COMP 3225

Natural Language Processing

Parts of Speech Tagging

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Overview

- Introduction to Parts of Speech (POS)
- Tagsets
- POS Tagging
- <break - discussion point>
- Hidden Markov Model (HMM) POS tagger

Introduction to Parts of Speech (POS)

- What is Parts of Speech?
  - The concept of Parts-of-Speech (POS) probably originated from Dionysius Thrax of Alexandria around 100 BC attempting to summarize Greek linguistic knowledge
  - Thrax defined eight POS which we still use today
    - Noun, Verb, Pronoun, Preposition, Adverb, Conjunction, Participle, Article
  - POS can also be called word classes, morphological classes or lexical tags
  - POS are generally assigned to individual words or morphemes
  - Labelling POS is called POS Tagging
- Proper names
  - A proper name is called a Named Entity, and can be a multi-word phrase (e.g. New York)
  - Labelling named entities is called Named Entity Recognition (NER)
  - Named entity types include Location, Person, Organization etc.

Introduction to Parts of Speech (POS)

- Why are POS and Named Entities useful?
  - POS gives us clues to neighboring words and syntactic structure
    - Nouns are preceded by determiners and adjectives ... the river
    - Verbs are preceded by nouns ... swimming in the river
    - Verbs have dependency links to nouns swimming $\xrightarrow{\text{dobj}}$ the river
  - POS tagging a key aspect of parsing natural language
  - NER is important to many natural language understanding tasks such as question answering, stance detection and information extraction
- Sequence labelling tasks
  - Input >> X >> Sequence of words
  - Output >> Y >> Sequence of labels
  - len(X) == len(Y)
- Both POS tagging and NER can be formulated as a sequence labelling task

Introduction to Parts of Speech (POS)

	Tag	Description	Example
Open Class	**ADJ**	Adjective: noun modifiers describing properties	*red, young, awesome*
	ADV	Adverb: verb modifiers of time, place, manner	*very, slowly, home, yesterday*
	NOUN	words for persons, places, things, etc.	*algorithm, cat, mango, beauty*
	VERB	words for actions and processes	*draw, provide, go*
	PROPN	Proper noun: name of a person, organization, place, etc..	*Regina, IBM, Colorado*
	INTJ	Interjection: exclamation, greeting, yes/no response, etc.	*oh, um, yes, hello*
Closed Class Words	**ADP**	Adposition (Preposition/Postposition): marks a noun's spacial, temporal, or other relation	*in, on, by under*
	AUX	Auxiliary: helping verb marking tense, aspect, mood, etc.,	*can, may, should, are*
	CCONJ	Coordinating Conjunction: joins two phrases/clauses	*and, or, but*
	DET	Determiner: marks noun phrase properties	*a, an, the, this*
	NUM	Numeral	*one, two, first, second*
	PART	Particle: a preposition-like form used together with a verb	*up, down, on, off, in, out, at, by*
	PRON	Pronoun: a shorthand for referring to an entity or event	*she, who, I, others*
	SCONJ	Subordinating Conjunction: joins a main clause with a subordinate clause such as a sentential complement	*that, which*
Other	**PUNCT**	Punctuation	; , ()
	SYM	Symbols like $ or emoji	$, %
	X	Other	asdf, qwfg

The 17 parts of speech in the Universal Dependencies tagset for English

Cite: Nivre, J., de Marneffe, M.-C., Ginter, F., Goldberg, Y., Hajiˇc, J., Manning, C. D., McDonald, R., Petrov, S., Pyysalo, S., Silveira, N., Tsarfaty, R., and Zeman, D. (2016). Universal Dependencies v1: A multilingual treebank collection. LREC.

