

Statistical Natural Language Processing

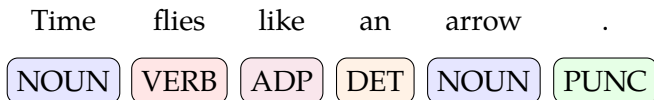
Part of speech tagging

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Part of speech tagging



- Part of speech (POS or PoS) tags are morphosyntactic classes of words
- The words belonging to the same POS class share some syntactic and morphological properties

Traditional POS tags

what you learn in (primary?) school

noun apple, chair, book

verb go, read, eat

adjective blue, happy, nice

adverb well, fast, nicely

pronoun I, they, mine

determiner a, the, some

preposition in, since, past, ago (?)

conjunction and, or, since

interjection uh, ouch, hey

With minor differences, this list of categories has been around for a long time.

When we say 'traditional' ...



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- The POS tags were around for thousands of years
- POS tags in modern linguistics are based on Greek/Latin linguistic traditions
- But others, e.g., Sanskrit linguists, also proposed POS tags
- The choice POS tags are often language dependent

What are the POS tags good for

- Linguistic theory
- Parsing
- Speech synthesis: pronounce *lead*, *wind*, *object*, *insult* differently based on their POS tag
- The same goes for machine translation
- Information retrieval: if *wug* is a noun, also search for *wugs*
- Text classification: improves many tasks

Open vs. closed class words

Open class words (e.g., nouns) are productive

- new words coined are often in these classes
- we often cannot rely on a fixed lexicon
- they are typically ‘content’ words

Closed class words (e.g., determiners) are generally static

- the lexicon does not grow
 - they are typically ‘function’ words
- This distinction is often language dependent

Some issues with traditional POS tags

- Not all POS tags are observed in (or theorized for) all languages
- Often finer granularity is necessary
 - *book, water* and *Marry* are all nouns, but
 - The book is here
 - * The Marry is here
 - We have water
 - * We have book

POS tagsets in practice

example: Penn treebank tagset

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

POS tagsets in practice

example 2: STTS tagset

POS	description	examples
...
KOUI	subordinating conjunction	um [zu leben], anstatt [zu fragen]
KOUS	subordinating conjunction	weil, daß, damit, wenn, ob
KON	coordinative conjunction	und, oder, aber
KOKOM	particle of comparison, no clause	als, wie
NN	noun	Tisch, Herr, [das] Reisen
NE	proper noun	Hans, Hamburg, HSV
PDS	substituting demonstrative	dieser, jener
PIS	substituting indefinite pronoun	keiner, viele, man, niemand
PIAT	attributive indefinite	kein [Mensch], irgendein [Glas]
PIDAT	attributive indefinite	[ein] wenig [Wasser],
PPER	irreflexive personal pronoun	ich, er, ihm, mich, dir
PPOSS	substituting possessive pronoun	meins, deiner
PPOSAT	attributive possessive pronoun	mein [Buch], deine [Mutter]
PRELS	substituting relative pronoun	[der Hund,] der
PRELAT	attributive relative pronoun	[der Mann ,] dessen [Hund]
...

POS tagset choices

- The choice tagsets depends on the language and application
- Example tag set sizes (for English)
 - Brown corpus, 87 tags
 - Penn treebank 45 tags
 - BNC, 61 tags
- Differences can be large, for Chinese Penn treebank has 34 tags, but tagsets with about 300 tags exist
- For other languages, the choice varies roughly between about 10 to a few hundred

Shift towards more 'universal' tag sets

- The variation in POS tagset choices often makes it difficult to
 - compare alternative approaches
 - use the same tools on different languages of data sets
- There has been a recent trend for 'universal' tag sets
- The result is a smaller POS tag set (back to the tradition)
- But often supplemented with *morphological features*

POS tagsets in recent practice

example: Universal Dependencies tag set

ADJ	adjective	PART	particle
ADP	adposition	PRON	pronoun
ADV	adverb	PROPN	proper noun
AUX	auxiliary	PUNCT	punctuation
CCONJ	coordinating conjunction	SCONJ	subordinating conjunction
DET	determiner	SYM	symbol
INTJ	interjection	VERB	verb
NOUN	noun	X	other
NUM	numeral		

Morphological features

- Annotating words with morphological features has been common in (non-English) NLP
- Morphological features give additional sub-categorization information for the word

- For example

nouns typically have a *number* feature

verbs typically have *tense, aspect, modality voice* features

adjectives typically have *degree*

- Morphological feature sets change depending on the language (typology)

Morphological features

an example

Time	flies	like	an	arrow	.
NOUN	VERB	ADP	DET	NOUN	PUNC
num=sing	num=sing pers=3 tense=pres		def=ind	num=sing	

POS tags are ambiguous

Time	flies	like	an	arrow	.
NOUN	VERB	ADP	DET	NOUN	PUNC
NOUN	NOUN	VERB	DET	NOUN	PUNC
fruit	flies	like	an	apple	.

