

Coreference Resolution

Working Title, First Draft: Content, not Wording

Patrick Kahardipraja, Olena Vyshnevskaya

1 Introduction

Coreference resolution, the task that involves determining all referring expressions that point to the same entity in a discourse model, plays a key role for various higher level NLP tasks that involve natural language understanding such as information extraction, question answering, machine translation, text summarization and textual entailment. In coreference resolution task, referring expressions (i.e. mentions) could be a common noun, a proper noun, or a pronoun, which refer to a real-world entity known as the referent. The main goal of a coreference resolution system is to group the mentions such that the corefering mentions are placed together in a coreference cluster.

In the recent years, neural-based coreference resolution approach are more popular, considering neural network capability to learn features automatically with multiple, hierarchical representations coupled with its high performance and ability to generalize better compared to rule-based approach.

Since the introduction of pre-trained BERT model (Devlin et al. 2019) there has been a lot of research showing how the model outperforms previous state-of-the-art task-specific NLP models. *cite some papers here* Joshi et al. (2019) has introduced BERT models into coreference resolution tasks. However, the researchers have also encoded other information on top of BERT embeddings.

Our first research question is based on the recent research which shows that the BERT model itself encodes a significant amount of semantic and syntactic information. Therefore, we decided to test how well the span representations using BERT embeddings from the model by Joshi et al. (2019) finetuned on Ontonotes dataset (Pradhan et al. 2012) can encode coreference resolution information without any layers of additional information about a given sequence.

As a baseline, we used original pre-trained BERT embeddings. To encode a mention span, we used a convolutional layer and a self-attention layer.

Our second research question, which naturally follows from the first one, whether the span representations encoded with a pre-trained BERT model simply modelling local coreference? Will it be able to encode non-local coreference dependencies?

We found that the span representations from within the coreference model by Joshi et al. (2019) reach *insert some numbers*. The baseline model is at *insert numbers*. This findings suggests that the pre-trained BERT model is a powerful tool for encoding information relevant to coreference resolution.

For our second research question (non-local VS local dependencies) we found that ... *what we found for local non-local*

Our code is publicly available on GitHub. ¹.

¹https://github.com/alyonavyshnevskaya/bert_for_coreference_resolution

2 Related Work

2.1 Approaches to Coreference Resolution

Most of the earlier systems to solve coreference resolution are rule-based. (Hobbs 1978) proposed a naïve tree-search algorithm for identifying antecedent with world knowledge based constraints to prune the antecedent search space, which started a long-series of syntax-based methods. (Lapin and Leass 1994) introduced an algorithm that maintain a discourse model consisting of potential antecedent references, where each antecedent was assigned a salience value based on several features. All the salience value are then summed to score and predict the most appropriate antecedent. Furthermore, (Kennedy and Boguraev 1996) extended the approach to avoid full syntactic parsing by using part-of-speech tagger, augmented with annotations of grammatical functions.

However, the field of coreference resolution underwent a shift since the first machine learning-based approach for coreference resolution was published (Connolly, Burger, and Day 1994). While rule-based systems have witnessed a short-lived revival in 2010s (Zhou, Ticea, and Hovy 2004; Haghighi and Klein 2009), their struggles with semantic understanding for the models led to their eventual demise. Architectures for machine learning-based coreference resolution models can be categorized as (1) mention-pair classifiers (Ng and Cardie 2002; Bengtson and Roth 2008), (2) mention-ranking models (Durrett and Klein 2013; Wiseman, Rush, S. Shieber, et al. 2015; Clark and Manning 2016a; Denis and Baldridge 2008), (3) entity-level models (Haghighi and Klein 2010; Wiseman, Rush, and S. M. Shieber 2016; Clark and Manning 2015; Clark and Manning 2016b), (4) latent-tree models (Fernandes, Santos, and Milidiu 2012; Martschat and Strube 2015; Björkelund and Kuhn 2014), and (5) span-ranking models (Lee, L. He, Lewis, et al. 2017; Lee, L. He, and Zettlemoyer 2018; Joshi et al. 2019).

While earlier machine learning based-approach depends on hand-crafted features, in the recent years neural-based architectures have been particularly successful in coreference resolution and NLP in general, enabled by word embeddings and contextual word representations. The first neural approach in coreference resolution is introduced by (Wiseman, Rush, S. Shieber, et al. 2015), where they extend mention-ranking model with a feed-forward neural network that can be viewed as piecewise scoring function to determine whether a mention is anaphoric or not. (Lee, L. He, Lewis, et al. 2017) proposed an end-to-end coreference resolution model that consider all spans of text and learn how to identify mentions and cluster them together using a pairwise scoring function. (Clark and Manning 2016a) proposed a novel approach to use reinforcement learning for coreference resolution. Using reward-rescaled max-margin objective and REINFORCE policy gradient algorithm (Williams 1992), they exploit the independent coreference decision in mention-ranking model to directly optimize for coreference evaluation metrics. Neural coreference resolution approach also typically require different levels of semantic representations of input sentences, which is usually done by computing representations at span level given the word embeddings. We focus on these span representation and examine their capability in encoding necessary information to make coreference decisions.

2.2 Probing Tasks

Along with the rise of deep learning architectures across a plethora of NLP tasks, there is also some concern regarding its interpretability and whether if neural-based approach is truly able to capture linguistic concepts. The most common method to explore linguistic properties in neural network components is by using the hidden state activations to predict the property of interest, also known as "probing tasks" (Conneau et al. 2018) or "auxiliary prediction tasks" (Adi et al. 2016). (Shi, Padhi, and Knight 2016) use the internal representations of LSTM encoder as an input to train logistic regression classifier that predicts various syntactic properties. (Conneau et al. 2018)

study the linguistic properties of fixed-length sentence encoders with a bidirectional LSTM and gated convolutional networks.

(Liu et al. 2019) explore representations produced by pretrained contextualizers and show that frozen contextual representations fed into linear models can show similar levels of performance as state-of-the-art task-specific models on many NLP tasks. They also introduced coreference arc prediction task, where linear models are used to predict whether if two mentions corefer. Concurrently, (Tenney et al. 2019) introduced edge probing framework, which focuses on linguistic analysis on sub-sentence level. Their approach uses a linear model with a projection layer and attention mechanism on top of frozen contextual vectors to predict linguistic properties. Clark further extend probing-based approach by proposing an attention-based probing classifiers and showed that attention heads in BERT corresponds to linguistic notions of syntax and coreference. Our approach is most similar to (Liu et al. 2019) and (Tenney et al. 2019), but we use span representation by (Lee, L. He, Lewis, et al. 2017) and focus on examining coreference phenomena.

3 Overview of Span-Ranking Architecture

The first coreference resolution model that is trained in an end-to-end manner without relying on any syntactic parser or hand-engineered mention detector is introduced by (Lee, L. He, Lewis, et al. 2017). To construct correct coreference clusters, the neural model learn to jointly model mention detection and coreference prediction using span-ranking approach. With span-ranking approach, the model is able to consider all spans in a document up to a defined maximum length as a candidate mention and select the corresponding antecedent for each mention based on the antecedent distribution. We will further refer to the model as *e2e-coref* in the paper.

The span-ranking architecture estimates the joint probability distribution of mention-spans that belong to the same cluster given the document, by calculating product of multinomials for each span:

$$P(y_1, \dots, y_n | D) = \prod_{i=1}^N P(y_i | D) \quad (1)$$

$$= \prod_{i=1}^N \frac{\exp(s(i, y_i))}{\sum_{y' \in \mathcal{Y}(i)} \exp(s(i, y'))} \quad (2)$$

where $s(i, j)$ is a pairwise score for a coreference link between span i and span j in document D . The coreference score is composed of three factors: (1) $s_m(i)$, mention score of i (i.e. how possible is the span i to be a mention), (2) $s_m(j)$, mention score of j and (3) $s_a(i, j)$, joint score of i and j (i.e. assuming that i and j are both mentions, how possible that they both refer to the same entity), formulated as the following:

$$s(i, j) = \begin{cases} s_m(i) + s_m(j) + s_a(i, j) & j \neq \epsilon \\ 0 & j = \epsilon \end{cases} \quad (3)$$

where ϵ is a dummy antecedent to represent that the span is not a mention or the case where it is a mention that coreferent with none of the previous mention span.

