Relation Extraction as Two-way Span-Prediction

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Abstract

The current supervised relation classification (RC) task uses a single embedding to represent the relation between a pair of entities. We argue that a better approach is to treat the RC task as a Question answering (QA) like span prediction problem. We present a span-prediction based system for RC and evaluate its performance compared to the embedding based system. We achieve state-of-the-art results on the TACRED and SemEval task 8 datasets.

1 Introduction

The relation extraction (RE) task revolves around binary relations (such as "[e_1] founded [e_2]") that hold between two entities. The task is to read a corpus and return entity pairs e_1, e_2 for which the relation holds (according to the text). This is often posed as a Relation Classification task (RC), in which we are given a sentence and two entities (where each entity is a span over the sentence), and need to classify the relation into one of |R| possible relations, or to a null “no-relation” class if none of the |R| relations hold between the given entities. Relation Extraction datasets, including the popular and large TACRED dataset (Zhang et al., 2017), all take the relation classification view, by providing tuples of the form (sentence, e_1, e_2, relation). Consequently, all state-of-the-art models follow the classification view: the sentence and entities are encoded into a vector representation, which is then being classified into one of the |R| relations. The training objective then aims to embed the sentence + entities into a space in which the different relations are well separated. We argue that this is a sub-optimal training architecture and training objective for the task, and propose to use span-predictions models, as used in question-answering models, as an alternative. Recent work by (Alt et al., 2020) analyzed the errors of current RC systems and showed that 10% of the errors are the result of predicting a relation that is based on other arguments in the sentence. Treating Relation Extraction as question answering (QA) has been previously explored by (Levy et al., 2017), who demonstrated that by posing each relation as a question, one can train a system that transfers well to new and unseen relations in a “zero-shot” setting. We improve upon the reduction of (Levy et al., 2017) by making it two-directional and demonstrate that by using span-based classification rather than objective one is more effective in a fully supervised setup: by converting RC datasets to the QA-inspired span-prediction form, we can train fully-supervised models for both TACRED and SemEval08 that surpass the current state-of-the-art on these datasets by 3.7F_1 points. We experiment with a number of different templates and show that our method can benefit from templates that add some prior semantic knowledge.

2 Related Work

Closest to our work is Levy et al. (2017), who used relation based questions to create zero-shot models for RE. We use a similar approach to transform relations into queries but also use reverse questions, and target also the fully supervised scenario. Other work that use QA-reductions to solve NLP tasks include reduction from coreference resolution (Wu et al., 2019), event extractions (Du and Cardie, 2020) and nested named entities (Li et al., 2019).

Recently, Jiang et al. (2019) presented a unified model for many NLP tasks, using a unified span-based classification method. Such predictors may also benefit from adopting a QA-like span modeling, as we present here.
3 Classification vs Span-prediction

Relation Classification A RC sample takes the form \((c, e_1, e_2, r)\) where \(c = [c_0, \ldots, c_n]\) is a context (usually a sentence), \(e_1\) and \(e_2\) correspond to head and tail entities and are given as spans over the sentence, and \(r \in R \cup \{\emptyset\}\) is a relation from a predefined set of relations \(R\), or \(\emptyset\) indicating that no relation from \(R\) holds. RC classifier takes the form of a multi-class classifier \(f(c, e_1, e_2) \mapsto r\). The training objective is to score the correct \(r \in R \cup \{\emptyset\}\) over all incorrect answers, usually using a cross-entropy loss. State-of-the-art methods (Baldini Soares et al., 2019) achieve this by learning an embedding function \(\text{embed}(c, e_1, e_2)\) that maps instances with the same relation to be close to the embedding of the corresponding relation in an embedding space. The embedding function is used on pre-trained LMs such as SpanBERT (Joshi et al., 2020), RoBERTA (Liu et al., 2019) and ALBERT (Lan et al., 2019).

QA vis Span-prediction A QA sample takes the form \((c, q, e_a)\) where \(c = [c_0, \ldots, c_m]\) is a context (a sentence or a paragraph), \(q = [q_0, \ldots, q_l]\) is a query, and \(e_a\) is the answer to the query represented as a span over the \(c\), or a special out-of-sequence-span indicating that the answer does not exist.¹ QA classifier takes the form of a span predictor, \(f(c, q) \mapsto e_a\). This predictor takes the form \(\text{arg max}_{e_a} \text{score}_{c, q}(e_a)\), where \(\text{score}_{c, q}(e_a)\) is a learned span scoring function, and \(e_a\) ranges over all possible spans. The training objective is to maximize the the score the correct spans above all other candidate spans. The scoring function in state-of-the-art models (McCann et al., 2018; He et al., 2015; Wu et al., 2019) also make use of pre-trained LMs.

