An intelligent question answering system based on RoBERTa-WWM under home appliance knowledge graph

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Abstract**—**Recently, the intelligent question answering (QA) system for home appliances has attracted wide attention in China because it can provide users with reasonable suggestions in time. However, the fuzzy boundaries of the Chinese "word groups" and the absence of a unified standard for Chinese question classification result in low efficiency of QA, which has hindered the development of the system for a long time. In this work, we developed a QA model based on RoBERTa-WWM to answer questions about home appliances in specific fields. More importantly, the RoBERTa-WWM-BiLSTM-CRF named entity recognition model and RoBERTa-WWM-TextCNN question semantic classification model were constructed to parse the correct semantics of questions from users, which provided algorithm support for the home appliance QA system. The results showed that the method outperformed baselines, and the QA model showed high interpretability and good performance.

Keywords-knowledge graph question answering; home appliance; named entity recognition; semantic classification

I. INTRODUCTION

The rapid development of e-commerce in China has recently led to a sharp increase in people shopping online. Since 2020, online sales of home appliances have accounted for over 50% and are expected to continue to increase [1]. Surging consumption, product diversification, and rapid update result in a severe imbalance between the supply and demand of consumer services. The intelligent question answering (QA) system based on the home appliance knowledge graph (KG) can provide timely and uninterrupted service, freeing customer service from answering many repetitive mechanical questions. Therefore, it can lower the service cost and improve the shopping experience. Generally, all service platforms can use the QA system to optimize service [2], indicating its broad prospects in the application.

The current QA system in the field of e-commerce is absent of flexibility because it is mainly based on rule matching or template matching and requires manual template configuration. For example, a customer service robot system developed by Li et al. [3] obtained the vector representation of the question and the answer by CNN training, followed by returning the corresponding answer by similarity matching. A cosmetic QA system based on KG built by Xue et al. [4] used a BERT-CRF model to identify the relevant entities of the question and then offered an answer according to a preset question template. In the field of home appliances, the low efficiency of template updating by hand can hardly keep up with the rapid update of products. The QA system based on semantic parsing is the solution to the abovementioned problem. The entity and intention of the question are determined by semantic parsing, followed by the automatic construction of the query statement. Then, the answer is found in the knowledge base, indicating that automated QA is realized.

However, some problems still need to be solved in the semantic parsing of home appliance questions. Firstly, the data on home appliances contain a lot of heterogeneous information combining numbers and letters, which makes it challenging to extract uniformly. Secondly, the question corpus of home appliances is relatively limited. Finally, Chinese word groups have fuzzy boundaries, unlike English ones with delimiters to mark the boundary [5]. The fundamental element of semantic expression in Chinese is a word group rather than a single word.

Herein, a RoBERTa-WWM Chinese pre-training language model was introduced to solve the abovementioned problems. The model was trained on a large-scale Chinese dataset and combined with the whole word masking (WWM) technology. It could effectively learn the semantic information of Chinese words and word groups, which was suitable for Chinese NLP tasks. In addition, a QA method based on the RoBERTa-WWM was proposed for the QA task of home appliances. RoBERTa-WWM-BiLSTM-CRF named entity recognition (NER) model and RoBERTa-WWM-TextCNN question semantic classification model were constructed in the method. They could analyze the correct semantics of questions to provide algorithm support for the home appliance QA system.

II. METHODOLOGY

A. Design of Automated QA Process

The automated QA mainly comprises question semantic parsing, retrieval of the Neo4j graph database [6], and answer generation (Fig. 1). The former contains NER and question semantic classification, which are used for entity extraction and classification of questions from users to understand query intentions. Based on the results obtained, the middle constructs Cypher query statements and then queries the corresponding results in the graph database. The latter will sort the results

This work was financially supported by the National Key R&D Program of China (2022YFB3305804).
DOI reference number: 10.18293/SEKE23-195
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queried by Cypher, match the question, and return the answer with the highest matching degree. For an empty query result, the corresponding prompt information will be returned.

