

Retraction

Retracted: An Analysis of the Historical Process of Cultural Confidence in Ideological and Political Education Based on Deep Learning

Mathematical Problems in Engineering

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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) Peer-review manipulation

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] X. Wang, "An Analysis of the Historical Process of Cultural Confidence in Ideological and Political Education Based on Deep Learning," *Mathematical Problems in Engineering*, vol. 2022, Article ID 8797533, 9 pages, 2022.

Research Article

An Analysis of the Historical Process of Cultural Confidence in Ideological and Political Education Based on Deep Learning

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Ideological and political education can improve people's ideological and moral character and psychological quality, improve social governance, and promote the harmonious development of society. However, the current data of ideological and political education have the trend of mass and diversification. In order to improve the effect of ideological and political education, this paper proposes an analysis method of the historical process of cultural self-confidence of ideological and political education based on in-depth learning. By preprocessing the ideological and political education data to obtain text keywords, the principal component analysis method is improved to reduce the dimension of the ideological and political education data, and the vector space model is used to complete the text balance processing of the reduced dimension data. The data sensitivity after dimensionality reduction is analyzed by data training, the historical text data mining model is constructed to extract data features, and the bidirectional recurrent neural network is used to complete data extraction. The semantic features of the extracted data are obtained by using the forward and reverse feature generation methods, and the historical process of the cultural confidence of ideological and political education is analyzed by using the two-way generation method. The experimental results show that the accuracy rate of the historical process analysis method of cultural self-confidence in ideological and political education based on deep learning is 95%, the recall rate is 94%, and the degree of collaborative performance is good.

1. Introduction

The so-called curriculum politics is to integrate the ideological and political education into the various links of subject course teaching and teaching reform, so as to achieve the goal of establishing morality and cultivating people and moistening things silently. Teachers of ideological and political theory course in colleges and universities should establish confidence in the value of ideological and political theory course with high cultural confidence. The spread and development of culture cannot be separated from the intrinsic self-confidence of culture as the driving force. Colleges and universities must shoulder the mission of integrating cultural self-consciousness and cultural self-confidence into the whole process of ideological and political education. At the same time, culture bears the blood of a nation's development, reflecting the historical changes of the past and present. It is not only the cornerstone of building national spirit, but also an important standard to measure a country's soft power and

comprehensive national strength. Analyzing the history of ideological and political education can help us to understand the present situation of ideological and political education and the development of cultural confidence. Deep learning is a new research direction in machine learning field. Deep learning is the inner rule and expression level of learning sample data. The information obtained in the process of learning is very helpful to the interpretation of data such as words, images, and sounds [1, 2]. Its ultimate goal is to enable machines, like humans, to analyze and learn, and recognize data such as words, images, and sounds. Deep learning is a complex machine learning algorithm that has achieved far more results in speech and image recognition than previous related technologies [3]. Deep learning has achieved a lot in search technology, data mining, machine learning, machine translation, natural language processing, multimedia learning, voice, recommendation and personalization technologies, and other related fields [4]. Deep learning makes machines imitate human activities such as audio-visual and thinking,

and solves many complex pattern recognition problems, which makes great progress in artificial intelligence. There is also research on the application of deep learning in teaching. Xu et al. [5] proposed a target detection algorithm based on deep learning, which can extract depth information to identify low-level defect information, fuse defect features with PAN network, and complete single size feature image output. Mallikarjuna et al. [6] identify aircraft gearbox vibration data in both time and frequency domains by constructing long- and short-term memory models and bidirectional long- and short-term memory models to ensure stable operation of aircraft engines. Akgul et al. [7] designed a real-time traffic sign recognition system that supports digital imaging, extracts traffic signs from public data sets through deep learning, develops RT-TSR software using convolution neural networks, completes coding under the TensorFlow and OpenCV frameworks using the Python programming language, and enhances traffic sign recognition by using parallel CNN training. Li et al. [8] proposed an optimal grasping attitude detection algorithm based on dual-network architecture, improved the target detection model of deep learning, improved detection speed and object recognition performance, designed a multi-target grasping detection network using convolution neural network, and established an IOU region evaluation algorithm to screen the optimal grasping region of the target to achieve attitude detection. Deng et al. [9] proposed a new method based on Lucas-Kanade optical flow, which improves the traditional SLAM framework and improves the perception ability of intelligent devices such as robots to indoor environment. Hu and Feng [10] proposed a lightweight symmetrical U-encoder-decoder-based image semantic segmentation network named UNET, which is constructed by depth-separable convolution to improve image semantic segmentation.

