Statistical Natural Language Processing

Part of speech tagging

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Part of speech tagging

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

- 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
prepositon	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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- POS tags in modern linguistics are based on Greek/Latin linguistic traditions
- But others, e.g., Sanskrit linguists, also proposed POS tags

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 some tasks
- As a back-off strategy for some language models

POS tagsets in practice

example: 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 ")
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*			

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 of 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 or 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 *number* and *case* 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	.

Part of speech 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 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 (simplified):

```
if the next word is ADJ
  and the next word is sentence final
  and the previous word is not a verb like 'consider'
then eliminate SCONJ
else eliminate ADV
```

- The rules above prefer SCONJ for cases like *I consider that funny.*

Transformation based tagging (TBL)

- The idea: learn a sequence of rules (similar to CG) using a tagged corpus
- The rules transform an initial POS assignment to (approximately) the POS tag assignment in the training corpus
- During test time apply the rules in the same order

Learning in TBL

1. Start with most likely tags for each word
2. Find the best rule that improves the tagging accuracy,
3. Repeat step 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

Transformation based learning
An example

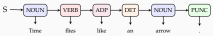
Time	flies	like	an	arrow	.
NOUN	NOUN	VERB	DET	NOUN	PUNC
NOUN	VERB	VERB	DET	NOUN	PUNC
NOUN	VERB	ADP	DET	NOUN	PUNC

- Start with most likely POS tags
- Apply: change NOUN to VERB if preceding word is NOUN and ...
- Apply: change VERB to ADP if preceding word is tagged as VERB
- Stop when none of the rules improve the result

ML methods for POS tagging

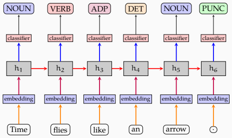
- POS tagging is a typical example of 'sequence labeling'
- Many of the ML methods introduced earlier can be used for POS tagging
- Sequence learning methods are more suitable, since the tags depend on the neighboring tags
  - Hidden Markov models (HMMs)
  - Hidden Markov max-ent models (HMMEMs)
  - Conditional random fields (CRFs)
  - Recurrent neural networks (RNNs)
  - Non-recurrent models of sequences (e.g., Transformer models)

POS tagging using Hidden Markov models (HMM)



- The tags are hidden
- Probability of a tag depends on the previous tag
- Probability of a word at a given state depends only on the current tag
- Parameters of the model can be learned
  - supervised from a tagged corpus (e.g., MLE)
  - unsupervised using EM (Baum-Welch algorithm)

RNNs for POS tagging



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
  - machine learning (sequence labeling)

  methods

Next:

- Text classification

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 *Mary* are all nouns, but

    The book is here
    * The Mary is here
    We have water
    * We have book

blank

blank

blank

blank