Coreference Resolution

Working Title, First Draft: Content, not Wording

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1 Introduction

Coreference Resolution (CR) is a vital part of Natural Language Understanding and Natural Language Processing (NLP). It's applications include information extraction, question answering, summarization, machine translation, dialog systems etc. The task consists of mention detection and mention clustering. Some systems only focus on one part, while others propose end-to-end solutions.

The notion of mention – a span of text referring to some entity – is central to the task of CR. Mentions can be one of the three kinds: pronouns, named entity, and noun phrases. When several mentions *corefer* they refer to the same entity.

Since the seventies automated solutions for coreference resolutions have been researched (Woods, Kaplan, and Nash-webber 1972; Winograd 1972; Hobbs 1978). Some of the challenges central to the field include semantic and syntactic agreement between mentions; encoding non-local dependencies; paraphrasing of repetitions.

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 represenations 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-locat

Our code is publicly available on GitHub. [1].

[1] https://github.com/alyonavyshnevska/bert_for_coreference_resolution

2 Related Work

2.1 Approaches to Coreference Resolution

Architectures for coreference resolution models are typically categorized as 1) mention-pair classifiers (Ng and Cardie 2002; Bengtson and Roth 2008), 2) mention-ranking classifiers (Durrett and Klein 2013; Wiseman, Rush, S. Shieber, et al. 2015; Clark and Manning 2016), 3) entity-level models (Haghighi and Klein 2010; Wiseman, Rush, and S. M. Shieber 2016), or 4) latent-tree models (Fernandes, Santos, and Milidiu 2012; Martschat and Strube 2015). Earlier solutions have been feature-based, while in the recent years neural classifiers have been particularly successful.

Nowadays a widely-adopted approach to coreference resolution are end-to-end models that perform mention detection, anaphoricity, and coreference jointly (Daniel Jurafsky 2019). Beforehand, the rule-based systems were in use. Notable mentions are work by Hobbs (1978), Lappin and Leass (1994). Hobbs (1978) invented a tree-search algorithm for identifying reference with robust results, which started a long series of syntax-based methods. Lappin and Leass (1994) combined syntactic and other features by assigning weights to those features and summing these up to score candidate mentions. Kennedy and Boguraev (1996) optimised the approach to avoid full syntactic parsing.

Yang et al. (2003) and Iida et al. (2003) helped establish mention-ranking approaches as influential solutions in the early 2000's. Ng (2005) pioneered the rise of end-to-end solutions. While rule-based systems have witnessed a short-lived revival in 2010s (Zhou, Ticrea, and Hovy 2004; Haghighi and Klein 2009), their struggles with semantic understanding for the models led to their eventual demise. The rise of neural architectures that dominated the NLP in the recent decade has inevitably established itself in coreference.

