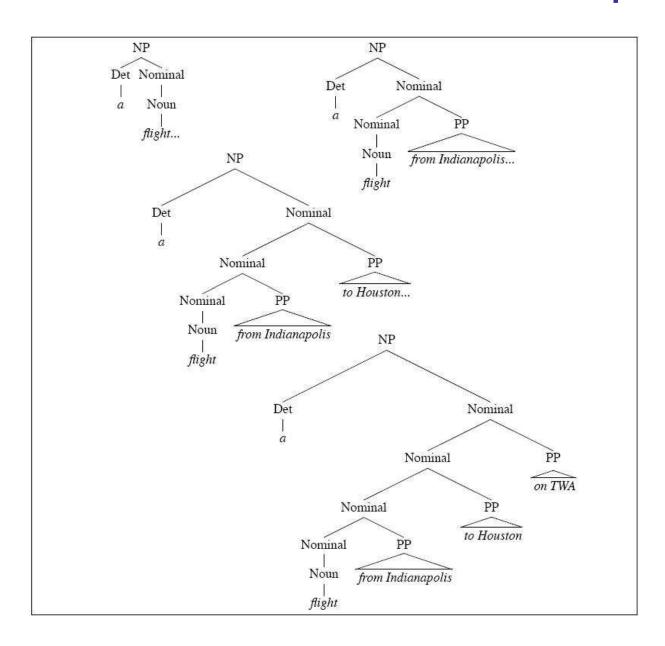
CS460/626: Natural Language Processing/Speech, NLP and the Web

Lecture 19, 24:
Algorithmics of Probabilistic Parsing; HMM-PCFG correspondence

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Shared Sub-Problems: Example



CKY Parsing: CNF

- CKY parsing requires that the grammar consist of ε-free, binary rules = Chomsky Normal Form
 - All rules of the form:
 - A \rightarrow BC or A \rightarrow a
 - What does the tree look like?
- What if my CFG isn't in CNF?

CKY Algorithm

function CKY-PARSE(words, grammar) returns table

```
for j ← from 1 to LENGTH(words) do

table[j-1,j] ← \{A \mid A \rightarrow words[j] \in grammar\}

for i ← from j-2 downto 0 do

for k ← i+1 to j-1 do

table[i,j] ← table[i,j] ∪

\{A \mid A \rightarrow BC \in grammar,

B \in table[i,k],

C \in table[k,j]\}
```

Illustrating CYK [Cocke, Younger, Kashmi] Algo

- S \rightarrow NP VP 1.0
- NP \rightarrow DT NN 0.5
- NP \rightarrow NNS 0.3
- NP \rightarrow NP PP 0.2
- $PP \rightarrow P NP 1.0$
- $VP \rightarrow VP PP$ 0.6
- $VP \rightarrow VBD NP$ 0.4

- DT \rightarrow the 1.0
- $NN \rightarrow gunman 0.5$
- NN \rightarrow building 0.5
- VBD \rightarrow sprayed 1.0
- NNS \rightarrow bullets 1.0

CYK: Start with (0,1)

To From	1	2	3	4	5	6	7
0	DT						
1							
2 ↓							
3							
4							
5							
6	-		-				

CYK: Keep filling diagonals

To From	1	2	3	4	5	6	7
0	DT						
1		NN					
2 \							
3							
4							
5							
6			-				

CYK: Try getting higher level structures

To From	1	2	3	4	5	6	7
0	DT	NP					
1		NN					
2							
3							
4							
5							
6							

CYK: Diagonal continues

To From	1	2	3	4	5	6	7
0	DT	NP					
1		NN					
2 \			VBD				
3							
4							
5							
6	-		-				

To From	1	2	3	4	5	6	7
0 →	DT	NP					
1		NN					
2			VBD				
3							
4							
5							
6							

To From	1	2	3	4	5	6	7
0	DT	NP					
1		NN					
2			VBD				
3				DT			
4							
5							
6				 -	 -	 -	

To From	1	2	3	4	5	6	7
0 →	DT	NP					
1		NN					
2			VBD				
3				DT			
4					NN		
5							
6							

CYK: starts filling the 5th column

To From	1	2	3	4	5	6	7
0 →	DT	NP					
1		NN					
2			VBD				
3				DT	NP		
4					NN		
5							
6							

To From	1	2	3	4	5	6	7
0	DT	NP					
1		NN					
2			VBD		VP		
3				DT	NP		
4					NN		
5							
6							

To From	1	2	3	4	5	6	7
0	DT	NP					
1		NN					
2			VBD		VP		
3				DT	NP		
4					NN		
5							
6							

CYK: S found, but NO termination!

