Research on Tourism Question Answering System Based on Xi’an Tourism Knowledge Graph

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Abstract. Question answering (QA) system provides a direct, efficient and accurate way for people to obtain information. At present, open domain QA systems such as Siri and Cortana are widely used in the general field, but they cannot meet the demand of some professional fields. This paper focuses on the background and needs of QA in the tourism field, researching the relevant technologies required for the implementation of QA system, and finally completes the construction of QA system based on the knowledge graph of tourism. The main research contents of this paper are as follows: 1. An algorithm to identify the tourism entities in questions is proposed according to the characteristics of the tourism entities. 2. Referring to the ideas of Liu et al., a convolutional neural network (CNN) model is introduced into attribute linking, but in order to improve the accuracy of attribute linking, we move the similarity calculation of questions and attributes from the outside of the model to the input layer of the model, and also introduce Attention mechanism. Integrate the technology of each module to design and implement a QA system for tourism. We experiment with the system on the constructed Xi’an tourism knowledge graph, and the results prove that the system we designed can answer the natural language questions raised by users about tourism.

1. Introduction

In recent years, with the growth of knowledge graph, people are paying more and more attention to seeking effective methods for applying these intellectual resources. To meet the needs of users, knowledge graph-based question answering (KG-QA), which takes natural language as query language and directly returns answer from the knowledge graph, has become a research focus.

Question answering is auto replying to specific answers to natural language questions raised by users. There are two mainstream research directions for QA: semantic parsing-based (SP-based) method and information retrieve-based (IR-based) method. SP-based method focused on converting natural language questions into a series of formal logical forms. Berant J et al. [1] proposed a novel semantic parsing framework for question answering using a knowledge base. Fader A et al. [2] considered the problem of open-domain question answering, and achieve robustness by breaking fully open questions into smaller subquestions, including problem interpretation and query reformulation. IR-based method was tend to extract effective features from questions and extract answers through comparison with the knowledge in the knowledge graph. Yao et al. [3] proposed an information extraction method combining problem features and features in Freebase topic map, and in order to make up for the problem of domain mismatch or overfitting, mining and mapping among ClueWeb corpus, KB relation and natural language text was used to obtain the correlation degree relation between each relation R and the whole problem Q. Bordes A et al. [4] proposed based on a Freebase, according to the problems in keywords in the knowledge base to determine the candidate answers, construct a model to study problems and the
representation of the candidate answer, and then through the representation of correlation to calculate questions and candidate answers to choose the correct answers, the discomfort list, rules, syntax and dependency tree analytical conditions, such as beyond the best results. As deep learning develops, a neural network based (NN-based) method was introduced to the QA task and has achieved impressive results. NN-based methods belong to IR-based method, the difference is the NN-based method is used word vector as input. Dong L et al. [5] introduced the multi-column convolutional neural network to understand the problem, which does not rely on manual features and rules, and trains the column network and word vector in the way of multi-task learning by using problem definition. Chen et al. [6] presented a neural attention-based model to represent the questions and leveraged the global knowledge inside the underlying KB, aiming at integrating the rich KB information into the representation of the answers. Lan Y et al. [7] explored the use of a “matching-aggregation” framework to match candidate answers with questions and made use of question-specific contextual relations to enhance the representations of candidate answer entities. Su L et al. [8] proposed an answer acquisition method for KBQA systems based on a dy-namic memory network. Jin H et al. [9] presented ComQA-a three-phase KBQA framework by which end-users can ask complex questions and get answers in a natural way.

With the development of KG-QA, the service in the general field of QA system such as apple's Siri has been able to be used by users [10]. However, there are few researches on KG-QA system in professional field, especially in the field of tourism [11-14]. Tourism has become the most dynamic industry in the global economy. Tourists have higher and higher requirements for tourism services, but the existing mainstream search engines cannot meet people's needs. Therefore, it is of great significance to research the KG-QA in the field of tourism. In our work, we mainly study the QA system based on Chinese tourism domain knowledge graph.

In summary, the contributions of this paper are as follows:

- We propose an entity recognition algorithm to identify the entity in natural language question.
- We refer to the idea of liu et al. to introduce the CNN model for attribute linking. The difference is that we calculate the similarity between the question and the attribute words at the input layer of the model, and introduce the attention mechanism to weight the result of the similarity degree, and get the final attribute after the convolution pooling operation.
- Integrate the technology of each module to design and implement a QA system for tourism and finally the experiment is carried out in the constructed Xi'an tourism knowledge graph, and the result proves that our system can get the correct answer.

2. System Detail

Figure 1 shows the Overview of the KG-QA System Framework. For the natural language question raised by users, QA system firstly uses entity recognition algorithm to identify the entity in the question, and links the identified entity with the entities in the knowledge graph to find the entity with the highest similarity with the question entity. Then, the CNN model is used to link the question and the attributes of the knowledge graph to find the attribute of the knowledge graph that match the question well. Finally, we extract answer from the knowledge graph based on the entity and attribute obtained from the links. We will describe these sections in detail as the following. In section 2.1, an entity matching introduced: an entity recognition and entity linking, mainly introducing the entity recognition algorithm proposed according to the characteristics of Chinese tourism entities. In section 2.2, the improving CNN model is described applied in attribute linking. In section 2.3, we described how to extract the answer based on the matching entity and attribute.
2.1. Entity Matching

Entity matching is divided into two parts: entity recognition and entity linking. Entity recognition aims to identify entity from natural language questions. Entity linking is to link the entities in the knowledge graph to match the entity with the highest similarity with the question entity.

