Neural Mention Detection

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Abstract

Mention detection is an important aspect of the annotation task and interpretation process for applications such as coreference resolution. In this work, we propose and compare three neural network-based approaches to mention detection. The first approach is based on the mention detection part of a state-of-the-art coreference resolution system; the second uses ELMo embeddings together with a bidirectional LSTM and a biaffine classifier; the third approach uses the recently introduced BERT model. Our best model (using a biaffine classifier) achieved gains of up to 1.8 percentage points on mention recall when compared with a strong baseline in a HIGH RECALL setting. The same model achieved improvements of up to 5.3 and 6.5 p.p. when compared with the best-reported mention detection system and the Clark and Manning (2016a) pipeline system respectively. Thirdly, by using better mentions from our mention detector, we can improve the end-to-end Lee et al. (2018) system by up to 1.7% and 0.7% respectively.

Keywords: Mention Detection, Deep Neural Network, Coreference Resolution

1. Introduction

Mention detection (MD) is the task of identifying mentions of entities in text. It is an important preprocessing step for downstream applications such as coreference resolution (Poesio et al., 2016). As such, the quality of mention detection affects very deeply both the quality of an annotation and the performance of a model for such applications (Chamberlain et al., 2016; Poesio et al., 2019). Comparing to the simplified version that focuses on classifying named entity mentions for named entity recognition (NER), the full MD task for coreference resolution is more complex in two respects: firstly, it identifies more mention types, such as nominal mentions and pronouns; secondly, the mentions can be nested, so the task cannot be treated as a simple sequence labelling task, as is the norm in NER systems. The most recent neural network approaches such as ELMo (Peters et al., 2018) and BERT (Devlin et al., 2019), have achieved substantial improvements in the NER benchmark CONLL 2003 data set. However, most of the MD system used by the state-of-the-art coreference systems do not take advantage of these advances and still heavily rely on parse trees (Björkelund and Kuhn, 2014; Wiseman et al., 2015; Wiseman et al., 2016; Clark and Manning, 2016a; Clark and Manning, 2016b). They either use all the NPs as candidate mentions (Björkelund and Kuhn, 2014; Wiseman et al., 2015; Wiseman et al., 2016) or use the rule-based mention detector from the Stanford deterministic system (Lee et al., 2013) to extract mentions from NPs, named entity mentions and pronouns (Clark and Manning, 2015; Clark and Manning, 2016b).

There are only very few studies that attempt to apply neural network approaches to the MD task. Lee et al. (2017; Lee et al., 2018) first introduced a neural mention detector as a part of their end-to-end coreference system; however, the system does not output intermediate mentions, hence the mention detector cannot be used by other coreference systems directly. To the best of our knowledge, Poesio et al. (2018) introduced the only standalone neural mention detector. By using a modified version of the NER system of Lample et al. (2016), they showed substantial performance gains at mention detection on the benchmark CONLL 2012 data set and on the CRAC 2018 data set when compared with the Stanford deterministic system (Lee et al., 2013). To build a high accuracy standalone MD system is not only important for the downstream applications, but also beneficial for annotation tasks that require mentions (Chamberlain et al., 2016; Poesio et al., 2019).

In this paper, we compare three neural architectures for MD. The first system is a slightly modified version of the mention detection part of the Lee et al. (2018) system. The second system employs a bi-directional LSTM on the sentence level and uses biaffine attention (Dozat and Manning, 2017) over the LSTM outputs to predict the mentions. The third system takes the outputs from BERT (Devlin et al., 2019) and feeds them into a feed-forward neural network to classify candidates into mentions and non-mentions. We evaluate these three models on both the CONLL and the CRAC data sets, with the following results. Firstly, we show that better mention performance of up to 1.5 percentage points can be achieved by training the mention detector alone. Secondly, our best system achieves improvements of 5.3 and 6.5 percentage points when compared with Poesio et al. (2018)’s neural MD system on CONLL and CRAC respectively. Thirdly, by using better mentions from our mention detector, we can improve the end-to-end Lee et al. (2018) system and the Clark and Manning (2016a) pipeline system by up to 0.7% and 1.7% respectively.

2. Related Work

Mention detection. Despite neural networks having shown high performance in many natural language processing tasks, the rule-based mention detector of the Stanford deterministic system (Lee et al., 2013) remains frequently used in top performing coreference systems (Clark and Manning, 2015; Clark and Manning, 2016a; Clark and Manning, 2016b). This performance difference is measured on mention recall, as we follow Lee et al. (2018) to use fixed mention/token ratio to compare the mentions selected by their joint system.
ning, 2016b), including the best pipeline system itself based on neural networks (Clark and Manning, 2016a). This mention detector uses a set of predefined heuristic rules to select mentions from NPs, pronouns and named entity mentions. Many other coreference systems simply use all the NPs as the candidate mentions (Björkelund and Kuhn, 2014; Wiseman et al., 2015; Wiseman et al., 2016).

