Neural Relation Prediction for Simple Question Answering over Knowledge Graph

Amin Abolghasemi, Saeedeh Montazi∗

Department of Computer Engineering,
Amirkabir University of Technology, Tehran, Iran

Abstract

Relation extraction from simple questions aims to capture the relation of a factoid question with one underlying relation from a set of predefined ones in a knowledge base. Most recent methods take advantage of neural networks for matching a question with all relations in order to find the best relation that is expressed by that question. In this paper, we propose an instance-based method to find similar questions of a new question, in the sense of their relations, to predict its mentioned relation. The motivation roots in the fact that a relation can be expressed with different forms of question and these forms mostly share similar terms or concepts. Our experiments on the SimpleQuestions dataset show that the proposed model achieved better accuracy compared to the state-of-the-art relation extraction models.

Keywords: Question answering, Knowledge base, Relation prediction, Neural text matching

1. Introduction

With the growth of the Internet and rapid production of a vast amount of information, question answering systems, designed to find a relevant proper answer by searching throughout a data source, are of great importance. The

∗Principal corresponding author
Email address: montazi@aut.ac.ir (Saeedeh Montazi)
production of knowledge bases and the need to answer questions over such resources received researchers attentions to propose different models to find the answer of questions from the knowledge bases, known as KBQA\footnote{Knowledge Base Question Answering}. Answering factoid questions with one relation, also known as simple question answering, has been widely studied in recent years (Dai et al., 2016; Yin et al., 2016; He and Golub, 2016; Yu et al., 2017). A common approach that has been used in most of the researches is utilizing a two-component system, including an entity linker and a relation extractor. In this paper, we focus on the relation extraction component, which is also treated as a classification problem.

This topic demands certain tools to capture relation that is mentioned in the questions, as a part of the QA systems. In this paper, we aim to view this kind of relation prediction. The term “relation extraction” is originally referred to capturing relation between two entities, if there is any. In the case of simple questions, one of entities is already mentioned and the relation which represents the topic behind the words must be predicted in order to find the other entity. For instance, in the question “Which artist recorded georgia?”, “artist” conveys the topic and ”georgia” stands for the first entity. In this context, extracting relation from single-relation questions obtains higher accuracy compared to multi-relational ones. Having a large number of relations in a knowledge base, however, this simple question relation extraction is not a solved problem yet.

Classifying questions to predefined set of relations is one of the main approaches for this task (Mohammed et al., 2018). Moreover, matching question content with relations has also been proposed and shown promising results (Yin et al., 2016; Yu et al., 2017). In this paper, the relation extraction is viewed from a new perspective such that relation extraction is done within a question-question matching model, instead of only matching questions and relations. Indeed, while many of the previous works use a matching between question mention and relations, we use an instance-based method for classifying relations. The proposed model benefits from a text matching model, namely
MatchPyramid (Pang et al., 2016), and enhances it with a two-channel model for considering lexical match and semantic match between questions.

The structure of the paper is as follows: in Section 2, we give a concise overview of the existing approaches for relation classification and its application in KBQA. We also review the available neural text matching models which is the base of our instance-based model. Section 3 presents our approach and elaborately explains detail of our proposed model. In Section 4, we show the conducted evaluation experiments and discuss the results. Finally, we summarize our method in Section 5.

2. Related Works

2.1. Question Answering over Knowledge Base

One paradigm in proposed approaches for relation extraction in KBQA is based on semantic parsing in which questions were parsed and turned into logical forms in order to query the knowledge base (Berant et al., 2013; Berant and Liang, 2014). However, most of the recent approaches (Mohammed et al., 2018; Bordes et al., 2015; Dai et al., 2016; He and Golub, 2016; Yu et al., 2017) are based on automatically extracted features of terms; thanks to the prominent performance of neural network on representation learning (Mikolov et al., 2013a,b).

From another point of view, two mainstreams for extracting relations in KBQA are studied: (a) using a classifier which chooses the most probable relation among all (Mohammed et al., 2018); (b) matching questions and relations through learning of an embedding space for representing all relations and question words (Bordes et al., 2015; Dai et al., 2016; Yin et al., 2016; He and Golub, 2016; Yu et al., 2017), in which each relation is considered either as a meaningful sequence of words or as a unique entity.

Dai et al. (2016) considered the relation prediction, as well as the whole KBQA problem, as a conditional probability task in which the goal is finding the most probable relation given the question mention. To this aim, they used
Gated Recurrent Unit (GRU) neural network and Bidirectional Long Short-Term Memory (BiLSTM) alongside a Conditional Random Field (CRF) for parameterizing their probabilistic component.

