Journal on Artificial Intelligence
DOI:10.32604/jai.2020.011541
Article

Tech Science Press

A Survey of Knowledge Based Question Answering with Deep Learning

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Received: 21 May 2020; Accepted: 15 July 2020

Abstract: The purpose of automated question answering is to let the machine understand natural language questions and give accurate answers in the form of natural language. This technology requires the machine to store a large amount of background knowledge. In recent years, the rapid development of knowledge graph has made the knowledge based question answering (KBQA) more and more popular. Traditional styles of KBQA methods mainly include semantic parsing, information extraction and vector modeling. With the development of deep learning, KBQA with deep learning has gradually become the mainstream method. This paper introduces the application of deep learning in KBQA mainly from the following aspects: the development history of KBQA, KBQA methods using deep learning, common datasets used in KBQA, the comparison of various methods and the future trend.

Keywords: Deep learning; question answering; knowledge graph

1 Introduction

The question answering system refers to the technology that allows a machine to process the input questions from users and give corresponding answers. It is an advanced form of information service. From the input form, the question answering system no longer needs the user to consider how to design the formal question [1]. Unlike previous search engines, it does not return a list of relevant documents which is based on keywords, but directly convert to the correct answer using natural language. Therefore, question-answering is often seen as one of subversive technologies in the field of artificial intelligence. It has very important academic significance and application value.

A question answering system generally needs analytical understanding of the question and queries of the background knowledge. According to different sources of background knowledge, it can be divided into document-based question answering and knowledge-based question answering. The former task is called machine reading comprehension. It requires the machine to search for answers to questions from a given passage based on understanding the questions. The latter task, called KBQA, requires the machine to search or reason for correct answers based on a structured knowledge graph.

The knowledge graph is a concept put forward by Google in 2012, and its essence is the knowledge base of the semantic network. The knowledge graph transforms a large amount of Internet text data into structured knowledge through information extraction, association, and fusion [2]. The most common data format is a triple like “head entity-relationship-tail entity” or “entity-attribute-attribute value”. A large number of entities and their mutual relationship together constitute a huge semantic knowledge network, which is called the knowledge graph. The focus of KBQA research is how to understand the meaning of the question and to use the prior information of the knowledge base to get the answer.

There are three traditional styles of KBQA methods: Semantic parsing, information extraction, and vector modeling.

The semantic parsing (SP) style is a linguistic method. The main idea is to transform natural language questions into a series of logical form components, and then construct a bottom-up grammar tree for logical forms. By processing the logical form through a logical language such as Lamda-DCS [3], a query can be generated that can be manipulated directly in the knowledge base. Fig. 1 is a classic example of semantic parsing. The question "When was the plane invented" can be transformed into "Type.Time∩ThingInventTime.Plane."

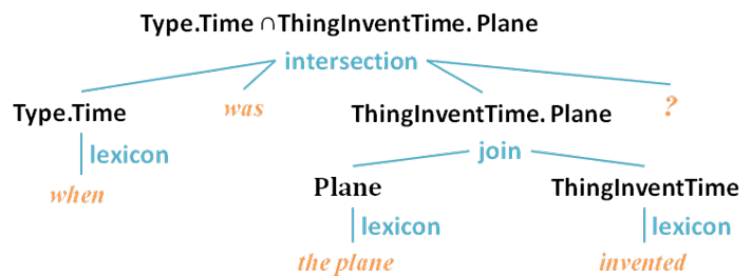

Figure 1: Process of sematic parsing

The information extraction (IE) style is another main algorithm framework of KBQA. It first determines the topic entity in a question, and then links it to an entity in the knowledge graph. The entity and its neighbors can be used to generate a query subgraph, and each node in the subgraph is a candidate answer to the question. The algorithm will extract the information of the problem to obtain its feature vector, and then establish a classifier to filter the candidate answers, and finally obtain the highest node as the answer.

