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Intelligent Management and Recommendation of AI Aesthetic Education Curriculum Resources in Big Data Environment

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SUMMARY: *According to the complexity and diversity of AI aesthetic education course resources and other characteristics, this paper designs an intelligent management and recommendation system for AI aesthetic education course resources, which realizes the intelligent management of AI aesthetic education course resources through the knowledge point annotation algorithm based on TextCNN-Transformer, and designs a multi-factor fusion collaborative filtering recommendation algorithm after the resource knowledge point annotation task. . The recommendation algorithm of multi-factor fusion collaborative filtering implements the intelligent recommendation of AI aesthetic education course resources by constructing the AI aesthetic education course resources knowledge graph, user knowledge graph, using the interest similarity calculation to obtain the recommendation score ranking of the AI aesthetic education course resources matched with the user's interests, and using the recommendation algorithm of multi-factor fusion collaborative filtering to implement the intelligent recommendation of AI aesthetic education course resources. The evaluation index system of the intelligent management and recommendation system of AI aesthetic education course resources is constructed, and the fuzzy evaluation method is combined to obtain the final score of the intelligent management and recommendation system of AI aesthetic education course resources designed in this paper.The performances of the TextCNN-Transformer model in the HM Loss, Sub Acc, Macro F1, and Micro F1 indexes were 0.0125 The RMSE and MAE of the recommendation algorithm of multi-factor fusion collaborative filtering on Filmtrust dataset reached 0.651 and 0.441 respectively.The fuzzy evaluation score of AI aesthetic education curriculum resources intelligent management and recommendation system is 84.646, which is in the interval of [80,90], with a good operational efficiency and a good construction of intelligent management and recommendation system is well constructed.*

KEYWORDS: *TextCNN-Transformer; knowledge point annotation algorithm; collaborative filtering recommendation; fuzzy evaluation; knowledge graph; intelligent management of curriculum resources*

1 Introduction

The study of aesthetics, serving as a vital educational field to nurture learners' aesthetic interests, enhance creativity and comprehensive quality [1]. Aesthetic education curriculum resources serve a pivotal function in the teaching of arts education, equipping both learners and educators with rich learning and teaching materials [2, 3]. However, with the swift advancement of digital technology, the number and variety of arts education curriculum resources are increasing, and how to manage and recommend these resources efficiently has become a challenging problem

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[4, 5]. For this reason, under the big data environment, an intelligent management and recommendation system for artificial intelligence (AI) aesthetic education curriculum resources has emerged, which uses large-scale data analytics and AI techniques to effectively organize and recommend learning materials to offer users with individualized learning and teaching experiences [6-8].

Big data technology can better manage and categorize aesthetic education curriculum resources [9]. Due to the abundance of resources in aesthetic education courses, including videos, texts, images, etc., these resources need to be categorized and managed according to different needs and goals enabling educators and learners to quickly find the materials they require [10-12]. Big data technology, on the other hand, is able to label and manage the resources and categorize them into corresponding educational resources by automatically identifying and analyzing their contents, thus enhancing the effectiveness of resource usage [13-15].

AI technology, by contrast, realizes customized intelligent suggestions grounded in resource management of big data [16]. AI can intelligently recommend aesthetic course materials for learners that are suitable for them based on personalized information such as students' interests, learning abilities, and learning history [17, 18]. In addition, by analyzing substantial quantities of learning information, the system is able to accurately predict students' learning needs and give corresponding recommendations, thus improving students' learning effectiveness [19, 20].

In this paper, TextCNN model is combined with Transformer model, so as to propose an automatic annotation algorithm for knowledge points of AI aesthetic education curriculum resources, and analyze the flow of knowledge point annotation algorithm based on TextCNN-Transformer. Sub Acc, HM Loss, Micro F1 and Macro F1 indicators are chosen as assessment criteria to compare the performance with traditional conventional ML approaches and sophisticated deep learning knowledge point labeling techniques. The labeled AI aesthetic education course resources are intelligently recommended by multi-factor fusion collaborative filtering recommendation algorithm, combined with Filmtrusto dataset, Ciao dataset for the experimental analysis of multi-factor fusion collaborative filtering recommendation algorithm. The fuzzy assessment approach is utilized to appraise the overall intelligent management and recommendation system of AI aesthetic education course resources, and the actual score of the construction of the intelligent management and recommendation system of AI aesthetic education course resources is obtained.

2 Automatic annotation of knowledge points for AI aesthetic curriculum resources

Serving as an essential component of quality education to promote the overall development of students, also known as aesthetic education, is to foster learners' capacity to identify, appreciate and create beauty. In the development of AI aesthetic education curriculum resources, it is necessary to focus on the integration of students' holistic literacy and vocational development, the rational advancement of educational materials, reflecting the framework of the curriculum, to ensure that the advancement of AI aesthetic education foundational course content satisfies the current needs of students' learning and growth. For example, colleges and universities combine students' career development needs with the Aesthetic Education general curriculum, and develop comprehensive general curriculum resources such as aesthetic education, language and culture, and civic education to meet students' learning and growth needs, thus broadening students' horizons and enhancing their comprehensive literacy and abilities. In order to rationally develop AI aesthetic education curriculum resources, this paper proposes an automatic annotation algorithm for the knowledge points of AI aesthetic education curriculum resources.

2.1 Knowledge point annotation process

Accurate automatic annotation of knowledge points is the basis for accomplishing intelligent tasks such as personalized cognitive diagnosis and personalized resource recommendation. The process of knowledge point annotation is shown in Figure 1.