Therefore, this article applies the deep study technology to the ideological and political education culture self-confidence historical process analysis. The data of ideological and political education were preprocessed with word segmentation assistant to eliminate sensitive words. Through the text emotion calculation method to extract ideological and political education cultural data features, feature keywords for dimensionality reduction processing complete the text balance processing. Based on deep learning theory, this paper analyzes the sensitivity of historical text data, constructs feature extraction of historical text data, and uses bidirectional recurrent neural network and attention model to extract historical text data. Through the forward and reverse feature generation methods, a two-way feature generation algorithm is designed to effectively analyze the historical process of ideological and political education and cultural confidence.

2. Balance of Historical Data Text of Confidence in Ideological and Political Education and Culture

2.1. Data Preprocessing. The socialist core value system is the essence of socialist advanced culture, and ideological and political education is an important carrier to build the

socialist core value system. The socialist core value system is a complete theoretical system. Its basic contents include the guiding ideology of Marxism, the common ideal of socialism with Chinese characteristics, the national spirit with patriotism as the core, the spirit of the times with reform and opening up as the core, and the socialist concept of honor and disgrace with “Eight Honors and Eight Disgraces” as the main content. Because the content of the socialist core value system is rich, rational, and systematic, it needs a good carrier to integrate the socialist core values into the national education in order to integrate them into the minds of the public. The ideological and political education is such a carrier to carry out the education of the socialist core value system. Through ideological and political education, the educated can consciously use Marxist positions, viewpoints, and methods to observe, analyze, and deal with problems, strengthen the young educatees’ belief in socialism with Chinese characteristics, and consciously participate in the great practice of China’s socialist modernization.

In order to analyze the history of self-confidence of ideological and political education culture accurately, it is necessary to preprocess the historical data of self-confidence of ideological and political education culture to reduce the interference of multi-noise data, so as to improve the accuracy of analyzing the history of self-confidence of ideological and political education culture.

Under normal circumstances, there is no division between the historical data of ideological and political education culture confidence, only by artificial reading to distinguish the pause. Therefore, this model adopts a word segmentation assistant to deal with the historical data of ideological and political education culture confidence [11]. In the historical data of self-confidence of ideological and political education culture, there are usually names of people, places, and special organizations in the texts. To this end, before word segmentation, we must pay attention to identify idiomatic nouns and names involving confidential documents, after the removal of its name can be word segmentation.

In order to make participate easier, auxiliary words such as “de,” “di,” and “de” which are not conducive to judging text sensitivity can be removed. In addition, NbZ method is used to remove auxiliary words. List all the words with similar contents, judge the similarity between the historical data and the sensitive words, record the minimum similarity, and compare several minimum similarity ranges. The process is shown in Figure 1.

In Figure 1, because the similarity between the self-confidence historical data of ideological and political education and culture is less than the similarity between the self-confidence historical data of ideological and political education and culture and the sensitive words is less than the final range, the sensitive factors of the self-confidence historical data of ideological and political education and culture are removed by default, and the preprocessing of the self-confidence historical data of ideological and political education and culture is completed.

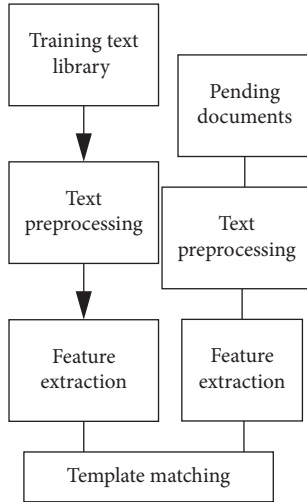


FIGURE 1: Pretreatment process.

