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English language education in smart housing design: enhancing the language skills of future residents

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Abstract This study explores the dynamic integration and optimization path of teaching resources in the construction of smart housing with data mining technology as the core. By constructing a multi-level semantic model (LDA and semi-supervised SSGLDA), a BERT-TextCNN knowledge point linking model and an intelligent search framework integrating Elastic Search, semantic annotation, knowledge network construction and personalized retrieval of teaching resources are realized. The empirical analysis shows that the word frequency statistics reveal the core features of teaching resources, with “Automation” topping the list with 7116 times, but “Smart Meter” (1696 times) and “Power Consumption” (838) about energy management is only 10% of the high-frequency vocabulary of smart housing, which highlights the shortcomings of the construction of technical resources about energy monitoring and control. Multi-modal resource fusion significantly improves the model performance, with the F1-Score reaching 0.7046 at K=30, which is 144%, 36%, and 54% higher than that of single video (0.2890), PPT (0.5165), and PDF resources (0.4582), respectively. Sentiment analysis tracking shows that the sentiment tendency of smart housing residents is strongly correlated with the teaching nodes, with the sentiment value of the “writing” module dropping to 0.15 during the midterm exam, and the sentiment value of the “listening test” during the final review stage rising to 0.49 against the trend, confirming the impact of resource suitability on the learning experience. This confirms the influence of resource appropriateness on the learning experience. In the knowledge point association model, the F1 value of the Enhanced-EL-FM model based on fuzzy matching of Levenshtein Distance reaches 85.76%, which is 3.72% higher than that of the perfect matching method, which verifies the optimization value of the algorithm's fault-tolerance for practical application. Data mining technology can effectively drive the semantic association and dynamic optimization of teaching resources, and the multimodal fusion and fuzzy matching strategy can significantly improve the accuracy of resource integration.

Index Terms data mining, English teaching resources, LDA model, knowledge point linking, BERT-TextCNN, intelligent housing

I. Introduction

With the rapid development of the information age, in the demand for energy saving and aging population increase and other factors, modern architecture has been rapid development in the direction of intelligence, intelligent buildings have emerged in large numbers, intelligent housing has been to become the inevitable direction of development of modern residential buildings [1], [2]. The current intelligent housing to residential platform based on the use of related construction equipment and network communications, information appliances and other equipment installation, integrated security system, information management system, information communication system, intelligent adjustment system, and for residential users to provide a set of services and management functions as one of the efficient, comfortable and environmentally friendly living environment [3]-[6]. Intelligent housing is designed to meet modern housing needs through the integrated management of modern building technology, computer network communication technology, integrated wiring technology, artificial intelligence and other technologies [7]-[9]. Intelligent housing is formed with the development of intelligent technology, social progress, and the continuous growth of people's needs, improvement, and development, and is an inevitable product of the information age.

In smart communities, the scenes and interaction frequency of residents communicating through English increase, and the language ability of residents is emphasized. On the one hand, globalization and diversification have led to an increase in the need for residents' cross-cultural communication skills in smart communities. On the other hand, there is an increased demand for English command vocabulary for smart home devices in smart housing [10], [11]. The language ability of residents is improved through English education, but traditional English teaching lacks real scene rehearsal, and the overlap between teaching materials and smart housing-related words is low. In the design of smart housing, the residential scenes are extracted by introducing the Internet of Things and other technologies to provide real scenes for English education, and combined with artificial intelligence technology to guide the oral pronunciation and vocabulary increase of English instructions in order to realize a better design of smart housing [12]-[14].

This paper focuses on the application of data mining technology in semantic modeling, knowledge point linking and intelligent search of teaching resources, and proposes a set of systematic methods to support the dynamic integration and optimal utilization of English teaching resources in future smart housing. By constructing a multi-level semantic model and integrating deep learning and knowledge graph technologies, the semantic annotation, knowledge point linkage and personalized search of teaching resources are realized to provide intelligent resource services for smart housing service users. The article first proposes semantic modeling methods based on LDA and semi-supervised LDA models. Unsupervised LDA is used to mine the implicit “document-topic-keyword” three-layer structure in the text of lesson plans to generate semantic metadata to annotate resource topics. Semi-supervised LDA (SSGLDA) is further introduced to guide topic modeling with a priori knowledge to enhance the relevance and accuracy of topic modeling by mixing the distribution of “regular topics” and “a priori word topics”. Teaching resource knowledge point linking encodes knowledge point description text and course text through BERT-TextCNN model, and generates representation vectors of candidate knowledge point entities and mentioned knowledge points. Combined with cosine similarity calculation, accurate matching between knowledge points is realized. The method improves the robustness of the linking model by optimizing the loss function, and finally outputs the association results between resources and knowledge points, which provides technical support for the construction of knowledge network of teaching resources. On this basis, a search optimization method integrating semantic matching and full-text search is proposed. By combining the extended query generated by BERT-TextCNN model with Elastic Search, the matching score and weight are dynamically adjusted to comprehensively calculate document relevance and optimize the ranking. The method extends the search scope by using multi-source Query, and at the same time adjusts the sorting strategy by combining the similarity score, which significantly improves the accuracy and coverage of resource retrieval and meets the user's personalized needs.

II. Data Mining-based Semantic Modeling and Intelligent Association Method for English Teaching Resources

II. A. Semantic Modeling of Educational Resources

II. A. 1) LDA “document, topic, keyword” three-layer model

In this study, the experimental documents are lesson plan texts extracted from web pages, denoted as D, and d is one of the documents. The goal is to discover the “small” topics and related keywords hidden inside the document d through LDA semantic analysis and modeling, and to annotate these “small” topics and keywords as semantic metadata of the document. For example, Figure 1 shows the LDA “document-topic-keyword” three-layer model, which indicates that a document d has n “small” topics $t_1 \sim t_n$, of which The topic t_i consists of m keywords $w_{i1} \sim w_{im}$. Topic t_i and the corresponding keywords w_{ij} are the two-dimensional matrix of “topic-keywords” obtained by LDA semantic modeling, and in the semantic annotation of online teaching resources, the topic t_i and keywords w_{ij} obtained by semantic modeling can be used as the semantic metadata of the document d as semantic metadata to provide resource retrieval services for English education service recipients in the intelligent housing environment.

