Part of Speech Tagging

Informatics 2A: Lecture 16

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1. Automatic POS tagging: the problem

2. Methods for tagging
   - Unigram tagging
   - Bigram tagging
   - Tagging using Hidden Markov Models: Viterbi algorithm

Reading: Jurafsky & Martin, chapters (5 and) 6.

Benefits of Part of Speech Tagging

- Essential preliminary to (anything that involves) parsing.
- Can help with **speech synthesis**. For example, try saying the sentences below out loud.
- Can help with **determining authorship**: are two given documents written by the same person? Forensic linguistics.

1. *Have you read 'The Wind in the Willows'?* (noun)
2. *The clock has stopped. Please wind it up.* (verb)
3. *The students tried to protest.* (verb)
4. *The students' protest was successful.* (noun)

Corpus annotation

A corpus (plural corpora) is a computer-readable collection of NL text (or speech) used as a source of information about the language: e.g. what words/constructions can occur in practice, and with what frequencies.
The usefulness of a corpus can be enhanced by *annotating* each word with a POS tag, e.g.

```
Our/PRP\$ enemies/NNS are/VBP innovative/JJ and/CC
resourceful/JJ ,/, and/CC so/RB are/VB we/PRP ./.
They/PRP never/RB stop/VB thinking/VBG about/IN new/JJ
ways/NNS to/TO harm/VB our/PRP\$ country/NN and/CC
our/PRP\$ people/NN, and/CC neither/DT do/VB we/PRP ./.
```

Typically done by an automatic tagger, then hand-corrected by a native speaker, in accordance with specified tagging guidelines.

POS tagging: difficult cases

Even for humans, tagging sometimes poses difficult decisions.

Various tests can be applied, but they don't always yield clear answers.

E.g. Words in -ing: adjectives (JJ), or verbs in gerund form (VBG)?

a boring/JJ lecture	a *very* boring lecture
	? a lecture that bores
the falling/VBG leaves	*the *very* falling leaves
	the leaves that fall
a revolving/VBG? door	*a *very* revolving door
	a door that revolves
	*the door seems revolving
sparkling/JJ? lemonade	? *very* sparkling lemonade
	lemonade that sparkles
	the lemonade seems sparkling

In view of such problems, we can't expect 100% accuracy from an automatic tagger.

Word types and tokens

- Need to distinguish word tokens (particular occurrences in a text) from word types (distinct vocabulary items).
- We'll count different inflected or derived forms (e.g. break, breaks, breaking) as distinct word types.
- A single word type (e.g. **still**) may appear with several POS.
- But most words have a clear most frequent POS.

Question: How many tokens and types in the following? Ignore case and punctuation.

> *Esau sawed wood. Esau Wood would saw wood. Oh, the wood Wood would saw!*

1. 14 tokens, 6 types
2. 14 tokens, 7 types
3. 14 tokens, 8 types
4. None of the above.

Extent of POS Ambiguity

The Brown corpus (1,000,000 word tokens) has 39,440 different word types.

- 35340 have only 1 POS tag anywhere in corpus (89.6%)
- 4100 (10.4%) have 2 to 7 POS tags

So why does just 10.4% POS-tag ambiguity by word type lead to difficulty?
This is thanks to *Zipfian distribution*: many high-frequency words have more than one POS tag.
In fact, more than 40% of the word tokens are ambiguous.

He wants **to/TO** go.	He wants **that/DT** hat.
He went **to/IN** the store.	It is obvious **that/CS** he wants a hat.
	He wants a hat **that/WPS** fits.

Some tagging strategies

We'll look at several methods or strategies for automatic tagging.

- One simple strategy: just assign to each word its *most common tag*. (So **still** will *always* get tagged as an adverb — never as a noun, verb or adjective.) Call this *unigram* tagging, since we only consider one token at a time.
- Surprisingly, even this crude approach typically gives around 90% accuracy. (State-of-the-art is 96–98%).
- Can we do better? We'll look briefly at bigram tagging, then at Hidden Markov Model tagging.

Bigram tagging

We can do much better by looking at *pairs of adjacent tokens*.

For each word (e.g. **still**), tabulate the frequencies of each possible POS *given the POS of the preceding word*.

Example (with made-up numbers):

still	DT	MD	JJ	...
NN	8	0	6	
JJ	23	0	14	
VB	1	12	2	
RB	6	45	3	

Given a new text, tag the words from left to right, assigning each word the most likely tag given the preceding one.

