POS and HMM

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September 23, 2022(Prepared for Fall 2022)

0.1 What are Part-of-Speech (POS) Tags?

Syntactic labels of words: This/DET is/VB a/DET simple/ADJ sentence/NOUN. These abstract away from the core word meanings. Sequences (i.e. legal ordering) are mostly (though not entirely) dependent only on the labels, not by the words themselves.

- Open class words ("content words")
  - nouns, verbs, adjectives, adverbs
  - mostly content-bearing. refer to objects, actions, features in the world
  - open class = there is no limit to what they are or can describe so new ones are added all the time (email, website, defenestrate)
- Closed class words ("function words")
  - pronouns, determiners, prepositions, connectives
  - there are a limited number of these
  - mostly functional: to tie the concepts of a sentence together

How many? It depends. Some kind of annotation standard is needed to decide, e.g., should proper and common nouns be separated? Should singular or plural nouns? Present/past/main/aux verbs?

Penn treebank: fairly detailed set of tags (45 of them) used frequently along with parsing (particularly constituent parsing). Some weird quibbles: why does 'to' get its own tag?

Tag	Description	Example	Tag	Description	Example
CC	coordin. conjunction	*and, but, or*	SYM	symbol	+,%, &
CD	cardinal number	*one, two*	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, sing.	*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*			

J&M Fig 5.6: Penn Treebank POS tags

Morphologically rich languages will often have 'morphosyntactic' tags = detailed breakdown of how the word parts combine, such as 'Noun+A3sg+P2sg+Nom' with possibly thousands of possibilities

Universal dependencies: 17 tags to try to catch phenomena that are distinct across all languages (there is also a 12 tag variant):

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

0.2 Why is it hard?

Why is it always hard? Ambiguity.

glass of **water/NOUN** vs **water/VERB** the plants

lie/VERB down vs tell a **lie/NOUN**

wind/VERB down vs a mighty **wind/NOUN** (note these last are homographs)

time	flies	like	an	arrow
NOUN	VERB	MODAL	DET	NOUN
VERB	NOUN			
ADJ	NOUN	VERB		

What knowledge do we need?

1) A component deciding based on the word itself (some words only nouns, like arrow, some words ambiguous, a priori tag probability)

2) A component deciding based on the tags of surrounding words (a sequence of two determiners is rare, as is two base form verbs. Determiner almost always followed by adjective or nouns

Could we just put this into a linear model, predicting one tag at a time?

0.3 Why do we care?

This is the first step toward full-sentence syntax (structure trees). POS tags can also be used as input to tasks people do care about (sentiment analysis, word sense disambiguation).

In neural network land, could these be inferred automatically as 'features'? With sufficient data, it seems they can, yes. But often there isn't enough data, and linguistic intuition guides the search space, so that we can start off with prior knowledge of meaningful relationships between words.

More importantly, beyond text classification, this is a *sequence labeling* task, and the approaches we learn here, are specifically helpful for this and other sequence labeling tasks, of which here are two:

- Named Entity Recognition (NER): label words as beginning to persons (PER), organizations (ORG), locations (LOC), or none of the above: Barack/PER Obama/PER spoke/N from/N the/N White/LOC House/LOC today/N ./N
- Information field segmentation: Given specific text type (e.g. classified ad), find which words belong to which "fields" for db creation (price/size/location, author/title/year): 3BR/SIZE apt/TYPE in/N West/LOC Adams/LOC ,/N near/LOC USC/LOC ./N Bright/FEAT ,/N well/FEAT maintained/FEAT ...

Key features of sequence labeling: Correct label depends on

- item to be labeled (NER: Smith is probably a person. POS: chair is probably a noun)
- labels of surrounding items (NER: if following word is an organization (e.g. Corp.), then this word is more likely to be an organization. POS: if preceding word is a modal verb (e.g. will), then this word is more likely to be a verb)

The Hidden Markov Model (HMM) combines these sources probabilistically.

0.4 Bayes' Law and Assumptions again

For word sequence $W = w_1, \ldots, w_n$ we want the most likely tag sequence $T = t_1, ..., t_n$, i.e.

$$\text{argmax}_T \, P(T|W) = \text{argmax}_T \, P(W|T)P(T)$$

Then we make some simplifying assumptions:

$$1) P(W|T) = P(w_1, \ldots, w_n|t_1, \ldots, t_n) = P(w_1|w_2, \ldots, w_n, t_1, \ldots, t_n)P(w_2|\ldots)\ldots P(w_n|t_1, \ldots, t_n)$$

$$\approx P(w_1|t_1)P(w_2|t_2)\dots P(w_n|t_n)$$

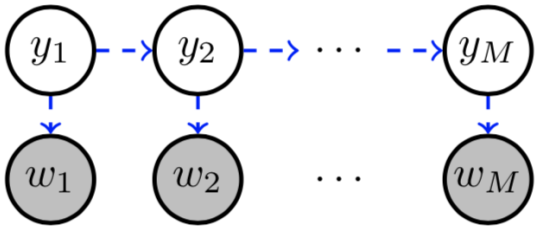
In other words we assume independence of all words and tags except w_i and t_i.