In this model, a bidirectional LSTM (Hochreiter and Schmidhuber 1997) is used to compute vector representations g_i of each possible span i from the word and character embeddings in the span. The word embeddings itself are a fixed concatenation of GloVe (Pennington, Socher, and Manning 2014) and Turian embeddings (Turian, Ratnov, and Bengio 2010). The character embeddings are learned using CNN, with three various window sizes. It also provide morphological information and

allows the model to deal with rare words. The span representation \mathbf{g}_i , which we will describe in detail in the following section, is then used to compute $s_m(i)$ and $s_a(i, j)$ via feed-forward neural networks as follows:

$$s_m(i) = \mathbf{w}_m \cdot \text{FFNN}_m(\mathbf{g}_i) \quad (4)$$

$$s_a(i, j) = \mathbf{w}_a \cdot \text{FFNN}_a([\mathbf{g}_i, \mathbf{g}_j, \mathbf{g}_i \odot \mathbf{g}_j, \phi(i, j)]) \quad (5)$$

where \odot denotes the Hadamard product between \mathbf{g}_i and \mathbf{g}_j , and $\phi(i, j)$ is a feature vector that encodes speaker and genre information from the metadata and the distance between a pair of span. The final coreference score is computed through a two-stage beam search as the model complexity is quartic in terms of the document length. In the first phase, a beam of up to λT candidate mention spans are considered based on the highest mention scores $s_m(i)$, where λ is a hyperparameter and T is the document length. Afterwards, only the filtered mentions are used to compute the joint score $s_a(i, j)$ during both training and inference, with the limitation that only up to K candidate antecedents that are considered for each mention.

While the first order model proposed by (Lee, L. He, Lewis, et al. 2017) works quite well for coreference resolution, scoring only pairs of entity mentions means that previous coreference decisions are not taken into account when computing coreference decisions that occur afterwards. This drawback makes the model more susceptible to predicting clusters that are locally consistent but globally inconsistent. In an attempt to improve the weakness of this approach, (Lee, L. He, and Zettlemoyer 2018) proposed a model that captures higher-order interactions between mention spans in predicted coreference clusters. The model utilizes span-ranking architecture to refine existing span representations iteratively with the antecedent distribution as an attention mechanism. We will further refer to the model as *c2f-coref* in the paper.

In order to refine the span representations, the higher-order model estimates the antecedent distributions $P_n(y_i)$, which is obtained using the softmax function:

$$P_n(y_i) = \frac{\exp(s(\mathbf{g}_i^n, \mathbf{g}_{y_i}^n))}{\sum_{y \in \mathcal{Y}(i)} \exp(s(\mathbf{g}_i^n, \mathbf{g}_y^n))} \quad (6)$$

where s is the scoring function from (Lee, L. He, Lewis, et al. 2017), \mathbf{g}_i^n is the representation for span i at iteration n . The refined span representations also allow the model to iteratively refine $P_n(y_i)$. Afterwards, the expectation of each span i are computed by using the current antecedent distribution as the attention weight:

$$\mathbf{a}_i^n = \sum_{y_i \in \mathcal{Y}(i)} P_n(y_i) \cdot \mathbf{g}_{y_i}^n \quad (7)$$

where \mathbf{a}_i^n can be viewed as the expected antecedent representation. The span representation \mathbf{g}_i^n is updated with the expected antecedent representation \mathbf{a}_i^n using coupled forget and input gates formulated as the following:

$$\mathbf{f}_i^n = \sigma(\mathbf{W}_f[\mathbf{g}_i^n, \mathbf{a}_i^n]) \quad (8)$$

$$\mathbf{g}_i^{n+1} = \mathbf{f}_i^n \odot \mathbf{g}_i^n + (1 - \mathbf{f}_i^n) \odot \mathbf{a}_i^n \quad (9)$$

where $\mathbf{f}_i^n \in [0, 1]$ is a gate vector that controls whether to retain the information from the current span representation or to update the span representation with the expected antecedent. Altogether, this mechanism allows the model to compute the final antecedent distribution conditioned on up to n other mention spans.

To alleviate the additional computational cost of higher-order inference, (Lee, L. He, and Zettlemoyer 2018) also proposed a coarse-to-fine beam search, which does not establish an a priori maximum

coreference distance. In order to prune potential mentions aggressively, the coreference score is reformulated as the following:

$$s_c(i, j) = \mathbf{g}_i^\top \mathbf{W}_c \mathbf{g}_j \quad (10)$$

$$s(i, j) = \begin{cases} s_m(i) + s_m(j) + s_a(i, j) + s_c(i, j) & j \neq \epsilon \\ 0 & j = \epsilon \end{cases} \quad (11)$$

where $s_c(i, j)$ a bilinear scoring function to compute a rough sketch of possible antecedents. To obtain the coreference score, the model executes a three-stage beam search. At the first stage, a beam of up to M candidate mention spans are considered based on the mention score $s_m(i)$. Afterwards, approximation of pairwise coreference score is computed based on $s_m(i) + s_m(j) + s_c(i, j)$ to keep top K candidate antecedents for each remaining mention spans. In the last phase, the final coreference score $s(i, j)$ is computed based on the surviving pairs of mention spans.

Recently, BERT (Devlin et al. 2019) has achieved state-of-the-art results on a wide array of NLP tasks, such as question answering and natural language inference, without any substantial task-specific architecture modifications. (Joshi et al. 2019) proposed to replace the bidirectional LSTM encoder in *c2f-coref* with BERT transformers and fine-tune it on coreference resolution task. Although BERT improves the state-of-the-art results in other tasks significantly, coreference resolution still proves to be a challenging task, as BERT encoder offers only a marginal performance increase. Furthermore, the model still struggles in modeling pronouns and resolving cases where mention paraphrasing is required. We refer the model by (Joshi et al. 2019) as *BERT-coref*.

4 Probing Mention-Span Representation

4.1 Span Representation

Span representation plays an important role in span-ranking model (Lee, L. He, Lewis, et al. 2017; Lee, L. He, and Zettlemoyer 2018; Joshi et al. 2019), since it is used to compute distribution over candidate antecedent spans. In order to be able to predict coreference relations accurately, span representation should also capture the information of the span’s internal structure and its surrounding context. In our experiments, we use the span representation which is first proposed in (Lee, L. He, Lewis, et al. 2017), but with BERT (Devlin et al. 2019) instead of a LSTM-based encoder to encode lexical information of the span and its surrounding, following (Joshi et al. 2019). The span representation is a vector embeddings which consists of context-dependent boundary representations with attentional representation of the head words over the span. The boundary representations are composed of first and last word-pieces of the span itself. The head words are automatically learned using additive attention (Bahdanau, Cho, and Bengio 2015) over each wordpieces in the span:

$$\alpha_t = \mathbf{w}_\alpha \cdot \text{FFNN}_\alpha(\mathbf{x}_t^*) \quad (12)$$

$$a_{i,t} = \frac{\exp(\alpha_t)}{\sum_{k=\text{start}(i)}^{\text{end}(i)} \exp(\alpha_k)} \quad (13)$$

$$\hat{\mathbf{x}}_i = \sum_{t=\text{start}(i)}^{\text{end}(i)} a_{i,t} \cdot \mathbf{x}_t \quad (14)$$

where $\hat{\mathbf{x}}_i$ is a weighted vector representation of wordpieces for span i . This representation is augmented by a \mathbb{R}^d feature vector which encodes the size of span i with $d = 20$. The final representation

g_i for span i is formulated as the following:

$$g_i = [\mathbf{x}_{start(i)}^*, \mathbf{x}_{end(i)}^*, \hat{\mathbf{x}}_i, \phi_i] \quad (15)$$

where $\mathbf{x}_{start(i)}^*$ and $\mathbf{x}_{end(i)}^*$ are first and last wordpieces of the span, and ϕ_i is the span width embeddings.