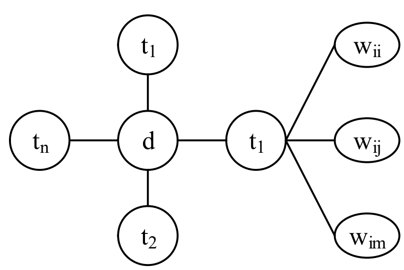

Figure 1: The three-layer model of "document - Topic - Word" of LDA

II. A. 2) Semi-supervised LDA models

Unsupervised LDA is a widely used topic modeling approach in the field of natural language processing, but it does not allow to include knowledge to guide the learning process. Semi-supervised LDA modeling (SSGLDA) utilizes a priori sets of words that the user believes to be representative of the topics of the text corpus to learn topics of particular interest to the user. In the regular topic model, each topic k is defined by a multinomial distribution ϕ_k on a word, and SSGLDA extends this concept by defining a topic as a mixture of two multinomial distributions: the "prior word subject" distribution and the "general topic" distribution, i.e., each document is a mixture of the general topic ϕ^r and its related prior word topic ϕ^s distribution, the algorithm is as follows.

(1) For each topic $k = 1 \dots T$, first generate polynomial distributions of regular topics, prior word topics, and distributions of parameter π_k, π_k controlling the probability of extracting words from the regular topic distribution and the prior word topic distribution.

$$\phi_k^r \sim Dir(\beta_r) \tag{1}$$

$$\phi_k^s \sim Dir(\beta_s) \tag{2}$$

$$\pi_k = Beta(1,1) \tag{3}$$

(2) For each prior word set $s = 1 \dots S$, define the group-topic distribution

$$\psi_s \sim Dir(\alpha) \tag{4}$$

(3) For each document d, set a binary vector $\vec{b}$ of length S, which is a list of prior word sets allowed by the document to be populated according to the document words. In addition, each a priori word set (for brevity, a priori word sets are referred to as groups) is associated with a polynomial distribution over regular topics, called a group-topic distribution. Based on the above concepts, a document-group distribution is extracted

$$\zeta^d \sim Dir(\tau_{\vec{b}}) \tag{5}$$

The group variable g groups documents that may discuss the same a priori set of words so that there is a clustering structure between the documents, which are sampled with the distribution of

$$g \sim Mult(\zeta^d) \tag{6}$$

The document-topic distribution θ_d is then obtained using the group-topic distribution of g.

$$\theta_d \sim Dir(\psi_g) \tag{7}$$

(4) For each $i = 1 \dots N_d$, extract a topic z_i as well as an indicator variable x_i.

$$z_i \sim Mult(\theta_d) \tag{8}$$

$$x_i \sim Bern(\pi_{z_i}) \tag{9}$$

If x_i is 0, then the selection word is

$$w_i \sim Mult(\phi_{z_i}^r) \tag{10}$$

If x_i is 1, then the selection word is

$$w_i \sim Mult(\phi_{z_i}^s) \tag{11}$$

If the binary vectors $\vec{b}$ are all 1, then set $\theta_d = \zeta^d$, then this model reduces to an LDA model with τ and β_r as hyperparameters. The hyperparameters are set to standard values in this study: $\alpha = 1.0$, $\beta = 0.01$, and $\tau = 1.0$.

II. B.Links to Teaching Resources Knowledge Points

After completing the semantic modeling of teaching resources, how to realize the dynamic association between knowledge points based on semantic metadata becomes the key. In this section, we will combine the deep learning technology to construct the vector representation model of candidate knowledge points and resource texts, and realize the accurate linking through similarity calculation.

II. B. 1) BERT-TextCNN-based entity characterization of candidate knowledge points

In the external knowledge base, for each knowledge point concept vocabulary, there is a corresponding knowledge point description text. In this paper, we encode the summary text description of each candidate knowledge point concept entity by the pre-trained BERT model introduced above, and obtain the vector used to characterize the candidate knowledge point concept entity. For a candidate knowledge point conceptual entity $entity_i$, its corresponding knowledge point description is the string $Desc_{entity_i}$, which is used as the input to the BERT model.The output vector encoded by the BERT model is $H_{entity_i} = \{h_{cls}, h_1, h_2, \ldots, h_l, h_{sep}\}$. The corresponding implicit vector h_{cls} of the identifier "CLS" is passed through the fully-connected layer with the activation function of tanh to obtain the output vector v_{entity_i} as the representation vector of the conceptual entity of the candidate knowledge point, i.e., $v_{entity_i} = \tanh(Dense)(h_{cls}))$. In this way, the set of representation vectors $V_{m_i} = \{v_{entity_1}, v_{entity_2}, \ldots, v_{entity_j}\}$ of the set of conceptual entities of the candidate knowledge points can be obtained.

For the representation of each mentioning knowledge point entity m_i , the course text $C = \{c_1, c_2, \ldots, c_l\}$ in which the mentioning knowledge point entity is located is first encoded by the pre-trained BERT model to obtain the representation vector V_C of the course text, and the representation vector V_C is obtained in the same way as the method for the representation vector of the candidate knowledge point entity.

The encoding vector of each character in the subtitle text calculated by the BERT model is $H_C = \{h_{cls}, h_1, h_2, \ldots, h_l, h_{sep}\}$, and for the extracted concept of mentioning knowledge points m_i , the plaintext substring represented by it can be represented as a binary group $Index_{m_i} = beg, end$ in the index position of the course text C , where beg indicates that the substring is in C end indicates the end position index of the substring in C . The encoding vector between the starting position index beg and the end position index end in $Index_{m_i}$ is extracted from the encoding vector H_C , which is expressed as $H_{m_i} = \left\{h_{beg}, h_{beg+1}, \ldots, h_{end}\right\}$. The representation vector H_{m_i} is obtained by passing the text convolutional network TextCNN to the representation vector V_{m_i} that mentions the conceptual entity of the knowledge point. The TextCNN model calculates the input H_{m_i} as follows:

(1) Define multiple one-dimensional convolutional kernels and use these convolutional kernels to do convolutional computation on the input separately to capture the correlation of neighboring characters.

