

Retraction

Retracted: Analysis of Network Information Retrieval Method Based on Metadata Ontology

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] C. Wang and K. Chen, "Analysis of Network Information Retrieval Method Based on Metadata Ontology," *International Journal of Antennas and Propagation*, vol. 2022, Article ID 2664639, 11 pages, 2022.

Research Article

Analysis of Network Information Retrieval Method Based on Metadata Ontology

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In order to solve the problem that people can accurately search for the network information they need, the research on network information retrieval methods becomes more important. This article is mainly about the research of network information retrieval methods based on metadata ontology calculations. This article constructs an LDA three-layer Bayesian model with a three-layer structure of document, topic, and single order. The three-layer structure obeys a random polynomial distribution and can be calculated the joint distribution probability of all variables in the LDA model greatly increases the calculation efficiency. Using a cross-modal information retrieval method, it can mine the common data features between different modal data and analyze the semantic correlation between different modal data, improve the accuracy of search, and solve the existence of different modal data. There is a gap in the expression semantics between heterogeneous and different modal data. The experimental results in this paper show that the text feature extraction of the network information retrieval method based on the metadata ontology calculation has a good performance in terms of accuracy, and the accuracy of the extraction and clustering results is as high as about 90%. The improved CCA algorithm used is better than the traditional CCA and the accuracy is improved by 23%, which is 12% higher than the LDA-CCA algorithm.

1. Introduction

With the emergence and development of the World Wide Web, web-based information retrieval tools appeared and developed rapidly. In the information society, network retrieval has become one of the important ways for readers to obtain information. Improve learning efficiency. With the tremendous development and increasing popularity of technology, the Internet has become the most important way for people to obtain information, and its scale is also growing at an alarming rate. According to the data released by the Research Institute in Nature, as of 2016, the total number of screen names has reached 800 million, and broadband Internet users accounted for 500 million, of which 95% use search engines. Compared with 2014, it has increased by 300 million. From these data, it can be seen that the Internet is gradually entering people's lives, learning, and research. In

China, the development of search engines cannot be underestimated. The establishment of Baidu has provided secondary search engines for famous websites such as Sina and Yahoo. Skynet search, which is funded and developed by the state, has been able to provide services, and it has a powerful search function. The most famous domestic Baidu search engine version is also officially released. With the unpredictable changes in the online world, Baidu is also constantly pursuing technological innovation. Today, with the development of search engines, people have begun to explore more intelligent retrieval. And with the continuous popularization of the Internet, the multimodal information on the Internet is also increasing exponentially. Traditional retrieval methods such as document retrieval and image retrieval can no longer satisfy the needs of modern information retrieval. Without powerful analysis and retrieval tools, it is difficult for users to access the massive

heterogeneous media data. Finding interesting information quickly will inevitably continue to lead to the continued decline in user search behavior.

With the sustained development of the network, the traditional single-modal information retrieval method has gradually been unable to satisfy the demand of modern people for obtaining the required information. Coupled with the development of modern data mining technology, the traditional way of obtaining information has been unable to satisfy modern people demand. Since the past information retrieval method was monomodal, it was generally only in the way of document retrieval and image retrieval. To a large extent, it is difficult to achieve multimodal information retrieval, but people's needs are gradually turning to multimodal. Information retrieval method. At the same time, with the continuous improvement of information retrieval technology, multimodal information retrieval technology has also improved a lot. And also, domestic and foreign scholars have made many improvements in the traditional information retrieval theory and also proposed many novel retrieval algorithms. Among them, deep learning builds multi-hidden-layer models and massive training data, abstracts layer by layer, and then mines the essential content of the data, so as to finally enhance the performance of classification or prediction. The input of the high-level features in the neural network depends on the output of the features extracted by the underlying neural layer. The convolutional neural network in the deep learning algorithm is a typical and effective algorithm. Its biggest character is that it can transform a simple text document into the meaning of a multilayer structure and continuously extract the largest feature through multiple hidden layers, unmatched by traditional machine learning algorithms.

At present, people cannot live without the Internet everywhere, and to find what people need is inseparable from online information search. The following people have their own views on this. Kapetanios proposed that information sources like the Web are representations of social activities. In this case, within the information source, evidence of access to the community through the existence of an ever-increasing collection of documents can be used to measure recall and accuracy. However, as a part of information retrieval metrics, recall and precision also require technology to retrieve relevant documents. This is a kind of information retrieval within the network concept. For solving this problem, the concept of collecting stars from the tree and the degree of social participants in the social network was proposed, and a measurement formula for recall and accuracy was produced, which has a better effect. Although he proposed the concept of collecting stars from trees, his search method could not accurately locate the content he wanted to search [1]. Vechtomova proposed that canonical correlation analysis is a beneficial tool for detecting the linear relationship between two sets of multivariate variables. Its nuclear generalization, that is, nuclear CCA is proposed to describe the nonlinear relationship between two variables. For the problem of high-dimensional data feature selection, although kernel CCA can achieve the effect of dimensionality reduction, it will also produce the

so-called over-fitting phenomenon, so a new kernel CCA algorithm is considered through the random Kaczmarz method. Although he proposed a new CCA algorithm, his algorithm is not as concise and easy to use as the improved algorithm in this article [2]. Tabrizi et al. raised the issue of providing privacy for users requesting data from distributed storage systems through the network. From the user's point of view, DSS is considered to be a multi-terminal destination of the network. Therefore, a novel PIR scheme is proposed, which allows users to restore files from the storage system with low communication costs, while allowing certain servers in the system to collude in seeking to reveal the identity of the requested file. The network is modeled as a random linear network, that is, a random linear combination of all nodes in the network forwarding incoming data packets. Although he created a novel PIR scheme, his research direction is the problem of user privacy. This scheme is more difficult to implement, and it is not as convenient as the network information exploration of the ontology calculation in this article [3].

