Proceedings of the 2nd International Conference on Software Engineering and Machine Learning
DOI: 10.54254/2755-2721/74/20240468

Research and application of Chinese semantic understanding teaching system based on knowledge graph and deep learning

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Abstract. Text data in network environments has been increasingly emphasized. However, text data in network environments exhibit atypical characteristics, posing significant challenges to users. Through research on text classification, information extraction, semantic computation, and other aspects, natural language processing can rapidly and accurately extract valuable information from massive texts, providing an effective approach for addressing this problem. Nevertheless, existing machine learning methods suffer from issues such as reliance on complex feature construction, insufficient flexibility of traditional models, inability to model various text sets, and error-prone pipeline models. This paper discusses a Chinese semantic understanding teaching system based on knowledge graph and deep learning. Deep learning represents a novel approach to natural language processing, overcoming shortcomings of traditional methods, including allowing network models to flexibly model text under massive parameter conditions, providing new research ideas for machine translation and effectively avoiding the propagation of generalization errors. Experimental results demonstrate that, in different operation instances, the system's CPU (Central Processing Unit), memory operation, and GPU (Graphics Processing Unit) operate within the ranges of 2~4GHz, 15~19GB, and 8~10GB, respectively. For applications requiring extensive computation such as scientific computing, data analysis, and deep learning, CPUs with higher frequencies, generally exceeding 3.5GHz or even higher, are typically required. It can be observed that the system's resource utilization is relatively low, and the system exhibits good operational performance.

Keywords: Chinese semantic understanding teaching system, knowledge graph, deep learning, information extraction.

1. Introduction

In recent years, artificial intelligence technologies based on cognitive psychology and computers have developed rapidly. Many scholars have conducted extensive research and experiments on using

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DOI: 10.54254/2755-2721/74/20240468

intelligent educational systems to cultivate students' abilities. In fact, it has been found that intelligent educational systems have a significant impact on cultivating individual intelligence and have achieved good results. Communicating with intelligent systems using natural language is the goal of many researchers. Currently, there are two ways to communicate with natural language systems in existing intelligent educational systems: one is to pre-store the answers to questions in a knowledge base, and learners' speech or text inputs are analyzed and classified by the system to achieve intelligent matching of questions and answers; the other is that the answers to questions are not stored in the system, and the system first understands the questions input by learners, which contain a large amount of contextual information. This paper presents a detailed introduction to deep learning and knowledge graphs, and then discusses how to construct a Chinese semantic understanding teaching system using these two technologies, and finally verifies the feasibility of the system through experiments.

In Chapter 3, this paper introduces knowledge graphs, deep learning, and Chinese semantic understanding teaching systems based on knowledge graphs and deep learning. In Chapter 4, it presents the experimental results of the Chinese semantic understanding teaching system based on deep learning and knowledge graphs, and finally concludes the entire paper.

2. Related Works

For Chinese semantic understanding systems, experts have conducted specialized research. Wang Q proposed a method for expanding sentiment lexicons based on the K-means++ algorithm and word distance and pointwise mutual information. From the experimental results, the expanded Chinese movie review sentiment lexicon can improve the accuracy and precision of sentiment analysis [1]. Shi W studied an algorithm for extracting RGB-D (Red Green Blue-Depth) scanning data based on semantic maps. Using a dual-stream network based on distinguishable mask loss, effective extraction and fusion of RGB and depth information achieve robust segmentation of image semantics [2]. To extract semantic structures from document images, Xu C proposed an end-to-end dilated convolutional network architecture and utilized dilated convolution and residual networks to represent image features and predict pixel labels. Experimental results show that semantic data distribution imbalance and network depth are important factors affecting document semantic segmentation performance [3]. Huang D studied an adaptive semantic encoding algorithm based on reinforcement learning. Based on the convolutional semantic encoder semantic extraction method, semantic extraction of image data is achieved. Experimental results demonstrate that the algorithm has strong robustness to noise and can reconstruct images with good visual semantic consistency at lower bit rates [4]. Zhou W proposed a multi-level, multi-mode fusion method that constructs a high-level semantic model to effectively fuse multi-level coarse features. Finally, through extensive testing on two standard RGB-T (red green blue-thermal) databases, it is proven that the performance of the proposed algorithm is superior to existing algorithms [5]. Some systems may lack accurate inference and logical reasoning capabilities for semantics, leading to incomplete and inaccurate understanding. Additionally, due to the requirement of large databases, systems may experience prolonged loading times.