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- Closed Classes - fixed membership
  - Typically function words used for structuring grammar (of, it, and, you)
- Open Classes - open membership
  - Noun (including proper noun), verb, adjective, adverb, interjection

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- Nouns
  - Common Noun - concrete terms, abstractions and verb-like terms
    - Count Noun - occur in the singular and plural (goat/goats, relationship/relationships, and irregular ones like sheep/sheep)
    - Mass Noun - homogeneous groups (snow, salt)
  - Proper Noun - names of things

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- Verbs - actions and processes
- Adjective - properties or qualities of nouns

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- Adverb - modifier words
  - Locative Adverb - direction or location of some action (here, downhill)
  - Degree Adverbs - extent of some action (extremely, very, somewhat)
  - Manner Adverbs - manner of some action (slowly, slinkily, delicately)
  - Temporal Adverbs - time of action or event (yesterday, Monday)

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- Interjection - exclamation (oh, hey, alas), greetings (hello, goodbye) and question responses (yes, no, uh-huh)

Tagsets

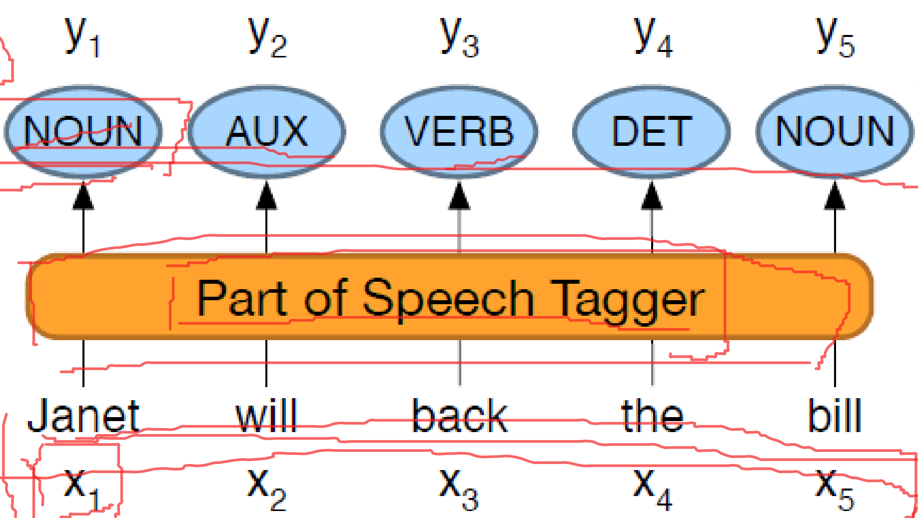
- A list of POS labels is called a Tagset
- Tagsets come in different shapes and sizes
  - Penn Treebank (45 labels)
  - Brown Corpus (87 labels)
  - C7 Tagset (146 labels)
- Penn Treebank

Tag	Description	Example	Tag	Description	Example	Tag	Description	Example
CC	coord. conj.	*and, but, or*	NNP	proper noun, sing.	*IBM*	TO	"to"	*to*
CD	cardinal number	*one, two*	NNPS	proper noun, plu.	*Carolinas*	UH	interjection	*ah, oops*
DT	determiner	*a, the*	NNS	noun, plural	*llamas*	VB	verb base	*eat*
EX	existential 'there'	*there*	PDT	predeterminer	*all, both*	VBD	verb past tense	*ate*
FW	foreign word	*mea culpa*	POS	possessive ending	*'s*	VBG	verb gerund	*eating*
IN	preposition/ subordin-conj	*of, in, by*	PRP	personal pronoun	*I, you, he*	VBN	verb past participle	*eaten*
JJ	adjective	*yellow*	PRP$	possess. pronoun	*your, one's*	VBP	verb non-3sg-pr	*eat*
JJR	comparative adj	*bigger*	RB	adverb	*quickly*	VBZ	verb 3sg pres	*eats*
JJS	superlative adj	*wildest*	RBR	comparative adv	*faster*	WDT	wh-determ.	*which, that*
LS	list item marker	*1, 2, One*	RBS	superlatv. adv	*fastest*	WP	wh-pronoun	*what, who*
MD	modal	*can, should*	RP	particle	*up, off*	WP$	wh-possess.	*whose*
NN	sing or mass noun	*llama*	SYM	symbol	+,%, &	WRB	wh-adverb	*how, where*

Cite: Marcus, M. P., Santorini, B., and Marcinkiewicz, M. A. (1993). Building a large annotated corpus of English: The Penn treebank. Computational Linguistics 19(2), 313–330

POS Tagging

- POS tagging is the process of assigning a POS tag to each word in a text
  - Input sequence >> X >> $x_1; x_2; ::: ; x_n$ of (tokenized) words
  - Output sequence >> Y >> $y_1; y_2; ::: ; y_n$ of POS tags
  - Each output y_i corresponding exactly to one input x_i



LSTM

POS Tagging

- POS Tagging is a disambiguation task
  - Words are ambiguous - they have more than one possible POS
  - Goal is to find the correct tag for any given situation
- Example
  - 'book' can be a verb (<u>book</u> that flight) or a noun (hand me that <u>book</u>).