2.2 State of the Art Coreference Models

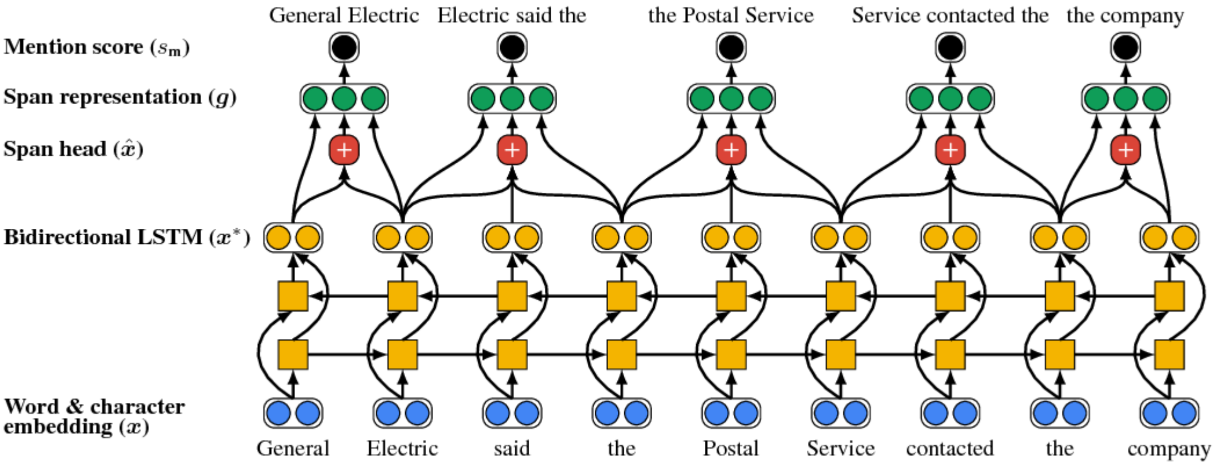


Figure 1: Figure 1: First step of the end-to-end coreference resolution model, which computes embedding representations of spans for scoring potential entity mentions. Low-scoring spans are pruned, so that only a manageable number of spans is considered for coreference decisions. In general, the model considers all possible spans up to a maximum width, but we depict here only a small subset. (Lee, He, Lewis, et al. 2017)

Lee, He, Lewis, et al. (2017) have proposed an span-ranking approach, which the authors describe as most similar to mention ranking, with reasoning over a larger space by detecting mentions and predicting coreference jointly in one end-to-end model. We will further refer to the model as *e2e-coref*.

The authors showed that from the space of all possible spans their model implicitly learns to produce meaningful mention candidates. A head-finding attention mechanism also learns a task-specific preference for head words, which has a strong correlation with head-word definitions in rule-based systems.

Building on to of the span-ranking neural architechture in Lee, He, Lewis, et al. (2017), Lee, He, and Zettlemoyer (2018) proposed a model that captures higher order interactions between spans in predicted clusters. We will further refer to this model as *c2f-coref*. It also alleviates the additional computational cost of higher-order inference due to a coarse-to-fine approach, which allows the model to at first compute a rough sketch of likely antecedents, and only at a later stage apply a more exhaustive inference. Hence, the coarse-to-fine approach expands the set of coreference links that the model is capable of learning.

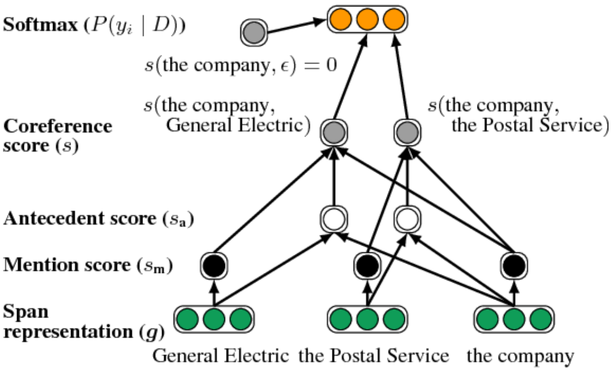

Softmax ($P(y_i \mid D)$)
s(the company, ϵ) $= 0$
s(the company, General Electric)
s(the company, the Postal Service)
Coreference score (s)
Antecedent score (s_a)
Mention score (s_m)
Span representation (g)
General Electric
the Postal Service
the company