Could also consider trigram (or more generally n-gram) tagging, etc. But the frequency matrices would quickly get very large, and also (for realistic corpora) too 'sparse' to be really useful.

Problems with bigram tagging

- One incorrect tagging choice might have knock-on effects:

	The	still	smoking	remains	of	the	campfire
Intended:	DT	RB	VBG	NNS	IN	DT	NN
Bigram:	DT	JJ	NN	VBZ	. . .		

- No lookahead: choosing the 'most probable' tag at one stage might lead to highly improbable choice later.

	The	still	was	smashed
Intended:	DT	NN	VBD	VBN
Bigram:	DT	JJ	VBD?	

We'd prefer to find the *overall most likely* tagging sequence given the bigram frequencies. This is what the Hidden Markov Model (HMM) approach achieves.

Hidden Markov Models

- The idea is to model the agent that might have generated the sentence by a semi-random process that outputs a sequence of words.
- Think of the output as visible to us, but the internal states of the process (which contain POS information) as hidden.
- For some outputs, there might be several possible ways of generating them i.e. several sequences of internal states. Our aim is to compute the sequence of hidden states with the highest probability.
- Specifically, our processes will be 'NFAs with probabilities'. Simple, though not a very flattering model of human language users!

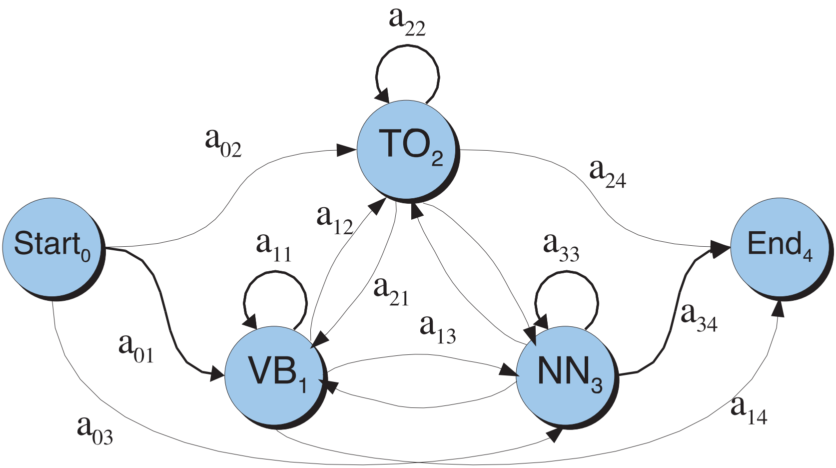
Definition of Hidden Markov Models

For our purposes, a Hidden Markov Model (HMM) consists of:

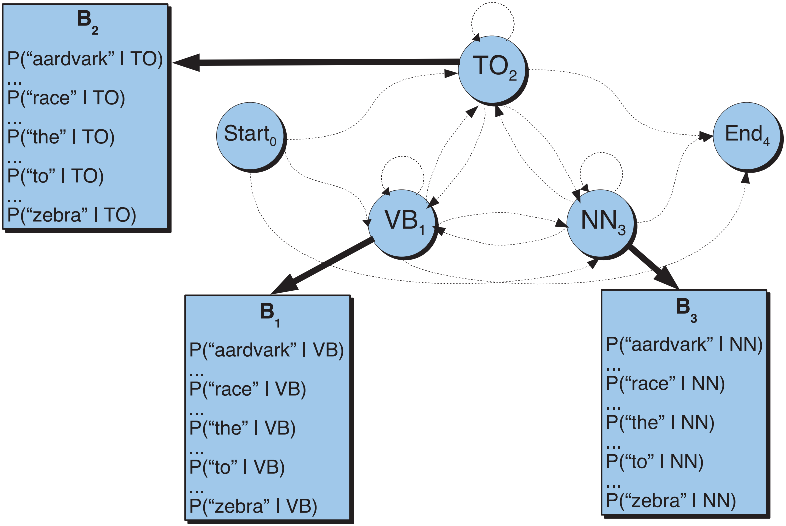
- A set $Q = \{q_0, q_1, \ldots, q_n\}$ of states, with q_0 the start state. (Our non-start states will correspond to *parts-of-speech*).
- A transition probability matrix $A = (a_{ij} \mid 0 \leq i \leq n, 1 \leq j \leq n)$, where a_{ij} is the probability of jumping from q_i to q_j. For each i, we require $\sum_{j=1}^{n} a_{ij} = 1$.
- For each non-start state q_i and word type w, an emission probability $b_i(w)$ of outputting w upon entry into q_i. (Ideally, for each i, we'd have $\sum_w b_i(w) = 1$.)