To From	1	2	3	4	5	6	7
0	DT	NP			S		
1		NN					
2			VBD		VP		
3				DT	NP		
4					NN		
5					-		
6							

To From	1	2	3	4	5	6	7
0	DT	NP			S		
1		NN					
2			VBD		VP		
3				DT	NP		
4					NN		
5						P	
6							

To From	1	2	3	4	5	6	7
0 ->	DT	NP			S		
1		NN					
2			VBD		VP		
3				DT	NP		
4					NN		
5						P	
6							

CYK: Control moves to last column

To From	1	2	3	4	5	6	7
0	DT	NP			S		
1		NN					
2			VBD		VP		
3				DT	NP		
4					NN		
5						P	
6							NP NNS

To From	1	2	3	4	5	6	7
0	DT	NP			S		
1		NN					
2			VBD		VP		
3				DT	NP		
4					NN		
5						P	PP
6							NP NNS

To From	1	2	3	4	5	6	7
0	DT	NP			S		
1		NN					
2			VBD		VP		
3				DT	NP		NP
4					NN		
5						P	PP
6							NP NNS

To From	1	2	3	4	5	6	7
0 ->	DT	NP			S		
1		NN					
2			VBD		VP		VP
3				DT	NP		NP
4					NN		
5						P	PP
6							NP NNS

CYK: filling the last column

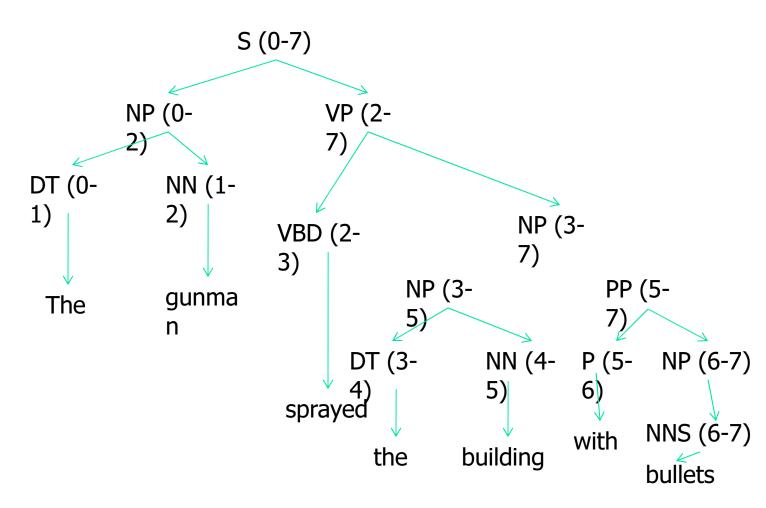
To From	1	2	3	4	5	6	7
0 ->	DT	NP			S		
1		NN					
2			VBD		VP		VP
3				DT	NP		NP
4					NN		
5						P	PP
6							NP NNS

CYK: terminates with S in (0,7)

To From	1	2	3	4	5	6	7
0	DT	NP			S		S
1		NN					
2			VBD		VP		VP
3				DT	NP		NP
4					NN		
5						P	PP
6							NP NNS

CYK: Extracting the Parse Tree

The parse tree is obtained by keeping back pointers.



Probabilistic parse tree construction

Probabilistic Context Free Grammars

$S \to$	NP VP	1.0
■ 5 →	NP VP	1.0

■ NP
$$\rightarrow$$
 DT NN 0.5

■ NP
$$\rightarrow$$
 NNS 0.3

■ NP
$$\rightarrow$$
 NP PP 0.2

$$\blacksquare PP \to P NP \qquad 1.0$$

•
$$VP \rightarrow VP PP$$
 0.6

•
$$VP \rightarrow VBD NP$$
 0.4

■ DT
$$\rightarrow$$
 the 1.0

■ NN
$$\rightarrow$$
 gunman 0.5

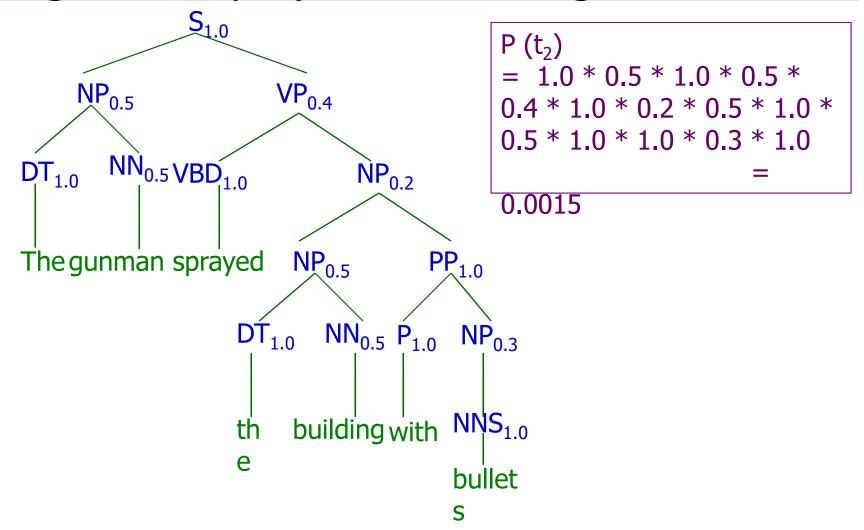
• NN
$$\rightarrow$$
 building 0.5

• VBD
$$\rightarrow$$
 sprayed 1.0

■ NNS
$$\rightarrow$$
 bullets 1.0

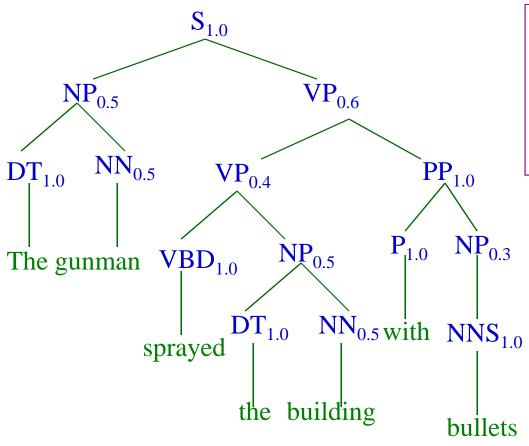
Another Parse t₂

The gunman sprayed the building with bullets.