- There are many ways you can build a POS tagger
  - Rule-based taggers
    - Set of possible POS for a word >> hand-crafted disambiguation rules
    - EngCG tagger >> 56,000 entries each with a set of morphological and syntactic features
  - Transformation-based taggers
    - Supervised learning of tagging rules + small set of hand-crafted templates
    - Brill tagger
  - Hidden Markov Model (HMM) >> this lecture
  - Conditional Random Fields (CRF) >> NER lecture

Break

- Panopto Quiz - discussion point
- What would be the PENN Treebank POS tags for the following sentence:
  "At the same time, it develops multinational operations"

IN DT NN NN , PRP VBZ NN NNS
IN DT NN NN , VBG VBZ NN NNS
IN DT JJ NN , VBG VBZ JJ NNS
IN DT JJ NN , PRP VBZ JJ NNS
IN DT JJ RB , PRP VBZ JJ NNS

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NN	sing or mass noun	*llama*	SYM	symbol	*+,%, &*	WRB	wh-adverb	*how, where*

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- What would be the PENN Treebank POS tags for the following sentence: "At the same time, it develops multinational operations"

IN DT NN NN , PRP VBZ NN NNS
IN DT NN NN , VBG VBZ NN NNS
IN DT JJ NN , VBG VBZ JJ NNS
IN DT JJ NN , PRP VBZ JJ NNS
IN DT JJ RB , PRP VBZ JJ NNS

Verb 3rd person singular

Personal Pronoun

Preposition

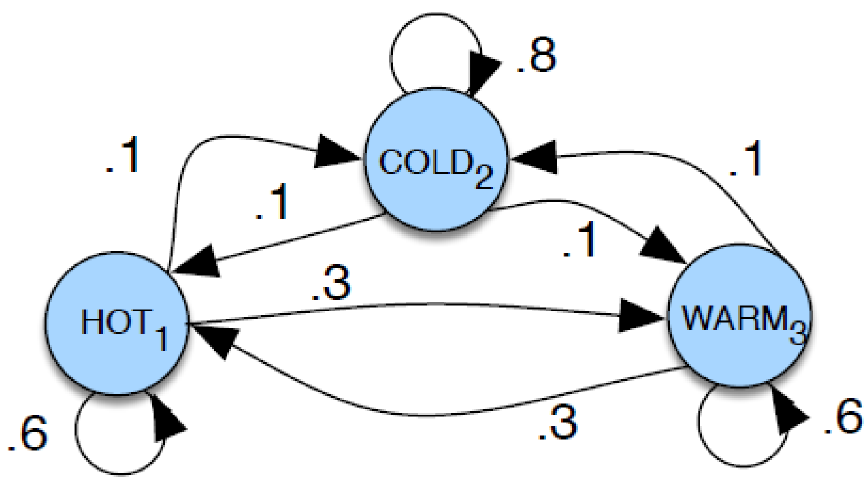
Adjective

Hidden Markov Model (HMM) POS tagger

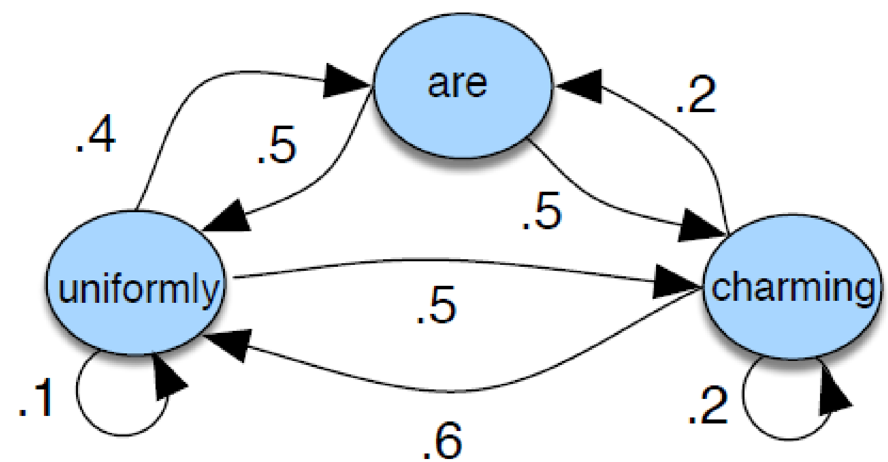
- Markov chain
  - Model of the probability of a next state given the current state
  - Very strong assumption >> future depends only on current state (not past)
  - State = set of variables (words)
- Sequence of state variables = $q_1, q_2, \ldots q_i$

