Personalized Push of Multimedia Japanese Education Materials in Colleges and Universities Based on Multi Task Deep Learning

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Keywords: Multi Task Deep Learning; Multimedia Japanese Education Materials in Colleges and Universities; Personalized Push; Context; Semantics

Abstract: Personalized push of multimedia Japanese education materials in Colleges and universities can improve the efficiency and adaptive matching level of Japanese teaching materials. This paper proposes a personalized push algorithm of multimedia Japanese education materials in Colleges and Universities Based on multi task deep learning. This paper constructs a deep learning model of multimedia Japanese education materials under the multi view fusion mechanism. By filtering and recommending the content, it carries out adaptive knowledge mapping analysis and deep learning on the summary, title, semantic knowledge, etc. of the learning materials. According to the dependency of semantic knowledge, it establishes a multi task deep learning model of multimedia education materials in Colleges and universities. In the process of deep learning, it mines the deep semantic correlation feature quantity, and realizes the personalized recommendation of multimedia Japanese education materials according to the clustering results of the feature quantity. The simulation results show that this method can improve the accuracy of recommendation, effectively use the automatic classification results in different semantic states to achieve data recommendation, and is superior to various views and models, can better achieve the automatic classification and category recommendation of Japanese teaching resources, effectively use the multi view knowledge and semantic information, and improve the efficiency of multimedia Japanese education materials.

1. Introduction

With the continuous development of text mining technology and intelligent recommendation algorithm, it is becoming more and more important to use computer language algorithm to realize the automation and personalized recommendation service of text, resources and other information. In the process of recommending the subject categories and directions of multimedia Japanese education in Colleges and universities, the optimal classification and identification of educational materials are realized through the calculation of machine learning, and the recommendation system for multimedia Japanese educational materials in Colleges and universities is established[1]. The content-based recommendation model and the collaborative filtering based recommendation model are used to realize the feature fusion of multi view semantic knowledge retrieval. Combined with the complementarity analysis of the three views of the paper title, keywords and abstract of educational materials, the convolutional neural network and deep learning method are used to carry out the personalized push of multimedia Japanese educational materials in Colleges and universities. The personalized push algorithm of Japanese educational materials is studied to improve the efficiency of retrieving educational materials.Efficiency, improve the utilization level of Japanese Education materials[2].

At present, the traditional multimedia Japanese education materials recommendation methods are mainly divided into content-based filtering recommendation methods and collaborative filtering recommendation methods. According to the historical information of individual chemists in the multimedia Japanese education materials in Colleges and universities (including published papers, browsing records, download information, subject direction, and research topics)[3], the information that scholars are interested in is calculated, and the highly similar Japanese information is recommended to scholars. In literature [4], the paper recommendation model of multi view fusion

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textrcnn is proposed to realize the optimal physical examination of learning materials such as papers, which is superior to the single view and the existing classic deep learning methods. The multi view knowledge fusion performance is better. In reference [5], it is proposed to realize intelligent recommendation of information such as news based on user implicit feedback signal and multidimensional interest recommendation model. According to the characteristics of user browsing, the learning materials are divided into static interest points and dynamic interest points, and the dynamic recommendation of educational learning materials is realized through the construction of knowledge entities. In the process of recommendation, the above methods are faced with serious problems such as data sparsity, lack of computing power and huge cost.

Aiming at the problems of traditional methods, this paper proposes a personalized push algorithm for multimedia Japanese education materials in Colleges and Universities Based on multi task deep learning. Firstly, the deep learning model of multimedia Japanese education materials under the multi view fusion mechanism is constructed, and then the personalized recommendation of multimedia Japanese education materials is realized according to the clustering results of feature quantity. Finally, a simulation experiment is carried out to show the superior performance of this method in improving the ability of using multimedia Japanese educational materials.

2. Deep learning model of Japanese educational materials

2.1 Construction of conceptual model of basic knowledge

The framework of the model is shown in Figure 1, which mainly includes three parts: data acquisition and preprocessing, improved multimedia Japanese education materials recommendation method and experimental evaluation.