The innovations of this article are: (1) The LDA three-layer Bayesian model is constructed, which has a three-layer structure of documents, topics, and a single order. The three-layer structure obeys the random polynomial distribution, and all the variables in the LDA model can be calculated. The joint distribution probability of greatly increases the computational efficiency. (2) The cross-modal information retrieval method is used, which can mine the common data characteristics between different modal data and analyze the semantic correlation between different modal data, improve the search accuracy, and solve the different modal data. There is a gap between heterogeneous and different modal data expression semantics. (3) The double convolutional neural network algorithm is applied, and it greatly improves the performance than the traditional CCA algorithm.

2. Network Information Retrieval Method Based on Metadata Ontology Calculation

2.1. Metadata. Metadata, also known as intermediary data and relay data, is the data that describe the data, mainly the information describing the properties of the data. Metadata is mainly information describing data attributes, which is used to support functions such as indicating storage location, historical data, resource search, and file records. Metadata is a kind of electronic catalog. In order to achieve the purpose of cataloging, it is necessary to describe and collect the content or characteristics of the data, so as to achieve the purpose of assisting data retrieval. Information awareness includes three levels: information cognition, information emotion, and information behavior tendency. Information retrieval methods include: common law, retrospective, and segmented. Common law is a method of searching for documents using search tools such as bibliography, abstracts, and indexes. The common law can be further divided into the forward inspection method and the reverse inspection method. The forward check method is to search in chronological order from the past to the present, which is expensive and inefficient; the backward check

method is to search from the recent to the long-term in reverse chronological order. The reverse check method (also known as the reverse check method) is the opposite of the sequential search method. It is a method of searching the accounting statements, account books, and original documents according to the order of accounting processing. It emphasizes the recent data and the current information. Metadata technology was first proposed for library book management. The most common definition of metadata is: "data about data" [4]. Metadata plays a very important role in information description, information retrieval, information integration, and sharing [5]. Metadata can be used to describe information, processes, and object data. Features such as attributes, structure, and behavior, business definitions, and operational features such as activity indicators and usage history. At present, the application of metadata technology has been extended to the fields of fault diagnosis, intrusion detection, ORACLE database, image classification, pervasive computing, information sharing, grid data management, data mining, smart home, and target recognition [6]. For applications in different fields, the research of big data is further proposed. In different application areas, the types of metadata used are also different, and the quality standards for metadata are also different, mainly from different dimensions, users, and usage perspectives [7]. However, the specific functions of metadata technology are mainly manifested in the following aspects.

2.1.1. Data Management. According to application requirements, metadata can describe the complete picture of information resources. Users can understand and recognize information resources by managing metadata, evaluating metadata and other information, and decide whether to choose, without having to browse the original data resources. For example, the document "Research on Intelligent Self-describing Data Dictionary in Distributed Information Fusion System" studies data selection, data sharing, and system performance evaluation. The document "Data Source Management in Grid Data Fusion System" combines metadata and class objects, uses classes to manage data sources in the grid data fusion system, and uses data mining methods to manage effective classes. Metadata can also be used to manage mass storage files [8].

2.1.2. Data Resource Sharing. Combining metadata with information network nodes can realize information sharing in the information grid, thereby improving the reliability, availability, and access efficiency of the system. At present, in order to solve the problem of intelligence information management and sharing in ASRS and even higher-level military information systems, all countries have taken the standardized design and application of unified intelligence data formats as specific breakthroughs, conducted comprehensive and in-depth research, and successively adopted national military standards. The research results are solidified and promoted in the form [9]. The emergence of various independent, goods-to-person Automated Warehousing and Retrieval Systems (AS/RS) has helped warehousing, distribution, and manufacturing operations transition from sorting trays and boxes to picking individual items.

2.1.3. Interoperability of Data. There is no interrelationship between information resources, but through interrelated metadata, a multilevel and multipath retrieval approach can be provided for each information resource. For example, the combination of semantic metadata and ontology for information fusion can realize the integration and fusion of distributed heterogeneous data sources [10].

2.1.4. Solving the Problem of Data Uncertainty. In the information fusion system, due to the existence of sensor measurement error and the uncertainty of data source, the problem of data uncertainty always exists. Metadata can solve the uncertainty of information, which is for data sharing and the mutual exchange of complex and heterogeneous data. The operation provides technical ways to improve the query performance of the data query system, but the disadvantage is that it may affect the storage space and real-time function of the system data [11].

2.2. Convolutional Neural Network. Deep learning is a very popular research direction in the field of computer artificial intelligence in recent years. Compared with traditional shallow machine learning, it can dig out more hidden features. As a part of the deep neural network algorithms of deep learning, the convolutional extension network has been widely used in many fields and has realized excellent results. In the 1990s, LeCunetal et al. proposed the LeNet-5 network in the area of image processing for digit recognition. This network is also a convolutional neural network, which mainly includes 4 convolutional layers and 2 fully connected layers. The model's input is the original handwritten font image [12].

