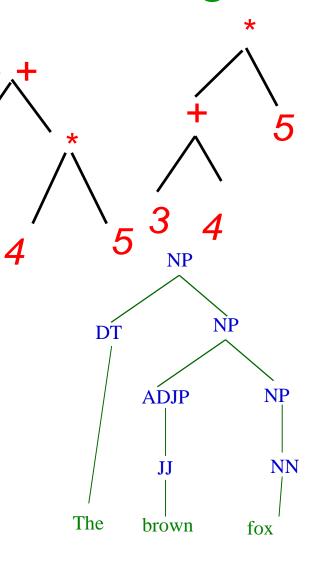
CS626: Speech, NLP and Web

Parsing cntd
Pushpak Bhattacharyya
Computer Science and Engineering
Department
IIT Bombay
Week 6 of 2nd September, 2024

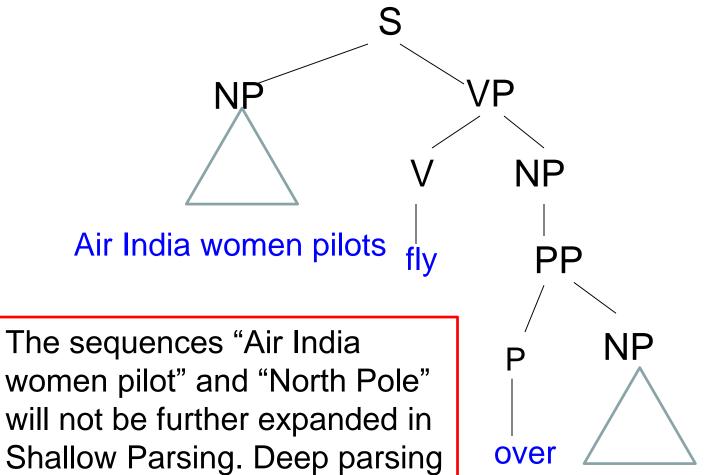
1-slide recap of week of 19th Aug

- Evidence of deep structure: *unlockable* → + *un+lockable* or *unlock+able*
- Structural ambiguity
- Two kinds of parsing: CP and DP
- POS tagging facilitates chunking and parsing: short phrases and deep trees
- Parsing is important: e.g., aspect based SA
- Generative grammar, CFG
 - $S\rightarrow NP VP; NP\rightarrow NP PP$
- Algorithmics of parsing: top down (TD), bottom up (BU), TDBU, CYK
- BI notation- vimp for NLP



Observations on Shallow and Deep Parsing

"Air India women pilots fly over North Pole"



North Pole

women pilot" and "North Pole" will not be further expanded in Shallow Parsing. Deep parsing Will not stop until the tokens (terminals are reached)

BIO for Chunk (non recursive phrase)

```
Air/B India/I women/I pilots/I fly/O over/O North/B Pole/I./O
```

Target phrases:

Air India women pilots North Pole

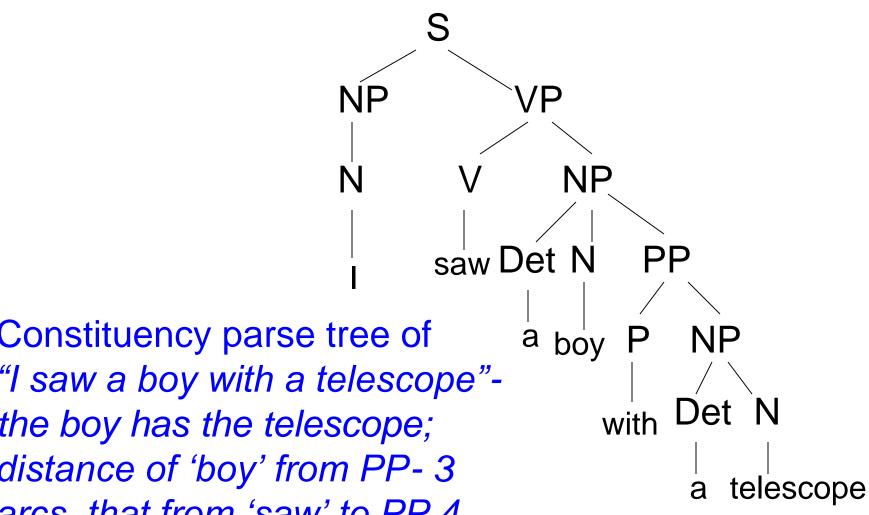
Chunk Extraction: *local* information adequate