4.2 Coreference Arc Prediction

We focus on coreference arc prediction task, which is a part of probing tasks suite for contextual word embeddings (Liu et al. 2019; Tenney et al. 2019). In this task, a probing model is trained to determine whether if two mentions refer to the same entity. As datasets for coreference resolution usually only contains annotations for corefering mentions, we produce negative samples following the approach by (Liu et al. 2019). For every pair of mentions (w_i, w_j) , where they belong to the same coreference cluster and w_i is an antecedent of w_j , we generate a negative example (w_{random}, w_j) where w_{random} belongs to a different coreference cluster. This method ensures that the ratio between positive and negative examples is balanced. We also follow the approach of (Tenney et al. 2019) by using spans of wordpieces for mentions, as (Liu et al. 2019)’s approach is limited on single-token mentions and therefore unable to fully exploit the information in the mention-span.

4.3 Probing Model

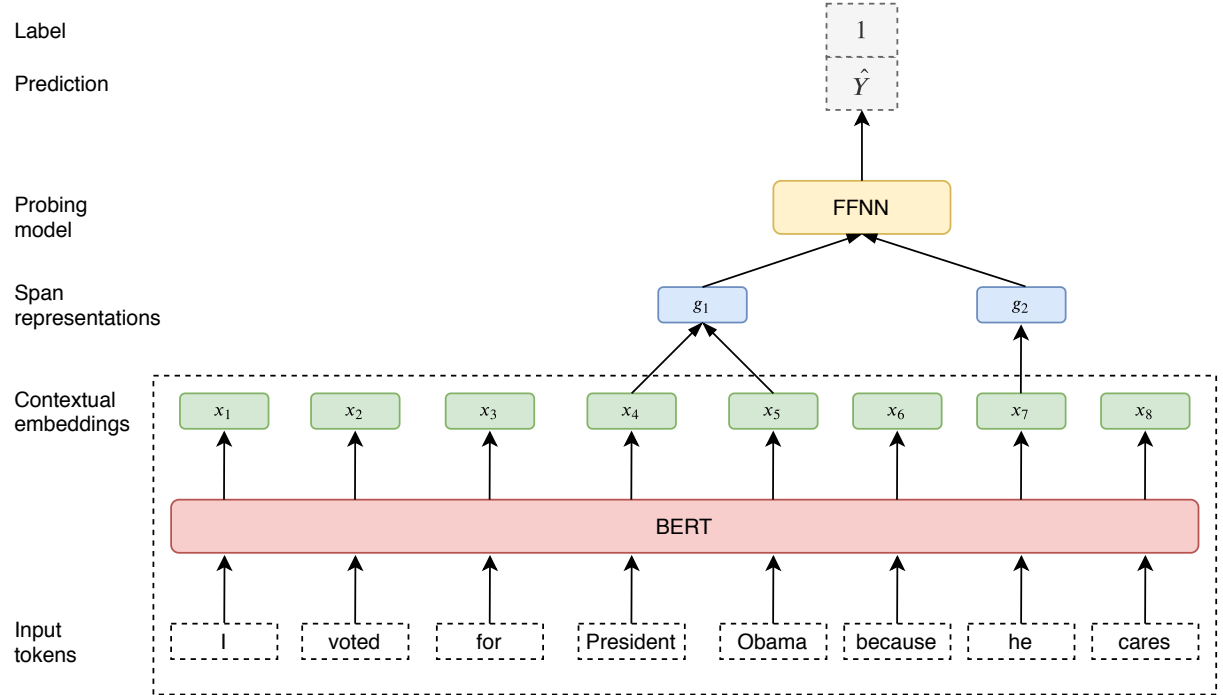


Figure 1: Probing architecture for span representation. The feed-forward neural network is trained to extract information from the span representations g_1 and g_2 , while all the parameters inside the dashed line are frozen. The example depicts a mention-pair, where g_1 corresponds to span representation of "President Obama", while g_2 corresponds to "he". We predict \hat{Y} as positive for this example.

Our probing model is a simple feed-forward neural network, which is designed with a limited capacity to focus on what information that can be extracted from the span representations. As the input to our probing model, we take the span representation for pair of mention-spans

$\mathbf{g}_1 = [\mathbf{x}_{start(1)}^*, \mathbf{x}_{end(1)}^*, \hat{\mathbf{x}}_1, \phi_1]$ and $\mathbf{g}_2 = [\mathbf{x}_{start(2)}^*, \mathbf{x}_{end(2)}^*, \hat{\mathbf{x}}_2, \phi_2]$, where both \mathbf{g}_1 and \mathbf{g}_2 are concatenated together and passed to the FFNN. The FFNN consists of a single hidden layer followed by a sigmoid output layer. The model is trained to minimize the binary cross-entropy with respect to the gold label $Y \in \{0, 1\}$. The probing architecture is shown in Figure 1.

We explore mention-span representations obtained from BERT. BERT (Devlin et al. 2019) is a language representation model which uses deep Transformer architecture (Vaswani et al. 2017), trained jointly with masked language model and next sentence prediction objective on BooksCorpus (Zhu et al. 2015) and English Wikipedia, with an approximate total of 3,300M tokens. It also enables significant improvement in many downstream tasks with relatively minimal task-specific fine-tuning. To study the quality of mention-span representations, we extract mention-span embeddings from BERT-base (12-layer Transformer, 768-hidden) and BERT-large (24-layer transformer, 1024-hidden). We also want to compare the effect of fine-tuning BERT-based models on the quality of span representations, therefore we use two variant of BERT models: a) fine-tuned on coreference resolution task and b) without any fine-tuning.

5 Experiments

We attempt to investigate to what extent can *BERT-coref* span representation encode coreference relations. We also want to answer whether if the span representation is able to encode long-range coreference phenomena effectively, or is it just simply modeling local coreference relation? Our experiments, which we describe below, are intended to analyze coreference information contained in the span representation used in the span-ranking model.

5.1 Dataset

For our experiments, we use the coreference resolution annotation from the CoNLL-2012 shared task based on the OntoNotes dataset (Pradhan et al. 2012). The dataset comprises of roughly one million words from various genre such as newswire, magazine articles, broadcast news, broadcast conversations, web data and conversational speech data, and the New Testament in English, which was splitted into 2802 training documents, 343 validation documents, and 348 test documents. On average, the training documents contain 454 words. The largest document contains a maximum of 4009 words. Beside entities, coreference is also annotated for mentions that refer to the same event (e.g. "The European economy **grew** rapidly over the past years, **this growth** helped raising..."). The main evaluation of the dataset is the average F1 score of three metrics – *MUC* (Vilain et al. 1995), *B³* (Bagga and Baldwin 1998) and *CEAF_{φ4}* (Luo 2005). Since OntoNotes only provide annotations for positive examples, we generate our own negative examples according to the aforementioned method (§4.2). We also cast the original annotation provided in the dataset into JSON format in order to work with *BERT-coref*.

5.2 Implementation and Hyperparameters

We extend the original Tensorflow implementation of *BERT-coref*² in order to build our probing model with Keras frontend (Chollet 2015). Our probing model are trained for 50 epochs, using early stopping with patience of 3 and batch size of 512. For optimization, we use Adam (Kingma and Ba 2015) with a learning rate of 0.001. The weights of the probing model is initialized with Kaiming initialization (K. He et al. 2015) and the size of the hidden layer is $d = 1024$ with rectified linear units (Nair and Hinton 2010).

²<https://github.com/mandarjoshi90/coref>

As mentioned previously, we use both pre-trained BERT model without fine-tuning the encoder weights and BERT model that has been fine-tuned on coreference resolution task (i.e. on OntoNotes annotations). For fine-tuned BERT model, we take the models that yield the best performance on (Joshi et al. 2019), which were trained using 128 wordpieces for BERT-base and 384 wordpieces for BERT-large. The fine-tuned model was trained using splitted OntoNotes documents where each segment non-overlaps and fed as a separate instance. This is done as BERT can only accept sequences of at most 512 wordpieces and typically OntoNotes documents require multiple segments to be read entirely. In all of our experiments, we use the cased English BERT models.

