Extracting Multiple-Relations in One-Pass with Pre-Trained Transformers

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1 Introduction

Relation extraction (RE) tasks aim to find the semantic relation between a pair of entity mentions from texts. It plays a key role in many important NLP problems such as automatic knowledge base completion (Surdeanu et al., 2012; Riedel et al., 2013; Verga et al., 2016) and question answering (Yih et al., 2015; Yu et al., 2017).

One particular type of relation extraction tasks is multi-relation extraction (MRE). MRE aims to recognize relations of multiple pairs of entity mentions in an input paragraph. This task has important and practical implications, since it is more common to have a paragraph containing multiple pairs of entities. Existing approaches on MRE tasks (Qu et al., 2014; Gormley et al., 2015; Nguyen and Grishman, 2015) propose to adopt the methods for Single-Relation Extraction tasks to solve MRE tasks. These works treat each pair of entity mentions as an independent instance; and rely on features describing the words’ relations to the two entities as additional structural information. But these type of methods have a major drawback - they need to encode the same paragraph multiple times to predict the relations between different entity pairs (multi-pass). These multiple passes over a single paragraph are computationally expensive and can become prohibitive especially when encoding the paragraphs using deep models.

In this paper, we focus on tackling the inefficient multi-pass issue of existing solutions in MRE tasks. We successfully make use of pre-trained general-purposed language encoders, specifically, the Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2018), to encode the input paragraph only once (one-pass) and also achieve a new state-of-the-art accuracy. The key idea of our approach is to enable the representation of a paragraph to distinguish relation mentions associated with different entity mentions, i.e., the paragraph representations should be entity-aware. However, the pre-trained encoders themselves are not entity-aware since they take only raw texts as inputs, which is a problem. Thus, we propose and evaluate two novel designs to solve this problem: (1) we introduce a structured prediction layer for predicting multiple relations for different entity pairs; (2) we make the self-attention layers to be aware of the positions of all entities in the input paragraph.

With the aforementioned model design, our approach can accurately predict multiple relations for all entity pairs in a single pass of the input paragraph. Our experiments confirmed that our approach achieves the state-of-the-art results on the ACE 2005 benchmark. To the best of our knowledge, this work is the first approach that can solve

Abstract

Most approaches to extraction multiple relations from a paragraph require multiple passes over the paragraph. In practice, multiple passes are computationally expensive and this makes difficult to scale to longer paragraphs and larger text corpora. In this work, we focus on the task of multiple relation extraction by encoding the paragraph only once (one-pass). We build our solution on the pre-trained self-attentive (Transformer) models, where we first add a structured prediction layer to handle extraction between multiple entity pairs, then enhance the paragraph embedding to capture multiple relational information associated with each entity with an entity-aware attention technique. We show that our approach is not only scalable but can also perform state-of-the-art on the standard benchmark ACE 2005.
MRE task accurately to achieve state-of-the-art results and fast (in one-pass).

2 Background

2.1 Multi-Relation Extraction

Multi-relation extraction (MRE) is an important information extraction task and can be applied to several real-world problems. Several benchmarks were constructed for evaluation in MRE tasks such as ACE (Walker et al., 2006) and ERE (Linguistic Data Consortium, 2013).

In an MRE task, the input is a text paragraph containing \( N \) words \( x = \{x_1, \ldots, x_N\} \) and \( M \) entity mentions \( e = \{e_1, \ldots, e_M\} \). Different mentions \( e_i \) and \( e_j \) can be the same type of entity or two different entities. The task is to predict a relation \( r_{ij} \) between each pair \((e_i, e_j)\). \( r_{ij} \) is from a list of pre-defined relations \( R \) or is a special class NA meaning no relations exist between \((e_i, e_j)\).

Many MRE approaches have been proposed to solve this challenging problem. These approaches focus either on feature and model architecture selections (Gormley et al., 2015; Nguyen and Grishman, 2015), or on domain adaptation of MRE models (Fu et al., 2017; Shi et al., 2018). However, these approaches require multiple passes over the paragraph, as they treat MRE as multiple passes of a SRE model. To the best of our knowledge our work is the first one to investigate solving of MRE in a single pass over the paragraph, and also achieves state-of-the-art performance.

It is worth noting that our task is different from the one in (Verga et al., 2018). Verga et al. (2018) focus on one-pass extraction of a single relation between a pair of entities, each of which could have multiple mentions. By comparison, we focus on one-pass extraction of multiple relations between different pairs of entity mentions. Different mention pairs of the same entity pair could have different relations. Their method cannot distinguish relation mentions between different pairs of entity mentions, therefore does not fulfill the goal of MRE, as confirmed by our experiments.

