A Question-answering Based Framework for Relation Extraction Validation

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Abstract

Relation extraction is an important task in knowledge acquisition and text understanding. Existing works mainly focus on improving relation extraction by extracting effective features or designing reasonable model structures. However, few works have focused on how to validate and correct the results generated by the existing relation extraction models. We argue that validation is an important and promising direction to further improve the performance of relation extraction. In this paper, we explore the possibility of using question answering as validation. Specifically, we propose a novel question-answering based framework to validate the results from relation extraction models. Our proposed framework can be easily applied to existing relation classifiers without any additional information. We conduct extensive experiments on the popular NYT dataset to evaluate the proposed framework, and observe consistent improvements over five strong baselines.

1 Introduction

Relation extraction (RE) aims to identify the target relations of entity pairs based on their contexts. It is typically modeled as the relation classification (RC) problem with pre-defined relation classes (Zhou et al., 2005; Zeng et al., 2015; Lin et al., 2016; Han et al., 2018a; Jiang et al., 2019). For example, the entity pair (Microsoft, Bill Gates) should be classified into the relation founder given the context “Bill Gates co-founded Microsoft with his childhood friend Paul Allen”.

RE has been extensively studied for many years. The early works mainly build relation extractors using hand-crafted features (Zhou et al., 2005) or kernel methods (Bunescu and Mooney, 2005). In recent years, deep learning-based RE models are extensively proposed and they are powerful to utilize the background knowledge of entities and learn implicit features from complex sentences (Zeng et al., 2014, 2015; Pawar et al., 2017; Feng et al., 2018). In general, most of the existing RE works can be categorized into the model-level research, that is, they improve the performance of RE from the perspective of feature engineering or model design.

However, for multiple reasons, e.g., data noise (Lin et al., 2016; Luo et al., 2017), limited data size (Han et al., 2018b) or difficulty in structure selection (Raschka, 2018), it is increasingly hard to significantly improve the performance through feature engineering or model design. In this paper, we argue that the validation at the result level is also important to further improve the state-of-the-art RE performance. That is, given the results predicted by a RE model, we hope to detect the wrong predictions and further correct them.

It is unrealistic for the RE model to conduct the validation by itself, since there is no information indicating the correctness of the predicted relations. This necessitates the introduction of an additional model (i.e., validation model) for our purpose. Nevertheless, it is difficult to get explicit supervision to learn a validation model that could identify the correctness of a candidate relation. Fortunately, we observe that relation classification (RC) is closely related to the task of knowledge base completion (Wang et al., 2014; Shi and Weninger, 2018). The former aims to predict the semantic relation given the head and tail entities, while the latter tries to predict the tail entity given the head entity and the relation.

Inspired by this intrinsic relatedness, we try to validate the candidate relations by the task of tail entity prediction with the help of question answering (QA) models. Specifically, given an entity pair and a candidate relation, we construct a question based on the head entity and the relation. Then we predict whether the question can be answered with the tail entity using a QA model. Intuitively, when the candidate relation is correct, the constructed
question is expected to be confidently answered by the QA model with the tail entity (under the context sentence). But when the candidate relation is incorrect, the QA model should give a low score, because the tail entity is no longer a valid answer.

Our validation process can be summarized as the following four steps. First, given an entity pair, a relation classifier is learned to generate the score distribution over the pre-defined relations based on the context sentences. Second, a small set of candidate relations are selected, since it is unnecessary to validate all the relations. Then, for each selected relation, we employ the validation model to evaluate the correctness of these candidate relations. Finally, a more reasonable score for each candidate relation is estimated based on the results from the classifier and the validation model. A detailed example is presented in Sec 2.2.

Contributions. (1) To the best of our knowledge, we are the first to focus on using question answering-based tail entity prediction to validate the relation extraction results. (2) We propose a reasonable QA-based validation framework and prove its effectiveness through extensive experiments. It is noteworthy that our framework can be used as a plug-and-play component for most existing relation classifiers without additional information, which highlights its practical value. (3) To improve validation efficiency, two effective relation selection strategies are also proposed.