(2) Do temporal maximum pooling for all channels of the output separately, and then splice the pooled output values of these channels, which is the representation vector.

II. B. 2) Predicting Knowledge Point Associations of Teaching Resources under Cosine Similarity

Finally, the representation vector V_C of the resource subtitle text and the representation vector V_{m_i} of the conceptual entities mentioning the knowledge points are subjected to the Concatenate splicing operation and projected through a fully-connected layer with an activation function of tanh to obtain the output vector O_{m_i} :

$$O_{m_i} = \tanh\left(Dense\left(Concatenate\left([V_{m_i}, V_C]\right)\right)\right) \tag{12}$$

The cos similarity is computed by comparing the output vectors O_{m_i} of the conceptual entities of the mentioned knowledge points with each of the vectors in the set of representation vectors V_{m_i} of the set of conceptual entities of the candidate knowledge points, i.e., $\cos(v_{entity_i}, O_{m_i})$ from the set of conceptual entities of the candidate knowledge points $Entity_{m_i} = \left\{entity_1, entity_2, \ldots, entity_j\right\}$ to select the knowledge point concepts with the highest degree of similarity to associate with the mentioned knowledge point concepts, i.e., the final association result can be expressed as a binary $r_{m_i} = \{m_i, entity_i\}$.

For the training of the knowledge point linking model of teaching resources, this paper minimizes the difference between the cosine similarity between the mention knowledge point entity representation vector and the cosine similarity between the real linked candidate knowledge point entities and the remaining set of negative candidate knowledge point entities by minimizing the cosine similarity between the mentioned knowledge point entity representation vector and the remaining set of negative candidate knowledge point entities and using it as the loss function for the training of the model. The mathematical expression of the loss function is as follows:

$$L(r_m, r_+^{entity}, r_-^{entity}) = \sum_{j}^{n} \sum_{i=0} max\left(\cos ine\left(r_{m_j}, r_-^{entity}, i\right) - \cos ine\left(r_{m_j}, r_+^{entity}, j\right), 0\right)$$

where r_{m_j} is the representation vector of the j th entity to be linked to mention, $r_+^{entity_j}$ is the real candidate knowledge point entity, and $r_-^{entity_j}$ is the set of the remaining candidate knowledge point entities in the candidate knowledge point entities except the real candidate knowledge point entity, i.e., the set of negative candidate knowledge point entities.

After the training of the linking model of knowledge points of teaching resources, the conceptual linking result of the knowledge points contained in the text of the subtitles of teaching resources is $R = \{r_{m_1}, r_{m_2}, \ldots, r_{m_k}\}$, which completes the linking of the knowledge points between the teaching resources and the knowledge points in the knowledge base.

II. C.BERT-TextCNN model based matching result searching

Based on the semantic network formed by the links of knowledge points, the retrieval of teaching resources needs to be further optimized to meet user needs. In this section, BERT-TextCNN model and elastic search technology will be introduced to enhance the intelligence of resource retrieval through multi-dimensional matching and dynamic scoring strategies.

When using Elastic Search for full-text search, input a Query, Elastic Search will search a collection of related documents D_q from the indexed library and sort the documents d in D_q according to their matching degree with the Query. In order to make the search results better, this paper inputs the original Query inputted by the user, the $N-1$ Query derived from the BERT-TextCNN model matching, and the similarity score sim between this $N-1$ Query and the original Query into Elastic Search to construct a relevance calculation formula, which gives a final score after performing a This formula gives a final score after comprehensive evaluation.

(1) First of all, N Query and document d name, tags, description, teacher Name four fields to match the document d $MatchScore(Q,d)$, Match Score calculation specific process as shown in Figure 2, the calculation method as shown in Equation (13) and Equation (14), in which $Score(Q_i, d)$ is the BM25 score of the i th Query.

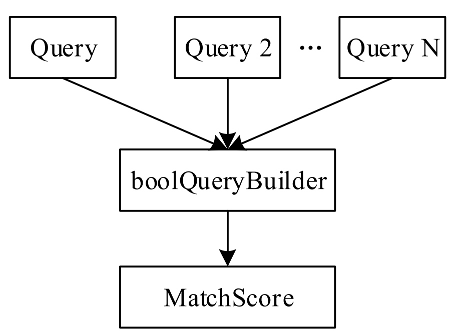

Figure 2: MatchScore calcula tion flow

$$MatchScore\left(Q_i, d\right) = Score\left(Q_i, d\right) \tag{13}$$

$$MatchScore\left(Q, d\right) = \sum MatchScore\left(Q_i, d\right) \tag{14}$$

In the above way a collection of documents D can be identified as the collection of content obtained from this search, and since multiple Queries are used for matching, the resulting collection of documents D can be described as Equation (15), which allows the search to be expanded.

$$D = D_Q \cup D_{Q_2} \cup \cdots \cup D_{Q_N} \tag{15}$$

(2) Based on the similarity sim_{Q_i} between $Query_i$ and the original Query, the weight W_i accounted for by $Query_i$ in this retrieval process is calculated, from which the $FunctionScore(Q_i,d)$ of $Query_i$ for document d can be derived. By setting the value of boostMode, we can control the merging way of calculating $FunctionScore(Q_i,d)$ for document d. In this paper, the selected boost Mode in calculating the FunctionScore is MUTIPLY, i.e., $FunctionScore(Q_i,d)$ product can be obtained from the Function Score of document d in this retrieval.The specific calculation process of Function Score is shown in Fig. 3, as shown in Eqs. (16)-(18), where $a=10$.