3. Methods

3.1. Research Status of Knowledge Graphs

A knowledge graph is a structured and semantic representation of knowledge, which organizes knowledge elements such as entities, relationships, attributes, etc., into a graph structure to describe and express knowledge and information in the real world [6–7]. Knowledge mapping is an important research direction in many areas such as natural language processing, intelligent question answering, information retrieval, recommendation systems, and intelligent dialogue. Knowledge mapping is a technique that expresses entities, concepts, and their relationships in the real world in the form of a graph. This graph structure consists of nodes representing entities or concepts and edges representing their relationships [8]. Through this approach, knowledge graphs can organize and represent large amounts of information in a structured and semantic way, making it easier for people to understand and use this

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information. The purpose of knowledge graphs is to organize human knowledge and information into a unified, standardized, and shareable knowledge base for computer understanding and processing. Knowledge graphs are one of the important research directions in the fields of artificial intelligence and the semantic web [9–10].

3.2. Deep Learning

The main model of deep learning is neural networks. The human brain can abstract information from direct inputs such as simple sounds, images, characters, etc., when processing information. Neural network models mimic the network structure of the human brain to extract information layer by layer [11–12]. The structure of the neural network model is similar to biological neurons, divided into neurons and connections between neurons. The structural diagram is shown in Figure 1, where the input values undergo a process of multiplication with weights and then summation, followed by passing through an activation function to obtain the output h, as shown in Figure 1 [13].

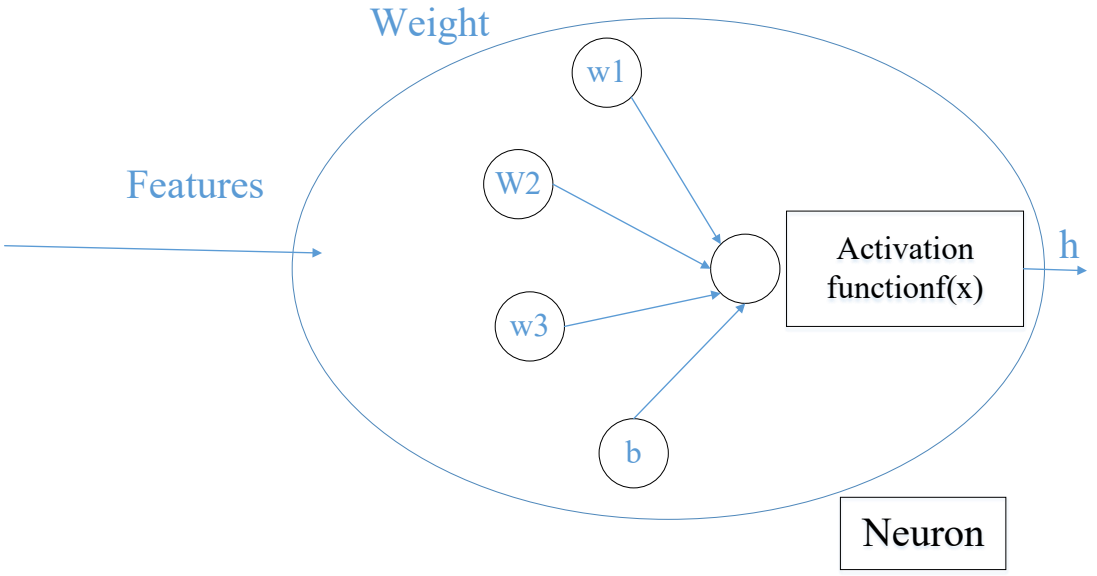

Figure 1. Structure of Neurons

Feedforward neural networks are the foundation of deep learning methods and are structured with input layers, hidden layers, and output layers. The information propagation in the model is as follows: the output h of the previous layer network is passed to the next layer network, and the result of the last hidden layer is the output of the entire network. In this network model, all information cannot be propagated backward, and the calculation results cannot be fed back to the previous layer, which can be considered as a directed acyclic structure [14–15].