2.2. Keyword Extraction. All content of the historical data text of ideological and political education culture is expressed by words. In a text, each word plays a different role in expressing the text theme. Therefore, extracting a keyword from the historical data text of ideological and political education culture self-confidence plays a more important role in expressing the theme of the text. This article uses the affective computing algorithm to extract text keywords, the expression of which is as follows [12]:

$$p_c = \exp\left(\frac{\vec{r}_c}{\sum_c^{z=1} \exp(\hat{r}_t)}\right). \quad (1)$$

In the formula, \vec{r} represents the affective content of each word after pretreatment, and \hat{r} is the affective parameter.

2.3. Dimension Reduction of Keywords. A typical feature of historical text data is that the dimension is high, and the higher the dimension is, the more difficult the classification will be in the later period. At present, there are five methods to reduce the dimension of historical text data: canonical correlation analysis [13], partial least squares [14], hyper-spectral learning [15], linear discriminant analysis [16], and shared subspace learning [17]. However, in the process of application, these methods will destroy the integrity of text to some extent. To solve this problem, this section adopts a new method to reduce the dimension of historical text data, i.e., improved principal component analysis method.

2.3.1. Reduction of Dimensions by Principal Component Analysis. Assuming that the text matrix to be reduced is Y , it is a $d \times m$ matrix, expressed as follows:

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1m} \\ y_{21} & y_{22} & \cdots & y_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ y_{d1} & y_{d2} & \cdots & y_{dm} \end{bmatrix}. \quad (2)$$

Step 1: Centralize the reduced dimension text matrix Y , and get the centralization matrix Y' .

Step 2: Calculate the eigenvalues and eigenvectors of Y' .

Step 3: Calculate cumulative contribution rates.

Step 4: According to the cumulative contribution rate in descending order of the feature value.

Step 5: Select the principal component corresponding to the first m characteristic value.

Step 6: Calculate the scores of m principal components to get the text set R with the new attribute.

2.3.2. Dimension Reduction of Text Based on Improved Principal Component Analysis. According to the number of projection vectors t in the projection matrix, the improved principal component analysis method projects the reduced dimension text vectors to t dimension. In a word, the feature set selected by principal component analysis is further extracted and compressed twice under the premise of minimizing information loss. The basic principles are as follows:

Based on the above analysis, the amount of information carried by the eigenvalue $\lambda_1, \lambda_2, \dots, \lambda_m$ decreases in turn, so y_{ij} is set as the j feature of the i type text, and all positive eigenvalues are transformed as follows:

$$P_i = \frac{\lambda_i}{\sum_{i=1}^k \lambda_i}, \quad i = 1, 2, \dots, k; 0 < P_i < 1. \quad (3)$$

Define the information function, represented as:

$$q(\lambda_i) = a_{ij}(1 + P_i), \quad i = 1, 2, \dots, k. \quad (4)$$

In the expression, a is the distribution probability of the j feature in the feature space of the i class.

$q(\lambda_i)$ is an increasing function, and the larger the value, the greater the amount of information λ_i contains, if $q(\lambda_1) \geq q(\lambda_2) \geq \dots \geq q(\lambda_k)$ is present and makes

$$\frac{\sum_{i=1}^t q(\lambda_i)}{\sum_{i=1}^k q(\lambda_i)} > 1 - b. \quad (5)$$

In the expression, b is a descriptive parameter of information, and $b \in (0, 50)$ is often used. Based on the projection matrix $C = (c_1, c_2, \dots, c_t)$, the feature set is projected and the dimensionality is reduced.

$$Z = C^t R. \quad (6)$$

2.4. Text Balancing. Because the whole operation process is accomplished by computer, and the language computer such as text is incomprehensible, so it is necessary to convert the text data into structured data. Among the text balancing methods, vector space model is the most commonly used, and the specific process is as follows:

The result of the text dimensionality reduction processing Z is represented as the following eigenvector:

$$Z = \{(t_1, w_1), (t_2, w_2), \dots, (t_n, w_n)\}. \quad (7)$$

In the expression, t_i is the i of the text, w_i is the weight of t_i , and n is the imbalance of the text.