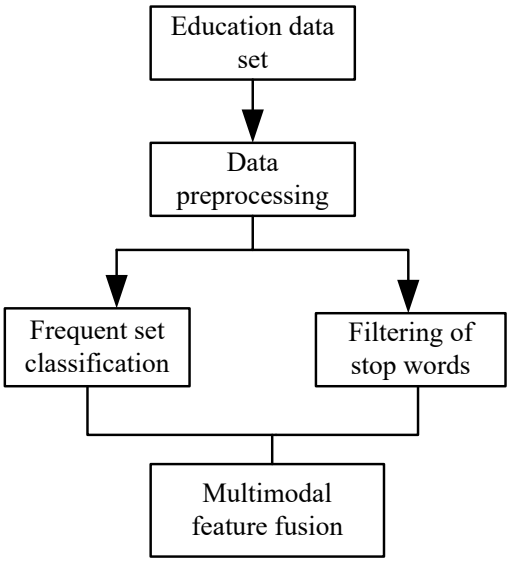


Figure 1 Multimedia Japanese education materials recommendation model

This paper constructs a deep learning model of multimedia Japanese education materials under the multi view fusion mechanism. Through the filtering and recommendation of the content, it carries out adaptive knowledge mapping analysis and deep learning on the summary, title, semantic knowledge, etc. of the learning materials[6]. Because this paper recommends the subject direction of multimedia Japanese Education materials, it fuses the three core views of title, keyword and summary. It constructs a fuzzy decision model of feature mining of multimedia Japanese education materials, considering the complementarity and coordination between the views. If the feature vector after data preprocessing and feature extraction is:

$$V(d)=\left(t_1w_1(d),t_2w_2(d),\cdots,t_nw_n(d)\right)(1)$$

Where, the document d contains n feature words and weights, t_i represents the ith feature

word, $w_i(d)$ represents the weight of the feature word in the document t_i, it is to effectively express the context semantic information and capture long sequence dependencies, but due to the large number of model parameters, the operation efficiency is low, so the construction of binary semantic distribution feature map is described as follows:

$$\theta : S \to S \times [-0.5, 0.5] \tag{2}$$

$$\theta(s_i) = (s_i, 0), s_i \in S \tag{3}$$

In the three core views of the title, keywords and abstract of the learning materials, the fusion language evaluation set $\boldsymbol{S}$, $\{v_1,...,v_M\}$ represents the reference set of learning materials with multi view fusion, $R = [R_{u,v}]_{N \times M}$ represents the feature words that contribute a lot to the classification task, and the text feature quantity is cleaned by using the full connection layer and softmax function, and the following formula is obtained:

$$C_{\Phi}(\boldsymbol{u}) = \Phi(\Phi^{-1}(u_1),.....\Phi^{-1}(u_n)), \boldsymbol{u} \in I^n \tag{4}$$

Where, u_i is the weight of the evaluation index constructed by the multi view fusion algorithm, $\Phi(.)$ is the distribution function for data dimensionality reduction by using the pooling layer, $\Phi^{-1}(\cdot)$ is the inverse function of Φ $(\cdot)$, and after extracting local features through convolutional neural network, the tree model for the allocation of multimedia Japanese education resources in Colleges and universities is obtained, as shown in Figure 2.

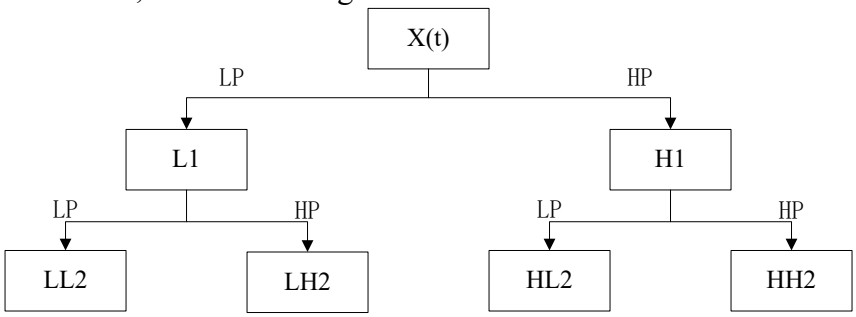


Figure 2 Tree model of multimedia Japanese education materials distribution in Colleges and Universities