Use argmax computation

Produce labels at positions

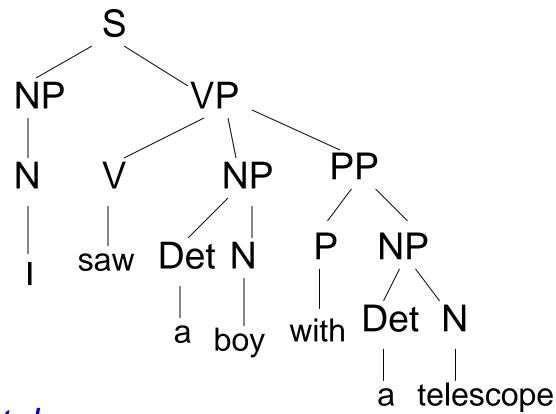
Use features ON and AROUND positions

What is the proof that there is underlying structure? Structural Ambiguity



"I saw a boy with a telescope"the boy has the telescope; distance of 'boy' from PP-3 arcs, that from 'saw' to PP 4 arcs

Constituency Parse Tree -2

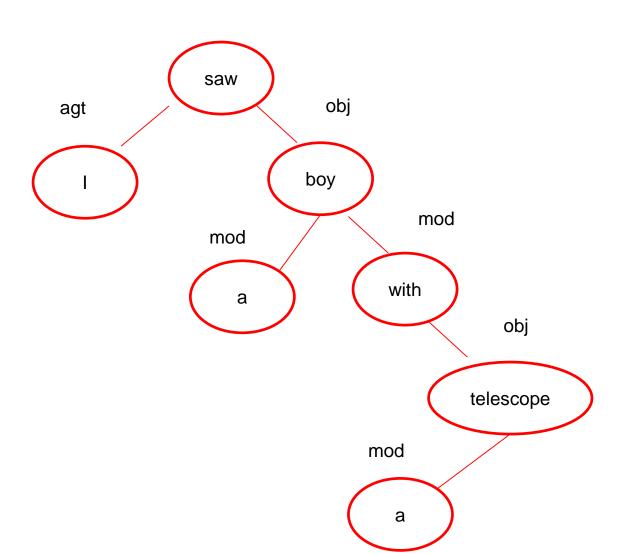


I saw a boy with a telescope-I have the telescope; distance of 'boy' from PP- 4 arcs, that from 'saw' to PP 3 arcs SANNIDHI Principle (proximity)

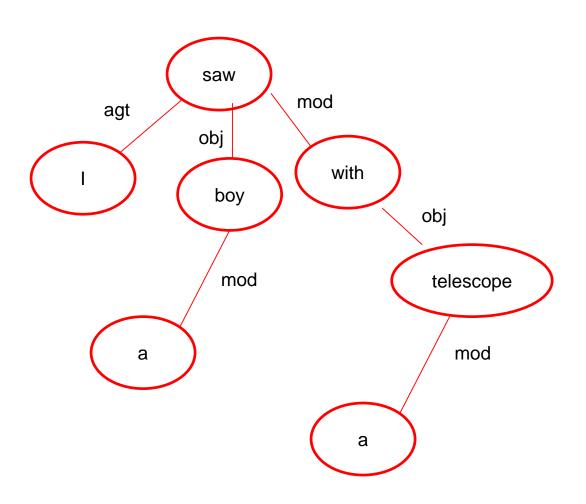
Foundation of Constituency Tree

- Parent child relation means parent is constituted of child(ren)
- If there are multiple children, i.e., multiple constituents, one of them is the head and others are modifiers
- Thus given VP→ V NP, VP is constituted of V and NP
- V is the head and NP the modifier for the VP