2 Overview

2.1 Framework Overview

Denote the relation extraction dataset as \( D = \{(e_1, e_2, s, r)\} \), where \( r \in \mathcal{R} \) is the true relation of the entity pair \((e_1, e_2)\) and \( \mathcal{R} = \{r_1, ..., r_l\} \) is the pre-defined relation set with \( |\mathcal{R}| = l \). The input of our framework is an entity pair \((e_1, e_2)\) with context \( s \), and the outputs are the scores of all the relations in \( \mathcal{R} \). In the framework, a relation classifier is first trained to predict the score \( p_j \) for each relation \( r_j \) (Sec 3.1). Assume \( k (k \ll l) \) candidate relations are selected. For each selected \( r_j \), we construct a question \( q_{e_1, r_j} \) (Sec 3.2) and employ a QA model to check its correctness (Sec 3.3). Finally, the updated score for \( r_j \) is obtained based on the scores from the relation classifier and the QA model (Sec 3.4). Besides, the candidate relation selection strategies are also described in Sec 3.4.

2.2 Example

We illustrate the pipeline in Figure 1, which mainly contains four steps:

(1) **RC score generation.** Given \((e_1, e_2) = (Jobs, Apple)\) and its context \( s \), a relation classifier first generates the scores for all the pre-defined relations.

(2) **Candidate relation selection for validation.** Intuitively, it is costly to conduct the validation for all the relations. Moreover, this is also unnecessary, since most relations can be filtered out by the RE model. Alternatively, we select a small set of candidate relations for further validation. A direct strategy is to choose the top-\( k \) relations with the highest scores (predicted by the RE model) as candidates, e.g., *co-founded* and *born_in* in Figure 1. This is reasonable since most wrong relations are predicted with lower scores by the RE model and we only need to focus on the relations with higher scores. Besides, this paper also presents another effective strategy to select the promising relation subset (see Sec 3.4).

(3) **Question construction and validation.** For each selected candidate relation \( r_j \), we validate the correctness with the help of a QA model. We construct the question \( q_{e_1, r_j} \) by directly concatenating the head entity \( e_1 \) with the candidate relation \( r_j \). For example, when \( e_1, r_j \) and \( e_2 \) are *Jobs*, *co-founded* and *Apple*, question \( q_{e_1, r_j} \) is “Jobs | co-founded”.

Then, given the context \( s \), a QA model is employed to judge whether \( q_{e_1, r_j} \) can be answered with the tail entity \( e_2 \). Intuitively, the context sentence \( s \) clearly expresses the relation *co-founded*, thus the question “Jobs | co-founded” should be confidently answered with the tail entity *Apple*. Therefore, in Figure 1, we can observe a high QA score (0.83). Meanwhile, the sentence does not express all the other candidate relations, so the question for these relations should be scored lower.

(4) **Score update.** For each candidate relation \( r_j \), we obtained two scores from the RC and QA models, respectively. The updated score for \( r_j \) is a combination of the two scores and the details are shown in Sec 3.4. In general, the updated score is more reasonable than the individual score from either the RC or the QA model.
Figure 1: An example to illustrate the idea of QA based validation. The true relation for (Jobs, Apple) is co-founded. The RC model is first used to generate the scores for all the relations. Then we select a small set of promising relations for further validation that is realized by a QA model. Finally, the updated scores are obtained by combining the scores from RC and QA models.

3 QA-based Validation Framework

3.1 Relation Classification (RC)

In general, the task of RE is popularly modeled as the problem of relation classification (RC). Given the context s of an entity pair t, the context representation s is learned through an encoder, e.g., a convolutional network (Zeng et al., 2015), a recurrent network (Zhang and Wang, 2015), or a self-attention network (Du et al., 2018). During this process, some extra information may also be incorporated into the encoder to improve the performance. For instance, position embeddings (Zeng et al., 2014) and domain knowledge (Zhou et al., 2005; Weston et al., 2013; Li et al., 2019a). The representation s is further used to predict the score distribution over the pre-defined relation set R, which is denoted as \{p(r_1 | s), ..., p(r_j | s)\}.