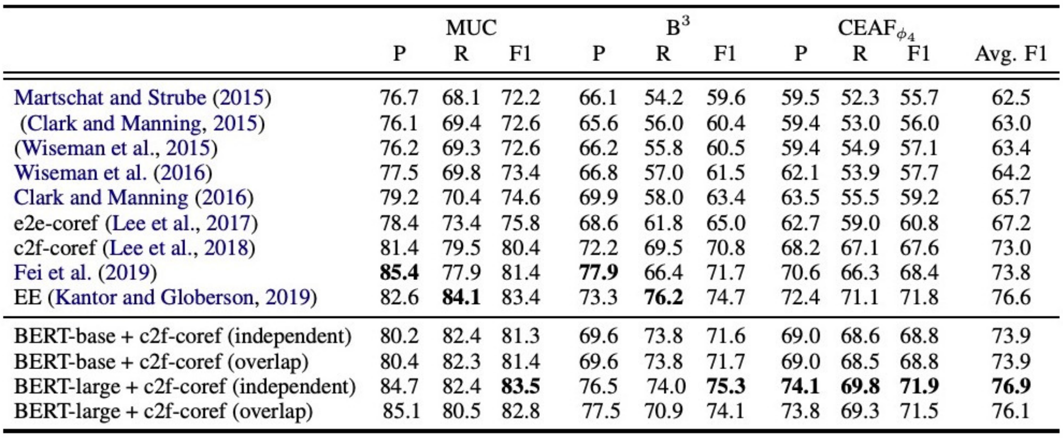
Figure 2: Second step of end-to-end model by Lee, He, Lewis, et al. (2017). Antecedent scores are computed from pairs of span representations. The final coreference score of a pair of spans is computed by summing the mention scores of both spans and their pairwise antecedent score.

To encode the span representations Lee, He, Lewis, et al. (2017) use bidirectional LSTM (Hochreiter and Schmidhuber 1997) to encode the lexical information of the inside and outside of each span. Lee, He, and Zettlemoyer (2018) additionaly use the newly published ELMo embedding representations by Peters et al. (2018) at the input to the LSTMs.

Joshi et al. (2019) took the architechture of Lee, He, and Zettlemoyer (2018) and improved the performence of the model further by replacing the LSTM-based encoder with the BERT transformer Devlin et al. (2019). We further refer to the model by Joshi et al. (2019) as *bert-coref*.

Devlin et al. (2019) made a significant break-through with their pre-trained BERT model. It can be finetuned with one additional output layer to create state-of-the-art models for a wide range of NLP tasks, such as question answering and language inference, without substantial taskspecific architecture modifications. BERT's training examples consist of 128 and 512 word pieces. Such passage-level training has been an important improvement over the previous methods. It helps the model learn dependencies over text sequences longer than one sentence, such as the previous state of the art model ELMo (Peters et al. 2018). Two model sized have been presented by Devlin et al. (2019): BERT-base(12 transformer blocks, hidden size 768, 12 self-attention heads, total Parameters=110M) and BERT-large (24 transformer blocks, hidden size 1024, 16 self-attention heads, total Parameters=340M).

Joshi et al. (2019) treat the first and last word-pieces in a mention (concatenated with the attended version of all word pieces in the span) as span representations. The researchers test both models with BERT-base and BERT-large transformers. With this change to the c2f-coref model the authors gain an additional 3.9% improvement on the OntoNotes compared to the already high results of Lee, He, and Zettlemoyer (2018). A quantitative analysis is shown in figure 3. A qualitative analysis done by the authors suggests that BERT-large (unlike BERT-base) is significantly better at distinguishing between related yet distinct entities or concepts.



