

# Parts of Speech

Nouns, verbs, adjectives, adverbs, prepositions, . . .

- ▶ Efficiently assignable with high accuracy
- ▶ Valuable in many NLP tasks
- ▶ Commonly thought of as mapping to the real world
  - ▶ Objects
  - ▶ Properties
  - ▶ Actions
- ▶ In linguistics, understood via
  - ▶ Distributional properties (co-occurrences with other words)
  - ▶ Morphology, including the affixes they take, e.g., -tion, -ize
  - ▶ Intonational
- ▶ 45 POS tags defined in the Penn Treebank ( $\approx$  1993)
  - ▶ Includes variants such as tense and aspect
  - ▶ Includes punctuation

## Closed versus Open Class

- ▶ Borrowings need special handling
  - ▶ a priori
  - ▶ schadenfreude
- ▶ Distinguishing mass nouns from count nouns
  - ▶ No plurals vs. plurals
  - ▶ Roughly, Real numbers vs. Natural numbers, but not quite (give examples)
- ▶ Syntactic substitutability
- ▶ Conjoinable, i.e., with *and*

# Closed versus Open Class

- ▶ Closed class or function words
  - ▶ Change slowly
  - ▶ Prepositions, particles, determiners (~ articles), conjunctions, pronouns, auxiliary verbs, numerals
  - ▶ Lend structure to language
- ▶ Open classes
  - ▶ Nouns
  - ▶ Verbs
  - ▶ Adjectives
  - ▶ Adverbs

# Penn Treebank Tagset

From the Wall Street Journal and Brown corpora

Dependency grammars (introduced later) have another tagset

Tag	Description	Example	Tag	Description	Example	Tag	Description	Example
CC	coordinating conjunction	<i>and, but, or</i>	PDT	predeterminer	<i>all, both</i>	VBP	verb non-3sg present	<i>eat</i>
CD	cardinal number	<i>one, two</i>	POS	possessive ending	<i>'s</i>	VBZ	verb 3sg pres	<i>eats</i>
DT	determiner	<i>a, the</i>	PRP	personal pronoun	<i>I, you, he</i>	WDT	wh-determ.	<i>which, that</i>
EX	existential 'there'	<i>there</i>	PRP\$	possess. pronoun	<i>your, one's</i>	WP	wh-pronoun	<i>what, who</i>
FW	foreign word	<i>mea culpa</i>	RB	adverb	<i>quickly</i>	WP\$	wh-possess.	<i>whose</i>
IN	preposition/ subordin-conj	<i>of, in, by</i>	RBR	comparative adverb	<i>faster</i>	WRB	wh-adverb	<i>how, where</i>
JJ	adjective	<i>yellow</i>	RBS	superlatv. adverb	<i>fastest</i>	\$	dollar sign	\$
JJR	comparative adj	<i>bigger</i>	RP	particle	<i>up, off</i>	#	pound sign	#
JJS	superlative adj	<i>wildest</i>	SYM	symbol	<i>+, %, &amp;</i>	"	left quote	' or "
LS	list item marker	<i>1, 2, One</i>	TO	"to"	<i>to</i>	"	right quote	' or "
MD	modal	<i>can, should</i>	UH	interjection	<i>ah, oops</i>	(	left paren	[, (, {, <
NN	sing or mass noun	<i>llama</i>	VB	verb base form	<i>eat</i>	)	right paren	], ), }, >
NNS	noun, plural	<i>llamas</i>	VBD	verb past tense	<i>ate</i>	,	comma	,
NNP	proper noun, sing.	<i>IBM</i>	VBG	verb gerund	<i>eating</i>	.	sent-end punc	. ! ?
NNPS	proper noun, plu.	<i>Carolinas</i>	VBN	verb past part.	<i>eaten</i>	:	sent-mid punc	: ; ... --

## Penn Treebank Markup Example

Large effort on developing NL resources: tagset, labeled datasets, . . .

- ▶ Preliminary findings were reported in today's New England Journal of Medicine.

Preliminary/adjective	findings/plural-noun
were/verb-past	reported/verb-part-participle
in/preposition	today/singular-noun
's/possessive	New/proper-noun-singular
England/proper-noun-singular	Journal/proper-noun-singular
of/preposition	Medicine/proper-noun-singular
./sentence-ending	

- ▶ Typical way of writing:  
Preliminary/JJ findings/NNS were/VBD reported/VBN in/IN  
today/NN 's/POS New/NNP England/NNP Journal/NNP of/IN  
Medicine/NNP ./.
- ▶ Does today possess the New England Journal of Medicine?
- ▶ Why isn't all of New England Journal of Medicine one noun?