2.2 Pre-Trained Language Encoders

Recently, pre-trained general-purposed language encoders, such as CoVe (McCann et al., 2017), ELMo (Peters et al., 2018), GPT (Radford et al., 2018) and BERT (Devlin et al., 2018), have generated a lot of interest in the NLP community. These approaches benefit from training on huge unlabeled text corpora in order to achieve generalizable text embeddings.

Our approach builds on top of the representations from the pre-trained deep bidirectional transformers (BERT). We first briefly describe BERT and then (in Section 3) show how our approach uses it. Transformers in BERT consist of multiple layers, each of which implements a self-attention sub-layer with multiple attention heads. Each output of a self-attention sub-layer, \( z_i \), is computed as the weighted sum of linearly transformed input elements, which are the outputs of the previous layers \( h_i \):

\[
z_i = \sum_{j=1}^{N} \frac{\exp e_{ij}}{\sum_{k=1}^{N} \exp e_{ik}} (h_j W^V)
\]

The self-attention scores \( e_{ij} \) are computed by comparing each pair of the input elements:

\[
e_{ij} = \frac{(h_i W^Q)^T(h_j W^K)}{\sqrt{d_z}}
\]

where \( d_z \) is the dimension of the output from self-attention sub-layer, and \( W^Q, W^K, W^V \) are parameters of the model. BERT is pre-trained on both word-level and sentence-level language modeling tasks. As a result, it has achieved substantial improvements when fine-tuned on benchmarks with smaller labeled data, e.g., textual entailment, reading comprehension and many text classification tasks.

Despite the above successes, there are limited studies on applying these encoders to tasks with structured inputs. This is mainly because the models are pre-trained to optimize the language modeling objectives with raw texts as inputs. However, in some tasks, such as the MRE task, the structural information is crucial. In MRE, the same paragraph may represent different relations for different entity pairs. A model will output the same results for a paragraph if the target entities are ignored during encoding. Therefore, in this work, we take the MRE task as an example to study how to better infuse structural information into the pre-trained encoders.

Another problem of the pre-trained encoders is that they are deep models with large hidden states, thus run much slower compared to previous networks. Therefore their usages give rise to an obvious trade-off between accuracy and speed. The

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\(1\)Since in MRE, the arguments are always entity mentions. In this paper we use the terms entity mention and entity interchangeably.
Explosions were heard in southern suburbs of Baghdad and Iraqi artillery fired back.

Figure 1: Overview of our proposed MRE system.

problem becomes more serious in standard MRE pipeline, which requires to re-encode the whole same paragraph for every entity pair. As a result, it is crucial in practice if an MRE model could predict multiple relations for all entity pairs with only one-pass of paragraph encoding.

3 Proposed Approach

In this section, we describe our MRE solution which is built on top of the pre-trained language encoder BERT. As shown in the method descriptions and experiments, the transformer architecture used in BERT makes it easier to deeply infuse structural input information (instead of shallow infusion as additional input features in previous work) into the encoding stage to better solve the MRE task.\(^2\)

Departing from the standard BERT structure, we first add a structured prediction layer to enable MRE with only one-pass encoding of the input (Section 3.1). Second, we introduce an entity-aware self-attention mechanism (Section 3.2) for the infusion of relational information with regard to multiple entities at each hidden state. The overall proposed framework is illustrated in Figure 1.

3.1 Structured Prediction of Multi-Relations with BERT

The BERT model has been applied to classification, sequential labeling and text span extraction (for reading comprehension) (Devlin et al., 2018). However, the types of final prediction layers used in the above tasks do not fit the structured prediction natural of the MRE task. Note that in MRE, we essentially do edge prediction over a graph with entities as nodes. Inspired by (Dozat and Manning, 2018; Ahmad et al., 2018), we propose a simple yet efficient approach for multi-relation prediction. After the input paragraph has been encoded by BERT, we take the representations of entity mentions from the final BERT layer. Since one entity mention may contain multiple words and the BERT uses byte pair encoding (BPE), usually one mention can correspond to multiple hidden states. Therefore, we perform average-pooling over all the tokens’ hidden states to get a single representation for each entity mention. Finally, for a pair of entity mentions \((e_i, e_j)\), we denote their representation vectors as \(o_i\) and \(o_j\).