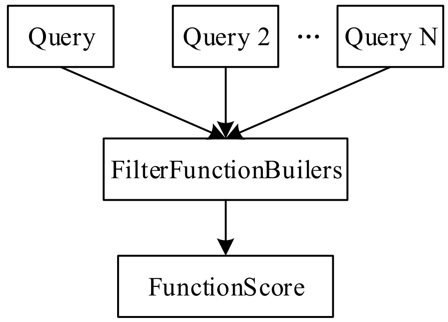

Figure 3: FunctionScore calcula tion flow

$$FunctionScore(Q_i,d)=W_i * Score(Q_i,d) \tag{16}$$

$$W_i=\begin{cases}-a\ln\left(1-sim_{Q_i}\right), & sim_{Q_i}<1\\ 100, & sim_{Q_i}=1\end{cases} \tag{17}$$

$$FunctionScore(Q,d)=\prod FunctionScore(Q_i,d) \tag{18}$$

(3) The combination of Match Score and Function Score can be changed by setting the score mode, and the score mode selected in this article is SUM. The Match Score and FunctionScore obtained in the first two steps are combined to calculate the final score, and the documents in the set D obtained in step (1) are sorted with this score, and the final sorted data is sent to the frontend and displayed. The specific calculation method is shown in equation (19).

$$FinalScore(Q,d)=MatchScore(Q,d)+FunctionScore(Q,d) \tag{19}$$

III. Research on multimodal analysis and integration and optimization of English teaching resources on smart housing

In Chapter 2, a knowledge network framework on English teaching resources for future smart housing is constructed through semantic modeling and intelligent association methods. In order to further validate the practical value of the framework and explore the optimization path of resource integration, this chapter will systematically carry out empirical research on teaching resources based on multi-source data collection, word frequency analysis, model performance evaluation, and sentiment tendency mining to reveal the data-driven resource optimization strategies and dynamic association effects.

III. A. Data collection and processing

In a study on the integration and analysis of English language teaching resources for future smart housing, data sources need to balance diversity and typicality. The study obtains structured data from relevant English education materials. Unstructured data, on the other hand, covers MOOC subtitles, transcribed texts of teaching videos, anonymized discussion board records and web-crawled open resources (e.g., BBC Learning website).

In this paper, we focus on continuing the analysis of multimodal teaching resources, and multimodal teaching resources are only keyword extracted for three types of resources, namely PPT, PDF and video, so data preprocessing is carried out.

Data processing first through OCR, speech recognition and other technologies to PDF, audio and video into text, and cleaning noise, eliminating advertising code, non-English characters. Subsequently, text normalization is carried out. Unify case, deal with abbreviations and word form reduction. HanLP is used to extract and construct a domain dictionary for Chinese teaching terms. Quality control needs to verify the sample representativeness and establish a dynamic updating mechanism, screen the teaching high-frequency phrases by TF-IDF, and utilize Apache Airflow to grab new resources regularly.

III. B. Word Frequency Analysis of English Teaching Resources

The frequency of words in a document often represents its importance to the document, the higher the frequency, the more important the word is to the document, the more the word represents the core content of the document, based on this, it is necessary to carry out word frequency statistics for the English teaching resources about intelligent housing. Run python for the statistics of high-frequency words in English teaching resources, due to the existence of synonyms or similar words in the participle, therefore, build a synonym table for synonym merging, and in the process of word frequency statistics, merge the synonym word frequency in the document for processing, and statistically sum up the word frequency. After the synonym merging process, the words with the top 50 word frequencies are obtained, and the results of the high-frequency word statistics (the top 50) of the English teaching resources about smart housing are shown in Table 1.

Table 1: The top 50 High-frequency Words in English Teaching Resources

Number	Word	Frequency	Number	Word	Frequency
1	Automation	7116	26	Smart Hub	2045
2	Bluetooth	5524	27	Smart Lighting	1893
3	Cloud Computing	4267	28	Smart Lock	1730
4	Connectivity	4024	29	Smart Meter	1696
5	Device	3627	30	Smart Speaker	1686
6	Energy Efficiency	3448	31	Smart Thermostat	1686
7	Gateway	3257	32	Surveillance Camera	1591
8	Home Assistant	3250	33	Sustainability	1571
9	HVAC	3181	34	Voice Assistant	1528
10	Integration	3120	35	Voice Command	1518
11	Internet of Things	3117	36	Wi-Fi	1447
12	Machine Learning	3002	37	Wireless	1293
13	Mobile App	2954	38	Zigbee	1292
14	Monitor	2937	39	Z-Wave	1095
15	Motion Sensor	2912	40	API (Application Programming Interface)	1078
16	Network	2893	41	Biometrics	1065
17	Occupancy Sensor	2846	42	Data Privacy	953
18	Password Protection	2816	43	Encryption	947
19	Protocol	2774	44	Firmware	929
20	Real-Time	2654	45	Geofencing	924
21	Remote Control	2628	46	Interoperability	873
22	Security System	2501	47	Machine-to-Machine	867
23	Sensor	2375	48	Power Consumption	838
24	Smart Appliance	2212	49	User Interface	805
25	Smart Doorbell	2051	50	Virtual Assistant	787

Table 1 reveals the core content and technical focus of teaching resources. The high-frequency words about smart housing cover a wide range, and the word frequency span is significant (7116~787). The top 10 terms focus on the core technology framework of smart housing, with "Automation" with a frequency of 7116, "Bluetooth" (5524), and "Cloud Computing" (4267) ranking among the top three, highlighting the fundamental position of intelligent technology and communication protocols. "Energy Efficiency" (3448) and "Sustainability" (1571) appear frequently, reflecting the focus of teaching resources on green and smart housing design.