The vector modeling style (VM) style is similar to the information extraction style. The first step is to determine the topic entity of the question, and then generate the topic subgraph according to the corresponding linking entity in the knowledge base and its surrounding nodes. However, unlike the IE style, the VM style maps the question and candidate answers of the training set to vectors of the same low-dimensional space to obtain their distributed expressions. The algorithm will then train a model based on these data to make the mapping vector of the question and the corresponding answer as close as possible in the low-dimensional space. Using the trained model, we can filter the candidate answers and select the answer which has the highest score. IE and VM are sometimes treated as the same kind of algorithm. The rest of the paper also refers to them as the IE style.

Since 2015, deep learning technology has been widely used in KBQA. Methods of KBQA that use deep learning can also be divided into two main paradigms: semantic parsing with deep learning and information extraction with deep learning. The former mainly add various neural network models to the traditional semantic parsing framework to improve specific components, such as feature extraction, relationship recognition and similarity calculation. The latter mainly uses deep neural networks when mapping questions and answers to low-dimensional spaces and calculating their similarity. This type of method is sometimes seen as an end-to-end system based on deep learning.

The rest of this paper is organized as follows: Section 2 introduces information extraction methods using deep learning, Section 3 introduces semantic analysis methods using deep learning, and Section 4 introduces the dataset related to KBQA field. Section 5 analysis currently challenges and future trends. And Section 6 summarizes the full paper.

2 Information Extraction with Deep Learning

The information extraction method maps the natural language questions and the entities and relationships of the knowledge base to feature vectors in the same low-dimensional space, and then transforms the task into similarity matching between the question-vectors and vectors of corresponding entities and relationships in the knowledge base.

In the early information extraction method, the vector representation of the question is mostly based on simple models like bag-of-words. Although this method avoids the trouble of manually extracting features, it also ignores the grammatical structure of the question. In this way, it is difficult for the algorithm to correctly handle questions like “Bob’s father’s mother’s son” and “Bob’s mother’s father’s son”. Similar approachs are also used for candidate answers, which results in the model not being able to effectively utilize the information in the knowledge base.

In order to improve this situation, new types of network need to be used in computing the distributed representation of questions and candidate answers. There have been many related work attempts to add different kinds of deep neural networks in this process, such as convolutional neural network (CNN), attention mechanism, and memory network.

2.1 CNN

Yih et al. [4] uses CNN instead of traditional bag-of-words to calculate the vectorized representation of questions and answers. As an early attempt to apply deep learning to KBQA, this article focuses on single-relationship questions, which are most common on various community sites. Examples of such questions include: “Who is the president of America?” and “Who invented the basketball?” The author built a semantic-based CNN model (CNNSM) to train two different mapping models: One links a mention from the question to an entity in the knowledge base and the other maps a relation pattern to a relation.

CNNSM’s key idea is to use CNN to map the relationship patterns in natural language questions and the relationships in the knowledge base to the same low-dimension space. Many of other deep learning methods are similar. The difference is that the networks they use are different. Further, CNN can detect entities in the knowledge base and mentons in questions. Therefore, CNNSM is able to calculate the semantic similarity between the input question and the candidate triples, and then select the answer based on the score order.

It can be seen that the CNN used in CNNSM is obviously superior to the traditional bag-of-words method. The latter simply marks the existence or absence of the word in the question and loses a lot of semantic information. The network model in CNNSM handles the question as a letter-trigrams vector, which helps the model go beyond the form of word representation and solves the out-of-vocabulary (OOV) problem. This is a successful attempt by the deep learning model in KBQA. Although this method is mainly for simple single-relation questions, it is still very instructive.

Dong et al. [5] proposed a multi-column convolutional neural network (MCCNN) model, which is a further exploration of the use of CNN in KBQA. The vectorization method of the answer in the traditional information extraction style has two main drawbacks: one is that it does not consider the word order of the question, which makes it impossible to distinguish between “Who’s Bob’s mom’s son” and “Who’s Bob’s son’s mom”. This can be solved by adding a simple CNN. The other is that traditional models cannot distinguish some features of answers: Answer Tpye, Answer Context (the knowledge base submap around the entity), Anwser Path (the path between the subject and the answer). For this problem, the author coded these three features separately using different CNNs.