5.3 Baseline

As our baseline, we use span representations introduced in the edge probing framework (Tenney et al. 2019). First of all, we take concatenated contextual embeddings for pair of mention-span $e^{(1)} = [x_1^{(1)}, x_2^{(1)}, x_3^{(1)}, \dots, x_n^{(1)}]$ and $e^{(2)} = [x_1^{(2)}, x_2^{(2)}, x_3^{(2)}, \dots, x_n^{(2)}]$ as inputs. We then project the concatenated contextual embeddings $e^{(1)}$ and $e^{(2)}$ to improve performance:

$$e^{(i)} = Ae^{(i)} + b \quad (16)$$

where $i = (1, 2)$, A and b are weights of the projection layer. The parameters in the projection layer are shared between representations $e^{(1)}$ and $e^{(2)}$. Afterwards, we apply self-attentional pooling operator in (§4.1) over the projected representations to yield a fixed-length span representations. This also helps to model head words for each mention-span. These mention-span representations are then concatenated together and passed to the probing model to predict whether they corefer or not. It is important to note that the self-attention pooling is computed only using tokens within the boundary of the span. As a result, the model can only access information about the context surrounding the mention span through the contextual embeddings. We take the contextual embeddings from activations of original pre-trained BERT final layer, while freezing the encoder. The baseline probing architecture is depicted in Figure 2.

We compare the span representation used in the span-ranking model against the baseline, as it measures the performance that the probing model can achieve from the representation that is constructed from lexical priors alone, without any access to the local context within the mention-span. The resulting baseline span representations have a dimension of $d = 768$ for BERT-base and $d = 1024$ for BERT-large.

5.4 Long-range Coreference

We want to understand better about the capability of *BERT-coref* span representations. Is it able to encode long-range coreference, or is it just simply modelling local coreference? We also want to answer how well does the model learn from local and long-range context within the mention-span. In order to answer both of these questions, we extend our baseline by introducing a convolutional layer to incorporate surrounding context and improves the baseline span representation, following (Tenney et al. 2019). We replace the projection layer in our probing architecture with a fully-connected 1D CNN layer with a kernel width of 3 and 5, stride of 1 and same padding to properly include contextual embeddings at the beginning and end of the mention-span. This is equivalent to seeing ± 1 and ± 3 tokens around the center word respectively. We also initialize the weights of the CNN layer with Kaiming initialization (K. He et al. 2015). Using this extended probing architecture with CNN layer as another baseline, which we will refer to as *CNN-baseline* in this paper, enables us to see the contribution of local and non-local context to the performance of the probing model.

To investigate whether if the span representation is able to capture long-range coreference relation or not, we see how our probing model performs with various distance between mention-spans. We

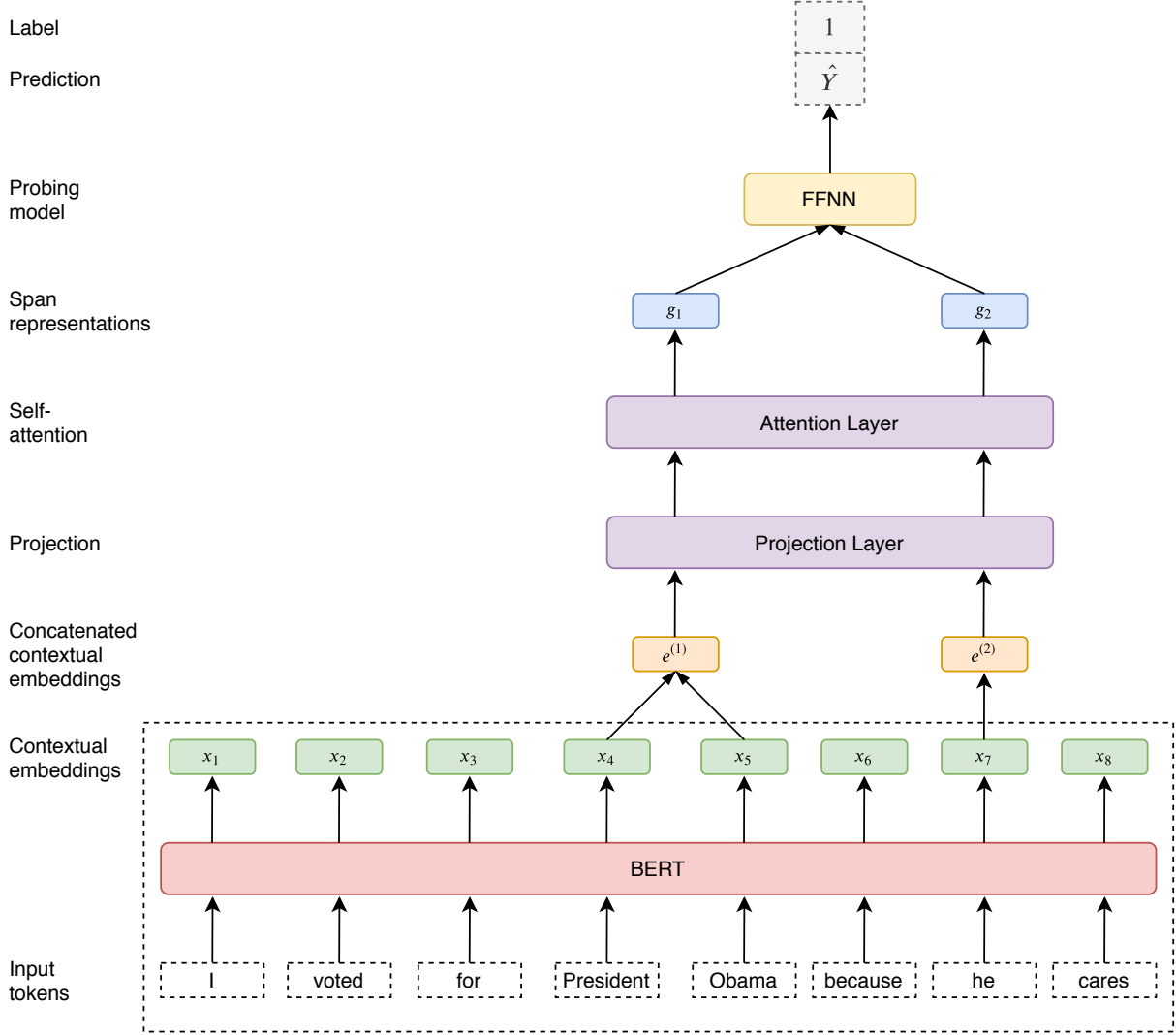


Figure 2: Probing architecture for baseline span representation. All parameters inside the dashed lines are frozen, while we train the feed-forward neural network to extract coreference information from the concatenated contextual embeddings $e^{(1)}$ and $e^{(2)}$. We used shared weights for both projection and self-attentional layer so that the model can learn the similarity between representation of mention-spans.

separate pairs of mention-spans that appear in the OntoNotes test set into several buckets, based on the distance between last token of mention-span w_i and first token of mention-span w_j , where w_j occurs after w_i . Each bucket contains at least 50 examples of pairs of mention-spans.

6 Results

6.1 Comparison of Probing Models

We report the accuracies and F1 scores of our probing model with span representations constructed from BERT encoder. Table 1 compares the performance of probing model using span representations finetuned on OntoNotes dataset against baseline span representation and *CNN-baseline* that utilize original pre-trained BERT encoder. Using a simple linear probing model, we demonstrate that span representation in *BERT-coref* encodes a significant amount of coreference information, as we are able to train the probing model to predict whether a pair of mention spans corefer or not based

on their span representations alone. Both BERT-base c2f and BERT-large c2f consistently scores above 90% (accuracy and F1 score) on OntoNotes test set.

	Accuracy	F1 Score
BERT-base c2f (cased, fine-tuned)	92.93	93.02
BERT-large c2f (cased, fine-tuned)	93.65*	93.68*
BERT-base CNN (cased, original, kernel=3)	89.51	89.91
BERT-base CNN (cased, original, kernel=5)	89.04	89.28
BERT-large CNN (cased, original, kernel=3)	90.27	90.35
BERT-large CNN (cased, original, kernel=5)	88.09	88.28
BERT-base (cased, original) baseline	90.37	90.65
BERT-large (cased, original) baseline	91.47	91.69

Table 1: Comparison of the probing model’s performance with various mention-span representations evaluated on OntoNotes test set. Asterisk denotes the best performance on each metric. BERT-large c2f improves the accuracy and F1 score over the probing baseline by 3.28% and 3.03% for the base variant, while for BERT-large baseline, the improvements are 2.18% and 1.99% respectively.