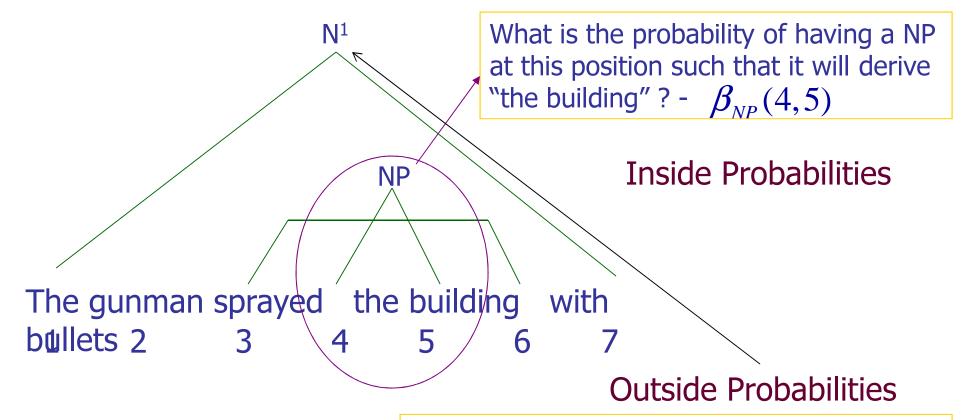
Example Parse t₁

The gunman sprayed the building with bullets.



$$P(t_1)$$
 = 1.0 * 0.5 * 1.0 * 0.5 * 0.6 * 0.4 * 1.0 * 0.5 * 1.0 * 0.5 * 1.0 * 1.0 * 0.3 * 1.0 = 0.00225

Interesting Probabilities



What is the probability of starting from N¹ and deriving "The gunman sprayed", a NP and "with bullets" ? - $\alpha_{NP}(4,5)$

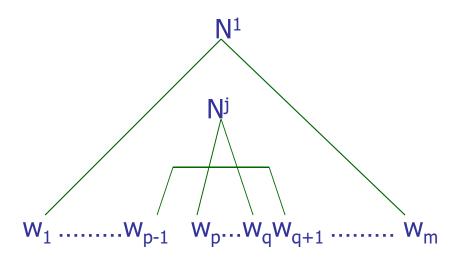
Interesting Probabilities

- Random variables to be considered
 - The non-terminal being expanded.
 E.g., NP
 - The word-span covered by the non-terminal. E.g., (4,5) refers to words "the building"
- While calculating probabilities, consider:
 - The rule to be used for expansion : E.g., NP \rightarrow DT NN
 - The probabilities associated with the RHS nonterminals: E.g., DT subtree's inside/outside probabilities & NN subtree's inside/outside probabilities

Outside Probability

α_j(p,q): The probability of beginning with N¹
 & generating the non-terminal N^j_{pq} and all words outside w_p...w_q

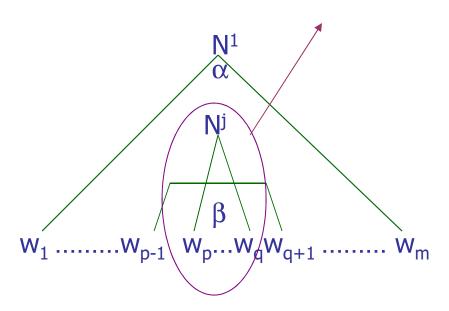
$$\alpha_{j}(p,q) = P(w_{1(p-1)}, N_{pq}^{j}, w_{(q+1)m} \mid G)$$



Inside Probabilities

• $\beta_j(p,q)$: The probability of generating the words $w_p...w_q$ starting with the non-terminal

Nj_{pq}. $\beta_j(p,q) = P(w_{pq} \mid N_{pq}^j, G)$

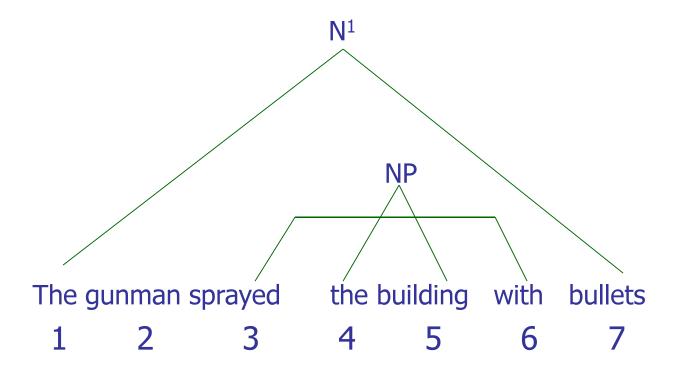


Outside & Inside Probabilities: example

 $\alpha_{NP}(4,5)$ for "the building"

= $P(\text{The gunman sprayed}, NP_{4.5}, \text{ with bullets } | G)$

 $\beta_{NP}(4,5)$ for "the building" = $P(\text{the building } | NP_{4,5}, G)$



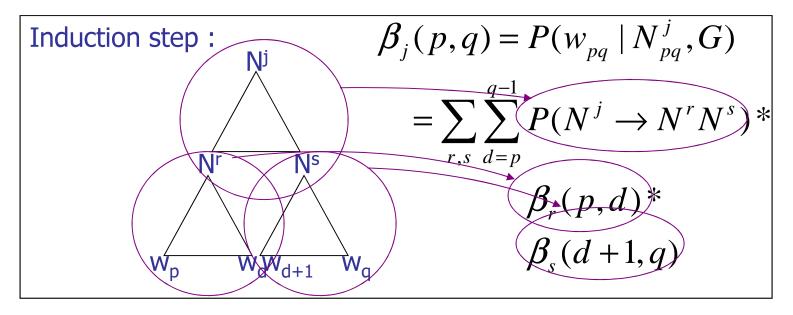
Calculating Inside probabilities $\beta_j(p,q)$

Base case: $\beta_j(k,k) = P(w_k \mid N_{kk}^j, G) = P(N_{kk}^j \rightarrow w_k \mid G)$

- Base case is used for rules which derive the words or terminals directly
 - *E.g.,* Suppose $N^{j} = NN$ is being considered & $NN \rightarrow building$ is one of the rules with probability 0.5

$$\beta_{NN}(5,5) = P(building \mid NN_{5,5}, G)$$
$$= P(NN_{5,5} \rightarrow building \mid G) = 0.5$$

Induction Step: Assuming Grammar in Chomsky Normal Form



- Consider different splits of the words indicated by d
 E.g., the huge building
 Split here for d=2 d=3
- Consider different non-terminals to be used in the rule: NP → DT NN, NP → DT NNS are available options Consider summation over all these.