Compared with the traditional information extraction method, MCCNN uses CNN to actively explore the path between the topic entity in the question and the candidate answers in the knowledge base, as well as the expected answer type. The author confirmed in the experiment that these two features have a greater impact on the screening of answers. In addition, MCCNN’s network framework has good scalability.

Although CNN can effectively improve the model’s ability to understand questions, MCCNN cannot handle questions like “who is Bob’s first son” because such methods are limited by the “retrieve-vectorization-sort” framework based on the topic subgraph. This is because the information extraction style lacks deep semantic analysis of the question, and the subsequent chapters will discuss in detail the comparison between semantic analysis and information extraction.

2.2 Attention Mechanism

The attention mechanism was first applied to the field of images [6], which simulates the attention of the human brain's focus. For example, while viewing an image, although we accepted the entire image, we focused on the objects of interest in the image. That is to say, people have different weights for the degree of attention of each position in the picture. In the NLP field, the attention mechanism was first applied to machine comprehension and showed good results.

As mentioned above, the deep learning-based information extraction method can be divided into several main steps: determining the topic entity, determining candidate answers according to the topic entity, calculating distributed expressions of questions and answers, and calculating their similarities. The core of each method is how to get an effective distributed representation of the question and candidate answers.

Zhang et al. [7] tried to use attention mechanism in KBQA. The starting point is that for different types of answers, the focus of our concerns is different. Based on the information of the candidate answers, we can calculate different distributed expressions of the same problem.

Similar to MCCNN, Zhang believes that the features of the answer can be divided into the answer entity, the answer type, the answer context (the entity connected to the answer entity in the knowledge base subgraph), the answer relationship (the relationship between the subject word and the answer entity), and so on. Take the question "Who is the American president", one of the candidate answer entities is "Barack Obama", so the "president" and "American" in the question are the main focus of the question. When considering the answer type/business/board_member, "who" should be the most important word. Some questions may be more concerned with the type of answer, while in others, the answer relationship may contain the most important information. This shows that the focus will change with different questions and answers. Obviously, in order to achieve this function, we need to design attention mechanisms in the model to help us find out which form of expressions of the answer is the most appropriate. Unlike MCCNN, Zhang et al. used novel crossover-focused neural networks instead of CNNs with different parameters to handle different answer features.

The cross-attention model includes answer-towards-question attention and question-towards-answer attention. The former attaches weights to the words output by the LSTM according to the embedded expression of the answer, this is useful for learning flexible and ample question representation, and the latter help adjust the question-answer weight. After the model is trained, the similarity between the question and the answer can be calculated at different angles. Then we can obtain the final score of the candidate answe after the weighted summation.

2.3 Memory Network

Memory networks are another emerging neural network model. People want machines to be able to call the information contained in the intrinsic memory like humans when dealing with certain questions (machine translation, dialogue systems). For machines, these forms of memory include the context of the document and the knowledge base. Many memory models have been born, one of the most famous memory models is the long and short memory network LSTM, which retains historical input information. But this kind of network is essentially an internal expression, and its mechanism is similar to computer memory, so it only stores a part of short-term memory, which will be eliminated when the task ends.

In order to simulate human long-term memory of knowledge, it is necessary to simulate the memory mechanism of external expression, just like the hard disk of a computer. Two well-known memory models, neuroturing machines and memory networks have been born in this field. The memory network is ideal for KBQA.

Facebook AI invented the memory network in 2014 [8] and proposed an improved version the following year [9]. The network mainly includes four modules of I, G, O and R, and its structure is shown in the Fig. 2. Where the module I encodes the input sentence into a vector, G updates the memory slot based on the vector, O is responsible for the output vector, and R decodes the output vector into a natural language. In this process, the module O first selects the memory most relevant to the input question, and takes the resulting output together with the input as a new input, and then gets the memory most relevant to them. The model will repeat this process to output top-k answers that are most relevant to the input question.