Current QA systems use a threshold to find negative instances. Let \(e\) be the span with the highest score in the sentence. model response is \(e\) if \(\text{score}(e) - \text{score}(\text{no-answer}) < \tau\) and “no answer” otherwise, where the threshold \(\tau\) is found using grid search based on the training data.

3.1 Method Comparison

The question \(q\) in QA can be thought of as involving a span \(e_q\) and event \(r_q\). Under this view, the QA classifier can be written as \(f(c, e_q, r_q) \mapsto e\), while the RC classifier is \(f(c, e_1, e_2) \mapsto r\). Note that both methods include a context, two spans, and a relation/event, but the RC models classify from two spans to a relation (from a fixed set), while the QA model classifiers from a span and a relation (from a potentially open set) into another span. Let’s review the implications of this difference:

embedding While the two methods use embedding for classification. The input for this embedding changes. In RE the embedding \(e_{re}\) is obtained using Equation 1 while the QA embedding \(e_{qa}\) is obtained using Equation 2

\[
e_{re} = \text{embd}(\text{CLS}|c|\text{SEP}).
\]

\[
e_{qa} = \text{embd}(\text{CLS}|q|\text{SEP}|c|\text{SEP}).
\]

Where \(\text{embd}(\cdot)\) is the embedding function, and \(\text{CLS}\) and \(\text{SEP}\) are reserved tokens. The addition of the query \(q\) to the embedding allows the embedding function to focus on a specific relation. For example, consider the sentence “Martha gave birth to John last February”. The entity John connects to two relations: “date of birth” and “parents of”. The RE embedding will have to contain data for both relations, while in the QA case the embedding can be focused on the existence (or nonexistence) of one of the entities based on the query \(q\). Focusing on a specific relation in the embedding stage (which involves most of the computation of the model) allows more to use all of the model computation to a specific relation.

Semantic information The templates that are used in QA models can contain valuable information for the model. They can 1. contain semantic information that is correlated to the target relation (e.g. questions that represent the relation) and 2. they contain information that can help generalize over different relations².

More demanding loss function During training, embedding based models classify spans in texts to one of \(|R| + 1\) relation types. QA models are also required to classify the relation according to

²Consider the relation “title of” and the question “Who own the title X?” and the relation “parent of” and the question “Who is the parent of X?”. While both relation are different, both contain an entity of type “person”, which is indicated by the use of the word “Who” in both questions.
its type (when the model is required to predict if the context contains an answer), but they are also required to predict the span of the missing argument. This means that the QA models are required to predict the relation between relation entities.

4 Reducing RC to Span-prediction

Given the uncovered similarity between RC and span-predicting QA, we now reduce RC to span-prediction.

Given an RC instance \((c, e_1, e_2) \mapsto r\) we can create an QA instance \((c, q = (e_q, r_q)) \mapsto e_a\) as follows. Let \(t_r(e)\) be a template function associated with relation \(r\). The function takes an entity \(e\) and returns a question. For example, a template for date-of-birth relation might be \(t_{dob} = \text{"When was } c \text{ born"}\), and \(t_{dob}(\text{Sam}) = \text{When was Sam born?}\).

We map the RC instance \((c, e_1, e_2) \mapsto r\) to a QA instance \((c, q = t_r(e_1)) \mapsto e_2\). The relation holds if the span returned from the QA module is compatible with \(e_2\). A similar approach was taken by (Levy et al., 2017). Alternatively, we could have used a different template, and reverse the roles of \(e_1\) and \(e_2\), creating the QA instance \((c, q = t^2_r(e_2)) \mapsto e_1\). We propose to use both approaches, by associating a relation \(r\) with two templates, \(t^1_r\) and \(t^2_r\), creating the two corresponding QA instances, and combining the two QA answers. As a concrete example, given the RC instance:

\[
\text{RC:}(c, \text{Sam, 1991}) \mapsto \text{date-of-birth}
\]

we create the two QA instances:

\[
\text{QA1:}(c, \text{When was Sam born?}) \mapsto 1991
\]

\[
\text{QA2:}(c, \text{Who was born in 1991?}) \mapsto \text{Sam}
\]

Note that while in this example we formulate the questions in English, simpler template might also be used. We explore different template types in Section 5.