He and Golub (2016) applied attentional character-level LSTM decoder to embed questions and character-level Convolutional Neural Networks (CNN) to embed knowledge base relations.

Yin et al. (2016) employed an attentive max-pooling CNN for matching a question with all relations. Using this attentive max-pooling caused the model to have an augmented representation of question for question-relation matching.

Following Yin et al. (2016), Yu et al. (2017) proposed a hierarchical residual BiLSTM for relation prediction. They used the idea behind residual networks (He et al., 2015) and applied a residual connection to ease the learning process of two layer BiLSTM. In the current research, following Yu et al. (2017), we propose a new relation prediction model which uses question-relation matching as well as question-question relevance computation.

2.2. Neural Text Matching

The growing area of text matching develops models to investigate the relationship and the degree of matching between sequences of words. This comparison mechanism is a substantial core for various tasks, including ad-hoc retrieval, paraphrase identification, question answering, and semantic web search (Hu et al., 2014). In this regard, three main categories are considered in the context of deep matching models, namely representation-focused, interaction-focused, and hybrid (Guo et al., 2016). In representation-focused models, an abstract contextual representation of texts are extracted through neural networks and then these representations are used to estimate the matching score between them. BiMMP (Wang et al., 2017) and ARC I (Hu et al., 2014) are examples of these models. On the other hand, interaction-focused models compute the similarity between two sequences of words in a procedure, such that different patterns and structures of interactions are learned with the help of neural networks based on local interactions of two sequences (Guo et al., 2016).
MatchPyramid (Pang et al., 2016) and aNMM (Yang et al., 2016) are examples of these models. Hybrid models aim to benefit from the advantages of both techniques. ARC II (Hu et al., 2014) is an example of this category.

In this paper, owing to its superior performance, which is reported in Section 4, we take advantage of an interaction-focused model in the hierarchy of our model, based on MatchPyramid.

3. Proposed Model

In our research, we look at the problem of relation extraction of KBQA from a new point of view to propose our instance-based solution for the task. Before describing the model in detail, we provide an overview of the problem. Given pairs of question and relation in our training data, denoted as \((Q, R)\), and pairs of question and relation in our test data, denoted as \((Q', R')\), for each \(Q'\), we aim to predict the most probable relation \((R'')\), which interprets the question precisely. Having different lexical representation for each question about a relation, there are similar words from different range of similarity that occur in the questions of the same relation. Based on these similarities, we argue that the resemblance of questions can be used to detect the relation that lies behind question words. In this regard, following Yin et al. (2016), we first extract the entity mentions out of question words and put a symbol (e.g. \(< e >\)) in its place, so that we will have a question pool in which each question is labeled with its relation that can be considered as a paraphrase of that question. For each new question \((Q')\), we find the most resemble question \((Q)\) in our question pool, and assign its corresponding relation as the relation for \(Q'\). To do so, we need a model to compute the resemblance of each pair of questions and find the most similar one to \(Q'\). Nevertheless, due to existence of multiple form of questions for a relation to be paraphrased, we take the relation of the majority among k top ranked similar questions to \(Q'\). In this sense, we are using an instance-based method by computing the relatedness of each new \(Q'\) to all train questions.

The architecture of our model is depicted in Figure 1. As can be seen,
the proposed model consists of two neural networks, namely $Q^\prime$-$Q$ and $Q^\prime$-$R$, which work alongside each other and do the computations in parallel in order to provide the output of the whole component. The core idea behind $Q^\prime$-$Q$ model, the left part of the architecture, is to compute a matching score that
represents the similarity of two questions (Q’ with Q). Additionally, following Yu et al. (2017), we add another neural network (Q’-R), the right part of the architecture, to compute the matching score of Q’ with the relation of Q (R). By doing so, we are enhancing the matching signals between Q’ and Q to estimate the overall score.

In the first step, our proposed model projects the input question as well as the available questions and relations of training data into an embedding space. To do so, each sequence of words (Q’, Q and R) are fed to an embedding layer and all of their corresponding vectors are fetched. In this work, we use pre-trained vectors due to the fact that current neural embeddings which are learned by using large scale text corpora provide rich enough representation. In the next step, input vectors are fed to the two neural networks.