We concatenate \(o_i\) and \(o_j\) and pass it to a linear classification layer\(^3\) to predict the relation \(r\) between \(e_i\) and \(e_j\):

\[
P(r(e_i, e_j)|X, e_i, e_j) = \text{softmax}(W^L_o [o_i : o_j] + b),
\]

where \(W^L_o \in \mathbb{R}^{2d_z \times l}\), \(d_z\) is the dimension of BERT embedding at each token position, and \(l\) is the number of relation labels, i.e., \(l = |\mathcal{R}|\). Figure 1 illustrates the above structured prediction strategy. For different pairs of entities, e.g., (Iraqi

\(^2\)We can also use other transformer-based pre-trained encoders, e.g. (Radford et al., 2018) to solve this problem. The comparison among different pre-trained transformers is out of the scope for this paper.

\(^3\)We also tried to use MLP and Bioaff instead of the linear layer for the classification, which perform worse as shown in the experiments. We assume that this is because the embeddings learned by BERT are powerful enough for linear classifiers.
anti

Explosions

were

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in

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and

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Anti-aircraft

artillery

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back

Figure 2: Illustration of the tensor \( \{a_{ij}^K\} \). Each cell is a vector (either a type embedding vector \( a_{ij}^K \) or a zero vector). The \( \{a_{ij}^V\} \) follows the same pattern with independent parameters.

and artillery), (southern suburbs, Baghdad), different final-layer embeddings are used for relation prediction. For entities containing multiple words (southern suburbs) or being tokenized into multiple sub-tokens (Baghdad), average-pooling is applied to get the mention embeddings.

Training The training objective of an input paragraph \( s \) is defined as the sum over the log-likelihood of all the entity pairs whose relation labels are required for prediction, denoted as \( E_s \),

\[
L_s = \sum_{(e_1, e_2) \in E_s} \log P(r(e_1, e_2) | X, e_1, e_2).
\]

During prediction, all relations between the designated entity pairs in a single paragraph are extracted with one-pass of the BERT encoding process.

3.2 Entity-Aware Self-Attention based on Relative Distance

This section describes an approach to encode multi-relation information into the hidden states of the model. By highlighting the entity positions in the attention layer, the hidden state of each token focuses more on how the token interacts with all the entities, and the hidden state of each entity is encouraged to capture features indicating multiple relations. As a result, the encoder is aware of all the entity mentions in the paragraph and thus can capture relational information associated with all the mentions.

The key idea of our approach is to use the relative distances between a single word and all the entities to guide the attention computation. Following (Shaw et al., 2018), we achieve this with the following formulation. For each pair of word tokens \((x_i, x_j)\) with the input representations from previous layer \( h_i \) and \( h_j \), if there is a distance category \( c_{ij} \) (defined later), we extend the computation of self-attention in Eq. 1 and 2 as:

\[
z_i = \sum_{j=1}^{N} \frac{\exp e_{ij}}{\sum_{k=1}^{N} \exp e_{ik}} (h_j W^V + a_{ij}^K), \quad (3)
\]

and

\[
e_{ij} = \frac{h_i W^Q (h_j W^K + a_{ij}^V)}{\sqrt{d_z}}. \quad (4)
\]

Here \( a_{ij}^V \) and \( a_{ij}^K \) can be viewed as (two different sets of) embeddings of the category \( c_{ij} \). During fine-tuning of BERT models, these type embeddings are trained from scratch, together with the pre-trained BERT parameters. An additional benefit of our method is that the category embeddings can capture important task-specific information such that the pre-trained BERT parameters won’t be changed dramatically.\(^4\)

Specifically, we define the relative distance category \( c_{ij} \) as follows:

\- If either \( x_i \) or \( x_j \) is inside an entity, we define a category \( c_{ij} \) as the clipped relative distance:

\[
c_{ij} = \text{clip}(j - i, k) \quad x_i \in \text{entity} \quad \quad (5)
\]

\[
c_{ij} = \text{clip}(i - j, k) \quad x_j \in \text{entity} \quad \quad (6)
\]

The \( \text{clip}(\cdot, k) \) operator maps all the numbers larger than \( k \) to \( k \), and those smaller than \(-k\) to \(-k\), \( k \) is a hyperparameter to be tuned on the development set.

\- If neither \( x_i \) nor \( x_j \) are entity mentions, we explicitly assign a zero vector to \( a_{ij}^K \) and \( a_{ij}^V \). In this situation, the computation of self-attention scores will be the same as in the standard BERT self-attention.

\- When both \( i \) and \( j \) are inside entities, we define \( c_{ij} \) as in Eq. 5 (the row-wise definition). This is

\(^4\)This is implied by our initial experiments: when sub-sampling 10% training data, the performance drop of the entity-aware self-attention approach is smaller than using entity indicator on input-layer.
from the intuition that the row-wise attention plays a more important role for encoding entity information, as the attention and states computed in Eq. 3 and Eq. 4 are summed column-wise.