There are various possible strategies to combining the two answers. Based on preliminary tests we choose the following strategy: the two QA answers are combined with an OR operation: if either of the returned span is compatible with the expected span,\(^3\) the relation \(r\) is returned, and if neither of them is compatible, the answer is no-relation.

Note that this reduction solves a binary version of RC, where the relation is given and the classifier needs to decide if it holds or not. This can be extended to the multi-class version by creating a version for each of the relevant relations.\(^4\) \(^5\)

Supervised training This above reduction allows to use a trained QA model for answering RC instances. We now describe how to use it for training QA model for an RC dataset. This is achieved by transforming an RC training dataset into QA form. For each RC training instance \((c, e_1, e_2, r)\), where \(r \in R \cup \{\emptyset\}\), we consider all relations \(r' \in R\) which are compatible with \((e_1, e_2)\).\(^6\) We then generate two QA instances for each of the compatible relations. Instances that are generated with the templates of the gold-relation \(r\) are marked as positive instances (their answer is either \(e_1\) or \(e_2\), as appropriate), while instances that are generated from \(r' \neq r\) are negative examples (their answer is the no-answer span).

Thresholds As discussed above, the QA model uses a global threshold \(\tau\) to distinguish between answerable and non-answerable questions, given a context. We observe that the optimal threshold value for each question is different. When translating an RC dataset to QA form, the number of questions template is fixed \((2|R|)\), allowing us to set an individual threshold \(\tau^i_r\) for each question template. The threshold is set using the QA model’s threshold setting procedure, but considering the set of questions generated from each template separately. As we see in the experiments section, using the individual thresholds improves results.

5 Experiments and Results

Datasets We compare ourselves on two RC datasets. TACRED (Zhang et al., 2017) is the currently most popular and largest RC dataset. It contain 106,264 labeled sentences (train + dev + test), 20% of the data is composed from the 41 different relations where the rest 80% contains ”no relation” instances. The relations are “classic” RC relations involving persons, locations, organizations, dates and so on. SemEval 2010 Task 8 (SemEval) (Hendrickx et al., 2010), is a smaller dataset, con-

\(^3\)Two non-empty spans are said to be compatible if either of them contain the other.

\(^4\)A relation is relevant for a given pair of entities if the entities ner-types match that of the relation.

\(^5\)In the rare case (less than \(4\%)\) that our model predicts more than one relation, we return the first relation discovered (chosen at random).

\(^6\)A relation is compatible with a pair of entities if it is between entities with the same named-entity types.
| Model                              | P   | R   | F1  |
|-----------------------------------|-----|-----|-----|
|                                   | TACRED |     |
| MTB (BERT)                        | -   | -   | 70.1|
| token-TACRED (ours, BERT)         | 63.3| 78.4| 70  |
| relation-TACRED (ours, BERT)      | 67  | 76  | 71.2|
| QA-TACRED (ours, BERT)            | 71.1| 72.6| 71.8|
| KEPLER (RoBERTa + KG, sota)       | 72.8| 72.2| 72.5|
| token-TACRED (ours, ALBERT)       | 72.2| 74.6| 73.4|
| relation-TACRED (ours, ALBERT)    | 74.6| 75.2| 74.8|
| QA-TACRED (ours, ALBERT)          | 73.3| 71.8| 72.6|
| QA-TACRED (only head q, ALBERT)   | 75.8| 65.4| 70.2|
|                                   | SemEval |     |
| MTB (BERT)                        | -   | -   | 89.2|
| QA-SemEval (ours, BERT)           | 90.7| 93.2| 91.9|
| LiTian (sota)                     | 94.2| 88.0| 91.0|

Table 1: Supervised results on the TACRED and SemEval datasets.

We now turn to use the reduction for fully supervised results. We convert both the TACRED and SemEval training sets to QA form as described above, resulting in QA-TACRED and QA-SemEval, and train QA models on the resulting datasets. Additionally, we use two more types of templates. A token template, where we add a new token that represent each relation, one of the entities, and an indicator if it’s a head or tail entity. The second relation template uses the relation name instead of an arbitrary token. We then apply the models to the respective RC test sets.