3.1. Q’-Q Network

Q’ and Q are fed to the Q’-Q network, which is inspired by Matchpyramid (Pang et al., 2016). Initially, an interaction matrix between the words of Q and Q’ is computed. This interaction matrix has been used in several interaction-focused neural learning to match models (Pang et al., 2016; Mitra et al., 2017; Wan et al., 2016; Xiong et al., 2017; Hu et al., 2014) due to the fact that it provides good representation to compute matching degree between two piece of texts. Indeed, an interaction matrix is a matrix computed based on two sequence of words, in which, each element at the \(i^{th}\) row and \(j^{th}\) column stands for the similarity between the \(i^{th}\) word of the first sequence and \(j^{th}\) word of the second sequence. Accordingly, the \((i,j)\) element not only records the exact matches between the words of two sequences, but also estimates the degree of semantic similarity between them (Pang et al., 2016). There are several similarity functions that can be used for creating this matrix; e.g. Cosine similarity, indicator function, dot product, tensor network, etc. In this work, our matrix is computed based on the Cosine similarity. In addition, we add another interaction matrix in which indicator function is used as the similarity function. The idea behind using indicator function in interaction matrix comes from the fact
that the range of difference between words that can be used to express a question about a unique topic/relation (e.g. location of birth) is not too wide and they have relatively low diversity. By doing so, we add an additional bias, which we believe that exists inherently in the problem, to our model. This makes our convolutional neural network a 2-channel network, which reflects both lexical and semantic match between text sequences. The impact of adding this extra input channel is provided in Section 4. Then, this matching matrix is fed to a convolutional neural network to compute a vector (matching vector) which is followed by a Multilayer Perceptron (MLP) to compute the matching score between Q’ and Q from the question pool.

3.2. Q’-R Network

Following Yu et al. (2017), on the other side of our model, we utilize a Q’-R network which consists of BiLSTMs to extract contextual representation of question and relation words. Indeed, we are treating the relation words as a meaningful series of words. Then, the computation of similarity between these two enhanced representation is used to estimate the degree of matching between the question Q’ and the corresponding relation of Q (R). Finally, overall degree of matching between (Q,R) and Q’ is estimated as a combination of the scores from both networks.

4. Evaluation

4.1. Dataset

Following the previous works by Yin et al. (2016) and Yu et al. (2017), we use the common benchmark dataset of the simple question answering, namely SimpleQuestions, which was originally introduced by Bordes et al. (2015). This dataset contains 108442 questions gathered with the help of English-speaking annotators. Yin et al. (2016) proposed a new benchmark for evaluating relation extraction task on SimpleQuestion. In this benchmark, every question, whose entity is replaced by a unique token, is labeled with its ground truth relation as
its positive label, and all other relation of the gold entity that is mentioned in the question are considered as negative labels. We use the same dataset which contains 72239, 10310 and 20610 question samples as train, validation, and test sets respectively.

4.2. Experimental Setup

The hyper-parameters are tuned over validation set and they are finally configured with: (1) 64 units for BiLSTMs, (2) single layer for convolutional network, and (3) 256 neurons for MLP on matching vector. The embeddings are initialized with 300-dimension glove word vectors (Pennington et al., 2014). It is worth mentioning that the interaction layer consists of two square matrices whose length is equal to the longest question. All the experiments are implemented with Keras library and performed on a Linux machine which has an Intel TM Core i7-6700 3.40 GHz CPU with 16 Gigabyte memory alongside Nvidia GeForce GTX 1080Ti GPU.

4.3. Results

As mentioned, our instance-based idea for question answering over knowledge graph requires a text matching model to find similar question to the input question.

Considering the available text matching models, in the first step of our experiments, we trained different text matching models on the training data. The obtained results are reported in Table 1. As can be seen, the MatchPyramid model performs the best on the proposed model. Considering these results, MatchPyramid has been used as the base of our model in further steps.

In the next step, we evaluate the performance of our model while considering exact lexical match as a separate channel in the our Q’-Q network. To this end, three experiments were done and compared: (1) single-channel semantic text matching (Cosine function), (2) single-channel lexical match (indicator function), and (3) two-channel lexical and semantic text matching. The results of these experiments are reported in Table 2. As can be seen in the results, the
Table 1: Comparison of different neural text matching models on the proposed instance-based Q'-Q network

| Model                                      | Accuracy (%) |
|--------------------------------------------|--------------|
| ARC I (Hu et al., 2014)                    | 89.35        |
| ARC II (Hu et al., 2014)                   | 88.44        |
| MatchPyramid (Pang et al., 2016)           | 91.75        |
| BiMPM (Wang et al., 2017)                  | 90.73        |

Table 2: The impact of different text matching channels on the proposed instance-based Q'-Q network

| Model                                                      | Accuracy (%) |
|------------------------------------------------------------|--------------|
| Single-channel semantic text matching                      | 91.75        |
| Single-channel lexical match                               | 90.71        |
| Two-channel lexical and semantic text matching             | 92.30        |

The impact of adding an extra input channel is obvious as it is compared with single one. The better performance of the semantic channel shows the importance of semantic text matching in the QA system. The further improvement using an additional channel for lexical match indicates that although lexical match is considered implicitly in the normal MatchPyramid model, it is not enough for considering this issue in the QA task and the proposed two-channel model can better cover both semantic and lexical similarities.

