [16] introduced an automated recommendation algorithm for learning resources utilizing convolutional neural networks, which employs convolutional neural networks to predict relevant factors in textual information. The convolutional neural network utilizes the topic model as input and employs the implicit factor model as output. The convolutional neural network extracts the feature of the learning resource, and combining the preferences of the learners, personalized recommendations for the learning resource are provided. Shu et al. [17] utilized convolutional neural networks to extract text information from learning resources and applied content-based recommendation algorithms, thereby enhancing the quality of learning resource recommendations. Hanafi et al. [18] introduced a dynamic convolutional neural network as a novel approach to enhance the accuracy of collaborative filtering recommendation system comments and address the issue of sparse data in comments. Zhang et al. [19] developed a time model and constructed a dynamic convolutional recommendation model to overcome the limitations of existing recommendation algorithms that rely on convolutional neural networks. The aim was to accurately predict the dynamic trends in user preferences and item lifecycle. Zieba et al. [20] proposed a neural network collaborative filtering model that introduces basic auxiliary information, effectively capturing the relationship between users and items. Through a novel multi-branch neural network, the aim was to identify shared and unique preferences among users, ultimately constructing a collaborative filtering recommender. Huo et al. [21] introduced a learning resource recommendation model based on deep belief networks. This model takes into account learner characteristics and course content attribute features. By combining learner behavior characteristics, a user course feature vector is generated and used as input to the deep model. The course learner ratings are utilized as supervised data to facilitate learning. Doleck et al. [22] presented a personalized recommendation approach for learning resources, leveraging deep learning technology. This method involves processing the input through a feature selection model based on MIFS and processing the output through a learner learning resource bipartite graph association model. The goal is to determine the suitability of recommending specific learning resources. Zou et al. [23] integrated natural language processing and deep learning technology to classify new users. By calculating the similarity in learning levels between the target user and other classified users, a set of similar users was identified. This process involved evaluating learning level similarity and combining the calculations to determine the final set of similar users. The recommended learning resources were based on this analysis.

1.2. **Motivation and contribution.** As the Internet continues to thrive, there is a rapid surge in the abundance of online learning resources. However, users face the challenges of information overload and learning loss, making it extremely difficult to find learning resources that meet their personal needs. To address this issue, researchers have proposed an innovative method of actively recommending potential interest items through in-depth analysis of users' interests, hobbies, and historical behaviors. However, in the domain of recommending learning resources, data sparsity has become a major challenge due to the issue of detailed interaction data between users and resources. In addition, recommendation of learning resources also requires timeliness and accuracy in the recommended content. To tackle these challenges, this study presents a method for recommending online learning resources, utilizing attention convolutional neural networks. Specifically, this method integrates attention mechanisms with convolutional neural networks and collaborative filtering algorithms to effectively address the temporal issues in learning resource recommendation. By introducing an attention mechanism, this model can intelligently focus on key information in the user's historical behavior and provide personalized learning resource recommendations to better meet their interests and preferences. This innovative method has performed well in the experiment, demonstrating its outstanding effectiveness in solving the problems of learning confusion and information overload. The contributions of this study primarily manifest in the following areas:

(1) This study introduces a novel approach for recommending learning resources using attention convolutional neural networks. This method effectively addresses issues of data sparsity and timing in learning resource recommendation.

(2) By integrating attention mechanism with convolutional neural networks and collaborative filtering algorithms, the accuracy and recall of recommendations have been enhanced.

(3) In the experiment, this method displayed superiority in metrics like hit rate and normalized cumulative loss gain in the domain of learning resource recommendation, thereby affirming its effectiveness and feasibility.

2. **Relevant theoretical analysis.**

2.1. **Convolutional Neural Network.**

The Convolutional Neural Network (CNN) is a feedforward neural network that has evolved from multi-layer perceptrons. It is extensively utilized in diverse domains such as computer vision [24] and natural language processing [25]. The prototype of Convolutional Neural Network was first proposed by LeCu [26]. There are two main factors that distinguish convolutional neural networks from other types of neural networks: local connections and weight sharing. Unlike the densely connected multi-layer perceptron, the idea of local connections in CNNs is inspired by the structure of visual neurons in the human visual system. The principle of this mechanism is to connect the previous layer of neurons only to a portion of the latter layer, thereby reducing the number of connections. And weight sharing refers to the fact that for a certain layer of a neural network, the weights on all neurons in that layer are the same. By employing local connection and weight sharing, the objectives are to simplify the model and decrease its complexity. A typical convolutional neural network consists of multiple layers, including an input layer, convolutional layers, pooling layers, fully connected layers, and an output layer. Typically, there are several convolutional and pooling layers within the network. Figure 1 shows a convolutional neural network model for processing natural language.

Convolutional neural networks enhance BP neural networks by introducing convolutional layers and operations. In CNN, the two-dimensional convolutional formula is defined as follows:

$$s(i,j) = (X * W)(i,j) = \sum_{m}\sum_{n} x(i+m, j+n)w(m,n) \tag{1}$$

In this case, W represents the convolutional kernel and X represents the input. If X is a two-dimensional input matrix, W is also a two-dimensional matrix. Similarly, if X is a multidimensional tensor, W is also a multidimensional tensor.