We observe that both BERT-base c2f and BERT-large c2f performs better in predicting coreference arc between a pair of mention-spans compared to their respective baseline (by 2.37 points for accuracy and 2.18 F1 points on average). We find that although training the contextual probing model to learn contextual features for coreference arc prediction helps in encoding the necessary coreference information into the baseline span representation, it still cannot outperform the probing model that utilizes span representation in *BERT-coref*. This might be caused by better coreference-related features that is learned by BERT encoder when it is fine-tuned on OntoNotes.

We find that fine-tuning the span representation on coreference resolution task helps to encode local and long-range context inside the mention-span efficiently. This can be observed from the performance of *CNN-baseline*, where the probing model is trained using 1D CNN layer with kernel width of 3 and 5 to allow us to see contribution of local and long-range dependencies, but ultimately still perform lower compared to *BERT-coref*. Surprisingly, our baseline span representation which is constructed from only lexical prior performs better compared to the *CNN-baseline* span representation on both metrics. We attribute this due to our decision of taking contextual embeddings from the final layer of pre-trained BERT, as most transferrable representations from contextual encoders trained with language modeling objective tend to occur in the intermediate layers, and that the topmost layers might be overly specialized for next-word prediction (Liu et al. 2019; Peters, Neumann, Iyyer, et al. 2018; Peters, Neumann, Zettlemoyer, et al. 2018; Blevins, Levy, and Zettlemoyer 2018; Devlin et al. 2019). This may cause the CNN layer to learn suboptimal representations of the mention-span.

6.2 Ablations

To find out the importance of each component in *BERT-coref* span representations, we do ablation study on each part of the representation and report the accuracy and F1 score of the probing model on the test set of the data, which is depicted on Table 2. The head-finding attention mechanism is crucial for coreference-arc prediction, as it contributes the highest to the final result with 0.98 and 0.95 points for accuracy and F1 score on average, respectively. This is consistent with previous findings from (Lee, L. He, Lewis, et al. 2017), where attention mechanism is shown to be able to learn representation that is important for coreference. We also observe that span-width embeddings play an important role in determining coreference relation, seeing that without them the performance degrades on average by 0.4 and 0.37 for accuracy and F1. Contrary to the head-finding attention and

span-width embeddings, boundary representations did not contribute much to the model’s performance. We hypothesize that although boundary representations encode rich amount of information for coreference resolution, it is not significant for coreference arc prediction, as the model does not have to predict distribution over possible spans.

	Accuracy	F1 Score	Δ Accuracy	Δ F1 Score
BERT-base c2f (cased, fine-tuned)	92.93	93.02		
- boundary representations	92.88	92.96	−0.05	−0.06
- head-finding attention	92.05	92.16	−0.88	−0.86
- span-width embeddings	92.46	92.56	−0.47	−0.46
BERT-large c2f (cased, fine-tuned)	93.65	93.68		
- boundary representations	93.47	93.49	−0.18	−0.19
- head-finding attention	92.57	92.65	−1.08	−1.03
- span-width embeddings	93.32	93.41	−0.33	−0.27

Table 2: Comparison of the probing model on OntoNotes test set with various components removed. The head-finding attention and span-width embeddings contribute significantly to the performance of the probing model.

6.3 Encoding Long-range Coreference

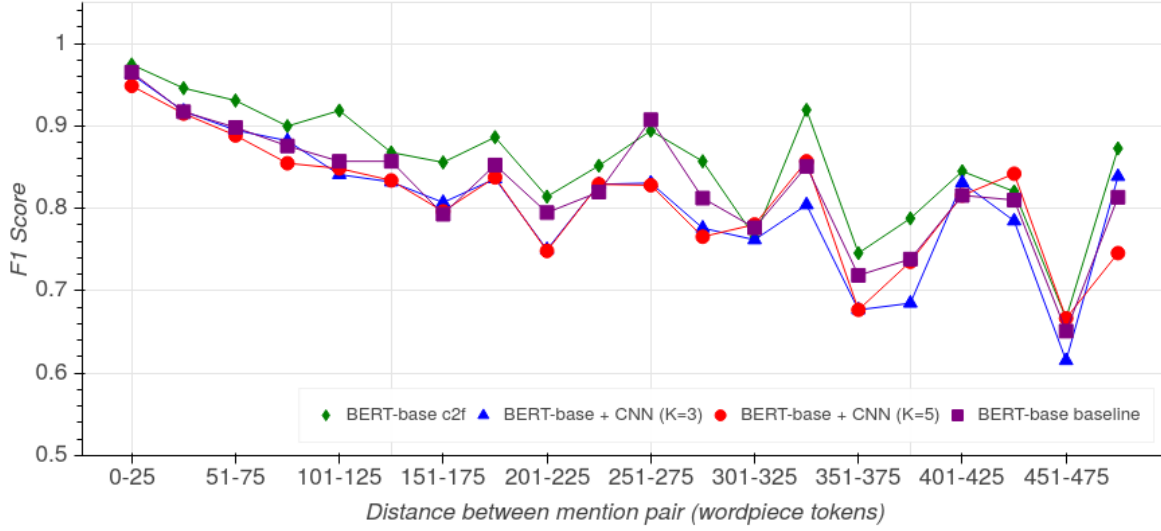
We compare how our probing model performs with various span separation distance in order to explore whether if the span representation is able to encode long-range coreference or not. Figure 3 depicts F1 score as a function of the distance of wordpiece tokens between a pair of mention-spans. Although performance with BERT models degrade with larger distance over pair of mention-span, the span representation in *BERT-coref* holds up better in general compared to the baseline or *CNN-baseline*. The BERT-base variant experiences minor degradation in performance to 5 points when $d = 125$ tokens, while for BERT-large, the F1 score dropped only by 7 points between $d = 0$ tokens and $d = 250$ tokens, which suggests that the depth of Transformer layer helps to encode long-range coreference. However, we lack sufficient evidence to suggest that the span representation is able to encode long-range coreference relation efficiently, seeing that although already the encoder has been fine-tuned on OntoNotes, the model still cannot perform consistently across distant spans, with the lowest F1 score of 0.67 and 0.75 points for BERT-base and BERT-large respectively, when $d = 451$ to 475 tokens.

7 Discussion

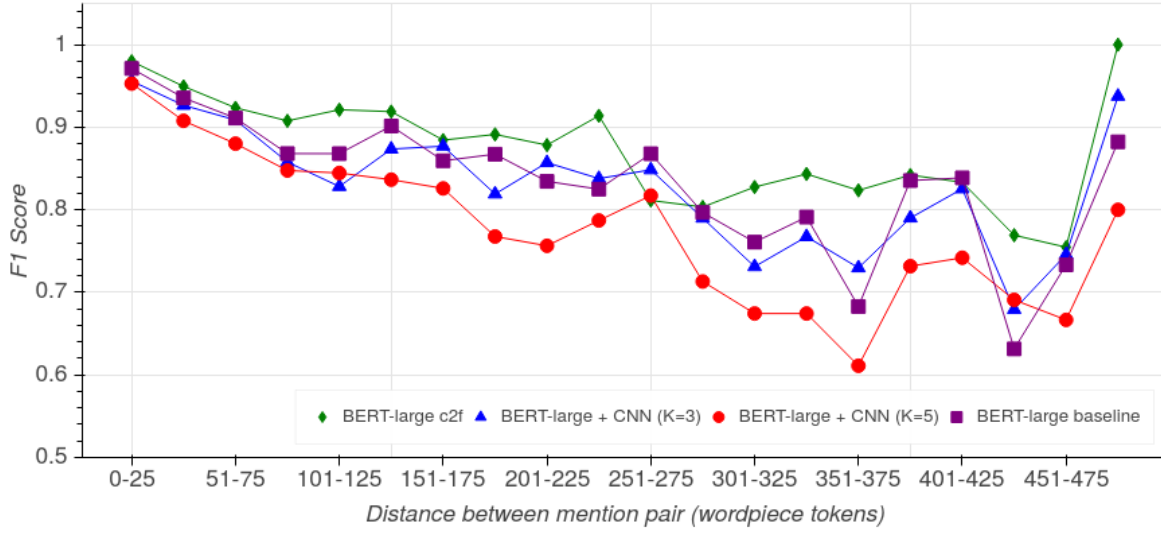
7.1 Design of Qualitative Analysis

Our aim is to present qualitative error analysis for predicted coreference between mention-pairs. We identify and characterize a set of challenging errors common to state-of-the-art systems dealing with coreference resolution in English. Such qualitative analysis enables us to detect patterns in errors that our system produces and to discuss underlying reasons for such errors. As true positives we treat the pair of one mention and another mention belonging to the same coreference chain which matches the corresponding mention in the gold standard.

