Research Article

Design of Hierarchical Retrieval Model of Digital English Teaching Information Based on Ontology

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In order to improve the effect of English teaching information retrieval, this paper designs a hierarchical retrieval model of digital English teaching information through ontology and constructs an intelligent system structure that can be used for hierarchical retrieval of digital English teaching information. Moreover, this paper proposes a method for judging the similarity of English teaching information structure based on non-negative matrix factorization and develops a hierarchical retrieval model of digital English teaching information based on ontology according to an improved algorithm. In addition, this paper uses the hierarchical search idea to design the hierarchical structure and study the system framework and hierarchical process. Finally, this paper verifies the performance of the system through simulation experiments. The experiment shows that the hierarchical retrieval model of digital English teaching information based on ontology proposed in this paper meets the basic needs of this paper to build an English teaching information system and can play a certain role in English teaching.

1. Introduction

At present, with the improvement of storage and computing capabilities, the research and application of big data for English teaching has gradually become a hot spot. Among them, multimedia English teaching data such as text, images, video, voice, and 3D images are the core of big data. The multi-modal characteristics of multimedia English teaching data make multi-modal data fusion the main means to solve such problems. That is, multi-modal data fusion plays a key role in the modeling and retrieval of multimedia big data [1]. At the same time, due to the potential semantic relevance between English teaching multi-modal data, modeling of English teaching multi-modal data has become a frontier research field of data mining. In the field of intelligent retrieval [1], users can submit data of any modal to obtain modal results containing similar semantic information. In the field of image captioning, machines can be trained to independently label and recognize image text. In the field of classification, object-oriented multi-angle English teaching multi-modal information can be used to describe the target object, so as to obtain more accurate English teaching information recognition and object classification effects [2].

For a long time, there has been a lot of research on English teaching information fusion of multi-modal data. Among them, the research on multi-modal data retrieval is a major research field, that is, the data of different modalities are directly compared to obtain various types of English teaching information modal data with the most similar semantics to the query data as the result. In the study of combined modality retrieval, the research focuses on the case where the query and the result share the same combination of modalities. In cross-modal retrieval research of English teaching information, it is necessary to assume that queries and results come from different modalities. However, what the two have in common is that the model needs to be able to directly compare the characteristics of multi-modal data to obtain data with similar semantics of English teaching information.
This paper uses ontology to design a hierarchical retrieval model of digital English teaching information, constructs an intelligent system structure that can be used for hierarchical retrieval of digital English teaching information, and improves the effect of modern English teaching.

2. Related Work

The most representative method of statistical correlation analysis is canonical correlation analysis (CCA). CCA mainly solves the scenario of data fusion of two different modalities. It first finds the linear combination of variables in each heterogeneous data set and then learns a subspace by seeking to maximize the statistical correlation of the combined variables. CCA itself is unsupervised, but in subsequent studies, semantic information is often added to expand the capabilities of the CCA model. Literature [3] applies CCA to the fusion of images and text and uses logistic regression to achieve semantic abstraction, followed by [4] using supervised CCA to further improve the model accuracy. These traditional CCA-based models can only capture the linear association of data. In order to obtain a more expressive common space, the use of a deep neural network as a mapping function has gradually become the mainstream method. Literature [5] adopts a multi-layer fully connected network to input features. Mapping is performed to further improve the accuracy. The generalized canonical correlation analysis (GCCA) proposed in [6] is suitable for multiple modal inputs. It learns the common space by minimizing the F-norm between each mapped vector and the shared representation, that is, after processing by GCCA, all modal information can be reconstructed. At the same time, the information of all modalities is optimally reconstructed. Literature [7] uses GCCA to effectively complete data fusion. Literature [8] applies GCCA to classification problems and achieves good results. However, GCCA also has the problem of insufficient expressive power due to the use of linear mapping. The DeepGCCA proposed in [9] solves this problem well. It can learn shared representations from arbitrary multi-modal inputs and map all inputs into a common space in a non-linear mapping manner, which further sets this mapping to be bootable, allowing end-to-end training of models.

The tensor CCA proposed in [10] extends the traditional CCA to process multi-dimensional data matrices and applies it to action classification in videos. This extension greatly improves the performance of the model. Furthermore, for the case of two-dimensional input, the 2D-CCA proposed in [11] learns a common space by directly maximizing the correlation of two-dimensional input features, thereby avoiding the computational burden of vectorizing two-dimensional features. Literature [12] proposed local 2D-CCA (L2DCCA) to further make up for the neglect of local correlation in 2D-CCA, which weights two-dimensional features according to the proximity of local information, of local information, so that in the process of correlation measurement increase local correlation information so that L2DCCA can capture correlation more accurately. Literature [13] uses tensor CCA to capture high-dimensional statistical associations of vector feature inputs. In particular, Kim proposes two structures for tensor correlation maximization by applying a canonical transformation to the unshared pattern. In this way, features with a good balance between flexibility and descriptive power can be obtained. It can be seen that CCA and its variation model have important applications in common space learning.