We also suppose we're given an observed sequence $w_1, w_2 \ldots, w_T$ of word tokens generated by the HMM.

Transition Probabilities



Emission Probabilities



Transition and Emission Probabilities

	VB	TO	NN	PPPS
<s>	.019	.0043	.041	.67
VB	.0038	.035	.047	.0070
TO	.83	0	.00047	0
NN	.0040	.016	.087	.0045
PPPS	.23	.00079	.001	.00014

	I	want	to	race
VB	0	.0093	0	.00012
TO	0	0	.99	0
BB	0	.000054	0	.00057
PPSS	.37	0	0	0

How Do we Search for Best Tag Sequence?

We have defined an HMM, but how do we use it? We are given a **word sequence** and must find their corresponding **tag sequence**.

- It's easy to compute the probability of generating a word sequence $w_1 \dots w_T$ via a specific tag sequence $t_1 \dots t_T$: let t_0 denote the start state, and compute

$$\prod_{i=1}^{n} P(t_i|t_{i-1}).P(w_i|t_i) \tag{1}$$

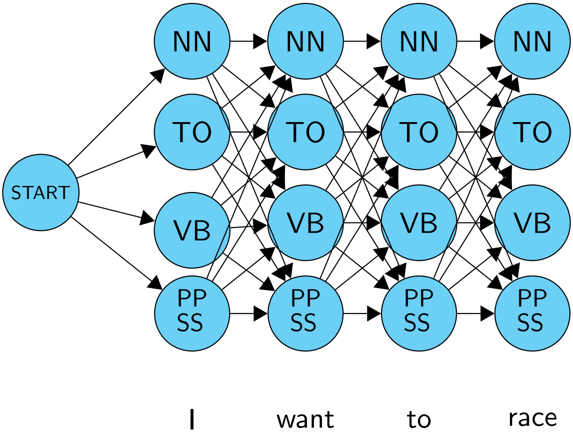
  using the transition and emission probabilities.
- But how do we find the most likely tag sequence?
- We can do this efficiently using **dynamic programming** and the **Viterbi algorithm**.

Question

Given n word tokens and on average T choices per token, how many tag sequences do we have to evaluate?

1. $|T|$ tag sequences
2. n tag sequences
3. $|T| \times n$ tag sequences
4. $|T|^n$ tag sequences

The HMM trellis



The Viterbi Algorithm

q_4	NN	0				
q_3	TO	0				
q_2	VB	0				
q_1	PPSS	0				
q_o	start	**1.0**				
		<s>	I	want	to	race
			w_1	w_2	w_3	w_4

1. Create probability matrix, with one column for each observation (i.e., word token), and one row for each non-start state (i.e., POS tag).
2. We proceed by filling cells, column by column.
3. The entry in column i, row j will be the **probability of the most probable route to state** q_j **that emits** $w_1 \dots w_i$.

The Viterbi Algorithm

q_4	NN	0	$1.0 \times .041 \times 0$			
q_3	TO	0	$1.0 \times .0043 \times 0$			
q_2	VB	0	$1.0 \times .19 \times 0$			
q_1	PPSS	0	$1.0 \times .67 \times .37$			
q_o	start	**1.0**				
		<s>	I	want	to	race
			w_1	w_2	w_3	w_4

- For each state q_j at time i, compute $v_i(j) = \max_{k=1}^{n} v_{i-1}(k) a_{kj} b_j(w_i)$
- $v_{i-1}(k)$ is **previous Viterbi path probability**, a_{kj} is **transition probability**, and $b_j(w_i)$ is **emission probability**.
- There's also an (implicit) **backpointer** from cell (i, j) to the relevant $(i-1, k)$, where k maximizes $v_{i-1}(k) a_{kj}$.

The Viterbi Algorithm

q_4	NN	0	0	$.025 \times .0012 \times 0.000054$		
q_3	TO	0	0	$.025 \times .00079 \times 0$		
q_2	VB	0	0	$.025 \times .23 \times .0093$		
q_1	PPSS	0	**.025**	$.025 \times .00014 \times 0$		
q_0	start	**1.0**				
		<s>	I	want	to	race
			w_1	w_2	w_3	w_4

- For each state q_j at time i, compute $v_i(j) = \max_{k=1}^{n} v_{i-1}(k) a_{kj} b_j(w_i)$
- $v_{i-1}(k)$ is **previous Viterbi path probability**, a_{kj} is **transition probability**, and $b_j(w_i)$ is **emission probability**.
- There's also an (implicit) **backpointer** from cell (i, j) to the relevant $(i-1, k)$, where k maximizes $v_{i-1}(k) a_{kj}$.