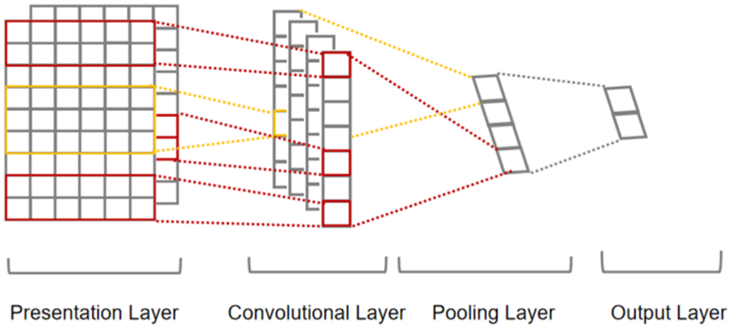


Figure 1. Structure diagram of convolutional neural network

The pooling layer's output is typically fed into the flattening layer as input. The fully connected layer, which includes all neurons from the preceding and succeeding layers, utilizes activation functions to classify based on the input features. The activation function can be categorized into linear and nonlinear types. The linear activation function formula is:

$$f(x) = x \tag{2}$$

Nonlinear activation functions include Sigmoid, Tanh, ReLU, PReLU, Swish, Softmax functions, etc. The commonly used sigmoid function formula is:

$$S(x) = 1/(1 + e^{-x}) \tag{3}$$

Among them, x is the input, and the sigmoid activation function maps $(-\infty, +\infty)$ to (0,1), which can be used for binary classification.

The formula for the ReLU function is:

$$R(x) = \max(0, x) \tag{4}$$

The Tanh function formula is:

$$T(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{5}$$

The Tanh function has been improved on the sigmoid function by mapping $(-\infty, +\infty)$ to the interval of $[-1, 1]$. Tanh performs well when there are significant differences in features, and continuously expands the feature effect during the loop process. The Softmax activation function formula is:

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \tag{6}$$

Among them, z represents the input, j represents the current classification, K represents the classification set, and k belongs to the classification set. Traverse all values in the set to add the results.

2.2. **Attention mechanism.** When the human brain processes external information, it filters and concentrates, ignoring unimportant parts [27]. Whether appreciating artistic works or using sensory organs, we demonstrate this innate attention cognitive ability, which is to choose to focus on important content and ignore other information. Deep learning models benefit from a vast amount of data to improve their expressive and learning capabilities. However, as the data volume increases, the information within the model also grows, posing challenges in discerning the most crucial information for effective training tasks [28]. To address this issue, convolutional neural networks introduce attention mechanisms and draw on human attention abilities. Through the attention mechanism, convolutional neural networks can focus on the data most relevant to the task, ignoring other parts, thereby improving the interpretability of the model. Attention mechanisms have achieved significant results in fields such as dialogue systems, emotion analysis, and machine translation, and have various manifestations, such as soft attention, hard attention, self attention, etc. This article mainly introduces key value pair attention [29]. Figure 2 depicts the operation process of key values on attention.

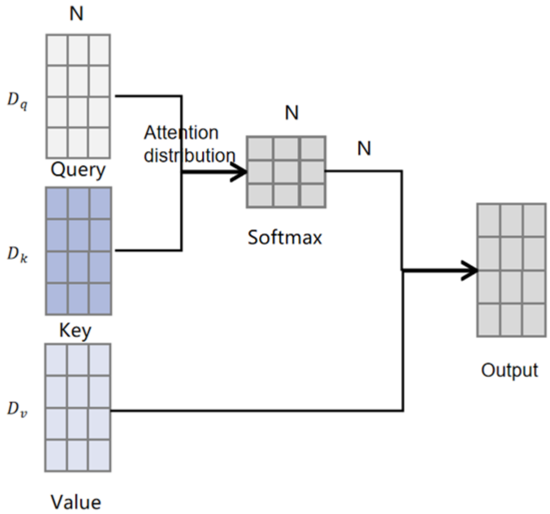


Figure 2. Key Value Pair Attention Mechanism

In the attention mechanism based on key-value pairs, "keys" are used to calculate attention distribution, and "values" are used to aggregate data. To begin with, the similarity between the query vector Q (Query Vector) and the key K (Key) is computed using techniques such as dot product, cosine similarity, or convolutional neural networks. Next, the softmax function is applied to obtain the attention weight distribution, which is then used to add the weight to the corresponding value V (Value) and obtain the final result. The formula is given as follows, where s represents the scoring function and k_n represents the value of key K.

$$a_n = \frac{\exp(s(k_n, q))}{\sum_{i=1}^{N} \exp(s(k_i, q))} \tag{7}$$

$$\text{attention}(Q, K, V) = \sum_{n=1}^{N} a_n v_n \tag{8}$$

3. Design of Recommendation Model Based on Attention Neural Network.

3.1. **Overall structure of model.** Personalized recommendation for learning resources involves the selection of suitable resources from a vast collection, ensuring efficiency, diversity, proactive nature, and timeliness in the recommendations. To fulfill these criteria, we have developed a personalized recommendation model for learning resources using attention-based convolutional neural networks, as shown in Figure 3.