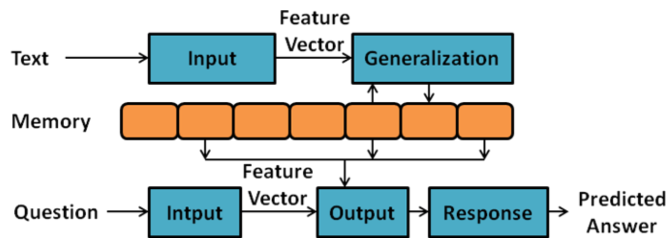

Figure 2: Memory Network

Bordes et al. first applied memory networks to KBQA [10]. The motivation for this article is that the authors believed that simple questions based on <object, relation, object> triples are still not well solved, So they built a Simple Question dataset consisting of this type of questions, where the answer to each question is the tail entity in the triple. In addition, the authors stored the content of the knowledge base as an external memory in the memory module to test the performance of the memory network on the dataset. The article flow is divided into three steps: storing knowledge, training the network, and connecting the new knowledge base Reverb to test the generalization ability of the model.

In the storing procedure, the author selected two subsets of Freebase [11], FB2M and FB5M, as the knowledge base. And after doing some preprocessing, they stored the entries in the form of bag-of-symbols into the memory slot. The output module converts the question into a form of bag-of-ngrams, and then activates the associated entries from the memory as candidate triples. After the correlation calculation, the output component performs a decoding operation on the selected triple with the highest score to obtain the final answer. This work validates the enormous potential of memory networks to manage large-scale knowledge base entries.

Miller et al. [12] have improved the method of using the key-value pair mechanism to make it more efficient to store the prior knowledge from different data sources required by QA. Thus memory network can be better applied to KBQA tasks. The author believed that QA based on knowledge base has structured knowledge that is convenient for query, but the knowledge is incomplete, and the answers to many questions cannot be found in the knowledge base. QA based on wiki documents has a wider coverage of knowledge, but because the included knowledge is unstructured and cannot directly find the answer, it is often necessary to contact multiple documents for reasoning. In order to be able to synthesize the advantages of documents and KB, the author proposed an improved memory network, with the subject/entity in the KB or the sentence in the document as the key, the object in the KB or the word window in the document as the value. This flexible storage mechanism enables it to use KB, wiki documents, and IE as prior knowledge. In addition, a new dataset MovieQA was proposed in the article to verify the function of the memory network.

3 Semantic Parsing with Deep Learning

Information extraction combined with deep learning shows good results when solving simple questions, but due to the limitations of its overall algorithm framework, such methods cannot solve questions with complex semantics. This is because ordinary neural networks have difficulty recognizing the various constraints and implicit information that exist in a question. At present, in order to make the QA system better handle more complex questions, it is still necessary to perform semantic analysis on the question itself. Just as different information extraction methods use different kinds of neural networks, each semantic analysis method also uses unique grammar rules to deepen the understanding of the question.

Yih et al. [13] not only applied deep learning to KBQA based on semantic parsing, but also borrowed the concept of query subgraphs in the information extraction paradigm. Their query graphs have more complex structures. The generation process of the query graph mainly includes: topic entity linking, core inference chain, adding constraints to expend the query graph.

The query diagram proposed by the author contains four types of nodes: grounded entities, existing variables, lambda variables, and aggregation functions. The grounded entity is the real entity in the knowledge base. The existing variable mainly refers to the intermediate node (like the CVT node of Freebase), the lambda variable refers to the answer entity, and the aggregation function is used to represent the constraint in the question. Fig. 3 is an example of a query graph. This query graph has some additional conditions than the query graph used by the information extraction method.

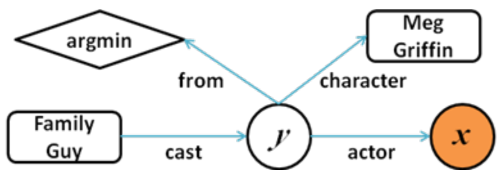

Figure 3: A query subgraph

Therefore, the task becomes the generation of the stage query graph (the model is abbreviated as STAGG) and selects the most appropriate query graph. Considering that the traditional semantic parsing method does not use the information of the knowledge base, the author uses the knowledge to pruning in the search process of generating the query graph, which greatly reduces the search space.

