Abstract

The performance of relation extraction models has increased considerably with the rise of neural networks. However, a key issue of neural relation extraction is robustness: the models do not scale well to long sentences with multiple entities and relations. In this work, we address this problem with an enriched attention mechanism. Attention allows the model to focus on parts of the input sentence that are relevant to relation extraction. We propose to enrich the attention function with features modeling knowledge about the relation arguments and the shortest dependency path between them. Thus, for different relation arguments, the model can pay attention to different parts of the sentence. Our model outperforms prior work using comparable setups on two popular benchmarks, and our analysis confirms that it indeed scales to long sentences with many entities.

1 Introduction

Relation extraction is an important task for extracting structured information from unstructured text, e.g., for knowledge graph population. It is typically modeled as a classification task given a sentence and two potential relation arguments, which we call query entities in the remainder of the paper. Current state of the art applies different types of neural networks, such as recurrent neural networks (RNNs) (Miwa and Bansal, 2016; Zhang et al., 2017), convolutional neural networks (CNNs) (Zeng et al., 2014; Zhang et al., 2018) or transformer architectures (Devlin et al., 2019). Especially the integration of attention (Bahdanau et al., 2015) has been shown to improve results (Huang et al., 2017; Zhang et al., 2017) as it helps the model to focus on relevant parts of the input.

For robust relation extraction, however, a model needs to detect not only key phrases like “was born in”, “married” or “at the age of” but also has to determine to which entities they belong. This is particularly challenging when the context between two query entities includes other entities, as in the sentence in Figure 1: The context between “Barack Obama Sr.” and “1936”, for example, includes the entity “Barack Obama”. If an automatic extraction model only learns relation-specific key words or key phrases (as max pooling or attention layers do), it will struggle with such long sentences containing diverse information. From the sample sentence, a key word-based model might extract, for example, the incorrect relation born_in(Barack Obama, 1936) instead of the correct one born_in(Barack Obama Sr., 1936).

In this paper, we study the possibility to enrich the attention layer of a state-of-the-art model with additional information (features) to increase the robustness of attention-based relation extraction models. In particular, we address the task with a long-short term memory network architecture and investigate two different attention functions: Additive attention (Bahdanau et al., 2015) as also used by Zhang et al. (2017) and dot-product attention which gets more and more popular nowadays due to transformer networks (Vaswani et al., 2017). Previous work on relation extraction (i.a., Fundel et al., 2006; Mintz et al., 2009; Rink and Harabagiu, 2010; Miwa and Sasaki, 2014) showed the benefit of features derived from (i) the short-
est path between query entities in a dependency parse tree and (ii) information about the types of the query entities. Our approach builds upon these observations. In particular, we investigate the following features for the attention function: for dependency-enriched attention, a representation of the shortest path between the two query entities, as well as several token-level features, such as the distance of each token to the query entities in the dependency parse tree; for entity-enriched attention, embeddings representing the query entities, and embeddings representing their types.

Our model outperforms prior work using comparable setups on TACRED and achieves state-of-the-art results on ACE 2005, two popular benchmark datasets for relation extraction. Our analysis shows that the additional features help the network to pay more attention to words which are relevant to the two query entities but not to other entities in the sentence, alleviating the challenges shown in Figure 1. Thus, our work increases the scalability of relation extraction models to longer sentences with mentions of multiple entities and relations.

In summary, our main contributions are:

- We propose to enrich the attention mechanism with additional features. This way, the model can attend to the parts of the sentence which are relevant to the query entities and ignore other parts which might include relation information about other entities.

- Our approach is broadly applicable. Although we train long short-term memory networks in this work, our enriched attention mechanism is complementary to the underlying model and can thus be included in any attention-based neural network. Similarly, the concept of enriched attention is general and can be used for other tasks as well.

- We outperform prior work with comparable setups on two popular benchmarks and perform an in-depth analysis demonstrating that our enriched attention methodology indeed increases the robustness of the model in the case of long sentences and multiple entities per sentence.