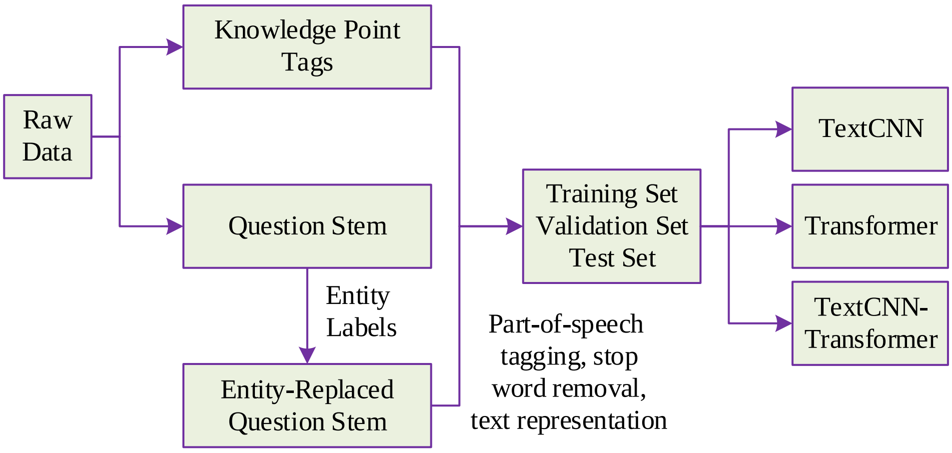

Figure 1: The process of the knowledge point annotation

2.2 Transformer model

2.2.1 Principle of operation

The Transformer model uses an encoding-decoding architecture, and the model consists of a total of six encoder layers and decoder layers. Among them, every encoder layer is composed of a self-attention mechanism alongside a feed-forward neural network. The role of the self-attention layer is to help the model learn the contextual semantics of the current node when encoding not only focusing on the words of the present node only. And the decoder layer not only has the self-attention layer and the feed-forward layer included in the encoder layer, but also adds an additional attention layer in the middle of the self-attention module and the feed-forward layer, which helps the current node to focus on what needs to be focused on at the moment.

When training, first, the model needs to vectorize the source text data, and subsequently feed the vectorized data into the encoder layer, and then feed the data back to the feed-forward neural network layer after the self-attention layer has processed the data. Then the output obtained from the parallel computation continues to be fed into the next encoder layer, and there are 6 encoder layers in total. Upon finishing the encoding stage, then the decoding phase begins. Each step of the decoding phase outputs an element of the output sequence until a special termination symbol is reached, which indicates that the decoder of the Transformer model has completed its output.

The self-attention layer in the decoder behaves in a different pattern than the encoder: in the decoder, the self-attention layer is only allowed to process those positions in the output sequence that are more forward. It masks out the later positions before the softmax step.

The decoder finally outputs a vector of real numbers, which goes into a linear transformation layer, which constitutes a straightforward fully connected neural network that maps the vector generated by the decoder into a considerably larger vector referred to as the log odds. Next, a Softmax layer is connected. The Softmax layer then serves to convert the scores from the linear transformation layer into probabilities, and the token associated with the cell carrying the greatest probability represents the output of the current time step.

2.2.2 Transformer-based Knowledge Point Annotation Modeling

1) Transformer model shows significant advantages in natural language processing.

The structure of Transformer model is as follows:

(1) Input

Since the Transformer model is completely based on the self-attention mechanism, which cannot obtain the positional information of words. Therefore, when inputting the model, position encoding should be added to each word vector. The formula for position encoding is shown below:

$$PE\left(pos, 2i\right) = \sin\left(\frac{pos}{10000^{\frac{2i}{d_{model}}}}\right) \tag{1}$$

$$PE\left(pos, 2i+1\right) = \cos\left(\frac{pos}{10000^{\frac{2i}{d_{model}}}}\right) \tag{2}$$

where pos denotes the absolute position of the word in the sentence, d_{model} denotes the dimension of the word vector, i denotes the i th dimension in the word vector, and $2i$ and $2i+1$ denote the parity.

(2) Coding component

The coding component is composed of multi-layer encoders, each of which comprises two constituent sublayers, namely the multi-head attention mechanism and the feed-forward network sublayer. In practical applications, usually multiple sets of vectors are operated in parallel. Suppose the word vector matrix added to the positional encoding is $E \in R^{n \times d_{model}}$, n denotes the number of words in the sequence, and the word vectors go through $W^Q \in R^{d_{model} \times l}$, $W^K \in R^{d_{model} \times l}$, $W^V \in R^{d_{model} \times l}$ three weight matrices are transformed to get $Q \in R^{n \times l}$, $K \in R^{n \times l}$, $V \in R^{n \times l}$ matrices, which are computed as follows:

$$Q = E \times W^Q \tag{3}$$

$$K = E \times W^K \tag{4}$$

$$V = E \times W^V \tag{5}$$

where $W^Q = [q_1, q_2, ..., q_l]$, $W^K = [k_1, k_2, ..., k_l]$, $W^V = [v_1, v_2, ..., v_l]$, and the three matrices Q, K, and V function as the query matrix, key matrix, and value matrix, respectively, which can be utilized to compute the $Attention$ value.

a. Calculate the correlation between each word in the input sequence and normalize it.

b.Use the $soft\max$ function to transform the correlation between words into a matrix of probability distributions between $\left[0,1\right]$, i.e., the attention distribution.

c.The resulting attention weights serve as the coefficient of each vector of the value matrix V to get the $Attention$ value, which is calculated as follows:

$$Z = Attention(Q, K, V) = soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right) \times V \tag{6}$$

where $Z \in R^{n \times l}$, and d_k denotes the dimensions of Q, K, and V matrices, i.e., l.

In the actual calculation, the multi-head attention mechanism is generally used, i.e., the h group W^Q, W^K, W^V weight matrices are used to get the h group Q, K, V matrices, and after each group is calculated to get a Z matrix, it is spliced together, and by learning the distribution of the attention in more than one space, it can efficiently capture more feature information. Its calculation formula is as follows:

$$MultiHead(Q, K, V) = Concat(head_1, \cdots, head_h)W^O \tag{7}$$

$$\begin{aligned} head_i &= Attention(Q_i, K_i, V_i) \\ &= Attention\left(E \times W_i^Q, E \times W_i^K, E \times W_i^V\right) \end{aligned} \tag{8}$$

where $Concat(head_1, \cdots, head_h) \in R^{n \times hl}$, and $W^O \in R^{hl \times l}$ denotes the weight matrix.