Simplify Z to

$$Z = W = \{w_1, w_2, \dots, w_n\}. \quad (8)$$

The degree of balance of two similar texts Z_1 and Z_2 is $bla(Z_1, Z_2)$; that is, the degree of balance of two feature vectors is calculated according to the following formula:

$$bla(Z_1, Z_2) = (W_1, W_2) = \sum_{i=1}^n W_{1i} w_{2i}. \quad (9)$$

The larger the $bla(Z_1, Z_2)$ is, the higher the degree of eigenvector balance is. According to the balance degree of the two feature vectors, the root of a text word can be extracted quickly. Based on the artificially defined rules, the root extraction method using the index can not only effectively extract the root of a word, but also does not need to use the artificially defined rules, so as to obtain the text balance processing results.

3. Feature Extraction of Historical Text Data Based on Deep Learning

3.1. Analysis of Historical Text Data Sensitivity. Historical text data sensitivity is to establish a cognitive connection between numbers and business, and identify the business meaning, problems, and reasons behind historical text data through numbers and business in a positive or negative way. Based on the deep learning theory, in order to improve its efficiency and accuracy, the model should be trained before being put into use. In this study, Ydht method is used to train the model, and the formula of output layer is as follows:

$$\begin{cases} p(h_i x_w, \theta_i) = \sigma(x_w^T \theta_{i-1}), h_i = 1, \\ p(h_i | x_w, \theta_i) = 1 - \sigma(x_w^T \theta_{i-1}), h_i = 0. \end{cases} \quad (10)$$

In the expression, p stands for historical data sensitivity, h_i for sensitivity coefficient, x_w for sensitivity, and θ_i for sensitivity level. The final results show that 1 and 0 represent the normal operation of the model, and accurate results can be obtained.

The specific model workflow is shown in Figure 2.

3.2. Construction of Feature Extraction of Historical Text Data. Firstly, a model of historical text data mining is constructed, in which the input layer corresponds to a large amount of historical text data and the output layer corresponds to the target text. The output function of historical text data is

$$b_r = f\left(\sum_{i=1}^m \alpha_i \times W_{ir} + T_r\right), \quad r = 1, 2, 3, \dots, u. \quad (11)$$

The input function for historical text data is

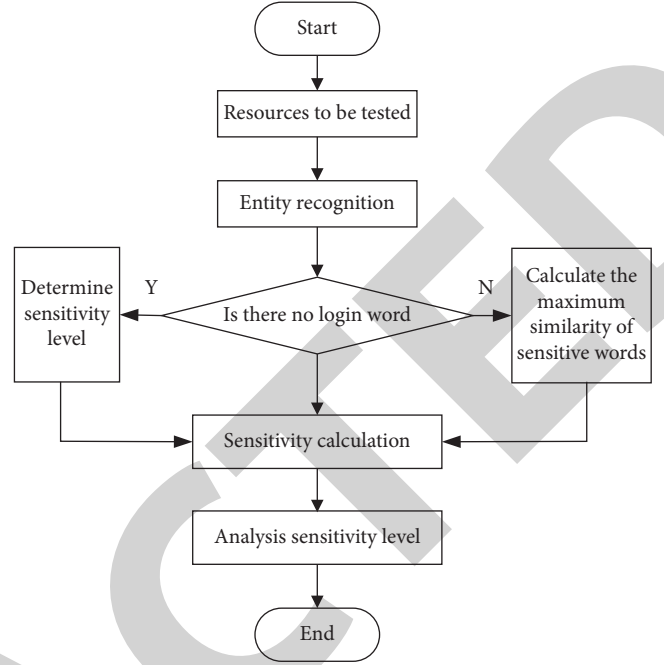


FIGURE 2: Sensitivity analysis process.

$$c_j = f\left(\sum_{r=1}^{\mu} b_r \times V_{rj} + \theta_j\right), \quad j = 1, 2, 3, \dots, n. \quad (12)$$

In the formula, α_i is the input of historical text data in semantic network, W_{ir} is the weight of connection between layers in semantic network model, V_{rj} is the partial derivative function of output and input layer, and the threshold of output and input layer is T_r and θ_j , respectively.

The steps of constructing the mining model for historical text data are as follows.

Step 1: W_{ir} , T_r , V_{rj} , and θ_j take arbitrary values within the network semantic interval (0, 1).

Step 2: Set the input value and output value of the historical text data mining model as $c_j^{(k)}$ and c_j , respectively, and get the error value $d_j = c_j(1 - c_j)(c_j^{(k)} - c_j)$ between them.