Dependency Parse Tree - 1



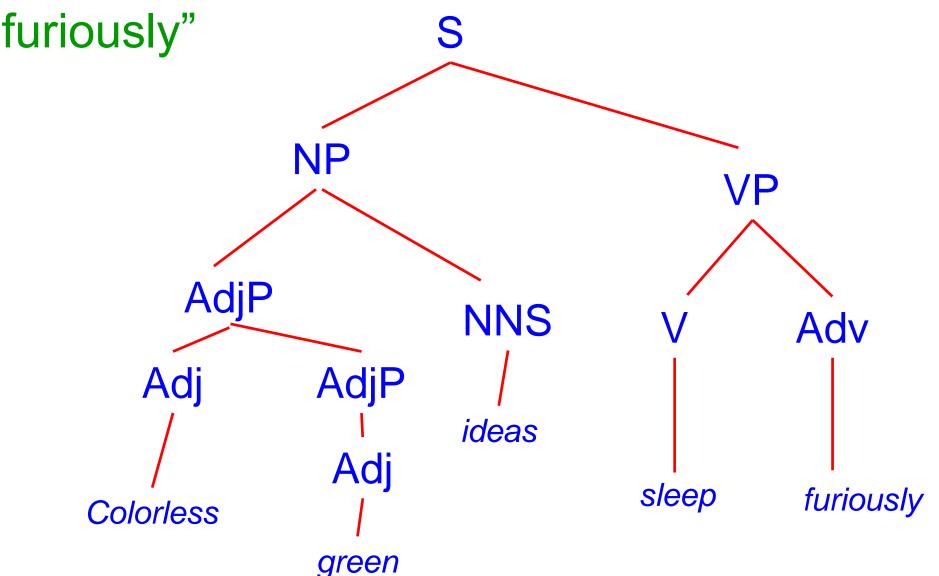
Dependency Parse Tree - 2



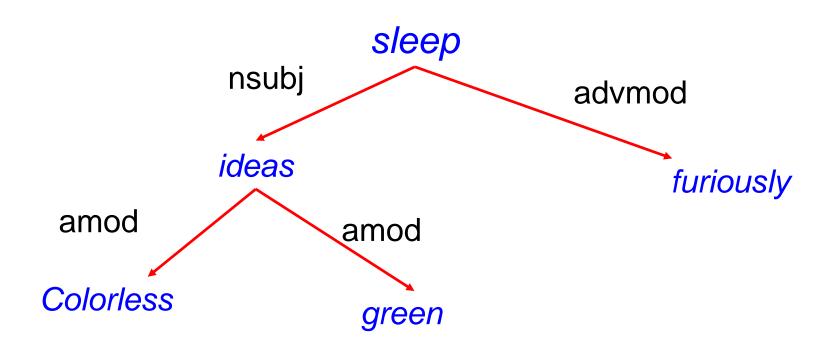
Foundation of Dependency Tree (DT)

- Parent child relation is head-modifier
- Labelled DT: the head-modifier relation is further specified with the type, e.g., nsubj meaning nominal subject, dobj meaning direct object and iobj meaning indirect object of the main verb (mv).
- E,g, Jack_{nsubj} gave_{mv} a book_{dobj} to Jill_{iobj}.

Constituency parse tree of a famous sentence: "Colorless green ideas sleep



Dependency parse tree of "Colorless...": Head Modifier Relations



Syntax-Semantics

Syntax and semantics influence each other

 However, they can be independent tooas in the "colourless green ideas..."
 sentence

Consistent with neurolinguistics- Broca's and Wernicke's areas

⊅6rsing:pushpak

Grammar and Parsing Algorithms

A simplified grammar

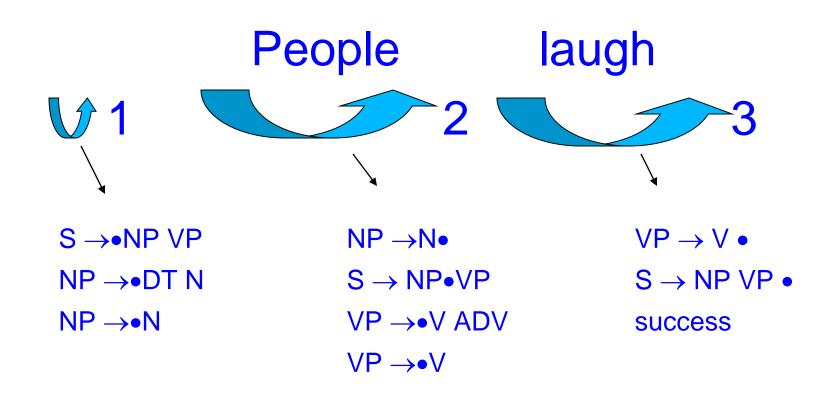
- S \rightarrow NP VP
- NP \rightarrow DT N | N
- VP \rightarrow V ADV | V
- The above captures declarative sentences
- 4 kinds of sentences as per traditional grammar
 - Declarative (Sun rises in the east)
 - Interrogative (Does sun rise in the east?)
 - Imperative (Rise in the east please)
 - Exclamatory (Oh, sun rises in the east!)