The feedforward neural network is composed of two fully connected layers, the first layer uses the activation function Relu, and the second layer does not use the activation function, which can improve the fitting ability of the model, and its calculation formula is shown below:

$$\max(0, XW_1 + b_1)W_2 + b_2 \tag{9}$$

where X is the output of the multi-head attention layer.

(3) Decoding component

The decoding component contains an identical number of decoder layers as the encoder, and the decoder includes three sub-layers of multi-head attention with mask, ordinary multi-head attention and feed-forward neural network.

2) Algorithm flow of Transformer-based knowledge point labeling model

Within this study, we construct the knowledge point labeling system leveraging Transformer under the TensorFlow framework. Since the knowledge point labeling task belongs to the text classification task and does not need to use the decoding part for text generation, only the encoding part is used in this task. In this task, the output of the encoding part is fed directly into the fully connected layer for knowledge point labeling.

2.3 TextCNN-Transformer-based Knowledge Point Labeling

2.3.1 TextCNN models

Convolutional neural network has convolutional layer and pooling layer, which can be used to extract local features. TextCNN is a variant of CNN, which can realize the extraction of different sizes of local features by setting different sizes of filter kernel, which can make the feature representations captured by the neural network diversified and more representative.

TextCNN model in the text matrix consists of word vectors, the filter kernel size of 2, 3, 4, respectively, after convolution pooling to obtain the feature vector, its dimension = the number of convolution kernel size * the quantity of convolution kernels for each kind of ruler rain, TextCNN is divided into the following four layers:

Convolutional Layer: In the TextCNN model of this paper, there are three filters with convolutional kernel dimensions 2, 3, and 4, which are capable of extracting distinct textual characteristics respectively. The filters change the node matrix of size $3\times3\times1$ into a unit node matrix, assuming that $wvi_{x,y}$ is used to denote the weight of the input node (x,y) of the filter for the i th node in the output unit node matrix, and bi is used to denote the corresponding bias parameter of the i th output node, then The value $a(i)$ of the i th node in the unit matrix is:

$$a(i)=f\left(\sum_{x=1}^{3}\sum_{y=1}^{3}c_{x,y}\times wvi_{x,y}+bi\right) \tag{10}$$

where $c_{x,y}$ is the value of node (x,y) in the filter. f is the activation function. The unit vector composed of all $a(i)$ is the feature map derived from the convolutional layer denoted as A, and A can be used as an input to the pooling layer.

Pooling layer: the pooling mechanism of the pooling layer enables the model to concentrate on certain features rather than the specific location of the features, and at the same time, it can get the effect of dimensionality reduction, reduce the computational overhead and the number of parameters, and to a certain extent, it can also prevent the occurrence of overfitting.

Fusion layer: the features obtained from the 3 pooling layers are concatenated and merged into a vector that is more representative for text vectors.

Full Link Layer: acts as a classifier for the ultimate categorization of the text by adding an implicit layer and a final Softmax layer after the fusion layer.

2.3.2 Model for automatic annotation of knowledge points

TextCNN model uses convolutional kernel to extract local features in text, while there are certain constraints in capturing global characteristics. Transformer model uses self-attention mechanism to extract global dependencies in text, while there are certain constraints in capturing local characteristics. Therefore, this paper fuses the two models to formulate the TextCNN-Transformer model. The overall structure of the architecture includes input layer, feature extraction layer, feature fusion layer and output layer. In the feature extraction layer, two neural network layers, TextCNN layer and Transformer layer, are employed to derive local features and global dependencies respectively, and then they are spliced together in the feature fusion layer to form the overall feature vector of the AI aesthetic education curriculum resources, and finally, the knowledge point annotation is completed by the fully connected layer and softmax.

Algorithmic flow of knowledge point annotation model based on TextCNN-Transformer:

Step1: Do preprocessing on the dataset text. According to the characteristics of the AI aesthetic education curriculum resources, combined with the entities labeled above, determine the specified words and domain deactivation words, and do the word division, deactivation and de-punctuation processing on the dataset text.

Step2: Divide the dataset. The proportion of training set, validation set and test set is 6:2:2.

Step3: Forward propagation and calculate the loss function. Use TensorFlow framework for the training task of Text CNN-Transformer model, randomly initialize the word vectors, input the model, extract the local feature vectors in the Text CNN layer, extract the long-term relationship feature vectors in the Transformer layer, stitch the feature representations, map them to the feature space, and calculate the loss function.

Step4: Backpropagation, update parameters. In the process of training, the word vector, convolution kernel and other parameters are constantly updated and optimized.

Step5: Fine-tune the model's hyperparameters. According to the experimental outcomes, human beings make adjustments to the hyperparameters of the model to identify the hyperparameter settings that make the model labeling performance the best.

Step6: Evaluate the training effect of the model.

3 Intelligent labeling of AI aesthetic curriculum resources

3.1 Evaluation indicators

Subset Accuracy classifies a data instance as accurate solely when all forecast labels are the same as the true label. The value of this metric ranges from 0 to 1. The higher the value, the stronger the model works on this metric, which is defined as follows:

$$sub\ acc = \frac{1}{n}\sum_{i=1}^{n} I\left(Y_i^p = Y_i^g\right) \tag{11}$$

where n is the number of resources within the AI aesthetic test program. Y_i^p represents the predicted label set of resource X_i. Y_i^g represents the true label set of resource X_i. $I(\cdot)$ is a binary indicator function where $I(True)=1$ and $I(False)=0$.

The Hamming loss is used to measure the ratio of knowledge points that are incorrectly predicted, including relevant labels being missed, or irrelevant labels being predicted. The lower the value of this indicator, the more effectively the model works on this indicator, and the Hamming loss is defined as follows:

$$h\ loss = \frac{1}{n}\sum_{i=1}^{n} \frac{1}{q}\left|Y_i^p \Delta Y_i^g\right| \tag{12}$$

q is the number of knowledge point labels. Δ represents the symmetric difference between the two sets.