We conducted our error analysis the two models that are the focus of this paper: BERT-base c2f (cased, fine-tuned) and BERT-large c2f (cased, fine-tuned). A subset of the test dataset was used for the analysis. The predictions of both models on the same subset of 1250 predictions were



(a)



(b)

Figure 3: F1 score of probing model as a function of separating distance between two mention-spans with BERT-base (3a) and BERT-large (3b) on test set. The performance with either BERT-base or BERT-large tend to fall off as distance between wordpiece token increases.

analysed. The errors were grouped into the following categories: *Similar Word Forms*, *Anaphora*, *Gender*, *Mention Paraphrasing*, and *Temporal and Spatial Agreement*. Although *Gender* can be considered a subcategory of *Pronouns*, the decision to separate it is motivated by the curiosity to find out whether gender bias is present in the models. The raw predictions that have been analysed can be accessed in our Github repository.

Moreover, the errors were also categorised into *True positives*, *True Negatives*, *False Positives*, and *False Negatives*. The numbers are accessible in the table 3 and 4. We observe that false positives constitute 4,08% of the predictions for BERT-base c2f, while false negatives make up 3,36% of predictions for the model. BERT-base c2f yields only 3,2% false positives, although a slightly higher 3,5% false negatives.

Tables 5, 6, and 7 portray a detailed overview of the errors made by both models in each category. As one observes immediately, mentions that are separated by a large distance have a higher error rate than mentions separated by smaller distances.

	True Coreferent	True Non-Coreferent	Precision
Predicted Coreferent	575 True Positives	51 False Positives	0.92
Predicted Non-Coreferent	42 False Negatives	580 True Negatives	
Recall	0.93		

Table 3: Confusion Matrix for BERT-base c2f. Subset Size is 1250 data points.

	True Coreferent	True Non-Coreferent	Precision
Predicted Coreferent	576 True Positives	40 False Positives	0.93
Predicted Non-Coreferent	44 False Negatives	588 True Negatives	
Recall	0.93		

Table 4: Confusion Matrix for BERT-large c2f. Subset Size is 1250 data points.

We can confidently conclude that BERT-base c2f and BERT-large c2f perform better at resolving coreference locally. The most difficult for all models is anaphora resolution, which is consistent with previous research. The least problematic category for all models is Gender. Out of the 1250 analysed examples on one mention led to errors – *Scooter Libby*. The mention has been consistently marked as coreferent with *she* and *her*.

7.2 Similar Word Forms

The word forms of the two mentions are similar, or the same graphemes appear in both mentions, but they refer to different entities.

7.3 Anaphora

Pronouns coreference spanning over 100 tokens is intrinsically difficult, even for a human. The model predicts pronouns relating to a mention 200 tokens in distance.

Agreement is good even when predicting over 200 words. - Them == her colleagues guesses correctly

7.4 Gender

Usually in context of a gender pronoun relating to a name of a person. no problems with common names. In the analysed subsample only one source of errors – **Scooter Libby** is predicted to corefer with *she*. Interestingly, a male name is considered to be female and not the other way around, as one would expect.

Category	Snippet	base c2f	large c2f
Similar Word Forms	... in some of the questioning eh of <i>Miller</i> , I think ... you have <i>Judy Miller</i> there (13) <i>Director Men Xianlong, Mr. Meng Xianlong, of the Command Center of the Beijing Municipal Traffic Administration ...</i> hear what <i>Director Meng said ...</i> (7)	3	0
Anaphora	... it was very prompt with <i>traffic management and emergency repair ...</i> ah, because <i>it</i> involved various (5) ... <i>the number of science and technology consulting enterprises ...</i> more than double of <i>that ...</i> (10)	9	5
Gender	none	0	0
Mention Paraphrasing	When someone sews a patch over a hole in an old coat , they ... If they do, the patch will shrink (22)	1	1
Temporal and Spatial	... people from economic circles, who even predicted that in <i>1998 ...</i> They pointed out that, <i>this year</i> , except ... (13) ... the Jiang-Huai area ... experience continuous rainfall. ... the Huang-Huai area will bid ... (23)	1	2
Total		14	8

Table 5: Error Analysis of BERT-base c2f and BERT-large c2f models for examples with short-range coreference (0-25 tokens apart). False positives are denoted **bold**, false negatives – *cursive*.

7.5 Mention Paraphrasing

Error in failing to label two mentions as referring to the same entity on one hand and labelling two distinct mentions as coreferent on the other hand.

Goods and Intellectual property Rights are deemed coreferent by joshi base: legally speaking different things. Might occur in similar laws.

Jesus and Young Man. Part of the dialog between Jesus and a young man.

7.6 Temporal and Spatial Agreement

Mention paraphrasing with reference to a specific date (e.g. January 3 and yesterday) and a specific spacial areas (two Chinese provinces).

1996 and 1997 are labeled as coreferent by joshi’s base model. Or this year and 1994. This is a mistake that a human will likely not do.

The most difficult for

7.7 Other Languages

The results we introduced in this paper has been tested solely on an English corpus. Hence, the high results may be a phenomena particular to this language. For morphologically or syntactically complex languages the models would have struggled more. A benefit of using neural models for coreference resolution is their ability to use contextualized word embeddings to capture similarity between words, a property that many traditional feature-based models lack. However, a similar

Category	Snippet	base c2f	large c2f
Similar	... the big news for me was Miller recounting what ...		
Word Forms	Tate by the way tells the Times that that account is false (76) ... this is the Dick Cheney aide she agreed to refer ... I think the agreement was strange (85)	3	5
Anaphora	Actually, this morning, <i>some listeners</i> , ah, happen to tell ... a lot of <i>them</i> as well as a lot of our friends ... (44) ...the reactions of citizens. – an SMS. I saw it ... took the subway here. Do you think that ... (96)	15	14
Gender	... killed a piece written by a reporter about Scooter Libby ... They didn' t say that you know until she walked out (58)	0	1
Mention	... when importing and exporting goods ...		
Paraphrasing	The owners of intellectual property rights who ... (77) ... as many as three times the role of Valerie Plame ... millions of dollars in legal fees in Miss Miller's case. (54)	8	4
Temporal and Spacial	... the Huang-Huai area through southern North China ... there will also be less snow in Northwest China (80) ... some areas of South China, Southwest China , and ... southern North China and the Huang-Huai area ... (80)	2	2
Total		28	26

Table 6: Error Analysis of BERT-base c2f and BERT-large c2f models for examples with middle-range coreference (26-100 tokens apart). False positives are denoted **bold**, false negatives – *cursive*.

analysis should be done for other languages before one can generalize that machine-learning based models outperform rule-based models universally.