Lee et al. (2017) first introduced a neural network based end-to-end coreference system in which the neural mention detection part is not separated. This move proved very effective; however, as a result the mention detection part of their system needs to be trained jointly with the coreference resolution part, hence can not be used separately. The system has been later extended by Zhang et al. (2018) and Lee et al. (2018). Zhang et al. (2018) added biaffine attention to the coreference part of the Lee et al. (2017) system, improving the system by 0.6%. Biaffine attention is also used in one of our approaches (BIAFFINE MD) in a totally different manner, i.e. we use biaffine attention for mention detection while in Zhang et al. (2018) biaffine attention was used for computing mention-pair scores. The Lee et al. (2018) system is the current state-of-the-art coreference system. In this new system, the Lee et al. (2017) model is substantially improved through the use of ELMo embeddings (Peters et al., 2018).

Other machine learning based mention detectors include Uryupina and Moschitti (2013) and Poesio et al. (2018). The Uryupina and Moschitti (2013) system takes all the NPs as candidates and trains a SVM-based binary classifier to select mentions from all the NPs. Poesio et al. (2018) briefly discuss a neural mention detector that they modified from the NER system of Lample et al. (2016). The system uses a bidirectional LSTM followed by a FFNN to select mentions from spans up to a maximum width. The system achieved substantial gains on mention F1 when compared with the (Lee et al., 2013) on CONLL and CRAC data sets. **Named entity recognition.** A subtask of mention detection that focuses only on detecting named entity mentions is studied more frequently. However, most of the proposed approaches treat the NER task as a sequence labelling task which can not be directly applied to the MD task for coreference, as the later usually allow nested mentions. The first neural network based NER model was introduced by Collobert et al. (2011), who used a CNN to encode the tokens and apply a CRF layer on top. After that, many other network architectures for NER MD have also been proposed, such as LSTM-CRF (Lample et al., 2016; Chiu and Nichols, 2016), LSTM-CRF + ELMo (Peters et al., 2018) and BERT (Devlin et al., 2019).

### 3. System architecture

Mention detection is the task of extracting candidate mentions from the document. For a given document $D$ with $T$ tokens, we define all possible spans in $D$ as $N^I_{i=1}$ where $I = \frac{T(T+1)}{2}$, $s_i, e_i$ are the start and the end indices of $N_i$ where $1 \leq i \leq I$. The task for an MD system is to assign all the spans ($N$) a score ($r_m$) so that spans can be classified into two classes (mention or non mention), hence is a binary classification problem.

In this paper, we introduce three MD systems that use the latest neural network architectures\(^2\). The first approach uses the mention detection part from the start-of-the-art coreference resolution system (Lee et al., 2018), which we refer to as LEE MD. We remove the coreference part of the system and change the loss function to sigmoid cross entropy, that is commonly used for binary classification problems. The second approach (BIAFFINE MD) uses a bi-directional LSTM to encode the sentences of the document, followed by a biaffine classifier (Dozat and Manning, 2017) to score the candidates. The third approach (BERT MD) uses BERT (Devlin et al., 2019) to encode the document in the sentence level; in addition, a feed-forward neural network (FFNN) to score the candidate mentions. The three architectures are summarized in Figure 1 and discussed in detail below.

All three architectures are available in two output modes: HIGH F1 and HIGH RECALL. The HIGH F1 mode is meant for applications that require highest accuracy, such as preprocessing for annotation. The HIGH RECALL mode, on the other hand, predicts as many mentions as possible, which is more appropriate for preprocessing for a coreference system since mentions can be further filtered by the system during coreference resolution. In HIGH F1 mode we output mentions whose probability $p_m(i)$ is larger then a threshold $\beta$ such as 0.5. In HIGH RECALL mode we output mentions based on a fixed mention/word ratio $\lambda$; this is the same method used by Lee et al. (2018).

#### 3.1. LEE MD

Our first system is based on the mention detection part of the Lee et al. (2018) system. The system represents a candidate span with the outputs of a bi-directional LSTM. The sentences of a document are encoded bidirectional via the LSTMs to obtain forward/backward representations for each token in the sentence. The bi-directional LSTM takes as input the concatenated embeddings ($\langle x_t \rangle_{t=1}^{T}$) of both word and character levels. For word embeddings, GloVe (Pennington et al., 2014) and ELMo (Peters et al., 2018) embeddings are used. Character embeddings are learned from convolution neural networks (CNN) during training. The tokens are represented by concatenated outputs from the forward and the backward LSTMs. The token representations ($\langle x_t \rangle_{t=1}^{T}$) are used together with head representations ($h^*_t$) to represent candidate spans ($N^*_t$). The $h^*_t$ of a span is obtained by applying an attention over its token representations ($\langle x^*_t \rangle_{t=1}^{T}$), where $s_t$ and $e_t$ are the indices of the start and the end of the span respectively. Formally, we compute $h^*_t$, $N^*_t$ as follows:

\[ a_t = \text{FFNN}_a(x^*_t) \]
\[ a_{i,t} = \exp(a_t) \]
\[ h^*_t = \sum_{t=s_t}^{e_t} a_{i,t} \cdot x_t \]
\[ N^*_t = [x^*_s, x^*_e, h^*_t, \phi(i)] \]

\(^2\)The code is available at https://github.com/juntaoy/dali-md
where $\phi(i)$ is the span width feature embeddings.