As shown in Figure 1, a convolutional neural network consists of a feature extractor consisting of convolutional and subsampling layers. In a convolutional layer of a convolutional neural network, a neuron is only connected to some of its neighbors. The structure contains more neural network layers. In this structure, multiple two-dimensional planes form each neural network layer, and each plane is composed of N -independent neuron nodes. When the vector matrix of the data is input, the filter in the convolutional neural network will process the matrix to generate the C1 feature layer. Then the vector on the C1 feature layer is biased and weighted, and finally a new feature layer is generated by the activation layer operation, which is the S2 layer. Then convolution operation is performed on the S2 feature layer to generate a C2 feature layer, and then the operation on C1 is repeated on C2. By analogy, the C3 feature layer is obtained, which is input to the fully connected layer, and the final output result is gotten. Generally, the final connected one is used as a classifier.

Weight sharing means that, given an input image, use a convolution kernel to scan the image, and the number in the convolution kernel is called the weight. For avoiding the phenomenon of excessively large parameters, the convolutional neural network adopts two more effective ways to solve the problem: local receptive fields and weight sharing. The so-called local receptive field refers to a process from local to global cognition. We believe that adjacent areas in a

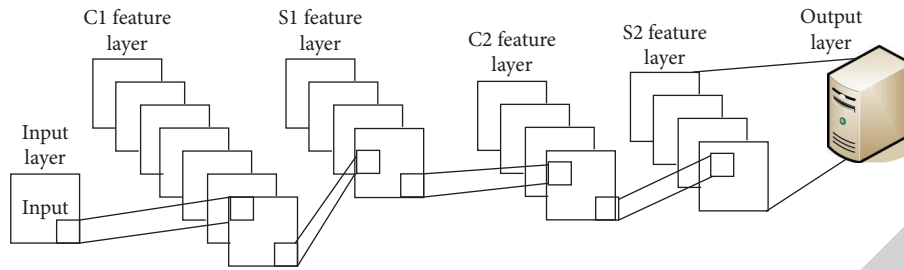


FIGURE 1: Convolutional network structure diagram.

picture are relatively close, if they are not adjacent or distant areas are not very close. In the fully connected layer, each neuron node is connected to each other randomly, so we can think that the local receptive field is that a neuron node is only connected to the neuron node of the upper layer. In this way, the number of connections between neuron nodes can be reduced to a certain extent, and the weight parameters can be reduced accordingly [13].

The so-called weight sharing means that the weight parameters of a certain neuron node and the neuron nodes of the upper layer are the same, which means that all the neuron nodes on the same level use the same weight parameters, so the number of parameters in the network can be reduced to a certain extent, and the complexity of selecting parameters will also be reduced [14]. As mentioned earlier, the output of each neuron is the input of the next neuron connected to it, and the input data of each neuron is processed by the activation function. Since the feature vectors extracted by the convolutional layer and the pooling layer of the convolutional neural network are linearly related, that is to say, the convolution operation in the convolutional neural network is based on linearity, so the extracted features are also linear features [15]. In order to make the convolutional neural network have stronger generalization ability and be able to handle nonlinear operations, it is necessary to introduce an activation function in the convolutional neural network. The purpose of introducing the activation function is to enable the CNN model to simulate complex nonlinear functions [16].

2.3. Network Information Retrieval. Information retrieval is the main way for users to query and obtain information, and it is the method and means of finding information. With the advent of information and a networked society, information retrieval is no longer the "patent" of a few search experts. People's search needs are no longer just for scientific research and related activities. Information retrieval has become popular and deep in people's work, all aspects of study and life. Since its appearance in 1987, it has developed into a huge globalized network resource space after more than 20 years. However, this huge information warehouse does not support organized information management and retrieval as people imagine. As a result, various information retrieval tools based on the Internet came into being and developed rapidly [16].

2.4. Cross-Modal Information Retrieval. The so-called information retrieval refers to the search user inputting query

expectations into a retrieval system. The retrieval system returns the retrieval information needed by the user through calculation. The retrieval prediction input by the user can be image, text or audio information, etc. [17]. Traditional retrieval methods such as document retrieval and image retrieval can no longer satisfy the needs of modern information retrieval. Without a powerful analysis and retrieval tools, it is difficult for users to access massive heterogeneous media data. Finding the information of interest quickly will inevitably continue to cause the user's search behavior to continue to decline [18]. The information that exists in the Internet is not only based on the text as a carrier, but also based on a combination of text, image, and video, which we call multi-modal information [19].

In the cross-modal field of artificial intelligence, the goal is to achieve semantic alignment and complementation of different forms of information similar to the human brain. The so-called cross-modal information retrieval is the cross retrieval of multimodal information such as images and text or images and videos. This article mainly paid attention to the research of cross retrieval between images and texts. To achieve cross retrieval between the two most common media content, images and texts, first, the images and texts must be represented by a certain feature vector, respectively, that is, the image data are mapped to image feature space, and text data are mapped to text feature space [20]. However, the feature space of the two is not directly related. For example, the CCA algorithm can map the feature vector space of the two to two linearly related feature vector spaces through the training of many "image-sample" sample pairs. The space is linearly related, which can directly measure the similarity between image and text feature vectors, thus providing a theoretical basis for image-text cross retrieval.