	MUC			B^3			CEAF$_{\phi_4}$			
	P	R	F1	P	R	F1	P	R	F1	Avg. F1
Martschat and Strube (2015)	76.7	68.1	72.2	66.1	54.2	59.6	59.5	52.3	55.7	62.5
(Clark and Manning, 2015)	76.1	69.4	72.6	65.6	56.0	60.4	59.4	53.0	56.0	63.0
(Wiseman et al., 2015)	76.2	69.3	72.6	66.2	55.8	60.5	59.4	54.9	57.1	63.4
Wiseman et al. (2016)	77.5	69.8	73.4	66.8	57.0	61.5	62.1	53.9	57.7	64.2
Clark and Manning (2016)	79.2	70.4	74.6	69.9	58.0	63.4	63.5	55.5	59.2	65.7
e2e-coref (Lee et al., 2017)	78.4	73.4	75.8	68.6	61.8	65.0	62.7	59.0	60.8	67.2
c2f-coref (Lee et al., 2018)	81.4	79.5	80.4	72.2	69.5	70.8	68.2	67.1	67.6	73.0
Fei et al. (2019)	**85.4**	77.9	81.4	**77.9**	66.4	71.7	70.6	66.3	68.4	73.8
EE (Kantor and Globerson, 2019)	82.6	**84.1**	83.4	73.3	**76.2**	74.7	72.4	71.1	71.8	76.6
BERT-base + c2f-coref (independent)	80.2	82.4	81.3	69.6	73.8	71.6	69.0	68.6	68.8	73.9
BERT-base + c2f-coref (overlap)	80.4	82.3	81.4	69.6	73.8	71.7	69.0	68.5	68.8	73.9
BERT-large + c2f-coref (independent)	84.7	82.4	**83.5**	76.5	74.0	**75.3**	**74.1**	**69.8**	**71.9**	**76.9**
BERT-large + c2f-coref (overlap)	85.1	80.5	82.8	77.5	70.9	74.1	73.8	69.3	71.5	76.1

Figure 3: OntoNotes: BERT improves the c2f-coref model on English by 0.9% and 3.9% respectively for base and large variants. (Joshi et al. 2019)

2.3 Coreference Arc Prediction Task

Recently, there has been interesting work done to simplify state-of-the-art task-specific NLP models. Liu et al. (2019) show evidence that frozen contextual represenations of word sequences fed into linear models can show similar levels of performance as state-of-the-art task-specific models on many NLP tasks. The authors use probing models, also known as auxiliary or diagnostic classifiers (Shi, Padhi, and Knight 2016; Kádár, Chrupała, and Alishahi 2017) to analyse the linguistic information within contextual word representations. To test how the probing model performs in comparison to ELMo, the authors tested the models on a coreference arc prediction task, where the model predicts whether two mentions corefer. The Ontonotes dataset was used. To train the probing model the authors generate negative examples, where mentions that do not corefer are fed into the probing model alongside the mentions that do corefer. In our work we will also build our experiments similar to coreference arc prediction tasks suggested by the authors.

Tenney et al. (2019) introduced edge probing task design. For coreference resolution, the models had to determining whether two spans of tokens refer to the same entity. In order to investigate how good the contextual word representation models can model long-range dependencies, the authors used a fixed-width convolutional layer on top of the word representations to build spans of word pieces. The authors concluded that using the CNN layers on top of BERT-large pretarined model has performed particularly well on difficult semantic tasks, such as coreference resolution. Hence, in out work we will also follow the approach of the authors to construct our baseline.

3 Overview of End-to-End Span-ranking Model

4 Probing Mention-span Representations

4.1 Span Representation

Span representation plays an important role in span-ranking model (Lee, He, Lewis, et al. 2017), 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, 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 2015] over each word-pieces in the span:

$$\begin{aligned}
\alpha_t &= \boldsymbol{w}_\alpha \cdot \text{FFNN}_\alpha(\boldsymbol{x}^*_t) \\
a_{i,t} &= \frac{exp(\alpha_t)}{\sum\limits_{k=start(i)}^{end(i)} exp(\alpha_k)} \\
\hat{\boldsymbol{x}}_i &= \sum_{t=start(i)}^{end(i)} a_{i,t} \cdot \boldsymbol{x}_t
\end{aligned}$$

where $\hat{\boldsymbol{x}}_i$ is a weighted vector representation of word-pieces 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 $\boldsymbol{g}_i$ for span i is formulated as the following:

$$\boldsymbol{g}_i = [\boldsymbol{x}^*_{start(i)}, \boldsymbol{x}^*_{end(i)}, \hat{\boldsymbol{x}}_i, \phi_i]$$

where $\boldsymbol{x}^*_{start(i)}$ and $\boldsymbol{x}^*_{end(i)}$ are first and last word-pieces 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 word-pieces 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

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 $\boldsymbol{g}_1 = [\boldsymbol{x}^*_{start(1)}, \boldsymbol{x}^*_{end(1)}, \hat{\boldsymbol{x}}_1, \phi_1]$ and $\boldsymbol{g}_2 = [\boldsymbol{x}^*_{start(2)}, \boldsymbol{x}^*_{end(2)}, \hat{\boldsymbol{x}}_2, \phi_2]$, where both $\boldsymbol{g}_1$ and $\boldsymbol{g}_2$ 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 4.

