# Language Technology

http://cs.lth.se/edan20/

Chapter 8: Part-of-Speech Tagging Using Stochastic Techniques

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# Training Set

1 A /

Part-of-speech taggers use a training set where every word is hand-annotated (Penn Treebank and CoNLL 2008).

Index	Word	Hand annotation	Index	Word	Hand a	nnotation
1	Battle	JJ	19	of	IN	
2	_	HYPH	20	their	PRP\$	
3	tested	JJ	21	countrymen	NNS	
4	Japanese	JJ	22	to	TO	
5	industrial	JJ	23	visit	VB	
6	managers	NNS	24	Mexico	NNP	
7	here	RB	25	,	,	
8	always	RB	26	a	DT	
9	buck	VBP	27	boatload	NN	
10	up	RP	28	of	IN	
11	nervous	JJ	29	samurai	FW	
12	newcomers	NNS	30	warriors	NNS	
13	with	IN	31	blown	VBN	
14	the	DT	32	ashore	RB	The same of
15	tale	NN	33	375	CD	
16	of	IN	34	years	NNS	一
17	the	DT	35	ago	RB	
18	first	JJ	36	. (0)(5	<b>→</b> ← <b>=</b> →	

# Part-of-Speech Tagging with Linear Classifiers

Linear classifiers are efficient devices to carry out part-of-speech tagging:

- The lexical values are the input data to the tagger.
- The parts of speech are assigned from left to right by the tagger.

Given the feature vector:  $(w_{i-2}, w_{i-1}, w_i, w_{i+1}, w_{i+2}, t_{i-2}, t_{i-1})$ , the classifier will predict the part-of-speech tag  $t_i$  at index i.

ID	FORM	PPOS	
	BOS	BOS	Padding
	BOS	BOS	
1	Battle	NN	
2	-	HYPH	
3	tested	NN	
	***		
17	the	DT	
18	first	JJ	
19	of	IN	
20	their	PRP\$	
21	countrymen	NNS	Input features
22	to	TO	
23	visit	VB	Predicted tag
24	Mexico		↓
25			
26	a		
27	boatload		
34	years		
35	ago		
36			
	EOS		Padding
	EOS		

#### Feature Vectors

ID	Feature vectors							PPOS
	$W_{i-2}$	$w_{i-1}$	$w_i$	$w_{i+1}$	$W_{i+2}$	$t_{i-2}$	$t_{i-1}$	
1	BOS	BOS	Battle	-	tested	BOS	BOS	NN
2	BOS	Battle	-	tested	Japanese	BOS	NN	HYPH
3	Battle	-	tested	Japanese	industrial	NN	HYPH	JJ
19	the	first	of	their	countrymen	DT	JJ	IN
20	first	of	their	countrymen	to	JJ	IN	PRP\$
21	of	their	countrymen	to	visit	IN	PRP\$	NNS
22	their	countrymen	to	visit	Mexico	PRP\$	NNS	TO
23	countrymen	to	visit	Mexico	,	NNS	TO	VB
24	to	visit	Mexico	,	a	TO	VB	NNP
25	visit	Mexico		a	boatload	VB	NNP	,
34	ashore	375	years	ago		RB	CD	NNS
35	375	years	ago		EOS	CD	NNS	RB
36	years	ago		EOS	EOS	NNS	RB	27.80

# POS Annotation with the Noisy Channel Model

Modeling the problem:

$$t_1, t_2, t_3, ..., t_n \rightarrow \text{noisy channel} \rightarrow w_1, w_2, w_3, ..., w_n.$$

The optimal part of speech sequence is

$$\hat{T} = \underset{t_1, t_2, t_3, ..., t_n}{\text{arg max}} P(t_1, t_2, t_3, ..., t_n | w_1, w_2, w_3, ..., w_n),$$

The Bayes' rule on conditional probabilities:

$$P(A|B)P(B) = P(B|A)P(A).$$

$$\hat{T} = \arg\max_{T} P(T)P(W|T).$$

P(T) and P(W|T) are simplified and estimated on hand-annocorpora, the "gold standard".