The model consists of two primary components, with the first part being the training of the model. We train two attention convolutional neural network models using real data, one to predict learners' ratings of learning resources, and the other to predict learners'

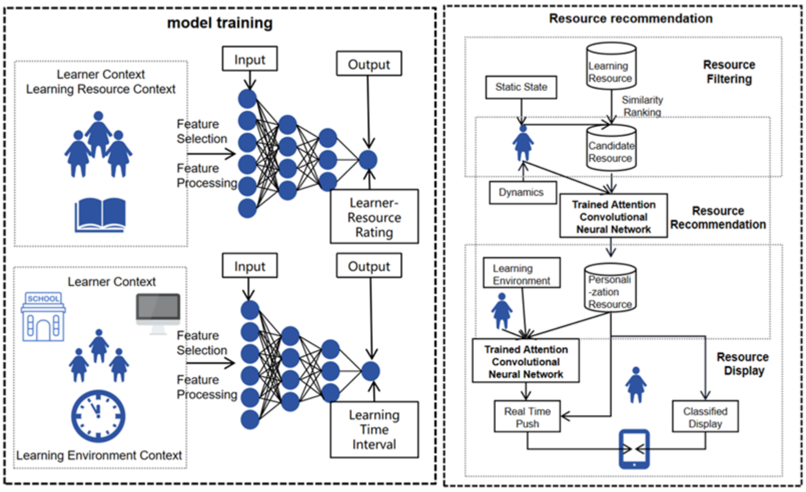


Figure 3. Personalized Recommendation Model for Learning Resources Based on Attention Neural Network

learning time intervals. These models are based on the learner's context and the context of learning resources for learning. The context of learners includes characteristics such as gender, grade, interests, and hobbies, while the context of learning resources includes learning duration, difficulty, user evaluation, etc. Through the training of these models, we can accurately predict learners' ratings of relevant learning resources, thereby achieving accurate personalized recommendation of learning resources.

The second part involves resource recommendation, where trained attention-based convolutional neural network models and recommendation algorithms are employed to deliver personalized learning resource recommendations for learners. The resource recommendation module is divided into three modules: resource filtering, recommendation, and presentation. The resource filtering module uses a similarity sorting algorithm to filter out irrelevant resources based on learners' interests and text information of resources, forming a candidate resource set. The candidate resource set has a high similarity and controllable quantity with learners' interests to improve recommendation efficiency. Next, the candidate resources enter the recommendation module, using attention convolutional neural networks to predict ratings and recommend personalized learning resources through sorting. The resource display module can actively push resources based on learners' learning time intervals through classification display to meet their needs and improve recommendation accuracy.

3.2. **Feature extraction of learners and learning resources.** The attribute feature extraction based on attention convolutional neural networks is first preprocessed, transforming the auxiliary information of learners and learning resources into an embedding matrix. Then, the embedding vectors in the matrix are abstracted at multiple levels through n hidden layers to learn their feature information. As shown in Figure 4:

Firstly, the operation performed by the input layer is to input m-dimensional data into m neurons. In the embedding layer, the m-dimensional data is mapped to c-dimensional data, and then trained in the hidden layer. Let E be the user feature embedding vector and the project feature embedding vector, respectively. Place the embedding vector into the hidden layer for training, taking the user feature vector as an example, according to the following formula:

$$L_1 = \mathrm{ReLU}(w_1 \cdot E_u + b_1) \tag{9}$$

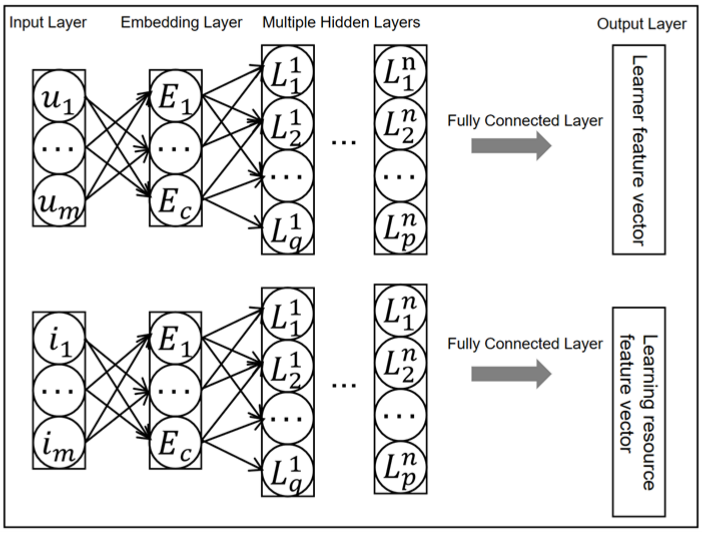


Figure 4. Attribute feature extraction architecture diagram

$$L_2 = \mathrm{ReLU}(w_1 \cdot L_1 + b_2) \tag{10}$$

$$\vdots$$

$$L_n = \mathrm{ReLU}(w_{n1} \cdot L_{n-1} + b_i) \tag{11}$$

Among them, L is the user feature vector output after training for each layer, ReLU is the activation function, and w_i, b_i are the weights and biases of the i-th layer, respectively.

Finally, perform a fully connected operation to output the user attribute feature vector. The project attribute feature vectors are also processed in the same way.