8 Conclusion and Future Work

- so what have we learned about coref in general and local dependencies in particular
- everything we don't have the time for
- mention other corpora that could be used for finetuning (Winogrande, GAP...)
- apply roberta, spanbert (sota result, architecture still use c2f)
- try building span representations from intermediate layers, use scalar mixing
- comparing attention head of Joshi's and
- Efficient and long-range Transformers to capture long-range dependencies better, e.g. Compressive Transformers or any other sparse variant
- limitation of probing model, use control tasks?
- want to test span representation with frozen embeddings but trained attention, but alas GPU power is not enough
- rather than focus on span representation, focus on fine-tuning or pre-training task?

american/british english consistency oxford comma?, citation style

Category	Snippet	base c2f	large c2f
Similar Word Forms	... they contacted Clinton’ s office back in ... the first time that the Clinton forces learned about ... (370) ... of the different departments of <i>Beijing Municipality</i> ... received this order from the <i>municipal government</i> (200)	11	8
Anaphora	... took so long is that not only was she negotiating ... And on that point Arianna on that ... (180) ... the news on the day of <i>the accident</i> ... instead of the east and <i>it</i> did not (277)	23	22
Gender	... not accept the waiver of confidentiality that Scooter Libby offered ... her notes while they were defending her (1141)	0	1
Mention Paraphrasing	... but first Judy Miller and the New York Times finally ... in covering the controversy the editors killed ... (226) ... read a statement from a Sixty Minutes spokesman ... When Mister Carson the representative spoke ... (241) .	11	14
Temporal and Spacial	... and only 582 million US dollars last year ... momentum can not be restrained, this year ... (379) ... News Agency, the UN, <i>February 13th</i> , Today ... multi-national forces on <i>the 13th</i> at 4 (153)	6	5
Total		51	50

Table 7: Error Analysis of BERT-base c2f and BERT-large c2f models for examples with long-range coreference (over 100 tokens apart). False positives are denoted **bold**, false negatives – *cursive*.

References

- Adj, Yossi et al. (2016). “Fine-grained Analysis of Sentence Embeddings Using Auxiliary Prediction Tasks”. In: *CoRR* abs/1608.04207. arXiv: [1608.04207](https://arxiv.org/abs/1608.04207). URL: [http://arxiv.org/abs/1608.04207](https://arxiv.org/abs/1608.04207).
- Bagga, Amit and Breck Baldwin (1998). “Algorithms for Scoring Coreference Chains”. In: *In The First International Conference on Language Resources and Evaluation Workshop on Linguistics Coreference*, pp. 563–566.
- Bahdanau, Dzmitry, Kyunghyun Cho, and Yoshua Bengio (2015). “Neural Machine Translation by Jointly Learning to Align and Translate”. In: *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*. Ed. by Yoshua Bengio and Yann LeCun. URL: [http://arxiv.org/abs/1409.0473](https://arxiv.org/abs/1409.0473).
- Bengtson, Eric and Dan Roth (2008). “Understanding the Value of Features for Coreference Resolution”. In: *Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing*. Honolulu, Hawaii: Association for Computational Linguistics, pp. 294–303. URL: <https://www.aclweb.org/anthology/D08-1031>.
- Björkelund, Anders and Jonas Kuhn (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)*. Baltimore, Maryland: Association for Computational Linguistics, pp. 47–57. DOI: [10.3115/v1/P14-1005](https://doi.org/10.3115/v1/P14-1005). URL: <https://www.aclweb.org/anthology/P14-1005>.
- Blevins, Terra, Omer Levy, and Luke Zettlemoyer (2018). “Deep RNNs Encode Soft Hierarchical Syntax”. In: *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*. Melbourne, Australia: Association for Computational Linguistics,

- pp. 14–19. DOI: [10.18653/v1/P18-2003](https://doi.org/10.18653/v1/P18-2003). URL: <https://www.aclweb.org/anthology/P18-2003>.
- Chollet, François et al. (2015). Keras. <https://keras.io>.
- Clark, Kevin and Christopher D. Manning (2015). “Entity-Centric Coreference Resolution with Model Stacking”. 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)*. Beijing, China: Association for Computational Linguistics, pp. 1405–1415. DOI: [10.3115/v1/P15-1136](https://doi.org/10.3115/v1/P15-1136). URL: <https://www.aclweb.org/anthology/P15-1136>.
- Clark, Kevin and Christopher D. Manning (2016a). “Deep Reinforcement Learning for Mention-Ranking Coreference Models”. In: *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*. Austin, Texas: Association for Computational Linguistics, pp. 2256–2262. DOI: [10.18653/v1/D16-1245](https://doi.org/10.18653/v1/D16-1245). URL: <https://www.aclweb.org/anthology/D16-1245>.
- Clark, Kevin and Christopher D. Manning (2016b). “Improving Coreference Resolution by Learning Entity-Level Distributed Representations”. In: *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Berlin, Germany: Association for Computational Linguistics, pp. 643–653. DOI: [10.18653/v1/P16-1061](https://doi.org/10.18653/v1/P16-1061). URL: <https://www.aclweb.org/anthology/P16-1061>.
- Conneau, Alexis et al. (2018). “What you can cram into a single $\$&!#^*$ vector: Probing sentence embeddings for linguistic properties”. In: *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Melbourne, Australia: Association for Computational Linguistics, pp. 2126–2136. DOI: [10.18653/v1/P18-1198](https://doi.org/10.18653/v1/P18-1198). URL: <https://www.aclweb.org/anthology/P18-1198>.
- Connolly, Dennis, John D. Burger, and David S. Day (1994). “A Machine Learning Approach to Anaphoric Reference”. In: *Proceedings of the International Conference on New Methods in Language Processing (NeMLaP)*. ACL.
- Denis, Pascal and Jason Baldridge (2008). “Specialized Models and Ranking for Coreference Resolution”. In: *Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing*. Honolulu, Hawaii: Association for Computational Linguistics, pp. 660–669. URL: <https://www.aclweb.org/anthology/D08-1069>.
- Devlin, Jacob et al. (2019). “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding”. In: *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*. Minneapolis, Minnesota: Association for Computational Linguistics, pp. 4171–4186. DOI: [10.18653/v1/N19-1423](https://doi.org/10.18653/v1/N19-1423). URL: <https://www.aclweb.org/anthology/N19-1423>.
- Durrett, Greg and Dan Klein (2013). “Easy Victories and Uphill Battles in Coreference Resolution”. In: *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*. Seattle, Washington, USA: Association for Computational Linguistics, pp. 1971–1982. URL: <https://www.aclweb.org/anthology/D13-1203>.
- Fernandes, Eraldo, Cicero dos Santos, and Roy Miliđiu (2012). “Latent Structure Perceptron with Feature Induction for Unrestricted Coreference Resolution”. In: *Joint Conference on EMNLP and CoNLL - Shared Task*. Jeju Island, Korea: Association for Computational Linguistics, pp. 41–48. URL: <https://www.aclweb.org/anthology/W12-4502>.
- Haghighi, Aria and Dan Klein (2009). “Simple Coreference Resolution with Rich Syntactic and Semantic Features”. In: *Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing: Volume 3 - Volume 3*. EMNLP 09. Singapore: Association for Computational Linguistics, pp. 1152–1161. ISBN: 9781932432633.
- Haghighi, Aria and Dan Klein (2010). “Coreference Resolution in a Modular, Entity-Centered Model”. In: *Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics*. Los Angeles, California: Association for Computational Linguistics, pp. 385–393. URL: <https://www.aclweb.org/anthology/N10-1061>.
- He, Kaiming et al. (2015). “Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification”. In: *Proceedings of the 2015 IEEE International Conference on Com-*