As shown in Figure 2, by constructing a rich media database of image, text, audio, and video and applying advanced artificial intelligence analysis technology, the cross retrieval of text, pictures, audio, and video files is realized. The left side is the traditional information retrieval method, and the right side is the cross-modal information retrieval method, which can realize cross-modal retrieval such as document retrieval and document viewing. Therefore, a cross-link between the two modal features of graphics and text must be established. A deeper understanding is the key to the cross-link between the two modal features of graphics and text. For example, in an image retrieval system, you can retrieve a clear sky image by matching "I blue spots," while a text retrieval system can also retrieve the text sky through the keyword "sky." Therefore, the

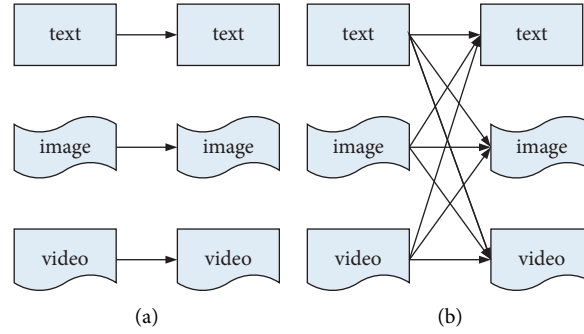


FIGURE 2: (a) Single-modal retrieval. (b) Multimodal retrieval.

cross-modal information retrieval system must also understand that there is a matching relationship between the “sky” text and the visual attribute “blue”. Therefore, when processing images and texts, it is necessary to go through multiple hidden layers for higher-level abstraction and extraction of features between various modalities [21].

2.5. LDA Model. LDA is a very commonly used topic model in natural language processing, the full name is latent Dirichlet distribution, referred to as LDA. The LDA model is the document-topic model, which means that the distribution of topics forms a document, and the distribution of words forms a topic. From this, it can be seen that the LDA model contains three layers of structure: document, topic and word, word to topic, and topic to document are all obeyed random polynomial distribution [22]. Bayes’ theorem is a theorem about the conditional probability (or marginal probability) of random events A and B . Therefore, the LDA model is a three-layer Bayesian possibility model. The Bayesian probability formula is:

$$\begin{aligned} P(B_j|A) &= \frac{P(AB_j)}{P(A)} \\ &= \frac{P(B_j)P(A|B_j)}{\sum_{j=1}^n P(B_j)P(A|B_j)}. \end{aligned} \quad (1)$$

Select the most possible hypothesis $F_j \in F$ for a set sample C from a set of candidate hypotheses f , namely,

$$\begin{aligned} f_{MAP} &= \arg \max_{f_j \in F} P(f|C) \\ &= \arg \max_{f_j \in F} \frac{P(C|f)P(f)}{P(C)} \\ &= \arg \max_{f_j \in F} P(C|f)P(f). \end{aligned} \quad (2)$$

From the Bayesian formula, the Bayes theorem can be described as below:

$$P(d_i|y_1, y_2, y_n) = \frac{P(y_1, y_2, y_n|d_i)P(d_i)}{P(y_1, y_2, y_n)}, \quad (3)$$

then:

$$\begin{aligned} P(y_1, y_2, y_n|d_i) &= \prod_{k=1}^n P(y_k|d_i), \\ P(d_i|Y) &= \frac{\prod_{k=1}^n P(y_k|d_i)P(d_i)}{P(y_1, y_2, y_n)}, \end{aligned} \quad (4)$$

$$d_{NB}(Y) = \arg \max_{f_j \in F} P(d_i) \prod_{K=1}^n P(y_k|d_i).$$

According to the above formula, it is necessary to conduct product operations, namely,

$$d_{NB}(Y) = \arg \max_{f_j \in F} \left[\log P(d_i) + \sum_{K=1}^n P(y_k|d_i) \right]. \quad (5)$$

Then:

$$P(D_j|Y) = P(D_j) \prod P^{w_k}(y_k|D_j). \quad (6)$$

As shown in Figure 3, corpus refers to a large-scale electronic text database that has been scientifically sampled and processed, which stores the language materials that have actually appeared in the actual use of the language. There are three levels: α and β are called word level at the corpus level; η is at the topic level called topic level; the remaining two parameters ξ and ω at the document level are called document level parameters. Since the two parameters at the word level are at the corpus level and are the same for each document, only one sampling is required. The topic-level parameter η has different values relative to different ones, which means that the topic probability corresponding to each document is different, so the η value needs to be set for each document during the generation process. The remaining two parameters can be seen from the above figure. ξ is generated by the parameter η , while ω is generated by the two parameters ξ and β . Special attention should be paid to the one-to-one correspondence between ω and ξ .

According to the above figure, the LDA model contains a three-layer structure, namely, document, topic and word, word to topic, and topic to document all obey random polynomial distribution. The LDA model is also called a three-layer Bayesian probability model. According to the

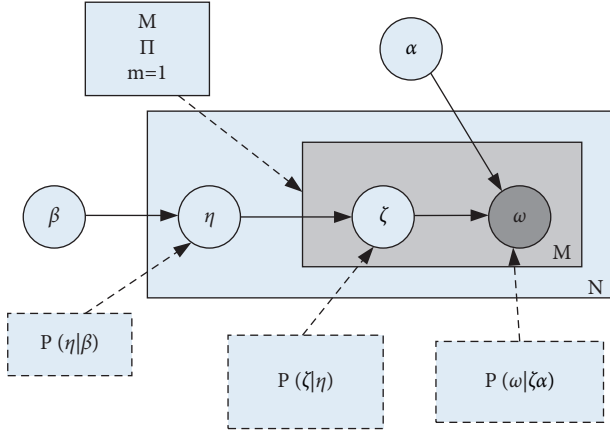


FIGURE 3: Schematic diagram of the Bayesian probability model of LDA.

process of LDA generation, the joint distribution probability of all variables in the LDA model can be calculated:

$$p(\eta, \xi, \omega, \Phi | \beta, \alpha) = \prod_{j=1}^c p(\omega | \Phi^j) p(\xi | \eta^c) p(\eta^c | \beta) p(\Phi | \alpha). \quad (7)$$