Literature [14] proposed a cross-modal multi-deep neural network (CMDDN), which is a hierarchical structure of multi-deep networks. CMDDN preserves both inter- and intramodal correlations to generate complementary representations for each modality and then combines these representations hierarchically through cascade learning to obtain the final common space. On the use of CNN, the literature [15] proposed deep SM, which uses CNN to extract high-level features for deep semantic matching to generate an efficient common space. Literature [16] proposes a deep bidirectional representation learning model, which uses two CNNs to simultaneously model and train matched and unmatched image/text pairs to build a common space with semantic aggregation.

Literature [17] jointly trains a deep convolutional network to learn aligned representations, thereby constructing a common space for multi-modal input such as images, text, and speech. The idea of using joint learning for multiple modalities has greatly improved the performance and range of applications of the resulting common space. Similarly, recurrent neural networks (RNNs) and LSTMs can be used for common space learning to generate image captions. Literature [18] uses hierarchical multi-modal LSTMs to capture fine-grained correlations between image regions and phrases to enhance common space learning.

3. English Teaching Information Retrieval Algorithm Based on Ontology

The concept of ontology comes from the field of philosophy. The study of the essence of the objective existence of things is the interpretation or explanation of the objective existence. It focused on the abstract nature of objective entities, which was later used in computer science. The definition of ontology has not been unified in the computer field, and the most recognized is the accurate formal description of the shared conceptual model. Compared with traditional knowledge expression, knowledge sharing has become the core of ontology. Through standardized concepts or terminology, ontology provides a unified framework for members in a certain field and plays a positive role in understanding and communication between people from different backgrounds. Therefore, it plays an increasingly prominent role in artificial intelligence, computer language, database theory, semantics, biology, medicine, agriculture, and finance. This article is to study the application of the ontology-based English teaching information hierarchical retrieval algorithm in English teaching information processing.

In ontological retrieval technology, case retrieval is the first step of the process, and the accuracy of its results directly affects the progress of subsequent steps. Therefore, the
importance of ontological retrieval based on the principle of similarity for the design of English teaching information and even the entire cycle of English teaching information is self-evident, and it has received extensive attention from experts and scholars.

Non-negative matrix factorization is widely used in text classification, image analysis, and complex networks. Similar to matrix decomposition methods such as singular value decomposition and eigenvalue decomposition, non-negative matrix decomposition also implements linear dimensionality reduction, but it restricts all components after decomposition to be non-negative real numbers. This decomposition method is more in line with intuitive understanding: the whole is composed of parts. Therefore, non-negative matrix factorization can grasp the essence of English teaching information structure data in a sense. This characteristic shows that the dimensionality reduction data after non-negative matrix decomposition can retain the essential characteristics of the original English teaching information structure.

The purpose of the non-negative matrix factorization algorithm is to find two non-negative matrices so that their product is close to the original matrix. The problem can be described as follows: after a non-negative matrix $G = [g_{ij}]_{p \times q} (g_{ij} \geq 0)$ is given, two non-negative matrices $W_{p \times r} = [w_{ij}]_{p \times r}$ and $H_{r \times q} = [h_{ij}]_{r \times q}$ are found by a suitable method, so that

$$G_{p \times q} = \begin{bmatrix} y_1 & y_2 & \cdots & y_q \end{bmatrix}_{p \times q} \approx WH,$$

$$= \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1r} & h_{11} & h_{12} & \cdots & h_{14} \\ w_{21} & w_{22} & \cdots & w_{2r} & h_{21} & h_{22} & \cdots & h_{24} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ w_{p1} & w_{p2} & \cdots & w_{pr} & h_{r1} & h_{r2} & \cdots & h_{rq} \end{bmatrix},$$