Step 3: Calculate the historical text data allocation variance $e_r = b_r(1 - b_r) \cdot (\sum_{j=1}^n V_{rj} \cdot d_j)$ hidden in the model.

Step 4: Weight the thresholds in the historical text data model:

$$\Delta V_{vj}(t+1) = \lambda \left(\sum_{j=1}^n d_j \times V_{rj} \right) + \eta, \quad (13)$$

$$\Delta W_{ij}(t+1) = \sum_{k=1}^N (\beta a_k e_r) + \delta \Delta W_{ir}(t).$$

In the expression, λ and β represent the learning steps of the semantic network model and η and δ represent the momentum factors.

Step 5: Normalize the thresholds in each layer of the model: $\Delta T_r(t+1) = \beta \sum_{r=1}^N e_r + \delta$.

Step 6: Keep repeating the above steps until the mining error reaches the target value, to achieve the historical text data mining model.

3.3. Bidirectional Recurrent Neural Network Coding in Deep Learning. The bidirectional recurrent neural network (BiRNN for short) mainly trains each intermediate semantic vector training sequence to use forward and backward recurrent neural networks. The two network algorithms are the same, but the directions are different [18]. In the forward recurrent neural network, the potential state of semantic vectors in each unstructured table document is stored in the data of the current sentence and the preceding sentence. BiRNN can be used to encode the text data for the prephase and the postphase. Among them, the active unit is used to deal with the problem of incomplete gradient in the long sequence training by using the network method of long and short memory. Set the unstructured table document to $E = (e_1, e_2, \dots, e_m)$, and the weight of the hidden layer t_h in the h time period is

$$\begin{cases} j_h \\ g_h \\ U_h \\ \tilde{d}_h = \begin{bmatrix} \beta \\ \beta \\ \beta \\ \tan t \end{bmatrix} V \times [t_{h-1}, x_j], \\ E_h = g_h \oplus E_{h-1} + j_h \oplus \tilde{d}_h, t_h = U_h \oplus \tan t(E_h). \end{cases} \quad (14)$$

In the formula, the input layer is set to j_h ; the forget door layer is set to g_h ; the output layer is set to U_h ; the refresh candidate vector is set to \tilde{d}_h ; the weight matrix and the excitation function are set to V and β ; and the point-by-point calculation is set to \oplus .

3.4. Attention Model. The encoder-decoder framework is a common form of analysis for text-processing problems and is widely used [19]. In this paper, it is used to extract document data from unstructured historical text data tables. One unstructured table document in the classified table document X is Y , which generates intermediate semantic vectors in the encoder-decoder framework. Assuming that the unstructured form document is $Y = \{y_1, y_2, \dots, y_n\}$, the input Y is encoded, and the input Y is transformed into D by nonlinear transformation. For decoder, the intermediate semantic vector output x_j is established according to the obtained D and historical semantic vector output x_1, x_2, \dots, x_{j-1} . Provisions:

$$x_j = f(D, x_1, x_2, \dots, x_{j-1}). \quad (15)$$

Because of differences in unstructured form document data, the intermediate semantic vector required for

decrypting the attention model is imported in the encoder-decoder framework.

3.5. Historical Text Data Extraction. Automatic data extraction model based on deep learning can decode RNN, make attention model AM compatible with it, and implement data extraction to remove the correlation and redundancy between data [20]. Assume that the state of the BiRNN hidden layer in the encoder is (t_1, t_2, \dots, t_m) and $(t'_1, t'_2, \dots, t'_m)$, and the state of the RNN hidden layer in the decoder in the h time period is $(\bar{t}_1, \bar{t}_2, \dots, \bar{t}_m)$. The data \bar{t}_m extraction method is as follows:

$$Q_{x_j(h)} = P(\bar{t}_h, t_h, t'_h). \quad (16)$$

In the formula, the P describes the processing value entered after the state of the two RNN hidden layers before and after the BiRNN in the encoder is fused with the state of the RNN hidden layer in the decoder; q_{h-1} describes the probability that the previous data in the unstructured table document are extracted into the desired data; LSTM describes the long-term and short-term memory network method.