To make the task computationally tractable, the model only considers the spans up to a maximum length of $l$, i.e. $e_i - s_i < l$, $(s_i, e_i) \in N$. The span representations are passed to a FFNN to obtain the raw candidate scores ($r_m$). The raw scores are then used to create the probabilities ($p_m$) by applying a sigmoid function to the $r_m$: \[
    r_m(i) = \text{FFNN}_m(N^*_i) \\
    p_m(i) = \frac{1}{1 + e^{-r_m(i)}}
\]

For the HIGH RECALL mode, the top ranked $\lambda T$ spans are selected from $l T$ candidate spans ($\lambda < l$) by ranking the spans in a descending order by their probability ($p_m$). For the HIGH F1 mode, the spans that have a probability ($p_m$) larger than the threshold $\beta$ are returned.

### 3.2. Biaffine MD

In our second model, the same bi-directional LSTM is used to encode the tokens of a document in the sentence level. However, instead of using the concatenations of multiple word/character embeddings, only ELMo embeddings are used, as we find in preliminary experiments that the additional GloVe embeddings and character-based embeddings do not improve the accuracy. After obtaining the token representations from the bidirectional LSTM, we apply two separate FFNNs to create different representations ($h_s/h_e$) for the start/end of the spans. Using different representations for the start/end of the spans allows the system to learn important information to identify the start/end of the spans separately. This is an advantage when compared to the model directly using the output states of the LSTM, since the tokens that are likely to be the start of the mention and end of the mention are very different. Finally, we employ a biaffine attention (Dozat and Manning, 2017) over the sentence to create a $l_s \times l_e$ scoring metric ($r_m$), where $l_s$ is the length of the sentence. More precisely, we compute the raw score for span $i (N_i)$ by:

$$
    h_s(i) = \text{FFNN}_s(x_{s_i}^e) \\
    h_e(i) = \text{FFNN}_e(x_{e_i}^s) \\
    r_m(i) = h_s(i)^T W_m h_e(i) + h_s(i) b_m
$$

where $s_i$ and $e_i$ are the start and end indices of $N_i$, $W_m$ is a $d \times d$ metric and $b_m$ is a bias term which has a shape of $d \times 1$.

The computed raw score ($r_m$) covers all the span combinations in a sentence, to compute the probability scores ($p_m$) of the spans we further apply a simple constraint ($p_m$) such that the system only predict valid mentions. Formally:

$$
    p_m(i) = \left\{ \begin{array}{ll}
        \frac{1}{1 + e^{-r_m(i)}} & s_i \leq e_i \\
        0 & s_i > e_i
    \end{array} \right.
$$

The resulted $p_m$ are then used to predict mentions by filtering out the spans according to different requirements (HIGH RECALL or HIGH F1).

### 3.3. BERT MD

Our third approach is based on the recently introduced BERT model (Devlin et al., 2019) which encodes sentences by deep bi-directional transformers. Our model uses a pre-trained BERT model to encode the documents in the sentence level to create token representations $x_{t_i}^s$. The pre-trained BERT model uses WordPiece embeddings (Wu et al., 2016), in which tokens are further split into smaller word pieces as the name suggested. For example in sentence:

We respect ##fully invite you to watch a special edition of Across China.
The token “respectfully” is split into two pieces (“respect” and “fully”). In the case that tokens have multiple representations (word pieces), we use the first representation of the token. An indicator list is created during the data preparation step to link the tokens to the correct word pieces.

After obtaining the actual word representations, the model then creates candidate spans by considering spans up to a maximum span length \( l \). The spans are represented by the concatenated representations of the start/end tokens of the spans. This is followed by a FFNN and a sigmoid function to assign each span a probability score:

\[
N^*_i = [x^*_a, x^*_e]
\]

\[
r_m(i) = \text{FFNN}_m(N^*_i)
\]

\[
p_m(i) = \frac{1}{1 + e^{-r_m(i)}}
\]

We use the same methods we used for our first approach (LEE MD) to select mentions based on different settings (HIGH RECALL or HIGH F1) respectively.

3.4. Learning

The learning objective of our mention detectors is to learn to distinguish mentions form non-mentions. Hence it is a binary classification problem, we optimise our models on the simple but effective cross entropy:

\[
- \sum_i y_i \log p_m(i) + (1 - y_i) \log(1 - p_m(i))
\]

where \( y_i \) is the gold label \( y_i \in \{0, 1\} \) of \( i \)th spans.