#### The First Term: N-Gram Approximation

$$P(T) = P(t_1, t_2, t_3, ..., t_n) \approx P(t_1)P(t_2|t_1)\prod_{i=3}^n P(t_i|t_{i-2}, t_{i-1}).$$

If we use a start-of-sentence delimiter  $\langle s \rangle$ , the two first terms of the product,  $P(t_1)P(t_2|t_1)$ , are rewritten as  $P(\langle s \rangle)P(t_1|\langle s \rangle)P(t_2|\langle s \rangle,t_1)$ , where  $P(\langle s \rangle)=1$ .

We estimate the probabilities with the maximum likelihood,  $P_{MLE}$ :

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$$P_{MLE}(t_i|t_{i-2},t_{i-1}) = \frac{C(t_{i-2},t_{i-1},t_i)}{C(t_{i-2},t_{i-1})}.$$



#### Sparse Data

If  $N_p$  is the number of the different parts-of-speech tags, there are  $N_p \times N_p \times N_p$  values to estimate.

If data is missing, we can back off to bigrams:

$$P(T) = P(t_1, t_2, t_3, ..., t_n) \approx P(t_1) \prod_{i=2}^n P(t_i|t_{i-1}).$$

Or to unigrams:

$$P(T) = P(t_1, t_2, t_3, ..., t_n) \approx \prod_{i=1}^{n} P(t_i).$$

And finally, we can combine linearly these approximations:

$$P_{LinearInter}(t_i|t_{i-2}t_{i-1}) = \lambda_1 P(t_i|t_{i-2}t_{i-1}) + \lambda_2 P(t_i|t_{i-1}) + \lambda_3 P(t_i|t_{i-1}) + \lambda_3$$

#### The Second Term

The complete word sequence knowing the part-of-speech sequence is usually approximated as:

$$P(W|T) = P(w_1, w_2, w_3, ..., w_n|t_1, t_2, t_3, ..., t_n) \approx \prod_{i=1}^n P(w_i|t_i).$$

Like the previous probabilities,  $P(w_i|t_i)$  is estimated from hand-annotated corpora using the maximum likelihood:

$$P_{MLE}(w_i|t_i) = \frac{C(w_i, t_i)}{C(t_i)}.$$

For  $N_w$  different words, there are  $N_p \times N_w$  values to obtain. But in this case, many of the estimates will be 0.

### The POS Tagging Equation

$$\hat{T} = \underset{T}{\operatorname{arg\,max}} P(T)P(W|T).$$

Using a bigram approximation, we have:

$$\hat{T} = P(t_1) \prod_{i=2}^{n} P(t_i|t_{i-1}) \times \prod_{i=1}^{n} P(w_i|t_i).$$

With:

$$P_{\mathsf{MLE}}(t_i|t_{i-1}) = \frac{C(t_{i-1},t_i)}{C(t_{i-1})}$$

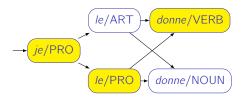
and

$$P_{\mathsf{MLE}}(w_i|t_i) = \frac{C(w_i, t_i)}{C(t_i)}.$$



#### An Example

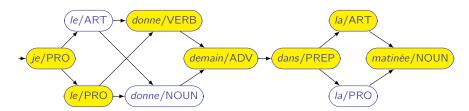
Je le donne 'I give it'



- $P(pro|\emptyset) \times P(art|\emptyset, pro) \times P(verb|pro, art) \times P(je|pro) \times P(le|art) \times P(donne|verb)$
- ②  $P(pro|\emptyset) \times P(art|\emptyset, pro) \times P(noun|pro, art) \times P(je|pro) \times P(le|art) \times P(donne|noun)$
- $P(pro|\emptyset) \times P(pro|\emptyset, pro) \times P(verb|pro, pro) \times P(je|pro) \times P(le|pro) \times P(donne|verb)$
- $P(pro|\emptyset) \times P(pro|\emptyset, pro) \times P(noun|pro, pro) \times P(je|pro) \times P(le|pro) \times P(donne|noun)$

#### Viterbi (Informal)

Je le donne demain dans la matinée 'I give it tomorrow in the morning'





# Viterbi (Informal)

The term brought by the word *demain* has still the memory of the ambiguity of *donne*:  $P(adv|verb) \times P(demain|adv)$  and  $P(adv|noun) \times P(demain|adv)$ .

This is no longer the case with dans.