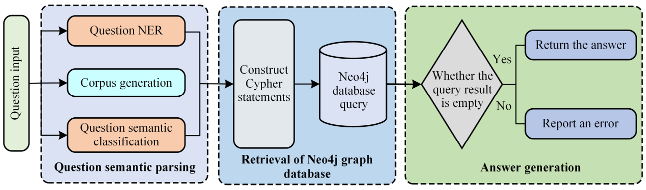

Fig. 1 Design of automated QA process

B. *Question Corpus Generation and Data Preprocessing*

Question corpus was automatically generated to construct the corpus dataset based on crawling the data of e-commerce websites because rich question corpus data can improve the accuracy of the training model. Then, the BIO markup tool based on a dictionary was used for data preprocessing in the NER task. Finally, the question classification method was constructed for the semantic classification task.

1) Question corpus generation based on the home appliance KG: A method of question corpus generation based on template rules was designed according to the features of the home appliance questions, as shown in Fig. 2.

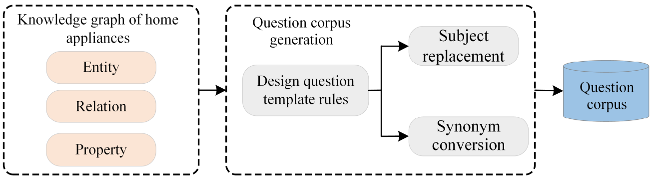

Fig. 2 A method of question corpus generation

a) The information on the entity (home appliance model, company name, and brand name), property (home appliance energy efficiency level, size, weight, and power), and relation (company and brand; home appliance and brand) obtained from the home appliance KG was used as base data to generate the question corpus.

b) After analyzing the question structure form and designing the question template rule, entity data of different types in the KG were generated as questions according to the rules. Extending the question into a natural language question can make every entity label have a relevant relation or property label. Meanwhile, there is also no semantic ambiguity in the extended question. Subject replacement and synonym conversion were used to generalize and generate more training corpus to ensure the corpus data's diversity and accuracy because questions may cover many question-setting scenarios. Meanwhile, some mood particles or transitional words can be added to the question, which makes the corpus richer.

c) Based on the question template, the entity, relation, and property in the KG are populated by the rules to achieve the automatic generation of the question corpus.

2) BIO sequence labeling of question corpus: NER usually contains entity boundary recognition and entity type determination. The NER task of Chinese, a pictograph, is more challenging than that of some pinyin scripts, such as English. More precisely, "word group" is a vague concept in Chinese, and identifiers for marking word group boundaries, such as spaces in English, are also absent [5]. In addition, Chinese does not have morphological indications such as letter case in English. Therefore, the task of Chinese NER is usually regarded as a sequence labeling question.

Sequence labeling can be divided into raw labeling and joint segmentation and labeling depending on the difference in tag granularity. The former labels each word, which can be regarded as its direct classification, while the latter indicates the same label for consecutive words. Joint segmentation and labeling were used in this work because the entity consists of several words. Compared with raw labeling, there may be dependencies between adjacent word labels in the joint segmentation and labeling. Therefore, BIO labeling is generally used to convert joint segmentation and labeling into raw labeling. BIO labeling can convert each label with a cross-word in the joint segmentation and labeling into two new labels. For example, the "品牌 (brand)" entity label "BRAND" was converted into "B-BRAND" and "I-BRAND". "B" and "I" refer to the initial word and the following word of the entity, respectively, while "O" represents a word that does not belong to any of the predefined word fragment types. Some examples of labeling are shown in Table I.

TABLE I. EXAMPLES OF BIO LABELING

美	的	有	哪	些	冰	箱	？
B-BRAND	I-BRAND	O	O	O	B-TYPE	I-TYPE	O

A corpus BIO labeling tool was prepared based on a dictionary. The dictionary of the required labeling entity could be made successfully according to the entity information from the KG. The data of each line consist of an entity name and a label, separated by spaces. After reading the question corpus, the sentence of each line was split into a single word or character to generate a labeling result set with the same length as the corpus, which was filled with an "O" label by default. Then, the entity matching the dictionary in the corpus was set to the corresponding labels after traversing the labeled entities in the dictionary. The corpus could only be written to the file once fully labeled.

3) Design of a question classification method: The result of question classification can make a direct impact on the accuracy of the QA system. A unified standard is absent for Chinese question classification, especially in domain-specific QA systems. Therefore, classification methods need to be designed based on data characteristics.