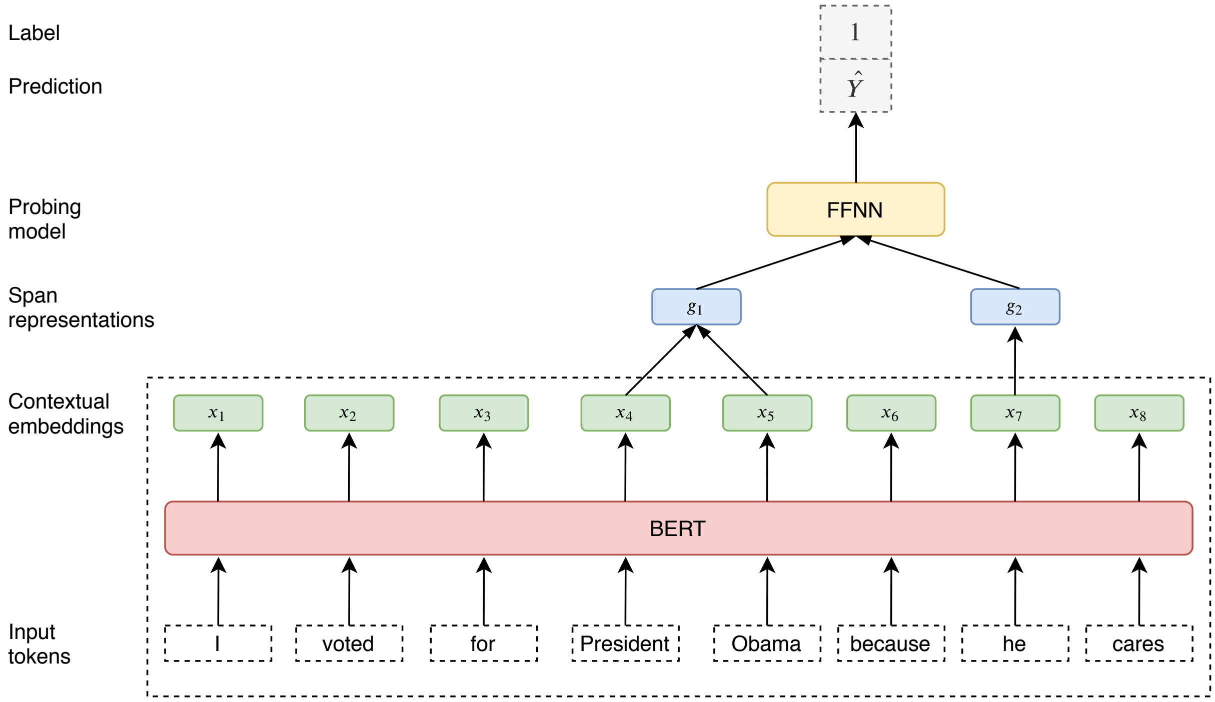


Figure 4: Probing architecture for span representation. The feed-forward neural network is trained to extract information from the span representations $\boldsymbol{g}_1$ and $\boldsymbol{g}_2$, while all the parameters inside the dashed line are frozen. The example depicts a mention-pair, where $\boldsymbol{g}_1$ corresponds to span representation of "President Obama", while $\boldsymbol{g}_2$ corresponds to "he". We predict $\hat{Y}$ as positive for this example.

