McGill at CRAC 2023: Multilingual Generalization of Entity-Ranking Coreference Resolution Models

Ian Porada & Jackie Chi Kit Cheung

Mila, McGill University ian.porada@mail.mcgill.ca

Overview

We apply the **entity-ranking model** originally proposed by **Xia et al.** (2020).*

I'll go over:

- 1. Model details
- 2. Things we tried

*Incremental Neural Coreference Resolution in Constant Memory (Xia et al., EMNLP 2020)



Intuition

Process spans left to right:

score each candidate mention pairwise against a running list of entities.

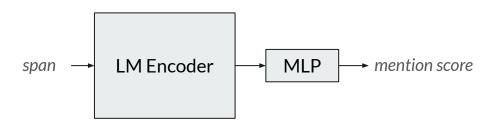
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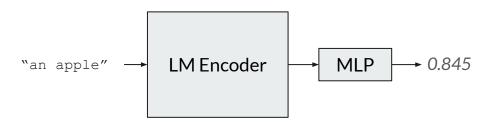
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- Keep the spans with the top "**0.4** * **n**" mention scores as candidate mentions
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 - o E.g.{"he", "ate", "an apple", "it", "good", "he ate an", ...}
- Remove all spans with a negative score
 - o E.g. candidate mentions = {"he", "ate", "an apple", "it", "good"}

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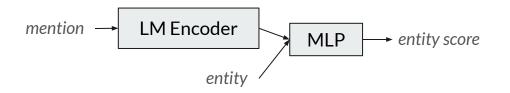
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1. E = \{he\}
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- 1. $E = \{he\}$
- 2. $E = \{he, an apple\}$
- 3. $E = \{he, (an apple, it)\}$

Experiments

Data Processing

- 1. Input: Use udapi to convert CorefUD to json
 - a. For GUM, we extract speaker information from headers
 - b. We treat zero anaphors as the underscore token ("_")
- 2. Output: Use`udapy -s corefud.MoveHead` to calculate syntactic heads

Experiment 2: Mixing strategy

Mixing strategy (XLM-R base encoder)	CoNLL F1 (exact match)
Uniform	62.78
Proportional	64.68
Proportional w.r.t. = min(size, 500)	64.86

Experiment 1: Encoder

Encoder (large size)	CoNLL F1 (exact match)	
XLM-Roberta	67.32	
MT5	64.76	



Conclusion

Entity-ranking models serve as a reasonable baseline with some simple adaptations.

system	head-match	partial-match	exact-match	with singletons
1. CorPipe	74.90	73.33	71.46	76.82
2. Anonymous	70.41	69.23	67.09	73.20
3. Ondfa	69.19	68.93	53.01	68.37
4. McGill	65.43	64.56	63.13	68.23
5. DeepBlueAI	62.29	61.32	59.95	54.51
6. DFKI-Adapt	61.86	60.83	59.18	53.94
7. ITUNLP	59.53	58.49	56.89	52.07
8. BASELINE	56.96	56.28	54.75	49.32
9. DFKI-MPrompt	53.76	51.62	50.42	46.83