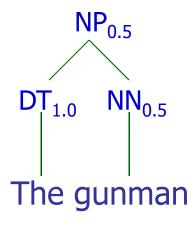
The Bottom-Up Approach

- The idea of induction
- Consider "the gunman"
- Base cases : Apply unary rules

 $DT \rightarrow the$

Prob = 1.0

 $NN \rightarrow gunman$ Prob = 0.5



- Induction: Prob that a NP covers these 2 words
 - = P (NP \rightarrow DT NN) * P (DT deriving the word "the") * P (NN deriving the word "gunman")
 - = 0.5 * 1.0 * 0.5 = 0.25

Parse Triangle (probablity of output observation, the sentence)

- A parse triangle is constructed for calculating $\beta_i(p,q)$
- Probability of a sentence using $\beta_i(p,q)$:

$$P(w_{1m} \mid G) = P(N^1 \to w_{1m} \mid G) = P(w_{1m} \mid N_{1m}^1, G) = \beta_1(1, m)$$

Parse Triangle

to from	The (1)	gunman (2)	sprayed (3)	the (4)	building (5)	with (6)	bullets (7)
0	$\beta_{DT} = 1.0$						
1		$\beta_{NN} = 0.5$					
2			$\beta_{VBD} = 1.0$				
3				$\beta_{DT} = 1.0$			
4					$\beta_{NN} = 0.5$		
5						$\beta_P = 1.0$	
6							$\beta_{NNS} = 1.0$

• Fill diagonals with $\beta_j(k,k)$

Parse Triangle

	The (1)	gunman (2)	sprayed (3)	the (4)	building (5)	with (6)	bullets (7)
1	$\beta_{DT} = 1.0$	$\beta_{NP} = 0.25$					
2		$\beta_{NN} = 0.5$					
3			$\beta_{VBD} = 1.0$				
4				$\beta_{DT} = 1.0$			
5					$\beta_{NN} = 0.5$		
6						$\beta_P = 1.0$	
7							$\beta_{NNS} = 1.0$

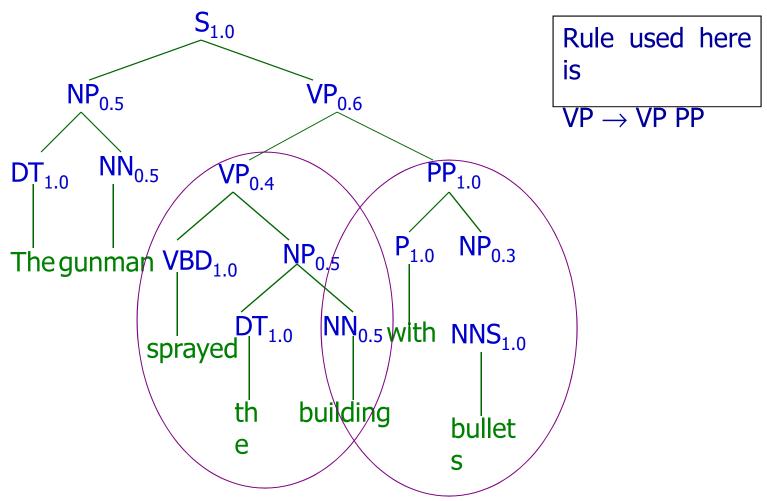
Calculate using induction formula

$$\beta_{NP}(1,2) = P(\text{the gunman} \mid NP_{1,2}, G)$$

= $P(NP \to DT \ NN) * \beta_{DT}(1,1) * \beta_{NN}(2,2)$
= $0.5 * 1.0 * 0.5 = 0.25$

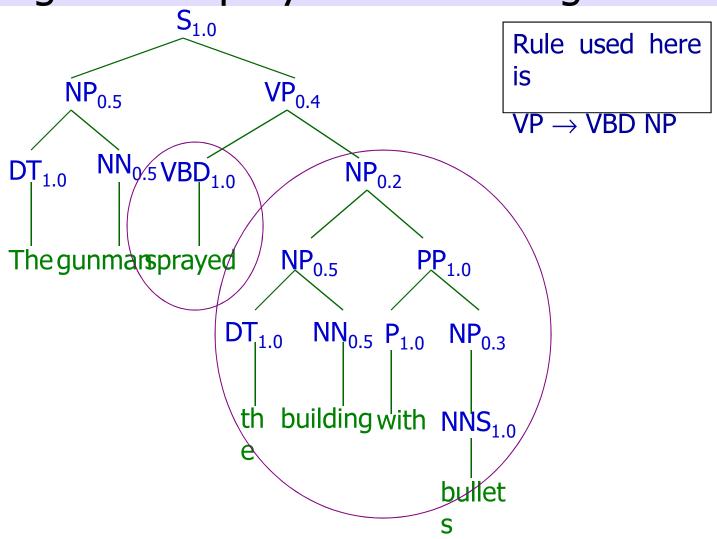
Example Parse t₁

The gunman sprayed the building with bullets.