The vocabulary can be classified into the following five categories: smart devices and technologies (accounting for about 48%): including specific devices such as "Smart Lock" (1730), "Smart Thermostat" (1686), and "Surveillance Camera" (1591), as well as technical protocols such as "IoT" (3117) and "Zigbee" (1292); Interaction and control (22%): represented by "Voice Assistant" (1528), "Remote Control" (2628), and "Mobile App" (2954), emphasizing the way users interact with intelligent systems. Security and privacy (12%): such as "Data Privacy" (953), "Encryption" (947), and "Biometrics" (1065), reflecting the in-depth discussion of the smart housing security mechanism in teaching resources. Energy management (10%): In addition to energy efficiency and sustainability, terms such as "Smart Meter" (1696) and "Power Consumption" (838) reflect the teaching focus of energy monitoring technology. Networks and protocols (8%): including "Wi-Fi" (1447), "Protocol" (2774), and "Network" (2893), focusing on the communication infrastructure of smart housing.

Among them, 7 words in the top 10 belong to the technical category (such as "Automation" and "IoT"), and the total word frequency accounts for 38%, indicating that the teaching content is highly dependent on the analysis of technical terms. At the same time, 24 kinds of smart devices (such as door locks, lighting, and speakers) are also involved, among which "Smart Lighting" (1893) and "Smart Speaker" (1686) have similar word frequencies, reflecting the balanced coverage of device application scenarios.

The word frequencies of the top 30 high-frequency words of ELA resources about smart housing obtained from Table 1 are shown in Figure 4.

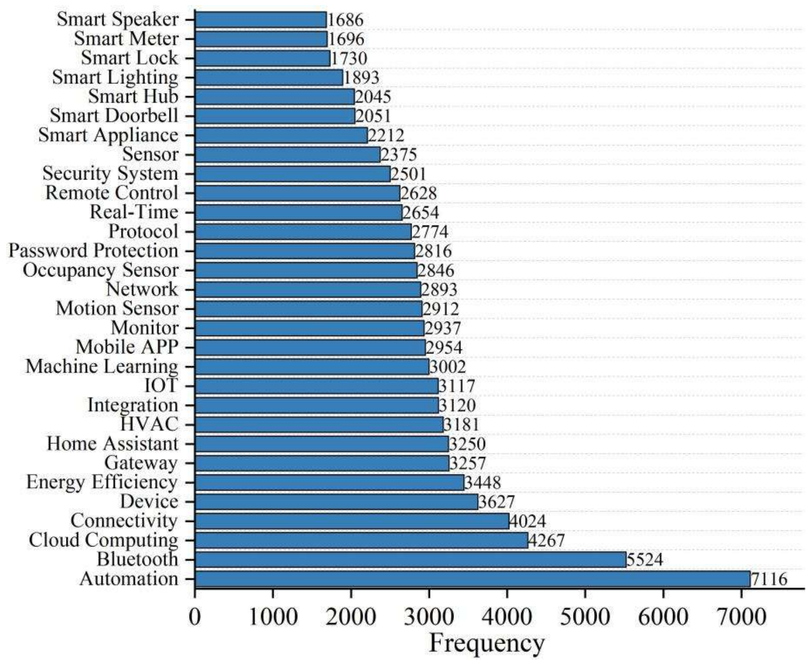

Figure 4: The top 30 high-frequency words in college English teaching resources

From Figure 4, we can see that there is a significant head effect in the word frequency data, with the sum of the top 5 words being 24,598, accounting for 28.7% of the sum of the top 50 words, which emphasizes the core position of automation and connectivity technologies. At the same time, there is a long-tailed distribution, and the frequency of the last 20 words, such as “Virtual Assistant” and “User Interface”, is less than 1,000, which indicates that the penetration of emerging technologies in teaching and learning is still in the early stage.

III. C. F1-Score Optimization Solution

Based on the content distribution characteristics of teaching resources revealed by high-frequency word analysis, this section further compares the model performance differences of different resource types (video, PPT, PDF) and multimodal fusion through F1-Score metrics to explore the resource integration effect under the optimal parameters.

III. C. 1) Algorithm parameterization

The damping factor is 0.82, span is 5, and the number of iterations is 100.

Iteration for optimal solution N=50, F1 for video resource, PPT resource and PDF resource is taken as mean value.

III. C. 2) Experimental analysis

Fig. 5 shows the algorithm K value and F1 distribution for three different resource types, video, PPT and PDF, and the fused multimodal resource F1.

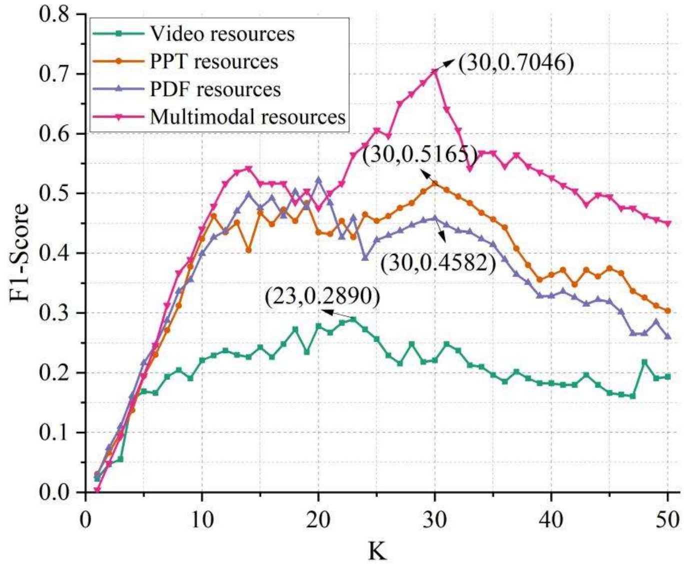

Figure 5: The values of algorithm K and the distribution of F1 for different resource

The F1 score of the video resource reaches a maximum value of 0.2890 when the K value reaches 23, and then with the K value increasing in a downward trend, when K=50, F1=0.1933, the overall effect of bias, the video resource in the expansion of the knowledge points cited with the scene of the multi-text thought, which led to the text-based conversion of the extraction and the text-only type of deviation is larger; PPT resource F1 score in the K value of small growth faster, after reaching 11 in a smooth state, K value to 30 when the F1 appeared to be the maximum value of 0.5165, after the K value increases with a downward trend, when K = 50, F1 = 0.3036; PDF resources F1 score and PPT resources towards extremely similar, because PDF resources are based on PPT resources converted. When the K value reaches 30, the F1 value is the largest, 0.4582, and then it starts to decline gently; the multimodal resources after fusion become a gradual upward trend with the increase of the K value, and also when the K value is 30, the F1 value is the largest, 0.7046. After the multimodal resources, the F1 scores of the multimodal resources gradually decline, but on the whole, they remain at the high level, which is better than the other three individual English teaching resources.