By calculating the marginal distribution probability of the formula, the generation probability formula of document C can be obtained as:

$$p(C | \beta, \alpha) = \iint p(\eta^c | \beta) p(\Phi | \alpha) \prod_{j=1}^c p(\omega | \eta^c, \Phi) d\Phi d\omega^{(c)}. \quad (8)$$

According to the above two formulas, the generation probability formula of the entire document set can be calculated as:

$$p(C | \beta, \alpha) = \prod_{c=1}^C \iint p(\eta^c | \beta) p(\omega | \alpha) \prod_{j=1}^{M_c} p(\omega | \eta^c, \Phi) d\Phi d\eta^c. \quad (9)$$

2.6. CCA Canonical Correlation Analysis. Creating new features is a very difficult task that requires extensive expertise and a lot of time. The essence of machine learning applications is basically feature engineering. To realize the cross retrieval between the two most common media content of image and text, the image and text must be, respectively, represented by a certain feature vector, that is, image data are mapped to image feature space, and text data are mapped to text feature space [23]. The basic principle of the CCA algorithm is: macroscopically analyze the correlation between the two modal data spaces, and extract two representative integrated variables $I1$ and $T1$ from these two modal data spaces $I1$ and $T1$ are not directly. The relationship between these two variables is projected to $I2$ and $T2$, respectively, through the CCA algorithm for linear correlation processing, and the correlation between the two modes is reflected through $I2$ and $T2$. Assuming that there are N samples in two sets of random variables, all N samples are linearly transformed to obtain the following two sets of data:

$$\begin{aligned} S_y \bar{\omega}_y &= (\bar{\omega}_y^T Y_1, \bar{\omega}_y^T Y_n), \\ S_x \bar{\omega}_x &= (\bar{\omega}_x^T X_1, \bar{\omega}_x^T X_n). \end{aligned} \quad (10)$$

The essence of the CCA algorithm is projection + correlation analysis. The projection standard selected is to project the data into one dimension so that the correlation coefficient of the two sets of data can reach the maximum. What the CCA algorithm is:

$$\begin{aligned} \rho &= \max_{\bar{\omega}_y, \bar{\omega}_x} \text{corr}(S_y \bar{\omega}_y, S_x \bar{\omega}_x) \\ &= \max_{\bar{\omega}_y, \bar{\omega}_x} \frac{(S_y \bar{\omega}_y, S_x \bar{\omega}_x)}{\|S_y \bar{\omega}_y\| \|S_x \bar{\omega}_x\|}. \end{aligned} \quad (11)$$

2.7. Ontology Calculation. Calculator ontology is an electronic engineering term, a shared vocabulary, and is a material for people to use knowledge in their own areas of interest. With the great innovation and improvement of heterogeneous data integration technology, simple data integration and data encapsulation of heterogeneous data on different data sources can no longer meet actual needs. The above-mentioned traditional methods only solve the grammatical heterogeneity of heterogeneous data. It solves well the semantic heterogeneity and knowledge heterogeneity of data. It has a good conceptual hierarchy, supports logical reasoning, and has a strong ability to express knowledge and concepts. Semantic analysis can be carried out through the ontology, and the data with the same concept or semantic information can be summarized and extracted, so the related data can be integrated. In addition, the ontology can be reused, which can greatly reduce the analysis of domain knowledge. Because of the unique advantages of ontology, it is gradually used by scholars in the fields of information retrieval, knowledge reasoning, and knowledge mining [24, 25]. The current ways to integrate heterogeneous data using Ontology can be roughly divided into three types:

Single ontology method: This method has only a unique global ontology in the entire data integration process. Based on this, a vocabulary set for the semantic description of words is given. In this model, the global ontology associates all information sources. This data integration method can integrate all information sources in the same field and can get a global and unified view. Because the global ontology and each data source are directly connected, if the data source changes, the global ontology and the mapping between the global ontology and the data source will also change.

Multi-ontology method: As the name suggests, this method has multiple ontologies. These ontologies are also called local ontologies. Each local ontology is linked to a data source, and each data source does not need to be associated with each other. Therefore, when the data source is changed, only the corresponding

ontology needs to be modified in advance. Generally, the structure of the ontology does not need to be modified. The multi-ontology method overcomes the problems in the single-ontology method, but because there is no global ontology in this method, it is difficult to communicate between various data sources.

Hybrid ontology method: In the hybrid ontology method, there is a local ontology linking each data source, and there is a global ontology linking all local ontologies. This method combines the advantages of the single-ontology method and the multi-ontology method. When adding and modifying data sources, only the local ontology needs to be changed, and there is no need to make major changes to the global ontology. At the same time, due to the existence of the global ontology, the comparison of terms between local ontology is also convenient.

3. Network Information Retrieval Method Experiment Based on Metadata Ontology Calculation

Information retrieval refers to the search user inputting query expectations into a retrieval system. The retrieval system returns the retrieval information needed by the user through calculations. The retrieval expectations entered by the user can be images, text, or audio information. The basis of information retrieval is based on text data mining and analysis. A series of text processing forms a training data set and then realizes the task of information retrieval.

3.1. Experimental Subjects. The corpus used is Chinese Wikipedia corpus, Sogou natural language corpus, and Harbin Institute of Technology Chinese corpus. In these three corpora, the experiment data of 7 categories of document text are extracted, respectively. The image text used in the training set is 7000, and each category is 1000. The size of the test data set is 2800 pairs of text and image, and the rest are the same. A total of 7,000 image-text pairs are extracted from each category of 1,000 images. Each text image pair is composed of pictures and multiple tags and keywords marked around the pictures.

