Part of speech tags

CS 585, Fall 2017 Introduction to Natural Language Processing http://people.cs.umass.edu/~brenocon/inlp2017

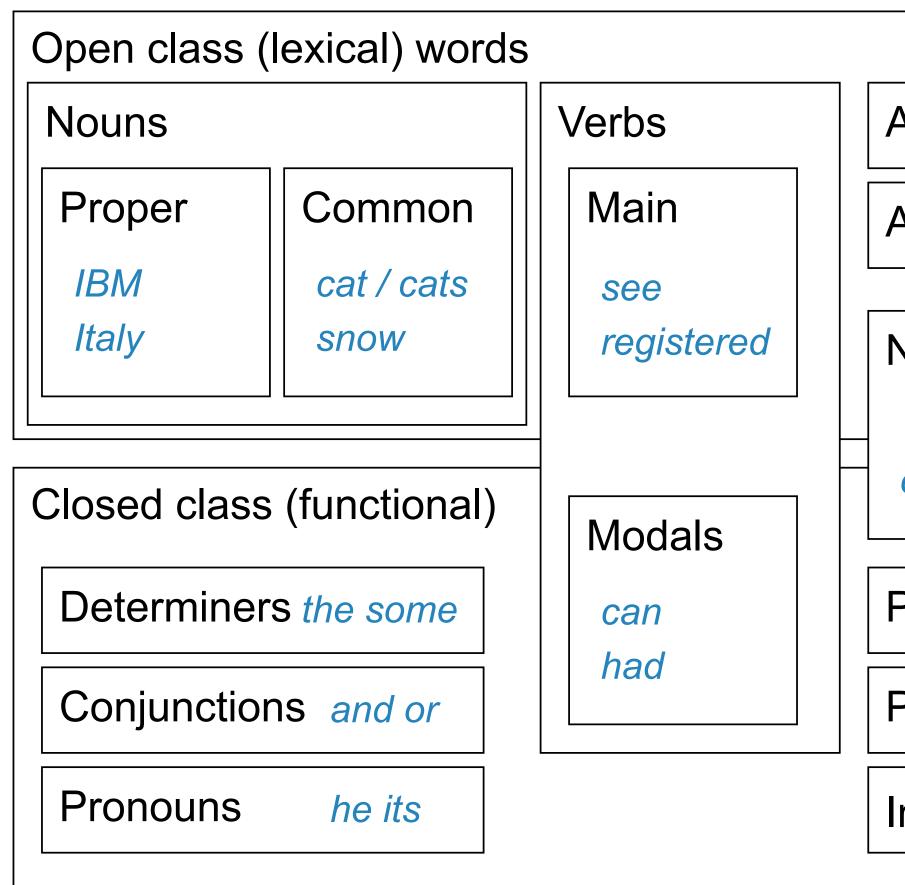
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What's a part-of-speech (POS)?

- Syntax = how words compose to form larger meaning-bearing units
- POS = syntactic categories for words
 - You could substitute words within a class and have a syntactically valid sentence.
 - Give information how words can combine.
 - I saw the <u>dog</u>
 - I saw the cat
 - I saw the {table, sky, dream, school, anger, ...}

Schoolhouse Rock: Conjunction Junction https://www.youtube.com/watch?v=ODGA7ssL-6g&index=1&list=PL6795522EAD6CE2F7

Open vs closed classes



slide credit: Chris Manning

Adjectives	old older	oldest
Adverbs	slowly	
Numbers	<i>r</i> i	nore
122,312		
one		
Preposition	s to with	
Particles	off up	more
nterjection	s Ow Eh	

Many tagging standards

- Penn Treebank (45 tags) ... the most common one
- Coarse tagsets: 12 to 20 (e.g. Petrov 2012, Gimpel 2011)
- UD project: coarse tags, but fine-grained grammatical features
 - <u>http://universaldependencies.org/u/pos/index.html</u>
 <u>http://universaldependencies.org/u/feat/index.html</u>

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Why do we want POS?

- Useful for many syntactic and other NLP tasks.
 - Phrase identification ("chunking")
 - Named entity recognition (names = proper nouns... or are they?) • Syntactic/semantic dependency parsing

 - Sentiment
- Either as features or heuristic filtering
- Esp. useful when not much training data

POS patterns: sentiment

• Turney (2002): identify bigram phrases, from unlabeled corpus, useful for sentiment analysis.