3.3. **Matrix decomposition.** In this article, attention-based convolutional neural networks are utilized to extract text features from project text information, with the aim of enhancing the extraction of user attribute features and project attribute features. The user and project features inputted in this chapter are extracted from the user and project feature matrix using attention convolutional neural networks, rather than directly using traditional matrix decomposition algorithms to obtain them from the rating matrix. Therefore, it can make the model data more dense on a real basis. In model optimization, to address the issue of overfitting due to sparse data in matrix decomposition after training, L2 regularization terms are used to reduce the size of weights, and the model's ability to solve overfitting problems is improved by reducing model complexity. The loss function is shown in Formula (12):

$$Loss = \sum_{i=1}^{N} \sum_{j=1}^{M} I_{i,j}(r_{i,j} - R_{i,j})^2 + \lambda \sum_{j=1}^{N} \|v_j\| \tag{12}$$

Among them, the value of I_{ij} is 0 or 1. When the user has overrated the project, the value is 1, and when the user has not overrated the project, the value is 0. At this point, the learner feature vector u_i is represented as:

$$u_i = (w_1 \times f_1(u) + b_1) \tag{13}$$

The feature vectors of learning resources v_j are represented as:

$$v_j = (w_2 \times f_2(v) + b_2) \tag{14}$$

where w_1, w_2 represents the weights of user and project feature training, and b_1, b_2 represents the bias amount.

Using the Adam algorithm for optimizing parameter training, the updated formula for learning rate is:

$$u_i = u_j - \eta \frac{\partial}{\partial u_j} L(U, V) \tag{15}$$

$$v_j = v_i - \eta \frac{\partial}{\partial v_i} L(U, V) \tag{16}$$

4. Data processing.

4.1. Datasets. To ensure the suitability of the personalized learning resources recommended by this method for learners, a series of experiments were carried out for verification. The experimental data encompasses not only learning resource data but also historical learning data of the learners. Public datasets like edX and World UC offer a wide range of attributes, including course data, learner information, and learner behavior data. This article collected specific online learning data from a dataset of an online learning platform at a university. By considering the actual learner and learning resource conditions, additional data was incorporated into the experimental dataset following relevant rules. The MIFS-based feature selection method processed the model, resulting in the extraction of learner resource features. These features form a subset that is required as input throughout the entire process of the method. In practical tasks, many machine learning features have table discretization, as shown in Table 1. This article adopts a unique encoding method for the features. As an example, suppose a learning record indicates that the learning resources pertain to the field of computer science and are in the form of video format. If the learner engages with these resources at 9 am, the corresponding resource sample can be represented as [100000], [01000], [10000], or [1000] through unique hot coding.

Table 1. Partial interrelated characteristic description and numeric representation.

Feature	Numerical representation	Meaning
Theme attribution/preference	1,2,3,4,5,6	Including computers, economic management, literature and history, life sciences, art and design, and others
Media type/preference	1,2,3,4,5	Including videos, audio, text, images, slides, etc
Grade of difficulty/level	1,2,3,4,5	Including easy, relatively easy, moderate, difficult, and difficult
Content Type/Preferences	1,2,3,4	Including concept explanation, test case studies, introduction, and course review
Learning time	1,2,3,4	Starting from 8am, every six hours is a time period
Terminal system	1,2,3	IOS, Android, Windows

The number of times learners use learning resources not only reflects their level of interest, but also provides a basis for recommending resources. To present the learning frequency of learners and learning resources in a clear and concise manner, and to effectively showcase the proposed method's efficacy and readability, a sample of 20 learners and 20 learning resources will be randomly selected. The details of this example can be found in Table 2. For example, learner L_2 uses resources R_3 4 times.

Table 2. Examples of the cumulative learning number of resources

	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	...	R_{15}	R_{16}	R_{17}	R_{18}	R_{19}	R_{20}
L_1	1	1	0	6	4	5	2	3	...	5	1	2	5	1	0
L_2	0	0	4	2	5	1	0	1	...	2	0	5	5	2	1
L_3	5	1	0	3	1	0	2	4	...	0	1	0	5	0	4
L_{15}	3	0	2	1	1	2	5	1	...	4	0	2	3	5	4
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
L_{20}	5	1	2	0	1	4	3	3	...	4	0	3	0	2	4

4.2. **Evaluation indicators.** The focus of this article revolves around the question of whether it is advisable to recommend learning resources to learners. According to the previous bipartite graph model, it can be specifically divided into propensity recommendation and propensity non-recommendation, so it can be regarded as a classification problem; On the other hand, the specific frequency of learners' use of learning resources largely reflects their interests, so it can also be seen as a regression problem. In the realm of recommendation and data mining, the most commonly used evaluation indicators are accuracy and error, which are two main indicators. Combined with commonly used recommendation system evaluation indicators, classification will use precision, recall, and F_1 score values. Usually, there is a contradiction between the accuracy and recall rates, so it is necessary to consider them comprehensively, that is, use the F_1 score value for evaluation; Regarding regression analysis, performance evaluation measures such as mean square error, root mean square error, and mean absolute error are utilized.