Among them, convolutional networks can effectively extract more abstract spatial features by downsampling or reducing the convolution stride in the spatial domain, but this invariance will adversely affect the dense prediction of more detailed spatial information [16]. To address this issue, DeepLabv3 is an image compression algorithm based on dilated convolution. This algorithm can exclude the first two levels of downsampling on ImageNet and extract dense information by extending the corresponding convolution kernel. Another issue is the multiscale nature of targets. There are usually four patterns for solving this problem. The first method is to use an image pyramid to extract images of different dimensions, such as a similar multiscale training method in Yolov3 [17–18]. The second is an encoder-decoder architecture, which starts with encoding from multiple scales and then parses the image during the decoding process. The third method is to concatenate additional modules onto the original model to obtain more information. The fourth dimension is spatial cone sampling, which obtains multiscale information of the target by filtering or sampling the feature map. In the DeepLabv3 architecture, using

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dilated convolution technology introduces a larger receptive field in all cascaded modules and spatial cone sampling, while also integrating multiscale information. In this model, multiple scales of dilated convolutions and BN (Batch Normalization) layers are included, which are crucial for model learning [19–20].

3.3. Chinese Semantic Understanding Teaching System based on Knowledge Graph and Deep Learning

Natural language processing (NLP) technology is a special algorithmic structure and processing logic that can run on computers to process human language information. With the development of technology, it is gradually being applied to other fields and combined with other forms. Keyword-based text generation is one such application. Using recurrent neural networks to process time-series data, a sentence generation system based on recurrent neural networks is established. Its steps can be divided into the following:

(1) Building a Corpus

Collect text materials similar to literature, history, biographies, etc., to establish a large corpus with specific characteristics. Then, select the processed corpus to obtain the required knowledge.

(2) Feature Representation

Its structure is simple and can reduce the complexity of vector calculations, so commonly used text representation methods adopt the bag-of-words model. However, this model also has its flaws. For example, in the case of a large number of samples, the feature dimension of the text will be excessively high, leading to dimension explosion. Additionally, vector matrices are sparse and may lead to overfitting. Currently, Word2vec1461 is the most widely used vocabulary vector training method in NLP. Based on this, training of word vectors is conducted using the Skip-Gram model on corpora obtained from the internet.

(3) Data Input

In relation extraction, labeling the relationships between objects directly affects the accuracy of model extraction. In relation extraction, there are two common labeling methods: one is to use tools like SVM (support vector machines) or BOW (bag of words) to predict confidence scores for unlabeled samples and prioritize manually labeling highly confident predictions. This method requires sufficient knowledge of the labeled domain and some understanding of the labeled domain. The second method is to use remote monitoring for labeling. To solve traditional learning problems based on semantic information, this paper adopts a method of remote supervised labeling, aligning existing language text entity models with public knowledge bases and entities from various major fields to obtain effective relation extraction training samples.

Through reading and preprocessing the corpus, the corpus is processed. Firstly, the text is segmented, and part-of-speech tagging is applied to classify words into three types: nouns, verbs, and adjectives. Artificial neural networks are suitable for continuous input data with time changes. This method uses long-term information in the recurrent latent space and trains it with existing implicit vectors. Long Short-Term Memory (LSTM) is a special type of artificial neural network. LSTM neural networks can access long-term information as needed and effectively overcome the problem of gradient descent. LSTM modifies the internal neuron structure of RNN, and its memory unit structure diagram is shown in Figure 1. Given a text input sequence $X = \{x_1, x_2, \cdots, x_n\}$, where x_t is a high-dimensional word vector in the text, the representation of the hidden vector h_t at time t is as follows:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{1}$$

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{2}$$

$$\widetilde{C_t} = tanh(W_c.[h_{t-1}, x_t]) + b_c \tag{3}$$

$$C_t = f_t \times C_{t-1} + i_t \times \widetilde{C_t} \tag{4}$$

$$o_t = \sigma(W_0.[h_{t-1}, x_t] + b_0) \tag{5}$$

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$$h_t = o_t \times tanh(C_t) \quad (6)$$

The main function of the entity recognition module is text input and entity recognition.

First, the module utilizes functions such as on Open, get Text, read File, etc., to complete the corresponding text input and reading at the text input end. When the user inputs text, they first enter the text on the "text import" key, then select the text to be input on the "open" key in the function area, and then input the text. Secondly, in terms of cognitive understanding, when the associated user inputs text into the front-end page, the getTokens method of the middle control will convert the corresponding mathematical lesson plan into text format, and use formatting technology to convert the text format into a format recognized by the named entity recognition model. Finally, the associated processing layer inputs the received data into the designated entity recognition model and feeds back the corresponding language text entity identification results to the middle control layer, and then feeds back the identification results to the front end to display the identification results to the relevant users.