3.2. Experimental Process. As shown in Figure 4, Multimodality refers to the integration or fusion of two or more biometrics technologies, using the unique advantages of its multiple biometrics technologies, combined with data fusion technology, to make the authentication and identification process more accurate and secure. When inputting the text or image that needs to be retrieved for retrieval, the model first preprocesses and extracts the features of the input query multimodal data and uses the deep convolutional neural network to learn across modalities in the training set and get the input data association matrix and generate the feature representation of the largest correlation space, and then semantically map it through the semantic concept classifier obtained by training to obtain its semantic feature vector in

the semantic space, and then use the cross-media retrieval algorithm to calculate each image in the test set.

3.3. Experimental Method. Since the text information data is not continuous in structure and the structure of the image is very different, it is quite difficult to directly use it as the input of the convolutional neural network. Therefore, in order to apply the convolutional neural network to natural language processing, it is necessary to mathematically transform the natural language text into a vector space, so that it can be used as the input corpus of the convolutional neural network, and then the features of the text can be extracted.

As shown in Figure 5, the words in the Chinese document are not related in structure but are related in semantics. Therefore, the first step in the preprocessing of Chinese text is to perform word segmentation of the Chinese document. The text is also directly used word2vec for word vectorization, the data after the document text segmentation are converted into low-latitude word vectors, all words are vectorized to form short word vectors, then according to the relationship between the word and the text Combining these short word vectors into a word vector matrix, then this word vector matrix can represent a text.

Just like text data, there are noise data in the image, so it is also necessary to denoise the image data. The space structure of the extracted vector is shown by a 128-dimensional floating-point array.

As shown in Figure 6, the common machine learning method K-means clustering is put into the convolutional neural network, and the features extracted through the totally connected layer of the convolutional neural network are the representation of the feature vector. The last is the feature vector combination, that is, all the images and the statistical word frequency data are fused together, which is the space of the feature vector of the image.

4. Network Information Retrieval Methods Based on Metadata Ontology Calculation

4.1. Performance Analysis of Extracting Text Features. As shown in Table 1, 400 documents were extracted from the 7 categories extracted from the three corpora as the training data set of the designed model, a total of 2800 text documents. Then 200 to 400 texts are randomly selected from the remaining documents in these seven categories as the test data set of the model.

As shown in Figure 7, it is the correct rate of clustering the document text features extracted by the convolutional neural network in the three data sets by the K-means clustering algorithm. Among them, in the Chinese Wikipedia data set, the highest accuracy rate of feature classification is aerospace text data, with an accuracy rate of 88.49%. The aerospace text in this category has 180 titles; the second most accurate is medical text documents. Indeed, about half of the space category. In the Sogou natural language corpus data set, the category with the highest feature classification is economic text data, with an accuracy of 88.34%, and the test entry for this category is 200.

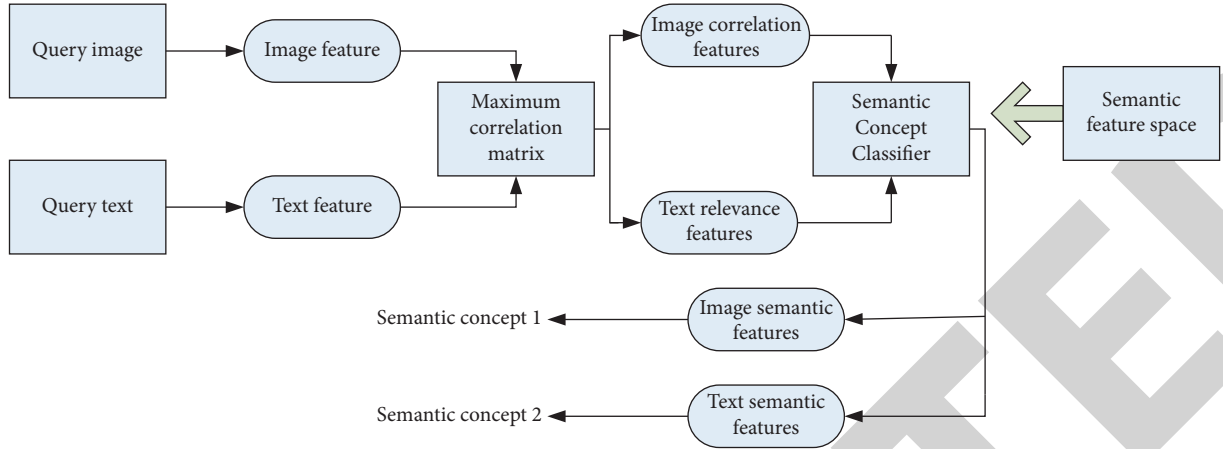


FIGURE 4: Cross-modal retrieval framework.

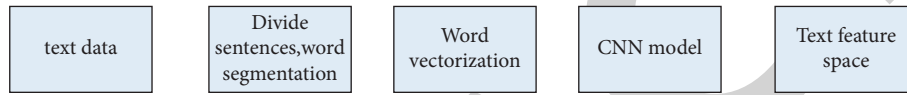


FIGURE 5: Text preprocessing process.

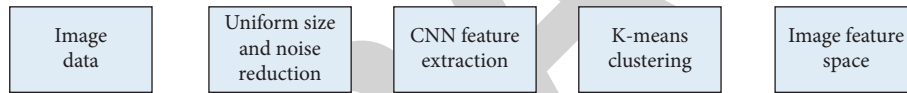


FIGURE 6: Image preprocessing process.

TABLE 1: Model feature extraction test data set.

