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Question Answering System Based on Neural Networks

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Abstract: This paper presents a neural network model for Arabic Question Answering(QA) , that is capable of generating answers to simple factoid questions, with the help of the facts in a knowledge-base. The model is constructed for sequence-to-sequence learning. It has the ability to consult the knowledge-base, and a corpus of question-answer pairs with their associated triples in the knowledge-base. The experimental results demonstrate that the proposed model can effectively handle the variations of questions and answers, and produce correct answers in natural language text by utilizing the facts stored in the knowledge-base.

Keywords— **Question Answering, Neural Network, Information Retrieval.**

I. Introduction

In the era of information explosion, the way of information storage highlights the revolution of information query. In the era of relational database, Standard Query Language is employed to query data. In the era of Web , search engines (e.g., Google) are used to retrieve information(Liu et. al, 2016). In the age of artificial intelligence, neural networks and knowledge-bases are adopted for these purposes. Recently, deep learning approach is being adopted in the field question answering. That is, a neural network is used for generating the answer (e.g., using Recurrent Neural Network(RNN)) based on the question being asked. We propose a model that employs deep learning techniques. More importantly, the proposed model is trained in an end-to-end manner, and based on that there is no need to construct the QA system using linguistic approach, e.g., creating linguistic tools like semantic parser. However, there is one drawback of this approach to QA, storing all the knowledge in a neural network to satisfy a desired precision in real QA is practically impossible. Making this as a difficulty, which goes deeply in the method in which knowledge is acquired, represented and stored. The more generally and fully distributed way of representation and neural network is valuable at representing smooth and shared patterns, i.e., modeling the variety/diversity and flexibility of language. On the other hand, the success of memory-based neural network models has highly expanded the ways of storing and accessing text information, either in short-term memory (Bahdanau et al., 2015) or in long-term memory (Weston et al., 2015). Therefore, it is a good choice to combine a neural model of knowledge-base and a neural model for QA with an external memory, which is also attributed to the classical approach of template-based QA from knowledge-base. In this paper, we propose a model called Question Answering Based on Neural Network. Answers can be generated to simple factoid questions by this model by accessing a knowledge-base. It is actually a decoder which is controlled by another neural network, so it can switch between generating a common word(e.g. هو "he") and producing a phrase (e.g., جاك أديسون"Jack Addison") retrieved with a certain probability from knowledge-base. The model has been trained on a dataset consisting of question-answer pairs which are associated with triples in the knowledge-base, where all components of the model are tuned jointly. The experimental results demonstrates the proposed model can effectively grasp the variation of the language and produce correct and natural answers to the questions by consulting the facts in the knowledge-base. The experimental results also shows that the proposed model can perform better than the Retrieval-based QA model .

II. Methodology

In this section we discuss the dataset and the QA learning task of our QA system.

A. Data

We constructed a new dataset by gathering data from the web. We first constructed a knowledge-base from Arabic Wikipedia web site. We extract entities and related triples (subject, predicate, object) from the structured sections (e.g. HTML tables) of the web pages. Next, a normalization is applied to the extracted data and aggregation to form a knowledge-base. Second, we used general knowledge question-answer pairs by extracting from one Arabic Wikipedia site. We heuristically and automatically construct training and test data for the QA by combining the question-answer pairs with the triples in the knowledge-base. For each question-answer pair, a list of candidate triples with the subject fields appearing in the question, is retrieved.

B. The QA learning

We adopt a supervised learning task for our QA system namely: a sequence-to-sequence learning task. The QA system receive a sequence of words as a question and produce another sequence of words as answer. In order to provide correct answers, the system is associated with a knowledge-base, which contains a set of facts. During the process of answering, the system consults the Knowledgebase, returns a set of candidate facts and provides a correct answer for the question by using the right fact. The produced answer may contain two types of “words”: common words for formulating the answer (indicated as common word) and the other is specialized words

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in the knowledge-base indicating the answer (indicated as knowledgebase-word). To train a model for the task, we suppose that each training example consists of a question-answer pair with the knowledgebase-word specified in the answer. We limit this study to the case of simple factoid questions in which each question answer pair is associated with a single fact ,i.e., one triple of the knowledgebase. Forward relation QA will be considered, in which the question is on subject part, the answer is from object part and predicate of the triple.