Figure 2 illustrates the resulted category embeddings for all the $c_{ij}$s.

4 Experiments

4.1 Settings

This section evaluates our proposed method on the popular MRE benchmark, ACE 2005. We also report results on the commonly used single-relation benchmark SemEval 2010 task 8 (Hendrickx et al., 2009), where only one relation is required to be predicted from each paragraph.

Data Following previous work (Gormley et al., 2015), we adopt the multi-domain setting and use the English portion of the ACE 2005 corpus (Walker et al., 2006). We train on the union of news domain (nw and bn), tune hyperparameters on half of the broadcast conversation (bc) domain, and evaluate on the remainder of broadcast conversation (bc), the Telephone Speech (cts), Usenet Newsgroups (un), and Weblogs (wl) domains. For the SemEval data, we use the standard data split.

Methods We compare with the published results from previous works that predict a single relation per pass (Gormley et al., 2015; Nguyen and Grishman, 2015; Fu et al., 2017; Shi et al., 2018), as well as the following modifications of BERT that could achieve MRE in one-pass.

• **BERTSP**, i.e. BERT w/ structured prediction only, which is our method in Section 3.1.
• **Entity-Aware BERTSP**, i.e. our full model, which makes use of the structural information with the methods from both Section 3.1 and 3.2.
• **BERTSP w/ position embedding on the final attention layer.** This is a more straightforward way to achieve MRE in one-pass derived from previous works using position embeddings (Nguyen and Grishman, 2015; Fu et al., 2017; Shi et al., 2018). In this method, the BERT model encodes the paragraph until the last attention-layer. Then for each entity pair, it takes the hidden states, adds the relative position embeddings corresponding to the target entities, and makes the relation prediction for this pair. For an input paragraph, most of the BERT layers run only once thus we consider it as an MRE-in-one-pass method.

• **BERTSP w/ entity indicators on input layer.** which replaces our structured attention layer, and directly adds indicators of entities (transformed to embeddings) to each token’s word embedding5. This method is an extension of (Verga et al., 2018) to the MRE scenario.

For our experiments, most model hyperparameters are the same as in pre-training. We tune the training epochs and the new hyperparameter $k$ (in Eq. 5) on the development set.

4.2 Results on ACE 05

Main Results Table 1 gives the overall results on ACE 2005. The first observation is that our model architecture achieves much better results compared to the previous state-of-the-art methods, both without and with domain adaptation techniques. Note that although our method was not designed for domain adaptation, it outperforms such methods which further demonstrates its effectiveness.

Among all the BERT-based approaches, fine-tuning the out-of-box BERT does not give reasonable results, because the sentence embeddings cannot distinguish different entity pairs. While our BERTSP can successfully adapt the pre-trained BERT to the MRE task, and achieves comparable results with the state-of-the-art (w/o DA). Our structured fine-tuning of attention layers brings a further improvement of about 5.5%, in the MRE one-pass setting. It also improves most over the BERTSP method compared to the other two MRE in one-pass methods.

Performance Gap between MRE in One-Pass and Multi-Pass Usually, the MRE-in-one-pass models can also be used to train and test with one entity pair per pass (Single-Relation per Pass results in Table 1). Therefore, we compare the same methods when applied to the multi-relation and single-relation settings. For BERTSP w/ entity indicators on inputs, it is expected to perform slightly better in the single-relation setting, because of the mixture of information from multiple pairs. A two percent gap is observed as expected. By comparison, our full model has a much smaller performance gap between two different

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5 Note the usage of relative position embeddings does not work for one-pass MRE, since each word corresponds to a varying number of position embedding vectors. Summing up the vectors confuses the information. It works for the single-relation per pass setting, but the performance lags behind using only indicators of the two target entities.
Table 1: Main Results on ACE 2005.

| Method | dev | bc  | cts | wl  | avg |
|--------|-----|-----|-----|-----|-----|
| Hybrid FCM (Gormley et al., 2015) | -   | 63.48 | 56.12 | 55.17 | 58.26 |
| Best published results w/o DA (from Fu et al.) | - | 64.44 | 54.58 | 57.02 | 58.68 |
| BERT fine-tuning out-of-box | 3.66 | 5.56 | 5.53 | 1.67 | 4.25 |

