NNE: A Dataset for Nested Named Entity Recognition in English Newswire

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Why recognize nested named entities?

- Most NER tools capture only flat mention structure, reflecting the available annotated datasets
- Ignores important information useful for downstream tasks, e.g.:

Entity-entity relationships

Why use NNE?

ltem	NNE	GENIA	ACE05
Documents	2,312	2,000	464
Sentences	49,208	18,546	12,548
Sentences w. nesting	32,387	9,533	4,266
Tokens	1.1M	0.5M	0.3M
Mentions	279,795	92,681	30,966
Entity types	114	36	7
Mentions per sentence	5.69	4.99	2.46
Top-level mentions	118,525	76,582	23,464
Maximum depth	6	4	6

... the Ontario Supreme Court said it will postpone ...

STATE

GOVERNMENT

Entity attribute values

Former	U.N.	Ambassador	Jeane	Kirkpatrick	•••
	ORG:OTHER	ROLE	FIRST	NAME	
	ROLE			PER	
	ROLE				
		PER			

Part-whole relationships

... this wealthy Southern California beach community ...

STATE

REGION

- **Large**, **nested**, **fine-grained** named entity recognition dataset
- ► 279,795 mentions of 114 entity types with up to 6 layers nesting
- Built on the Penn Treebank, providing opportunity for joint exploration with other NLP tasks

Benchmark Results

Annotation Schema and Process

- ► Use the flat **BBN** annotation as a *starting point*
- Augment with nested structure and fine-grained entity types
- Annotate all named mentions including time, date and numerical entities
- Annotate all structural elements including nested mentions
- Add consistent substructure to avoid spurious ambiguity e.g., University of Toronto
- ► 4 annotators, background in linguistics and/or computational linguistics
- ► 270 hours total annotation time
- 2x annotation of Sections 00 and 23; 4x annotation of Section 02
- 17 hours additional time for adjudicating multiple Sections 00, 02, 23
- 0.907 Fleiss' kappa over token-level tag stacks on Section 02

BiLSTM-CRF-OUTER 89.9 38.0 53.5 BiLSTM-CRF-INNER 93.8 62.0 74.7 BiLSTM-CRF-UNION 92.2 85.8 88.9 Hypergraph [1] 91.8 91.0 91.4 Transition [2] 77.4 70.1 73.6

Ρ

- Flat NER models can achieve high precision but suffer from low recall
- Hypergraph-based model performs best on our dataset, but with substantially **low decoding speed**

Using NNE

- NNE comprises new standoff annotation over the Penn Treebank
- Also includes code for knitting, evaluation and analysis Freely available under permissive licences

References

[1] Bailin Wang and Wei Lu. Neural Segmental Hypergraphs for Overlapping Mention Recognition. In EMNLP. 2018.

[2] Bailin Wang et al. A Neural Transition-based Model for Nested Mention Recognition. In EMNLP. 2018.