Combining top-down and bottomup strategies

Top-Down Bottom-Up Chart Parsing

- Combines advantages of top-down & bottom-up parsing.
- Does not work in case of left recursion.
 - e.g. "People laugh"
 - People noun, verb
 - Laugh noun, verb
 - Grammar $S \rightarrow NP VP$ $NP \rightarrow DT N \mid N$ $VP \rightarrow V ADV \mid V$

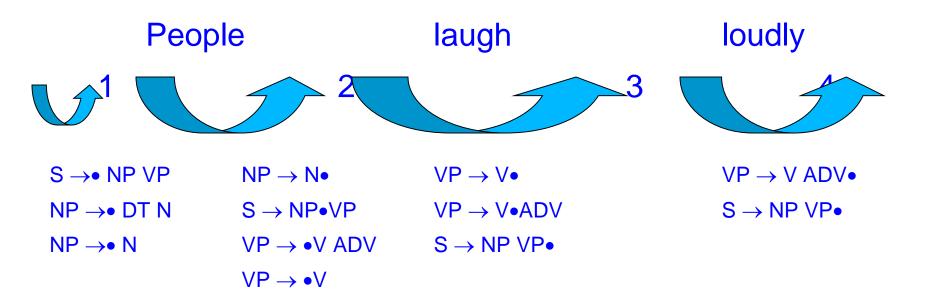
Transitive Closure



Arcs in Parsing

- Each arc represents a <u>chart</u> which records
 - Completed work (left of •)
 - Expected work (right of •)

Example



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An important parsing algorithm

CYK Parsing

A segment of English

- $S \rightarrow NP VP$
- NP → DT NN
- NP → NNS
- NP \rightarrow NP PP
- $PP \rightarrow P NP$
- $VP \rightarrow VP PP$
- VP → VBD NP

- DT \rightarrow the
- NN → gunman
- NN → building
- VBD → sprayed
- NNS → bullets

GENERATIVE GRAMMAR, due to Noam Chomsky

Foundational Question

- Grammar rules are context free grammar (CFG) rules
- Is CFG enough powerful to capture language?

- CFG cannot accept/generate aⁿbⁿcⁿ
- Corresponding language phenomenon: Jack, Mykel and Mohan play tennis, soccer and cricket respectively.

CYK Parsing: 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	-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	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						Р	
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						Р	
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						Р	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						Р	PP
6							NP NNS

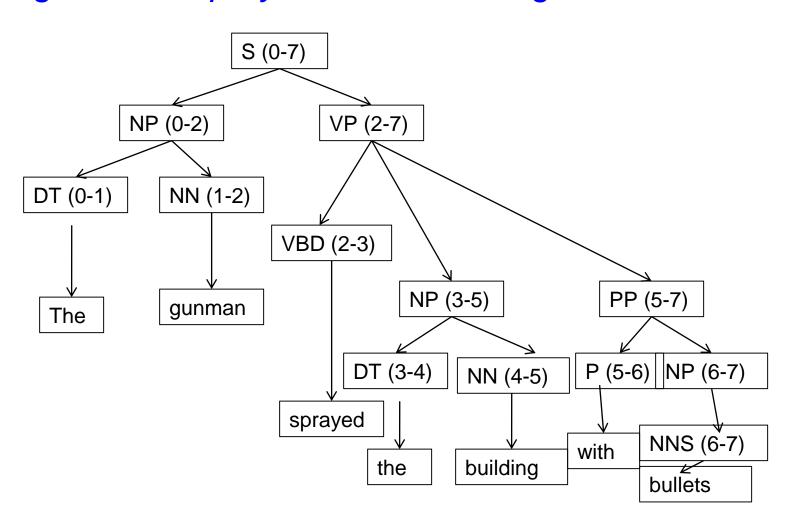
CYK: terminates with S in (0,7)