4. Design of Feature Generation Method of Ideological and Political Education and Cultural Confidence

4.1. Forward Feature Generation Method. The single-layer neural network structure of the algorithm operation model is shown in Figure 3.

In the selection of machine learning algorithms [21], cloud computing such as Sina and Tencent has both high storage and fast computing capabilities, but Sina has a higher starting point and is China's first and largest provider of PaaS (platform-as-service, platform services), which fully covers the needs of IaaS, PaaS, and SaaS layers. It is simple, efficient, reliable, and multi-functional and has good learning effects. The generation process of forward text semantic features is shown in Figure 4.

Single-layer neural network outputs single-point text semantic features, referring to each text semantic corresponding to a separate feature [22, 23]. As shown in Figure 4, each neural network layer has a text encoder, which is trained from bottom to top by the supervise-free means of deep learning. The visibility layer of Sina cloud algorithm is the text information module of deep learning algorithm operation model. Sina cloud algorithm is used to learn text semantics, simulate netizen thinking, and redefine text semantics. With the above development, the specific gravity of neurons in single-layer neural networks has changed, and the single-layer neural networks are developed according to the gradient. The whole text semantics of standard neural network is trained to generate low-level text forward semantic features.

4.2. Reverse Feature Generation Method. The generation process of semantic features of reverse text is shown in Figure 5.

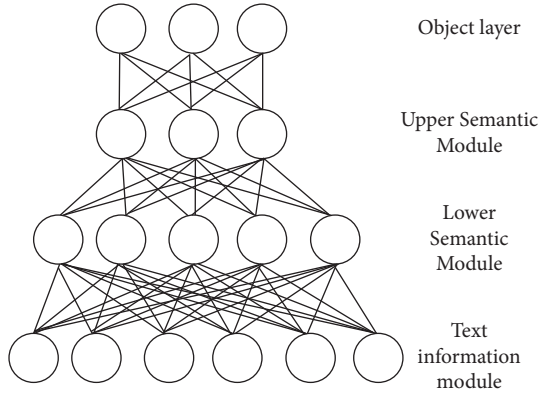


FIGURE 3: Single-layer neural network for algorithm operation model.

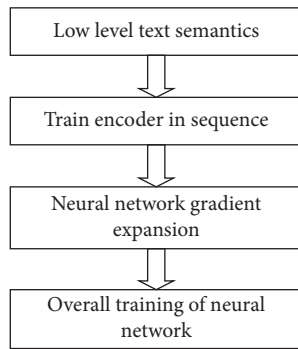


FIGURE 4: Forward text semantic feature generation process.

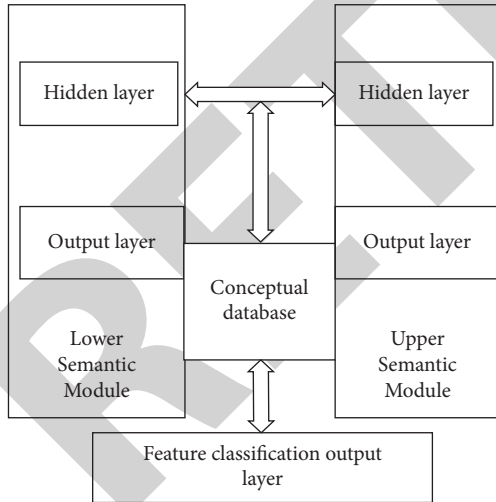


FIGURE 5: Reverse text semantic feature generation process.

Reverse text semantic features are called “reverse features” because Sina cloud algorithm cannot fully realize that some text semantic information has higher-order statistical features. As shown in Figure 5, the deep learning algorithm builds the hidden layer and the output layer in the upper and lower semantic modules, respectively, and uses convolution operation in the lower semantic module to analyze the deep reverse of the semantic features of the positive text. The

learning of single neural network is bottom-up, and the deep learning of concept database is top-down. Input data from object layer can supplement the mining loopholes of text information. After this process, we begin to extract high-level text semantic features, and the whole process is basically the same as the process of extracting semantic features of positive text.