$$\textbf{Markov Assumption:} \quad P(q_i = a|q_1 \ldots q_{i-1}) = P(q_i = a|q_{i-1})$$

- Prob of state q_i depends only on state q_{i-1}



(a)



(b)

Hidden Markov Model (HMM) POS tagger

- Markov chain
  - Model of the probability of a next state given the current state
  - Very strong assumption >> future depends only on current state (not past)
  - State = set of variables (words)
- Sequence of state variables = q_1, q_2, ... q_i

Markov Assumption: $P(q_i = a|q_1 ... q_{i-1}) = P(q_i = a|q_{i-1})$

- Markov Model >> all events (words and tags) must be observed

$Q = q_1 q_2 \dots q_N$	a set of N **states**
$A = a_{11} a_{12} \dots a_{N1} \dots a_{NN}$	a **transition probability matrix** A, each a_{ij} representing the probability of moving from state i to state j, s.t. $\sum_{j=1}^{n} a_{ij} = 1 \quad \forall i$
$\pi = \pi_1, \pi_2, ..., \pi_N$	an **initial probability distribution** over states. π_i is the probability that the Markov chain will start in state i. Some states j may have $\pi_j = 0$, meaning that they cannot be initial states. Also, $\sum_{i=1}^{n} \pi_i = 1$

Hidden Markov Model (HMM) POS tagger

- Hidden Markov Model >> POS tags are hidden states, which we must infer from observed words

Markov Assumption: $P(q_i|q_1,\ldots,q_{i-1}) = P(q_i|q_{i-1})$

Output Independence: $P(o_i|q_1,\ldots q_i,\ldots,q_T,o_1,\ldots,o_i,\ldots,o_T) = P(o_i|q_i)$

$Q = q_1 q_2 \ldots q_N$	a set of N **states**
$A = a_{11} \ldots a_{ij} \ldots a_{NN}$	a **transition probability matrix** A, each a_{ij} representing the probability of moving from state i to state j, s.t. $\sum_{j=1}^{N} a_{ij} = 1 \quad \forall i$
$O = o_1 o_2 \ldots o_T$	a sequence of T **observations**, each one drawn from a vocabulary $V = v_1, v_2, \ldots, v_V$
$B = b_i(o_t)$	a sequence of **observation likelihoods**, also called **emission probabilities**, each expressing the probability of an observation o_t being generated from a state q_i
$\pi = \pi_1, \pi_2, \ldots, \pi_N$	an **initial probability distribution** over states. π_i is the probability that the Markov chain will start in state i. Some states j may have $\pi_j = 0$, meaning that they cannot be initial states. Also, $\sum_{i=1}^{n} \pi_i = 1$

Hidden Markov Model (HMM) POS tagger

- Compute A matrix (tag transition probability) by counting
- WSJ corpus >> MD occurs 13124 times, and is followed by VB 10471 times

$$P(t_i|t_{i-1}) = \frac{C(t_{i-1},t_i)}{C(t_{i-1})} \qquad P(VB|MD) = \frac{C(MD,VB)}{C(MD)} = \frac{10471}{13124} = .80$$

- Compute B matrix (word observation probability) by counting
- WSJ corpus >> Of the 13124 occurrences of MD, it is associated with the word 'will' 4046 times

$$P(w_i|t_i) = \frac{C(t_i,w_i)}{C(t_i)} \qquad P(will|MD) = \frac{C(MD,will)}{C(MD)} = \frac{4046}{13124} = .31$$

- If we were going to generate a MD tag, how likely is it that this tag will have the word 'will'?