# Part of Speech Tagging Challenge

- ▶ Many words can take multiple tags depending on context
  - ▶ ~ 14–15% of the words in the Wall Street Journal and Brown corpora

Adjective	earnings growth took a back/JJ seat
Mass noun	a small building in the back/NN
Verb present tense	a clear majority of senators back/VBP the bill
Verb	Dave began to back/VB toward the door
Particle	enable the country to buy back/RP about debt
Adverb	I was twenty-one back/RB then

- ▶ Simple baseline: most frequent class

# Part of Speech Tagging as Sequence Tagging

- ▶ Markov (first-order): next state depends on current state but not history
  - ▶ Suffix closure
  - ▶ Fusion closure
  - ▶ Limit closure
- ▶ Hidden Markov Model (HMM)
  - ▶ States,  $Q$ : parts of speech or POS tag
  - ▶ Transition probability,  $A$ : one POS to the next
  - ▶ Observations,  $O$ : (sequence of) words from vocabulary
  - ▶ Observation likelihood,  $B$ : probability of word given POS
  - ▶ Initial probability distribution,  $\pi$ : of starting with a POS
- ▶ HMM assumptions
  - ▶ Probability of POS depends only on previous POS
  - ▶ Probability of word depends only on POS

# HMM Part of Speech Tagging: Estimation

- ▶ Estimate transition probabilities via bigram model on corpus

$$P(q_i|q_{i-1}) = \frac{\text{count}(q_{i-1}, q_i)}{\text{count}(q_{i-1})}$$

- ▶ Estimate  $i$ th part of speech given the previous part of speech
- ▶ Estimate emission probabilities via POS distributions on corpus

$$P(o_i|q_i) = \frac{\text{count}(q_i, o_i)}{\text{count}(q_i)}$$



## HMM Part of Speech Tagging: Final Form

- ▶ We seek the most probable POS sequence ( $Q = q_1^n$ ) for a given word sequence

$$\hat{Q} = \operatorname{argmax}_Q P(Q|O)$$

- ▶ Applying Bayes

$$\hat{Q} = \operatorname{argmax}_Q \frac{P(O|Q)P(Q)}{P(O)}$$

- ▶ The observation sequence is given—thus,  $P(O)$  is fixed, so drop it
- ▶ Markov: each POS depends only on its predecessor
- ▶ Each word depends only on the POS
- ▶ Combined model

$$\hat{q}_1^n = \operatorname{argmax}_{q_1^n} \prod_i^n P(o_i|q_i)P(q_i|q_{i-1})$$

# Viterbi Algorithm

## Dynamic programming

- ▶ Like the minimum edit distance algorithm, but involves
  - ▶ Products of probabilities, not sums of edit costs
  - ▶ Maximum over a different set of paths
- ▶ To compute a Viterbi matrix,  $V$ 
  - ▶ Each column: an observation (word)
  - ▶ Each row: a state (POS)
  - ▶  $V[s, t]$ : (maximum) probability of being at POS  $s$  after seeing the first  $t$  words
  - ▶ Three probabilities:  $\pi$ , entry;  $A$ , transition;  $B$ , emission
- ▶ Initialize first column to product of probability of beginning from the respective state and the probability of emitting the first word from it

$$V_{s,1} = \pi_s B_s(o_1)$$

- ▶ Iteratively, compute

$$V_{s,t} = \max_i^N V_{[i,t-1]} A_i B_s(o_t)$$

# Extensions

Languages like Turkish with complex morphology remain difficult

- ▶ Use trigrams instead of bigrams
  - ▶ Gain in accuracy  $\sim 0.5\%$
  - ▶ Need to extend Viterbi to look at a history of two
- ▶ Usual need for addressing sparsity: smoothing and interpolation
- ▶ Beam search: limit search to beam width  $\beta \ll N$
- ▶ Insert end of sentence marker to facilitate search
- ▶ Unknown words
  - ▶ Base POS probabilities on affixes, e.g., *-tion* indicates nouns, *-ize* verbs, *-ly* adverbs, and *-able* adjectives