Table 1. Patterns of tags for extracting two-word phrases from reviews.			
	First Word	Second Word	Third Word
			(Not Extracted)
1.	JJ	NN or NNS	anything
2.	RB, RBR, or RBS	JJ	not NN nor NNS
3.	JJ	JJ	not NN nor NNS
4.	NN or NNS	JJ	not NN nor NNS
5.	RB, RBR, or	VB, VBD,	anything
	RBS	VBN, or VBG	

(plus co-occurrence information) <

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Table 2. An example				
the author has classified as <i>recommended</i> . ⁶				
Extracted Phrase	Part-of-Speech	Semantic		
	Tags	Orientation		
online experience	JJ NN	2.253		
low fees	JJ NNS	0.333		
local branch	JJ NN	0.421		
small part	JJ NN	0.053		
online service	JJ NN	2.780		
printable version	JJ NN	-0.705		
direct deposit	JJ NN	1.288		
well other	RB JJ	0.237		
inconveniently	RB VBN	-1.541		
located				
other bank	JJ NN	-0.850		
true service	JJ NN	-0.732		

POS patterns: simple noun phrases

Quick and dirty noun phrase identification <u>http://brenocon.com/JustesonKatz1995.pdf</u> <u>http://brenocon.com/handler2016phrases.pdf</u>

Grammatical structure: Candidate strings are those multi-word noun phrases that are specified by the regular expression $((A | N)^+ | ((A | N)^*(NP)^?)(A | N)^*)N$,

Tag Pattern	Example
AN	linear function
NN	regression coef
AAN	Gaussian rand
ANN	cumulative dis
NAN	mean squared
NNN	class probabili
NPN	degrees of free

Table 5.2 Part of speech tag patterns for collocation filtering. These patterns were used by Justeson and Katz to identify likely collocations among frequently occurring word sequences.

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POS Tagging: lexical ambiguity

Can we just use a tag dictionary (one tag per word type)?

Types:		WSJ	
Unambiguous	(1 tag)	44,432 (86%)	
Ambiguous	(2 + tags)	7,025 (14%)	

Brown 45,799 (**85%**) 8,050 (**15%**)

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- Ambiguous wordtypes tend to be the common ones.
 - I know **that** he is honest = IN (relativizer)
 - Yes, **that** play was nice = DT (determiner)
 - You can't go **that** far = RB (adverb)

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 - Many ambiguous words have a skewed distribution of tags
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- Why so high?
 - Many ambiguous words have a skewed distribution of tags
 - Credit for easy things like punctuation, "the", "a", etc.
 - Is this actually that high?
 - I get 0.918 accuracy for token tagging
 - ...but, 0.186 whole-sentence accuracy (!)

% accuracy nt to run!

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tagging curacy (!)

POS tagging can be hard for humans, too

- Mrs/NNP Shaefer/NNP never/RB got/VBD around/RP to/TO joining/VBG
- All/DT we/PRP gotta/VBN do/VB is/VBZ go/VB around/ **IN** the/DT corner/NN
- Chateau/NNP Petrus/NNP costs/VBZ around/RB \$/\$ 250/CD

Need careful guidelines (and do annotators always follow them?) PTB POS guidelines, Santorini (1990)

4 Confusing parts of speech

This section discusses parts of speech that are easily confused and gives guidelines on how to tag such cases.

CD or JJ

Number-number combinations should be tagged as adjectives (JJ) if they have the same distribution as adjectives.

EXAMPLES: a 50-3/JJ victory (cf. a handy/JJ victory)

Hyphenated fractions one-half, three-fourths, seven-eighths, one-and-a-half, seven-and-three-eighths should be tagged as adjectives (JJ) when they are prenominal modifiers, but as adverbs (RB) if they could be replaced by double or twice.

EXAMPLES: one-half/JJ cup; cf. a full/JJ cup one-half/RB the amount; cf. twice/RB the amount; double/RB the amount

Some other lexical ambiguities

- Prepositions versus verb particles
 - turn into/P a monster
 - take out/T the trash
 - check it out/T, what's going on/T, shout out/T

Careful annotator guidelines are necessary to define what to do in many cases. •<u>http://repository.upenn.edu/cgi/viewcontent.cgi?article=1603&context=cis_reports</u> •<u>http://www.ark.cs.cmu.edu/TweetNLP/annot_guidelines.pdf</u>

Test:

turn slowly into a monster *take slowly out the trash

Some other lexical ambiguities

- Prepositions versus verb particles
 - turn into/P a monster
 - take out/T the trash
 - check it out/T, what's going on/T, shout out/T
- this, that -- pronouns versus determiners
 - i just orgasmed over this/O
 - this/D wind is serious

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How to build a POS tagger?

- Key sources of information:
 - I. The word itself
 - 2. Word-internal characters
 - 3. POS tags of surrounding words: syntactic context
- Approach: supervised learning (text => tags)
 - Today/Thursday: with the Hidden Markov Model
 - Next week: Conditional Random Field (arbitrary features)