(1)

where $c$ is established, the value condition of $r$ is $(n + m)r \leq nm$, the matrix $G$ is expressed in the form of a column vector, and $y_i$ is the $i$-th column vector that is composed of $G$. When the columns of the original matrix $G$ are linearly independent, the $q$ vectors can be used as the basis to form a linear space $V_q$. The operation of non-negative matrix factorization is to map $y_i$ from the $q$-dimensional linear space $V_q$ to the $r$-dimensional linear space $V_r$ formed by each column vector of $W$. We set

$$\eta_i = \begin{bmatrix} w_{11} & w_{21} & \cdots & w_{pr} \end{bmatrix}^T,$$

$$\eta_1 = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1r} \end{bmatrix}^T,$$

$$\eta_2 = \begin{bmatrix} w_{21} & w_{22} & \cdots & w_{2r} \end{bmatrix}^T,$$

$$\vdots$$

$$\eta_r = \begin{bmatrix} w_{p1} & w_{p2} & \cdots & w_{pr} \end{bmatrix}^T,$$

(2)

where $\eta_i$ is linearly independent, so it can be expanded from $\eta_i$ into an $r$-dimensional linear space $V_r$. It can be seen from formula (1) that $y_i = \sum_{k=1}^r \eta_k h_{kj}$ represents that $y_i$ is mapped from the $q$-dimensional linear space $V_q$ to the $r$-dimensional linear space $V_r$. Since $\eta_i$ is a set of bases of space $V_r$ and $y_i$ can be expressed linearly by this set of bases, according to the knowledge of linear algebra, $(h_{11}, h_{21}, \cdots, h_{rq})$ is also the coordinates of low-dimensional space $y_i$ under this set of bases. Furthermore, the ranks of matrices $W$ and $H$ are both less than the rank of matrix $G$. Therefore, the matrix $W$ represents a set of bases for the linear combination approximation of the original matrix $G$; $H$ is the non-negative projection coefficient matrix of the sample set $G$ on the basis matrix $W$; and the coefficient matrix $H$ can replace the original non-negative matrix $G$.

In order to find a set of approximate decompositions of non-negative matrices, an objective function should be constructed to measure the degree of similarity between matrices. Two measurement methods are defined as follows:

Euclidean distance is

$$E(A, B) = \|A - B\|_F^2 = \sum_{i,j} (A_{ij} - B_{ij})^2,$$

(3)

where $\|\cdot\|_F$ is the Frobenius norm of matrix $u$, which is used to measure the distance between matrices $A$ and $B$. If and only when $A = B$, $E(A, B)$ takes the minimum value of 0.

K-L divergence is

$$D(A, B) = \sum_{i,j} \left( A_{ij} \log \frac{A_{ij}}{B_{ij}} - A_{ij} + B_{ij} \right).$$

(4)

K-L divergence, also known as relative entropy, information divergence, and information gain, initially represents a measure of the asymmetry between two probability distributions. That is, the number of extra bits required to encode samples from the probability distribution $\pi_2$ is used using coding based on the probability distribution $\pi_1$. Typically, $\pi_2$ represents the true distribution of the data, and $\pi_1$ represents the theoretical distribution of the data or the approximate distribution of $\pi_2$. The K-L divergence here is used to measure the distance between matrices $A$ and $B$, if and only when $A = B$, $D(A, B)$ takes the minimum value of 0.

Based on the above measurement method, if $A = G, B = WH$, then the non-negative matrix factorization can be converted into an optimization problem, and two types of objective functions can be obtained:

$$(W, H) = \arg\min_{W \geq 0, H \geq 0} E(WH, G),$$

(5)

$$(W, H) = \arg\min_{W \geq 0, H \geq 0} D(WH, G).$$

(6)

Solving the approximate solution of problem (1) is equivalent to solving optimization problems (5) and (6). Although the above two objective functions are convex functions for $W$ and $H$ alone, if $W$ and $H$ are considered at the same time, they are not convex functions. Therefore, the global optimal solution of the objective function cannot be obtained. Use the multiplicative updates (MU) algorithm and use alternate iteration algorithms to update $W$ and $H$, respectively. That is, the algorithm first fixes $W^{(k)}$, calculates $H^{(k+1)}$, and then uses $H^{(k+1)}$ to calculate $W^{(k+1)}$. This not only speeds up the algorithm’s collection speed but also reduces the computational complexity. The content of the algorithm is as follows:
The original}

corresponding adjacency matrix is as follows:

\[
W_{ia} \leftarrow W_{ia} \frac{(GH^T)_{ia}}{(WHH^T)_{ia}},
\]

\[
H_{aj} \leftarrow H_{aj} \frac{(WH^T)_{aj}}{(WH)_{aj}}.
\]

Under the iterative rule, the Euclidean distance function \(E(WH, G)\) is monotonous and non-increasing, and the sufficient and necessary condition for the value of \(E(WH, G)\) to no longer change is that \(W\) and \(H\) is its stable points.

\[
W_{ia} \leftarrow W_{ia} \frac{\sum_i H_{ai}G_{ij}/(WH)_{ia}}{\sum_i H_{ai}},
\]

\[
H_{aj} \leftarrow H_{aj} \frac{\sum_i W_{ia}G_{ij}/(WH)_{ij}}{\sum_i W_{ia}}.
\]

Under the iterative rule, the K–L divergence function \(D(WH, G)\) is monotonous and non-increasing, and the sufficient and necessary condition for the value of \(D(WH, G)\) to no longer change is that \(W\) and \(H\) is its stable points.