$$2)P(T) = P(t_1,\dots,t_n) = P(t_n|t_{n-1},\dots,t_1)P(t_{n-1}|t_{n-2},\dots,t_1)$$

$$\approx P(t_n|t_{n-1})P(t_{n-1}|t_{n-2})\dots P(t_2|t_1)P(t_1)$$

In other words we assume a tag is conditioned only on the previous tag. This is called the 'Markov' assumption.

We call $P(W|T)$ the *emission probability* and $P(T)$ the *transition probability*. A plate diagram helps (this is fig. 7.2 of Eisenstein):



Small implementation note: there's no specific conditioning on the beginning or ending of a sentence, but it does seem like a good kind of probability to have. So in practice we can imagine sentences all beginning with, e.g. 'BOS' and ending with 'EOS'. Note the probability of the first tag is $P(t_1)$ with no conditioning, but since the first tag is always the same (and the same word is always drawn from it) we don't need to include those probabilities. It is, however, helpful to know $P(t_2|\text{BOS})$ and to include a proper draw for ending, i.e. $P(\text{EOS}|t_n)$.

These probabilities are generally learned empirically and then smoothed (it's much more important to smooth the emission probabilities...why?). Here are tables of empirically learned probabilities (these are from Jurafsky and Martin):

$t_{i-1}\backslash t_i$	NNP	MD	VB	JJ	NN	...
<s>	0.2767	0.0006	0.0031	0.0453	0.0449	...
NNP	0.3777	0.0110	0.0009	0.0084	0.0584	...
MD	0.0008	0.0002	0.7968	0.0005	0.0008	...
VB	0.0322	0.0005	0.0050	0.0837	0.0615	...
JJ	0.0306	0.0004	0.0001	0.0733	0.4509	...
...	...	...	...	...	...	...

$t_i\backslash w_i$	Janet	will	back	the	...
NNP	0.000032	0	0	0.000048	...
MD	0	0.308431	0	0	...
VB	0	0.000028	0.000672	0	...
DT	0	0	0	0.506099	...
...	...	...	...	...	...

So here are the probabilities that would be used to calculate the probability of the tagged sentence Time/NOUN flies/VERB like/MODAL an/DET arrow/NOUN:

BOS	Time	flies	like	an	arrow	EOS
	$P(\text{N}\|\text{BOS})$	$P(\text{V}\|\text{N})$	$P(\text{M}\|\text{V})$	$P(\text{D}\|\text{M})$	$P(\text{N}\|\text{D})$	$P(\text{EOS}\|\text{N})$
	$P(\text{time}\|\text{N})$	$P(\text{flies}\|\text{V})$	$P(\text{like}\|\text{M})$	$P(\text{an}\|\text{D})$	$P(\text{arrow}\|\text{N})$	

0.5 Viterbi Search

Things become tricky when trying to tag a new sequence; we want, remember, $\text{argmax}_T\, P(W,T)$ but finding this requires searching over the exponential number of sequences; even for a 5

word sequence over the 17-tag UD set, that's $17^5 = 1,419,857$ sequences. We turn instead to the Viterbi algorithm, a dynamic programming algorithm which uses the following intuition:

If we are at word $n-1$ and have already calculated the best tag sequence ending in each of the 17 tag types at word $n-1$, then the best tag sequence to word n (which has tag EOS) is one of 17 options: the best tag sequence to word $n-1$ ending in tag 1 times the score for tag 1 to EOS, etc.

But the best tag sequence to tag 1 at word $n-1$ is one of 17 options: the best tag sequence to $n-2$ ending in tag 1 times the score for transition from tag 1 to tag 1 (times the emission for word $n-1$ with tag 1), etc.