The Viterbi Algorithm

q_4	NN	0	0	.000000002	.000053 × .047 × 0	
q_3	TO	0	0	0	.000053 × .035 × .99	
q_2	VB	0	0	**.00053**	.000053 × .0038 × 0	
q_1	PPSS	0	**.025**	0	.000053 × .0070 × 0	
q_0	start	**1.0**				
		<s>	I	want	to	race
			w_1	w_2	w_3	w_4

- For each state q_j at time i, compute $v_i(j) = \max_{k=1}^{n} v_{i-1}(k) a_{kj} b_j(w_i)$
- $v_{i-1}(k)$ is **previous Viterbi path probability**, a_{kj} is **transition probability**, and $b_j(w_i)$ is **emission probability**.
- There's also an (implicit) **backpointer** from cell (i, j) to the relevant $(i-1, k)$, where k maximizes $v_{i-1}(k) a_{kj}$.

The Viterbi Algorithm

q_4	NN	0	0	.000000002	0	.0000018 × .00047 × .00057
q_3	TO	0	0	0	**.0000018**	.0000018×0×0
q_2	VB	0	0	**.00053**	0	.0000018×.83×.00012
q_1	PPSS	0	**.025**	0	0	.0000018 × 0 × 0
q_0	start	**1.0**				
		<s>	I	want	to	race
			w_1	w_2	w_3	w_4

- For each state q_j at time i, compute $v_i(j) = \max_{k=1}^{n} v_{i-1}(k) a_{kj} b_j(w_i)$
- $v_{i-1}(k)$ is **previous Viterbi path probability**, a_{kj} is **transition probability**, and $b_j(w_i)$ is **emission probability**.
- There's also an (implicit) **backpointer** from cell (i, j) to the relevant $(i-1, k)$, where k maximizes $v_{i-1}(k)a_{kj}$.

The Viterbi Algorithm

q_4	NN	0	0	.000000002	0	4.8222e-13
q_3	TO	0	0	0	**.0000018**	0
q_2	VB	0	0	**.00053**	0	**1.7928e-10**
q_1	PPSS	0	**.025**	0	0	0
q_0	start	**1.0**				
		<s>	I	want	to	race
			w_1	w_2	w_3	w_4

- For each state q_j at time i, compute
  $v_i(j) = \max_{k=1}^{n} v_{i-1}(k) a_{kj} b_j(w_i)$
- $v_{i-1}(k)$ is **previous Viterbi path probability**, a_{kj} is **transition probability**, and $b_j(w_i)$ is **emission probability**.
- There's also an (implicit) **backpointer** from cell (i,j) to the relevant $(i-1,k)$, where k maximizes $v_{i-1}(k)a_{kj}$.

The Viterbi algorithm: second example

Let's now tag the newspaper headline:

deal talks fail

Note that each token here could be a noun (N) or a verb (V).
We'll use a toy HMM given as follows:

	to N	to V
from start	.8	.2
from N	.4	.6
from V	.8	.2

Transitions

	deal	fail	talks
N	.2	.05	.2
V	.3	.3	.3

Emissions

The Viterbi matrix

This time we'll omit the (trivial) first column, but show more of the working, as well as the backtrace pointers.

	deal	talks	fail
N	$.8\text{x}.2 = .16$	$\leftarrow .16\text{x}.4\text{x}.2 = .0128$ (since $.16\text{x}.4 > .06\text{x}.8$)	$\swarrow .0288\text{x}.8\text{x}.05 = .001152$ (since $.0128\text{x}.4 < 0.0288\text{x}.8$)
V	$.2\text{x}.3 = .06$	$\nwarrow .16\text{x}.6\text{x}.3 = .0288$ (since $.16\text{x}.6 > .06\text{x}.2$)	$\nwarrow .0128\text{x}.6\text{x}.3 = .002304$ (since $.0128\text{x}.6 > 0.0288\text{x}.2$)

Looking at the highest probability entry in the final column and chasing the backpointers, we see that the tagging N N V wins.