According to the noisy channel model and the bigram assumption, the term brought by the word dans is  $P(dans|prep) \times P(prep|adv)$ .

It does not show the ambiguity of le and donne.

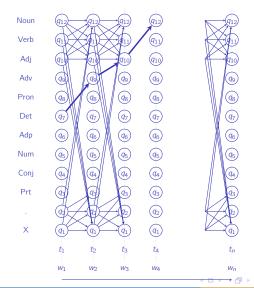
The subsequent terms will ignore it as well.

We can discard the corresponding paths.

The optimal path does not contain nonoptimal subpaths.



#### Trellis Representation



# Filling the Trellis

i\δ	$\delta_1$	$\delta_2$	$\delta_3$	$\delta_4$	$\delta_5$	$\delta_6$	$\delta_7$	$\delta_8$
PREP	0	1						
ADV	0	/1						
PRO	0	// <sub>1</sub>						
VERB	0							
NOUN	0 //	/ > /						
ART	0							
<s></s>	1.0	0	0	0	0	0	0	0
	<g>&gt;</g>	Je	le	donne	demain	dans	la	matinée

To fill the  $\delta_3$  column, for each cell i, we compute

$$\max_{i} P(j|i) \times P(le|j) \times \delta_2(i).$$

The pronoun cell, for instance, is filled with

$$\max_{i} P(PRO|i) \times P(Ie|PRO) \times \delta_{2}(i).$$



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### Worked Example in English

That round table might collapse

Looking up the words in a dictionary shows a lot of ambiguity: What is the part of speech of *That*? determiner? pronoun? relative pronoun?

Correct tags:

That/determiner round/adjective table/noun might/modal verb collapse/verb.

Using the Penn Treebank tagset:

That/**DT** round/**JJ** table/**NN** might/**MD** collapse/**VB**.



# Statistics from the Corpus

```
$ cut -f2,5 <corpus.txt | sort | uniq -c | grep " That\t"
 438 That DT
   5 That IN
   3 That WDT
$ cut -f2,5 <corpus.txt | sort | uniq -c | grep " round\t"
   5 round J.J
  23 round NN
  3 round VB
   1 round VRP
$ cut -f2,5 <corpus.txt | sort | uniq -c | grep " table\t"
  35 table NN
$ cut -f2,5 <corpus.txt | sort | uniq -c | grep " might\t"
 328 might MD
  4 might NN
$ cut -f2,5 <corpus.txt | sort | uniq -c | grep " collaps
  57 collapse NN
   1 collapse NNP
     collando VB
```

# Baseline Tagger

**1** Tag using the most frequent part of speech:

Words: That round table might collapse NN MD Tagger: DT NNNN Reference: DT - 11 NN MD **VB** 

- Evaluate your tagger:
  - Accuracy:

$$\frac{\text{\#Correct tags}}{\text{\#Tags}} = \frac{3}{5} = .6$$

Confusion matrix:

↓Correct	Tagger $ o$						
	DT	JJ	MD	NN	VB		
DT	1	0	0	0	0		
JJ	0	0	0	1	0		
MD	0	0	1	0	0		
NN	0	0	0	1	0		
VB	0	0	0	1	0		



### Viterbi: The First Column of the Trellis

```
DT
         0.0
                §1
                ξ2
IN
         0.0
11
         0.0
                0.0
MD
         0.0
                0.0
NN
         0.0
                0.0
NNP
         0.0
                0.0
VB
         0.0
                0.0
VBP
                0.0
         0.0
WDT
                ξ3
         1.0
                0.0
<s>
                That
                                                                             collapse
                               round
                                               table
                                                             might
         <s>
                P(That|t_1)
                              P(round|t_2)
                                               P(table|t_2)
                                                              P(might|t_{4})
                                                                             P(collapse|t_5)
```

Computing the values:

