

## *Retraction*

# **Retracted: Question and Answer Techniques for Financial Audits in Universities 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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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] Q. Li, "Question and Answer Techniques for Financial Audits in Universities Based on Deep Learning," *Mathematical Problems in Engineering*, vol. 2022, Article ID 4875859, 8 pages, 2022.

## Research Article

# Question and Answer Techniques for Financial Audits in Universities Based on Deep Learning

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Financial auditing in universities is highly specialized, with a huge knowledge system and rapid updates. Auditors will encounter various problems and situations in their work and need to acquire domain knowledge efficiently and accurately to solve the difficulties they encounter. The existing audit information software, however, is mostly aimed at the management of audit affairs and lacks the relevant functions to acquire and retrieve knowledge of specific audit domains. In this study, we use deep learning theory as support to conduct an in-depth study on the key technologies of question and answer systems in the field of financial auditing in universities. In the question-answer retrieval stage, the local information and the global information of the sentence are first modelled using a two-way coding model based on the attentional mechanism, and then, an interactive text matching model is used to interact directly at the input layer, and a multilayer convolutional neural network model cable news network (CNN) is used to extract the fine-grained matching features from the interaction matrix; this study adopts two matching methods. We have conducted comparative experiments to verify the effectiveness and application value of the entity recognition algorithm based on this study's algorithm and the question-answer retrieval model based on multi-granularity text matching in the university financial audit domain.

## 1. Introduction

In recent years, China's financial auditing of colleges and universities has been developed in an unprecedented way by combining national conditions, absorbing international advanced ideas, and groping on the road of practice, constantly improving and refining. With the flourishing development of computer science and technology, audit informatization has become a wave that promotes the development and progress in the field of financial auditing in universities, improving audit efficiency, and saving audit costs [1].

Financial auditing in colleges and universities is a scout to punish and prevent corruption. Financial audit of colleges and universities refers to the auditing and supervision of the assets, funds, profit and loss, and liabilities of state-owned colleges and universities and their holding colleges and universities independently, objectively, and impartially according to laws and regulations, to judge whether they are

true and lawful and to give evaluation and audit opinions in the form of audit reports [2]. The purpose of financial audit of universities is to verify and reveal the true operation status of state-owned universities and their holding universities; to investigate and deal with illegal and irregular behaviors in financial income and expenditure; and to prevent the loss of state-owned assets and to facilitate the macro-control of the government [3].

In this process, the majority of university financial auditors are eager to quickly and fully understand the knowledge and new policies of all aspects of university financial auditing, so that they can have justifications and evidence to obtain the corresponding domain knowledge efficiently and accurately in the face of university financial auditing affairs [4]. As a result, university financial auditors have a huge and urgent need for domain knowledge in their work and are eager to learn domain knowledge quickly to solve the problems they encounter [5]. Therefore, it is necessary to provide them with a Q&A service that can

answer questions and solve problems in a professional and intelligent manner [6].

Financial auditors in higher education can satisfy their need for domain knowledge acquisition using search engines (e.g., Baidu and Google) to retrieve information on the Internet [7]. However, traditional search engines return to the user a large number of links to keyword-related Web pages based on the keywords entered by the user, and there are many unsatisfactory aspects, mainly in the following areas [8].

Because traditional search engines cannot meet people's needs for accurate and efficient access to information, many large companies, research institutes, and scholars at home and abroad have turned their attention to more intelligent, professional, and personalized automatic question and answer systems and are constantly researching and exploring them. Question answering system (QA) can answer questions in natural language (a sentence or a paragraph of text, or even a named entity such as a person's name or a place's name) based on the user's input, which is more efficient, accurate, and concise than traditional search engines that are accurate, concise, and clear [9].

In view of the high degree of specialization in university financial auditing, the huge knowledge system, and the large workload of auditors who are eager to obtain domain knowledge efficiently and accurately, it is necessary for us to use advanced theoretical knowledge in natural language processing and machine learning to build a question and answer system for auditors in the field of university financial auditing, which can answer auditors' questions intelligently, efficiently, professionally, and concisely and help auditors obtain domain knowledge accurately, thus assisting auditors to improve work efficiency and audit quality [10].