Because English words are divided by Spaces, but there is no obvious mark of division of words with Chinese, it is necessary to segment the question first, and then to identify the entity. Chinese word segmentation is based on the existing word segmentation table. However, entities such as tourist attractions in the tourism field are constantly updated, so it is unrealistic to add every entity to the word segmentation table. However, the inaccuracy of word segmentation will lead to the decrease of the accuracy of entity recognition. To solve this problem, we have carried out many experiments on word segmentation and part of speech tagging on tourism entities, and found that most tourism entities are composed of nouns. Based on the characteristics of tourism entities and the grammatical characteristics of Chinese questions, we design a tourism entity recognition algorithm.

After identifying the question entity, in order to get the accurate value in the knowledge graph, we need to link the obtained entity with the entity set in the knowledge graph to get the final entity. The flow chart of the entire entity matching algorithm is shown in Figure 2.

2.2. Attribute Matching

Attribute matching refers to attribute linking. Unlike entity matching, which consists of entity recognition and entity linking, attribute matching only requires attribute linking, that is, directly linking the question with the attributes in the knowledge graph.
Lin et al. [15] extracted the attribute semantic information in the problem through the CNN model and processed all the attributes in the knowledge graph in the same model. Then the similarity algorithm is used to calculate the similarity between the extracted problem feature and the extracted attribute feature. This section refers to the above idea and introduces CNN model into the attribute linking experiment. The difference is that we calculate the similarity in the input layer of CNN. We send an attribute in the knowledge graph and the natural language question into model at the same time, calculate the similarity between the two, convolution pooling the similarity matrix, and finally link to the correct attribute.

**Input layer**: this layer receives the text data of questions and attributes, maps questions and attributes into word vectors after word segmentation, calculates the similarity between question words and attribute words respectively, and finally obtains the similarity matrix.

**Convolution layer**: this layer receives the similarity matrix obtained by the input layer and convolves the matrix. Convolution operation is essentially a process of extracting local features through "sliding window". The sliding window starts from the upper left, from left to right, and from top to bottom, and moves by a fixed distance each time. In our work, the size of sliding window is set as 2*2, formula (1) is used for convolution operation:

\[ Z = W \ast X + b \]  

(1)

Where \( X \) represents the matrix vector, \( W \) is the weight of the convolution layer, and \( b \) is the bias. It is important to note that all data shares weights and offset values.

**Pooling layer**: after the convolution operation of similarity matrix, the result matrix is transferred to the pooling layer. The pooling layer is mainly to retain the main features, while reducing the parameters and calculations of the next layer to prevent overfitting. Common average pooling and maximum pooling are commonly used. Common pooling operations include mean-pooling and max-pooling. Mean-pooling is the calculation of the average value of the local area and max-pooling is the calculation of the maximum value of the local area. Since the text similarity calculation focuses on the value with high similarity, this paper adopts the max-pooling method to achieve the pooling layer, that is, to select the maximum value in the local area.

**Output layer**: after the pooling operation is completed, the results are fed into the output layer. The output layer realizes the full connection of the convolution layer, the pooling layer and sets condition to end the convolution pooling cycle. The average value of the data obtained after the end of the cycle is calculated, and the attribute with the highest average value is output.

2.3. **Attention Mechanism**

The visual attention mechanism is a brain signal processing mechanism peculiar to human vision. Human vision quickly scans the global image to obtain the target area that needs attention, and then invests more attention resources in this area to obtain more detailed information about the target that needs attention, and suppress other useless information. In essence, the attentional mechanism in deep learning is similar to the selective visual attentional mechanism of human beings. The core goal of the attention mechanism applied to the question and answer task is to select information that is more critical to the current task goal from a large amount of information [16-17].

In order to make the important information be perceived by the model, we introduce the attention mechanism into the input layer of the model and make attention weighting for the similarity obtained after calculation. The attention-weighted formulae (2) and (3) are as follows.

\[ A_{i,j} = score(Q[i:], p[j:]) \]  

(2)

\[ score(x, y) = \frac{1}{1 - dis(x,y)^2} \]  

(3)

We define \( Q \) in the formula to represent the problem, \( i \) represent the word after the word segmentation, \( p \) is the attribute word segmentation, and \( j \) is the word after the attribute word segmentation, and \( dis(x, y) \) represents the similarity between \( x \) and \( y \).

2.4. **Answer Select**
Choose the answer based on the entities and attributes in the knowledge graph linked to in sections 2.1 and 2.2 above. This means, we simply compare the linked entities and attributes to the triples in the knowledge graph and if the entity and attribute of the triples are equal to the entity and attribute of the links, then the attribute value of the triples is the final answer.

