New supertaggers for the ERG

for the DELPH-IN summit

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Introduction: Supertagging

- Supertagging is like POS tagging:
  - Sequence-to-sequence statistical problem
    - input seq: sentence or text
    - output seq: tags corresponding to each token*
  - usually with more fine-grained tags
  - e.g. lexical types in HPSG grammars

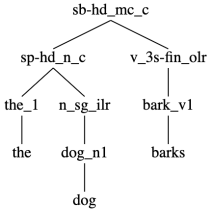
Supertagging is useful for e.g. :

- word sense disambiguation
- parse ranking
- improving parsing speed

Supertagging helps eliminate unlikely possibilities:

- Without tagging:
  - many tokens can be mapped to more than one lexical entry/type

1



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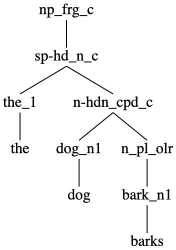
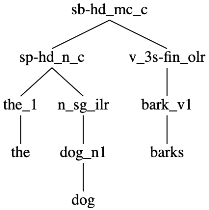


Supertagging accuracy is important

- Supertagging can mean discarding all possibilities but one
- If a wrong lexical type is predicted:
  - the chances of getting the parse right are 0

1



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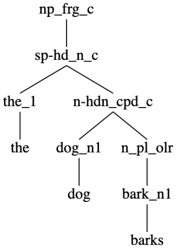

Prior work on supertagging for HPSG

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 **related** work on CCG (Liu et al. 2021):
  - 95.5% accuracy in domain
  - 81% and 92.4% on two out-of-domain datasets

New experiments with ERG 2020

- Supertagging (no ubertagging yet!)
- Single tag accuracy (top 1)
- Tagset: 1127 (no min frequency)
- Not yet integrated into any parser

dataset[11]	description	sent	tok	train tok[12]	MaxEnt	SVM	neural
cb	technical essay	769	17,244	0	88.96	89.53	**91.94**
ecpr	e-commerce	1207	11,550	24,934	91.80	91.99	**95.09**
jh*,tg*,ps*, ron*	travel brochures	2102	34,098	147,166	90.45	91.21	**95.44**
petet	textual entailment	602	7135	1578	92.88	95.31	**96.93**
vm32	phone customer service	1034	8730	86,630	93.57	94.29	**95.62**
ws213-214	Wikipedia	1613	29,697	161,623	91.31	92.02	**93.66**
wsj23	Wall Street Journal	1000[13]	22,987	959,709	94.27	94.72	**96.05**
all	all test sets as one	8,327	131,441	1,381,645	91.57	92.28	**94.46**
all	average	8,327	131,441	1,381,645	91.89	92.72	**94.96**
speed (sen/sec)	average	8,327	131,441	1,381,645	1024	**7414**	125

Neural model details

- NCRF++ library (Yang and Zhang 2018)
  - fast for POS but not CCG/HPSG supertagging
- almost out of the box:
  - unknown label handling added

Parameter	value	default/tuned
lstm layers	2	tuned
hidden dim.	800	tuned
word embeddings	glove840B	pretrained
word emb. dim.	300	N/A
char emb. dim.	50	tuned
momentum	0	default
dropout	0.5	default
l2	1^{-8}	default

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- scikit-learn SVM (Pedregosa et al. 2011) might be the practical model to integrate into ACE for sentence-by-sentence processing
  - Neural models even more accurate but need faster implementation
  - Any takers? :)

References

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