§1 
$$P(DT|BOS) \times P(That|DT)$$

§2 
$$P(IN|BOS) \times P(That|IN)$$

§3 
$$P(WDT|BOS) \times P(That|WDT)$$

where 
$$P(DT|BOS) = \frac{C(BOS, DT)}{C(BOS)}$$
 and  $P(That|DT) =$ 



#### The Rest

DT	0.0	§1	0.0	0.0	0.0	0.0
IN	0.0	§2	0.0	0.0	0.0	0.0
JJ	0.0	0.0	§4	0.0	0.0	0.0
MD	0.0	0.0	0.0	0.0	§9	0.0
NN	0.0	0.0	§5	§8	§10	§11
NNP	0.0	0.0	0.0	0.0	0.0	§12
VB	0.0	0.0	§6	0.0	0.0	§13
VBP	0.0	0.0	§7	0.0	0.0	0.0
WDT	0	§3	0.0	0.0	0.0	0.0
<s></s>	1.0	0.0	0.0	0.0	0.0	0.0
	<g>&gt;</g>	That	round	table	might	collapse
		$P(That t_1)$	$P(round t_2)$	$P(table t_2)$	$P(might t_4)$	$P(collapse t_5)$



#### The Rest: Second Column

DT	0.0	§1	0.0	0.0	0.0	0.0
IN	0.0	§2	0.0	0.0	0.0	0.0
JJ	0.0	0.0	§4	0.0	0.0	0.0
MD	0.0	0.0	0.0	0.0	§9	0.0
NN	0.0	0.0	§5	<b>§</b> 8	§10	§11
NNP	0.0	0.0	0.0	0.0	0.0	§12
VB	0.0	0.0	§6	0.0	0.0	§13
VBP	0.0	0.0	§7	0.0	0.0	0.0
WDT	0	§3	0.0	0.0	0.0	0.0
<g>&gt;</g>	1.0	0.0	0.0	0.0	0.0	0.0
	<g>&gt;</g>	That	round	table	might	collapse
		$P(That t_1)$	$P(round t_2)$	$P(table t_2)$	$P(might t_4)$	$P(collapse t_5)$

#### **§4** Thee competing terms:

- $P(JJ|IN) \times \S 2,$

We take the maximum and we multiply it by P(round|JJ) store the path.



#### The Rest: Second Column

DT	0.0	§1	0.0	0.0	0.0	0.0
IN	0.0	§2	0.0	0.0	0.0	0.0
JJ	0.0	0.0	§4	0.0	0.0	0.0
MD	0.0	0.0	0.0	0.0	§9	0.0
NN	0.0	0.0	§5	<b>§</b> 8	§10	§11
NNP	0.0	0.0	0.0	0.0	0.0	§12
VB	0.0	0.0	§6	0.0	0.0	§13
VBP	0.0	0.0	§7	0.0	0.0	0.0
WDT	0	§3	0.0	0.0	0.0	0.0
<g>&gt;</g>	1.0	0.0	0.0	0.0	0.0	0.0
	<g>&gt;</g>	That	round	table	might	collapse
		$P(That t_1)$	$P(round t_2)$	$P(table t_2)$	$P(might t_4)$	$P(collapse t_5)$

#### **§5** Three competing terms:

- $P(NN|IN) \times \S 2,$

We take the maximum and we multiply it by P(round|NN) store the path.

§6 ..



# Viterbi: The Complete Algorithm

Operations

Operations
$\delta_1(i) = \pi_i b_i(o_1), 1 \le i \le N_p$
$\psi_1(i) = null$
$\delta_{t+1}(j) = b_j(o_{t+1}) \times \max_{1 \leq i \leq N_p} \delta_t(i) a_{ij}, 1 \leq j \leq N_p$ , and $1 \leq j \leq N_p$
$t \le n-1$
$\psi_{t+1}(j) = rg\max_{1 \leq i \leq N_p} \delta_t(i) a_{ij}$
$P* = \max_{1 \le i \le N_p} \delta_n(i)$
$s_n* = \arg\max_{1 \le i \le N_p} \delta_n(i)$
The optimal path sequence is given by the backtrack-
ing: $s_n^*, s_{n-1}^* = \psi_n(s_n^*), s_{n-2}^* = \psi_{n-2}(s_{n-1}^*), \dots$

Stone

### Supervised Learning: A Summary

Needs a manually annotated corpus called the **Gold Standard**The Gold Standard may contain errors (*errare humanum est*) that we ignore

A classifier is trained on a part of the corpus, the **training set**, and evaluated on another part, the **test set**, where automatic annotation is compared with the "Gold Standard"

**N-fold cross validation** is used avoid the influence of a particular division Some algorithms may require additional optimization on a development set

Classifiers can use statistical or symbolic methods