(1) Classification evaluation indicators

Classification models rely on several terms to ensure accurate predictions. These terms include TP (True Positive), which represents the correctly predicted number of positive samples - indicating the resources learners will use or use multiple times; FP (False Positive), which represents the number of positive samples incorrectly predicted - resources predicted to be used but are rarely utilized; TN (True Negative), representing the correctly predicted number of negative samples - learning resources that predicted learners rarely use; and FN (False Negative), which represents the number of negative samples incorrectly predicted - resources predicted as unused but are being used. In summary, higher precision (P), recall (R), and F_1 score values (F) indicate better performance. This implies that recommended learning resources have a higher chance of being learned by learners, aligning more closely with their needs. Their mathematical calculation formula is shown in Equation (17):

$$P = \frac{TP}{TP + FP} \tag{17}$$

$$R = \frac{TP}{TP + FN} \tag{18}$$

$$F = \frac{2 \times P \times R}{P + R} \tag{19}$$

(2) Regression evaluation indicators

To assess the disparity between the actual usage of learning resources by learners and the predicted counts, the following indicators are utilized: Mean Absolute Error (MAE), which combines the absolute values of errors to prevent positive and negative offsets and calculates their average; Mean Squared Error (MSE), which calculates the mean of the sum of squared prediction errors to address non-additive positive and negative errors; and

Root Mean Squared Error (RMSE), representing the square root of the mean squared error and indicating the degree of dispersion in the predicted values. The smaller the error, the closer the predicted learning frequency is to the actual frequency, indicating a good recommendation result. Their calculation formula is shown in Equation (18):

$$MAN = \frac{1}{n}\sum_{i=1}^{n}|X_i - Y_i| \tag{20}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2 \tag{21}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2} \tag{22}$$

where n represents the number of samples, X_i represents the i-th actual value, and Y_i represents the i-th predicted value.

5. **Experiments and analysis of results.**

5.1. **Classification experiment.** To enhance the accuracy of the experimental results, a ten-fold cross-validation method was employed, dividing the experimental dataset into ten parts. To minimize errors, a rotating approach was implemented, utilizing nine parts as training data and one part as testing data in the ten-fold cross-validation process. In practical situations, due to the temporal continuity of learners' resource learning, cross training is conducted using data from the previous period of time, and the trained model is then validated against data from the later period of time. This provides a more objective explanation of the actual usage of the recommended learning resources, and four samples with increasing sizes are formed by different numbers of learners and learning resources. The specific description is shown in Table 3.

Table 3. Data sample description

	Sample 1	**Sample 2**	**Sample 3**	**Sample 4**
Number of learners	50	80	80	100
Time (days)	15	15	30	30
Number of learning records	7528	12015	24088	30021

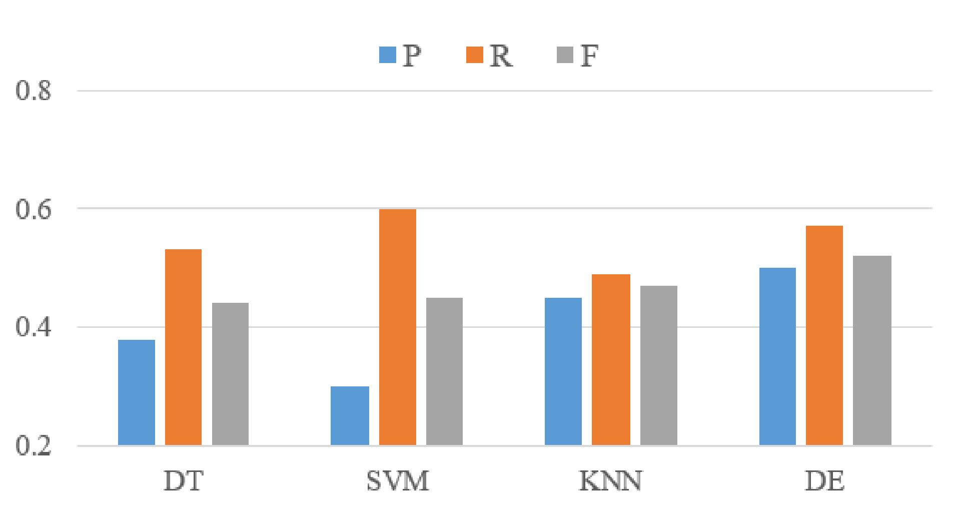
The experimental environment is the Windows Server 2012 R2 operating system, configured with 64GB of RAM, and MatlabR2017b is used as the programming language environment. The performance data of each comparative algorithm in the experiment are shown in Table 3 and Table 4. These comparative algorithms are classic machine learning algorithms that are called and implemented through the MatlabR2017b application toolbox. In terms of classification, comparative algorithms include the Decision Tree (DT) algorithm, the Support Vector Machine (SVM) algorithm, and the k-nearest neighbor (KNN) algorithm. In terms of regression, comparative algorithms include Fine Regression Tree (RT), Support Vector Machine (SVM), and Linear Regression (LR). These comparison algorithms are standard algorithms built into the MatlabR2017b environment.

In the classification results, as the sample size of the dataset changes, the models constructed by the *precision* (P) and *recall* (R) of each algorithm, as well as the use of machine learning algorithms to solve, are feasible and effective. In classification evaluation metrics, it is often challenging to achieve high values for both *precision* (P) and