III. The QA Model

The knowledge-base consists of a set of triples (subject, predicate, object), each referred to as T = (Ts, Tp, To). Inspired by the work on neural machine translation (Cho et al., 2014b;Bahdanau et al., 2015;Sutskever et al., 2014) and neural natural language dialogue (Shang et al., 2015;Serban et al., 2015;Vinyals and Le, 2015), and the work on question answering with knowledge-base (Bordes et al., 2014; 2015), We present an end-to-end neural network model for QA. Our QA model consists of Question Analyzer, Knowledge Retriever, Answer Generator, and an external knowledge-base. More details about these components are described in the following sections.

A. Question Analyzer

The question is given as sequence of words, the analyzer transforms it to a vector representation. In our implementation, we use a bidirectional RNN as in (Bahdanau et al., 2015), which uses two independent RNNs . In our case, we use gated recurrent unit (GRU)(Chung et al., 2014) for processing the sequence forward and backward.

B. Knowledge Retriever

Knowledge Retriever fetches facts which are relevant from the knowledgebase. The knowledge retriever first performs term-level to retrieve a list of candidate triples. After obtaining the list of candidate triples, the retriever checks the relevance of each candidate triple with the question (Bordes et al., 2014).

C. Answer Generator

Answer generator adopts an RNN to produce an answer based on the information extracted from the question stored in the short-term memory and the relevant facts returned from the long term memory.

D. Training

There are various parameters to be learned for question analyzer and answer generator. These parameters include the weights in the RNNs. Knowledge retriever's parameters include a matrix or the weights in the multi-layer perceptron(MLP) and the convolution layer, and the word retrieval which is common between the question analyzer RNN and the knowledge-base. Our model contains a retrieval operation, and also can be trained by maximizing the likelihood of the observed data, since the Answer generator's composite form of probability provides a formal way to produce words from the knowledgebase vocabulary and common vocabulary.

IV. Experiments and Results

The Arabic texts in the data are split into sequences of words. Since the distributions of word in questions and answers are different, we employ different vocabularies for them. We use all the words in the predicates of the triples and , the most frequent words in the questions, covering 94.3% of the word usages in the questions. We employ the most frequent words in the answers with a coverage of 93.4%. we choose two baseline methods: a neural dialogue model, a retrieval-based QA model and the KB-retrieval aspect of our model.

A. Neural Responding Machine (NRM)

NRM (Shang et al.,2015) is a generative neural network based model which is designed especially for short-text conversation. The NRM model is trained with the question-answer pairs. NRM remembers all the knowledge from the QA pairs in the model even it does not have access the knowledge-base during training and testing.

B. Retrieval-based QA

Information retrieval system is used to index the knowledge-base, in which each triple is dealt as a document. During the test phase, a question is employed as the query and the top returned triple is retrieved as the answer. This method is not able to generate natural language answers.

We evaluate the performance of the models in terms of accuracy, i.e., the ratio of answered questions correctly. We use 200 factoid questions from the test set. Table 1. shows the resulted accuracies of the models using the test set. NRM has the lowest accuracy, lacking of ability to accurately remember the answers and generalize to the case of questions unseen/new in the training data. Our QA model outperformed the other two models.

Table 1. Test Accuracies

Models	Accuracy
NRM	22%
Retrieval-based QA	40.2%
Our QA Model	53%

V. Conclusion

We have proposed a simple end-to-end neural network model for Arabic Question Answering. The model is capable to query a knowledge-base. The experimental results show that the proposed model has the ability of generating correct answers to factoid questions by using the facts in the knowledgebase.

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