2 Related Work

Neural relation extraction. Related work builds upon different input representations: the whole sentence (Zhang et al., 2017), a combination of three contexts (Adel and Schütze, 2019), the textual context between the query entities (Zeng et al., 2014), entity graphs (Christopoulou et al., 2018), span graphs (Luan et al., 2019), the dependency tree of the sentence (Guo et al., 2019) or the shortest dependency path between the query entities (Xu et al., 2015; Toutanova et al., 2015; Xu et al., 2015; Cai et al., 2016; Huang et al., 2017; Zhang et al., 2018). Veyseh et al. (2020) combine information from the dependency tree with the textual context. In contrast, we use the whole sentence as input and utilize information from the dependency tree as features for the attention function. Another feature known to improve relation extraction is type information of query entities (Mintz et al., 2009; Yao et al., 2010; Ling and Weld, 2012; Del Corro et al., 2015; Lin et al., 2020). We propose to integrate type information into the attention layer as further features.

Previous work uses different architectures, such as RNNs (Miwa and Bansal, 2016; Zhang et al., 2017), CNNs (Zeng et al., 2014; Huang et al., 2017; Zhang et al., 2018), graph convolutional neural networks (GCNs) (Guo et al., 2019) or transformer networks (Alt et al., 2019; Soares et al., 2019). Note that the latter approach typically requires extensive pre-training. Attention for relation extraction is not only popular in the context of transformers (Vaswani et al., 2017; Devlin et al., 2019) but also with other models, such as CNNs (Huang et al., 2017), GCNs (Guo et al., 2019) or RNNs (Zhang et al., 2017). We use the latter approach as a baseline model.

Extending the attention function. Enriching attention for natural language processing was proposed by, i.a., Li et al. (2019a) via incorporating relation indicating keywords into the attention function, by Adel and Schütze (2017) via exploiting external information from gazetteers, by Zhong et al. (2019) via integrating common sense knowledge into transformer models and by Zhang et al. (2017) via position-aware attention. In contrast, we propose to integrate a variety of dependency tree- and entity type-based features into attention to increase the robustness of the model and to be able to cope with sentences consisting of multiple entity pairs. Our approach is purely data-driven and does not require knowledge about the target relations. This is in contrast to the approach by Li et al. (2019a). Moreover, we also compare
two different attention functions and show that our features can be integrated into both of them.

3 Model

We describe the basic model in Section 3.1 and explain the enriched attention layer as well as the different features in Section 3.2.

3.1 Baseline Model for Relation Extraction

We build upon the model by Zhang et al. (2017), one of the state-of-the-art approaches for relation classification. The model consists of four main components: The input layer, two stacked LSTM layers, an attention layer, and the output layer. To enable a direct comparison to prior work, we take input, LSTM, and output layers from Zhang et al. (2017) and only replace their attention layer by our enriched attention layer (see Section 3.2).

Input layer. Each token is represented by a concatenation of its word embedding, its part-of-speech embedding, and its named-entity-tag embedding. As word embeddings, we use pre-trained 300-dimensional GloVe embeddings\(^2\) (Pennington et al., 2014) as well as a concatenation of GloVe and ELMo embeddings\(^3\) (Peters et al., 2018). Part-of-speech and named-entity-tag embeddings are randomly initialized. All embeddings are fine-tuned during training.

LSTM layers. The token representations are fed into two stacked unidirectional LSTM layers to obtain context-aware representations. To compute a representation for the whole sentence, the hidden states of the last LSTM layer are combined using a weighted sum with attention weights.

Output layer. Finally, the sentence representation is fed into a linear layer which maps it to a vector of the number of output classes. A softmax activation function is used to obtain a probability distribution over the output classes.

3.2 Enriched Attention Layer

Models for relation extraction often do not scale well to long sentences with mentions of multiple entities and relations. This is especially harmful when relation extraction is used as a component for a downstream task, such as knowledge base population. Previous work, such as Huang et al. (2017) or Adel and Schütze (2019) found this to be one of the most frequent mistakes in the relation extraction part of slot filling systems. Therefore, we study the integration of various additional signals into the attention layer of relation extraction models, such as information from the dependency parse tree and information about the query entities.