The home appliance KG was used as a knowledge base. Meanwhile, the entity types with properties were extended to "entity class" and "entity-property class". The entity type is regarded as the entity class, such as home appliance and company. The entity's property belongs to the "entity-property class", and each property is regarded as a subclass, as shown in Table II.

Introducing a subclass can subdivide the question class to improve the accuracy of question classification and further clarify the question intention. For example, the question "美的BCD-606WKPZM的参数有哪些？(What are the parameters of Midea BCD-606WKPZM?)" belongs to "家电(home appliance)" without a specific property class, while the question "美的 BCD-606WKPZM 的节能等级是什么？(What is the energy efficiency level of Midea BCD-606WKPZM?)" is directly ascribed to "家电-能效等级 (home appliance-energy efficiency level)". By NER, the latter's semantics was found to ask about the energy efficiency level of the home appliance with a model of "BCD-606WKPZM". Then, a Cypher query statement "MATCH (n)-[r:`能效等级`]-(b) where n.name=' BCD-606WKPZM ' RETURN b" was constructed for this question, and the result was returned to the user after querying the KG to realize the automated QA.

TABLE II. EXAMPLES OF HOME APPLIANCE QUESTION CLASSIFICATION

Class	Subclass
家电 (home appliance)	/
家电-属性 (home appliance-property)	家电-能效等级 (home appliance-energy efficiency level) 家电-商品重量 (home appliance-product weight)
品牌 (brand)	/
品牌-属性 (brand-property)	品牌-成立时间 (brand-establishment date) 品牌-所属公司 (brand-company)
公司 (company)	/
公司-属性 (company-property)	公司-简介 (company-brief introduction) 公司-口号 (company-slogan)

C. *RoBERTa-WWM Pre-trained Language Model*

RoBERTa-WWM pre-trained language model is an improved version of the BERT model [7]. It is more suitable for Chinese NLP tasks due to using large-scale training data, removing the Next Sentence Prediction pre-training task, changing static masking into dynamic masking, and introducing WWM. The node property information of the home appliance Chinese KG is composed of word groups, so the RoBERTa-WWM model is more suitable for home appliance QA than the BERT model. Based on the former, the question corpus dataset was used to fine-tune the model, and question NER and semantic classification were designed and achieved, which could improve the quality of the QA model.

D. *NER Model based on RoBERTa-WWM-BiLSTM-CRF*

The QA model needs to extract entity information of questions by NER first. With corpus enrichment and computing power improvement, the NER task generally uses the method based on a deep learning model. Due to both close relations, Chinese semantics should be determined by combining the context; therefore, the improved RoBERTa-WWM pre-training language model was used for the Chinese NLP task. Herein, with BiLSTM-CRF [8] as a baseline model, the RoBERTa-WWM was introduced to construct the RoBERTa-WWM-BiLSTM-CRF model (Fig. 3) to carry out the NER of the home appliance questions.

The model mainly comprises RoBERTa-WWM Chinese pre-trained language model, Bi-directional Long Short-Term Memory (BiLSTM) layer, and Conditional Random Field (CRF) layer. RoBERTa-WWM encodes the input text and passes the obtained sequence vector representation to BiLSTM. The BiLSTM layer performs further semantic encoding of the sequence vectors, after which it outputs the score of each class label corresponding to each character. In the CRF layer, the final prediction sequence is obtained by the constraint information between the adjacent labels to get the suitable class of each character. The algorithm module was introduced in the following.

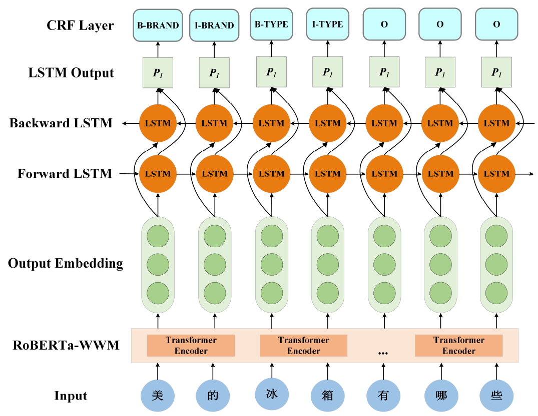

Fig. 3 Structure of RoBERTa-WWM-BiLSTM-CRF model

1) *BiLSTM:* The RoBERTa-WWM layer treats the training data to obtain an accurate semantic vector representation. The input of the result into the BiLSTM network can improve the model's ability to capture the dataset's contextual features. BiLSTM consists of LSTMs, of which everyone contains a forget gate, an input gate, and an output gate. These gates control the proportion of information that is forgotten and passed on to the next time node. The calculation formulas can be found in a previous study [9].