4. Experiments

We ran two series of experiments. The first series of experiments focuses only on the mention detection task, and we evaluate the performance of the proposed mention detectors in isolation. The second series of experiments focuses on the effects of our model on the downstream applications: i.e., we integrate the mentions extracted from our best system into state-of-the-art coreference systems (both end-to-end and the pipeline system). The rest of this section introduces our experimental settings in detail.

4.1. Data Set

We evaluate our models on two different corpora, the CONLL 2012 English corpora (Pradhan et al., 2012) and the CRAC 2018 corpora (Poesio et al., 2018).

The CONLL data set is the standard reference corpora for coreference resolution. The English subset consists of 2802, 342, and 348 documents for the train, development and test sets respectively. The CONLL data set is not however ideal for mention detection, since not all mentions are annotated, but only mentions involved in coreference chains of length \( > 1 \). This has a negative impact on learning since singleton mentions will always receive negative labels.

The CRAC corpus uses data from the ARRAU corpus (Uryupina et al., 2019). ARRAU consists of texts from four very distinct domains: news (the RST subcorpus), dialogue (the TRAINS subcorpus) and fiction (the PEAR stories). This corpus is more appropriate for studying mention detection as all mentions are annotated. As done in the CRAC shared task, we used the RST portion of the corpora, consisting of news texts (1/3 of the PENN Treebank). Since none of the state-of-the-art coreference systems predict singleton mentions, a version of the CRAC dataset with singleton mentions excluded was created for the coreference task evaluation.

4.2. Evaluation Metric

For our experiments on the mention detection, we report recall, precision and F1 scores for mentions. For our evaluation that involves the coreference system, we use the official CONLL 2012 scoring script to score our predictions. Following standard practice, we report recall, precision, and F1 scores for MUC, B^3 and CEAF_{φ4} and the average F1 score of those three metrics.

4.3. Baseline System

For the mention detection evaluation we use the Lee et al. (2018) system as baseline. The baseline is trained end-to-end on the coreference task and we use as baseline the mentions predicted by the system before carrying out coreference resolution.

For the coreference evaluation we use the state-of-the-art Lee et al. (2018) system as our baseline for the end-to-end system, and the Clark and Manning (2016a) system as our baseline for the pipeline system. During the evaluation, we slightly modified the Lee et al. (2018) system to allow the system to take the mentions predicted by our model instead of its internal mention detector. Other than that we keep the system unchanged.

4.4. Hyperparameters

For our first model (LEE MD) we use the default settings of Lee et al. (2018). For word embeddings the system uses 300-dimensional GloVe embeddings (Pennington et al., 2014) and 1024-dimensional ELMo embeddings (Peters et al., 2018). The character-based embeddings are pro-

| Model         | Parameter               | Value |
|---------------|-------------------------|-------|
| LEE, BIA      | BiLSTM layers           | 3     |
| LEE, BIA      | BiLSTM size             | 200   |
| LEE, BIA      | BiLSTM dropout          | 0.4   |
| BER           | Transformer layers       | 12    |
| BER           | Transformer size         | 768   |
| BER           | Transformer dropout      | 0.1   |
| LEE, BIA, BER | FFNN layers             | 2     |
| LEE, BIA, BER | FFNN size               | 150   |
| LEE, BIA, BER | FFNN dropout            | 0.2   |
| LEE, BIA, BER | Embeddings dropout       | 0.5   |
| LEE, BIA, BER | Optimiser               | Adam  |
| LEE, BIA      | Learning rate            | 1e-3  |
| BER           | Learning rate            | 2e-5  |
| LEE, BIA, BER | Training step            | 40K   |

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duced by a convolution neural network (CNN) which has a window sizes of 3, 4, and 5 characters (each has 50 filters). The characters embeddings (8-dimensional) are randomly initialised and learned during the training. The maximum span width is set to 30 tokens. For our BIAFFINE MD model, we use the same LSTM settings and the hidden size of the FFNN as our first approach. For word embeddings, we only use the ELMo embeddings (Peters et al., 2018).

For our third model (BERT MD), we fine-tune on the pre-trained BERT that consists of 12 layers of transformers. The transformers use 768-dimensional hidden states and 12 self-attention heads. The WordPiece embeddings (Wu et al., 2016) have a vocabulary of 30,000 tokens. We use the same maximum span width as in our first approach (30 tokens).

The detailed neural network settings can be found in Table 1.

5. Results and Discussions

In this section, we first evaluate the proposed models in isolation on the mention detection task. After that, we integrate the mentions predicted by our system into coreference resolution systems to evaluate the effects of our MD systems on the downstream applications.