## 2. Related Work

In the 21st century, computer technology has developed rapidly and widely spread to all aspects of production and life [11]. At the same time, domestic universities have absorbed the advanced ideas of international universities and kept in line with them, so China's auditing work has also entered the era of information technology and is on par with international standards [12]. The financial audit of contemporary universities has significant characteristics, the scope and field of audit are expanding, the content of audit becomes more and more complex, the audit subject is also developing along the trend of diversification, and the corresponding audit technology is also more scientific [13].

Reference [14] proposed a semantic Web-based question and answer system built on the powerful and easy-to-use structured data of freebase. A typical representative of a semantic Web-based Q&A system is jacana-freebase [15], where natural language interrogatives entered by the user are transformed by the Q&A system into graph query statements against the semantic Web knowledge base.

Reference [16] used a recurrent neural network to represent the interrogative sentences as word vectors, considering the dependent syntax of the interrogative sentences. In addition,  $t$  implemented a question and answer system for

single-relationship problems using convolutional neural networks, the main idea of which is to train matching relations between entities and entities, which are represented by semantic vectors. Reference [17] proposed the concept of word vectors, which is a distributed representation of meaningful words using neural networks. Reference [18] proposed a neural network language model, i.e., modelling the  $n$ -gram, which solves the problem of word vector dimensional catastrophe. Reference [19] proposed the widely known Centralne Biuro Obrotu Wierzytelnościami (CBOW) word vector model and Skip-gram word vector model using more contextual information to share parameters through recurrent neural networks, and its open-source project word2vec was more widely used by researchers, and the distributed representation technique of words matured. In [16], based on word vectors and word-level neural networks, the transfer probability matrix is added to the named entity recognition task to improve performance; Collobert constructed a multilayer convolutional neural network model for four annotation tasks, with input raw sentences for vector representation without artificial features. Kim proposed a multichannel CNN model for the sentence classification task [20].

## 3. Preprocessing of the Corpus

Corpus preprocessing is to remove useless and invalid phrases from the large amount of unstructured text crawled, so that the efficiency of domain entity recognition can be improved and the recognition effect can be better. The corpus preprocessing mainly includes three stages: sentence division, word division, and screening of deactivated words.

- (1) Split-sentence processing.
- (2) Word processing.
- (3) Deactivation word screening.
- (4) Dependency syntax analysis. Research has shown that every word in a sentence is dependent in some way on another word. Dependency syntax analysis allows the identification of semantic dependencies between words and the understanding of their relational categories. In entity recognition tasks, dependency syntax analysis can be used to capture functional information about entities and improve the quality of sequence annotation.

Typically, the dependency syntax analysis algorithm starts at the root node and expands downwards from the top to generate a dependency syntax analysis tree. For ease of understanding, this study uses the Dependency Viewer tool to build the dependency syntax analysis tree.

Taking the question "What are the steps in a fixed asset audit?" as an example, the dependency syntax analysis gives an example of the dependency syntax analysis tree in Figure 1.

After dividing the corpus into sentences and words in the field of university financial auditing, 8304 words were collected, and after filtering them for deactivated words, a total of 5873 valid words were obtained.

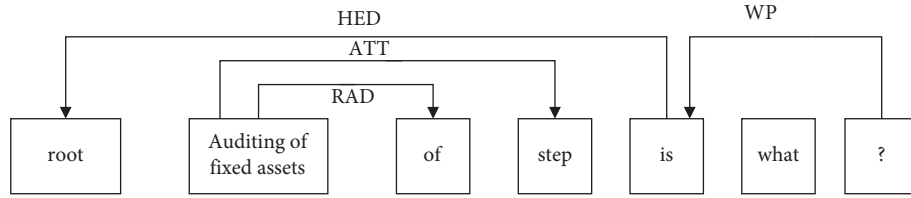


FIGURE 1: Example of a dependency syntax analysis tree.

TABLE 1: Training data format.