2) *CRF:* The BiLSTM can output meaningless characters without considering the dependency between adjacent labels. As a discriminant model, the CRF adds some practical constraints between labels to reduce the number of invalid predictive label sequences significantly. According to the sequence input, CRF can predict the corresponding state sequence and consider inputting the dependency between the current state feature and each label to find the optimal label sequence. In the CRF model, the output sequence $X=\{x_1,x_2,\cdots,x_n\}$ of the BiLSTM layer corresponds to a set of candidate state sequence labels Y_x. The final label sequence $Y=\{y_1,y_2,\cdots,y_n\}$ is determined by calculating the score of each label sequence, as shown in (1).

$$score(x,y)=\sum_{i=1}^{n}P_{i,y_i}+\sum_{i=1}^{n+1}A_{y_{i-1},y_i} \tag{1}$$

The symbol P represents the score matrix with a size of $n*k$ that BiLSTM outputs, where n and k indicate the sequence number of words and tags, and $P_{i,j}$ means the score of the j-th tag of the i-th word. The symbol A indicates the transition score matrix with a size of k+2 containing the start and end tags of the sentence, and $A_{i,j}$ represents the fraction of the process that label i is transferred to label j.

Finally, normalizing each label sequence's score can obtain the probability (2). The final tag sequence of the sentence shows the highest probability.

$$P(y|x)=\frac{\exp(score(x,y))}{\sum_{y'\in Y_x}\exp\left(score\left(x,y'\right)\right)} \tag{2}$$

E. Question Semantic Classification Model based on RoBERTa-WWM-TextCNN

A deep learning model was used to classify questions because the traditional question classification method has low generalization ability and high calculation cost. Compared with the Word2vec word vector, RoBERTa-WWM pre-training model has a higher text representation ability in Chinese NLP tasks; meanwhile, the short text classification model TextCNN outperforms conventional models in terms of simple structure and fast training speed [10]. Therefore, a question semantic classification model RoBERTa-WWM-TextCNN was proposed. First, the question context modeling and sentence-level semantic representation were carried out based on the pre-trained model RoBERTa-WWM. Then, the vector corresponding to the "[CLS]" symbol output from the RoBERTa-WWM last layer was used to represent the question context. Finally, feature extraction and subsequent classification process were carried out by using the fully connected layer of TextCNN. As shown in Fig. 4, the pipeline of the method is composed of a word embedding layer, a convolutional layer, a max-pooling layer, and a fully connected layer.

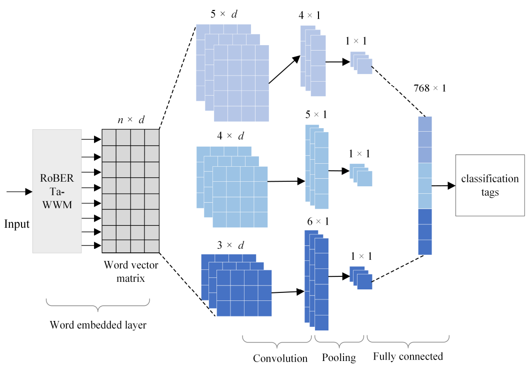

Fig. 4 Question semantic classification model based on RoBERTa-WWM-TextCNN

a) Word embedding layer: By encoding input text data using RoBERTa-WWM, a word vector matrix $E\in\mathbb{R}^{n\times d}$ was generated, where n and d represent the length of the input sentence and the dimension of the word vector, respectively. For $x_i\in\mathbb{R}^d$ representing the i-th input word vector, the input sentence X can be described as $X=[x_1,x_2,\ldots,x_n]$.