We explore mention-span representations obtained from BERT. BERT (Devlin et al. 2019) is a language representations model which uses deep Transformer architecture [Vaswani 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 the proposed span representation using BERT embeddings and fine-tuned on corefence resolution task can 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 1995], B^3 [Bagga and Baldwin 1998] and $CEAF_{\phi}4$ [Luo 2015]. 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 [cite Keras]. 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] with a learning rate of 0.001. The weights of the probing model is initialized with Kaiming initialization [Kaiming] and the size of the hidden layer is $d = 1024$ with ReLU activation function.

As mentioned previously, we use both original 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 word-pieces for BERT-base and 384 word-pieces 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 word-pieces 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 $e^{(1)} = [x_1^{(1)}, x_2^{(1)}, x_3^{(1)}, ..., x_n^{(1)}]$ and $e^{(2)} = [x_1^{(2)}, x_2^{(2)}, x_3^{(2)}, ..., x_n^{(2)}]$ as inputs. We then project the concatenated contextual embeddings $e^{(1)}$ and $e^{(2)}$ to improve performance:

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

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 non-finetuned BERT final layer, while freezing the encoder. The baseline probing architecture is depicted in Figure 5.

[2] https://github.com/mandarjoshi90/coref

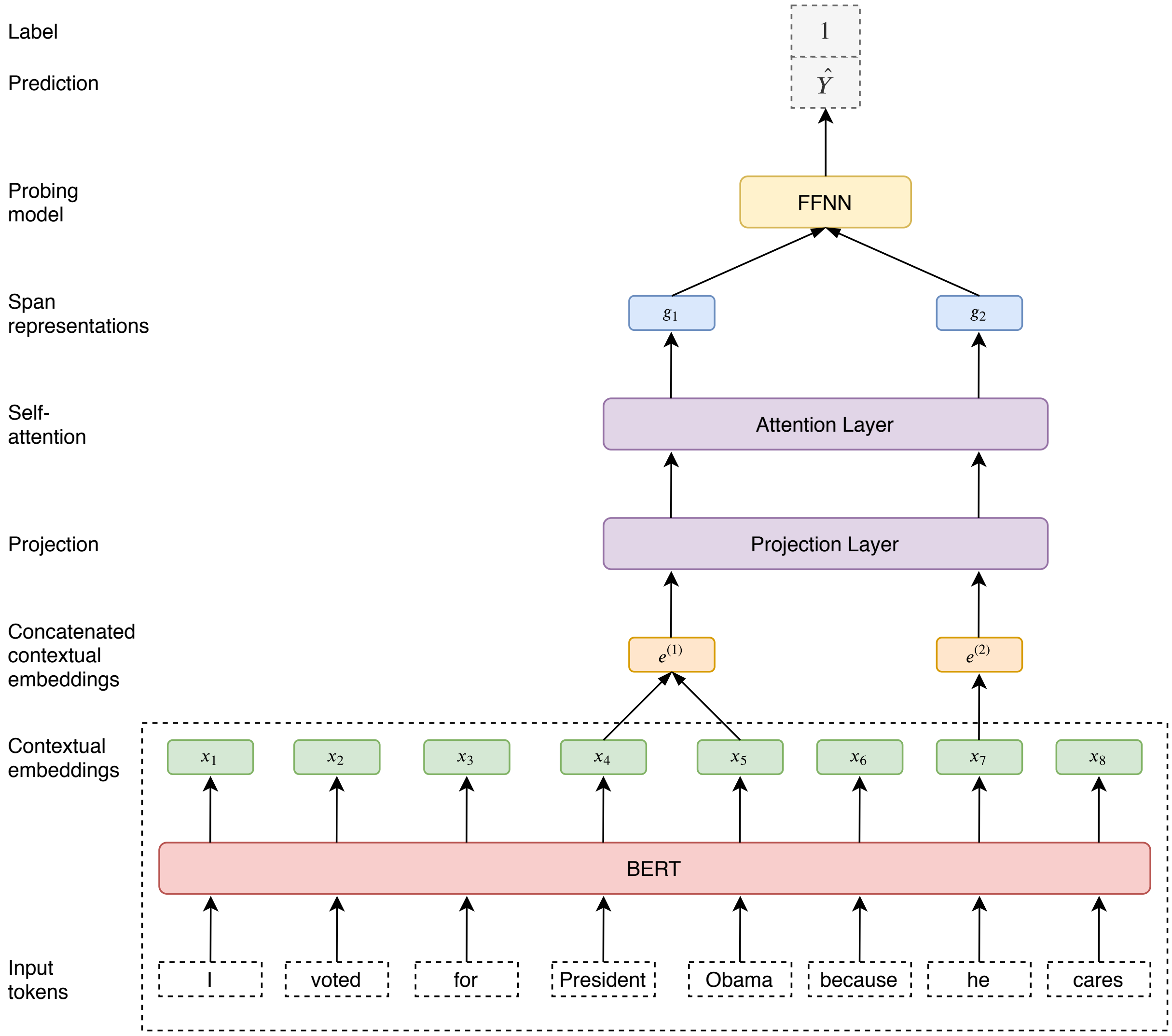