Formulas (7) and (8) describe an iterative update process, that is, every time the elements in \(W\) and \(H\) are updated, the original \(W\) and \(H\) are used for calculation. Research shows that the multiplicative update algorithm has convergence.

Generally, English teaching information is described in a hierarchical structure. In the English teaching information structure, nodes represent English teaching information features or English teaching information, and edges represent the assembly or affiliation relationship between information layers. As shown in Figure 1, from top to bottom, the points above the same edge represent the parent item, and the points below are called the child items. The information feature in Figure 1 is both the parent of \(c\) and the child of \(o\). The number beside the side indicates the quantity of component parts required to produce the parent part of the unit.

For the English teaching information structure described in Figure 1, the corresponding adjacency matrix is as follows:

\[
Z = \begin{bmatrix}
a & a & b & c & d & e & f & g & h & i \\
a & 0 & 3 & 2 & 0 & 0 & 0 & 0 & 0 & 0 \\
b & 0 & 0 & 0 & 2 & 0 & 1 & 0 & 1 & 0 \\
c & 0 & 0 & 0 & 0 & 4 & 0 & 2 & 0 & 0 \\
d & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
e & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
f & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
g & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
h & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
i & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 
\end{bmatrix}.
\]

For the English teaching information structure represented by the ontology system, the SQWRL query language can retrieve the parent item to which the information layer belongs and the number of component items required to form the parent item of the unit.

The information structure of the English teaching information received by the university from the client is \(T_g\), which is the goal that the designer needs to achieve. The existing English teaching information structure in the college English teaching information database is \(T_g^{(i)} (i = 1, 2, 3, \ldots, n)\). These can be called querying English teaching information structure; then the steps of the method for determining the similarity of English teaching information structure based on non-negative matrix factorization are as follows:

The algorithm constructs adjacency matrices \(M_g\) and \(M_g^{(i)}\) for \(T_g\) and \(T_g^{(i)}\), and both are described by column vectors. We use \(M_g\) as an example, and \(M_g = [a_1, a_2, \ldots, a_m]\), where \(a_i\) is the column vector of \(i (i = 1, 2, \ldots, m)\) of \(M_g\) and \(m\) is the total number of column vectors in \(M_g\).

The algorithm constructs the adjacency vector \(\beta = [a_1^T, a_2^T, \ldots, a_m^T]^T\), that is, connects all the columns of the adjacency matrix into a column vector.

The algorithm combines the target English teaching information structure and the adjacency vector of the query English teaching information structure to form a matrix \(S = S_{hk \times (n+1)},\) and the structure of \(S\) is \(\left[ \beta_g, \beta_1, \beta_2, \ldots, \beta_n \right]\). It covers the structure information of all English teaching information including target English teaching information and querying English teaching information, which can be called the library matrix.

The algorithm performs non-negative matrix decomposition on the library matrix \(S\) so that \(S \approx PQ\); then \(\beta_i (i = g, 1, 2, \ldots, n)\) is expressed as a linear combination of the column vectors in the matrix \(P\) as follows:

\[
\beta_i = \sum_{k=1}^{r} q_{ki} P(\ast, k),
\]

where \(P(\ast, k)\) is the \(k\)-th column vector of matrix \(P\) and \(q_{ki}\) is the element of the \(k\)-th row and \(i\)-th column of matrix \(Q\).

Formula (11) shows that \(\beta_i\) is mapped from the \(m^2\)-dimensional space to the \(r\)-dimensional space \((m^2 < r)\),
and the element of the i-th column of Q is the vector coordinate of $\beta_i$ in the new space. Therefore, the similarity of the two can be judged by calculating the distance between the target English teaching information structure and the low-dimensional vector corresponding to each query English teaching information structure.

In actual production, in order to reduce the redundancy of English teaching information data, the existing English teaching information structure generally cannot be combined with each other. Therefore, each column $\beta_i$ of the library matrix $S$ is linearly independent, which satisfies the full-rank condition of non-negative matrix decomposition. Therefore, it is theoretically feasible to apply this method to determine the similarity of English teaching information structure.