b) Convolutional layer: The convolution module of TextCNN was employed to extract the intrinsic features of the input text. Notably, the width (d) of the convolution kernel $w\in\mathbb{R}^{h\times d}$ is consistent with the dimension of the word vector. Here, h represents the height of the convolution kernel, and the widths of three convolution kernels were 3, 4, and 5. The input and output channels of the convolution kernel were determined to be 1 and 256, respectively. The convolution kernel was convolved with the i-th window $x_{i:i+h-1}\in\mathbb{R}^{h\times d}$ of the word vector matrix E to obtain the feature c_i (3). Herein, f and b represent the ReLU activation function and the bias, respectively. We used (3) to obtain several features, followed by concatenating to produce a feature vector (4) with a dimension of n–h+1.

$$c_i=f\left(w\cdot x_{i:i+h-1}+b\right) \tag{3}$$

$$c=\left[c_1,c_2,\ldots,c_{n-h+1}\right] \tag{4}$$

c) Pooling layer: Each feature was obtained by max-pooling operation (5). Then, the results of all convolution kernels were concatenated to form a new feature vector.

$$c_m=\max\{c\} \tag{5}$$

d) Fully connected layer: In this layer, dropout was added to prevent overfitting, and the softmax function was used to output the probability of each classification. Finally, the classification result with the highest probability was output.

III. Experiments

A. Dataset

The home appliance KG consisted of 27,408 entity nodes and 57,440 relations. The original questions were derived from the relevant data of e-commerce websites or obtained by corpus generation based on rules. The questions of 32,652 obtained by these two methods were divided into a training set, a test set, and a verification set based on a ratio of 8:1:1.

1) *NER dataset:* The NER dataset was obtained by BIO sequence labeling of the question corpus, of which the major labeled entities contain the model, brand, type, and company of home appliances. The maximum number of models was as high as 13,068, as shown in Table III, and the labeled data were written into files in a format of <word, label>.

TABLE III. Labels of NER Data

Entity type	Label	Number
Home appliance model	MODEL	13068
Home appliance type	TYPE	23
Company	COMPANY	158
Brand	BRAND	188
Placeholder word	NONE	/

2) *Dataset of question semantic classification:* The dataset was obtained by tagging and classifying the original questions according to the abovementioned classification method. Then, data were written to the files of the training set, the test set, and the validation set in the format of <question, classification, tag>, as shown in Table IV.

TABLE IV. EXAMPLES OF QUESTION SEMANTIC CLASSIFICATION

Question	Classification	Tag
小米扫地机器人 STYTJ02ZHM 有多重？ (What is the weight of the Xiaomi sweeping robot STYTJ02ZHM?)	家电-商品重量 (home appliance-product weight)	1
热水器 JSQ25-S6D13 的参数有哪些？ (What are the parameters of the water heater JSQ25-S6D13?)	家电(home appliance)	2
美的集团股份有限公司的口号是什么？ (What is the slogan of Midea Group Co., LTD.?)	公司-口号 (company-slogan)	3

B. *Environment Settings*

All experiments were carried out in the server, configured with an 18-core CPU, 128 GB memory, three GPUs of 24 GB video memory, and a system of Ubuntu. RoBERTa-WWM was used for text vector representation in the models of NER and question semantic classification. The network layer number of the model, the hidden layer dimension, and the number of attention heads were set as 12, 768, and 12, respectively. The parameter settings of the model are shown in Table V and Table VI.

TABLE V. PARAMETER SETTING OF NER

Parameter	Value	Parameter	Value
Hidden_layers	12	Droupout	0.5
Hidden_state	768	Learning_rate	1e–5
Hidden_unit (LSTM)	128	Max_seq_length	128
Epoch	20	Batch_size	32

TABLE VI. PARAMETER SETTING OF QUESTION SEMANTIC CLASSIFICATION

Parameter	Value	Parameter	Value
Hidden_layers	12	Droupout	0.2
Hidden_state	768	Learning_rate	5e–6
Num_filters	256	Max_seq_length	128
Kernel_size	3, 4, 5	Epoch	10

C. *Evaluation Index*

The values of precision rate (P), recall rate (R), and $F1$, calculated by (6–8), were used as evaluation indexes in NER and question semantic classification. The symbols T_p, F_P, and F_N represent the number of positive samples also predicted to be positive, the number of negative samples predicted to be positive, and the number of positive samples predicted to be negative, respectively. Therefore, $T_p + F_P$ indicates the total number of samples predicted to be positive, while $T_p + F_N$ corresponds to the total number of positive examples in the dataset. The harmonic mean of P and R is represented by $F1$, which can provide a more comprehensive evaluation of the model. A higher $F1$ value indicates a more effective model.