Regarding the j th class label y_j, $1 \le j \le q$, four basic quantities characterizing the binary classification performance on this label can be defined for Y^p:

$$\begin{aligned}
TP_j &= \left\{x_i \mid y_j \in Y_i^g \cap y_j \in Y_i^p, 1 \le i \le n\right\} \\
FP_j &= \left\{x_i \mid y_j \notin Y_i^g \cap y_j \in Y_i^p, 1 \le i \le n\right\} \\
TN_j &= \left\{x_i \mid y_j \notin Y_i^g \cap y_j \notin Y_i^p, 1 \le i \le n\right\} \\
FN_j &= \left\{x_i \mid y_j \in Y_i^g \cap y_j \notin Y_i^p, 1 \le i \le n\right\}
\end{aligned} \tag{13}$$

Utilizing these four quantities, two essential evaluation metrics can be derived.

The macro F1 score indicator has a value range of 0-1, and the greater the value, the more effectively the model works on that indicator, as defined below:

$$F1_{macro} = \frac{1}{q}\sum_{j=1}^{q}\frac{2TP_j}{2TP_j + FP_j + FN_j} \tag{14}$$

The Micro F1 score is suitable for the case where the data distribution is unbalanced, but a larger number of categories will have a greater impact on the Micro F1. Since the data distribution in the dataset of this paper is not balanced, this paper focuses on the performance of the model on the Micro F1 score. The value of this indicator ranges from 0-1, and the larger the value, the better the model works on this indicator, which is defined as follows:

$$F1_{micro} = \frac{\sum_{j=1}^{q} 2TP_j}{\sum_{j=1}^{q}\left(2TP_j + FP_j + FN_j\right)} \tag{15}$$

3.2 Experimental setup

The configuration of the experimental environment is presented in Table 1. All the experiments are fully implemented based on pyton3.10 and PyTorch and are conducted in the designated experimental environment as outlined in the table.

Table 1: Experimental environment setting

Configuration name	Parameter/model
CPU	Intel Xeon Gold 6142 CPU 3.5GHz
GPU	NVIDIA GeForce RTX 3080
Developing capacity	8GB
CUDA core number	8704
CUDA version	CUDA 12.1
RAM	64GB
PyTorch version	2.2.x
Python version	3.10
OS	Linux

3.3 Comparative experiments

In this chapter, a number of leading-edge approaches for annotating the knowledge points of test questions are selected to compare with the TextCNN-Transformer-based knowledge point annotation method in this paper. All experiments use Word2Vec word embeddings by default to obtain text representations, and the dimension of word embeddings is 500.

1) Binary Relevance (BR): the knowledge point tagging task is decomposed into multiple independent binary classification problems.

2) Labeled Power Set (LP): the knowledge point tagging task is converted into a multi-category classification problem to be solved by considering all instances in the training set with the same label as a unified category.

3) Multi-Label K Nearest Neighbor (MLKNN): adapts the KNN algorithm to solve the knowledge point labeling problem.

4) RCNN: captures contextual information in text using RNN and constructs a textual representation using a convolutional neural network.

5) FastText: learns and obtains word vectors of three categories by using N-grams, and then obtains sentence representations with good semantic information based on the mean value approach.

6) DPCNN: The model is designed to be deeper by introducing equal-length convolution and adding 1/2 pooling layer to make the model have a wider sensory field, and the introduction of jump-layer connection accelerates the initialization speed of the model and addresses the issue of gradient dispersion due to the increased depth of the model hierarchy.

7) TextCNN

8) Transformer

The comparison results with other knowledge point auto-labeling models are shown in Fig. 2.

TextCNN-Transformer model's performance on HM Loss indicator is 0.0125, with the smallest indicator value, indicating that the model has the best HM Loss indicator.

For the Sub Acc metric, the TextCNN-Transformer model has 13.3% more than the Transformer model.

The Sub Acc metric value of 0.4687 for the TextCNN model is better, but the TextCNN-Transformer model is 5.32% higher than the TextCNN model.

Among the three traditional machine learning methods, BR, MLKNN, and LP, the MLKNN algorithm is more prominent. When benchmarked against sophisticated deep learning knowledge point labeling techniques, TextCNN-Transformer model is outstanding in HM Loss metrics, Sub Acc metrics. The TextCNN-Transformer-based knowledge point annotation method is effective in annotating the knowledge points of AI aesthetic education curriculum resources.

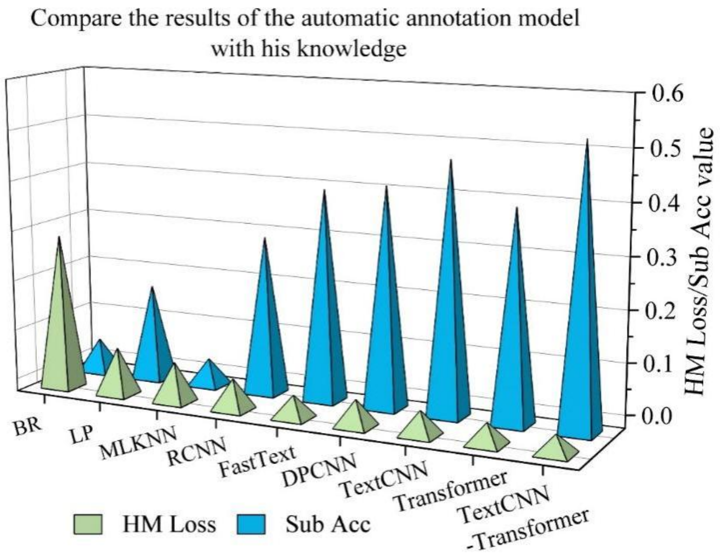

Figure 2: Compare the results of the automatic annotation model with his knowledge

The outcomes of the architecture comparison regarding Micro F1 metrics and Macro F1 metrics are illustrated in Figure 3.