3.2 Question Construction

Given an entity pair t = (e_1, e_2) and a candidate relation r_j, we construct a question q_{e_1,r_j} for e_1 and r_j. In this paper, the question is constructed by directly concatenating the head entity string e_1 with the relation string r_j. For example, in Figure 1, (Jobs, co-founded) will generate the question “Jobs | co-founded”. Intuitively, q_{e_1,r_j} is meaningful only when e_1 matches r_j in semantics, otherwise, q_{e_1,r_j} is meaningless (e.g., “Jobs | located in”), which indicates r_j is not the correct relation. Thus, the question itself provides some informative features to help us identify the correctness of the relation.

3.3 Question Answering Model

3.3.1 Dataset generation

Instead of using additional information, we train our validate (QA) model by constructing samples based on the RE dataset, which highlights the practical value of the framework since additional information cannot be easily obtained. Given an entity pair t = (e_1, e_2) and its context s in the RE dataset D, for each candidate relation r_j in R, a question q_{e_1,r_j} is first constructed. We also add an additional token “null” in the first position of s. Then if r_j is the correct relation of t, the answer of this question is a_{e_1,r_j} = e_2, and the answerable flag f_{e_1,r_j} is set as 1 (True); otherwise, a_{e_1,r_j} is set as “null” (the first token in s) and f_{e_1,r_j} is 0 (False). Then, the QA dataset Q can be denoted as \{(q_{e_1,r_j}; s; a_{e_1,r_j}, f_{e_1,r_j})\}.

3.3.2 Model selection

In this paper, we fine-tune the pre-trained ALBERT (Lan et al., 2019) as our QA model to fulfill the validation task. As a lite version of BERT (Devlin et al., 2019), ALBERT significantly reduces the size of parameters as well as the training time. Meanwhile, it achieves new state-of-the-art results on the SQuAD 2.0 (Rajpurkar et al., 2018) and other NLP datasets.
3.3.3 Fine-tuning details

Based on the existing work (Lan et al., 2019), we fine-tune the pre-trained ALBERT model on our dataset Q. Our QA model will predict two results for each sample: the start and end positions of the answer in the context and the answerable probability. Specifically, given a sample \(\psi = (q_{e1,r_j}, s; a_{e1,r_j}, f_{e1,r_j})\) in Q, we formalize the answer prediction as follows. For the \(l\)-th position (corresponding to word \(w_l\)) in the context \(s\), the QA model predicts two probabilities: \(p_{l}^{st}\) and \(p_{l}^{ed}\), where \(p_{l}^{st}\) (\(p_{l}^{ed}\)) denotes the probability that \(w_l\) is the starting (ending) word of the answer. Besides, the model also predicts an answerable probability \(\psi_{ans}\). Thus, the loss functions for each sample \(\psi\) are defined as follows:

\[
\begin{align*}
\text{loss}^{\psi}_{\text{position}} &= -\log p_{l}^{st} - \log p_{l}^{ed}, \\
\text{loss}^{\psi}_{\text{ans}} &= -f_{e1,r_j} \log \psi_{ans} - (1 - f_{e1,r_j}) \log (1 - \psi_{ans}),
\end{align*}
\]

where \(f_{e1,r_j}\) is the answerable flag in sample \(\psi\). \(l_s\) (\(l_e\)) denotes the true start (end) position of the answer \(a_{e1,r_j}\) in \(s\). If \(a_{e1,r_j} = \text{“null”}\) (i.e., unanswerable), then \(l_s\) and \(l_e\) are set as 0. The loss \(\text{loss}^{\psi}_{\text{position}}\) is about the position prediction while \(\text{loss}^{\psi}_{\text{ans}}\) is about the answerable prediction.

The loss function on Q is defined as:

\[
\mathcal{L}_{QA}(\Phi) = \frac{1}{2|Q|} \sum_{\psi \in Q} \left(\text{loss}^{\psi}_{\text{position}} + \text{loss}^{\psi}_{\text{ans}}\right), \tag{2}
\]

where \(|Q|\) and \(\Phi\) are the parameters to be fine-tuned.