In recent years, cognitive psychology has made fruitful achievements in problem-solving research, especially in the characterization of problems and research on problem-solving strategies, laying a solid theoretical foundation for automated problem-solving. It is a linguistic discipline that starts from the perspective of human experience and cognition, focusing on semantic research, aiming to reveal the cognitive laws of language. In existing problem-solving systems, good results can be obtained through research on semantic understanding. Therefore, from a cognitive perspective, it is an inevitable trend for future semantic understanding to draw on existing research results. In order to reveal the inherent connections between knowledge and better express each element, it is necessary to process the samples at a deeper level, which means conducting simple analysis on them. Currently, commonly used methods include association analysis, factor analysis, multidimensional scaling analysis, self-organizing maps, addressable network maps, cluster analysis, latent semantic analysis, and minimum spanning tree methods, etc.

4. Results and Discussion

Firstly, experiments utilized a multi-threaded web crawler program to search for a comprehensive list of idioms on a Chinese dictionary website and extracted idiom-related information from the site. Due to the large number of idioms, this paper selected idioms with three, four, and five characters to obtain their data. Finally, the experiment was able to find 35,899 idioms from the word "911", or 28,327 idioms found in the "Chinese Dictionary". However, because the idioms contain different information, such as inconsistent or overlapping tables of synonyms or antonyms (which may also be empty), and there is also a lot of overlap between the two corpora, the Chinese idiom database needs to be cleaned and processed. The experimental analysis results of the system are presented below. In the data graph, "A", "R", and F1 respectively represent accuracy, recall, and F1 value.

4.1. Text Classification Results and Analysis

Contrast experiments were conducted using machine learning models such as Support Vector Machines (SVM), Naive Bayes, and deep learning models such as Text CNN (Convolutional Neural Networks), VDCNN (Very Deep Convolutional Neural Networks), and DPCNN (Deep Pyramid Convolutional Neural Networks). The experimental results of each model are shown in the figure below.

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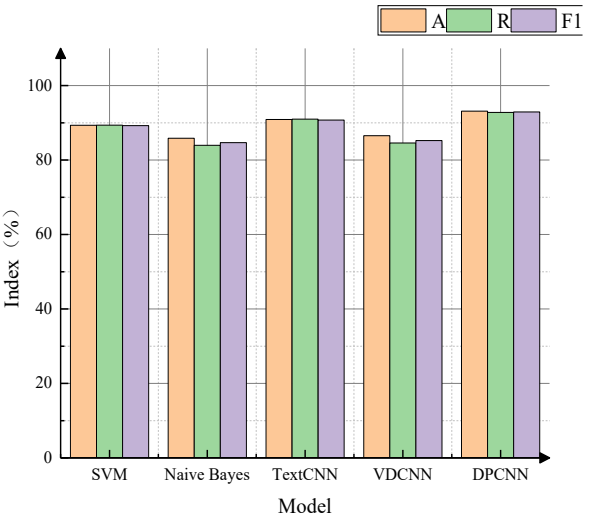

Figure 2. Text Classification Results (%)

From Figure 2, it can be seen that the three indicators of accuracy, recall, and F1 for text classification using different models are between 80% and 100%. It can be observed from the figure that the three indicators of the classification results of the deep convolutional neural network algorithm are higher than those of other algorithm models.

4.2. Entity Extraction Performance

Contrast experiments were conducted using models such as BiLSTM-CRF, Lattice LSTM-CRF, etc., and the entity extraction results of each model are shown in Figure 3.

BERT-BiLSTM-MUL-CRF: Combines the BERT (Bidirectional Encoder Representations from Transformers) model with BiLSTM (Bidirectional Long- and Short-Term Memory) layer and CRF (Conditional Random Field) layer.

Lattice LSTM-CRF: Combines the LSTM and CRF components.

LRCNN-CRF: Combines the LSTM, CNN (Convolutional Neural Network), CRF, and rethinking mechanism.

BiLSTM-CRF: Combines the BiLSTM and CRF components.

RNN-LSTM: RNN and LSTM components (this paper).