We now describe our proposed enriched attention layer and its features in detail. The features are illustrated in Figure 2.

3.2.1 Attention Functions

We distinguish between two different levels for the integration of features into the attention layer: local and global. Local features are token-specific, i.e., for calculating the attention weights of hidden state \(i\), we use different features than for calculating the attention weights of hidden state \(j\) (\(i \neq j\)). Global features are sentence-specific, i.e., they are the same for calculating the attention weights of all hidden states for a particular input sentence.

Given local features \(l_i \in \mathbb{R}^L, 1 \leq i \leq n\) with \(n\) being the sentence length, and global features \(g \in \mathbb{R}^G\), we compare their integration into two different attention functions: additive attention using an additional hidden layer as proposed by Bahdanau et al. (2015) (called \(\oplus\)-att in the remainder of the paper) and dot-product attention as used in transformer networks (Vaswani et al., 2017) (called \(\odot\)-att).

In both cases, attention weights \(\alpha_i\) for each token \(i\) are calculated by normalizing attention scores \(e_i\) (see Equations 2 and 3) using the softmax function:

\[
\alpha_i = \frac{\exp(e_i)}{\sum_{j=1}^{n} \exp(e_j)}
\]

\(\oplus\)-att. The attention score \(e_i\) for token \(i\) is calculated as follows:

\[
e_i = v^\top \tanh(W_h h_i + W_q q + W_s p_i^s + W_o p_o^s + W_l l_i + W_g g)
\]

(2)

with \(v \in \mathbb{R}^A, W_h \in \mathbb{R}^{A \times H}, W_q \in \mathbb{R}^{A \times H}, W_s, W_o, W_l, W_g \in \mathbb{R}^{A \times P}, W_l \in \mathbb{R}^{A \times L}, W_g \in \mathbb{R}^{A \times G}\) being the trainable parameters of the attention layer and \(A\) being its hyperparameter. The hyperparameters \(L\) and \(G\) are the dimension of the local features \((l_i \in \mathbb{R}^L)\) and the dimension of the global
features \((g \in \mathbb{R}^G)\), respectively. The LSTM hidden state size from the previous layer is denoted by \(H\): \(q, h_i \in \mathbb{R}^H\) with \(h_i\) being the hidden state corresponding to token \(i\). Following Zhang et al. (2017), we also integrate \(q\), the last hidden state of the sentence, and position features \(p_i^e, p_i^p \in \mathbb{R}^P\) where \(p_i^e\) encodes the distance of token \(i\) to the first query entity and \(p_i^p\) encodes the distance of token \(i\) to the second query entity. The dimension of the position features is called \(P\).

\[ e_i = \frac{q \cdot k_i + l_i \cdot l_i + g \cdot g}{\sqrt{d}} \tag{3} \]

with \(q_i, k_i\) being the query and key vectors, computed as in Vaswani et al. (2017) with learned weight matrices \(W_Q, W_K\) based on the LSTM hidden states: \(q_i = W_Q h_i, k_i = W_K h_i\). Similarly, a value vector \(v_i = W_V h_i\) is computed and later multiplied with the attention weights \(\alpha_i\) (cf., Equation 1). Following Vaswani et al. (2017), we scale the attention score with the square root of \(d\), the dimension of the key and query vectors.

### 3.2.2 Dependency-Enriched Attention

Previous work, especially work on non-neural models (i.a., Bunescu and Mooney, 2005; Mintz et al., 2009; Rink and Harabagiu, 2010; Miwa and Sasaki, 2014) has shown that features based on the results of dependency parsing are beneficial for relation extraction. The intuition is that the shortest path between two entities in a dependency parse tree contains relevant information about the relation between them and less noise than the text sequence between them. This is shown in Figure 2 as well: While the text sequence between the query entities “Barack Obama Sr.” and “1936” also contains information about “Barack Obama”, the shortest path between the query entities only consists of the word “born” which is relevant for determining the correct relation.