The functions used in the deep learning process of the hidden layers of semantic modules derived from the upper and lower layers are

$$\begin{aligned} I(h_k^{\text{low}}) &= 2VW_k^{\text{low}} + b_k^{\text{low}}, \\ I(h_k^{\text{high}}) &= \sum_{k=1}^n W_k^{\text{high}} p + b_k^{\text{high}}. \end{aligned} \quad (17)$$

Among them, low and high represent the lower semantic module and the upper semantic module, respectively, h_k refers to the k neuron in the hidden layer, W_k is the convolution kernel of h_k , b_k is the text semantic characteristic error of h_k , V is the volume of standard neural network, n is the number of hidden neurons in the upper semantic module, and p is the posterior probability.

The forward semantic derivation module has two posterior probabilities, namely, the hidden layer p_1 and the output layer p_2 , which are expressed as follows:

$$\begin{aligned} p_1 &= \frac{\exp[I(h_k^{\text{low}})]}{1 + \sum \exp[I(h_k^{\text{low}})]}, \\ p_2 &= \frac{1}{1 + \sum \exp[I(h_k^{\text{low}})]}, \\ p &= \sqrt{p_1^2 + p_2^2}. \end{aligned} \quad (18)$$

4.3. Design of Bidirectional Generation Algorithm for Characteristics of Historical Process. To a great extent, the learning effect of the operational model of the deep learning algorithm is related to the usability of the semantic features of the generated text [24]. According to the previous literature, the derivation problems mainly include the selection of the derivation algorithm, the control of the learning efficiency, the processing of the similar characteristics of information, the management of the proportion of neurons, and the improvement of the model operation rate [25, 26]. Some derivation issues have been addressed above, such as assigning text encoders to all modules for distributed text semantic extraction, and separate upper and lower semantic modules for implicit and output layers to reduce confusion about the similarity of text information. Following is the design of the model calculation rate derivation method.

In the standard neural network, good proportion of neurons can give full play to the learning effect of deep learning, but too much emphasis on learning effect will constrain the model speed. The number of neurons in the hidden layer of the semantic module of forward derivation is much less than that of the hidden layer of the semantic

TABLE 1: Setting simulation parameters of historical data of ideological and political education and culture confidence.

Serial number	Data text	Number of text occurrences/quantity	Number of words/quantity
1	Reform and opening up	241	265
2	Socialism	142	253
3	Role models	236	423
4	Ideological construction	104	342
5	Red tourism	278	118
6	Ecological civilization	93	323
7	Moral cultivation	155	354
8	Patriotism	161	291
9	Spiritual culture	127	124
10	Legal basis	173	291

module of reverse derivation. Therefore, using the average convolution core \tilde{W}_k of neurons instead of W_k will not have a great impact on the learning effect. Therefore, the deep learning process of the semantic module of forward and reverse derivation can be designed as follows:

$$I(h_k^{\text{high}}) = \sum_{k=1}^n \tilde{W}_k^{\text{high}} p + b_k^{\text{high}}. \quad (19)$$

5. Experiment and Comparative Analysis

In order to verify the effectiveness of the proposed algorithm, 2000 online cultural resources were randomly collected as experimental samples, including time and historical process. Simulation tests are carried out in MATLAB to verify the performance of this method, such as analysis accuracy. Lab Platform: The CPU model is Intel Xeon (R) E5-2650, the GPU model is GTX 1080 Ti, running 64 GB of memory, the OS version is Ubuntu 7.10, and the deep learning framework is PyTorch. Randomly select popular ideological and political education and cultural vocabulary from the experimental samples, set simulation parameters (as shown in Table 1), and carry out an analysis experiment on the historical process of online ideological and political education and cultural confidence.

It can be seen from Table 1 that the historical data of ideological and political education and cultural confidence have 10 aspects of data information, with the largest number since the reform and opening up.

5.1. Accuracy of Historical Process Data Analysis. Through the iteration, using the accuracy of P to study the historical process analysis results, the larger the P value, the more accurate the data analysis, the higher the value of the method. The calculation formula is as follows:

$$P = \frac{T}{T + M}. \quad (20)$$

In the formula, T and M represent the number of historical texts of the same type and different types divided into the same content, respectively. The accuracy rate of historical process data analysis is calculated by formula (20), which is taken as the test index. The test results of this method are shown in Figure 6.