Models We train span-predicting QA models using the architecture described in (Devlin et al., 2018), starting from either the BERT-Large (Devlin et al., 2018) or ALBERT (Lan et al., 2019) pre-trained LMs. BERT-large is used to compare the SOTA model reported in (Baldini Soares et al., 2019) on equal grounds, while ALBERT is a stronger pre-trained LM.

Comparisons We compare our results to several SOTA models, reporting the results from the corresponding papers. MTB (Baldini Soares et al., 2019) is a SOTA RC model which is based on BERT-large, and which does not involve any additional training material except for the the pre-trained LM. This is our most direct comparison. KEPLER (Wang et al., 2019) is a RoBERTa based RC model which incorporates additional knowledge in the form of a knowledge-graph derived from wikipedia and wikidata. This model holds the current highest reported RC results over TACRED. LiTian (Li and Tian, 2020) is the current top scoring model on the SemEval dataset. It uses a dedicated RC architecture, and uses the BERT pre-trained LM.

Results Table 1 presents the main results. Our BERT-based QA-reduction models significantly outperform the comparable SOTA MTB model on both datasets, and outperforms the current best SemEval model. The ALBERT-based relation reduction outperforms the current best TACRED model (KEPLER) on $F_1$, despite KEPLER using external data.

Ablation To assess the contribution of using questions in both directions, Table 1 reports also the ALBERT-based QA-reduction on TACRED in which we present two questions per relation, but where both questions use $e_1$ as the template argument and $e_2$ as the answer ("only head q"). This model has significantly less success than the two-way model, resulting in a drop of 2.4% $F_1$.

6 Conclusion In this work, we argue for the use of span-prediction methods, typically used for QA, to replace the standard RC architectures. This approach achieves state-of-the-art performance in supervised settings, with the moderate cost of supplying question templates that describe the relation.

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7E.g., the relation (John, CEO, per:title) will be represented as the questions "r2 h john" and "r2 t CEO".
8E.g., the above relation (John, CEO, per:title) will be represented as the questions "per:title h john" and "per:title t CEO".
9We used the implementations provided by Huggingface (Wolf et al., 2019). Following previous work, used the Adam optimizer, an initial learning rate of $3e^{-5}$, and up to 20,000 steps with early stopping on a dev-set.
10We also ran preliminary tests using (Liu et al., 2019) and (Joshi et al., 2020) that showed inferior results compared to ALBERT.
11The same paper reports an additional results based on external training data, which is not comparable. However, these results has since been superseded by the KEPLER model.
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**Question Templates For TACRED**

Tables 2 and 2 on the next page show the question templates we used on the TACRED dataset.
| Relation Name                            | Question                                                                 |
|-----------------------------------------|--------------------------------------------------------------------------|
| per:date_of_birth                       | Q1: When was $e_1$ born?                                                 |
|                                         | Q2 Who was born in $e_2$?                                                |
| per:title                               | Q1: What is $e_1$’s title?                                               |
|                                         | Q2 Who has the title $e_2$                                               |
| org:top_members/employees               | Q1: Who are the top members of the organization $e_1$?                   |
|                                         | Q2 What organization is $e_2$ a top member of?                           |
| org:country_of_headquarters             | Q1: In what country the headquarters of $e_1$ is?                        |
|                                         | Q2 What organization have it’s headquarters in $e_2$?                   |
| per:parents                            | Q1: Who are the parents of $e_1$?                                       |
|                                         | Q2 Who are the children of $e_2$?                                       |
| per:age                                 | Q1: What is $e_1$’s age?                                                 |
|                                         | Q2 Whose age is $e_2$?                                                  |
| per:countries_of_residence              | Q1: What country does $e_1$ resides in?                                 |
|                                         | Q2 Who resides in country $e_2$?                                        |
| per:children                            | Q1: Who are the children of $e_1$?                                      |
|                                         | Q2 Who are the parents of $e_2$?                                        |
| org:alternate_names                     | Q1: What is the alternative name of the organization $e_1$?              |
|                                         | Q2 What is the alternative name of the organization $e_2$?               |
| per:charges                             | Q1: What are the charges of $e_1$?                                      |
|                                         | Q2 Who was charged in $e_2$?                                            |
| per:cities_of_residence                 | Q1: What city does $e_1$ resides in?                                     |
|                                         | Q2 Who resides in city $e_2$?                                           |
| per:origin                              | Q1: What is $e_1$ origin?                                               |
|                                         | Q2 Who originates from $e_2$?                                          |
| org:founded_by                          | Q1: Who founded $e_1$?                                                  |
|                                         | Q2 What did $e_2$ found?                                                |
| per:employee_of                         | Q1: Where does $e_1$ work?                                              |
|                                         | Q2 Who is an employee of $e_2$?                                         |
| per:siblings                            | Q1: Who is the sibling of $e_1$?                                        |
|                                         | Q2 Who is the sibling of $e_2$?                                         |
| per:alternate_names                     | Q1: What is the alternative name of $e_1$?                              |
|                                         | Q2 What is the alternative name of $e_2$?                               |
| org:website                             | Q1: What is the URL of $e_1$?                                           |
|                                         | Q2 What organization have the URL $e_2$?                                |
| per:religion                            | Q1: What is the religion of $e_1$?                                      |
|                                         | Q2 Who believe in $e_2$?                                                |
| per:stateorprovince_of_death            | Q1: Where did $e_1$ died?                                               |
|                                         | Q2 Who died in $e_2$?                                                  |
| org:parents                             | Q1: What organization is the parent organization of $e_1$?              |
|                                         | Q2 What organization is the child organization of $e_2$?                |
| org:subsidiaries                        | Q1: What organization is the child organization of $e_1$?               |
|                                         | Q2 What organization is the parent organization of $e_2$?               |