3.3.4 Validation score generation

The validation (QA) model can be well fine-tuned by minimizing \(\mathcal{L}_{QA}(\Phi)\) in Equation 2. During the test phase, we first construct the sample \(\psi = (q_{e1,r_j}; a_{e1,r_j}, f_{e1,r_j})\) for the candidate relation \(r_j\) (to be validated) given an entity pair \(t\) and \(s\). Then the answerable, start and end probabilities are computed by the QA model. The validation score is defined as follows:

\[
\begin{align*}
p_{j,\text{QA}} &= \max_{i,j} \psi_{\text{ans}} \times \psi_{\text{confidence}}, \\
\psi_{\text{confidence}} &= \max_{i,j} \frac{p_{ij}^{st} p_{ij}^{ed}}{p_{j}^{st} p_{j}^{ed}}, \tag{3}
\end{align*}
\]

where \(i\) (\(j\)) denotes the \(i\)-th (\(j\)-th) position in \(s\). That is, \(\psi_{\text{confidence}}\) is the maximum probability among all the candidate answer strings (except “null”) in \(s\).

\(\psi_{\text{confidence}}\) measures the confidence level of the answerable score \(\psi_{\text{ans}}\). That is, if \(q_{e1,r_j}\) is answerable, then the QA model will give a very high score on a string within \(s\). In contrast, if the question is unanswerable, any string in \(s\) cannot be the answer and \(\psi_{\text{confidence}}\) will be very small.

3.4 Candidate Relation Selection and Score Update

Given a test entity pair and its context, we select a small set of promising relations for validation. In this paper, we provide two effective relation selection strategies.

3.4.1 Strategy I

The first strategy is to select the most confidently predicted scores by the QA model for validation. Specifically, for each test entity pair and all the relations in \(\mathcal{R}\), we generate the corresponding QA scores and then sort them in descending order. Intuitively, extreme scores, either very high or very low, indicate that the QA model confidently expresses whether a question is answerable or not. However, the scores in the middle range indicate less confidence. So we retrieve the top \(\alpha\) and last \(\beta\) percent ones among all the scores for validation. If the relation \(r_j\) is retrieved, its final score is updated by

\[
p'_{j} = \left(p_{j,\text{QA}} \times p_{j}\right)^{\frac{1}{1+\lambda}}. \tag{4}
\]

As shown in Equation 4, the final score \(p'_{j}\) for \(r_j\) is computed by a weighted multiplication of its QA score \(p_{j,\text{QA}}\) and the RC score \(p_{j}\), where \(\lambda > 0\) is a predefined constant that determines the relative importance between the two scores.

Otherwise, if a relation is not selected for validation, its updated score is computed by:

\[
p'_{j} = \left(c \times p_{j}\right)^{\frac{1}{1+\lambda}}, \tag{5}
\]

where \(c \in (0, 1)\) is a constant.

3.4.2 Strategy II

Given an entity pair, strategy II aims to validate the top-\(k\) relations based on the scores from the RC model, which has been illustrated in Figure 1. The basic assumption is that the relations predicted by the RC model with higher scores tend to contain the correct relation.

To be specific, for each entity pair we choose \(k\) (out of \(|\mathcal{R}|\)) relations with the highest scores from the RC model. Then, we compute the corresponding validation scores using the QA model, and use
them to update the scores of the top-$k$ candidate relations. If the relation $r_j$ is in the top-$k$ set, then the score is updated according to Equation 4. For the rest relations (out of top-$k$) in $R$, their updated scores are obtained by Equation 5.

Discussion Essentially, strategy I and II are designed from different perspectives. Strategy I tends to trust the scores from the validation (QA) model while strategy II tends to trust the results from the RC model. In general, strategy I is more suitable for the scene where the validation model is reliable and the pre-defined relation set is small. This is because strategy I needs to compute the QA scores for all the relations given an entity pair. In contrast, strategy II is more suitable for the scene where the RC model is reliable, because the selected relations are decided by the RC model. Besides, strategy II is not sensitive to the size of the relation set, since it does not need to compute all the QA scores of relations.