### Baselines w/ Domain Adaptation (Single-Relation per Pass)

| Method | dev | bc  | cts | wl  | avg |
|--------|-----|-----|-----|-----|-----|
| Domain Adversarial Network (Fu et al., 2017) | - | 65.16 | 55.55 | 57.19 | 59.30 |
| Genre Separation Network (Shi et al., 2018) | - | 66.38 | 57.92 | 56.84 | 60.38 |

### Multi-Relation per Pass

| Method | dev | bc  | cts | wl  | avg |
|--------|-----|-----|-----|-----|-----|
| BERTSP (our model in §3.1) | 64.42 | 67.09 | 53.20 | 52.73 | 57.67 |
| Entity-Aware BERTSP (our full model) | **67.46** | **69.25** | **61.70** | **58.48** | **63.14** |
| BERTSP w/ entity-indicator on input-layer | 65.32 | 66.86 | 57.65 | 53.56 | 59.36 |
| BERTSP w/ pos-emb on final att-layer | 67.23 | 69.13 | 58.68 | 55.04 | 60.95 |

### Single-Relation per Pass

| Method | dev | bc  | cts | wl  | avg |
|--------|-----|-----|-----|-----|-----|
| BERTSP (our model in §3.1) | 65.13 | 66.95 | 55.43 | 54.39 | 58.92 |
| Entity-Aware BERTSP (our full model) | 68.90 | 68.52 | 63.71 | 57.20 | 63.14 |
| BERTSP w/ entity-indicator on input-layer | 67.12 | 69.76 | 58.05 | 56.27 | 61.36 |

**Table 2** shows the running time of different models in three aspects: the training time to achieve the best model in Table 1, the total testing time of the methods on dev dataset, and the numbers of relations predicted per second on dev dataset. Our approach is significantly faster compared to all the other methods. It is also much faster compared to the baseline MRE-in-one-pass approach, BERTSP with position embeddings on the final attention layer, because this baseline runs the last layer one time for each entity pair.

### Training and Inference Time Analysis

Settings (and no consistent performance drop over domains).

The BERTSP is not expected to have a gap as shown in the table. We hypothesize it might be a random result caused by differences in training objectives (and epochs). For BERTSP w/ position embeddings on the final attention layer, we trained the model in the single-relation setting and testing with two different settings, so the results are the same.

**Prediction Module Selection** Finally, Table 3 evaluates the usage of different prediction layers, including replacing our linear layer with MLP or Biaff. Results show that the usage of the linear predictor gives significantly better results. This is consistent with the motivation of the pre-trained encoders: by unsupervised pre-training the encoders are expected to be sufficiently powerful thus adding more complex layers on top does not improve the capacity but leading to more free parameters and higher risk of over-fitting.

### 4.3 Additional Results on SemEval

We conduct additional experiments on the commonly used relation classification task, SemEval 2010 Task 8, in order to compare with models developed on this benchmark. From the results in Table 4, our proposed techniques also help to outperform the state-of-the-art on this single-relation benchmark.

Because this is a single relation task, the out-of-box BERT itself could achieve a reasonable result after fine-tuning. Adding structured attention to BERT gives about 8% improvement, due to the availability of the entity information during encoding. Adding structured prediction layer to BERT (BERTSP) also leads to a similar amount of improvement. However, the gap between BERTSP method with and without structured attention layer is small. This is likely because of the bias of data distribution: the assumption that only two target entities exist makes the two techniques have similar effects.
| Method                                      | Train (minutes) | Inference (seconds) | (relations/sec) |
|--------------------------------------------|-----------------|---------------------|-----------------|
| Single-relation BERT<sub>SP</sub>          | 412             | 347                 | 23              |
| Our multi-relation BERT<sub>SP</sub>        | 134             | 63                  | 126             |
| BERT<sub>SP</sub> + pos-emb on last-layer  | 401             | 105                 | 76              |

Table 2: Training and Inference Time Analysis

| Method                                      | dev | bc  | cts | wl  | avg  |
|--------------------------------------------|-----|-----|-----|-----|------|
| Our full model                             | 67.46 | 69.25 | 61.70 | 58.48 | 63.14 |
| replacing linear with MLP                   | 67.16 | 68.52 | 61.16 | 54.72 | 61.47 |
| replacing linear with biaff                 | 67.57 | 69.24 | 60.91 | 56.60 | 62.25 |

Table 3: Our model with different prediction modules.

5 Conclusion

We propose the first system that simultaneously extracts multiple relations with one-time encoding of an input paragraph. With the proposed structured prediction and entity-aware self-attention layers, we made better use of the pre-trained BERT model and achieve significant improvement on the ACE 2005 data.

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