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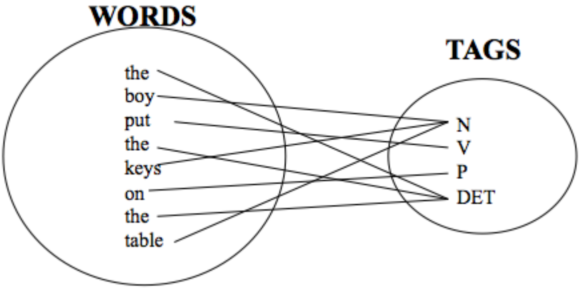

Parts of Speech: How many?

Open class words (content words)

- nouns, verbs, adjectives, adverbs
- mostly content-bearing: they refer to objects, actions, and features in the world
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Closed class words

- pronouns, determiners, prepositions, connectives, ...
- there is a limited number of these
- *mostly functional:* to tie the concepts of a sentence together

POS examples

- N noun chair, bandwidth, pacing
- V verb study, debate, munch
- ADJ adj purple, tall, ridiculous
- ADV adverb unfortunately, slowly,
- P preposition of, by, to
- PRO pronoun I, me, mine
- DET determiner the, a, that, those

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A Nice Tutorial on POS tags

https://sites.google.com/site/partofspeechhelp/

UPenn TreeBank POS tag set

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	*$*
NNPS	Proper noun, plural	*Carolinas*	#	Pound sign	#
PDT	Predeterminer	*all, both*	“	Left quote	(‘ or “)
POS	Possessive ending	*'s*	”	Right quote	(’ or ”)
PRP	Personal pronoun	*I, you, he*	(	Left parenthesis	([, (, {, <)
PRP$	Possessive pronoun	*your, one's*	)	Right parenthesis	( ],), }, >)
RB	Adverb	*quickly, never*	,	Comma	,
RBR	Adverb, comparative	*faster*	.	Sentence-final punc	(. ! ?)
RBS	Adverb, superlative	*fastest*	:	Mid-sentence punc	(: ; ... – -)
RP	Particle	*up, off*			

Using the UPenn tagset

Example Sentence

The grand jury commented on a number of other topics.

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POS tagged sentence

The/DT grand/JJ jury/NN commmented/VBD on/IN a/DT number/NN of/IN other/JJ topics/NNS ./.

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POS tagging problem

To determine the POS tag for a particular instance of a word

Ambiguous word types in the Brown Corpus

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- 12% of word types are ambiguous
- Breakdown of ambiguous word types:

Unambiguous (1 tag)	35,340
Ambiguous (2–7 tags)	4,100
2 tags	3,760
3 tags	264
4 tags	61
5 tags	12
6 tags	2
7 tags	1 ("still")

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  In the Brown corpus, *race* is a noun 98% of the time, and a verb 2% of the time
- A tagger for English that simply chooses the most likely tag for each word can achieve good performance
- Any new approach should be compared against the unigram baseline (assigning each token to its most likely tag)

Deciding the correct POS

Can be difficult even for people

- Mrs./NNP Shaefer/NNP never/RB got/VBD around/_ to/TO joining/VBG.
- All/DT we/PRP gotta/VBN do/VB is/VBZ go/VB around/_ the/DT corner/NN.
- Chateau/NNP Petrus/NNP costs/VBZ around/_ 2500/CD.

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Relevant knowledge for POS tagging

The word itself

- Some words may only be nouns, e.g. *arrow*
- Some words are ambiguous, e.g. *like, flies*
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Local context

- Two determiners rarely follow each other
- Two base form verbs rarely follow each other
- Determiner is almost always followed by adjective or noun

POS tagging: Two approaches

Rule-based Approach

- Assign each word in the input a list of potential POS tags
- Then winnow down this list to a single tag using hand-written rules

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Statistical tagging

- Get a training corpus of tagged text, learn the transformation rules from the most frequent tags (TBL tagger)
- Probabilistic: Find the most likely sequence of tags T for a sequence of words W

TBL Tagger

Label the training set with most frequent tags

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Add transformation rules to reduce training mistakes

- MD $\rightarrow$NN: DT_
- VBD$\rightarrow$VBN: VBD_

Probabilistic Tagging: Two different families of models

Problem at hand

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What gives rise to the two families?

Whether they generate the observed data from hidden stuff or the hidden structure given the data?

Generative vs. Conditional Models

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Generate the observed data from hidden stuff, i.e. put a probability over the observations given the class: $P(d,c)$ in terms of $P(d|c)$

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SVMs, perceptron, etc. are discriminative classifiers but not directly probabilistic

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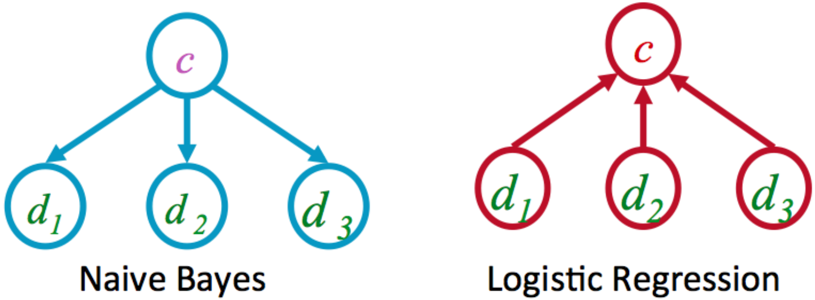

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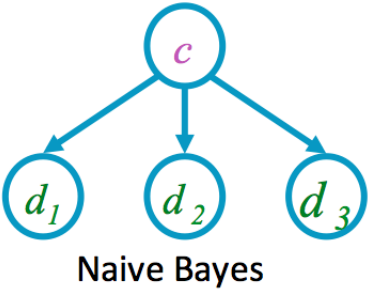

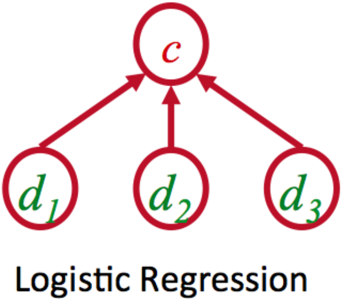

Joint vs. conditional likelihood

- A *joint* model gives probabilities $P(d,c)$ and tries to maximize this joint likelihood.
- A *conditional* model gives probabilities $P(c|d)$, taking the data as given and modeling only the conditional probability of the class.