New supertaggers for the ERG

for the DELPH-IN summit

Olga Zamaraeva & Carlos Gómez-Rodríguez
Department of Informatics/CITIC, Universidade da Coruña

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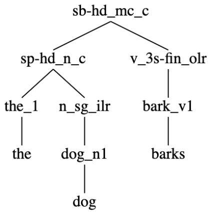
Supertagging helps eliminate unlikely possibilities:

- Without tagging:
  - orthographies are mapped to all possible lexical entries
  - parser has to consider each possibility
  - charts become too big

1



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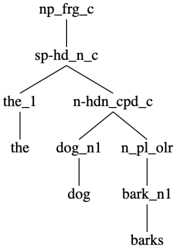
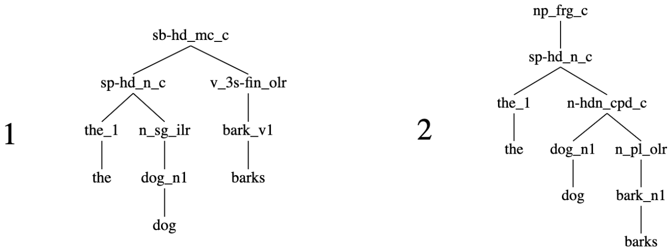


Supertagging is useful for e.g. :

- word sense disambiguation
- parse ranking
- improving parsing speed

Supertagging accuracy is important

- If a wrong lexical type is predicted:
  - the chances of getting the parse right are 0



Prior work on supertagging for HPSG

model	grammar	training tok	tagset size	speed-up factor
N-gram (Prins and van Noord 2004)	Alpino (Dutch)	24 mln	1365	2
HMM (Blunsom 2007)	ERG (English)	113K	615	8.5
MEMM (Dridan 2009)	ERG (English)	158K	676	12

- Dridan (2009):
  - 92% accuracy on in-domain data
  - 74.6% out of domain (up to 80.8% with additional training data)
- Recent work on CCG (Liu et al. 2021):
  - 95.5% accuracy in domain
  - 81% and 92.4% on two out-of-domain datasets

Experiments with ERG

- 2022:
  - Supertagging (no ubertagging)
  - Single tag accuracy (top 1)
- 2023:
  - Started integration into ACE
  - Added fine-tuned BERT

dataset	description	sent	tok	train tok	MaxEnt	SVM	NCRF++	BERT	D2009
cb	technical essay	713	17,244	0	88.96	89.53	91.94	**93.88**	74.61
ecpr	e-commerce	1088	11,550	24,934	91.80	91.99	95.09	**96.09**	
jh*,tg*,ps*, ron*	travel brochures	2116	34,098	147,166	90.45	91.21	95.44	**96.11**	91.47
petet	textual entailment	581	7135	1578	92.88	95.31	96.93	**97.71**	
vm32	phone conv.	1000	8730	86,630	93.57	94.29	95.62	**96.64**	
ws213-214	Wikipedia	1470	29,697	161,623	91.31	92.02	93.66	**95.59**	
wsj23	Wall Street J.	950	22,987	959,709	94.27	94.72	96.05	**97.26**	
all	all test sets as one	7,918	131,441	1,381,645	91.57	92.28	94.46	**96.02**	
all	average	7,918	131,441	1,381,645	91.89	92.72	94.96	**96.18**	
speed (sen/sec)	average	7,918	131,441	1,381,645	1024	**7414**	125	346	

Preliminary Spanish experiments

- Spanish treebanks are much smaller and ‘gold‘ is of lower quality
- Accuracy of the NCRF++ supertagger in the 70%s
  - BERT will be better but probably not much
- Will try to do some multilingual training
  - ...and also improve the Spanish treebanks

Integration into ACE

- For now:
  - Oracle-style experiments for effects on parsing speed
    - ACE gets list of supertags for each sentence
    - eliminates edges with wrong lexical type
- Not sure for now how to integrate the model itself for new input

Example (not a fair comparison!)

No tagging:

```
SENT: Abrams heard barks.

NOTE: 5 readings, added 1194 / 315 edges to chart (124 fully instantiated, 89 actives used, 92 passives used)    RAM: 3975k

NOTE: parsed 1 / 1 sentences, avg 3975k, time 0.02536s
```

Ubertagging:

```
NOTE: 3 readings, added 1133 / 258 edges to chart (101 fully instantiated, 83 actives used, 73 passives used)    RAM: 3661k

NOTE: parsed 1 / 1 sentences, avg 3661k, time 0.02434s
```

BERT oracle supertags:

```
NOTE: 3 readings, added 1052 / 177 edges to chart (73 fully instantiated, 78 actives used, 50 passives used)    RAM: 3413k

NOTE: parsed 1 / 1 sentences, avg 3413k, time 0.02154s
```

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  - added BERT
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  - added BERT
  - started integrating with ACE
  - tried training a supertagger for Spanish
- BERT is more accurate than other things
- scikit-learn SVM (Pedregosa et al. 2011) remains the fastest model
- ACE integration underway but for now only for treebank experiments

References

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