According to the above analysis, it is obtained that the corresponding features of each region contain different weights, so as to establish the user's dynamic vector model to realize local feature detection. The time series obtained by the user based collaborative filtering model is $x(t)$, $t = 0,1,\cdots,n-1$. In the face of large-scale paper corpus in the digital library, the distribution sequence is $D(M, d_{\min})$, considering the diversity of users' interests, enter the complementary parameters of keywords and abstracts to obtain the directed graph $G = (U, V)$, where $U = \{u_1, u_2, \ldots, u_n\}$ represents the long-distance dependence on the construction model parameters, content-based filtering and collaborative filtering based recommendation methods to obtain feature fusion multi view semantic knowledge[7].

2.2 Deep learning model

Using the deep learning model, the word frequency of multimedia Japanese education resources is counted according to the user's negative feedback information. According to the browsing records, download information, subject direction, research topics and other information, the recommended network information X and its life length L are obtained. For the time series of learning shallow text knowledge, the following is the result:

$$PE_x = \{y_x(1), y_x(2), \ldots, y_x(L_x)\}, \quad L_x \in N^+ \tag{5}$$

Calculate the predictive parameter value of semantic knowledge on the recommendation classification result model, and predict the active period as L. the distribution of influencing factors of personalized push of multimedia Japanese education materials in Colleges and universities is shown in Figure 3.

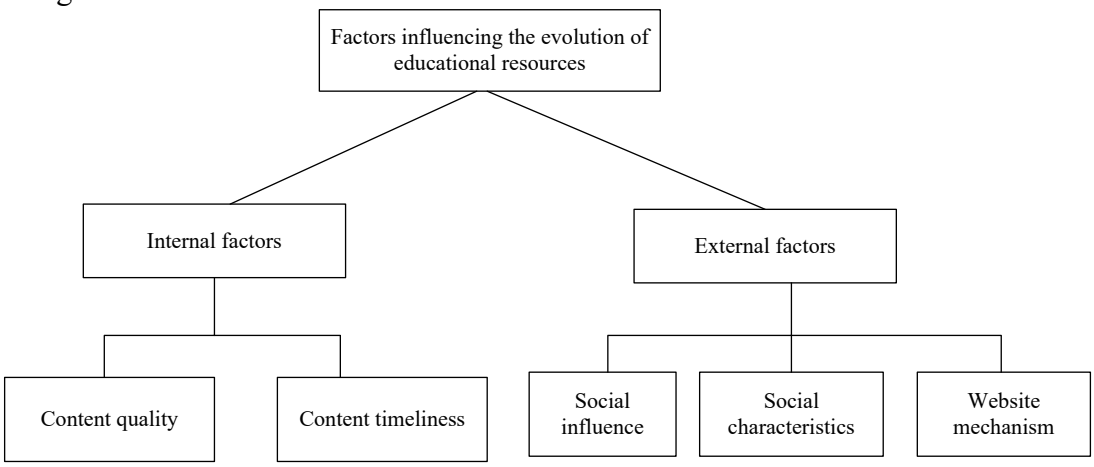


Figure 3 Distribution of influencing factors of personalized push of multimedia Japanese education materials in Colleges and Universities

The text recommendation model based on multi view fusion textrcnn was used to reconstruct the three views of title, keyword and summary, and the total number of process factors of deep learning was obtained

$$N_{\Delta t}^{tp} = \left| MB_{\Delta t}^{tp} \right| \quad (6)$$

Where, $MB_{\Delta t}^{tp}$ represents the content of the keyword view and summary view at the time $(t, t+\Delta t)$. The data set of the overall factor distribution set is divided into the training set as r. when $\Delta t = 1$ is required, the multi view fusion parameter is expressed as:

$$\max\left(N_{\Delta t=1}^{tp_i}\right) > \mathbf{r}_i \quad (7)$$

Due to the different values of threshold R and R in different stages of development of the recommendation platform, the bidirectional recurrent neural network is used to learn the context semantic features. The multi view fusion process of recommendation includes classifying and sorting the recommended content according to the sum value $\max\left(N_{\Delta t=1}^{tp_i}\right)$ and $\max\left(N_{\Delta t=24}^{tp}\right)$ of the key views, so as to realize the weight fusion and classification of the key features[8].