4 Experiments

4.1 Experimental Details

4.1.1 Dataset description

We evaluate our proposed framework on the NYT dataset (Riedel et al., 2010), which is widely used in the field of RE. The dataset contains 53 relations, including a special relation “NA” that indicates there is no pre-defined relation between the given entity pair. There are 522,611 sentences, 281,270 entity pairs and 18,252 relation facts in the training set. The testing set contains 172,448 sentences, 96,678 entity pairs and 1,950 relation facts.

4.1.2 Relation classifiers

In our experiments, we choose five relation classifiers as baselines and try to improve their results using our framework.

(1) CNN+ATT and (2) PCNN+ATT (Lin et al., 2016). CNN+ATT takes a convolutional neural network (CNN) to extract informative features from sentences. Besides, sentence-level attention (ATT) is used to alleviate the noise in a sentence bag. In PCNN+ATT, the CNN encoder is replaced with the piecewise convolutional neural network (PCNN), where the piecewise max pooling operation is adopted for feature extraction. For CNN/PCNN+ATT, we use the open-source toolkit\footnote{https://github.com/thunlp/OpenNRE}.

(3) CNN+HATT and (4) PCNN+HATT (Han et al., 2018a). Based on CNN/PCNN, (Han et al., 2018a) proposes a hierarchical attention mechanism that exploits hierarchical information of relations, thus generating CNN+HATT and PCNN+HATT. The hierarchical attention has been proven to be very effective and CNN/PCNN+HATT obtained state-of-the-art performance on the NYT dataset. For CNN/PCNN+HATT, we use the official code\footnote{2}

(5) RESIDE (Vashishth et al., 2018). In RE-SIDE, the relation alias information and entity types are introduced into RE task as soft constraints for relation prediction. To integrate these information, RESIDE employs graph neural networks (GNNs) to encode syntactic information from text. For RESIDE, we also use the official code\footnote{3}.

| Parameters | $k$ | $c$ | $\lambda$ | $\alpha$ | $\beta$ |
|------------|-----|-----|-----------|---------|--------|
| Strategy I | 0.9 | 10  | 10        | 20      | -      |
| Strategy II| 3   | 0.9 | 10        | -       | -      |
4.1.3 Experimental setup

4.2 Results and Analysis

For the relation classifiers, we follow the default parameter settings as described in the original papers. The details of our validation (QA) model has been described in Sec 3.3, and we implement it based on the open source\footnote{https://github.com/thunlp/HNRE}.

Note that many entity pairs in NYT contain multiple sentences. To construct samples for these entity pairs, we concatenate the multiple sentences to generate the context $s$. To control the length of the resulting context, and to reduce the noise brought by the parts of sentence far from the head and tail entities, we cut each sentence by the position of its head and tail entities. Specifically, the substring between the 40 tokens before the head entity and 40 words after the tail entity is preserved, and other parts are abandoned. Empirically, the cut sentences are shorter than 100 words, and thus the length of the concatenated context is acceptable.

We also explain how to deal with the special relation “NA” during validation. Since “NA” has no specific semantics, we did not construct samples involving “NA” when training our QA model. As a result, the QA score for “NA” will not be generated during validation. That is, in both the two relation selection strategies, the relation “NA” will be ignored although it is selected and the score of “NA” will be updated using Equation 5.

In our validation (QA) model, the ratio of positive (answerable) to negative (unanswerable) samples is set as 1:2. Other parameter settings in the QA model are shown in Table 1. Besides, the parameters used in our two strategies (Section 3.4) are presented in Table 3. All the parameters are obtained using cross-validation by splitting a subset from the training dataset.

In this section, we present the results and analysis on the proposed framework. Specifically, we compute the aggregate precision/recall curves, the Area Under precision/recall Curves (AUC) and the Precision@N for the five classifiers as well as their validated versions (both by strategy I and strategy II). Precision@N denotes the precision of the top $N$ predicted relational fact. The results updated by strategy I (strategy II) is denoted as “+ValStrgy I” (“+ValStrgy II”).