Some prior work on neural relation extraction uses the shortest dependency path between the two query entities directly as the input for the neural network (e.g., Toutanova et al., 2015; Huang et al., 2017; Zhang et al., 2018). We argue that there is a risk of losing information, for example, when the automatically extracted dependency parse tree is wrong. Therefore, we do not replace the original input sentence with a potentially noisy dependency path. Instead, we propose to use information from the dependency parse tree as an additional signal for the attention layer. As a result, the model can learn to pay more attention to the tokens on the shortest dependency path between the two query entities but it can also decide to ignore them if they are noisy or not helpful.

Given the dependency parse tree, we explore the following features for attention which are shown in the left part of Figure 2 for a sample sentence and two query entities.

#### (i) Dependency distance:

For each token, we calculate its distance \(d_{\text{e1}} \in \mathbb{R}^D\) and \(d_{\text{e2}} \in \mathbb{R}^D\) that are randomly initialized. The embedding dimension \(D\) is tuned on the development (dev) set. Note that the distance embeddings are not shown in Figure 2 for the sake of readability.

Furthermore, we use a flag \(f \in \mathbb{R}^1\) (binary, single-valued feature) to indicate whether a token...
is on the shortest dependency path between the two query entities.

Both the distances and the flag are token-dependent, i.e., local features. To integrate them in Equation 2, we concatenate them to one vector per token $l_i := [d^{i_1}_l; d^{i_2}_l; f_l] \in \mathbb{R}^D + 1$ with $[;]$ denoting vector concatenation.

(ii) Shortest path: Given a sentence and two query entities, we extract the shortest path between the two entities from the dependency parse tree (lower left part of Figure 2). To embed the shortest dependency path in vector space, we first represent the tokens on the path by their word embeddings and then feed them into an LSTM model with hidden state size $S$. The final representation $s \in \mathbb{R}^S$ of the shortest dependency path is the last hidden state of the LSTM.

Note that we use the same word embeddings as in the input layer of the network but the parameters of the LSTM model over the path are additional parameters, i.e., not shared with the sentence-level LSTM model from Section 3.1. The reason is two-fold: First, the linguistic structure of the shortest dependency path is inherently different to the structure of a sentence. Thus, trying to learn both structures using the same parameters could harm both sub-tasks. Second, we assume that it would put too much weight on a particular feature if we used the same distributions for the input representation and that feature. Thus, using independent weights for the second LSTM allows the attention layer to focus not only on the shortest dependency path but also on other signals.

The path is independent of the particular input token, i.e., a global feature. To integrate it in Equation 2 or 3, we set $g := s$.

3.2.3 Entity-Enriched Attention

Many studies on relation extraction show the positive impact of exploiting information about the types of the query entities (Mintz et al., 2009; Ling and Weld, 2012). This can be explained by the intuition that knowledge about the types can reduce the search space of possible relations (Roth and Yih, 2004; Yao et al., 2010; Ren et al., 2017). In the example of Figure 2, knowing that the second query entity is a date can help the model exclude relation types like city_of_birth which would require a query entity of type location. Here, we explore the applicability of entity type features in the context of attention. Since specific relation key phrases like “was born in” are only applicable to persons and locations but not to, e.g., organizations, the model can learn to ignore those phrases for organization entities but attend to them for persons and locations. The query entities are sentence-specific. Thus, the resulting features (see right part of Figure 2) are global features.

(iii) Entity types: We use embeddings $t^1, t^2 \in \mathbb{R}^T$ to represent the types of the two entities. Thus, $g$ from Equations 2 and 3 becomes a concatenation of the two embeddings: $g := [t^1; t^2]$. The embeddings are randomly initialized and learned during training. Their dimensionality $T$ is tuned on dev.

(iv) Wikipedia entities: The last feature we explore is a representation of the query entities themselves. To avoid overfitting to the entities of the training set, we do not learn entity representations from scratch but use pre-trained embeddings for Wikipedia entities (Yamada et al., 2017). Section 4.2 describes how we map the query entities to Wikipedia entities and handle unknown entities.

When integrating entity embeddings into Equation 2 or 3, the global feature $g$ becomes $[e^1; e^2]$ with $e^1, e^2 \in \mathbb{R}^{300}$ being the entity embeddings.