3. Realization of personalized push of multimedia Japanese education materials in Colleges and Universities

3.1 Multi task deep learning process

According to the dependency of semantic knowledge, this paper establishes a multi task deep learning model pushed by multimedia education materials in Colleges and universities. In the process of deep learning, it mines the deep-level semantic association feature quantity, uses the pooling layer to reduce the dimension of data and reduce the feature vector, extracts the fine-grained parameters after local features through convolutional neural network[9], and uses n to represent the attention mechanism fusion modeling parameters to obtain the mean value after the combination of deep network and entity embedding of knowledge map

$$r = \sum_{i=0}^{n} \max\left(N_{\Delta t=1}^{tp_i}\right) \times 0.8 / n \quad (8)$$

$$R=\sum_{i=0}^{n}\max\left(N_{\Delta t=24}^{tp_i}\right)\times 0.8/n \quad (9)$$

Considering the decoupled representation of multiple factors in the learning text, a single vector is used to represent the text and user interest. Instead, according to the text content and the user's historical click text sequence, the multi factor decoupled representation of the text and user interest is learned respectively, and the similarity matrix is obtained

$$D=\left(d_{ij}\right)_{M\times N} \quad (10)$$

The above formula represents the similarity between the representation of text content and user interest on various factors, thus enhancing the independence of all aspects of representation. The text decoupling representation is close to the relevance of its corresponding text:

$$sim_k=\frac{n_k}{M} \quad (11)$$

Wherein, n_k represents the number of non-zero lines in matrix D. by making the learned text decoupling representation close to its corresponding aspect center, the text level contrast loss function of Japanese education materials is obtained:

$$w(t_i,d)=\frac{tf(t_i,d)\times\log(\frac{N}{n_i}+0.01)}{\sqrt{\sum_{t_i\in d}[tf(t_i,d)\times\log(\frac{N}{n_i}+0.01)]^2}} \quad (12)$$

Wherein, $w(t_i,d)$ is to maximize the weight of consistency feature items between two enhanced texts in document d, $tf(t_i,d)$ is the word frequency of event feature items existing in the text sequence clicked by the user in document D, n is the total number of training texts, is the number of learning data distribution texts with feature items in the training text set, and the vectorization of event documents generated by randomly masking some words in the same text is expressed as n_i, that is $d_j=\left(t_{j1}:w_{j1},t_{j2}:w_{j2},\ldots,t_{ji}:w_{ji},\ \ldots,t_{jm}:w_{jm}\right)$, t_{ji} is the i-th feature item of the jth user level contrast loss document, is the weight based on the independent and identically distributed training set and test set, and M is the number of text recommendations under the change of user preference.

In order to enhance the main keywords, each word in the text is represented as a binary vector with a fixed size of V. The practice interval factor is introduced to capture the relationship and meaning between words. The N degree function, $w(t_i,d)$ positions represent the number of occurrences of the words corresponding to the index, and a piece of text is represented as a vector with a size of V to obtain the probability distribution weight of each topic by words

$$E=\sum_{i=1}^{k}\sum_{X\in C_i}\left|X-\overline{X_i}\right|^2 \quad (13)$$

Where: K is the total number of statistical text representation parameter distribution, and $\overline{X_i}$ is the clustering center of the distributed word vector of cluster C_i, that is, the average value. The keyword weight update formula is:

$$\alpha_i^k=\frac{m_i^k}{\sum_{i=1}^{M}m_i^k},\quad \alpha_i^k\in[0,1],\quad \sum_{i=1}^{M}\alpha_i^k=1 \quad (14)$$

Where, a_k is the initial weight vector of the word vector learned by matrix decomposition of the word co-occurrence matrix of x_k, m_i^k is the word frequency of word embedding, and β_k is the word frequency vector such as root, prefix and suffix. The multi task deep learning model is adopted, and the multi task deep learning model pushed by multimedia educational materials in

Colleges and universities is established according to the dependency of semantic knowledge[10].