3.1 Topic Entity Linking

This is the first step in the query graph generation process. The subject entity defines the range of nodes in the query graph, so incorrect links can lead to invalid reasoning. The authors use an entity linking system that is designed for short and noisy text. The accuracy of the entity link directly affects the performance of the entire algorithm. According to the author's analysis, about 8% of the errors came from incorrect entity linking. In addition, the author tested the effect of using the Freebase API as a linking tool, which caused the F1 score to drop by 4.1%.

3.2 Core Inference Chain

This step is used to derive the relationship between the subject entity and the answer entity. When the subject entity e is determined, the model will explore legitimate predicate sequences that can start from e. The predicate sequence also represents the path of the subject entity to the answer entity. In order to limit the search space, the path length is limited to 2. After all core inference chains are generated, CNN is used to measure the semantic similarity between the question and the predicate sequence.

3.3 Deep Convolutional Neural Networks

The author uses a siamese network to calculate the similarity between the question and the core chain of reasoning. The siamese network model consists of two networks dedicated to identifying whether two different inputs belong to the same class. In STAGG, one network is used for question patterns and the other is used for reasoning chains. After being processed into the form of letter-trigrams, the natural language is input into the network, and the feature vector is output after operations such as convolution and pooling.

3.4 Enhanced Constraints and Aggregation

In order to explicitly extract semantic information from questions, the authors consider constraints and aggregations. Without these, it may lead to an answer node pointing to more than one entity. In the example of "Who first voiced Meg on Family?" the model will output two actors who have been overtoned for Meg without the constraint "first".

By observing the questions in the training dataset, the authors proposed some rules to determine whether to add constraint nodes. These rules include: Whether the constraint entity appears in the question, some words in the name of the constraint entity appear in the question, the question contains the words “first, oldest, last, latest, from, to”. In addition, the process of observing questions and answers includes the identification of gender and kinship. These explicit operations can more clearly resolve the question semantics, but they also cause trouble for the algorithm design.

4 Datasets

High-quality knowledge base is critical to building a KBQA system. And also, KBQA research requires common Q&A datasets to compare the performance of different systems. Tab. 1 and Tab. 2 show some important knowledge base and Q&A datasets.

4.1 Freebase

Freebase, built by MetaWeb in 2007, is an open shared database of cross-linked data [11]. Google took over Freebase in 2010 and then migrated its data to Wikidata in 2015. Freebase knowledge was mainly build by artificial methods. Its data sources are mainly from Wikipedia, NNDB, Flickr and MusicBrainz. As of the end of 2014, Freebase already contained 68 million entities, 1 billion relationship information, and more than 2.4 billion factual triples.

4.2 DBPedia

DBPedia is a project aiming to extract structured content from the information of Wikipedia [14]. The 2016 release of the DBpedia dataset describes 6.0 million entities, out of which 5.2 million are classified in a consistent ontology. The types of the ontology include persons, places, music albums, films, video games, organizations, species and diseases. DBpedia uses the Resource Description Framework (RDF) to represent extracted information and consists of 9.5 billion RDF triples.

4.3 YAGO

YAGO is an open source knowledge base [15]. It is also mainly extracted from Wikipedia. As of 2019, YAGO3 [16] already contained more than 10 million entities and more than 120 million facts about these entities.

Table 1: KBQA knowledge base

Knowledge base	Year	Data source
Freebase	2007	Wikipedia, IMDB and Flickr
DBPedia	2007	Wikipedia
YAGO3	2013	Wikipedia, WordNet and GeoNames

4.4 WebQuestions

Webquestions, first proposed by Berant in 2013 [17], is one of the most used conmmon datasets for KBQA. The dataset is based on the Freebase construct and contains 5,810 question-answer pairs.Webquestions does not contain formal queries, which makes model training difficult.

4.5 SimpleQuestions

Simplequestions is built by Bordes et al. [10]. It is also based on Freebase. The whole dataset consists of simple questions, each of which can be answered based on a simple triple <object, relation, object>.

4.6 QALD

Question answering over linked data (QALD) challenge is a series of open evaluations on question answering over linked data since 2011 [18]. It is built on DBPedia and YAGO. QALD is small but contains more complex and colloquial questions.