User questions	Knowledge point title	Knowledge point answer	Label
What is accounting statement audit?	Definition of accounting statement audit	Corresponding answer a	1
What is the significance of accounting statement audit?	Definition of accounting statement audit	Corresponding answer a	0
What are the steps of accounting statement audit?	Audit steps of accounting statements	Corresponding answer b	1
How to audit accounting statements?	Audit steps of accounting statements	Corresponding answer b	1
What are the key points of accounting statement audit?	Audit steps of accounting statements	Corresponding answer b	0

#### 4. Question and Answer Search Model

We divide the Q&A system into two modules: entity recognition, as a pre-step of Q&A retrieval, plays an important role for Q&A retrieval, and it can be used as an important feature for Q&A matching. From our experimental analysis later, we can see that the entity information identified in the entity recognition stage can improve the accuracy of the Q&A retrieval model.

In the question-answer retrieval phase, the goal of question-answer matching is to find the most similar answer from the candidate knowledge base to return to the user, which can be abstracted into two academic tasks, one is question-question matching (paraphrase identification), which aims to calculate the semantic similarity of two interrogative sentences and determine one is question-answer selection, which aims to determine whether the answer can answer the corresponding question and is a question-answer relationship. Both can be defined as text matching tasks, and this section presents them in a unified way, with the following abstract definition:

$$\text{score} = F(x_1, x_2), \quad (1)$$

where  $x_1, x_2$  denotes the word sequence of the two input texts,  $F$  denotes the implicit relationship function learned by our model, for the question-question matching task,  $F$  denotes the degree of similarity, and for the question-answer matching task,  $F$  denotes the degree of correlation between the question and the answer.

**4.1. Data Preprocessing.** We crawled a huge knowledge base of questions and answers in the field of university financial auditing from Internet resources, processed it by some rules (special character processing, spam identification, etc.), generated question-answer knowledge in the form of questions and answers and possible descriptions of all user questions, and retrieved the knowledge base question—answer is retrieved from the candidate set of all user questions based on retrieval, and 10 items of each knowledge are recalled and manually reviewed and marked as our

training data. The format of the training data is shown in Table 1.

“User question” indicates the question asked by the user, “knowledge point title” indicates the knowledge base question we crawled, “knowledge point answer” indicates the answer to the knowledge point, and “label” indicates whether the knowledge point answer can be used as the answer to the user question. The “label” indicates whether the knowledge answer can be used as an answer to the user question, with “1” meaning that it can be used as an answer and “0” meaning that it cannot be used as an answer. The general question and answer matching only considers the relevance of the user question and the knowledge answer, but there may be some noise in the knowledge base we crawl, so the effect of matching the user question with the answer is not particularly satisfactory.

After constructing the training data, data preprocessing is required as input to the model. Traditional methods require extensive data preprocessing including word separation, dependent syntactic analysis, and feature construction, while the proposed question-answer matching model is based on the deep learning end-to-end model, which does not require excessive data preprocessing and manual feature definition and extraction and only requires word separation for the training data.

#### 4.2. Multi-Granularity Question and Answer Matching Model.

We fuse information at different levels of granularity, and the overall model structure is shown in Figure 2. The model consists of three modules: an input layer, a representation layer, and a matching layer. Based on the input matrix mapped in the input layer, the representation layer maps the two input texts into the same semantic space through two-way coded text relationship modelling, interactive text relationship modelling, entity information fusion, and attentional mechanism. Finally, the matching layer uses cosine similarity for the question-question matching (paraphrase identification) task based on the semantic vectors modelled in the representation layer, and the question-answer matching (answer selection) task is computed using an implicit semantic relation function.