Another Parse t₂

The gunman sprayed the building with bullets.



Parse Triangle

	The (1)	gunman	sprayed	the	building	with	bullets (7)
		(2)	(3)	(4)	(5)	(6)	
1	$\beta_{DT} = 1.0$	$\beta_{NP} = 0.25$				1	$\beta_{\rm S}=0.0465$
2		$\beta_{NN} = 0.5$					
3			$\beta_{VBD} = 1.0$		$\beta_{VP}=0.1$		$\beta_{VP} = 0.186$
4				$\beta_{DT} = 1.0$	$\beta_{NP} = 0.25$		$\beta_{NP} = 0.015$
5					$\beta_{NN} = 0.5$		
6						$\beta_P = 1.0$	$\beta_{PP} = 0.3$
7				_			$B_{NNS} = 1.0$

$$\beta_{VP}(3,7) = P(\text{sprayed the building with bullets } | VP_{3,7}, G)$$

$$= P(VP \to VP PP) * \beta_{VP}(3,5) * \beta_{PP}(6,7)$$

$$+ P(VP \to VBD NP) * \beta_{VBD}(3,3) * \beta_{NP}(4,7)$$

$$= 0.6 * 1.0 * 0.3 + 0.4 * 1.0 * 0.015 = 0.186$$

Different Parses

- Consider
 - Different splitting points :
 E.g., 5th and 3rd position
 - Using different rules for VP expansion : E.g., VP \rightarrow VP PP, VP \rightarrow VBD NP
- Different parses for the VP "sprayed the building with bullets" can be constructed this way.

The Viterbi-like Algorithm for PCFGs

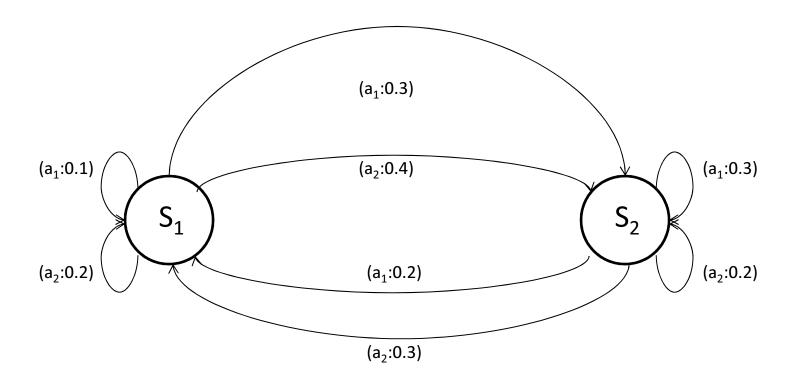
 $\delta_i(p,q)$ = highest inside probability parse of N_{pq}^i

- Very similar to calculation of inside probabilities $\beta_i(p,q)$
- Instead of summing over all ways of constructing the parse for w_{pq}
 - Choose only the best way (the maximum probability one!)

Three basic problems (contd.)

- Problem 1: Likelihood of a sequence
 - Forward Procedure
 - Backward Procedure
- Problem 2: Best state sequence
 - Viterbi Algorithm
- Problem 3: Re-estimation
 - Baum-Welch (Forward-Backward Algorithm)