By comparing the curves, it is possible to observe the performance differences of each resource type and their relative performance under different K values. Among them, the multimodal resource F1 value is optimal when K is 30.

III. D. Sentiment analysis of teaching resources

Based on the validation of the model performance, this section focuses on the actual application scenarios of teaching resources, and dynamically tracks the changes of students' feedback on the core teaching modules (listening, reading, and writing) through the word frequency normalization and sentiment tendency analysis in the time dimension, so as to reveal the impact of the resource design on students' learning experience.

In this study, we selected an English education course designed with intelligent housing as the object of study, and analyzed the teaching resource texts corresponding to the high-frequency words “listening test”, “reading comprehension”, and “writing” as the object of study. As a research object, we investigate the change rule of students' questions over time, and analyze the emotional tendency values of the corresponding texts by means of sentiment analysis.

III. D. 1) Word frequency normalization analysis

Figure 6 shows the variation of the relevant word frequency share over time. The word frequency share refers to the ratio of the number of word frequencies per day of a specific high-frequency word to the total number of word frequencies of that word, and this ratio has been normalized.

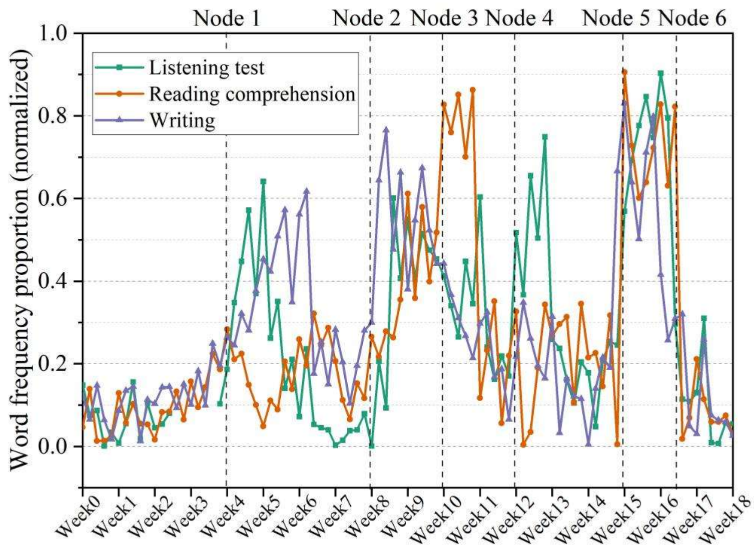

Figure 6: The change of word frequency proportion over time

The first dotted line segment in the figure represents node 1, which is the fourth week of the semester, and the course conducts a quiz on English listening, so the frequency of questions about the "listening test" increases. The second line segment is node 2, which enters the mid-term examination stage, and the word frequency of the teaching resources for the three parts of "listening test", "reading comprehension" and "writing" is greatly increased to the range of 0.4-0.6; node 3 is the key commentary on reading comprehension, so the frequency of questions about "reading comprehension" will increase. Node 4 is another hearing test, and the frequency of questions about "hearing test" increases. In the 15th week of node 5, the review stage of the final assessment was entered, and the frequency of questions for the three aspects of vocabulary also jumped significantly. Node 6 enters the stage of examination and grade inquiry, the semester is basically over, and the number of questions is reduced.

III. D. 2) Emotional disposition analysis

Figure 7 shows the change in the affective tendency values of the questioned text corresponding to high-frequency words with respect to time; higher affective tendency values indicate that students have fewer questions, more positive emotions, and a better sense of learning experience.

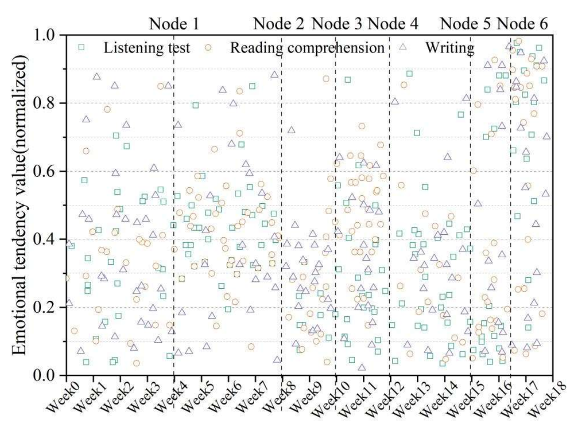

Figure 7: The change of the emotional tendency value over time

Combining the two graphs, the overall distribution trend shows that questions about these three high-frequency words are more frequent at the end of the semester compared to other times. In addition, the time when students ask more questions is generally related to the teaching schedule time nodes and emergencies, and when there are emergencies or problems exist students' affective value is low, and when the problem is solved the affective value will rise.

At the beginning of the semester, the affective tendency value is overall at a moderate level, about 0.35-0.55, reflecting students' receptive attitudes toward basic teaching resources.

During the listening test in week 4 of node 1, the emotion value of the questions related to the "listening test" dropped sharply to 0.32, and the sentiment value of "writing" also decreased slightly during the same period, indicating that the test stress led to a concentrated explosion of anxiety. It is worth noting that the sentiment value of "reading comprehension" remains at 0.48 at this node, indicating that the emotional fluctuations caused by non-assessment module resources are relatively flat.