Corpus	Computer	Agriculture	Physical education	Aerospace	History	Economic	Medicine	Number of texts
Chinese Wikipedia data	130	130	150	190	200	100	100	1000
Sogou Natural Language Data	200	200	200	200	200	200	200	1400
Harbin Institute of Technology Corpus Data	250	150	220	250	250	180	300	1600

According to the above analysis, it is obvious that the text feature extraction based on the convolutional neural network model performs well in terms of accuracy, and the accuracy of the extraction and clustering results is as high as about 90%. On the other hand, it can be seen that in the same corpus or different corpora, the category with the highest number of samples may not have the highest accuracy in the process of feature extraction and clustering. On the contrary, the category with a smaller number of samples may also be more accurate. Therefore, for convolutional neural networks, the number of samples in the training data set is not an important factor that influences the performance of its trait extraction. Another factor may also be caused by the common machine learning algorithm K-means clustering algorithm. This is the focus of this thesis in the next step of the work.

As shown in Table 2, it is not the more of iterations, the better the trait extraction of the model during the training process. If the model performance needs to be adjusted to the best state, the best number of iterations should be

continuously sought. Moreover, it is necessary to find different optimal iteration times for different corpora.

As shown in Figure 8, as the number of iterations during the training of the convolutional neural network model does not increase within a certain range, the accuracy of the model result test will also increase.

4.2. Relevant Performance Indicators on Cross-Modal Information Retrieval Tasks. As shown in Figure 9, during the comparative experiment, the model mentioned in this chapter performs well in cross-modal retrieval tasks compared to other cross-modal retrieval algorithm models, whether it is in image retrieval text or text retrieval image tasks. The results are ahead of other algorithm models.

From the above experimental results, it can be analyzed that the similarity between the study results caused by the cross-modal search task and the input corpus belonging to the same category is still relatively high.

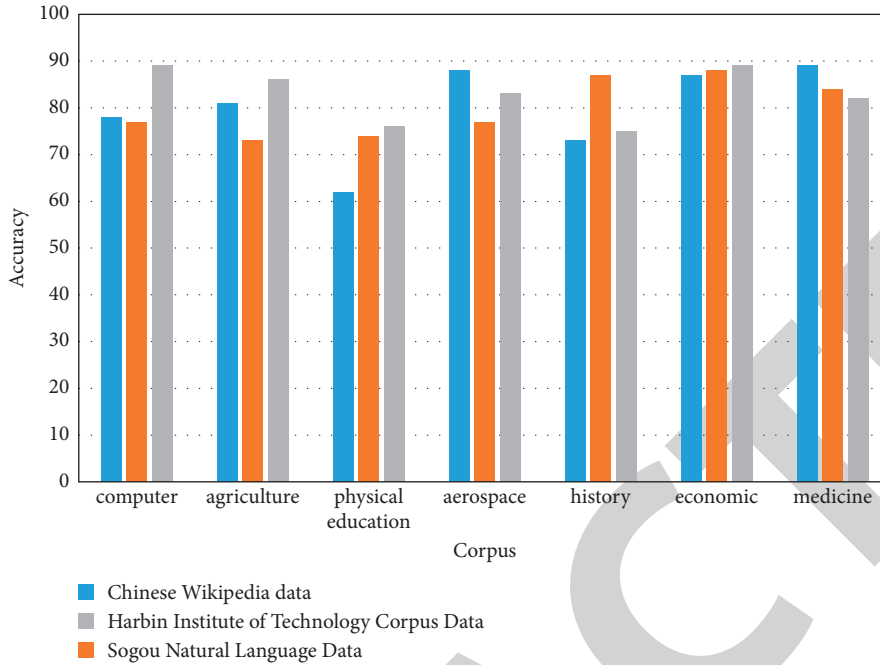


FIGURE 7: Convolutional neural network feature extraction accuracy rate in three data sets.

TABLE 2: Different accuracy of the model under different iteration times.

Number of iterations	50	100	150	200	250	300
Chinese Wikipedia data	42.33	57.86	64.21	66.86	66.75	66.80
Sogou Natural Language Data	44.22	56.31	61.43	68.96	68.94	68.22
Harbin Institute of Technology Corpus Data	41.16	52.63	62.21	65.54	66.75	66.18

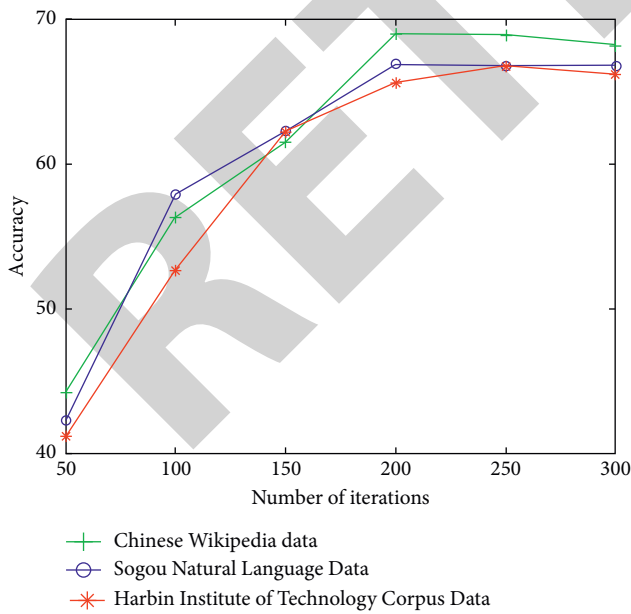


FIGURE 8: Comparison of different accuracy of the model under different iteration times.