4 Experiments and Analysis

In this section, we describe the datasets and our experiments, and presents our results and analysis.

4.1 Data

We evaluate our model on popular benchmarks for relation extraction: TACRED and ACE 2005.\footnote{LDC2018T24 and LDC2006T06.}

TACRED. The large-scale TAC Relation Extraction Dataset (Zhang et al., 2017) has been annotated via crowd-sourcing. It is a classification dataset in which only one entity pair per sentence is annotated with a relation. In total, it covers 41 relations between persons, organizations, geo-political entities, dates, numbers and nominal phrases like cause of death. Entity pairs without relations are labeled with no_relation.

ACE. ACE 2005 (Walker et al., 2006) is a manually labeled dataset with six relations between
persons, organizations, geo-political entities, locations, facilities, weapons and vehicles. For each sentence, all occurring entities and relations are annotated. Unlike TACRED, it does not provide a split into training, development and test set. To compare with prior work, we use the split by Miwa and Bansal (2016) and Li and Ji (2014). Following those previous work, we consider all entity pairs in a sentence as classification instances and introduce inverse relations (as independent class labels) to model the direction of relations. Thus, we consider twelve relations in total. All entity pairs not occurring in the manual annotations are labeled with no_relation.

Statistics. While TACRED consists of more relation classes, the main challenge of the ACE dataset is that relations between all entity pairs have to be extracted for each sentence. This results in very similar classification instances the model needs to distinguish. It also leads to a considerably higher amount of instances of the no_relation class and, thus, a class imbalance challenge. The sentence lengths are rather long in both datasets. See Table 1 for more statistics.

### 4.2 Pre-processing for Enriched Attention

Our features for enriched attention build on the following three pre-processing steps.

#### Dependency parsing
TACRED already provides the results of various pre-processing steps.
Table 6: Results on ACE 2005 test data for joint entity and relation extraction. Our scores are evaluated in a pipeline setting, using the relation extraction model with enriched attention based on the entities found with a bi-directional LSTM+CRF model.

| Model                              | Entities | Relations |
|------------------------------------|----------|-----------|
|                                    | dev      | test      | dev     | test     |
| (Li and Ji, 2014)                  | F1       | P         | R       | F1       | P         | R       | F1       | P         | R       | F1       | P         | R       | F1       |
| (Miwa and Bansal, 2016)            | 81.8     | 82.9      | 83.9    | 83.4     | 51.8     | 57.2     | 54.0     | 55.6     |
| (Sun et al., 2018)                 | -        | 83.9      | 83.2    | 83.6     | -        | 64.9     | 55.1     | 59.6     |
| (Li et al., 2019b)                 | -        | 84.7      | 84.9    | 84.8     | -        | 64.8     | 56.2     | 60.2     |
| enriched ⊕-att                | 86.9     | 89.1      | 89.0    | 89.0     | 56.6     | 57.2     | 59.3     | 58.2     |
| enriched ⊕-att + ELMo             | 86.9     | 89.1      | 89.0    | 89.0     | 59.6     | 59.6     | 64.8     | 62.1     |

Table 6: Results on ACE 2005 test data for joint entity and relation extraction. Our scores are evaluated in a pipeline setting, using the relation extraction model with enriched attention based on the entities found with a bi-directional LSTM+CRF model.

with Stanford CoreNLP (Manning et al., 2014) including automatic dependency parsing. We pre-process the ACE 2005 accordingly.

**Entity typing.** Both datasets provide entity type information. Examples are PERSON, DATE, NATIONALITY and TITLE in TACRED, and PER (person), FAC (facility) and VEH (vehicle) in ACE 2005. For a dataset without given entity types, types can be obtained automatically, for example using CoreNLP or fine-grained typing methods (Ling and Weld, 2012; Del Corro et al., 2015; Yaghoobzadeh et al., 2018).

