Coreference Resolution

Working Title

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1 Introduction

- Some nice long paragraphs about place of coreference in NLP
- Paragraphs about problems with coref
- Narrow down to loca/non-local coreference
- Very broadly what we intended to to
- Broadly what we have found

2 Related Work

- some long paragraphs about history of coref. mention mention-ranking, and others
- end-to-end and higher order
- bert, bert for coref

Tenney et al. (2019) Probing Model

Liu et al. (2019) Ling Knowledge and Transfer, Negative Samples

Joshi et al. (2019) Cert for coref

Lee, He, and Zettlemoyer (2018) Higher-Order

Lee, He, Lewis, et al. (2017) End-to-End

Devlin et al. (2019) Bert

3 Approach

3.1 Span Representation and Long-Range Coreference

We attempt to investigate to what extent the span representations proposed using BERT (Devlin et al. 2019) embeddings in Joshi et al. (2019) can encode coreference information, and whether it is able to encode non-local coreference phenomena or is it just simply modeling local coreference.

In order to analyse this, we consider 2 kinds of span representations: 1. BERT-based span representations finetuned on OntoNotes in Joshi et al. (2019) with first and last word-pieces (concatenated with the attention version of all word pieces in the span). 2. 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).

3.2 Arc Prediction Task

Both span representations will be then used as inputs for coreference arc prediction task Liu et al. 2019, where a probing model (in this case a simple FFNN) is used to predict coreference relations. The probing model is designed with limited capacity to focus on what information that can be extracted from the span representations. The probing model itself has a sigmoid output layer, which is trained to minimize binary cross entropy. Each negative samples (*w_entity*, *wb*) will be generated for every positive samples (*wa*, *wb*) where *wb* occurs after *wa* and *w_entity* is a token that occurs before *wb* and belong to a difference coreference cluster, to ensure a balanced data. By comparing the performance of the probing model using these two span representations, we can hypothesize to what extent that the proposed span representation in Joshi et al. (2019) can capture coreference information. We will also experiment with mention span separation distance to see how the probing model performs and whether if there is a degradation of accuracy and F1 score of the probing model with distant spans.

3.3 Data

We use OntoNotes (English) generating the positive and negative examples for the probing model. OntoNotes (English) is a widely used dataset on coreference resolution from the CoNLL-2012 shared task. 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 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.

4 Experiments

We evaluate the two models on the English OntoNotes 5.0 dataset Pradhan et al. 2012.

4.1 Implementation and Hyperparameters

. We extract the span representations from the coreference model by Joshi et al. (2019). The code is available on GitHub [1]. 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.

4.2 Baseline

5 Results

- some nice plots here
- some tables here

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

6 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

6.1 Future Work

- everything we don't have the time for
- mention other corpora that could be used for finetuning (Winogrande, GAP...)

7 Conclusion

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

References

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. URL: https://www.aclweb.org/anthology/N19-1423.

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