Node 2 midterm exam formed an emotional trough, and the affective values of the three types of resources synchronously fell below 0.3, with “writing” reaching the lowest point of 0.15, confirming the superimposed pressure of the comprehensive assessment on students' psychological state. After node 3 (reading comprehension assessment), the affective value of “reading comprehension” quickly rebounded to 0.52 within 2 weeks, which was 73% higher than that of node 2, indicating the effectiveness of targeted teaching interventions on emotional repair. During the same period, the affective value of “listening test” only recovered to 0.41, reflecting the long-term characteristics of listening skill improvement.

Although the second listening test at node 4 triggered emotional fluctuations again, the decrease from 0.41 to 0.38 was significantly smaller than that at node 1, confirming that repeated exposure to teaching resources can reduce students' anxiety sensitivity.

During the final review period of node 5, the affective values of the three types of resources show differentiated trends: the affective value of “writing” continues to decrease to 0.28, which is related to the increasing complexity of the writing task; the affective value of “listening test” rises to 0.49 against the trend, which may be attributed to the adaptive training effect of the resources of the model test; and the affective value of “reading comprehension” stabilizes in the range of 0.43-0.47, reflecting the emotional stabilizing effect of the resources of regular training.

After node 6 (the end of the exam), the emotional values of all modules exceeded 0.7, with “writing” reaching a peak of 0.78, forming a significant emotional release inflection point, which verifies the immediate improvement of the learning experience by relieving teaching pressure.

III. E. Research on the method of correlating knowledge points of teaching resources

Combining the results of resource content characteristics and sentiment analysis, this section verifies the robustness of the proposed knowledge point association model through experimental comparison, and explores the optimization effects of fuzzy matching and exact matching strategies on the dynamic linking of teaching resources.

III. E. 1) Experimental setup

In order to verify the effectiveness of the knowledge point association model of teaching resources proposed in this paper, experimental testing continues on the dataset constructed in this paper. For the implementation of the teaching resources knowledge point association model, this paper uses the Python language-based Pytorch deep learning framework and conducts model training and testing on the dataset. The evaluation metric for model testing is the F1 score, a statistical measure of model prediction accuracy under a binary classification task, which is able to take into account both the checking accuracy and recall of classification models.

III. E. 2) Model parameterization

In the construction of the model, the experimental setup of the pre-trained BERT language model in this paper has a neural network layer number of 13, the dimensionality of the network's implicit layer is 801, the number of attention headers is 12, the number of parameters of the model is 163,824,826, the implicit dimensionality of the LSTM model is 256, the convolutional kernel size of the TextCNN is 3, the pooling function selects 1-max pooling Maximum pooling, the regularization method selects Dropout, and its random inactivation rate parameter is set to 0.3. The optimizer used for model training is AdamW, the learning rate is 0.01, the number of rounds of model training is 50, and the size of the number of samples in each batch of training is 50.

In the process of model training, this paper uses the PipeLine pipeline scheme to divide the teaching resource knowledge point association model into two sub-models for training, i.e., train the teaching resource knowledge point recognition model first, and then train the teaching resource knowledge point linking model. The editorial distance parameter of the Levenshtein Distance algorithm used for the generation of candidate entities of teaching resource knowledge points is set to 3, and the pre-trained BERT language model used in the two sub-models adopts the strategy of weight parameter sharing.

III. E. 3) Comparison of experimental effects

In this part of the experimental comparative analysis, this paper tests the teaching resource knowledge point recognition model Enhanced-ER and the linking model Enhanced-EL respectively. For the effect test of each submodel, the text has tried to compare different classical mainstream deep learning models, and the experimental results and processes are as follows.

For the model comparison of English teaching resources knowledge point referent recognition, this paper chooses the classical LSTM-CRF as the benchmark model, and also compares the current BERT-CRF based on the pre-trained BERT language model as well as its improved version of the BERT-ENE model, and the experimental results of the teaching resources knowledge point entity recognition are shown in Figure 8.

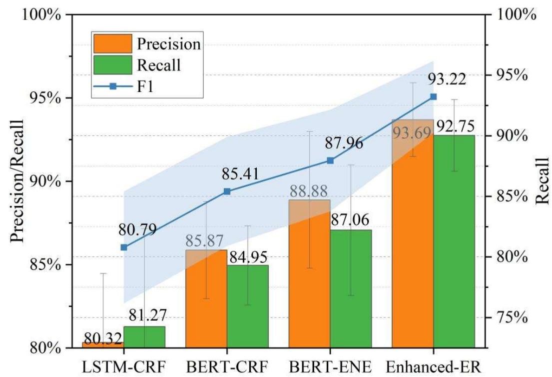

Figure 8: The entity recognition results of teaching resource knowledge points

As can be seen in the comparison results of teaching resource knowledge point entity recognition, the proposed teaching resource knowledge point recognition model in this paper performs more prominently on subtitled text of MOOC and other teaching resources, with the accuracy, recall and F1 of 93.69%, 92.75% and 93.22%, respectively. Among them, the F1 score is improved by 15.38% compared with the benchmark model LSTM-CRF and 5.98% compared with the currently known optimal model BERT-ENE. Compared with the benchmark model LSTM-CRF, the main reason for the improvement is that the model proposed in this paper uses the BERT pre-trained language model, which can better characterize the semantic information of subtitle text. In addition, the improved effect compared to the BERT-ENE model is mainly due to the text enhancement technique used in this paper, which can to some extent solve the problem of decreased recognition accuracy caused by the blurring of semantic boundaries of Chinese knowledge points.

In addition, this paper also shows the change curve of the loss value of the Enhanced-ER model during the training process as shown in Fig. 9, the model in the first 1,000 iterations, the loss value decreases the most, and the model converges the fastest. After about 3800 iterations, the fluctuation of the loss curve of the model starts to become smaller, the loss value starts to stabilize, and the model is close to convergence, with the loss value stabilizing at about 174. This proves that the model proposed in this paper is able to converge effectively and fast.

