CS674 Natural Language Processing

- Last classes
 - Noisy channel model
 - N-gram models
- Today
 - Part-of-speech tagging
 - introduction

Part of speech tagging

- "There are 10 parts of speech, and they are all troublesome." -Mark Twain
- POS tags are also known as word classes, morphological classes, or lexical tags.
- Typically much larger than Twain's 10:
 - Penn Treebank: 45
 - Brown corpus: 87
 - **–** C7 tagset: 146

Part of speech tagging

• Assign the correct part of speech (word class) to each word/token in a document

"The/DT planet/NN Jupiter/NNP and/CC its/PRP moons/NNS are/VBP in/IN effect/NN a/DT mini-solar/JJ system/NN ,/, and/CC Jupiter/NNP itself/PRP is/VBZ often/RB called/VBN a/DT star/NN that/IN never/RB caught/VBN fire/NN ./."

Needed as an initial processing step for a number of language technology applications

- Answer extraction in QA
- Base step in identifying syntactic phrases for IR systems
- Critical for word-sense disambiguation (WordNet apps)
- Information extraction

Why is p-o-s tagging hard?

- Ambiguity
 - He will race/VB the car.
 - When will the race/NOUN end?
 - The boat floated/ VBN down the river sank.
- Average of ~2 parts of speech for each word
- The number of tags used by different systems varies a lot. Some systems use
 < 20 tags, while others use > 400.

- ...

Hard for Humans

- particle vs. preposition
 - He talked over the deal.
 - He talked over the telephone.
- past tense vs. past participle
 - The horse walked past the barn.
 - The horse walked past the barn fell.
- noun vs. adjective?
 - The executive decision.
- noun vs. present participle
 - Fishing can be fun.

To obtain gold standards for evaluation, annotators rely on a set of tagging guidelines.

From Ralph Grishman, NYU

Among easiest of NLP problems

- State-of-the-art methods achieve ~97% accuracy.
- Simple heuristics can go a long way.
 - ~90% accuracy just by choosing the most frequent tag for a word (MLE)
 - To improve reliability: need to use some of the local context.
- But defining the rules for special cases can be time-consuming, difficult, and prone to errors and omissions

Penn Treebank Tagset

Tag	Description	Example	Tag	Description	Example
CC	Coordin. Conjunction	and, but, or	SYM	Symbol	+,%, &
CD	Cardinal number	one, two, three	TO	"to"	to
DT	Determiner	a, the	UH	Interjection	ah, oops
EX	Existential 'there'	there	VB	Verb, base form	eat
FW	Foreign word	mea culpa	VBD	Verb, past tense	ate
IN	Preposition/sub-conj	of, in, by	VBG	Verb, gerund	eating
JJ	Adjective	yellow	VBN	Verb, past participle	eaten
JJR	Adj., comparative	bigger	VBP	Verb, non-3sg pres	eat
JJS	Adj., superlative	wildest	VBZ	Verb, 3sg pres	eats
LS	List item marker	1, 2, One	WDT	Wh-determiner	which, that
MD	Modal	can, should	WP	Wh-pronoun	what, who
NN	Noun, sing. or mass	llama	WP\$	Possessive wh-	whose
NNS	Noun, plural	llamas	WRB	Wh-adverb	how, where
NNP	Proper noun, singular	IBM	\$	Dollar sign	\$
NNPS	Proper noun, plural	Carolinas	#	Pound sign	#
PDT	Predeterminer	all, both	"	Left quote	(' or '')
POS	Possessive ending	'S	"	Right quote	(' or '')
PP	Personal pronoun	I, you, he	(– – – – – – – – – – – – – – – – – – –	Left parenthesis	$([, (, \{, <)$
PP\$	Possessive pronoun	your, one's) — (Right parenthesis	([1, 1), [1, 2)
RB	Adverb	quickly, never	,	Comma	,
RBR	Adverb, comparative	faster		Sentence-final punc	(.1?)
RBS		fastest	:	Mid-sentence punc	
RP	Particle	up, off			

Approaches

- 1. **rule-based**: involve a large database of hand-written disambiguation rules, e.g. that specify that an ambiguous word is a noun rather than a verb if it follows a determiner.
- 2. **probabilistic**: resolve tagging ambiguities by using a training corpus to compute the probability of a given word having a given tag in a given context.
 - HMM tagger, Maximum Likelihood Tagger
- 3. **hybrid corpus-/rule-based**: E.g. transformationbased tagger (Brill tagger); learns symbolic rules based on a corpus.
- 4. **ensemble methods**: combine the results of multiple taggers.