$$P = T_P / (T_P + F_P) \tag{6}$$

$$R = T_P / (T_P + F_N) \tag{7}$$

$$F1 = 2PR / (P + R) \tag{8}$$

D. *Results and Discussion*

1) Home appliance NER: The RoBERTa-WWM-BiLSTM-CRF model was compared with several common models (such as BiLSTM, BiLSTM-CRF, and CNN-BiLSTM-CRF [11]) to verify its effect in NER, as shown in Table VII.

TABLE VII. NER RESULTS OF DIFFERENT MODELS

Model	*P* (%)	*R* (%)	*F*1 (%)
BiLSTM	85.6	82.8	84.1
BiLSTM-CRF	89.7	88.5	89.1
CNN-BiLSTM-CRF	92.5	90.1	91.3
RoBERTa-WWM-BiLSTM-CRF	94.6	93.5	94.0

The BiLSTM-CRF model exhibited superior performance to the BiLSTM model, indicating that the result obtained using BiLSTM alone may not be a globally optimal label sequence. CRF module can analyze the relation between adjacent labels to get the optimal entity label, thereby improving the precision of NER. Compared with the BiLSTM-CRF model, the P, R, and $F1$ values of the CNN-BiLSTM-CRF model were increased by 2.8%, 1.6%, and 2.2%, respectively, indicating that the CNN module is active in extracting local features. The combination of CNN and global features extracted by BiLSTM stood out in the NER task. The RoBERTa-WWM-BiLSTM-CRF model exhibited the highest P, R, and $F1$ values because the RoBERTa-WWM pre-trained language model has an excellent feature extraction ability to express the semantic information of Chinese words better.

The RoBERTa-WWM-BiLSTM-CRF model could recognize four kinds of entities well, while the recognition result of MODEL was lower than those of other entities (Fig. 5). It was due to many letters and combinations in the home appliance model, which hindered the model from learning characteristics.

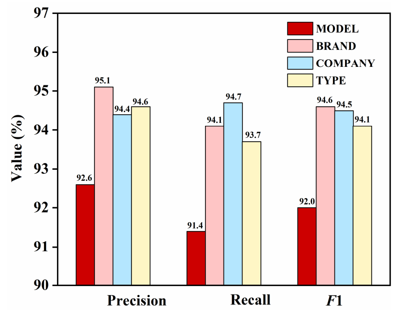

Fig. 5 Various NER results for RoBERTa-WWM-BiLSTM-CRF

2) Question semantic classification: As shown in Table VIII, the model of question semantic classification (RoBERTa-WWM-TextCNN) was compared with the traditional neural network models (BiLSTM and TextCNN).

TABLE VIII. RESULTS OF QUESTION SEMANTIC CLASSIFICATION FOR DIFFERENT MODELS

Model	*P* (%)	*R* (%)	*F*1 (%)
BiLSTM	92.8	91.7	92.2
TextCNN	93.6	92.7	93.1
RoBERTa-WWM-TextCNN	95.6	95.1	95.3

The P of the three models reached more than 90%, indicating that the deep learning model performed well in question semantic classification. TextCNN and BiLSTM showed similar results, and the P of the former was only 0.8%

higher, while it exhibited a simpler model and faster training speed. The introduction of TextCNN into the RoBERTa-WWM pre-trained language model increased the values of all indicators, which were higher than those of the other two models. For example, compared with the TextCNN model, the *P*, *R*, and *F*1 values of the RoBERTa-WWM-TextCNN model were improved by 2.0%, 2.4%, and 2.2%, respectively. It was ascribed to a multi-headed attention mechanism introduced by the RoBERTa-WWM model, which focused on the word in a sentence corresponding to a specific word from multiple perspectives. In contrast, the TextCNN model was poor in extracting semantic features because it was limited by the length and number of CNN convolution kernels. The RoBERTa-WWM model could learn word embedding features with contextual semantics using an unsupervised method in the pre-training stage to absorb much complex linguistic knowledge, which could express semantics better. The model could also adapt to the relevant contextual information in the subsequent fine-tuning stage, thereby working better than the abovementioned models.