5.1. Mention Detection Task

Evaluation on the CONLL data set. For mention detection on the CONLL data set, we first take the best model from Lee et al. (2018) and use its default mention/token ratio (λ = 0.4) to output predicted mentions before coreference resolution. We use this as our baseline for the HIGH RECALL setting. We then evaluate all three proposed models with the same λ as that of the baseline. As a result, the number of mentions predicted by different systems is the same, which means mention precision will be similar. Thus, for the HIGH RECALL setting we compare the systems by mention recall. As we can see from Table 2, the baseline system already achieved a reasonably good recall of 96.6%. But even when compared with such a strong baseline, by simply separately training the mention detection part of the baseline system, the stand-alone Lee MD achieved an improvement of 0.7 p.p. This indicates that mention detection task does not benefit from joint mention detection and coreference resolution. The BERT MD achieved the same recall as the Lee MD, but BERT MD uses a much deeper network and is more expensive to train. By contrast, the BIAFFINE MD uses the simplest network architecture among the three approaches, yet achieved the best results, outperforming the baseline by 0.9 p.p. (26.5% error reduction).

Evaluation on the CRAC data set.

For the CRAC data set, we train the Lee et al. (2018) system end-to-end on the reduced corpus with singleton mentions removed and extract mentions from the system by set λ = 0.4. We then train our models with the same λ but on the full corpus, since our mention detectors naturally support both mention types (singleton and non-singleton mentions). Again, the baseline system has a decent recall of 95.4%. Benefiting from the singletons, our lee MD and BIAFFINE MD models achieved larger improvements when compared with the gains achieved on the CONLL data set. The largest improvement (1.8 p.p.) is achieved by our BIAFFINE MD model with an error reduction rate of 39.1%. BERT MD achieved a relatively smaller gain (0.8 p.p.) when compared with the other models; this might as a result of the difference in corpus size between CRAC and CONLL data set. (The CRAC corpus is smaller than the CONLL data set.)

Comparison with the State-of-the-art. We compare our best system BIAFFINE MD with the rule-based mention detector of the Stanford deterministic system (Lee et al., 2013) and the neural mention detector of Poesio et al. (2018). For HIGH F1 setting we use the common threshold (β = 0.5) for binary classification problems without tuning. For evaluation on CONLL we create in addition a variant of the HIGH RECALL setting (BALANCE) by setting λ = 0.2; this is because we noticed that the score differences between the HIGH RECALL and HIGH F1 settings are relatively large (see Table 3). The score differences between our two settings on CRAC data set are smaller; this might because the CRAC data set annotated both singleton and non-singleton mentions, hence the models are trained in a more balanced way. Overall, when compared with the best-reported system (Poesio et al., 2018), our HIGH F1 set-

| Data   | Model         | R   | P   | F1  |
|--------|---------------|-----|-----|-----|
| CONLL  | Lee et al. (2018) | 96.6 | 28.2 | 43.7 |
|        | BIAFFINE MD   | 97.5 | 28.5 | 44.1 |
|        | BERT MD       | 97.3 | 28.4 | 44.0 |
| CRAC3  | Lee et al. (2018) | 95.4 | 34.4 | 50.6 |
|        | BIAFFINE MD   | 97.2 | 35.0 | 51.5 |
|        | BERT MD       | 96.2 | 34.7 | 51.0 |

Table 2: Performance comparison between our mention detectors and the baseline (Lee et al. (2018) system) in a HIGH RECALL setting.

| Data   | Model         | R   | P   | F1  |
|--------|---------------|-----|-----|-----|
| CONLL  | Lee et al. (2013) | 89.5 | 40.4 | 55.7 |
|        | Poesio et al. (2018) | 74.0 | 73.5 | 73.8 |
| CRAC3  | Lee et al. (2013) | 67.3 | 71.6 | 69.4 |
|        | Poesio et al. (2018) | 86.2 | 79.3 | 82.6 |

Table 3: Comparison between our BIAFFINE MD and the top performing systems on the mention detection task using the CONLL and CRAC data sets.
and the model trained without the joint learning. This confirms the performance gap between the end-to-end system and the newly trained model achieved an average F1 of 67.7% and this is 0.5 better than the original end-to-end Lee et al. (2017) system. Second, the mention selection function, the system actually becomes a pipeline system when \( \lambda \) is switched off, we keep all the other settings (include the mention scoring function) unchanged. We then train the modified system to obtain a new model. As illustrated in Table 4, the model trained using mentions supplied by our \textsc{Biaffine MD} achieved a F1 score slightly lower than the recall of our \textsc{Biaffine MD} on the reduced version (with singletons removed) of the original end-to-end system, nevertheless our mention detector has a better performance.

We think the performance drop might be the result of two factors. First, by replacing the original mention selection function, the system actually becomes a pipeline system, thus cannot benefit from joint learning. Second, the performance difference between our mention detector and the original mention selection function might not be large enough to deliver improvements on the final coreference results. To test our hypotheses, we evaluated our \textsc{Biaffine MD} with two additional experiments.