The Micro F1 score of the TextCNN-Transformer architecture is 0.8989, which is 4.24% higher than the Transformer model and 2.95% higher than the TextCNN model.

As evidenced by the figure, the FastText architecture performs more distinctly regarding the Micro F1 metrics, with a Micro F1 value of 0.8696, but it is 2.93% lower than the Micro F1 value of the TextCNN-Transformer model.

Compared with the traditional machine learning method, the TextCNN-Transformer model improves 67.8% on the Macro F1 metric than the BR model.

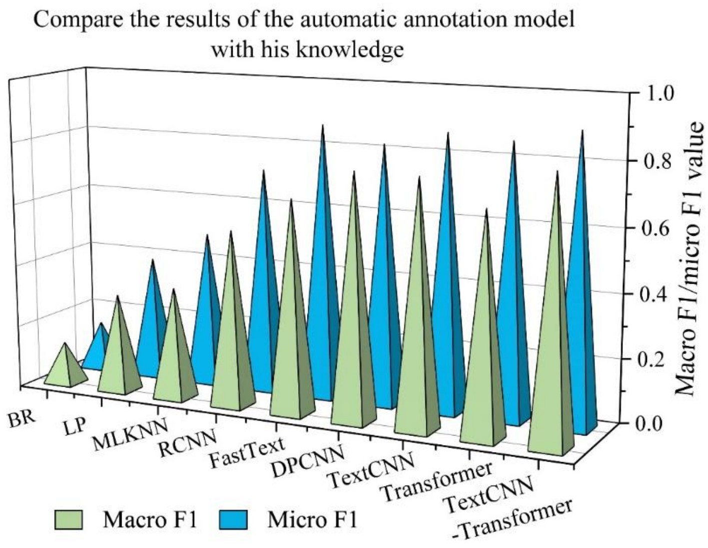

Figure 3: Comparison results of micro f1 indicators and macro f1 indicators

Combining the comparison results on the four metrics, the TextCNN-Transformer model attains superior performance across all four metrics when benchmarked against the cutting-edge deep learning knowledge point labeling approaches. Based on this, it is sufficiently proved that the TextCNN-Transformer model is superior to the other baseline models mentioned above. Using TextCNN-Transformer's knowledge point annotation method for AI aesthetic education curriculum resources knowledge point annotation can assist in promoting the subsequent intelligent recommendation of curriculum resources.

FLOPs indicator and params indicator on the indicator performance results of this paper's method are shown in Table 2. Comparison methods include RCNN, TextCNN, Transformer, etc. The parameter count of the Transformer architecture is about 11 times the parameter count of the proposed model, and the annotation effect of this paper's model is better than that of the Transformer model.

Table 2: Flops index and params indicators, the results of this method are shown

	FLOPs/M	Params/M
RCNN	161.36	0.62
FastText	0.35	0.31
DPCNN	130.83	0.56
TextCNN	114.96	1.17
Transformer	702.31	15.25
TextCNN-Transformer	60.26	1.54

4 Intelligent Recommendation of Knowledge Points for AI Aesthetic Education Curriculum Resources

In this chapter, a multi-factor fusion collaborative filtering recommendation algorithm is designed for the above characteristics after the labeling task. First, based on the accurate annotation of the AI aesthetic education course resources and the user's behavior on the system as well as the feedback, the knowledge graphs of the aesthetic education resources and users are constructed on Neo4j respectively. Then through the union of the target user information and knowledge graph, the AI aesthetic education course resource collection is quickly co-filtered to find the recall collection for the target user. Finally, through the scoring algorithm, the AI aesthetic education course resources in the recall set are scored and sorted, and the AI aesthetic education course resources that are most relevant to the needs of the target users are found and accurately pushed, so that the users can grow rapidly.

4.1 Resource Knowledge Mapping

By labeling the AI aesthetic education course resources, the similarity score between each resource is calculated, and the AI aesthetic education course resources whose similarity exceeds the threshold are connected to construct a knowledge graph.

For example, the AI aesthetic education course resources A, B difficulty similarity calculation formula is as follows:

$$S_{difficult}(a,b) = 1 - \left| \overline{d_a} \; \overline{d_b} \right| \tag{16}$$

where $\overline{d_a}$ is the average difficulty of AI Aesthetic Program Resources A and $\overline{d_b}$ is the average difficulty of AI Aesthetic Program Resources B. The knowledge point similarity scores are calculated as follows:

$$S_{knowledge}(a,b) = \frac{\sum_{i=0}^{n} \left| N(K_{a,i}) \cap N(K_{b,i}) \right|}{\min\left(\sum_{i=0}^{n} count\left(N\left(K_{a,i}\right)\right), \sum_{i=0}^{n} count\left(N\left(K_{b,i}\right)\right) \right)} \tag{17}$$

where the numerator is the sum of the number of intersections of each set of trivia points in the AI Aesthetic Education Curriculum Resources A and B. The denominator is the smallest value in the sum of the number of each trivia in the AI aesthetic education curriculum resources A and B. $N(K_{a,i})$ is the set of knowledge points of the smallest number of i in the AI aesthetic education curriculum resource A. $N(K_{b,i})$ is the AI Aesthetic Education Curriculum Resource B the i smallest set of knowledge points. The genre and style annotations correspond to one for each AI Aesthetic Curriculum Resource respectively, so AI Aesthetic Curriculum Resource A and AI Aesthetic Curriculum Resource B are scored as 1 if the genre and style are the same, and 0 if they do not overlap, which are denoted by S_{style} and S_{type} respectively. The formula for calculating the total score is as follows:

$$S_{score} = S_{difficult} * w_1 + S_{knowledge} * w_2 + S_{style} * w_3 + S_{type} * w_4 \tag{18}$$

The equations w_1, w_2, w_3, w_4 are the weights assigned to difficulty, knowledge, style, and genre, respectively.

