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

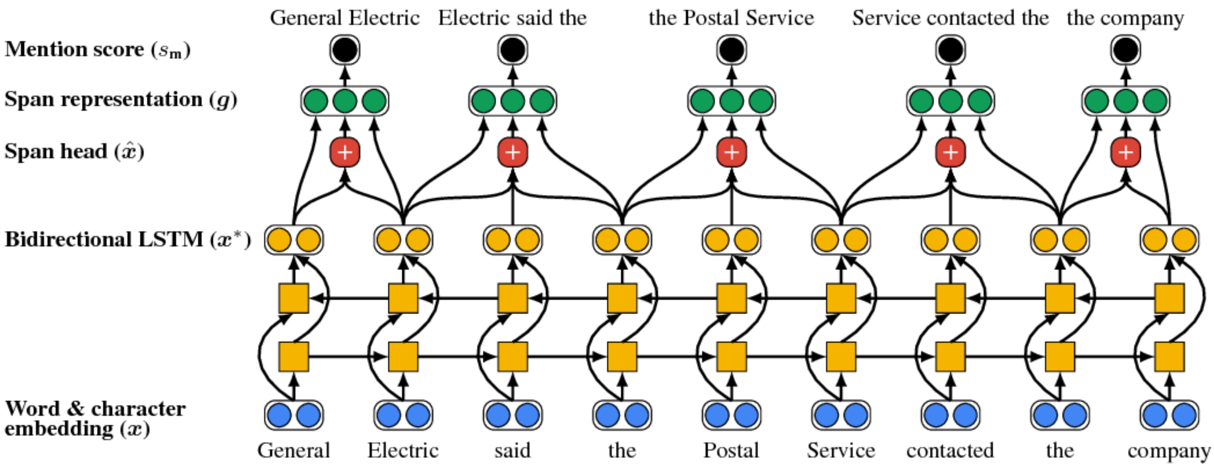

Figure 1: Figure 1: First step of the end-to-end coreference resolution model, which computes embedding representations of spans for scoring potential entity mentions. Low-scoring spans are pruned, so that only a manageable number of spans is considered for coreference decisions. In general, the model 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.

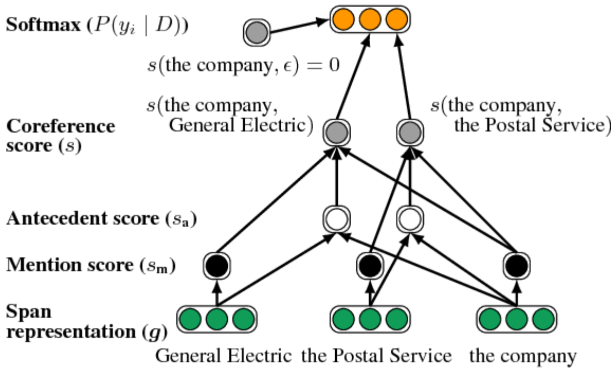

Figure 2: Second step of end-to-end model by Lee, He, Lewis, et al. (2017). Antecedent scores are computed from pairs of span representations. The final coreference score of a pair of spans is computed by summing the mention scores of both spans and their pairwise antecedent score.

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 BERT-coref

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:

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

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

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

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. We use the OntoNotes dataset (Pradhan et al. 2012) from the CoNLL-2012 shared task. As OntoNotes 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 $Y \in \{0, 1\}$. Our probing architecture is shown in Figure ...

We explore mention-span representations obtained from BERT. <Explain about BERT here>. 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. The BERT models used in all the experiments are cased.

4.4 Baseline

As our baseline, w euse pre-trained BERT embeddings (not finetuned on OntoNotes) for all tokens within the mention span, which is then passed through a convolutional layer (with kernel width of 3 and 5) to incorporate the local context and followed by self-attention pooling operator to produce a fixed-length span representations. This is to model head words, inspired by approach from Tenney et al. (2019).

4.5 Long-Range Coreference

In order to answer our second research question is whether the span representations encoded with a pre-trained BERT model simply modelling local coreference and will it be able to encode non-local coreference dependencies. In order to answer it, we bucket the test data into separate groups based on the the length of the coreference distance between the a mention and antecedent. We do separate qualitative and quantitative analysis on the buckets in order to analyse the differences in performance of our models based on how large the distance is.

4.6 Data

For our experiments we use the English coreference resolution data from the CoNLL-2012 shared task based on the OntoNotes dataset (Pradhan et al. 2012). It consists of about one million words of newswire, magazine articles, broadcast news, broadcast conversations, web data and conversational speech data, and the New Testament. The dataset is split 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. The main evaluation is the average F1 score of three metrics – *MUC*, B^3 and $CEAF_\phi 4$ on the test set according to the official CoNLL-2012 evaluation scripts. For our experiments we generate the positive and negative examples of coreferent expressions as training data for the probing model.

5 Experiments

We extract the BERT span representations from a pipeline provided in a GitHub repository by Joshi et al. (2019) [2].

5.1 Implementation and Hyperparameters

. We extract the span representations from the coreference model by Joshi et al. (2019). The model has been fine tuned on OntoNotes English data for 20 epochs using a dropout of 0.3, and learning rates of $1 * 10^{-5}$ and $2 * 10^{-4}$ with linear decay for the BERT parameters and the task parameters respectively. A batch size of 1 document has been used.

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

5.2 Baseline

6 Results

- some nice plots here
- some tables here

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...)

8 Conclusion

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

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