In the first experiment, we enabled the original mention selection function and fed the system slightly more mentions. More precisely, we configured our \textsc{Biaffine MD} to output 0.5 mention per token instead of 0.4 i.e. \( \lambda = 0.5 \). As a result, the coreference system has the freedom to select its own mentions from a candidate pool supplied by our \textsc{Biaffine MD}. After training the system with the new setting, we get an average F1 of 72.6% (see table 4), which narrows the performance gap between the end-to-end system and the model trained without the joint learning. This confirms our first hypothesis that by downgrading the system to a pipeline setting does harm the overall performance of the coreference resolution.

For our second experiment, we used the Lee et al. (2017) instead. The Lee et al. (2018) system is an extended version of the Lee et al. (2017) system, hence they share most of the network architecture. The Lee et al. (2017) has a lower performance on mention detection (93.5% recall when \( \lambda = 0.4 \)), which creates a large (4%) difference when compared with the recall of our \textsc{Biaffine MD}. We train the system without the joint learning, and the newly trained model achieved an average F1 of 67.7% and this is 0.5 better than the original end-to-end Lee et al. (2017) system (see table 4). This confirms our second hypothesis that a larger gain on mention recall is needed in order to show improvement on the overall system.

We further evaluated the Lee et al. (2018) system on the \textsc{Crac} data set. We first train the original Lee et al. (2018) on the reduced version (with singletons removed) of the \textsc{Crac} data set to create a baseline. As we can see from Table 4, the baseline system has an average F1 score of 68.4%. We then evaluate the system with mentions predicted by our \textsc{Biaffine MD}, we experiment with both joint learning disabled and enabled. As shown in Table 4, the model without joint learning achieved an overall score 0.1% lower than the baseline, but the new model has clearly a better recall on all three metrics when compared with the baseline. The model trained with joint learning enabled achieved an average F1 of 69.1% which is 0.7% better than the baseline.

### 5.2. Coreference Resolution Task

We then integrate the mentions predicted by our best system into the coreference resolution system to evaluate the effects of our better mention detectors on the downstream application.

#### Evaluation with the end-to-end system.

We first evaluate our \textsc{Biaffine MD} in combination with the end-to-end Lee et al. (2018) system. We slightly modified the system to feed the system mentions predicted by our mention detector. As a result, the original mention selection function is switched off, we keep all the other settings (include the mention scoring function) unchanged. We then train the modified system to obtain a new model. As illustrated in Table 4, the model trained using mentions supplied by our \textsc{Biaffine MD} achieved a F1 score slightly lower than the recall of our \textsc{Biaffine MD} on the reduced version (with singletons removed) of the original end-to-end system, nevertheless our mention detector has a better performance.

We think the performance drop might be the result of two factors. First, by replacing the original mention selection function, the system actually becomes a pipeline system, thus cannot benefit from joint learning. Second, the performance difference between our mention detector and the original mention selection function might not be large enough to deliver improvements on the final coreference results. To test our hypotheses, we evaluated our \textsc{Biaffine MD} with two additional experiments.

In the first experiment, we enabled the original mention selection function and fed the system slightly more mentions. More precisely, we configured our \textsc{Biaffine MD} to output 0.5 mention per token instead of 0.4 i.e. \( \lambda = 0.5 \). As a result, the coreference system has the freedom to select its own mentions from a candidate pool supplied by our \textsc{Biaffine MD}. After training the system with the new setting, we get an average F1 of 72.6% (see table 4), which narrows the performance gap between the end-to-end system and the model trained without the joint learning. This confirms our first hypothesis that by downgrading the system to a pipeline setting does harm the overall performance of the coreference resolution.

For our second experiment, we used the Lee et al. (2017) instead. The Lee et al. (2018) system is an extended version of the Lee et al. (2017) system, hence they share most of the network architecture. The Lee et al. (2017) has a lower performance on mention detection (93.5% recall when \( \lambda = 0.4 \)), which creates a large (4%) difference when compared with the recall of our \textsc{Biaffine MD}. We train the system without the joint learning, and the newly trained model achieved an average F1 of 67.7% and this is 0.5 better than the original end-to-end Lee et al. (2017) system (see table 4). This confirms our second hypothesis that a larger gain on mention recall is needed in order to show improvement on the overall system.

We further evaluated the Lee et al. (2018) system on the \textsc{Crac} data set. We first train the original Lee et al. (2018) on the reduced version (with singletons removed) of the \textsc{Crac} data set to create a baseline. As we can see from Table 4, the baseline system has an average F1 score of 68.4%. We then evaluate the system with mentions predicted by our \textsc{Biaffine MD}, we experiment with both joint learning disabled and enabled. As shown in Table 4, the model without joint learning achieved an overall score 0.1% lower than the baseline, but the new model has clearly a better recall on all three metrics when compared with the baseline. The model trained with joint learning enabled achieved an average F1 of 69.1% which is 0.7% better than the baseline.