4.2 User Knowledge Graph Construction

Collecting users' behavior of using AI aesthetic course resources in the learning platform can portray user profiles, which can be used to calculate the similarity adaption between users. Therefore, in this paper, user information is dynamically collected in the system, which is used to dynamically constitute the user knowledge graph. The cosine similarity between users is defined by the following formula:

$$w_{uv} = \frac{\sum_{i \in T(u) \cap T(v)} \frac{1}{|T(i)|} + (E(u) \cap E(v)) + (C(u) \cap C(v)) + \sum_{i \in S(u) \cap S(v)} (1 - s_i)}{\sqrt{N(u) || N(v)}} \tag{19}$$

This paper portrays the user portrait to the user AI beauty education course resources collection, use, sharing as a supplement. In the formula w_{uv} denotes the degree of similarity linking user U and user V, $T(u)$ for user u to do on the AI aesthetic education course resources collection, $T(i)$ fraction 1 is to penalize the user U, V common interest list of the popular AI aesthetic education courses resources for their similarity. $E(u)$ is the set of user u likes, $C(u)$ is the set of user favorites, and s_i represents the magnitude of the discrepancy in ratings of the first i AI aesthetic education course resource in the intersection of the set of user u and user v ratings. $N(u)$ is the set of completed AI aesthetic education course resources of user u. In this paper, with the aim of accelerating the construction speed of the user knowledge graph, an inverted lookup table B is established in the system, so as to improve the efficiency of the algorithm.

4.3 Scoring Ranking of Recall Sets

The screening process of AI aesthetic education course resources recall collection is: firstly, through the AI aesthetic education course resources knowledge graph and the user has completed the AI aesthetic education course resources collection $C1 = (c_1, c_2, c_3, c_4 ... c_n)$, and then find the collection $\overleftarrow{C1} = (\overleftarrow{c_1}, \overleftarrow{c_2}, \overleftarrow{c_3} ... \overleftarrow{c_i} ... \overleftarrow{c_m})$ which has a path with the nodes in this collection with the distance of 1 in the knowledge graph, where $\overleftarrow{c_i}$ contains the similarity scores on the paths between the nodes to prepare for the subsequent calculation of the scores.

The filtering process of the user recall set is as follows: first filter the set of users sharing a connection with the target user within the knowledge graph $\overleftarrow{U} = (\overleftarrow{u_1}, \overleftarrow{u_2}, \overleftarrow{u_3}, \overleftarrow{u_i} ... \overleftarrow{u_n})$, where $\overleftarrow{u_i}$ contains the affinity scores linking the target user node and the ii i th user node, and then sort the set $\overleftarrow{U}$ based on the user similarity, starting from the user with the highest similarity, to find the set $\overleftarrow{U}$ in the set of user collections of AI beauty education course resources in the collection of AI beauty education course resources that the target user has yet to done, combined into the set $\overline{C2}$.

In order to prevent the problem of highly close user relationships in specialized categories due to the high purpose of specialized training users, the number of AI beauty education course resources in the set $\overline{C2}$ must not exceed k. If k AI beauty education course resources are not filtered in the relationship node whose distance from the target user node is 1, they are filtered from the relationship node whose distance is 2, and so on.

The formula for calculating the interest score of the target user u on the i th AI beauty education course resource in the recall set $\overleftarrow{C}$ is shown below:

$$p(u,i) = \sum_{v \in S(u,k) \cap N(i)} w_{uv} r_{vi} \tag{20}$$

where $S(u,k)$ denotes the target user u in the user knowledge graph k the collection of users sharing analogous preferences, in order to highlight the user's own interests, as well as to avoid the situation where the user does not have users with similar interests, $S(u,k)$ contains the user himself, $S(u,k)$ is empty then the degree of overlap between the user's preferences and his own is 1, if it is not empty then the degree of overlap between the user's preferences and his own is the peak value in $S(u,k)$. $N(i)$ represents the collection of users who have completed the AI Aesthetic Program Resources i among all users. w_{uv} is the interest similarity between user u and user v. r_{vi} is the interest score of user v on AI aesthetic curriculum resources i.

After calculating the interest rating of the target user for every AI aesthetic education course resource in the recall set $\bar{C}$ by the above method, it is ranked to recommend the highest AI aesthetic education course resource to the user.

5 Intelligent Recommendation of AI Aesthetic Curriculum Resources

5.1 Data sets

The Movielens-100k, Filmtrust, and Ciao datasets are used for the experiments in this chapter. The details of the dataset are shown in Table 3.

Movielens is a personalized movie recommendation website that uses a scoring mechanism to represent the user's action behavior on movies, which consists of the user's rating of the movie, ranging from 1 to 5 where each item is rated at least once. In this paper, we use user id, item id, and rating information.Filmtrust dataset is a complete dataset crawled from Filmtrust, a movie recommendation website, which is composed of user ratings of movies, with ratings in the range of 0.5~4 points. The user id, item id, rating information, and trust information are used in this paper.

The Ciao dataset is a dataset crawled on the Ciao website, which contains user ratings and comments on numerous items with rating values in the form of 1~5 points. User id, item id, rating information, trust information are used in this paper.

Table 3: Statistical characteristics of data sets

	Movielens	Filmtrust	Ciao
Number of users	800	1300	15200
Project number	1800	2000	12000
Scoring number	100000	30000	70000
Sparse degree	0.052	0.012	0.0003

5.2 Comparative Experiments

The models are evaluated using the comparison algorithm as a reference as follows.

1) Probabilistic Matrix Factorization Algorithm (PMF), PMF employs regularized matrix factorization, which incorporates a stochastic model and optimizes it. Assuming that the feature

matrices of user U and user V both obey Gaussian distribution, the U and V feature matrices are obtained by the known values of the scoring matrix, and then the feature matrices are used to predict the unknown values in the scoring matrix.

2) Trust-based recommendation algorithm (SocialMF), the SocialMF model gives full play to the influence of trust propagation among users on their rating behavior, and combines with the probability matrix decomposition model for the prediction of ratings, so as to enhance the filtering performance of the architecture by incorporating the user trust information.