Table 2: TACRED question templates part 1
| Relation Name                      | Question                                                                 |
|-----------------------------------|--------------------------------------------------------------------------|
| per:other_family                   | Q1: Who are family of e1?                                                |
|                                   | Q2 Who are family of e2?                                                |
| per:stateorprovinces_of_residence | Q1: What is the state of residence of e1?                                |
|                                   | Q2 Who lives in the state of e2?                                        |
| org:members                       | Q1: Who is a member of the organization e1?                              |
|                                   | Q2 What organization e2 is member of?                                   |
| per:cause_of_death                 | Q1: How did e1 died?                                                    |
|                                   | Q2 How died by e2?                                                      |
| org:member_of                      | Q1: What is the group the organization e1 is member of?                  |
|                                   | Q2 What organization is a member of e2?                                 |
| org:number_of_employees/members    | Q1: How many members does e1 have?                                      |
|                                   | Q2 What organization have e2 members?                                   |
| per:country_of_birth               | Q1: In what country was e1 born                                         |
|                                   | Q2 Who was born in the country e2?                                      |
| org:shareholders                   | Q1: Who hold shares of e1?                                               |
|                                   | Q2 What organization does e2 have shares of?                            |
| org:stateorprovince_of_headquarters| Q1: What is the state or province of the headquarters of e1?            |
|                                   | Q2 What organization’s headquarters are in the state or province e2?    |
| per:city_of_death                  | Q1: In what city did e1 died?                                           |
|                                   | Q2 Who died in the city e2?                                             |
| per:country_of_birth               | Q1: In what city was e1 born?                                           |
|                                   | Q2 Who was born in the city e2?                                         |
| per:spouse                         | Q1: Who is the spouse of e1?                                            |
|                                   | Q2 Who is the spouse of e2?                                             |
| org:city_of_headquarters           | Q1: Where are the headquarters of e1?                                   |
|                                   | Q2 Which organization has its headquarters in e2?                       |
| per:date_of_death                  | Q1: When did e1 die?                                                    |
|                                   | Q2 Who died on e2                                                        |
| per:schools_attended               | Q1: Which schools did e1 attend?                                        |
|                                   | Q2 Who attended e2?                                                     |
| org:political/religious_affiliation | Q1: What is e1 political or religious affiliation?                      |
|                                   | Q2 Which organization has is political or religious affiliation with e2? |
| per:country_of_death               | Q1: Where did e1 die?                                                   |
|                                   | Q2 Who dies in e2?                                                      |
| org:founded                        | Q1: When was e1 founded?                                                |
|                                   | Q2 What organization was founded on e2?                                 |
| per:stateorprovince_of_birth       | Q1: In what state was e1 born?                                          |
|                                   | Q2 Who was born in state e2?                                            |
| org:dissolved                      | Q1: When was e1 dissolved?                                              |
|                                   | Q2 Which organization was dissolved in e2?                              |

Table 3: TACRED question templates part 2