#### Evaluation on the pipeline system.

We then evaluated our best model (\textsc{Biaffine MD}) with a pipeline system. We use the best-reported pipeline system by Clark and Manning (2016a) as our baseline. The original system used the rule-based mention detector from the Stanford deterministic coreference system (Lee et al., 2013) (a performance comparison between the Lee et al. (2013) EMD and our \textsc{Biaffine MD} can be found in Table 3). We modified the preprocessing pipeline of the system to use mentions predicted by our \textsc{Biaffine MD}. We ran the system with both mentions from the \textsc{High Recall} and \textsc{Balance} settings, as both settings have reasonable good mention re-

| Data   | Model          | MUC F1 | B³ F1 | CEAF φ₄ F1 | Avg. F1 |
|--------|----------------|--------|-------|-----------|---------|
|       |                | P     | R     |           |         |
| Lee et al. (2018) | + HIGH RECALL | 81.4  | 79.5  | 80.4      | 72.2    | 69.5    | 70.8    | 68.2    | 67.1    | 67.6    | 73.0    |
|        | + HIGH RECALL + joint | 80.0  | 79.5  | 79.7      | 70.5    | 69.5    | 70.0    | 67.3    | 66.9    | 67.1    | 72.3    |
| CONLL  | Lee et al. (2017) | 78.4  | 73.4  | 75.8      | 68.6    | 61.8    | 65.0    | 62.7    | 59.0    | 60.8    | 67.2    |
|        | + HIGH RECALL    | 78.6  | 74.0  | 76.2      | 68.9    | 62.2    | 65.4    | 63.2    | 59.6    | 61.4    | 67.7    |
|        | Clark and Manning (2016a) | 79.2  | 70.4  | 74.6      | 69.9    | 58.0    | 63.4    | 63.5    | 55.5    | 59.2    | 65.7    |
|        | + HIGH RECALL    | 78.7  | 72.4  | 75.4      | 69.4    | 59.7    | 64.2    | 62.2    | 57.7    | 59.9    | 66.5    |
|        | + BALANCE        | 80.3  | 72.5  | 76.2      | 71.2    | 60.4    | 65.3    | 64.6    | 57.1    | 60.6    | 67.4    |
| CRAC   | Lee et al. (2018) | 79.2  | 71.9  | 75.3      | 72.4    | 63.5    | 67.7    | 66.2    | 58.6    | 62.2    | 68.4    |
|        | + HIGH RECALL    | 76.2  | 73.1  | 74.6      | 68.4    | 65.5    | 66.9    | 65.1    | 61.8    | 63.4    | 68.3    |
|        | + HIGH RECALL + joint | 77.6  | 73.4  | 75.4      | 70.4    | 65.5    | 67.9    | 66.4    | 61.9    | 64.1    | 69.1    |

Table 4: Comparison between the baselines and the models enhanced by our \textsc{Biaffine MD} on the coreference resolution task.
call which is required to train a coreference system. After training the system with mentions from our IAFFINE MD, the newly obtained models achieved large improvements of 0.8% and 1.7% for HIGH RECALL and BALANCE settings respectively. This suggests that the Clark and Manning (2016a) system works better on a smaller number of high-quality mentions than a larger number but lower quality mentions. We also noticed that the speed of the Clark and Manning (2016a) system is sensitive to the size of the predicted mentions, both training and testing finished much faster when tested on the BALANCE setting. We did not test the Clark and Manning (2016a) system on the CRAC data set, as a lot of effects are needed to fulfil the requirements of the preprocessing pipeline, e.g. predicted parse trees, named entity tags. Overall our IAFFINE MD showed its merit on enhancing the pipeline system.

6. Conclusions
In this work, we compare three neural network based approaches for mention detection. The first model is a modified version of the mention detection part of the state-of-the-art coreference resolution system (Lee et al., 2018). The second model used ELMo embeddings together with a bidirectional LSTM, and with a biaffine classifier on top. The third model adapted the BERT model that based on the deep transformers and followed by a FFNN. We assessed the performance of our models in both mention detection and coreference tasks. In the evaluation of mention detection, our proposed models reduced up to 26% and 39% of the recall error when compared with the strong baseline on CONLL and CRAC data sets in a HIGH RECALL setting. The same model (IAFFINE MD) outperforms the best performing system on the CONLL and CRAC by large 5-6% in a HIGH F1 setting. In term of the evaluation on coreference resolution task, by integrating our mention detector with the state-of-the-art coreference systems, we improved the end-to-end and pipeline systems by up to 0.7% and 1.7% respectively. Overall, we introduced three neural mention detectors and showed that the improvements achieved on the mention detection task can be transferred to the downstream coreference resolution task.