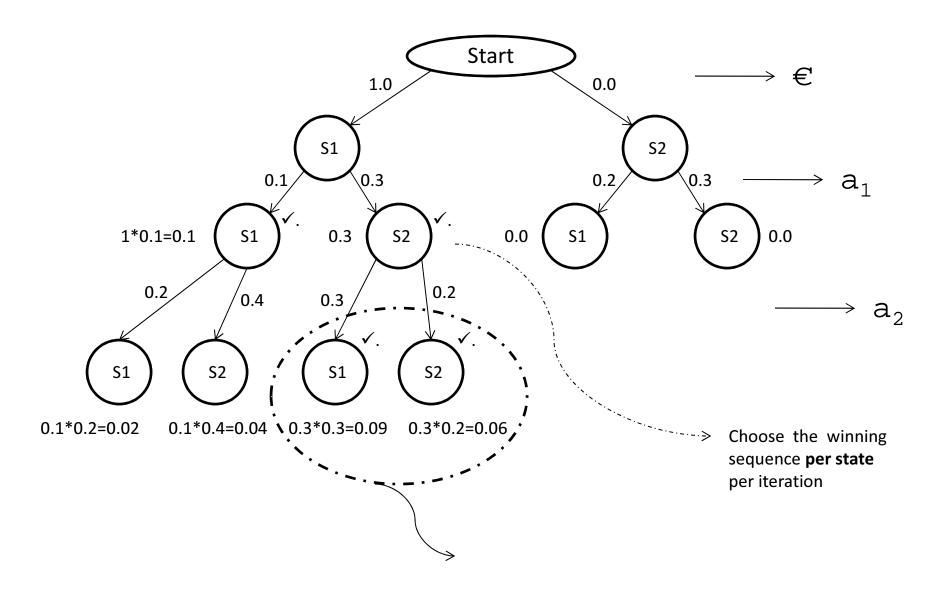
Probabilistic FSM



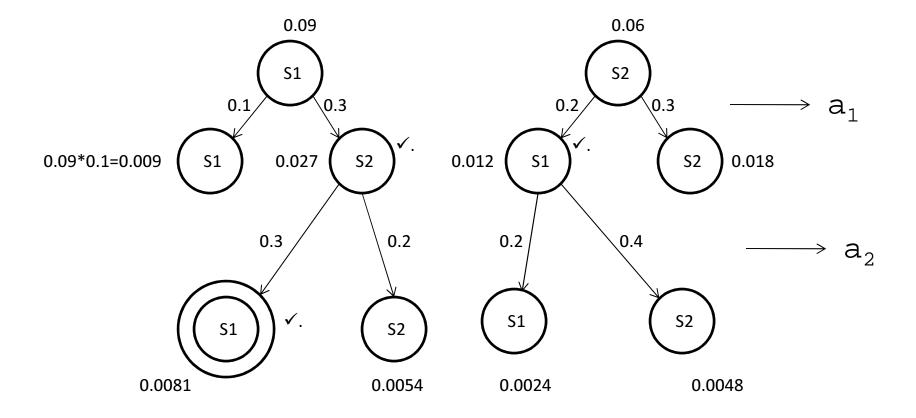
The question here is:

"what is the most likely state sequence given the output sequence seen"

Developing the tree



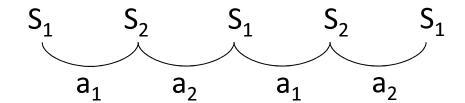
Tree structure contd...



The problem being addressed by this tree is $S^* = \arg\max_s P(S \mid a_1 - a_2 - a_1 - a_2, \mu)$

a1-a2-a1-a2 is the output sequence and μ the model or the machine

Path found: (working backward)

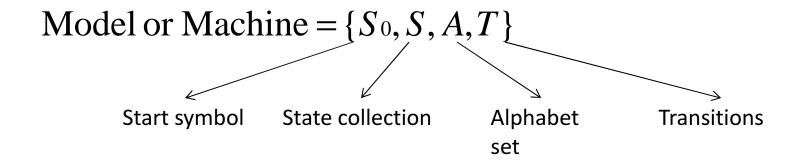


Problem statement: Find the best possible sequence

$$S^* = \arg \max P(S \mid O, \mu)$$

S

where, $S \to \operatorname{State} \operatorname{Seq}, O \to \operatorname{Output} \operatorname{Seq}, \mu \to \operatorname{Model} \operatorname{or} \operatorname{Machine}$



T is defined as
$$P(S_i \xrightarrow{a_k} S_j) \quad \forall_{i, j, k}$$

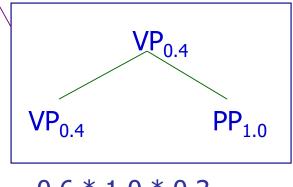
Calculation of $\delta_i(p,q)$

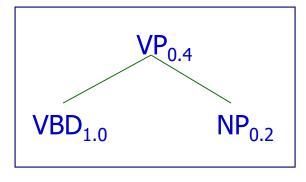
 $\delta_{VP}(3,7) = P(\text{sprayed the building with bullets} | VP_{3,7}, G)$ $= \max\{P(VP \to VP PP) * \delta_{VP}(3,5) * \delta_{PP}(6,7),$

 $P(VP \rightarrow VBD NP) * \delta_{VBD}(3,3) * \delta_{NP}(4,7)$

This rule is

chosen = $\max\{0.6*1.0*0.3, 0.4*1.0*0.015\} = 0.18$



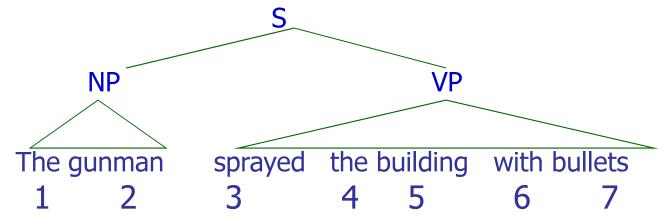


Viterbi-like Algorithm

- **Base case:** $\delta_i(k,k) = \beta_i(k,k)$
- Induction :
 - $\psi_i(p,q)$ stores
 - RHS of the rule selected
 - Position of splitting
 - Example : $\psi_{VP}(3,7)$ stores VP, PP and split position = 5 because VP \rightarrow VP PP is the rule used.
- Backtracing : Start from $\psi_1(1,7)$ and $\delta_1(1,7)$ and backtrace.

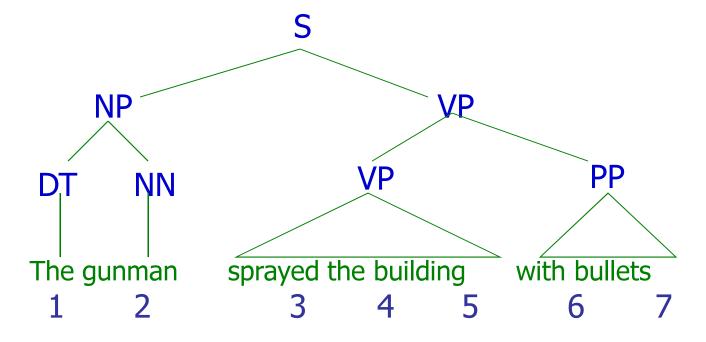
Example

• $\psi_1(1,7)$ records S \rightarrow NP VP & split position as 2



- $\psi_{NP}(1,2)$ records NP \rightarrow DT NN & split position as 1
- $\psi_{VP}(3,7)$ records VP \rightarrow VP PP & split position as 5