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

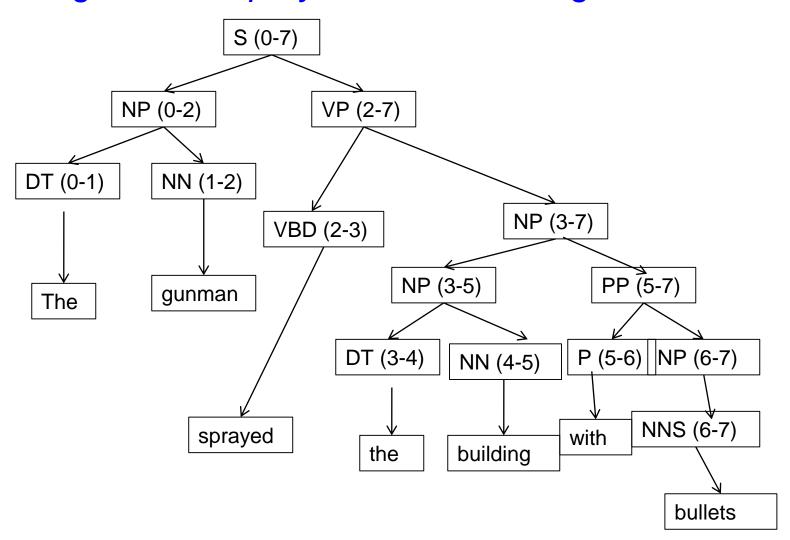
CYK: Extracting the Parse Tree

 The parse tree is obtained by keeping back pointers.

Parse Tree #1



Parse Tree #2



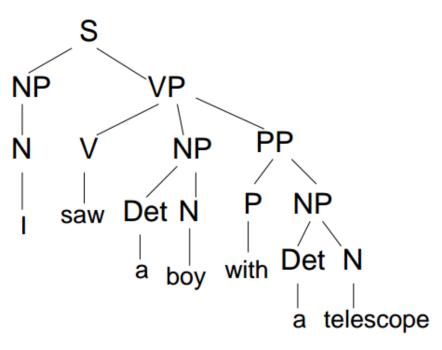
Notion of Domination

 A sentence is dominated by the symbol S through domination of segments by phrases

Analogy

- The capital of a country dominates the whole country.
- The capital of a state dominates the whole state.
- The district headquarter dominates the district.

Domination: Example



- Dominations
 - NP dominates "a telescope"
 - VP dominates "saw a boy with a telescope
 - S dominates the whole sentence
- Domination is composed of many sub-domination.
- I saw a boy with a telescope
 - Meaning: I used the telescope to see the boy

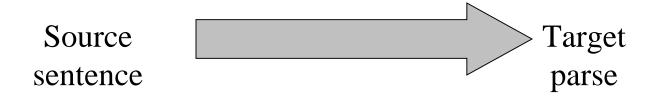
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Probabilistic parsing

Main source:

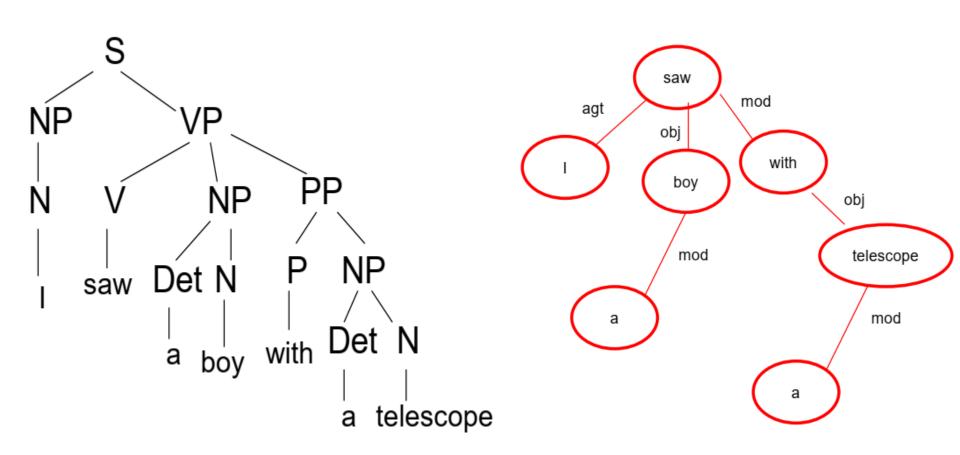
Christopher Manning and Heinrich Schutze, *Foundations of Statistical Natural Language Processing*, MIT Press, 1999.