Table 2: KBQA datasets

Datasets	Source	Questions	Complex questions
WebQuesions	Freebase	5810	Yes
SimpleQuesions	Freebase	108442	No
QALD	DBPedia&YAGO	50-500	Yes

5 Trend and Challenges

5.1 IE vs. SP

Through the analysis of the semantic analysis paradigm and the information extraction paradigm in the previous article, we can see that both have their own advantages and disadvantages. The information extraction method can rely on the neural network to automatically extract the features of the questions and answers, which makes the overall framework design of the algorithm clearer and simpler, and has good portability. On the other hand, due to the black box property of deep neural networks, such methods often do not adequately explain the meaning of the calculated distributed expression. The advantage of the semantic analysis method is that the results of the experiment can be well analyzed by using the manual design features. Correspondingly, this approach causes the algorithm to rely heavily on the content and type of the question in the dataset, so when faced with different question datasets, it is usually not possible to achieve better scalability. In addition, this also makes the design of the algorithm more complicated. Fig. 4 shows performance of different methods of KBQA on the Webquestion dataset. At present, the effect of semantic parsing with deep learning is better than other methods. Information extraction mainly focuses on simple problems and does not perform well when multiple entities or constraints are involved.

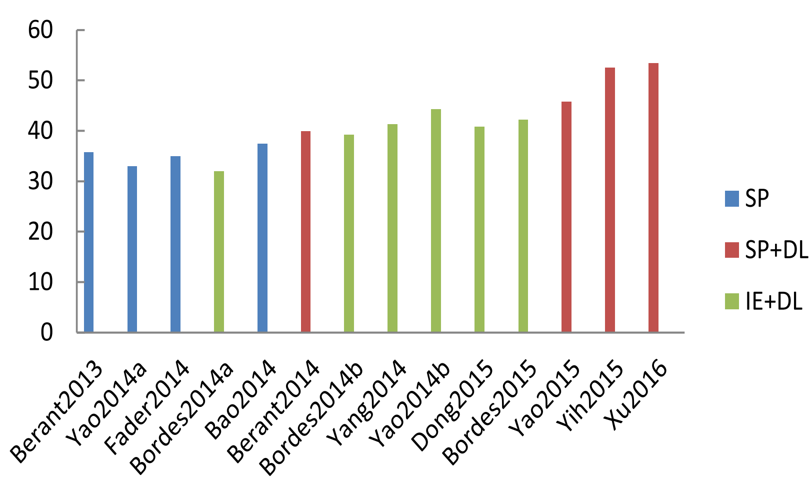

Figure 4: F1 Scores of different KBQA methods on Webquestion

5.2 Trend

With the addition of deep learning, the gap between the semantic parsing paradigm and the information extraction paradigm begins to shrink. Taking STAGG [13] as an example, many KBQA algorithms that have emerged in recent years have tried to combine the two paradigms, which allow them to combine the advantages of both. The concept of topic subgraph proposed in the information extraction style is similar to the way human thinking, and the semantic parsing style can better grasp the constraint information in the question. Therefore, how to design an excellent neural network that can better integrate the two paradigms is a trend in the future.

The performance of KBQA depends to a large extent on the quality of the knowledge base, but the size and integrity of the existing open knowledge base need to be improved. Therefore, the automatic and efficient construction of the knowledge base will be an important research direction. Future knowledge base systems should have the ability to automatically mine hidden relationships, which helps the system to update content in a timely and accurate manner. In addition, how to make good use of the prior knowledge of the knowledge base is also very important. Memory networks have proven to be an effective approach, and more complex memory networks may be one of the important research directions.

6 Conclusion

In this article, we review the history of the KBQA system, especially after deep learning has been added. We have introduced the KBQA system of information extraction and semantic analysis in detail, and introduced several typical papers that use deep learning techniques to improve these two methods. Later, we introduced the public datasets that are common in the KBQA domain. Finally, we carefully explored the current problems and future trends based on current research content and progress.

Funding Statement: The author(s) received no specific funding for this study.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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