Example

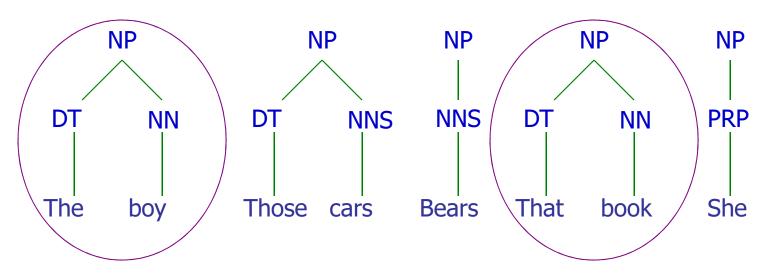


Grammar Induction

- Annotated corpora like Penn Treebank
- Counts used as follows:

$$P(NP \rightarrow DT NN) = \frac{\# NP \rightarrow DT NN \text{ is used}}{\# \text{An NP rule is used}} = \frac{2}{5}$$

Sample training data:

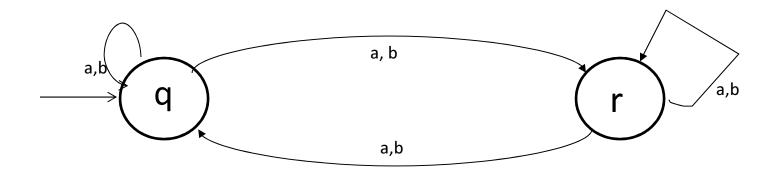


Grammar Induction for Unannotated Corpora: EM algorithm

Start with initial estimates for rule probabilities Compute probability of each parse of a sentence according to current estimates of rule probabilities **EXPECTATION PHASE** Compute expectation of how often a rule is used (summing probabilities of rules used in previous step) Refine rule probabilities so that training corpus likelihood increases

MAXIMIZATION PHASE

Baum-Welch algorithm: counts



String = abb aaa bbb aaa

Sequence of states with respect to input symbols

$$\xrightarrow{\text{O/p seq}} \overrightarrow{q} \xrightarrow{a} r \xrightarrow{b} q \xrightarrow{b} q \xrightarrow{b} q \xrightarrow{a} r \xrightarrow{a} q \xrightarrow{a} r \xrightarrow{b} q \xrightarrow{b} q \xrightarrow{b} q \xrightarrow{a} r \xrightarrow{a} q \xrightarrow{a} r$$
 State seq

Calculating probabilities from table

$$P(q \xrightarrow{a} r) = 5/8$$

$$P(q \xrightarrow{b} r) = 3/8$$

$$P(s^{i} \xrightarrow{W_{k}} s^{j}) = \frac{c(s^{i} \xrightarrow{W_{k}} s^{j})}{\sum_{l=1}^{T} \sum_{m=1}^{A} c(s^{i} \xrightarrow{W_{m}} s^{l})}$$

Table of counts

Src	Dest	O/P	Cou nt	
q	r	a	5	
q	q	b	3	
r	q	а	3	
r	q	b	2	

T=#states

A=#alphabet symbols

Now if we have a non-deterministic transitions then multiple state seq possible for the given o/p seq (ref. to previous slide's feature). Our aim is to find expected count through this.

Interplay Between Two Equations

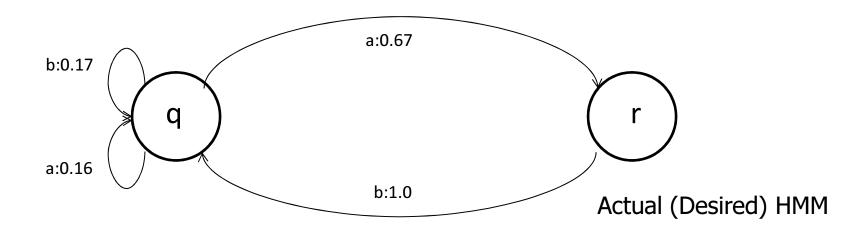
$$P(s^{i} \xrightarrow{W_{k}} s^{j}) = \frac{c(s^{i} \xrightarrow{W_{k}} s^{j})}{\sum_{l=0}^{T} \sum_{m=0}^{A} c(s^{i} \xrightarrow{W_{m}} s^{l})}$$

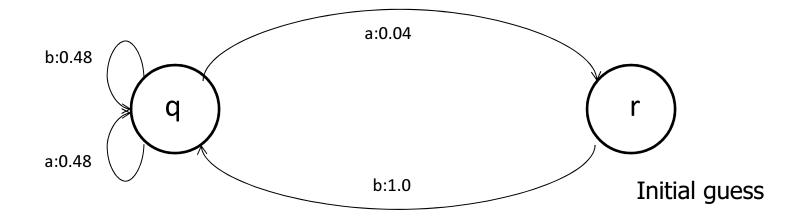
$$C(s^{i} \xrightarrow{W_{k}} s^{j}) = \sum_{S_{0,n+1}} P(S_{0,n+1} | W_{0,n}) \times n(s^{i} \xrightarrow{W_{k}} s^{j}, S_{0,n+1}, w_{0,n})$$

 W_k

No. of times the transitions $s \rightarrow s'$ occurs in the string

Illustration





One run of Baum-Welch algorithm: *string* ababb

$\in \rightarrow a$	$a \rightarrow b$	$b \rightarrow a$	$a \rightarrow b$	$b \rightarrow b$	$b \rightarrow \in$	P(path)	$q \xrightarrow{a} r$	$r \xrightarrow{b} q$	$q \xrightarrow{a} q$	$q \xrightarrow{b} q$
q	r	q	r	q	q	0.00077	0.00154	0.00154	0	0.0007 7
q	r	q	q	q	q	0.00442	0.00442	0.00442	0.0044	0.0088 4
q	q	q∱	r	q	q	0.00442	0.00442	0.00442	0.0044	0.0088 4
q	q	q	q	q	q	0.02548	0.0	0.000	0.0509 6	0.0764 4
Rounded Total →						0.035	0.01	0.01	0.06	0.095
New Probabilities (P) → State sequences							0.06 =(0.01/(0. 01+0.06+ 0.095)	1.0	0.36	0.581

^{*} ϵ is considered as starting and ending symbol of the input sequence string. Through multiple iterations the probability values will converge.