Figure 2: (a) and (b): Aggregate precision/recall curves under strategy I; (c) and (d): Aggregate precision/recall curves under strategy II.
Table 4: Precision@N for the two validating strategies.

| Precision@N (%) | N=100 | N=200 | N=300 | Mean | N=100 | N=200 | N=300 | Mean |
|-----------------|-------|-------|-------|------|-------|-------|-------|------|
| CNN+ATT         | 71.0  | 67.5  | 65.0  | 67.8 | PCNN+ATT | 73.0  | 74.0  | 71.3  | 72.8 |
| +ValStrgy I     | 70.0  | 69.0  | 68.7  | 69.2 | +ValStrgy I | 84.0  | 82.0  | 77.0  | 81.0 |
| +ValStrgy II    | 72.0  | 71.0  | 69.3  | 70.8 | +ValStrgy II | 75.0  | 75.5  | 70.7  | 73.7 |
| CNN+HATT        | 84.0  | 82.0  | 77.0  | 81.0 | PCNN+HATT | 83.0  | 81.5  | 77.3  | 80.6 |
| +ValStrgy I     | 85.0  | 81.0  | 78.3  | 81.4 | +ValStrgy I | 89.0  | 81.5  | 78.0  | 82.8 |
| +ValStrgy II    | 85.0  | 82.5  | 78.3  | 81.9 | +ValStrgy II | 90.0  | 83.5  | 78.7  | 84.1 |
| RESIDE          | 72.0  | 73.0  | 69.0  | 71.3 |       |       |       |      |
| +ValStrgy I     | 76.0  | 75.0  | 70.0  | 73.7 |       |       |       |      |
| +ValStrgy II    | 78.0  | 74.0  | 72.0  | 74.7 |       |       |       |      |

4.2.1 Overall evaluation results

Table 2 gives the AUC results, which quantify the overall performance of the models. We empirically compare the results from our two validation strategies with the baseline models. From Table 2 we observe that:

- (1) After applying the QA task as validation (with both the two strategies), the performance of all the models can be effectively improved. It indicates that our QA-based validation framework is effective for all the baselines. This is because some wrong predictions are corrected during the validation process.

- (2) CNN/PCNN+ATT/HATT use CNN or its variant as the sentence encoder while RESIDE takes GNN to learn the features from sentences. Both CNNs and GNNs are two representative neural network structures. They learn the relation-aware features in sentences from different perspectives. Using our framework, the performance of all the baselines are successfully improved, which indicates the validation model can learn complementary features that are not captured by both the CNN/GNN-based classifiers.

- (3) In general, the improvement after applying validation strategy I is more significant than strategy II. It indicates that the top $\alpha$ and last $\beta$ percent scores are more reliable for validation in our experiments. In particular, PCNN+HATT+ValStrgy I obtains new state-of-the-art results on the NYT dataset. Also note that, though strategy II is slightly inferior to strategy I, it takes much less time, as it does not require to compute all the relations in $\mathcal{R}$ for each entity pair in advance.

4.2.2 Effect of the validation on the high score predictions

Figure 2 shows the aggregate precision/recall curves. For clarity, we present the results from each validation strategy in two figures. Subplot (a) and (b) give the results from validation strategy I; (c) and (d) give the results from validation strategy II. We have the following observations from Figure 2: (1) Generally, curves from both validating strategies are on top of the ones of the baselines. This means both validating strategies are effective in improving the performance. (2) On subplot (b) and (d), for baselines PCNN+ATT/HATT, when recall is within the interval $(0, 0.1)$, there are significant improvements in precision for both strategies. It indicates that the validations successfully filter out the wrong high score predictions by validating with QA scores.