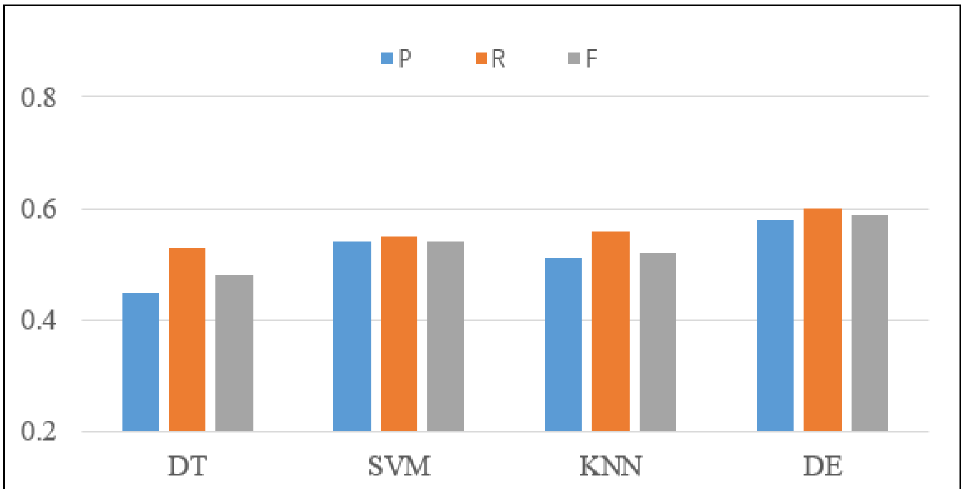
Table 4. Number of classification indicators

Classification Indicators				
Algorithm	Sample	Precision	Recall	F1-score
DT	1	0.38	0.53	0.44
	2	0.45	0.53	0.48
	3	0.57	0.57	0.57
	4	0.58	0.6	0.59
SVM	1	0.30	0.6	0.45
	2	0.54	0.55	0.54
	3	0.58	0.6	0.59
	4	0.66	0.61	0.63
KNN	1	0.45	0.49	0.47
	2	0.51	0.56	0.52
	3	0.62	0.68	0.57
	4	0.69	0.66	0.67
DE	1	0.5	0.57	0.52
	2	0.58	0.6	0.59
	3	0.74	0.76	0.7
	4	0.77	0.78	0.75

recall (R) simultaneously. For instance, in Sample 1, the SVM algorithm exhibits a high R value but a comparatively lower P value. During this period, the performance of the SVM algorithm cannot be judged unilaterally from one indicator, Therefore, using the $F1$ score value (F) as a comprehensive evaluation indicator for recommendation performance, it can be seen that the attention convolutional neural network (DE) designed in this paper outperforms other traditional machine learning algorithms in terms of F value and has a higher value. In order to verify the adaptability of this method to datasets of different scales, combined with Table 4 and Table 5, it can be seen that as learners accumulate learning time, in different time periods, due to the learners' situation or other factors at the time, various indicators will change, but the trend of change is still good, as shown in Figure 5. In various samples, an increase in the number of learners or learning time corresponds to an increase in the three indicators within the classification metrics. This suggests that a larger volume of learning records facilitates the correlation analysis between learners and learning resources, thereby enhancing recommendation performance. In terms of algorithm comparison, it is evident that the attention convolutional neural network model-based algorithm outperforms other algorithms. This observation highlights the consistency and specificity of the method proposed in this article in addressing the actual problem of learning resource recommendation.