**Entity linking.** To map the entities of our datasets to Wikipedia entities, we apply the AIDA entity linking system (Hoffart et al., 2011). To model out-of-knowledge-base entities with a meaningful representation in the same space, we use the embedding for the Wikipedia page about the type of the entity. The rationale behind that is that such embeddings represent a prototypical description of the respective entity types. An example is shown in Figure 2: Since the mention “1936” is not linked to a Wikipedia entity, the model uses the embedding of the type DATE, i.e., of the page en.wikipedia.org/wiki/calendar_date. Mappings from types to Wikipedia pages are provided in the appendix.

4.3 Training Details

We train our model with mini-batch stochastic gradient descent, using a batch size of 50 and an initial learning rate of 1.0. We decrease the learning rate exponentially with a factor of 0.9 based on the performance of the model on the development set. For regularization, we apply dropout (Srivastava et al., 2014) with a probability of 0.5 as well as word dropout which randomly replaces tokens with the unknown token symbol with a probability of 0.04. To cope with exploding gradients, we clip the gradients at a threshold of 5.0.

The GloVe word embeddings and the ELMo word embeddings have a dimensionality of 300 and 1024, respectively. The dimensions of both the named-entity-tag embeddings and part-of-speech-tag embeddings are 30. Each sentence is processed with a 2-layer unidirectional LSTM model with 200 hidden units per layer. The hyperparameters of enriched attention are tuned with grid search on the TACRED development set and used on both datasets. A complete list with all hyperparameters is provided in Table 2.

4.4 Results

Following Zhang et al. (2017), we report the test score that corresponds to the medium dev score out of five runs for each model variation. Following prior work on TACRED, we also report results of model ensembles. In particular, we train the same model configuration five times with different seeds for weight initialization. Afterwards, we merge their results using majority vote.

**Results on TACRED.** Table 3 provides the results of our model on the TACRED dataset in comparison to state of the art. Our model is best comparable to the model by Zhang et al. (2017) as it uses the same basic model components and the ⊕-att attention function is a direct extension of their position-aware attention. The results show that this extension increases the performance by 2 F1 points. Interestingly, adding ELMo embeddings does not further increase performance. Furthermore, our model performs better than the model by Zhang et al. (2018) who use dependency tree information on the input level while we use the

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5 Although there is a Wikipedia article for the year “1936”, most state-of-the-art entity linking systems do not consider numerical values / temporal expressions for linking.

6 We take the average of forward and backward embeddings from ELMo as word embeddings.
original text sequence as input and incorporate dependency tree information into the attention function. Our results do not reach the performance of the current state of the art by Soares et al. (2019) since we train our model from scratch on only the TACRED data while Soares et al. (2019) fine-tune a BERT model. Thus, their model is both much larger and more expensive to train and utilizes information from a large pre-training corpus.

In Table 4, we show an ablation study for different configurations of enriched \(\circ\)-attention. In particular, we investigate the impact of using different subsets of features for the attention function. The combination of all features leads to the best performance, indicating that all of them are useful for relation extraction.

**Results on ACE.** Tables 5 and 6 provide the results of our model on the ACE dataset in comparison to state of the art. We focus on systems that use the same or similar dataset split as we do and are, thus, directly comparable. There is another line of work on the ACE dataset which splits the dataset with respect to domains in order to investigate cross-domain generalization of models (e.g., Nguyen and Grishman, 2016; Veyseh et al., 2020). Since this introduces an incomparable experimental setup, we do not compare to those works here.

While Table 5 shows results for relation extraction with gold entities, Table 6 shows results for joint entity and relation extraction. For the latter, we use a pipeline setting with a standard state-of-the-art named entity recognition (NER) model, consisting of a bi-directional LSTM layer followed by a conditional-random-field output layer (e.g., Lample et al., 2016). The input tokens for the NER model are represented by a concatenation of Flair (Akbik et al., 2018), byte-pair-encoding (Heinzerling and Strube, 2018), GloVe (Pennington et al., 2014) and XLM_Roberta embeddings (Conneau et al., 2020). On ACE, enriched \(\circ\)-attention outperforms enriched \(\oplus\)-attention by a large margin. Also, ELMo embeddings boost the performance. This indicates a more challenging setup compared to TACRED, probably due to the higher number of no-relation instances and a large number of very similar evaluation instances that only differ in the choice of query entities. Our model with enriched \(\circ\)-attention and ELMo embeddings sets the new state of the art for both relation extraction with gold and predicted entities.