Noisy Channel Modeling



```
T^*= argmax [P(T|S)]
T
= argmax [P(T).P(S|T)]
T
= argmax [P(T)], since given the parse the <math>T sentence is completely determined and P(S|T)=1
```

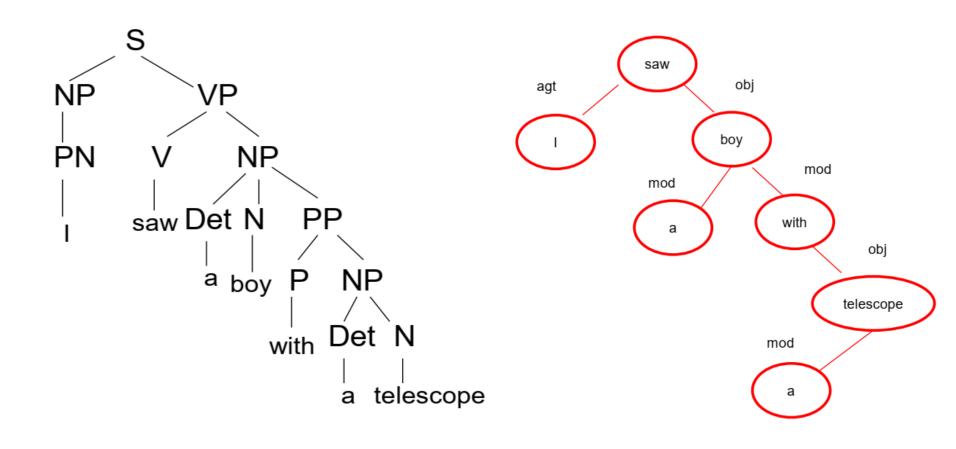
"I saw...": CP and DP #1



Bracketed Structure #1

```
Parse #1 (meaning: I have the telescope)
        [saw]<sub>VBD</sub>
                [the boy]<sub>NP</sub>
                [with [a telescope]<sub>NP</sub>]<sub>PP</sub>
        ]<sub>VP</sub>
```

"I saw...": CP and DP #2



Bracketed Structure #2

```
Parse #2 (meaning: the boy has the telescope)
              [I]_{NP}
                   [saw]<sub>VBD</sub>
                        [the boy]<sub>NP</sub>
                        [with [a telescope]<sub>NP</sub>]<sub>PP</sub>
                   ]<sub>NP</sub>
              ]_{VP}
```

Formal Definition of PCFG

- A set of terminals {w_k}, k = 1,....,V
 {w_k} = { child, teddy, bear, played...}
- A set of non-terminals {Nⁱ}, i = 1,...,n
 {Nⁱ} = { NP, VP, DT...}
- A designated start symbol S (sometimes given the symbol N¹)
- A set of rules {Nⁱ → ζ^j}, where ζ^j is a sequence of terminals & non-terminals
 e.g., NP → DT NN
- A corresponding set of rule probabilities

Rule Probabilities

 Rule probabilities are such that for for the same non terminal all production rules sum to1.

E.g., P(NP
$$\rightarrow$$
 DT NN) = 0.2
P(NP \rightarrow NNS) = 0.5
P(NP \rightarrow NP PP) = 0.3

Meaning of P(NP → DT NN)= 0.2, 20% of the training data parses use the rule NP → DT NN