We present the Precision@N results for the two validating strategies in Table 4. The Precision@N results show how the validation affects the precision of the top $N$ predictions. From Table 4 we observe that: (1) After the validation, there are improvements in the mean values of Precision@N in all five baselines with two validating strategies. This means the QA model manages to discern the wrong high score predictions. (2) After the validation, improvements on PCNN-based models are much more significant than on the CNN based models. This coincides with our observation on the precision/recall curves. (3) We also observe that the Precision@N results from strategy II are better than these from strategy I, which is different from the conclusion of the AUC metric. This phenomenon indicates strategy II generates higher scores for the correct relations compared with strategy I. But strategy I is better at reducing the score bias for more relations, which generates better over-
### Table 5: The details of the two examples used in the case study.

| Example | Entity Pair               | True relation | Context |
|---------|---------------------------|---------------|---------|
| #1      | (Cook county, Chicago)    | contains      | Now, the state is retooling the program to include all of Cook county, which encompasses Chicago and many of its suburbs. |
| #2      | (Powerset, San Francisco) | place_founded | ... a friend suggested he check out a San Francisco start-up, Powerset, which is trying to build a rival search engine. |

### Table 6: The detailed scores of the two examples predicted by our framework, where the updated scores are obtained using Equation 4 with $\lambda = 10$.

| Example #1 | Relation 1 (True) | Relation 2 (False) | RC score | QA score | Updated score |
|------------|-------------------|---------------------|----------|----------|--------------|
|            | contains          | neighborhood_of     | 0.1330   | 0.2221   | 0.8322       |
|            |                   |                     | 0.9997   | 0.0057   |              |
|            |                   |                     | 0.8322   | 0.0080   |              |
| Example #2 | relation_founded  | place_lived         | 0.0031   | 0.0533   |              |
|            |                   |                     | 0.8990   | 0.0073   |              |
|            |                   |                     | 0.5369   | 0.0087   |              |

5. **Related Work**

The early work for relation extraction manually designs a variety of relation-aware features (Zhang et al., 2006). In recent years, deep neural networks have been extensively used in RE task (Zeng et al., 2015; Du et al., 2018; Han et al., 2018b; Zhang et al., 2018; Guo et al., 2019; Li et al., 2019a). Many references also combine QA with information extraction (Jijkoun et al., 2004; Yao and Durme, 2014; Qiu et al., 2018; Li et al., 2019a). (Yao and Durme, 2014) shows that, with the help of information extraction, the QA task over structured data outperforms most baselines. (Levy et al., 2017) models RE as a simple QA problem, i.e., giving the head entity and the relation and predicting the head entity. (Qiu et al., 2018) builds a model to produce high-quality relation triples from sentences by QA.

### 4.3 Case Study

In this section, we give two examples showing how our QA based validation framework works. Due to limited space, we only consider one classifier (PCNN+ATT) in our case study. In Table 5 we present the basic information of the two examples. The corresponding RC scores, QA scores and the updated scores for the correct and wrong relations are presented in Table 6.

In Example #1, the true relation between Cook county and Chicago is contains. However, the RC model PCNN+ATT wrongly predicts the relation neighborhood_of as the target relation, i.e., outputting the score of 0.2221 for neighborhood_of and only 0.133 for contains. However, in the QA model, the question constructed by neighborhood_of cannot be answered by the tail entity Chicago. As a result, the QA model gives a very low score to the relation neighborhood_of. Instead, it gives a high score to contains. After updating the original RC score with the QA score, the score of the true relation contains increases to 0.8322, while the score of neighborhood_of decreases to 0.0080.

5 Similarly, other RC models can also be analyzed.

### 6 Conclusion and Future Work

In this paper, we focus on improving the performance of RE by conducting the validation and correctness of the existing RC models. The QA task is introduced as the validation task for RC. Further, we design a novel QA based validation framework that can be applied to any existing relation classifier. Besides, we also propose two candidate relation selection strategies to update the relation scores.

We argue that, in addition to the task of RE, our framework can also be applied to the tasks of knowledge graph completion, where a RC model is used as the validation model to check the correctness of the results by the KBC models. Besides, we will also apply the framework to more information extraction tasks, e.g., entity typing (Choi et al., 2018) and slot filling (Zhang et al., 2019).
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