In this paper, the Euclidean distance function is used as the objective function of matrix factorization. From this, we can see the similarity determination process of English teaching information structure based on non-negative matrix factorization as shown in Figure 2. In the figure, $I$ represents the total number of iterations. For different problems, the number of times required to stabilize $\|S-PQ\|_F$ during iterations is not the same. Therefore, the choice of $I$ depends on specific issues. Since the decomposition result of the algorithm is related to the selection of the initial values of $P$ and $Q$, in the actual calculation process, it is necessary to repeat the calculation of the matrix decomposition process many times and select the decomposition that minimizes $\|S-PQ\|_F$ as the final result.

The calculation of local differences combines all the information feature differences of similar editing operations and the weight of the editing operations themselves. Below, we take the basic English teaching information update operation as an example to illustrate the local differences under this operation. Converting the English teaching information structure $P_o$ to $P_n$ requires updating $k_i$ basic English teaching information. The set of operations for these is $\text{Update}_\text{basic} = \{(\text{part}_{1}, \text{part}_{1}), (\text{part}_{2}, \text{part}_{1}), \ldots, (\text{part}_{k}, \text{part}_{1})\}$. Since the main functions of the same series of English teaching information are similar, the information characteristics of the same basic English teaching information are also of the same importance to the overall English teaching information. The importance of the information features to which the $k_i$ basic English teaching information belongs to the overall English teaching information is $W_{b} = (w_{b_1}, w_{b_2}, \ldots, w_{b_{k_i}})$, where $w_{b_i} \in (0, 1), t = 1, 2, \ldots, k_i$; the basic English teaching information update operation partial difference is

$$\text{diff}_U\text{update}_{\text{basic}} = w_{ib} \frac{\sum_{i=1}^{k_i} \text{diff}(\text{part}_{1}, \text{part}_{1})w_{ib}}{\sum_{i=1}^{k_i} w_{ib}}$$

where $\text{diff}(\text{part}_{1}, \text{part}_{1})$ represents the difference in the subordinate information characteristics when the English teaching information part_{1} is updated to part_{1}, that is, the difference in information characteristics, which is given by the design team responsible for this part. The weight $W_{b}$ of the $K_i$ information feature and the weight $w_{ib}$ of the basic English teaching information update operation are integrated, and the result is the partial difference defined by the basic English teaching information update operation that is converted from the English teaching information structure $P_o$ to $P_n$. The local differences of other types of editing operations are defined as follows:

The mandatory English teaching information update operation is

$$\text{diff}_U\text{update}_{\text{mand}} = w_{a_{mn}} \frac{\sum_{i=1}^{k_i} \text{diff}(\text{part}_{1}, \text{part}_{1})w_{a_{mn}}}{\sum_{i=1}^{k_i} w_{a_{mn}}}$$

where $W_{a} = (w_{a_0}, w_{a_1}, \ldots, w_{a_{k_2}})w_{a_{mn}} \in (0, 1), t = 1, 2, \ldots, k_2$ is the importance of the subordinate information characteristics of $k_2$ mandatory English teaching information in English teaching information.

The update operation of the optional English teaching information is

$$\text{diff}_U\text{update}_{\text{opt}} = w_{a_{op}} \frac{\sum_{i=1}^{k_i} \text{diff}(\text{part}_{1}, \text{part}_{1})w_{a_{op}}}{\sum_{i=1}^{k_i} w_{a_{op}}}$$

where $W_{o} = (w_{o_0}, w_{o_1}, \ldots, w_{o_{k_4}})w_{o_{op}} \in (0, 1), t = 1, 2, \ldots, k_4$ is the importance of the subordinate information features of the $k_4$ optional English teaching information in English teaching information.

The input operation of optional English teaching information is

$$\text{diff}_{\text{input}_{\text{opt}}} = w_{i_{op}} \frac{\sum_{i=1}^{k_i} \text{Ins}_{\text{part}_{1}}w_{i_{op}}}{\sum_{i=1}^{k_i} w_{i_{op}}}$$

where $W_{i} = (w_{i_0}, w_{i_1}, \ldots, w_{i_{k_4}})w_{i_{op}} \in (0, 1), t = 1, 2, \ldots, k_4$ is the importance of the subordinate parts of these $k_4$ optional English teaching information in English teaching information.

The delete operation of mandatory English teaching information is

$$\text{diff}_{\text{delete}_{\text{mand}}} = w_{d_{mn}} \frac{\sum_{i=1}^{k_i} \text{Delete}_{\text{part}_{1}}w_{d_{mn}}}{\sum_{i=1}^{k_i} w_{d_{mn}}}$$

where $W_{d} = (w_{d_0}, w_{d_1}, \ldots, w_{d_{k_5}})w_{d_{mn}} \in (0, 1), t = 1, 2, \ldots, k_5$ is the importance of the subordinate information features of the $k_5$ optional English teaching information in the English teaching information.