4.3. Performance Analysis of Cross-Modal Information Retrieval Based on Metadata Ontology Calculation. We can find from Figure 10 that the proposed model has a higher accuracy rate in cross-modal retrieval tasks, no matter whether it is in image retrieval text or text retrieval image tasks. The above results are ahead of other algorithm models. This result shows that the model created in this paper can make images and texts with semantic consistency close to each other in the latent space of cross-modal retrieval.

In both text and image processing tasks, convolutional neural networks are used for highly abstract feature extraction, and the extracted specific vector space is used as the input of the CCA model for data training. Because of the cross-modal information retrieval, this article mainly focuses on semantics. For retrieval tasks, the LDA model is used to extract document and image topics, and the concept classifier proposed by Wang Shu is used for training on the concept classifier to form a semantic topic feature space, so as to achieve semantically related cross-modal information retrieval tasks.

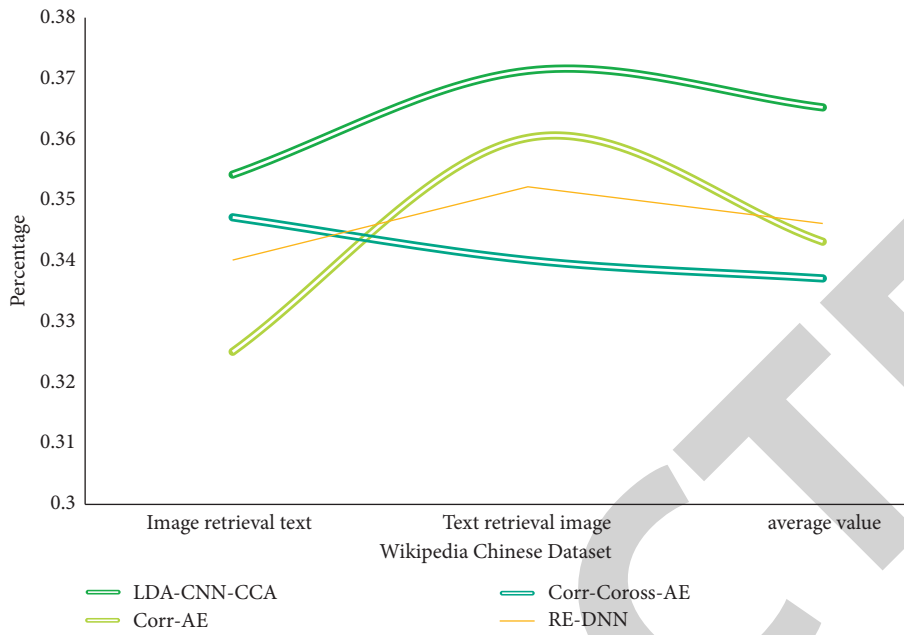


FIGURE 9: Cross-modal comparison experiment results.

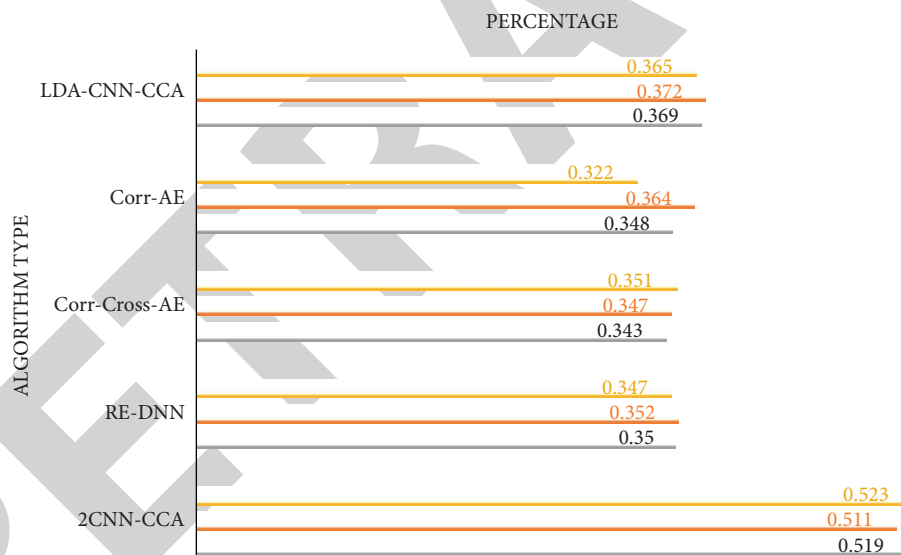


FIGURE 10: Analysis of cross-modal comparison experiment results.

5. Conclusion

This paper uses the network information retrieval method based on metadata ontology calculation and applies the convolutional neural network model to the Chinese text information retrieval task for how to improve the accuracy of Chinese text information retrieval. Before extracting the highly abstract features of text information, a series of preprocessing is performed on the data set. The data output through the word2vec model is an $N * M$ -dimensional vector matrix, so that the data received by the input layer of the convolutional neural network model the matrix is a word2vec vector matrix. Then use the CNN model to extract

highly abstract features from the Chinese text data. And through experimental demonstration, the results illustrate that it is nimble enough to apply a convolutional neural network to Chinese text information retrieval as a text feature extraction method, and the retrieval accuracy rate is high. The disadvantage of this article is that although the model does have great advantages in image processing, it still needs to improve the extraction of image semantic features in image semantic expression, and in the process of image semantic understanding, it is through text semantic feature mapping, to assist in understanding. Therefore, the next step can be to improve the image processing to improve the accuracy of network information retrieval.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare no potential conflicts of interest in this paper.

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