Probabilistic Context Free Grammars

0.3

1.0

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

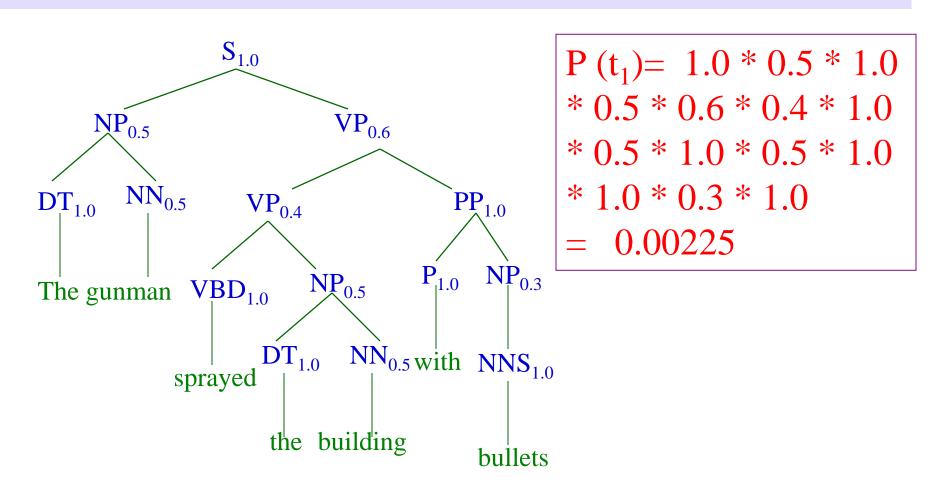
- 1.0 DT → the
 - $NN \rightarrow gunman 0.5$

1.0

- $NN \rightarrow building$ 0.5
- VBD \rightarrow sprayed 1.0
- NNS → bullets 1.0

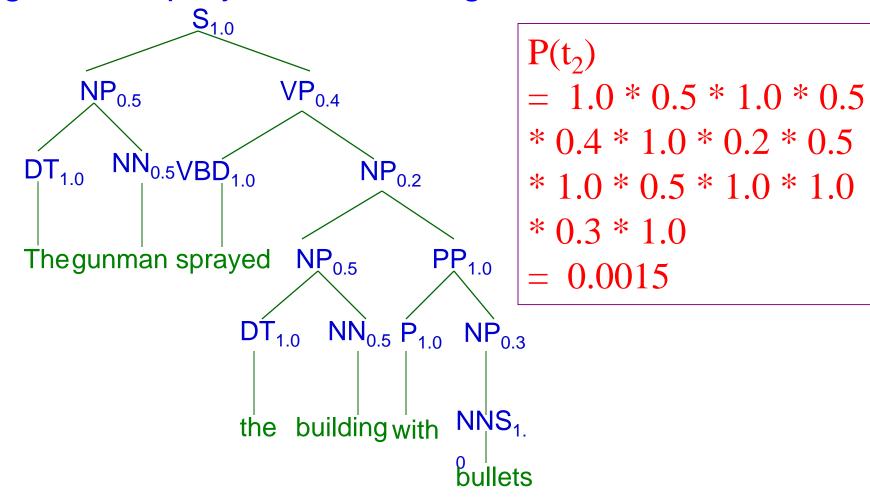
Example Parse t₁

The gunman sprayed the building with bullets.

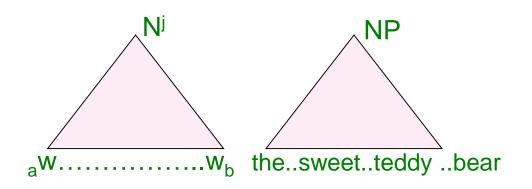


Another Parse t₂

The gunman sprayed the building with bullets.



Probability of a sentence (1/2)



Notation: (a,b etc. are BETWEEN-word indices)

- w_{ab} subsequence _aw….w_b
- N^{j} dominates $_{a}w....w_{b}$ or yield(N^{j}) = $_{a}w....w_{b}$

Probability of a sentence (2/2)

Probability of a sentence = $P(w_{0.l})$

(0 is the index before the first word and I the index after the last word. All other indices are between words)

$$= \Sigma_t(P(w_{0,l}, t))$$

$$= \Sigma_t(P(t). (P(w_{0,l}| t))$$

$$= \Sigma_t P(t). 1$$

where t is a parse tree of the sentence If t is a parse tree for the sentence $w_{0,l}$, this will be 1!!