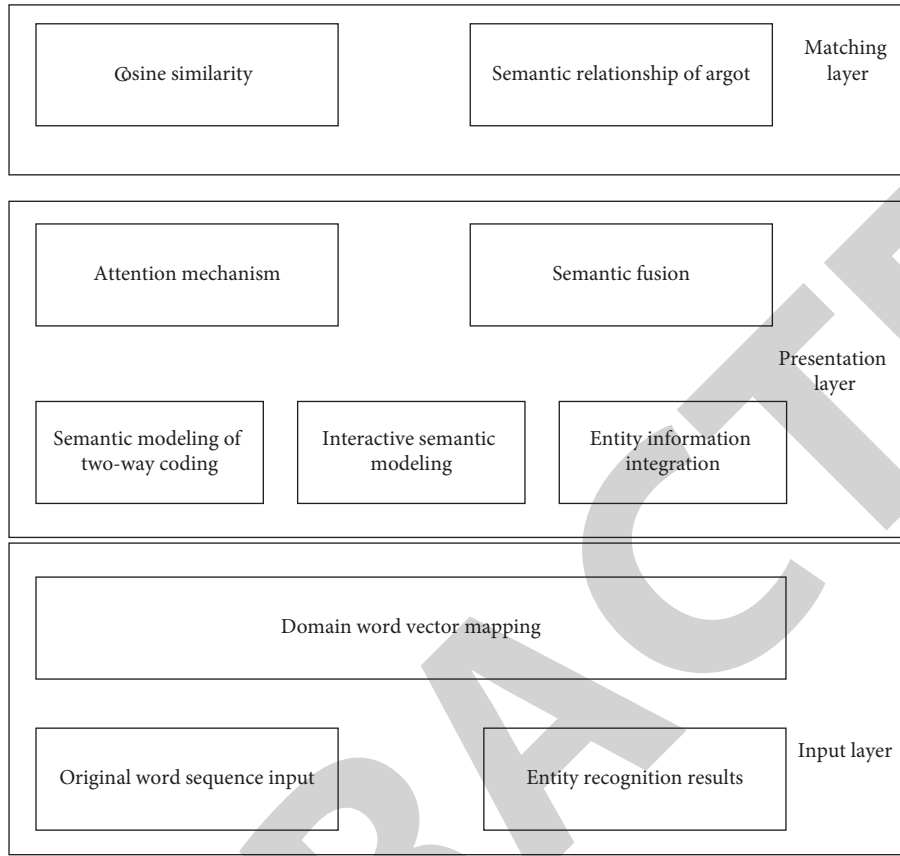


FIGURE 2: Structure of this matching model.

**4.3. Input Layer.** The input layer is the input to the whole model, including the raw word sequence input, and the input from the entity recognition results in Section 3. Assume that the two sentences input are  $S_1 = \{w_1, w_2, \dots, w_n\}$  and  $S_2 = \{w'_1, w'_2, \dots, w'_n\}$ . Using the entity recognition results from the square in Section 3 as  $E_1 = \{e_1, e_2\}$  and  $E_2 = \{e'_1\}$ , where  $w^{\text{word}} \in R^{d^{\text{word}} \times |V^{\text{word}}|}$  and  $d^{\text{word}}$  denote an entity that can consist of multiple words, the word sequence input is mapped to a word vector representation via a word vector matrix, where  $e_i$  denotes the word vector dimension,  $V^{\text{word}}$  denotes the lexicon size, and  $w^{\text{word}}$  is word learned through the model, as shown as follows:

$$r^k = w^{\text{word}} \cdot v^w. \quad (2)$$

Similarly, the entity inputs are mapped by means of an entity vector matrix  $w^{\text{entity}} \in R^{d^{\text{entity}} \times p^{\text{entity}}}$ ,  $d^{\text{entity}}$  denotes the entity vector dimension, which is small in order to be adequately trained, typically 10,  $v^{\text{entity}}$  denotes the number of entity types, and  $w^{\text{entity}}$  is also automatically learned by the model to obtain an entity vector representation; see the following equation:

$$r^e = w^{\text{entity}} \cdot v^e. \quad (3)$$

**4.4. Representation Layer.** The role of the representation layer is mainly to encode the input and map it to the same semantic space, as, for the input features of the matching layer, mainly including the two-way encoding semantic modelling based on attentional mechanism, interactive semantic modelling, entity information integration, and other major parts.