E. Automated QA

The model, generated from NER and question semantic classification, can be used for automated QA. The algorithm models can recognize the entity and classification information of the question. The latter corresponds to the relation in the KG, which can convert the question into triplet information <entity, property, ?> that the Neo4j graph database can understand, "?" representing the answer the user wants.

The question "小米扫地机器人 STYTJ02ZHM 有多重? (What is the weight of the Xiaomi sweeping robot STYTJ02ZHM?)" was taken as an example (Table IX). Model parsing was used to determine its entity and semantic classification information. Then, a Cypher query statement was constructed based on the abovementioned information, followed by querying the answer in the KG. The system would conduct a fuzzy query if the entity information were incomplete, e.g., "小米扫地机器人 STYTJ0 有多重? (What is the weight of the Xiaomi sweeping robot STYTJ0?)". The results were filtered by combining other entity information (such as "小米 (Xiaomi)" and "扫地机器人 (sweeping robot)") of the question. The remaining results were then matched with the question by similarity, returning the answer with the highest matching degree. If no entity or classification information were obtained after model parsing, the system automatically would return a friendly prompt.

TABLE IX. EXAMPLES OF AUTOMATED QA

Enter the question: 小米扫地机器人 STYTJ02ZHM 有多重？
NER: BRAND: ['小米'] TYPE: ['扫地机器人'] MODEL: ['STYTJ02ZHM']
Semantic classification: 家电-商品重量
Construct the Cypher query: MATCH (n)-[r:`商品重量`]-(b) where n.name='STYTJ02ZHM' RETURN n,b,r.
Return the answer: STYTJ02ZHM 的商品重量为 4.7 kg。

IV. CONCLUSIONS

An intelligent question answering (QA) model based on RoBERTa-WWM was developed according to the characteristics of Chinese questions in home appliances. Based on the data characteristics of the home appliance knowledge graph (KG), the question corpus generation method was designed, and the corpus dataset was constructed. Then, the named entity recognition model (RoBERTa-WWM-BiLSTM-CRF) and the question semantic classification model (RoBERTa-WWM-TextCNN) were constructed to parse the question semantics. Finally, the model's effectiveness was verified by comparing it with other deep learning models, and the function of automated QA was completed based on the training model.

In the future, we will work on acquiring more relevant knowledge in question corpus generation. In addition, more methods of multi-round continuous QA based on KG need to be developed under Chinese semantics.

REFERENCES

[1] C. C. f. I. I. Development. *2021 China home appliance market report*. Beijing: China center for information industry development2021.

[2] T. Jin, and H.-J. Wang. Research on the method of knowledge base question answering. Paper presented at: 2021 3rd International conference on machine learning, big data and business intelligence (MLBDBI)2021.

[3] C. Li. Design and implementation of customer service chatbot for e-commerce, University of electronic science and technology of china; 2019.

[4] S. Xue, and F. Ren, Knowledge graph based question and answer system for cosmetic domain. *International journal of advanced intelligence*, 11(1), 15–28, 2020.

[5] P. Liu, Y. Guo, F. Wang, and G. Li, Chinese named entity recognition: The state of the art. *Neurocomputing*, 473, 37–53, 2022.

[6] G. A. Atemezing, and A. Huynh. Knowledge graph publication and browsing using Neo4J. Paper presented at: The 1st workshop on squaring the circle on graphs2021.

[7] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:181004805*, 2018.

[8] D. C. Wintaka, M. A. Bijaksana, and I. Asror, Named-entity recognition on Indonesian tweets using bidirectional LSTM-CRF. *Procedia computer science*, 157, 221–228, 2019.

[9] Z. Huang, W. Xu, and K. Yu, Bidirectional LSTM-CRF models for sequence tagging. *arXiv preprint arXiv:150801991*, 2015.

[10] T. Zhang, and F. You. Research on short text classification based on textcnn. Paper presented at: Journal of physics: conference series2021.

[11] Y. Qin, G.-w. Shen, W.-b. Zhao, Y.-p. Chen, M. Yu, and X. Jin, A network security entity recognition method based on feature template and CNN-BiLSTM-CRF. *Frontiers of information technology & electronic engineering*, 20(6), 872–884, 2019.