Figure 5: Probing architecture for baseline span representation. All parameters inside the dashed lines are frozen, while we train the feed-forward neural network to extract coreference information from the concatenated contextual embeddings $e^{(1)}$ and $e^{(2)}$. We used shared weights for both projection and self-attentional layer so that the model can learn the similarity between representation of mention-spans.

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 span representation 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 the span representation from BERT encoder that is fine-tuned on coreference resolution task. 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. 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 [Kaiming]. 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 separate pair 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 pair 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 with 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 non-finetuned 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 modelling objectives tend to occur in the intermediate layers, and that the topmost layers might be overly specialized for next-word prediction [Blevins 2018, Peters 2018a, Peters2018b, Liu2019]. This may cause the CNN layer to learn suboptimal representations from the mention-span.

6.2 Ablations

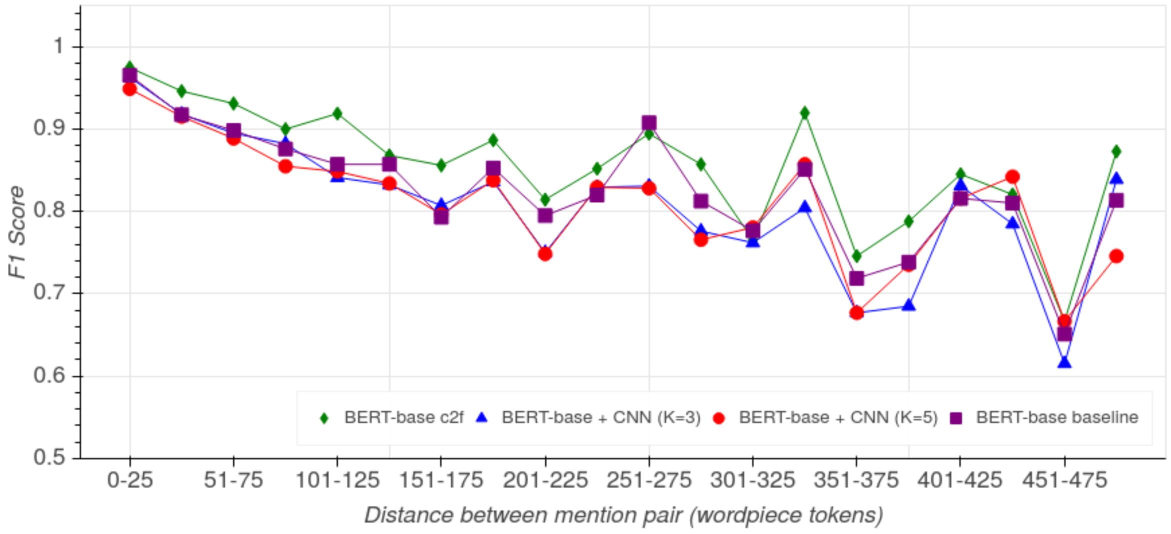
To find out the importance of each component in BERT-coref span representations, we do ablation study on each part of the representation and report the accuracy and F1 score of the probing model on the test set of the data, which is depicted on Table 2. The head-finding attention mechanism is crucial 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, 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	ΔAccuracy	ΔF1 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