(a) Sample 1



(b) Sample 2

(c) Sample 3

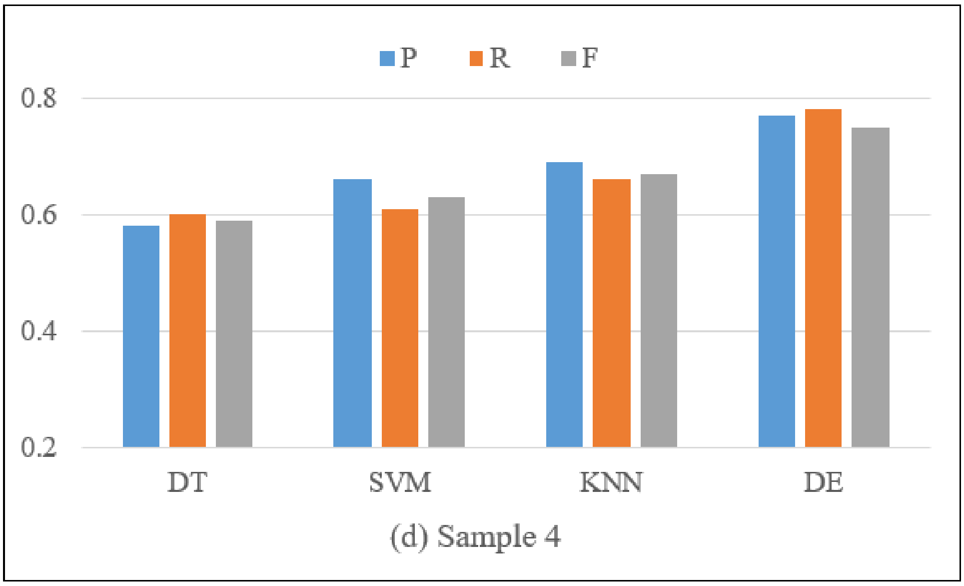


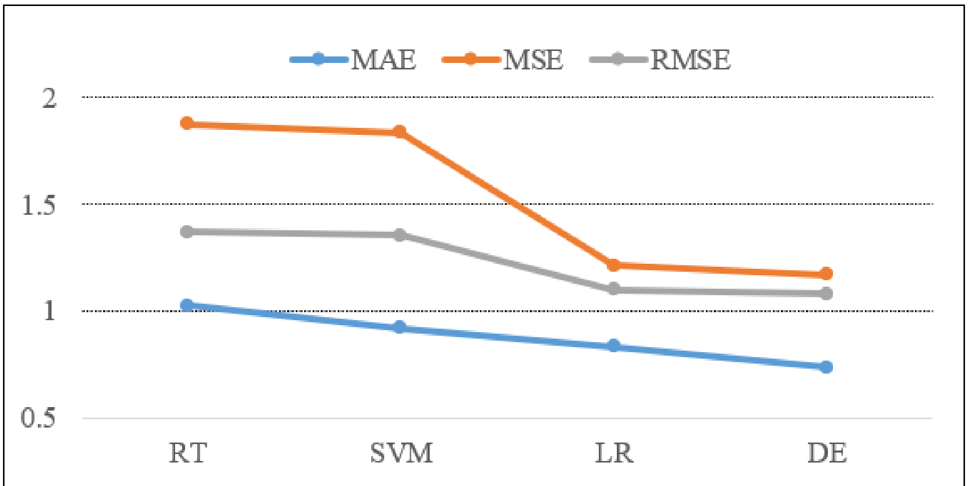
Figure 5. Bar chart of classification evaluation indicators

5.2. **Regression experiment.** By using classification methods, it is possible to predict whether learners will learn a certain resource. Regression analysis serves as a more effective approach for predicting the level of attention or interest that learners exhibit towards learning resources. It enables the prediction of the quantity of learning resources, which can then be compared with the actual number of learning occurrences. By conducting multiple error analyses, it becomes apparent that the predicted learning frequency closely aligns with the actual learning frequency. This indicates the suitability of the modeling method proposed in this article for regression analysis.

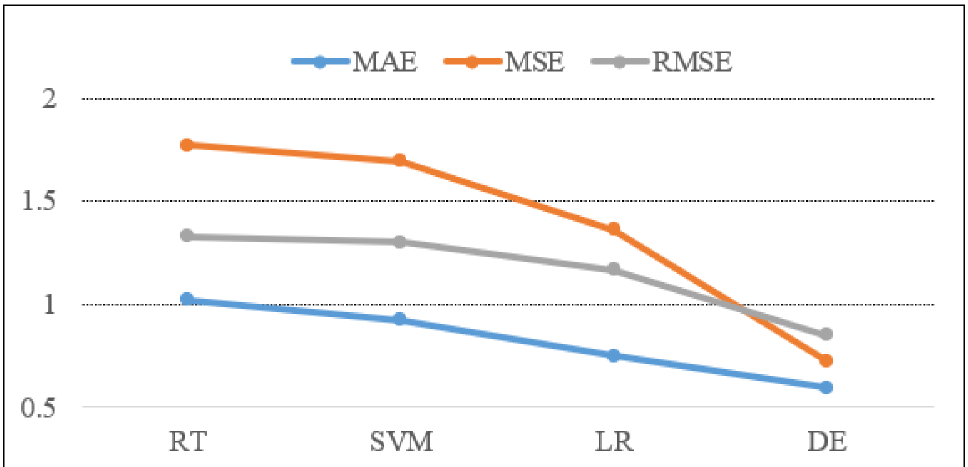
By examining different error metrics, an approximate evaluation of learners' attention towards specific resources can be obtained. This evaluation serves as a measure of the effectiveness of the recommendation method and offers valuable insights for enhancing the recommendation model. As depicted in Figure 5 and Figure 6, it is evident that the sample size has an impact on the observed changes, that is, as both the learner and the learning time change, the predicted frequency error also fluctuates, indicating its sensitivity and verifying the feasibility of using regression methods. The more records learners generate from learning resources, the more favorable the prediction of their learning frequency is. However, over time, the focus of learners may change, Thus, there is a possibility of significant prediction bias. Figure 5 and Figure 6 provide clear evidence that the DE algorithm exhibits the lowest error between predicted and actual results. This suggests that the enhanced attention convolutional neural network possesses strong adaptability in predicting learners' learning resource frequency and outperforms other algorithms. This is due to the increasing number of learning behavior records, which makes learners' resource learning patterns more pronounced. Through regression analysis of the error judgment, it is conducive to predicting learners' interests, and further screening of recommended learning resources can be made to improve learners' online learning experience.

Table 5. Number of regression indicators

Regression Indicators				
Algorithm	Sample	MAE	MSE	RMSE
DT	1	1.0277	1.877	1.3711
	2	1.0191	1.7687	1.3299
	3	0.9702	2.2778	1.5092
	4	0.9404	2.2019	1.4839
SVM	1	0.9223	1.8361	1.3550
	2	0.9206	1.6948	1.3019
	3	0.9138	2.1485	1.4658
	4	0.8768	1.9931	1.4118
KNN	1	0.8356	1.2124	1.1011
	2	0.7469	1.3598	1.1661
	3	0.7409	1.633	1.2779
	4	0.6379	1.9362	0.9674
DE	1	0.7376	1.1712	1.0822
	2	0.5929	0.7242	0.8511
	3	0.5834	0.7205	0.8488
	4	0.5652	0.6646	0.8152