3.1. Differences in Overall Attributes of English Teaching Information. It can be found from practical life that the differences in overall fuzzy attributes of English teaching information are transitive. In other words, when the difference between English teaching information $P_i$ and $P_j$ is small and the difference between $P_j$ and $P_k$ is also small, the difference between $P_i$ and $P_k$ is also small. $m_{ijk}^{\text{sp}} \in (0, 1)$ represents the difference between English teaching information $P_i$ and $P_j$ on the overall fuzzy attribute $S$. The larger the value, the greater the difference between the two.
According to the principle of transitivity, when $m_{ij} \cdot m_{jk}$ are large (the difference is large), $m_{ik}$ must also be large (the difference between $P_i$ and $P_k$ is also large). Because of $m_{ij} \cdot m_{jk} \in (0, 1)$, the product of the two can be approximately expressed as the difference $m_{ik}$ between $P_i$ and $P_k$, that is, $m_{ij} \cdot m_{jk} = m_{ik}$. In matrix theory, the matrix that satisfies such conditions is called a consistent matrix, so the consistency test of the expert’s score is converted to the
degree to which the score matrix is close to the consistent matrix.

The expert rating matrix is expressed in the form of a reciprocal matrix as follows:

\[
H' = \left[ h'_{ij} \right]_{n \times n} = \begin{bmatrix}
1 & m'_{i1} & m'_{i2} & \cdots & m'_{in} \\
\frac{1}{m'_{i1}} & 1 & m'_{i3} & \cdots & m'_{in} \\
\frac{1}{m'_{i2}} & \frac{1}{m'_{i3}} & 1 & \cdots & m'_{in} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
\frac{1}{m'_{in}} & \frac{1}{m'_{i3}} & \frac{1}{m'_{i4}} & \cdots & 1
\end{bmatrix}_{n \times n},
\]  \hspace{1cm} (17)

where \( m'_{ij} \) represents the difference between the overall fuzzy attributes of English teaching information \( P_i \) and \( P_j \), which are given by experts in related fields. The reciprocal matrix has the following properties:

The largest characteristic root of the \( n \)-th order reciprocal matrix \( A \) is \( \lambda \geq n \). When \( \lambda = n \), \( A \) is a consistent matrix. When \( \lambda \) is greater than \( n \), it means that the inconsistency is more serious, and the similarity of expert scores is more unreasonable, and then it needs to be rescored. At this time, it needs to be rescoped. The random consistency index \( RI \) measures the reasonable allowable range of the expert’s score. If \( CI/RI < 0.1^{[79]} \) (\( CI = (\lambda - n)/(n - 1) \)), the expert’s score is considered reasonable.

4. Design of Hierarchical Retrieval Model of Digital English Teaching Information Based on Ontology

On the basis of the above algorithm analysis, the ontology-based hierarchical retrieval model of digital English teaching information is developed. The web page should not be used as a format file for the long-term preservation of digital English teaching information. Before explaining the reasons, the environment of the layered model is shown in Figure 3.

The overall structure pattern of the hierarchical structure is shown in Figure 4(a). We can see from it that each layer consists of two parts: one is the structure, and the other is the interface of the structure. For example, the data layer includes the structure of the data layer and the interface provided by the data layer to the logic layer, and the logic layer includes the structure of the logic layer and the interface provided by the logic layer to the presentation layer.

From a macro point of view, the interface is a bridge between the data layer and the logic layer and between the logic layer and the presentation layer, and the digital flow is operated through the interface between them. From a microperspective, an interface is a series of method declarations, a collection of some method characteristics. The class that implements the VI is encapsulated, only provides a set of method declarations, and can perform certain functions, as shown in Figure 4(b).

English teaching digital information enters the data layer from the logic layer. In the process of the data layer, further verification of the content information and storage description information is required to ensure the security and integrity of the data. Because the storage description information of the content information is about to enter the database for long-term storage, the integrity and security of the data are very important for the English teaching digital information. The specific process is shown in Figure 5.
The database interface includes two kinds of public interface and special interface. The public interface means that all access to the database needs to call the public interface, which is extracted from the special interface, such as the connection and closing of the database. The special interface refers to the interface for adding, updating, modifying, and retrieving specific data, such as the interface for adding, updating, modifying, and retrieving content information. The data layer interface diagram is shown in Figure 6.

The logic layer can also be divided into I/O processes. In the I process, the logic layer must receive not only the data flow AIP of the data layer but also the data flow SIP of the presentation layer. In the O process, the logic layer must not only output to the database layer AIP but also output to the presentation layer DIP. After the logic layer receives the data AIP submitted to itself by the presentation layer, it then decomposes the AIP into basic data units. It is broken down into two parts, PDI and CI, and then PDI and CI are analyzed and verified, respectively.