7. Bibliographical References
Björkelund, A. and Kuhn, J. (2014). Learning structured perceptrons for coreference resolution with latent antecedents and non-local features. In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), volume 1, pages 47–57.
Chamberlain, J., Poesio, M., and Kruschwitz, U. (2016). Phrase detectives corpus 1.0 crowdsourced anaphoric coreference. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC 2016), Paris, France, may. European Language Resources Association (ELRA).
Chiu, J. P. and Nichols, E. (2016). Named entity recognition with bidirectional lstm-cns. Transactions of the Association for Computational Linguistics, 4:357–370.
Clark, K. and Manning, C. D. (2015). Entity-centric coreference resolution with model stacking. In Association for Computational Linguistics (ACL).
Clark, K. and Manning, C. D. (2016a). Deep reinforcement learning for mention-ranking coreference models. In Empirical Methods on Natural Language Processing (EMNLP).
Clark, K. and Manning, C. D. (2016b). Improving coreference resolution by learning entity-level distributed representations. In Association for Computational Linguistics (ACL).
Collobert, R., Weston, J., Bottou, L., Karlen, M., Kavukcuoglu, K., and Kuksa, P. (2011). Natural language processing (almost) from scratch. Journal of machine learning research, 12(Aug):2493–2537.
Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2019). Bert: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Annual Conference of the North American Chapter of the Association for Computational Linguistics.
Dozat, T. and Manning, C. (2017). Deep biaffine attention for neural dependency parsing. In Proceedings of 5th International Conference on Learning Representations (ICLR).
Lample, G., Ballesteros, M., Subramanian, S., Kawakami, K., and Dyer, C. (2016). Neural architectures for named entity recognition. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 260–270. Association for Computational Linguistics.
Lee, H., Chang, A., Peirsman, Y., Chambers, N., Surdeanu, M., and Jurafsky, D. (2013). Deterministic coreference resolution based on entity-centric, precision-ranked rules. Computational Linguistics, 39(4):885–916.
Lee, K., He, L., Lewis, M., and Zettlemoyer, L. (2017). End-to-end neural coreference resolution. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing.
Lee, K., He, L., and Zettlemoyer, L. S. (2018). Higher-order coreference resolution with coarse-to-fine inference. In Proceedings of the 2018 Annual Conference of
the North American Chapter of the Association for Computational Linguistics.

Pennington, J., Socher, R., and Manning, C. (2014). Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), pages 1532–1543.

Peters, M. E., Neumann, M., Iyyer, M., Gardner, M., Clark, C., Lee, K., and Zettlemoyer, L. S. (2018). Deep contextualized word representations. In Proceedings of the 2018 Annual Conference of the North American Chapter of the Association for Computational Linguistics.

Poesio, M., Stuckardt, R., and Versley, Y. (2016). Anaphora Resolution: Algorithms, Resources and Applications. Springer, Berlin.

Poesio, M., Grishina, Y., Kolhatkar, V., Moosavi, N., Roesiger, I., Roussel, A., Simonjetz, F., Uma, A., Uryupina, O., Yu, J., and Zinsmeister, H. (2018). Anaphora resolution with the arrau corpus. In Proc. of the NAACL Worskhop on Computational Models of Reference, Anaphora and Coreference (CRAC), pages 11–22, New Orleans, June.

Poesio, M., Chamberlain, J., Paun, S., Yu, J., Uma, A., and Kruschwitz, U. (2019). A crowdsourced corpus of multiple judgments and disagreement on anaphoric interpretation. In Proceedings of the 2019 Annual Conference of the North American Chapter of the Association for Computational Linguistics.

Pradhan, S., Moschitti, A., Xue, N., Uryupina, O., and Zhang, Y. (2012). CoNLL-2012 shared task: Modeling multilingual unrestricted coreference in OntoNotes. In Proceedings of the Sixteenth Conference on Computational Natural Language Learning (CoNLL 2012), Jeju, Korea.

Uryupina, O. and Moschitti, A. (2013). Multilingual mention detection for coreference resolution. In Proceedings of the Sixth International Joint Conference on Natural Language Processing, pages 100–108.

Uryupina, O., Artstein, R., Bristot, A., Cavicchio, F., Delogu, F., Rodriguez, K. J., and Poesio, M. (2019). Annotating a broad range of anaphoric phenomena, in a variety of genres: the ARRAU corpus. Journal of Natural Language Engineering.

Wiseman, S., Rush, A. M., Shieber, S., and Weston, J. (2015). Learning anaphoricity and antecedent ranking features for coreference resolution. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), volume 1, pages 1416–1426.

Wiseman, S., Rush, A. M., and Shieber, S. M. (2016). Learning global features for coreference resolution. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 994–1004.

Wu, Y., Schuster, M., Chen, Z., Le, Q. V., Norouzi, M., Macherey, W., Krikun, M., Cao, Y., Gao, Q., Macherey, K., et al. (2016). Google’s neural machine translation system: Bridging the gap between human and machine translation. arXiv preprint arXiv:1609.08144.

Zhang, R., Nogueira dos Santos, C., Yasunaga, M., Xiang, B., and Radev, D. (2018). Neural coreference resolution with deep biaffine attention by joint mention detection and mention clustering. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 102–107. Association for Computational Linguistics.