Assumptions of the PCFG model

Place invariance:

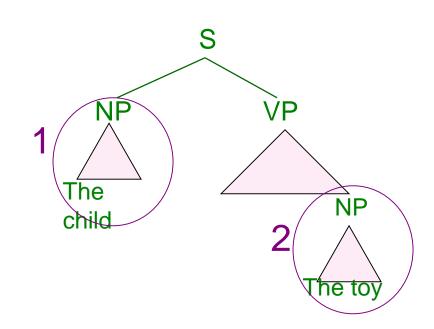
P(NP → DT NN) is same independent of location in the tree

Context-free:

$$P(NP \rightarrow DT NN | sisters of NP)$$

= $P(NP \rightarrow DT NN)$

Ancestor free:



Probability of a parse tree

Domination: we say the non-terminal N^i dominates from between-word indices k to l, symbolized as $N^i_{k,l}$, if $w_{k,l}$ is derived from N^i

P (tree | sentence)= P (tree | $S_{0,l}$), where $S_{0,l}$ means that the start symbol S dominates the word sequence $w_{0,l}$

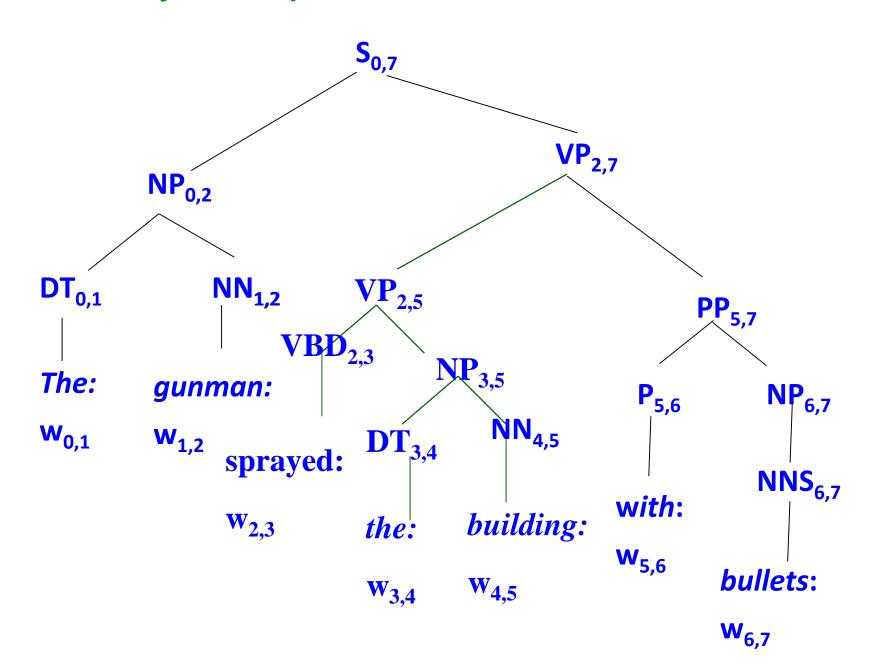
P(t/s) approximately equals joint probability of constituent non-terminals dominating the sentence fragments (next slide)

Indexed sentence

₀The ₁ gunman ₂ sprayed ₃ the ₄

₄building ₅ with ₆ bullets ₇. ₈

Probability of a parse tree



Probability of a parse tree (cont.)

```
P(t|s) = P(t|S_{0.7})
     (NP<sub>0.2</sub>, DT<sub>0.1</sub>, "the":w<sub>0.1</sub>, NN<sub>1.2</sub>, "gunman":w<sub>1.2</sub>,
     VP<sub>2.7</sub>, VP<sub>2.5</sub>, VBD<sub>2.3</sub>, "sprayed":w<sub>2.3</sub>,
     NP<sub>3.5</sub>, DT<sub>3.4</sub>, "the":w<sub>3.4</sub>, NN<sub>4.5</sub>, "building":w<sub>4.5</sub>,
      PP<sub>5.7</sub>, P<sub>5.6</sub>, "with": w<sub>5.6</sub>, NP<sub>6.7</sub>, NNS<sub>6.7</sub>, "bullets": w<sub>6.7</sub>
            |S_{0.7}|
```

Probability of a parse tree (cont.)

```
= P(NP_{0,2}, VP_{2,7} | S_{0,7}) * P(DT_{0,1}, NN_{1,2} | NP_{0,2}, VP_{2,7}, S_{0,7}) * ....
= P(NP_{0,2}, VP_{2,7} | S_{0,7}) * P(DT_{0,1}, NN_{1,2} | NP_{0,2}) *
```

(Using Chain Rule, Context Freeness and Ancestor Freeness- VP_{2.7} is NP_{0.2}'s sister and S its ancestor)