Hidden Markov Model (HMM) POS tagger

- Decoding = Given a model and a sequence of observations ($w_1 \ldots w_n$), find the most probable sequence of states ($t_1 \ldots t_n$)

$$\hat{t}_{1:n} = \underset{t_1 \ldots t_n}{\operatorname{argmax}} P(t_1 \ldots t_n | w_1 \ldots w_n)$$

- Apply Bayes' rule

$$P(x|y) = \frac{P(y|x)P(x)}{P(y)} \qquad \hat{t}_{1:n} = \underset{t_1 \ldots t_n}{\operatorname{argmax}} \frac{P(w_1 \ldots w_n | t_1 \ldots t_n) P(t_1 \ldots t_n)}{P(w_1 \ldots w_n)}$$

- Probability of seq of words does not vary by tag seq (so drop it)

$$\hat{t}_{1:n} = \underset{t_1 \ldots t_n}{\operatorname{argmax}} P(w_1 \ldots w_n | t_1 \ldots t_n) P(t_1 \ldots t_n)$$

POS

$P(x_i | x_{i-1})$

Hidden Markov Model (HMM) POS tagger

- Decoding (from last slide)

$$\hat{t}_{1:n} = \underset{t_1 \ldots t_n}{\operatorname{argmax}} P(w_1 \ldots w_n | t_1 \ldots t_n) P(t_1 \ldots t_n)$$

- Assumptions
  - Probability of word depends only on tag (independent on neighbours)
  - Probability of tag depends only on previous tag (bigram)

$$P(w_1 \ldots w_n | t_1 \ldots t_n) \approx \prod_{i=1}^{n} P(w_i | t_i) \qquad P(t_1 \ldots t_n) \approx \prod_{i=1}^{n} P(t_i | t_{i-1})$$

Matrix B Matrix A

- Decoding (using matrix A and B)

$$\hat{t}_{1:n} = \underset{t_1 \ldots t_n}{\operatorname{argmax}} P(t_1 \ldots t_n | w_1 \ldots w_n) \approx \underset{t_1 \ldots t_n}{\operatorname{argmax}} \prod_{i=1}^{n} \overbrace{P(w_i | t_i)}^{\text{emission}} \overbrace{P(t_i | t_{i-1})}^{\text{transition}}$$

Hidden Markov Model (HMM) POS tagger

- The Viterbi Algorithm is an efficient algorithm for HMM decoding using dynamic programming

function VITERBI(*observations* of len T,*state-graph* of len N) **returns** *best-path*, *path-prob*

create a path probability matrix *viterbi[N,T]*
for each state s **from** 1 **to** N **do** ; initialization step
  $viterbi[s,1] \leftarrow \pi_s * b_s(o_1)$
  $backpointer[\mathrm{s},1] \leftarrow 0$
for each time step t **from** 2 **to** T **do** ; recursion step
  for each state s **from** 1 **to** N **do**
    $viterbi[\mathrm{s,t}] \leftarrow \max_{s'=1}^{N} \; viterbi[s',t-1] * a_{s',s} * b_s(o_t)$
    $backpointer[\mathrm{s,t}] \leftarrow \operatorname{argmax}_{s'=1}^{N} \; viterbi[s',t-1] * a_{s',s} * b_s(o_t)$
$bestpathprob \leftarrow \max_{s=1}^{N} \; viterbi[s,T]$; termination step
$bestpathpointer \leftarrow \operatorname{argmax}_{s=1}^{N} \; viterbi[s,T]$; termination step
bestpath ← the path starting at state *bestpathpointer*, that follows backpointer[] to states back in time
return *bestpath*, *bestpathprob*

- Exercise >> Run through worked example of the Viterbi algorithm from 3rd edition (online) chapter 8 of course text

Required Reading

- Sequence Labelling for Parts of Speech
  - Jurafsky and Martin, Speech and Language Processing, 3rd edition (online) >> chapter 8

Questions

- Panopto Quiz - 1 minute brainstorm for interactive questions

  Please write down in Panopto quiz in **1 minute** two or three questions that you would like to have answered at the next interactive session.

  Do it **right now** while its fresh.

  Take a screen shot of your questions and **bring them with you** at the interactive session so you have something to ask.