In terms of recurrent neural network (CRNN) modelling, the RNN model can retain the contextual information of each word, and it is difficult to train the traditional model because it is difficult to solve the problem of long-distance dependency; therefore, we use the bidirectional long- and short-term memory recurrent neural network model (BiLSTM) for training, and the BiLSTM model can solve the problem of long-distance dependency, and the bidirectional LSTM model, which not only models the above information of words but also preserves the below information of words, enables a richer representation of word levels. For example, in the questions “What is the objective of the financial audit of the university?” and “what are the parts of the audit?” the input of the hidden unit corresponding to “objective” can not only retain “audit” but also include in the question “What is the objective of the audit?”. The BiLSTM model maps the two-word sequences to vectors in the same semantic space, as follows:



$$\begin{aligned}
h_i^{\text{forward}} &= \text{LSTM}^{\text{forward}}(s_i\{r_1^w, r_2^w, \dots, r_n^w\}), \\
h_i^{\text{backward}} &= \text{LSTM}^{\text{backward}}(s_i\{r_1^w, r_2^w, \dots, r_n^w\}), \\
h_i &= h_i^{\text{forward}} \cdot h_i^{\text{backward}},
\end{aligned} \quad (4)$$

where  $s_i$  denotes the input word vector matrix, LSTM denotes the long- and short-term memory recurrent neural network model operation, as described in detail in Section 2, and  $h_i$  denotes the forward and backward computation, respectively, and  $h_i$  denotes the concatenation of the forward and backward computed LSTM representation vectors as the semantic representation of the word.

We introduce attentional mechanisms. Combined with our model and the characteristics of the domain, we introduce two attentional mechanisms, one based on entity information and one based on answers. The two attentional mechanisms are only different in representation, and the principles are the same, so they are introduced in unison. The core idea of the attentional mechanism is to assign different weights to different words in a sentence, with the different weights representing the importance of the words, which is calculated as follows:

$$\begin{aligned}
\alpha_i &= \sigma(r_q^T M_q h_i), \\
h'_i &= \alpha_i \times h_i,
\end{aligned} \quad (5)$$

where  $M$  denotes the parameter matrix of the attentional mechanism, which is learned automatically by the model;  $r_q^T$  denotes the context vector involved in the weight calculation, which can be either the entity vector or the hidden layer vector of the BiLSTM hidden layer output by max-pooling or average pooling;  $\sigma$  denotes the nonlinear transformation function;  $\alpha_i$  denotes the different weights of each word based on the attentional mechanism;  $h_i$  denotes the hidden layer output of the BiLSTM; and  $h'_i$  denotes the hidden layer output after weighting based on the different weights. The attentional mechanism allows each word to be given a different weight based on different contextual information (different entities, different answers, etc.).

In terms of convolutional neural network (CNN) modeling, local features are generally extracted based on the original word vector through the convolution and pooling operations of the CNN model [21], while we use the output of each hidden layer (forward and backward outputs are concatenated) in the BiLSTM as the CNN model is calculated as follows:

$$r'_i = f\left(\text{conv}\left(h_i^{\text{Bi-LSTM}}\right)\right) + \text{bias}, \quad (6)$$

where conv represents the convolutional and pooling formulas in the convolutional neural network, which are described in detail in Section 2;  $h_i^{\text{Bi-LSTM}}$  represents the output of the bidirectional long- and short-term memory recurrent neural network model,  $f$  represents the nonlinear function, bias represents the bias, and  $r'_i$  represents the text semantic vector represented by the two-way coded text relationship modelling. In summary, the two-way encoding model based on the attention-based mechanism is shown in Figure 3.

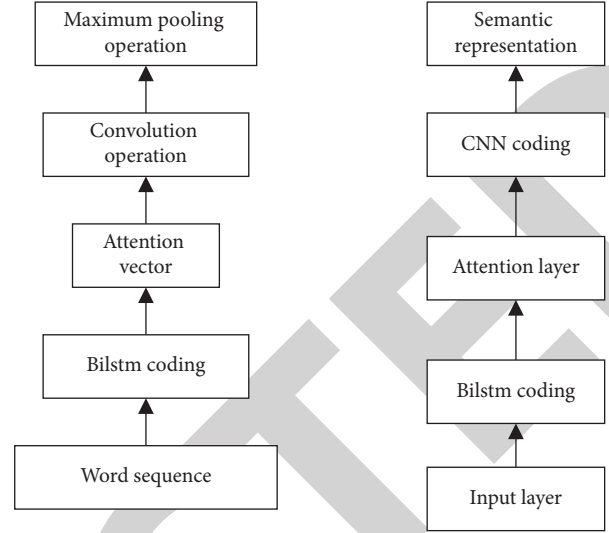


FIGURE 3: Two-way coding model with attentional mechanism.