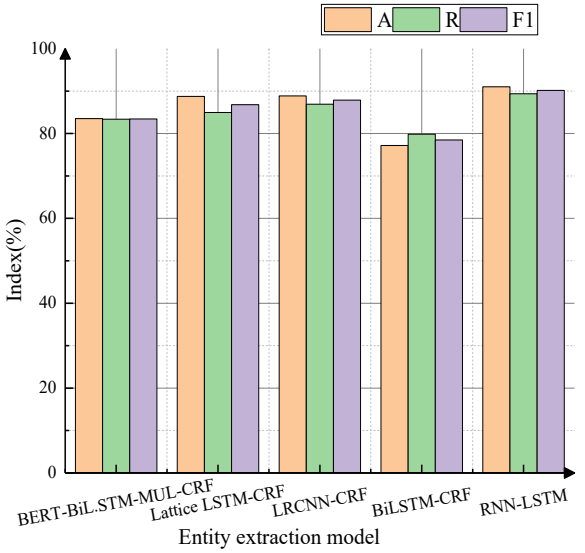

Figure 3. Entity Extraction Results

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From Figure 3, it can be seen that the accuracy, recall, and F1 value of entity extraction using the RNN-LSTM algorithm model are around 90%. The performance of entity extraction composed of other algorithm components is not as excellent as that of the RNN-LSTM algorithm.

4.3. System Running Time

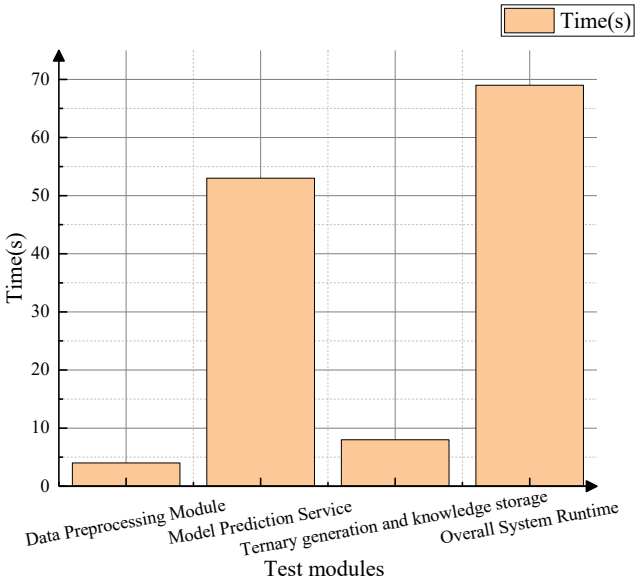

Figure 4. System Running Time

From Figure 4, it can be observed that the data processing module of the system takes nearly 5 seconds, the prediction service takes nearly 55 seconds, the time for triple generation and knowledge storage is around 8 seconds, and the overall running time of the system is close to 70 seconds, which is over 1 minute. Because the extraction system involves a large amount of data batch processing, it is a computationally intensive program and has relatively low requirements for real-time interaction. The system achieves the extraction of megabyte-level documents within minutes, meeting the usage requirements.

Table 1. System Resource Consumption

Number of runs	CPU(GHz)	Random access memory (GB)	GPU(GB)
1	2.5	15.5	8.1
2	2.4	16.7	9
3	2	18	10
4	3	17	8.8
5	4	19	9.1

In different operating instances, the system's CPU operates between 2 to 4 GHz, memory runs at 15 to 19 GB, and GPU ranges from 8 to 10 GB. For applications requiring heavy computations such as scientific computing, data analysis, and deep learning, a CPU with higher clock frequencies, typically above 3.5 GHz or even higher, is generally preferred. From Table 1, it can be observed that the system's resource utilization is relatively low.

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5. Conclusions

With the continuous development of artificial intelligence technology, the education sector has gradually begun to introduce these advanced technologies to enhance teaching effectiveness and learning experiences. Among them, the research and application of Chinese semantic understanding teaching systems based on knowledge graphs and deep learning have become one of the hot topics. This paper explores the research and application of this teaching system, as well as its potential impact in the field of education. By employing multi-layer neural networks to learn and abstract data, efficient processing of complex problems can be achieved. Furthermore, by integrating knowledge graphs and deep learning, a powerful semantic understanding system can be constructed, which can help students better understand Chinese semantics and provide personalized learning support.

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