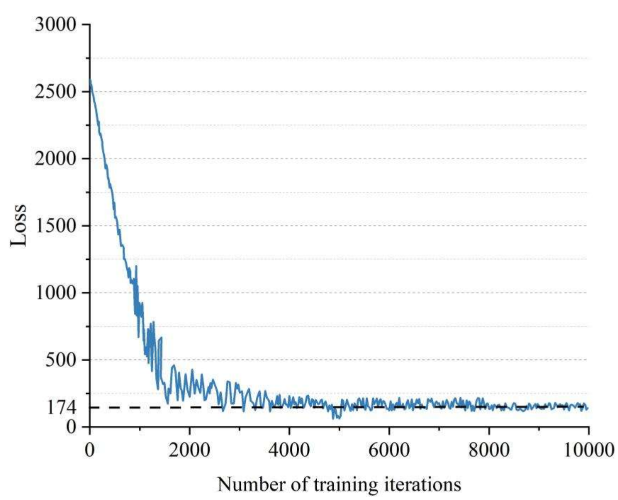

Figure 9: Loss curve of the Enhanced-ER model during the training process

For the comparison of Enhanced-EL, a knowledge point linking model for teaching resources, LSTM-Binary model and BERT-Binary model are selected as comparison models.LSTM-Binary model is based on LSTM model as a base model using a neuron as a binary classifier to realize knowledge point entity linking. Similarly, the BERT-Binary model uses the BERT language model as the base model and also uses a binary neuron as a classifier. These two models are the most commonly used in the current industry and the technology is already more mature.

In the linking of knowledge points of teaching resources, the generation of candidate knowledge point entities is the first and more critical link. In this paper, in the experiments of this part of the model comparison, different models are used to generate candidate knowledge point entities through the Levenshtein Distance algorithm, in order to prove the superiority of the effect of the model proposed in this paper. In addition, this paper will compare the effect of using the exact matching method to generate candidate knowledge point entities, to prove that the use of Levenshtein Distance algorithm to generate candidate knowledge point entities can improve the fault tolerance of the model in the real environment. The results of the teaching resources knowledge point linking experiment are shown in Figure 10.

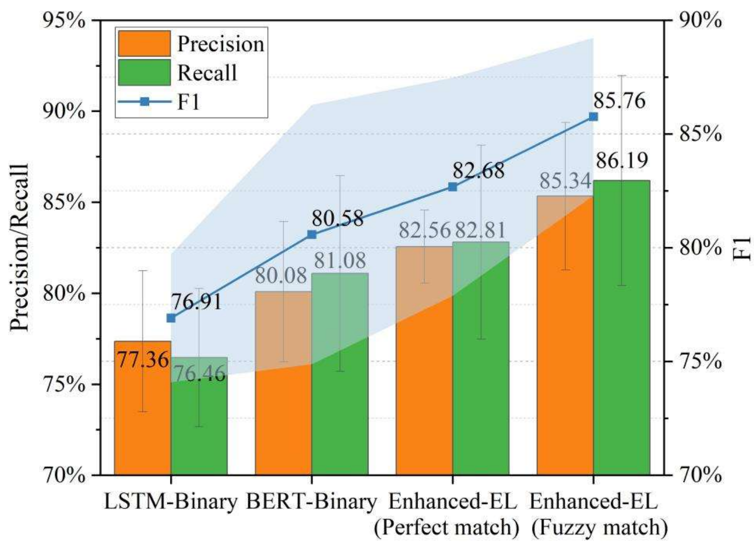

Figure 10: Comparison results of knowledge point links in teaching resources

Enhanced-EL-PM denotes the Enhanced-EL model that generates candidate knowledge point entities by using the exact matching method; Enhanced-EL-FM denotes the Enhanced-EL model that generates candidate knowledge point entities by using the fuzzy matching method. From the experimental results, it can be seen that in the case of Levenshtein Distance algorithm for generating candidate knowledge point entities, the accuracy, recall and F1 of the Enhanced-EL-FM model are 85.34%, 86.19%, and 85.76, respectively, and the F1 values are improved compared to LSTM-Binary and BERT-Binary, respectively, by by 11.51% and 6.44%. It can be found through the comparison of different matching methods that Enhanced-EL-FM using Levenshtein Distance fuzzy algorithm can more obviously improve the recall of teaching resources knowledge point links, which is 4.08% and 3.72% higher than that of Enhanced-EL-PM in terms of recall and F1 score, respectively. This indicates that the Levenshtein Distance algorithm into candidate knowledge point entities can to a certain extent make up for the shortcomings of the identification of the knowledge point entities of the teaching resources in the preorder, and maximize the fault-tolerance ability and robustness of the model.

IV. Conclusion

In this study, semantic modeling, dynamic association and multimodal integration of English teaching resources through data mining techniques are used to verify the feasible path of teaching resources optimization under digital transformation. The empirical results show that

(1) Multimodal resource integration significantly enhances the model performance. When K=30, the F1-Score of multimodal resources reaches 0.7046, which is 144%, 36% and 54% higher than that of a single video (0.2890), PPT (0.5165) and PDF (0.4582) resources, respectively, proving the synergistic effect of heterogeneous data from multiple sources.

(2) The analysis of affective tendency shows that the pressure of teaching nodes significantly affects students' experience. The affective value of “writing” module drops to 0.15 during the midterm examination, but the affective

value of “listening test” at the final revision stage rises to 0.49 against the trend, which proves the necessity of the dynamic resource adaptation mechanism. This confirms the necessity of the dynamic resource adaptation mechanism.

(3) The F1 value of the Enhanced-EL-FM model based on Levenshtein Distance fuzzy matching reaches 85.76%, which is 3.72% higher than that of the perfect matching method, and the recall rate is 4.08% higher, which verifies the optimization value of the algorithm's fault-tolerance to the actual teaching scenarios.

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