In the next step of our experiments, we added the Q'-R network to the Q'-Q network and evaluated the new combined architecture, presented in Figure 1, on the same dataset. Table 3 reports the performance of our model on classifying the relations in comparison with the state-of-the-art models. In this table, AMPCNN (Yin et al., 2016) is an attentive max-pooling CNN for matching a question with all relations. APCNN (dos Santos et al., 2016) and ABCNN (Yin et al., 2016) both employ an attentive pooling mechanism. These two models
| Model                                                               | Accuracy (%) |
|---------------------------------------------------------------------|--------------|
| AMPCNN (Yin et al., 2016)                                           | 91.3         |
| OWA-APCNN (dos Santos et al., 2016)                                 | 90.5         |
| OWA-ABCNN (Yin et al., 2016)                                       | 90.2         |
| BiCNN (Yih et al., 2015)                                           | 90.0         |
| Hier-Res-BiLSTM (HR-BiLSTM) (Yu et al., 2017)                       | 93.3         |
| Proposed Q'-Q + Q'-R model                                         | 93.41        |

Table 3: Results of the proposed model and the state-of-the-art QA systems

are not originally evaluated on relation prediction of simple questions. In fact, the authors of AMPCNN (Yin et al., 2016), conducted the corresponding experiments on a one-way-attention adaptation of these two models to compare them with the available methods in this task. Hier-Res-BiLSTM (Yu et al., 2017) uses hierarchical residual connections to ease the training procedure of BiLSTM. BiCNN (Yih et al., 2015) uses convolutional neural networks for matching a question with relations. The model is reimplemented for SimpleQuestions by Yu et al. (2017).

As it is shown, our proposed model outperforms the state-of-the-art models in relation extraction for SimpleQuestions dataset by a margin of 0.11 percentage. We believe that this improvement is an effect of the two contributions that we had in this paper, namely proposing a combined Q'-Q + Q'-R network and the two-channel text matching model in the Q'-Q network. The combined network helps to consider similarity of questions with other questions in the training data as well as the relations. Adding more matching signals helps to better detect relationship between two questions. More precisely, these signals are from question mentions which are paraphrases of their corresponding relations. This growth in accuracy comes from the aforementioned fact of the inherent low variance of words used in different question forms of an individual relation.
4.4. Error Analysis

In the last step of our experiments, we aim to find the main reasons of errors in the system. To this end, the test questions whose relations were not obtained correctly in our proposed model are analyzed.

Table 4 presents few examples from those questions. Among these questions, there are some predictions in which even the human supervision would assign incorrect relation; e.g., “what is the genre of the movie ¡e¿?” or “is ¡e¿ from the united states or canada?”, due to very close concepts in the relations or different levels of granularity in the available relations in the knowledge bases. In addition, some of questions are practically equivocal; e.g., “what are ¡e¿?” or “what’s an example of a ¡e¿ book?”. Indeed, this ambiguity exists in the training data. Hence, during the training process, an extra variance is imposed to the model. For instance, for the question “what are ¡e¿?”, there are four relations, namely /cvg/gameplay_mode/games_with_this_mode, /film/film_genre/films_in_this_genre, /common/topic/notable_types, and /music/album_content_type/albums, that are assigned to the aforementioned question. It seems that there is an upper bound for relation prediction on SimpleQuestions due to these kinds of indistinctness.

| Question                           | Gold Relation                  | Predicted Relation               |
|------------------------------------|--------------------------------|---------------------------------|
| what is the genre of the           | /media_common/netflix_title    | /film/film/                      |
| movie ¡e¿?                         | netflix_genres                 | genre                           |
| is ¡e¿ from the united states or    | /people/person/                | /people/person/                  |
| canada?                            | nationality                    | place_of_birth                   |
| what are ¡e¿?                      | /music/album_content_type/     | /music/genre/                    |
|                                   | /albums                        | albums                          |
| what ’s an example of a ¡e¿ book?  | /media_common/literary_genre   | /book/book_subject/              |
|                                   | books_in_this_genre            | works                           |

Table 4: Examples of errors in the proposed model
5. Conclusion and Future Work

In this paper, we proposed a new relation prediction model for simple questions. The proposed model contains two sub-network, a question-question network and a question-relation one, in which we try to match a new sample question with train questions and their corresponding relations respectively. The previous works just employ the semantic matching between a new sample question and relations, whereas our model considered the content of train questions while predicting relations. We believe that the words which are used in questions about a relation, convey useful semantic information about that relation. Thus, for future work, we would like to utilize these question words to predict relations from more complex questions.

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