3) Social recommendation algorithm based on probability matrix decomposition (SoRec), with the aim of improving the recommendation precision, although SoRec uses the user's rating and trust information, but different from SocialMF, let the user's these two types of information to share the user's latent feature matrix.

4) Personalized Recommendation Algorithm for Social Networks (FISS), which models the suggestion process more precisely and naturally by mining the reliability of global item similarity and inter-user trust values, reduces the recommendation error in the cold-start problem, and achieves personalized recommendation for users.

5) Double Regularization-based Matrix Decomposition Recommendation Algorithm (DRSVD++) improves the accuracy of the recommendation results by incorporating the social and associative relationships of users into the matrix decomposition model in a regularized way, which makes the model training penalize the potential features of the corresponding users and items.

5.3 Analysis of experimental results

With the purpose of enabling the observation of the gap between the real rating scores and the predicted rating scores, the root-mean-square error and the mean absolute deviation are adopted as the assessment criteria for the accuracy of the predicted rating scores, and the smaller the gap between the real rating scores and the predicted rating scores, the better the filtering effect of the architecture is indicated.

The performance indexes corresponding to various algorithms within the Filmtrust dataset are shown in Figure 4.

Under the condition that the training set is 60%, it can be seen from the data in the figure that the error of this paper's method outperforms that of the comparison method.

The RMSE values of the traditional PMF algorithm, SocialMF algorithm, and SoRec algorithm are 0.875, 0.855, and 0.832, respectively.The RMSE and MAE of this paper's algorithm reach 0.651 and 0.441, respectively.It optimizes the RMSE over the traditional PMF, SocialMF, and SoRec algorithms by 22.4%, 20.4%, and 18.1%, respectively, 18.1%.MAE, on the other hand, is optimized by 27.3%, 24.3 %, and 23.8%.

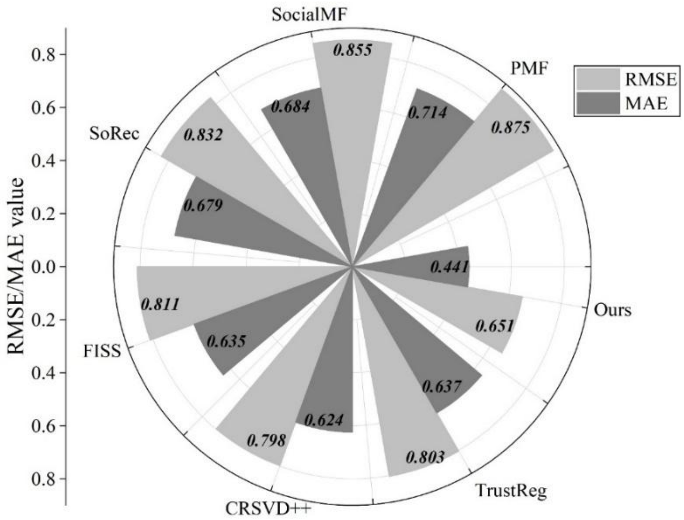

Figure 4: Filmtrust data concentrates different algorithms

The evaluation metrics corresponding to different algorithms in the Ciao dataset are shown in Figure 5.

The RMSE and MAE of this paper's algorithm are 0.628 and 0.509, respectively.The RMSE values of PMF algorithm and SocialMF algorithm are 1.332 and 1.054, respectively.The two comparative algorithms are 70.4% and 42.6% higher than this paper's algorithm's RMSE value, respectively.

The MAE value of FISS algorithm is 0.613, which is lower than CRSVD++ algorithm and PMF algorithm. However, the MAE value of FISS algorithm is 10.4% higher than the method of this paper. The accuracy of this paper's method is better and the error between it and the real rating score is minimized.

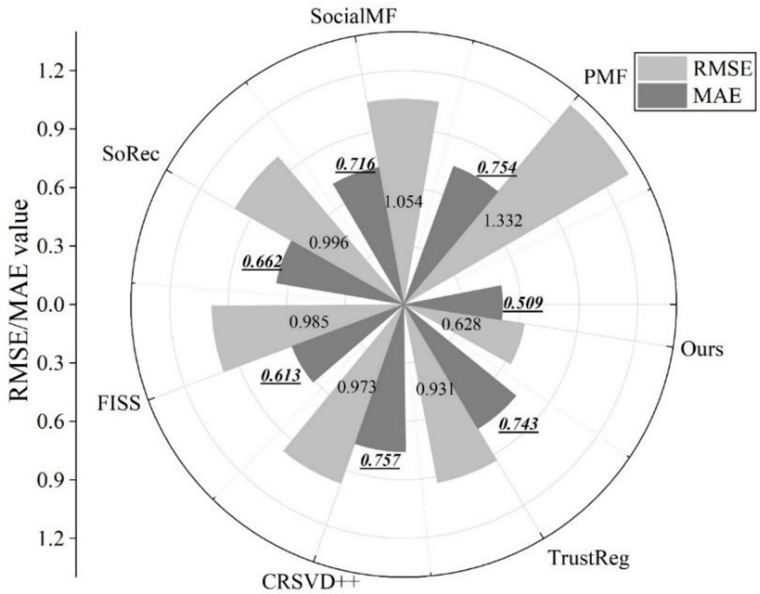

Figure 5: The corresponding evaluation indexes of different algorithms of ciao data

6 Evaluation of intelligent management and recommendation system of AI aesthetic education curriculum resources

6.1 Indicator Selection and Indicator Weights

With the aim of guaranteeing the impartiality and comprehensiveness of the selected indicators, the following principles need to be followed.

(1) Principle of scientificity

(2) Systematic principle

(3) Principle of operability

This paper combines the functional characteristics and positioning of the intelligent management and recommendation system of AI aesthetic education curriculum resources to design a set of indicator system that can objectively and comprehensively reflect the information resource system, which is structured into three components: the target layer, the guideline layer and the indicator layer. The target layer is the index system for evaluating the maturity of the construction of the intelligent administration and recommendation framework of AI aesthetic education course resources. The criterion layer consists of four elements, namely, resource richness, functional configuration, resource management configuration, and external use feedback. The indicator layer further refines the guideline layer into multiple evaluation indicators, which describe the four elements of the target layer respectively.