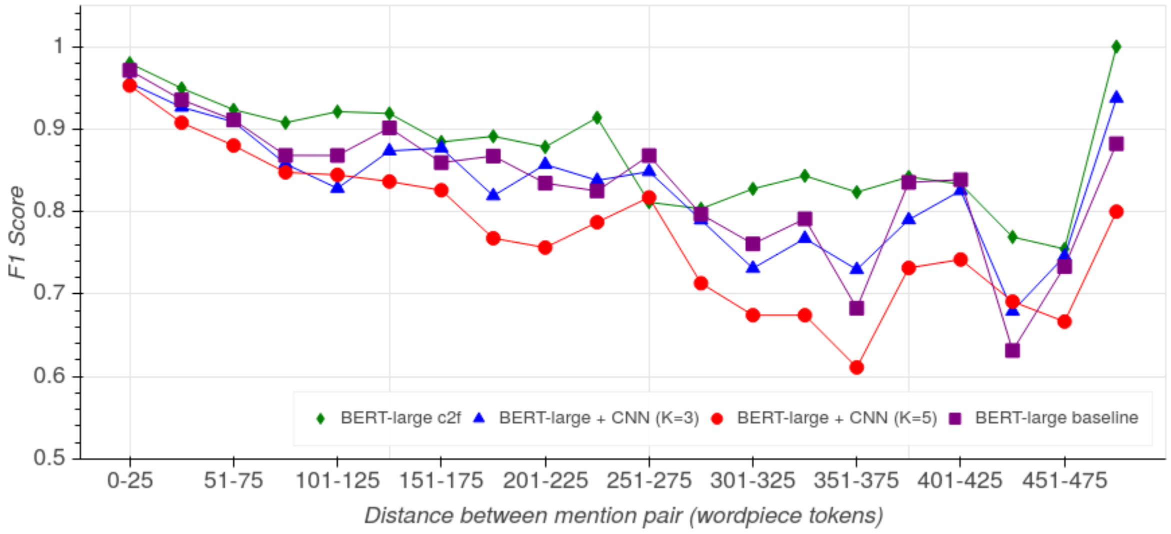
Table 2: Comparison of the probing model on OntoNotes test set with various components removed. The head-finding attention and span-width embeddings contribute significantly to the performance of the probing model.

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 6 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 the evidence that 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.



(a)



(b)

Figure 6: F1 score of probing model as a function of separating distance between two mention-spans with BERT-base (6a) and BERT-large (6b) on test set. The performance with either BERT-base or BERT-large tend to fall off as distance between wordpiece token increases.

7 Discussion

- long long analysis of what we've seen
- generalisations, parallels
- what do this results tell us about coref and nlp in general
- discussion of why they are the way the are

We found that the model by Joshi et al. (2019) has performed very well. However, since the research is heavily based on the English language, it may be a phenomena particular to this language. The nominal declension in Ukrainian, for example, has seven cases; adjectives, pronouns have gender specific forms. Therefore, a similar analysis should be done for other languages before one can generalize the findings universally.

A benefit of using neural models for coreference resolution is their ability to use word embeddings to capture similarity between words, a property that many traditional feature-based models lack.

7.1 Future Work

- everything we don't have the time for
- mention other corpora that could be used for finetuning (Winogrande, GAP...)
- apply roberta
- try building span representations from intermediate layers, use scalar mixing
- comparing attention head of Joshi's and baseline?

8 Conclusion

- so what have we learned about coref in general and local dependencies in particular

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