3.2 Clustering and recommendation of recommended content

At present, most of the methods to push the learning content of educational resources focus on the representation of general text, but these methods may have limitations when dealing with domain text. Domain text often involves some domain specific knowledge domain text. Considering the limitations of feature-based methods, ontology knowledge is integrated into deep neural network, assisted input is used for representation, and then the attention mechanism is used to select the information related to the articles in the fact description and input it to the task prediction layer for output. The keyword weight of learning resource ontology A is adjusted through the keyword weight of text y. the fact description and the domain knowledge of related learning resources are made through comparative learning, which is expressed as:

$$A = \{A_1, A_2, \ldots, A_k\} \quad (15)$$

$$B = \{B_1, B_2, \ldots, B_k\} \quad (16)$$

Where, n represents the total number of texts and the number of texts. The representation after cascading the element representation and the text representation is used for the text matching task. Based on the assumption that the training set and the test set are independent and identically distributed, the recommended resource allocation time series is obtained as follows:

$$PE_z = \{y_z(1), y_z(2), \ldots, y_z(n)\} \quad (17)$$

By imposing a clear priori constraint on the distribution of potential variables, the decoupling of potential representations is promoted from a statistical perspective, and the average, trend, and periodic three-dimensional characteristic quantities pushed by learning resources are obtained. The mutual information regularization term is obtained. Thus, the iterative function of the recommendation process is expressed as:

$$C_z(t) = \frac{\gamma y_z(t)}{A_z(t)} + (1-\gamma) C_z(t-L) \quad (18)$$

$$T_z(t) = \beta\left(A_z(t) - A_z(t-1)\right) + (1-\beta) T_z(t-1) \quad (19)$$

$$A_z(t) = \frac{\alpha y_z(t)}{C_z(t-L)} + (1-\alpha)\left(A_z(t-1) + T_z(t-1)\right) \quad (20)$$

Where l is the period of output change caused by the change of input factor, and unsupervised decoupling represents the learning factor respectively. In the above iteration process, the deep semantic association feature quantity is mined in the process of deep learning, and the personalized recommendation of multimedia Japanese education materials is realized according to the clustering results of the feature quantity.

4. Experimental test

In order to verify the performance of this method in the implementation of personalized recommendation of multimedia Japanese education materials, the keras deep learning framework was used to design the relevant model, and the data analysis software MATLAB and SPSS were used for empirical analysis. The Japanese education resources involving 11 disciplines (medicine, philosophy, library and information, business administration, mathematical statistics, ethnology, Chinese language and literature, law, economics, computer science and technology, and Finance) were collected through the python web crawler. After data cleaning and preprocessing, 25980 pieces of multimedia Japanese education resources information in Colleges and universities were obtained. See Table 1 for the specific data distribution.

Table 1 Experimental data set

Number	Category	Training set	Test set	Validation set	Data summary
0	medicine	1095	916	453	2464
1	philosophy	916	897	493	2307
2	library and information science	1047	967	409	2422
3	business administration	1185	903	492	2579
4	mathematical statistics	1100	829	474	2403
5	ethnology	931	861	472	2264
6	Chinese Language and Literature	1034	875	489	2398
7	jurisprudence	876	877	453	2206
8	economics	1179	873	426	2478
9	Computer Science and Technology	992	801	489	2282
10	Finance	930	831	413	2175
Total		11286	9629	5063	25978