POS tagging is essentially an ambiguity resolution problem.

POS tag ambiguity

More examples

- Some words are highly ambiguous

ADJ the *back* door

NOUN on our *back*

ADV take it *back*

VERB we will *back* them

- The garden-path sentences are often POS ambiguities
 - The *old man* the boats
 - The horse *raced passed* the barn fell
 - The complex *houses* married and single soldiers and their families

POS tagging: strategies

POS tagging can be solved in a number of different methods

- Rule-based methods: ‘constraint grammar’ (CG)
- Transformation based: Brill tagger
- Machine-learning approaches
Typical statistical approaches involve *sequence learning* methods:
 - Hidden Markov models
 - Conditional random fields
 - (Recurrent) neural networks

Rule-based POS tagging

typical approach

- Using a tag lexicon, start with assigning all possible tags to each word
- Eliminate tags based on hand-crafted rules
- Rules typically rely on the words and (potential) tags of the words in the context
- Result is not always full disambiguation, some ambiguity may remain
- Some probabilistic constraints may also be applied

Rule-based POS tagging

an example

- Among others, the word *that* can be
 SCONJ we know *that* it is bad
 ADV it is not *that* bad

An example rule for disambiguation (very simplified):

- | | | |
|---|------|---|
| 1 | if | the next word is ADJ, ADV |
| 2 | and | the following word is at the sentence boundary |
| 3 | and | the previous word is not a verb like 'consider' |
| 4 | then | eliminate SCONJ |
| 5 | else | eliminate ADV |

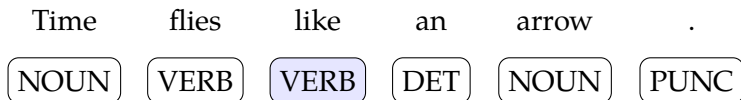
- 2 eliminates non-sentence final ADV
- 3 eliminates cases like *I consider that funny.*

Transformation based tagging

- The idea:
 - Start with assigning the most probably POS tag to all words
 - Apply a set of rules (similar to CG) from more specific to less specific
- The rules are learned

Transformation based learning

An example



- Start with most likely POS tags:
'like' is more likely to be a VERB than ADP

Transformation based learning

An example

Time	flies	like	an	arrow	.
NOUN	VERB	VERB	DET	NOUN	PUNC
NOUN	VERB	ADP	DET	DET	PUNC

- Start with most likely POS tags:
'like' is more likely to be a VERB than ADP
- Apply rule:
change VERB to ADP if preceding word is tagged as VERB

Learning in TBL

1. Start with most likely tags for each word
 2. Find the best rule that improves the tagging accuracy,
 3. Repeat 2 for all possible rules
- Rules need to be restricted, often templates are used. For example: Change tag x to tag y if
 - the preceding/following word is tagged z
 - the preceding word tagged v and the following word is tagged z
 - the preceding word tagged v and the following word is tagged z and two words before is tagged t

POS tagging using Hidden Markov models (HMM)

- HMMs are probabilistic models
- The probability of a sequence of words, \mathbf{w} is given the HMM model M

$$P(\mathbf{w}|M) = P(\mathbf{t})P(\mathbf{w}|\mathbf{t})$$

where \mathbf{t} is the tag sequence

- We assume given the tag t , the word is independent of the other words in the sequence
- $P(\mathbf{t})$ follows the Markov assumption
- Most state-of-the-art models are based on HMMs (or similar sequence learning models)
- More on HMMs on Wednesday

POS tagging accuracy

- Tagging each word with the most probable tag gives around 90% accuracy
- State-of-the art POS taggers (for English) achieve 95%–97%
- Human agreement on annotation also seems to be around 97%: not a lot of space for improvement
 - at least for well-studied resource-rich languages

Summary

- POS is an old idea in linguistics
- POS tags have uses in both linguistics, and practical applications
- Common methods for automatic POS tagging include
 - rule-based
 - transformation-based
 - statistical (more on this next week)

methods

Next:

Wed Sequence learning

Fri Exercises: classification