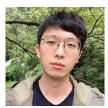


Anatomy of OntoGUM---Adapting GUM to the OntoNotes Scheme to Evaluate Robustness of SOTA Coreference Algorithms

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The Coreference Resolution Task

"I voted for Mary because Mary was most aligned with my values", John said.

Problems of Existing Coreference Datasets

Datasets	Out-of ON domain	Scheme compatibility	Multi-genre	Multi-coreference types	Singletons*
OntoNotes (Pradhan et al., 2013)	×	✓	✓	✓	×
WikiCoref (Ghaddar and Langlais, 2016)	✓	\checkmark	×	\checkmark	×
GAP (Webster et al., 2018)	✓	?	×	×	×
GUM (Zeldes, 2017)	✓	×	✓	\checkmark	✓
ARRAU (Poesio et al., 2018)	✓	×	\checkmark	\checkmark	✓
PreCo (Chen et al., 2018)	✓	×	✓	\checkmark	✓

^{*}Singletons: markables that are not referred to by other mentions in a document

Problems of Existing Out-of-domain Evaluation

 No study has investigated if contextualized embeddings encounter the same overfitting problem identified by Moosavi and Strube (2017)

- Previous work may underestimate the performance degradation on WikiCoref
 - embeddings were also trained on Wikipedia themselves (Moosavi and Strube, 2018)
 - -> higher coreference scores on Wikipedia texts

OntoGUM Dataset (Zhu et al., 2021)

- Conversion from GUM using gold standard syntax trees
- Statistics
 - 168 documents with 12 genres, ~150K tokens
 - 19,378 mentions, 4,471 clusters
 - Growing in size...
- Genres
 - Text: News / Fiction / Bio / Academic / Forum / Travel / How-to / Textbook
 - Speech: Interview / Political / Vlog / Conversation



Dataset Conversion

- OntoNotes ⊆ GUM
 - Don't need human annotation to recognize additional mentions in the conversion process
- Annotation layers used in the conversion
 - Coreference layer
 - Gold syntax trees
 - Gold speaker information (fiction, reddit and spoken data)
- Deterministic conversion
- Annotation agreement
 - Agreement study on 3 docs (2,500 tokens, 371 mentions), 8/371 errors
 - Span detection: ~0.96 CoNLL coreference score: ~0.92

Conversion process

- Conversion types
- Remove coreference relations
- Remove or adjust markables

- Order of Conversion steps
- > Remove bridging (markables) Remove cataphora (relations)
- > Contract verbal spans (markables)
- > Merge appositions (markables)
- > Remove NN compounding (markables)
- > Remove copula (markables)
- > Remove nested entities (markables)
- > Adjust chains by definiteness (relations)
- > Remove singletons (markables)

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Conversion example

An example of mention deletion interacting with copula (Remove copula)

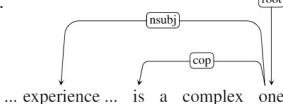
- GUM (before)

The viewing experience of art is a complex one ... The time it takes ...

- OntoGUM (after)

The viewing experience of art is a complex one ... The time it takes ...

Rule: ROOT -> COP



Experiments & Results 1/3

Models	OntoNotes	OntoGUM
dcoref (Manning et al. 2014, CoreNLP)	57.8	
e2e + SpanBERT (Joshi et al., 2019, SOTA)	79.6	

Experiments & Results 1/3

Models	OntoNotes	OntoGUM
dcoref (Manning et al. 2014, CoreNLP)	57.8	39.7
e2e + SpanBERT (Joshi et al., 2019, SOTA)	79.6	64.6

Both systems encounter a substantial degradation on OntoGUM

Experiments & Results 2/3

- Genre disparity does not guarantee low performance (e.g., vlog), and errors occur readily even in overlapping genres (e.g., news)
- Performance is correlated with the proportions of pronouns

Genres	PRON (R)	Other (R)	Total	CoNLL	Span
vlog	600 (.66)	309 (.34)	909	1	1
interview	1223 (.45)	1485 (.55)	2708	2	6
conversation	729 (.61)	323 (.39)	1052	3	2
speech	245 (.40)	364 (.60)	609	4	4
bio	796 (.34)	1529 (.66)	2325	5	3
fiction	1700 (.61)	1091 (.39)	2791	6	5
academic	262 (.21)	997 (.79)	1259	7	10
voyage	300 (.22)	1053 (.78)	1353	8	7
reddit	1337 (.55)	1077 (.45)	2414	9	8
news	340 (.19)	1483 (.81)	1823	10	9
whow	1001 (.47)	1129 (.53)	2130	11	11
textbook	165 (.34)	315 (.66)	480	12	12

Table 1: Genre-breakdown Statistics of OntoGUM

Experiments & Results 3/3

- Genre disparity does not guarantee low performance (e.g., vlog), and errors occur readily even in overlapping genres (e.g., news)
- Performance is correlated with the proportions of pronouns or gold speaker information

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Conclusion

- We release the largest open, gold, coreference dataset with new genres (singletons in release later) following the OntoNotes scheme
- We present the details of the conversion process
- Results showed a lack of generalizability of existing systems, especially in genres low in pronouns and lacking speaker information
- A genre-by-genre analysis reveals relative strengths and weaknesses of current approaches

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- We release the largest open, gold, coreference dataset with new genres (singletons in release later) following the OntoNotes scheme
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- Results showed a lack of generalizability of existing systems, especially in genres low in pronouns and lacking speaker information
- A genre-by-genre analysis reveals relative strengths and weaknesses of current approaches
 We hope people can use OntoGUM as an out-of-domain benchmark for systems developed using OntoNotes!