**4.5. Matching Layer.** The matching layer is mainly based on the semantic representation of the representation layer for matching score calculation. In our knowledge base, a knowledge point has both questions and answers, and these data are mined from the Internet without manual review, and if we simply match from the question dimension or the answer dimension, it may bring large deviations; for example, the questions are similar, but the answers are not good enough to solve the user's problem. Based on this difference, different matching methods are used for the two matching models.

**4.6. Model Training and Parameter Tuning.** Again, we developed the model based on the TensorFlow deep learning development environment developed by Google. The parameters of the model are word vector, entity type vector, LSTM parameters, CNN parameters, implicit relation parameters, and fully connected layer parameters [24, 25], where the implicit relation parameters represent the implicit relation matrix  $M$  in the question-answer matching process, and for all hyperparameters, we iterate through a gradient search to find the best combination of parameters. The final model parameters are shown in Table 2.

## 5. Financial Audit Entity Identification Experiments

To verify the advantages and disadvantages of the model proposed in this study and the effectiveness of the features introduced in this study, we have done two sets of experiments, one set of experiments is to compare the effect of the entity recognition model proposed in this study with the traditional method [26] and the other set of experiments is to compare the different features introduced in this study, and the detailed analysis is as follows.

**5.1. Experiments Comparing the Model in This Study with Traditional Methods.** As the area of study for this study is

TABLE 2: Table of model parameters.

Parameter name	Word vector dimension	Entity vector dimension	LSTM hidden layer dimension	LSTM layers	Convolution kernel size
Value	128	128	128	1	[128,3]
Parameter name	Matrix size	Dropout	Wight	Number of hidden layer nodes	Number of hidden layers
Value	[128, 64]	0.8	0.8	128	2

TABLE 3: Experimental results of entity recognition models.

Model	Accuracy (%)	Recall rate (%)	F1 value (%)
CRF-based	78.52	77.48	78.94
BiLSTM-based	80.01	79.87	80.12
BiLSTM + CRF + model	81.45	80.03	80.07
BiLSTM + CRF + Deixis	81.47	81.29	80.97
Paper model	80.14	83.47	82.59

the specialist field of financial auditing in universities, there is no publicly available experimental dataset on the Internet. To compare the experimental results and to validate the results of this study, the dataset used in this study was manually annotated by the author's team.

To compare this model with other models, we have selected three models that work well in other domains for implementation and tested them on our dataset, of which the CRF-based, BiLSTM-based, and LSTM-CRF-based models use manual feature design and feature extraction as input to the model, and BiLSTM-based and BiLSTM-CRF models use raw word input and learn automatically through deep learning models without introducing domain knowledge features similar to those proposed in this study. The model in this study is the BiLSTM and CRF model-based entity recognition method that fuses domain knowledge proposed in this study. The experimental results are shown in Table 3.

From the experimental results, it can be seen that the proposed multi-granular entity recognition model incorporating domain knowledge outperforms the traditional model in terms of accuracy, recall, and F1 value in the test set, fully validating the effectiveness of introducing domain knowledge features on top of the popular BiLSTM + CRF model. To illustrate the effectiveness of the different features, we have also conducted corresponding comparison experiments for different feature combinations.

**5.2. Validation Experiments for Domain Knowledge.** We added different features such as lexicality, entity lexicon, and indicator word information to the standard BiLSTM + CRF model for experimental validation to illustrate the role of different features separately, as shown in Table 4.