(a) Sample 1



(b) Sample 2

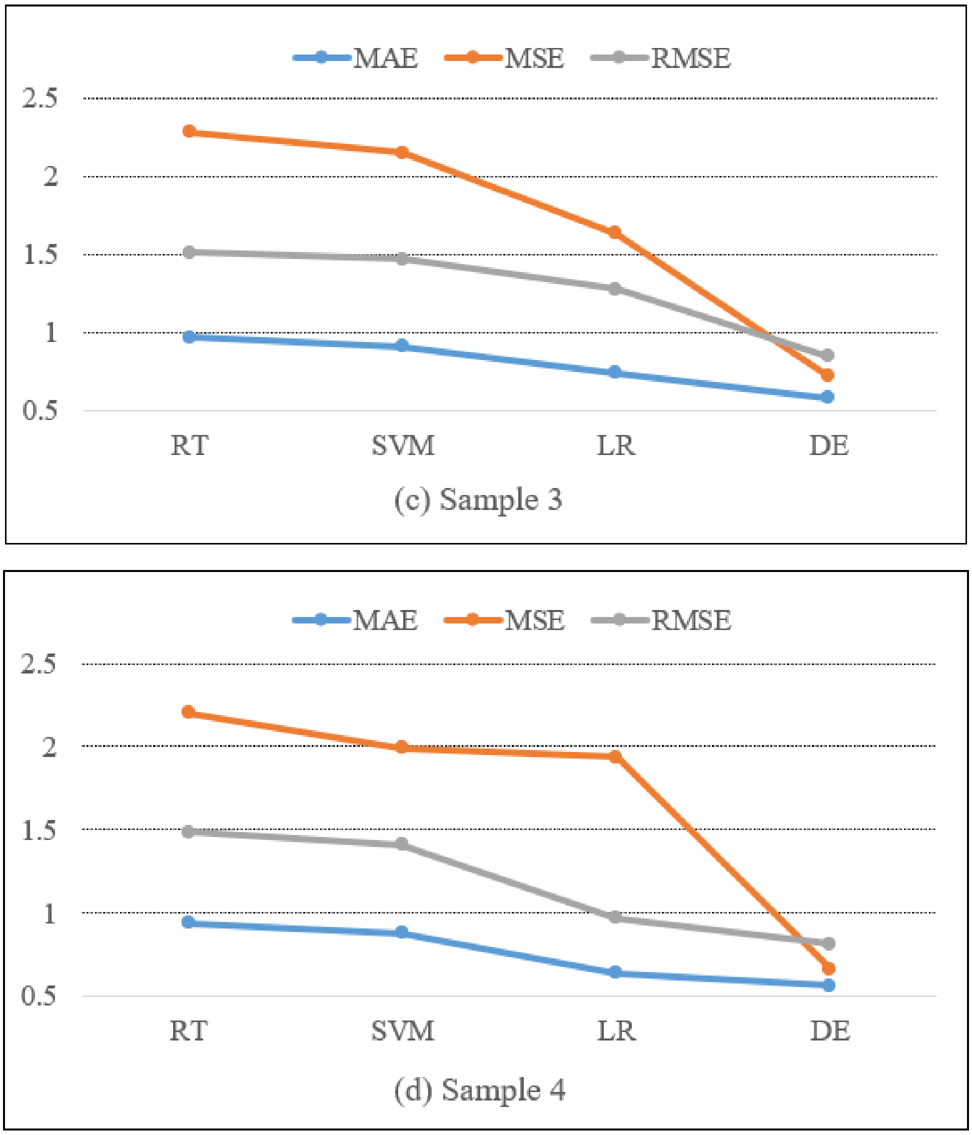


Figure 6. Curve of regression evaluation indicators

Through experimental analysis in both classification and regression, not only does it consider whether learners will learn about the resources, but it also predicts the level of interest or attention of learners towards the learning resources. The proposed recommendation method in this article is validated using various performance indicators, which demonstrate its effectiveness in modeling resource recommendation problems. Additionally, this method has the capability to address the recommendation challenge associated with new or unpopular objects to a certain extent. Furthermore, for the verification of various evaluation indicators, the attention convolutional neural network designed in this article also shows obvious advantages, indicating that the feature selection model based on MIFS and the learner resource bipartite graph association model have strong adaptability to the attention convolutional neural network, thereby demonstrating good recommendation performance and being suitable for online learning data of varying sizes. Furthermore, by leveraging the progression of time as the central theme, personalized learning resources recommended to learners based on historical learning data from previous periods can better cater to learners' needs.

6. **Conclusions.** As the Internet continues to evolve, the abundance of online learning resources is growing at a rapid pace, presenting challenges in finding resources that align with user requirements. In order to solve the problems of learning confusion and information overload, an effective method is to actively recommend potential interest projects to users by analyzing their interests, hobbies, and historical behaviors. The research focus of this article is on the issue of data sparsity in learning resource recommendation. Compared to other fields, learning resource recommendation involves detailed interaction data between users and resources. However, there are some difficult to solve problems in scalability and practical recommendation scenarios in domestic and foreign research. Therefore, this article has made improvements to learning resource recommendation. Traditional recommendation system models have problems with sparse data and cold start in learning resource recommendation, which pose a threat to recommendation effectiveness. In addition, learning resource recommendations also require the recommended content to be timely and accurate. To tackle these challenges, this study introduces a novel approach by combining attention convolutional neural networks with collaborative filtering algorithms for learning resource recommendation. By addressing the temporal aspect in resource recommendation, the proposed method surpasses other existing approaches in this domain, as demonstrated by the experimental results.

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