The logic layer should first accept the data stream AIP and perform security verification checks on the received AIP. For the AIP that does not meet the access to the logic layer, the reason for not entering the logic layer is generated, and a report that fails to enter the logic layer is generated and fed back to the presentation layer. After the inspection, the AIP that meets the logic layer is analyzed, and the AIP is divided into two parts: CI and PDI, and the relationship between the two is described by ID. After that, the generated CI and PDI
Figure 7: Flow chart of logical layer reception.

Figure 8: Continued.
are saved in the database, and the saved success report is generated and fed back to the presentation layer. The logic layer flow chart is shown in Figure 7.

The sending flow chart of the logic layer is shown in Figure 8(a). The interface diagram of the logic layer is shown in Figure 8(b).

On the basis of the above research, this paper verifies the effect of the hierarchical retrieval model of digital English teaching information based on ontology. Moreover, this paper constructs an ontology-based hierarchical retrieval model system for digital English teaching information through a simulation platform. The simulation test is carried out on the effect of layered processing of English education information of the simulation model, the effect of hierarchical retrieval, and the effect of system teaching improvement, and the results shown in Tables 1–3 are obtained.

Table 1: The hierarchical processing effect of the hierarchical retrieval model of digital English teaching information based on ontology.

| Num | Layered processing | Num | Layered processing | Num | Layered processing |
|-----|--------------------|-----|--------------------|-----|--------------------|
| 1   | 95.45              | 26  | 91.34              | 51  | 95.45              |
| 2   | 94.97              | 27  | 94.67              | 52  | 93.54              |
| 3   | 91.19              | 28  | 92.80              | 53  | 91.49              |
| 4   | 94.61              | 29  | 93.46              | 54  | 95.13              |
| 5   | 91.07              | 30  | 93.19              | 55  | 94.82              |
| 6   | 92.90              | 31  | 95.87              | 56  | 94.03              |
| 7   | 94.04              | 32  | 91.82              | 57  | 91.78              |
| 8   | 95.72              | 33  | 94.96              | 58  | 94.19              |
| 9   | 95.11              | 34  | 92.08              | 59  | 94.72              |
| 10  | 94.27              | 35  | 91.49              | 60  | 91.78              |
| 11  | 92.06              | 36  | 93.02              | 61  | 92.63              |
| 12  | 94.96              | 37  | 91.84              | 62  | 95.88              |
| 13  | 95.31              | 38  | 94.47              | 63  | 92.29              |
| 14  | 91.96              | 39  | 93.15              | 64  | 92.53              |
| 15  | 95.48              | 40  | 94.35              | 65  | 92.94              |
| 16  | 93.30              | 41  | 93.53              | 66  | 95.94              |
| 17  | 95.13              | 42  | 91.96              | 67  | 95.94              |
| 18  | 95.83              | 43  | 94.99              | 68  | 93.36              |
| 19  | 91.80              | 44  | 92.46              | 69  | 92.82              |
| 20  | 91.33              | 45  | 94.88              | 70  | 92.10              |
| 21  | 91.82              | 46  | 94.84              | 71  | 95.21              |
| 22  | 92.68              | 47  | 93.06              | 72  | 91.05              |
| 23  | 95.59              | 48  | 92.20              | 73  | 92.08              |
| 24  | 94.72              | 49  | 94.42              | 74  | 94.05              |
| 25  | 94.66              | 50  | 91.98              | 75  | 92.49              |

Figure 8: Logical layer structure: (a) the sending flow chart of the logic layer and (b) interface diagram of the logical layer.
Table 2: The hierarchical retrieval effect of the hierarchical retrieval model of digital English teaching information based on ontology.