From the experimental results, it can be seen that a variety of features introduced in this study can be useful for entity recognition. The lexical features can be seen as an additional supplement to the word vector information; for example, nouns are generally considered to be more likely to be entities, and this information can be learned automatically by the model, but as the word vector information is already rich in semantics, the introduction of lexical features

is not very useful. In contrast, the introduction of entity features improves the  $n$  value by 1.24% relative to the BiLSTM + CRF model, while the recall rate improves by 1.47%, indicating that the candidate domain entity lexicon can play an important role for some sparse entities. This is reflected in the significant increase in the recall rate; the introduction of the indicator information improves the F1 value by 0.87% relative to the BiLSTM + CRF model, while the accuracy rate improves by 0.92%, indicating that the indicator information can correct those entities that are easily misidentified and improve the accuracy rate. Finally, it can be seen that the combination of the three features can further improve the recognition effect compared with the introduction of entity words or indicator words alone, indicating that these features are complementary to each other and the combination can improve the final entity recognition effect.

**5.3. Question and Answer Search Experiment.** In the experiments, two types of evaluation criteria were chosen for evaluating the model, one is the AUC, which is not related to the selection threshold of the classification criteria, and the AUC is usually used to evaluate the goodness of the dichotomous classification model; the other is the metrics such as MAP and MRR, which are related to the ranking of the information retrieval, MAP denotes the mean accuracy rate.

Attentional mechanism plays an important role in the model of this study, we introduced answer attention and entity attentional mechanism, the difference between the two is that the answer attentional mechanism calculates the weight of each word in the question based on the coding vector of the answer, while the entity attentional mechanism calculates the weight of each word in the question based on the coding vector of the entity. The detailed results are shown in Table 5.

From the experimental results, we can see that the introduction of the attentional mechanism can improve the model's effectiveness to a certain extent, in which the entity attentional mechanism improves the effect better than the answer attentional mechanism, indicating that the entity attentional mechanism can make the model pay more

TABLE 4: Results of domain knowledge validity experiments.

Model	Accuracy (%)	Recall rate (%)	F1 value (%)
BiLSTM + CRF model	81.21	80.12	84.12
BiLSTM + CRF + part of speech	81.02	82.03	82.04
BiLSTM + CRF + entity	82.24	82.39	82.79
BiLSTM + CRF + Deixis	82.47	83.12	82.90
Paper model	82.74	84.57	86.35

TABLE 5: Experimental results of the attentional entry mechanism.

Model	Auc (%)	MAP (%)	MRR (%)
This model does not introduce attentional mechanism	79.01	67.47	65.98
This study models entity attentional mechanism	78.92	68.74	66.87
This study models the answer attentional mechanism	80.54	67.98	67.89
Paper model	81.23	70.01	69.53

TABLE 6: Experimental results for entry entity characteristics.

Model	Auc (%)	MAP (%)	MRR (%)
This model does not introduce entity features	81.11	70.01	69.21
In this study, model + entity features are introduced	82.37	69.47	68.71

attention to the entity information and reflect the core semantics of the user when performing the question representation.

To illustrate the importance of the entity feature information identified in the question-answer matching process, we compared the models without the introduction of entity features and the models with the introduction of entity features, respectively, and the detailed results are shown in Table 6.

From the experimental results, it can be seen that the introduction of entity features has an important role in the improvement of the question and answer matching model, with 0.74%, 0.85%, and 0.81% improvement in the Auc, MAP, and MRR indexes, respectively, and the introduction of entity features can incorporate the a priori knowledge of entity features into the model, which can automatically learn the role of entity features for the final matching relationship through a large amount of training data.

## 6. Conclusions

In this study, we propose a question and answer retrieval model based on multi-granularity text matching, incorporating matching features of different granularities. Firstly, a two-way code model, i.e., a long- and short-term memory recurrent neural network (BiLSTM) and a CNN model, is used to model the contextual and local information of the sentence, while an attentional mechanism is introduced to assign different weights to different words, allowing the model to focus more on the expression of specific words; then, an interactive text matching model is used in the input layer directly; finally, by fusing the entity recognition information, entity features are introduced to enhance the effectiveness of question and answer matching.

## Data Availability

The dataset used in this study is available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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