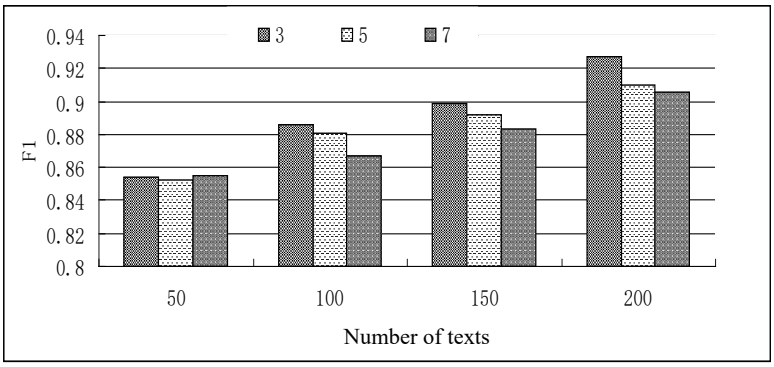
In terms of data preprocessing, this paper uses Python to write custom scripts to realize data cleaning. Firstly, the Chinese word segmentation is realized by using Jieba tool, and the stop words are filtered by combining with the dictionary; Secondly, word2vec algorithm is used to calculate the word vector; Finally, the paper recommendation experiment is conducted through the designed multi view fusion and multi task deep learning model. In terms of model parameter settings, the maximum length of text sequence is set to 500, the maximum number of features is set to 6000, the number of neurons in convolution layer and bilstm is set to 240, the training epoch is set to 30, and the learning rate is set to 0.00125. The optimizer selects Adam. First, this paper counts the text length after multi view fusion and data preprocessing. The statistical results are shown in Figure 4.

Figure 4 Distribution of text length of Japanese education resources

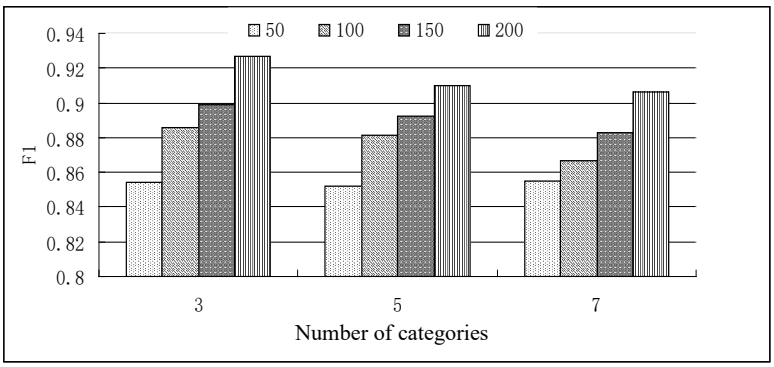
According to the distribution of Figure 4, the number of phrases in most categories is concentrated in the range of 150 to 350, while the number of phrases in the medical direction is mainly distributed above 550, and the sentence length of computer science and technology papers is relatively average. Because there is a strong semantic relationship among the phrases of the title, key words and abstract of the paper, and the subject direction of the paper can be effectively described from multiple views. For the distribution of text length of Japanese education resources, this paper uses the textrcnn method of multi view fusion for paper recommendation, and compares it with typical machine learning and deep learning algorithms. The comparison results are shown in Figure 5.

By analyzing Figure 5, we can see that the accuracy, recall and F1 values of the multi task deep learning push obtained by this method are 0.9155, 0.98552 and 0.9144, respectively, which are 0.033, 0.0321 and 0.0344 lower than those obtained by this method. Among the typical deep learning algorithms, textcnn algorithm is relatively better. The accuracy, recall and F1 value of its multi view fusion model are 0.9455, 0.9144 and 0.9544, respectively, which are 0.00878, 0.0121 and 0.0087 lower than those of this method. For dynamic detection, the median of the method in this paper is lower than that of other medians. In order to prove the correctness of the law obtained

above, the cyclic K value (1-100) is used to carry out the experiment, and the distribution of F1 value is shown in Figure 6.