| Num | Hierarchical search | Num | Hierarchical search | Num | Hierarchical search |
|-----|---------------------|-----|---------------------|-----|---------------------|
| 1   | 87.87               | 26  | 89.77               | 51  | 92.35               |
| 2   | 84.44               | 27  | 85.47               | 52  | 84.33               |
| 3   | 86.34               | 28  | 90.96               | 53  | 92.86               |
| 4   | 89.17               | 29  | 84.96               | 54  | 89.28               |
| 5   | 85.93               | 30  | 85.01               | 55  | 92.66               |
| 6   | 88.24               | 31  | 84.59               | 56  | 86.94               |
| 7   | 86.40               | 32  | 90.12               | 57  | 84.24               |
| 8   | 89.58               | 33  | 91.85               | 58  | 92.59               |
| 9   | 91.39               | 34  | 86.97               | 59  | 91.32               |
| 10  | 87.23               | 35  | 85.21               | 60  | 90.83               |
| 11  | 84.24               | 36  | 89.01               | 61  | 85.07               |
| 12  | 89.16               | 37  | 85.13               | 62  | 88.53               |
| 13  | 86.89               | 38  | 90.56               | 63  | 87.64               |
| 14  | 85.42               | 39  | 85.68               | 64  | 85.22               |
| 15  | 90.20               | 40  | 84.29               | 65  | 85.65               |
| 16  | 92.71               | 41  | 89.99               | 66  | 92.03               |
| 17  | 91.48               | 42  | 87.08               | 67  | 84.37               |
| 18  | 84.41               | 43  | 92.86               | 68  | 87.99               |
| 19  | 87.03               | 44  | 85.14               | 69  | 86.73               |
| 20  | 88.73               | 45  | 92.68               | 70  | 84.69               |
| 21  | 91.54               | 46  | 86.42               | 71  | 88.55               |
| 22  | 84.72               | 47  | 91.97               | 72  | 87.50               |
| 23  | 85.98               | 48  | 92.88               | 73  | 89.03               |
| 24  | 84.28               | 49  | 92.62               | 74  | 85.10               |
| 25  | 92.48               | 50  | 92.76               | 75  | 91.27               |

Table 3: The teaching improvement effect of the hierarchical retrieval model of digital English teaching information based on ontology.

| Num | Teaching evaluation | Num | Teaching evaluation | Num | Teaching evaluation |
|-----|---------------------|-----|---------------------|-----|---------------------|
| 1   | 89.24               | 26  | 81.46               | 51  | 78.03               |
| 2   | 89.27               | 27  | 87.53               | 52  | 79.62               |
| 3   | 85.09               | 28  | 90.05               | 53  | 80.55               |
| 4   | 89.28               | 29  | 82.98               | 54  | 89.55               |
| 5   | 89.51               | 30  | 87.08               | 55  | 89.46               |
| 6   | 77.21               | 31  | 88.88               | 56  | 88.31               |
| 7   | 89.21               | 32  | 85.97               | 57  | 89.12               |
| 8   | 77.25               | 33  | 78.03               | 58  | 87.21               |
| 9   | 85.11               | 34  | 84.28               | 59  | 86.11               |
| 10  | 77.32               | 35  | 82.05               | 60  | 80.23               |
| 11  | 80.97               | 36  | 87.89               | 61  | 81.47               |
| 12  | 89.09               | 37  | 80.25               | 62  | 88.02               |
| 13  | 85.98               | 38  | 78.70               | 63  | 85.52               |
| 14  | 81.23               | 39  | 90.22               | 64  | 86.29               |
| 15  | 85.52               | 40  | 78.17               | 65  | 81.57               |
| 16  | 87.53               | 41  | 78.58               | 66  | 81.84               |
| 17  | 88.77               | 42  | 87.40               | 67  | 79.16               |
| 18  | 90.80               | 43  | 81.01               | 68  | 84.56               |
| 19  | 84.42               | 44  | 86.64               | 69  | 85.55               |
| 20  | 90.62               | 45  | 82.52               | 70  | 79.27               |
| 21  | 87.43               | 46  | 89.12               | 71  | 81.97               |
| 22  | 83.53               | 47  | 85.51               | 72  | 84.07               |
| 23  | 88.56               | 48  | 84.33               | 73  | 82.63               |
| 24  | 87.34               | 49  | 83.52               | 74  | 90.42               |
| 25  | 79.41               | 50  | 84.58               | 75  | 81.10               |
From the above statistical analysis, the digital English teaching information hierarchical retrieval model based on ontology proposed in this paper meets the basic needs of this paper to build an English teaching information system and can play a certain role in English teaching.

5. Conclusion

This paper designs a common space for features from different modalities so that all the information contained in these features is mapped from the original space to this space. This enables the multi-modal data of English teaching information to share the same unified representation and makes its semantic comparison and mining become direct and effective. The mathematical basis of common space learning is that data of different modalities that describe the same target share similar semantics. Therefore, multi-modal data have potential common modes, which makes it possible to construct a common space. At present, the existing models all use this feature to learn a common space to clearly map different modal data into this space for intuitive mathematical similarity comparison and latent semantic mining. This paper designs a hierarchical retrieval model of digital English teaching information through ontology and constructs an intelligent system structure that can be used for hierarchical retrieval of digital English teaching information to improve the effect of modern English teaching. The simulation test shows that the hierarchical retrieval model of digital English teaching information based on ontology proposed in this paper meets the basic needs of this paper to build an English teaching information system and can play a certain role in English teaching.

Data Availability

The labeled data sets used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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