### 4.5 Analysis

Next, we present a qualitative attention weight analysis and a quantitative robustness analysis.

**Attention weight analysis.** Figure 3 shows a heatmap of attention weights for the enriched attention model on a sample sentence of the ACE development set. The beginning and end of the sentence have attention weights of 0 and are cut for better readability. We provide another example in the appendix. The different rows in the figure correspond to different query entities (marked as subject (“subj”) and object (“obj”)), the first column shows the gold relation label for the corresponding query entities which the model does not know but needs to predict. The figure shows that depending on the query entities, the model attends to different parts of the input sentence. It correctly focuses on those parts that are relevant for the query entities, such as “of the Spanish media” for the query entities “members” and “media” or “and friends of the two members” for the query entities “family” and “members”.

**Robustness analysis.** Figures 4-7 show the performance of our model with respect to sentence length, distance between query entities, number of entities per sentence and number of entities between the query entities on the ACE development set. For the former two, we count number of tokens and group the development set instances into bins (of size ten for sentence length and of size three for distance between query entities). To
give an example, the F1 score shown for sentence length 10 corresponds to the micro F1 score of all dataset instances with length 10 to 19. The graphs confirm that longer sentences with many entities are more challenging, leading to lower $F_1$ scores. Enriched attention still suffers from this problem but increases performance, especially for sentences with many entities.

5 Conclusion

In this paper, we proposed to enrich the attention layer of neural networks for relation extraction with additional features to increase their robustness and scalability in the case of long sentences with multiple entities. Our model outperforms prior work using comparable setups on the TACRED benchmark and achieves state-of-the-art results on the ACE 2005 benchmark. Our analysis shows that it is indeed effective for long sentences with many different entities, and correctly focuses on the relevant parts of the sentence. Directions for future work are the integration of enriched attention into transformer networks before pre-training as well as the exploration of enriched attention for other tasks.

Acknowledgments

We would like to thank the members of the BCAI NLP&KRR research group, especially Annemarie Friedrich, for their helpful comments.

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6 Appendix

6.1 Type Mapping

To represent out-of-knowledge base entities with Wikipedia embeddings, we utilize their type as described in Section 4.2 of the main paper. Table 7 provides the mapping of types to Wikipedia pages.

| Type                  | Wikipedia page          |
|-----------------------|-------------------------|
| PER                   | Person                  |
| ORG                   | Organization            |
| LOC                   | Location (geography)    |
| GPE                   | Nation                  |
| FAC                   | Physical plant          |
| VEH                   | Vehicle                 |
| WEA                   | Weapon                  |
| PERSON                | Person                  |
| ORGANIZATION          | Organization            |
| LOCATION              | Location (geography)    |
| CITY                  | City                    |
| STATE_OR_PROVINCE     | State (polity)          |
| COUNTRY               | Country                 |
| CAUSE_OF_DEATH        | Cause of death          |
| CRIMINAL_CHARGE       | Criminal charge         |
| DATE                  | Calendar date           |
| DURATION              | Time                    |
| IDEOLOGY              | Ideology                |
| NATIONALITY           | Nationality             |
| NUMBER                | Number                  |
| RELIGION              | Religion                |
| TITLE                 | Profession              |
| URL                   | Uniform Resource Locator| |

Table 7: Mapping of types (for datasets ACE 2005 and TACRED) to Wikipedia pages.

6.2 Attention Weight Analysis

Figure 8 shows the same analyses as Figure 3 in the main paper for another sentence containing even more gold relations.
Shaunie O’Neal gave birth to the couple’s third child at 1:52 a.m. at a Los Angeles-area hospital, team spokesman John Black said.

Figure 8: Attention weights for example sentence with different query entities from ACE development set. First column shows gold relation labels (not known to the model). P-W: PART-WHOLE