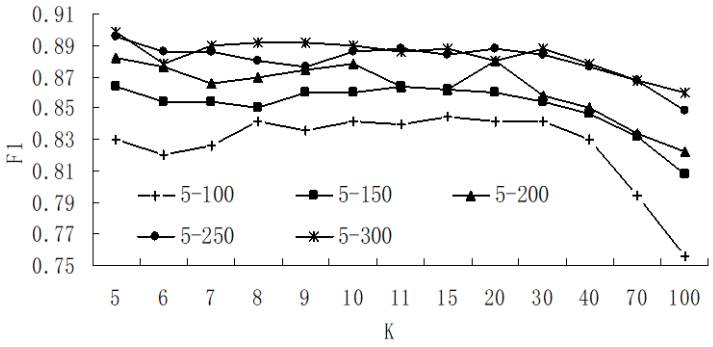


(a) Different text

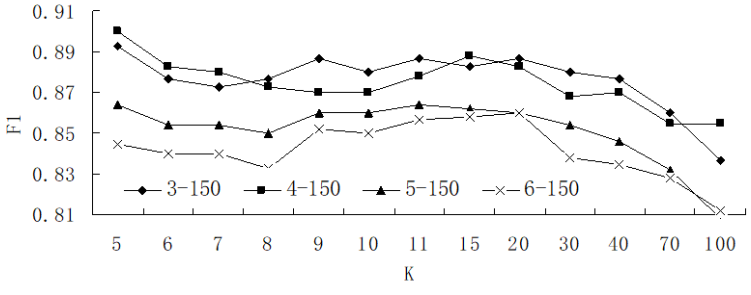


(b) Different categories

Figure 5 Comparison results of push performance



(a) Experimental results of five recommended classes under deep learning



(b) Experimental results of five classes of methods in this paper

Figure 6 Detection and analysis of push F1 value of five classes by different methods

By analyzing the above simulation results, we know that F1 value combines the advantages of accuracy and recall rate. This paper uses this index to compare the effect of multi view fusion algorithm and single view algorithm in detail. Among them, the F1 value of multi view fusion textrcnn is 8.65% higher than the title view, 18.22% higher than the keyword view, and 3.03% higher than the summary view. In addition, this paper further calculates the average F1 value of four traditional machine learning algorithms (decision tree, SVM, naive Bayes, and logistic regression) under each view. The title view is 0.7588, the keyword view is 0.6211, the summary view is 0.8577, and the multi view fusion is 0.8832, while the F1 value of this algorithm is increased by 16.32%, 31.76%, 9.59% and 6.11% respectively. Finally, the improved textrcnn model in this paper can effectively learn the characteristics of Title view, keyword view and summary view, further improve the algorithm effect, and is superior to various views and models, and can better realize the automatic classification and category recommendation of Japanese teaching resources

5. Conclusions

In this paper, a personalized push algorithm for multimedia Japanese education materials in Colleges and Universities Based on multi task deep learning is proposed. This paper constructs the deep learning model of multimedia Japanese education materials under the multi view fusion mechanism, and constructs the deep learning model of multimedia Japanese education materials under the multi view fusion mechanism. Through the content filtering and recommendation, the adaptive knowledge map analysis and deep learning are carried out on the summary, title, semantic knowledge, etc. of the learning materials. After the local features are extracted through the convolutional neural network, the tree model of the distribution of multimedia Japanese education materials in Colleges and universities is obtained. The deep learning model is used to carry out the word frequency statistics of multimedia Japanese education resources according to the negative feedback information of users. According to the browsing records, download information, subject direction, research topics and other information, the data dimension is reduced by using the pool layer, and the feature vector is reduced. After the local features are extracted through the convolutional neural network, the fine-grained parameters are obtained. According to the clustering results of the feature quantity, the multimedia Japanese education personalized recommendation of materials. Through research, it is concluded that using this method for personalized push of multimedia Japanese education materials in Colleges and universities can improve the accuracy of recommendation. The improved textrcnn model in this paper can effectively learn the characteristics of Title view, keyword view and summary view, further improve the algorithm effect, and is superior to various views and models, and can better realize the automatic classification and category recommendation of Japanese teaching resources.

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