In this paper, the hierarchical analysis approach is employed to ascertain the weights, and by summarizing the weights of the metrics across the 13 tertiary indicator layers, the overall weights of the various refined indicators can be obtained as shown in Figure 6.

The three-level indicators include 1-type of information resources, 2-quantity of information resources, 3-area covered by information resources, 4-information source statistics, 5-data storage capacity, 6-data collection and updating efficiency, 7-data computation and mining capacity, 8-thematic data cataloging and management, 9-resource allocation efficiency, 10-degree of resource use, 11-application expansion, 12-collaborative response efficiency, and 13-resource Recommendation Effect.

In this paper, we use the knowledge point annotation algorithm based on TextCNN-Transformer for AI aesthetic education curriculum resources data cataloging management. The percentage of data cataloging management of AI aesthetic education course resources is 0.5640, indicating that resource cataloging management is particularly important in the intelligent management and recommendation system of AI aesthetic education course resources. Next is the degree of resource use, accounting for 0.5435, in this paper, the use of multi-factor fusion collaborative filtering recommendation algorithm for AI aesthetic education course resource recommendation configuration.AI aesthetic education course resource intelligent management and recommendation system evaluation index design is reasonable and effective.

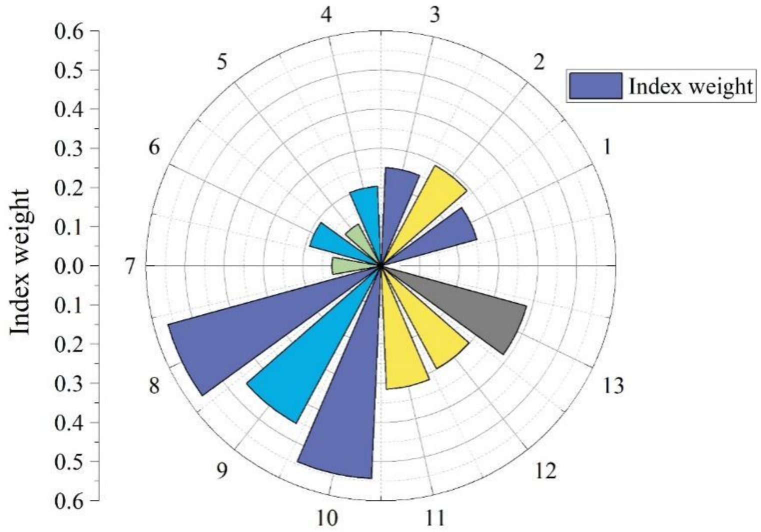

Figure 6: Weight of each indicator

6.2 Fuzzy evaluation

Considering the complexity and multiple fuzzy nature of the intelligent management and recommendation system of AI aesthetic education course resources designed in this paper, a fuzzy evaluation method is used to evaluate the designed system. This chapter establishes the corresponding score level according to the corresponding divided maturity level, i.e. $Z=\{z_1,z_2,z_3,z_4,z_5\}=\{50,60,70,80,90\}$.

The basic scoring data are obtained through the visit and research and after the evaluation and scoring of 6 experts. The fuzzy evaluation method is used to process the expert scoring data, and then the overall fuzzy evaluation vector is obtained. The scores of the intelligent management and recommendation system of AI aesthetic education curriculum resources are calculated sequentially, and the scores of resource richness, functional configuration, resource management configuration, and external use feedback are 85.129, 82.337, 86.495, and 84.621, respectively.The overall score of the intelligent management and recommendation system of the AI aesthetic education curriculum resources is 84.646.The construction of the system is in the [80, 90] intervals, and the intelligent management and recommendation system of AI aesthetic education course resources is well constructed. From the point of view of each sub-indicator, the functions of each part of the system are perfect, and the overall scoring results of the system are closer to the actual situation.

7 Conclusion

This paper applies the knowledge point annotation algorithm based on TextCNN-Transformer for the intelligent management of AI aesthetic education course resources, and the annotated AI aesthetic education course resources are intelligently recommended through the multi-factor fusion collaborative filtering recommendation algorithm. Establish evaluation indexes for the intelligent management and recommendation system of AI aesthetic education course resources, and use fuzzy evaluation method to carry out the comprehensive assessment of the intelligent administration and recommendation framework of AI aesthetic education course resources.

(1) The TextCNN-Transformer-based knowledge point annotation method outperforms other comparative methods in HM Loss, Sub Acc, Micro F1, and Macro F1 indicators. Combined with the model's performance on FLOPs indicators and params indicators, i.e.,

TextCNN-Transformer-based knowledge point annotation method has a significant advantage regarding the efficacy of automated labeling of knowledge points within AI aesthetic curriculum resources.

(2) The recommendation algorithm of multi-factor fusion collaborative filtering has RMSE values of 0.651 and 0.628, and MAE values of 0.441 and 0.509 on the public datasets Filmtrust and Ciao under the condition that the training set is 60%. The discrepancy between the predicted rating value and the actual rating value is small, and the model has a good recommendation effect.

(3) The intelligent management and recommendation system of AI aesthetic education course resources is constructed from four levels of resource richness, functional configuration, resource management configuration and external use feedback, and the final overall score of fuzzy evaluation is 84.646, and the construction of intelligent management and recommendation system of AI aesthetic education course resources is at a good level. The automatic annotation of knowledge points and collaborative filtering recommendation of AI beauty education course resources can realize the data-based and intelligent management of course resources.

About the Author

Quzi Hua was born in Wuxi, Jiangsu, P.R. China, in 1985. She obtained a master's degree from the Shanghai Theatre Academy in China. Currently, he teaches at Jiangnan Vocational College of Media Arts. Her main research directions include aesthetics and film screenwriting.

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