To make things complete, we assume all sequences start with a special BOS word that has an emission probability of 1 for the BOS tag

It's helpful to work through the following chart using the provided statistics; we'll do this in class (note that in code you probably want to add logs instead of multiplying probs):

```
for t in range(tagset):
  score[t][0] = emis[BOS][t]
for i, w in enumerate(words[1:]):
  for t in range(tagset):
    score[t][i] = max(score[:,i-1]*trans[t,:]*emis[w][t])
```

trans	N	V	D	P	A	EOS
BOS	.3	.1	.3	.2	.1	0
N	.2	.4	.01	.3	.04	.05
V	.3	.05	.3	.2	.1	.05
D	.9	.01	.01	.01	.07	0
P	.4	.05	.4	.1	.05	0
A	.1	.5	.1	.1	.1	.1

emis	BOS	a	cat	doctor	in	is	the	very
BOS	1	0	0	0	0	0	0	0
N	0	0	.5	.4	0	.1	0	0
V	0	0	0	.1	0	.9	0	0
D	0	.3	0	0	0	0	.7	0
P	0	0	0	0	1	0	0	0
A	0	0	0	0	.1	0	0	.9

v	w0=BOS	w1=the	w2=doctor	w3=is	w4=in	EOS
BOS	1	0	0	0	0	0
EOS	0	0	0	0	0	.000027216
N	0	0	.0756	.001512	0	0
V	0	0	.00021	.027216	0	0
D	0	.21	0	0	0	0
P	0	0	0	0	.0054432	0
A	0	0	0	0	.00027216	0

0.6 OK, but what about more interesting features and discriminative models?

In fact, we can use the perceptron algorithm here, just as we used it for simple whole-text label prediction. Let's revisit perceptron:

```
def train(labeled_sentences, options, featsize):
```

```
  # should be a better way to determine feat size
  # probably want to initialize differently
  model = {'theta': np.random(featsize)}
  for i in range(iterations): # user-determined
    for sentence, label in labeled_sentences:
      hyp = classify(sentence, options, model)
      if hyp != label:
        model['theta'] += features(sentence, label)-features(sentence, hyp)
  return model
def classify(sentence, options, model):
  scores = {}
  for option in options:
    scores[option] = evaluate(sentence, option, model)
  return max(scores.items(), key=operator.itemgetter(1))[0]
```

The real problem is the `classify` function, which I included here, or actually the `options` set. The point of `classify` is to find the maximum scoring sequence over all options. In sentiment classification there were only three sentiments, so you could just do 3 lookups and choose the best. But if there are t possible tags and the sequence is n words long, there are t^k possible *sequences*. Thankfully, dynamic programming in general (and the Viterbi algorithm specifically) lets us efficiently find the maximum score sequence. This then becomes what is known as *structured perceptron* since you are ultimately learning to predict the structured sequence of labels, and not just a single label at a time. We are no longer constrained to the emission and transition probabilities.

Here is the viterbi algorithm, rewritten to use general features, assuming an appropriate current θ and a `feats` function which returns features based on the last label t', the current word w, and the proposed current label t (column vector notation won't work here but the complexity hasn't increased despite the deeper nesting):

```
for t in range(tagset):
  score[t][0] = theta*feats(emptyset, BOS, t)
for i, w in enumerate(words[1:]):
  for t in range(tagset):
    score[t][i] = -infty
    for s in range(tagset):
      score[t][i] = max(score[t][i], score[s][i-1]*theta*feats(s, w, t))
```

What about logistic regression? Yes, this can be done as well (logistic regression over structures is called *conditional random fields* and the specific dependencies we allow make this a *linear chain conditional random field*), but it again requires efficiency changes, now to both inference and learning. For inference we have already seen how to efficiently calculate; the Viterbi algorithm is used to determine the argmax sequence. Because of the probabilistic nature of logistic regression, we need to calculate the sum of all scores (the denominator of softmax); this is an important component in gradient calculation. This can be calculated with a slight variant to the Viterbi algorithm called the *Forward algorithm* and its counterpart, the *Backward algorithm*.

Compare the Forward algorithm to the previous Viterbi algorithm:

```
for t in range(tagset):
  score[t][0] = theta*feats(\emptyset, BOS, t)
for i, w in enumerate(words[1:]):
  for t in range(tagset):
    score[t][i] = 0
    for s in range(tagset):
      score[t][i] += score[s][i-1]*theta*feats(s, w, t)
```

This calculates the partial score of **all** sequence labels from word 0 to t. The Backward algorithm does the same calculation, but starts at the end of the sequence:

```
for t in range(tagset):
  score[t][n] = 1
for i, w in reversed(enumerate(words)):
  for s in range(tagset):
    score[s][i] = 0
    for t in range(tagset):
      score[s][i] += score[t][i+1]*theta*feats(s, w, t)
```

Rather than directly calculate features, naturally, we can use neural networks, and this is in practice what is done today. However, the issue of exponential search still applies. Features are calculated via a bidirectional RNN and those features are provided to a CRF. The whole thing is differentiable and can be learned jointly (and is implemented using frameworks like PyTorch). The set of features for each possibility is also calculatable via the same dynamic programming approach used to calculate Forward/Viterbi.