3. Evaluation Results and Discussions

In this section, we first detail the data sets applied in the experiment in section 3.1. We evaluated the entity matching algorithm and attribute matching model in sections 3.2 and 3.3, respectively. In section 3.4, we show screenshots of the results of the QA system.

3.1. Data set

We use two data sets in our experiment. One data set is the self-constructed graph of Xi’an tourism knowledge, and the other is the data set provided by The Conference on Natural Language Processing and Chinese Computing (NLPCC).

1. Knowledge Graph of Xi’an Tourism. The entities in this knowledge graph include tourist attractions in Xi’an, restaurants, hotels, and shopping centers near the attractions, as well as introductions, address and prices of attractions, restaurants, hotels, and shopping centers. These entities are crawled from different travel websites, and the data is cleaned and imported into the neo4j graph database. The relationship attributes were set between the related entities, and finally a Xi’an tourism knowledge graph with more than 1,400 triples stored was obtained.

2. NLPCC2016KBQA data set. NLPCC is an annual academic conference of the CCF Chinese Information Technology Professional Committee sponsored by the Chinese Computer Federation, focusing on academic and applied innovation in the fields of natural language processing and Chinese computing. The data set used in the experiment is from the NLPCC ICCPOL KBQA task set, which contains a training set of 14,609 question-answer pairs and a test set of 9,870 question-answer pairs.

3.2. Entity Matching Evaluation

Since the entity recognition algorithm is proposed according to the characteristics of tourism entities, the constructed Xi’an tourism knowledge graph is used to carry out the entity recognition experiment. Entity matching includes entity recognition and entity linking. We combined the two experiments for evaluation. For entity linking, we use cosine similarity algorithm and jaccard similarity algorithm.

Among them, the cosine similarity is the cosine of the Angle between two vectors in the vector space as a measure of the size of the difference between two individuals, and the Gerald similarity is the ratio of different elements in two sets to all elements to measure the degree of difference between two sets. The evaluation results are shown in table 1.

| Algorithm | Jaccard distance | Cosine distance |
|-----------|------------------|-----------------|
| Evaluation result | 83.56% | 83.99% |

As can be seen from table 1, there is little difference between the accuracy of Jaccard similarity algorithm and that of cosine similarity algorithm in the entity link part. However, since Jaccard distance is highly dependent on the number of characters, we finally apply the cosine distance similarity algorithm to our experiment.

3.3. Attribute Matching Evaluation

The attribute linking experiment required both questions and attributes, so the constructed Xi’an tourism knowledge graph could not be used for evaluation. We used the NLPCC2016KBQA dataset for...
evaluation. The input of the CNN model uses the word vector trained by the Chinese wikipedia. The toolkit used for training is Google's open source word2vec, the model used is skip-gram, and the resulting word vector has a dimension of 400. The experiment is to reversely extract the attributes in the knowledge graph to form an attribute set, send each attribute and question to the CNN model for calculation, and output attribute with high similarity. Finally, determine whether the obtained attribute is accurate according to whether the output attribute is the same as the given attribute. We conducted four experiments: an experiment based on the ideas of Liu et al. with the attention mechanism (LA-CNN); an experiment with sequential adjustment of the above idea (SA-CNN); and an adjustment and increase of the attention mechanism experiment (ASA-CNN); experiment without removing stop words (N-ASA-CNN). The evaluation results of the three experiments are shown in Table 2.

| Model          | LA-CNN     | SA-CNN     | ASA-CNN     | N-ASA-CNN   |
|----------------|------------|------------|-------------|-------------|
| Training data set evaluation results | 37.16%     | 31.85%     | 39.31%      | 35.89%      |
| Testing data set evaluation results   | 43.52%     | 37.36%     | 45.71%      | 41.11%      |

3.4. Answer Select Results

QA system includes entity matching, attribute matching and answer selection, in which the first two parts are for the last part of the service. After matching the entity and attribute, select the answer. Figure 3 shows an example of how our QA system is implemented step by step. The user enters a question "大唐芙蓉园的地址是什么 (What is the address of Datang Furong Garden)". After entity matching and attribute matching, the entity "大唐芙蓉园 (Datang Furong Garden)" is obtained, the attribute "地址 (Address)" is obtained, and the triple is traversed according to the matched entity and attribute. Finally found the answer "西安市曲江新区芙蓉西路 99 号 (No. 99 Furong West Road, Qujiang New District, Xi’an)".

We asked questions on the QA system many times and got the correct answers, the results are shown in figure 4.

4. Conclusion

In our work, we mainly focus on the research of QA system based on tourism domain knowledge graph. We use the proposed entity recognition algorithm to identify question entity. We adjust the order of Liu
et al’s idea of attribute linking, first calculating the similarity between question and attribute and then feature extraction. The entire calculation process is performed in the CNN model. In order to improve the accuracy of the model, we also introduce the attention mechanism to the input layer of the model. Finally, we combined all the technologies in Chapter 2 to we build a QA system and verified it on the tourism knowledge graph of Xi’an. The experimental results show that the tourism domain QA constructed by us can be applied to the tourism domain knowledge graph.

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