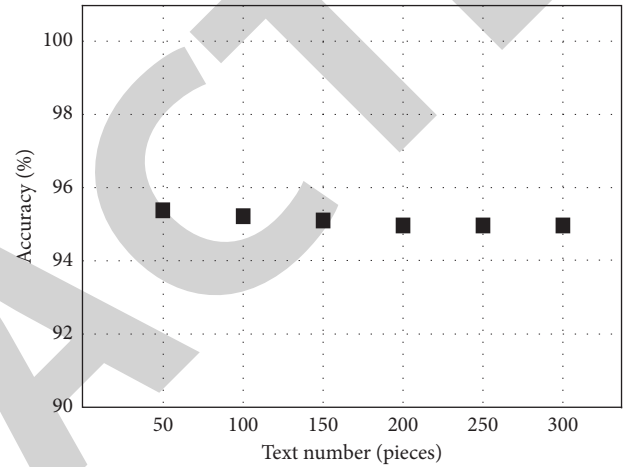


FIGURE 6: Historical process data analysis accuracy results.

According to Figure 6, with the increase of the number of texts, the accuracy of the classification is stable, and the accuracy is 95%. This is because the method extracts the features of ideological, political, educational, and cultural data by text emotion calculation, and improves the balance of feature vectors by dimension reduction.

5.2. Historical Process Data Analysis Recall Rate. The recall rate is based on the original sample, which means the probability of the positive sample in the positive sample. The recall rate R is the proportion of the positive sample in the total sample. Its calculation is shown in formula

$$R = \frac{T}{T + N}. \quad (21)$$

In this formula, N represents the sample that is actually positive. Formula (21) is used to calculate the recall rate of historical process data analysis, and 300 data of different types are randomly selected from the simulation parameters of historical data of ideological and political education and cultural confidence as test data. The results are shown in Figure 7.

According to Figure 7, the proposed method extracts the features of historical text data based on the bidirectional recurrent neural network coding and attention model.

To sum up, with the increase of the number of texts, the accuracy of information data classification of this method is

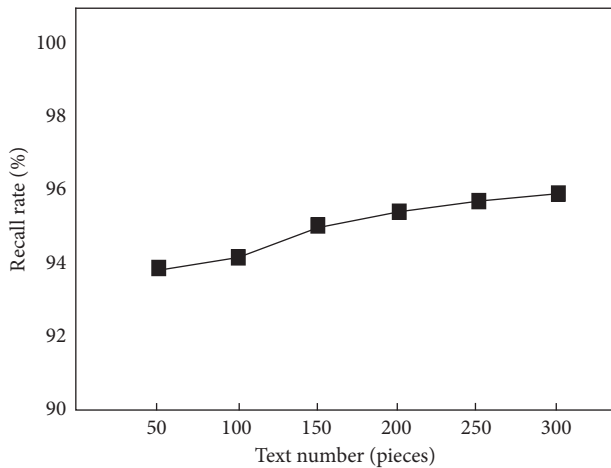


FIGURE 7: Historical process data analysis recall rate results.

relatively stable and tends to be stable when analyzing the number of texts of 200 historical processes, with an accuracy rate of 95%. According to the bidirectional cyclic neural network coding and attention model in deep learning, the feature extraction of historical text data is completed to improve the recall rate of historical process data analysis. The recall rate is high and has good performance.

6. Conclusion

To sum up, this paper puts forward a deep learning-based ideological and political education and cultural self-confidence in the historical process of analysis. Through deep learning and analyzing the sensitivity of historical text data, we can get the characteristics of balanced historical text data of ideological and political education culture. The conclusions are as follows:

- (1) The method proposed in this paper has high accuracy in analyzing historical process data and stable accuracy in information data classification. It tends to be stable when the number of historical process texts is analyzed to 200, and the accuracy is 95%.
- (2) According to the bidirectional recurrent neural network coding and attention model in deep learning, feature extraction of historical text data is completed to improve the recall rate of historical process data analysis with good performance.
- (3) It can effectively improve the precision of ideological and political education text mining, with strong convergence.

Data Availability

The raw data supporting the conclusions of this study can be obtained from the author upon request, without undue reservation.

Conflicts of Interest

The author declared that there are no conflicts of interest regarding this work.

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