Computational part (1/2)

$$\begin{split} &C(s^{i} \xrightarrow{W_{k}} s^{j}) = \sum_{s_{0,n+1}} [P(S_{0,n+1} \mid W_{0,n}) \times n(s^{i} \xrightarrow{W_{k}} s^{j}, S_{0,n+1}, W_{0,n})] \\ &= \frac{1}{P(W_{0,n})} \sum_{s_{0,n+1}} [P(S_{0,n+1}, W_{0,n}) \times n(s^{i} \xrightarrow{W_{k}} s^{j}, S_{0,n+1}, W_{0,n})] \\ &= \frac{1}{P(W_{0,n})} \sum_{t=0,n} \sum_{s_{0,n+1}} [P(S_{t} = s^{i}, W_{t} = w_{k}, S_{t+1} = s^{j}, S_{0,n+1}, W_{0,n})] \\ &= \frac{1}{P(W_{0,n})} \sum_{t=0,n} [P(S_{t} = s^{i}, W_{t} = w_{k}, S_{t+1} = s^{j}, W_{0,n})] \end{split}$$

$$S0 \xrightarrow{W_0} S1 \xrightarrow{W_1} S1 \xrightarrow{W_2} ... Si \xrightarrow{W_k} Sj ... \xrightarrow{W_{n-1}} Sn \xrightarrow{W_n} Sn+1$$

Computational part (2/2)

$$\sum_{t=0}^{n} P(S_{t} = s^{i}, S_{t+1} = s^{j}, W_{t} = w_{k}, W_{0,n})$$

$$= \sum_{t=0}^{n} P(W_{0,t-1}, S_{t} = s^{i}, S_{t+1} = s^{j}, W_{t} = w_{k}, W_{t+1,n})$$

$$= \sum_{t=0}^{n} P(W_{0,t-1}, S_{t} = s^{i}) P(S_{t+1} = s^{j}, W_{t} = w_{k} \mid W_{0,t-1}, S_{t} = s^{i}) P(W_{t+1,n} \mid S_{t+1} = s^{j})$$

$$= \sum_{t=0}^{n} F(t-1,i) P(S_{t+1} = s^{j}, W_{t} = w_{k} \mid S_{t} = s^{i}) B(t+1,j)$$

$$= \sum_{t=0}^{n} F(t-1,i) P(S_{t+1} = s^{j}, W_{t} = w_{k} \mid S_{t} = s^{i}) B(t+1,j)$$

$$= \sum_{t=0}^{n} F(t-1,i) P(s^{i} \xrightarrow{W_{k}} s^{j}) B(t+1,j)$$

$$= \sum_{t=0}^{n} F(t-1,i) P(s^{i} \xrightarrow{W_{k}} s^{j}) B(t+1,j)$$

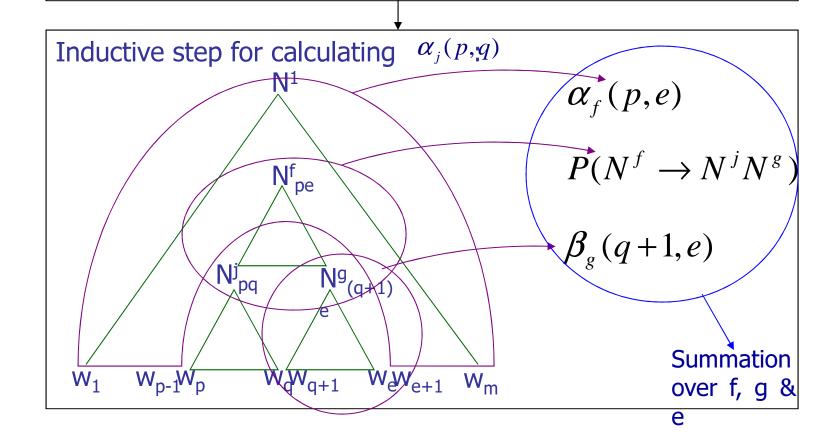
$$S0 \xrightarrow{W_{0}} S1 \xrightarrow{W_{1}} S2 \xrightarrow{W_{2}} ... Si \xrightarrow{W_{k}} Sj ... \xrightarrow{S_{n-1}} Sn \xrightarrow{W_{n}} Sn+1$$

Outside Probabilities $\alpha_j(p,q)$

Base case:

 $\alpha_1(1,m) = 1$ for start symbol

$$\alpha_j(1,m) = 0 \text{ for } j \neq 1$$



Probability of a Sentence

$$P(w_{1m}, N_{pq} \mid G) = \sum_{j} P(w_{1m} \mid N_{pq}^{j}, G) = \sum_{j} \alpha_{j}(p, q) \beta_{j}(p, q)$$

 Joint probability of a sentence w_{1m} and that there is a constituent spanning words w_p to w_q is given as:

 $P(\text{The gunman....bullets}, N_{4,5} \mid G)$ $= \sum_{j} P(\text{The gunman...bullets} \mid N_{4,5}^{j}, G)$ $= \alpha_{NP}(4,5)\beta_{NP}(4,5)$ $+ \alpha_{VP}(4,5)\beta_{VP}(4,5) + \dots$ The gunman sprayed the building with bullets