- puter Vision (ICCV). ICCV '15. USA: IEEE Computer Society, pp. 1026–1034. ISBN: 9781467383912. DOI: [10.1109/ICCV.2015.123](https://doi.org/10.1109/ICCV.2015.123). URL: <https://doi.org/10.1109/ICCV.2015.123>.
- Hobbs, Jerry R. (1978). “Resolving pronoun references”. In: *Lingua* 44.4, pp. 311–338. ISSN: 0024-3841. DOI: [https://doi.org/10.1016/0024-3841\(78\)90006-2](https://doi.org/10.1016/0024-3841(78)90006-2).
- Hochreiter, Sepp and Jürgen Schmidhuber (1997). “Long Short-Term Memory”. In: *Neural Comput.* 9.8, pp. 1735–1780. ISSN: 0899-7667. DOI: [10.1162/neco.1997.9.8.1735](https://doi.org/10.1162/neco.1997.9.8.1735). URL: <https://doi.org/10.1162/neco.1997.9.8.1735>.
- Joshi, Mandar et al. (2019). “BERT for Coreference Resolution: Baselines and Analysis”. In: *Empirical Methods in Natural Language Processing (EMNLP)*.
- Kennedy, C. and B.K. Boguraev (1996). “Anaphora for everyone: Pronominal anaphora resolution without a parser.” In: pp. 113–118.
- Kingma, Diederik P. and Jimmy Ba (2015). “Adam: A Method for Stochastic Optimization”. In: *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*. Ed. by Yoshua Bengio and Yann LeCun. URL: <http://arxiv.org/abs/1412.6980>.
- Lappin, S. and H. Leass (1994). “An algorithm for pronominal anaphora resolution”. In: vol. 20(4), pp. 535–561.
- Lee, Kenton, Luheng He, Mike Lewis, et al. (2017). “End-to-end Neural Coreference Resolution”. In: *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*. Copenhagen, Denmark: Association for Computational Linguistics, pp. 188–197. DOI: [10.18653/v1/D17-1018](https://www.aclweb.org/anthology/D17-1018). URL: <https://www.aclweb.org/anthology/D17-1018>.
- Lee, Kenton, Luheng He, and Luke Zettlemoyer (2018). “Higher-Order Coreference Resolution with Coarse-to-Fine Inference”. In: *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*. New Orleans, Louisiana: Association for Computational Linguistics, pp. 687–692. DOI: [10.18653/v1/N18-2108](https://www.aclweb.org/anthology/N18-2108). URL: <https://www.aclweb.org/anthology/N18-2108>.
- Liu, Nelson F. et al. (2019). “Linguistic Knowledge and Transferability of Contextual Representations”. In: *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*. Minneapolis, Minnesota: Association for Computational Linguistics, pp. 1073–1094. DOI: [10.18653/v1/N19-1112](https://www.aclweb.org/anthology/N19-1112). URL: <https://www.aclweb.org/anthology/N19-1112>.
- Luo, Xiaoqiang (2005). “On Coreference Resolution Performance Metrics”. In: *Proceedings of Human Language Technology Conference and Conference on Empirical Methods in Natural Language Processing*. Vancouver, British Columbia, Canada: Association for Computational Linguistics, pp. 25–32. URL: <https://www.aclweb.org/anthology/H05-1004>.
- Martschat, Sebastian and Michael Strube (2015). “Latent Structures for Coreference Resolution”. In: *Transactions of the Association for Computational Linguistics* 3, pp. 405–418. DOI: [10.1162/tacl_a_00147](https://www.aclweb.org/anthology/Q15-1029). URL: <https://www.aclweb.org/anthology/Q15-1029>.
- Nair, Vinod and Geoffrey E. Hinton (2010). “Rectified Linear Units Improve Restricted Boltzmann Machines”. In: *Proceedings of the 27th International Conference on International Conference on Machine Learning*. ICML'10. Haifa, Israel: Omnipress, pp. 807–814. ISBN: 9781605589077.
- Ng, Vincent and Claire Cardie (2002). “Identifying Anaphoric and Non-Anaphoric Noun Phrases to Improve Coreference Resolution”. In: *COLING 2002: The 19th International Conference on Computational Linguistics*. URL: <https://www.aclweb.org/anthology/C02-1139>.
- Pennington, Jeffrey, Richard Socher, and Christopher D. Manning (2014). “GloVe: Global Vectors for Word Representation”. In: *Empirical Methods in Natural Language Processing (EMNLP)*, pp. 1532–1543. URL: <http://www.aclweb.org/anthology/D14-1162>.
- Peters, Matthew, Mark Neumann, Mohit Iyyer, et al. (2018). “Deep Contextualized Word Representations”. In: *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*. New Orleans, Louisiana: Association for Computational Linguistics, pp. 2227–2237. DOI: [10.18653/v1/N18-1202](https://www.aclweb.org/anthology/N18-1202). URL: <https://www.aclweb.org/anthology/N18-1202>.

- Peters, Matthew, Mark Neumann, Luke Zettlemoyer, et al. (2018). “Dissecting Contextual Word Embeddings: Architecture and Representation”. In: *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*. Brussels, Belgium: Association for Computational Linguistics, pp. 1499–1509. DOI: [10.18653/v1/D18-1179](https://doi.org/10.18653/v1/D18-1179). URL: <https://www.aclweb.org/anthology/D18-1179>.
- Pradhan, Sameer et al. (2012). “CoNLL-2012 Shared Task: Modeling Multilingual Unrestricted Coreference in OntoNotes”. In: *Joint Conference on EMNLP and CoNLL - Shared Task*. Jeju Island, Korea: Association for Computational Linguistics, pp. 1–40.
- Shi, Xing, Inkit Padhi, and Kevin Knight (2016). “Does String-Based Neural MT Learn Source Syntax?” In: *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*. Austin, Texas: Association for Computational Linguistics, pp. 1526–1534. DOI: [10.18653/v1/D16-1159](https://doi.org/10.18653/v1/D16-1159). URL: <https://www.aclweb.org/anthology/D16-1159>.
- Tenney, Ian et al. (2019). “What do you learn from context? Probing for sentence structure in contextualized word representations”. In: *International Conference on Learning Representations*. URL: <https://openreview.net/forum?id=SJzSgnRcKX>.
- Turian, Joseph, Lev-Arie Ratinov, and Yoshua Bengio (2010). “Word Representations: A Simple and General Method for Semi-Supervised Learning”. In: *Proceedings of the 48th Annual Meeting of the Association for Computational Linguistics*. Uppsala, Sweden: Association for Computational Linguistics, pp. 384–394. URL: <https://www.aclweb.org/anthology/P10-1040>.
- Vaswani, Ashish et al. (2017). “Attention is All you Need”. In: *Advances in Neural Information Processing Systems 30*. Ed. by I. Guyon et al. Curran Associates, Inc., pp. 5998–6008. URL: <http://papers.nips.cc/paper/7181-attention-is-all-you-need.pdf>.
- Vilain, Marc et al. (1995). “A Model-Theoretic Coreference Scoring Scheme”. In: *Sixth Message Understanding Conference (MUC-6): Proceedings of a Conference Held in Columbia, Maryland, November 6-8, 1995*. URL: <https://www.aclweb.org/anthology/M95-1005>.
- Williams, Ronald J. (1992). “Simple Statistical Gradient-Following Algorithms for Connectionist Reinforcement Learning”. In: *Mach. Learn.* 8.3–4, pp. 229–256. ISSN: 0885-6125. DOI: [10.1007/BF00992696](https://doi.org/10.1007/BF00992696). URL: <https://doi.org/10.1007/BF00992696>.
- Wiseman, Sam, Alexander M. Rush, and Stuart M. Shieber (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*. San Diego, California: Association for Computational Linguistics, pp. 994–1004. DOI: [10.18653/v1/N16-1114](https://doi.org/10.18653/v1/N16-1114). URL: <https://www.aclweb.org/anthology/N16-1114>.
- Wiseman, Sam, Alexander M. Rush, Stuart Shieber, et al. (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)*. Beijing, China: Association for Computational Linguistics, pp. 1416–1426. DOI: [10.3115/v1/P15-1137](https://doi.org/10.3115/v1/P15-1137). URL: <https://www.aclweb.org/anthology/P15-1137>.
- Zhou, Liang, Miruna Ticea, and Eduard Hovy (2004). “Multi-Document Biography Summarization”. In: *Proceedings of the 2004 Conference on Empirical Methods in Natural Language Processing*, pp. 434–441.
- Zhu, Yukun et al. (2015). “Aligning Books and Movies: Towards Story-Like Visual Explanations by Watching Movies and Reading Books”. In: *Proceedings of the 2015 IEEE International Conference on Computer Vision (ICCV)*. ICCV ’15. USA: IEEE Computer Society, pp. 19–27. ISBN: 9781467383912. DOI: [10.1109/ICCV.2015.11](https://doi.org/10.1109/ICCV.2015.11). URL: <https://doi.org/10.1109/ICCV.2015.11>.