

CS626: Speech, Natural Language Processing and the Web

*Discriminative PoS Tagging; start of
parsing*

Pushpak Bhattacharyya
Computer Science and Engineering
Department
IIT Bombay

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Discriminative Labelling

Motivation

- HMM based POS tagging cannot handle “free word order” and “agglutination” well
- If *adjective after noun* is equally likely as *adjective before noun*, the transition probability is no better than uniform probability which has high entropy and is uninformative.
- When the words are long strings of many morphemes, POS tagging w/o morph features is highly inaccurate.

Variability in word order: problem for generative model

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NBT + न्यूज शहर Viral मूवी लाइफस्टाइल दुनिया बिज़नेस खेल एजुकेशन धर्म टेक ...

मुख्य भंडारा, पन्ना

ट्रेडिंग #दिल्ली में किसान महापंचायत #ब्रेकिंग न्यूज LIVE #इमरान खान की गिरफ्तारी तय #भारत-अमेरिका ड्रोन डील

Hindi News

पाकिस्तान

गिरफ्तारी से बचने को इमरान खान फरार, PTI नेताओं की धमकी- रेड लाइन क्रॉस की तो इस्लामाबाद कब्जा लेंगे!

जिसकी मदद से अमेरिका ने जवाहिरी को उड़ाया, ड्रैगन का फन कुचलने को भारत मंगा रहा वही ड्रोन

दिल्ली: बाहर निकलने से पहले पढ़ लें ट्रैफिक पुलिस की एडवायजरी, आज महापंचायत में जुटेंगे हजारों किसान

Jio 5G को मिलेगी कांटे की टक्कर! अडानी ग्रुप लॉन्च कर रहा 5G सर्विस

संपादकीय: भारत संग स्थायी शांति चाहते हैं नए PM शाहबाज शरीफ, कश्मीर और करनी में फर्क दिखेगा?

कोड करें आगे बढ़ें

आज ही शुरू करें FREE ट्रायल वलास

6-18 उम्र के बच्चों के लिए एक निःशुल्क कक्षा बुक करें।

WhiteHat Jr

Shahrukh Khan | Manish Sisodia CBI Raid | Google | Krishna Janmashtami Wishes and

Both SOV and SVO!

3569_file_Paper (1).pdf

27°C Cloudy

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Agglutination: problem for generative model

- *istahtaisinkohan* "I wonder if I should sit down for a while"
 - *ist*: "sit", verb stem
 - *ahta*: verb derivation morpheme, "to do something for a while"
 - *isi*: conditional affix
 - *n*: first-person singular suffix
 - *ko*: question particle
 - *han*: a particle for things like reminder (with declaratives) or "softening" (with questions and imperatives)

Agglutination in Manipuri

- Words in Manipuri can consists of ten or more morphemes
- *pusinhanjaramgadabanidako* (“I wish (I) myself would have caused to bring in the article”)
- *pu-sin-han-ja-ram-ga-da-ba-ni-da-ko*

Modelling in Discriminative POS Tagging

- T^* is the best possible tag sequence
- Summation dropped, because given W and feature engineering, F is unique; also $P(F|T)=1$
- The final independence assumption is that the tag at any position i depends only on the feature vector at that position

$$T^* = \arg \max_T P(T | W)$$

$$P(T | W) = \sum_F P(T, F | W) = P(T, F | W)$$

$$= P(F | W) \cdot P(T | F, W)$$

$$= 1 \cdot P(T | F) = P(T | F)$$

$$P(T | F) = \prod_{i=0}^{n+1} [P(t_i | F_i)]$$

Feature Engineering

- Running example: ^ ***brown foxes jumped over the fence .***
- *A. Word-based features*
 - f_{21} – dictionary index of the current word ('foxes'): integer
 - f_{22} – -do- of the previous word ('brown'): integer
 - f_{23} – -do- of the next word ('jumped'): integer
- *B. Part of Speech (POS) tag-based feature*
 - f_{24} – index of POS of previous word (here JJ): integer

Feature engineering cntd.

- *^ brown foxes jumped over the fence .*
- *C. Morphology-based features*
 - f_{25} — does the current word ('foxes') have a noun suffix, like 's', 'es', 'ies', etc.: 1/0- here the value is 1
 - f_{26} — does the current word ('foxes') have a verbal suffix, like 'd', 'ed', 't', etc.: 1/0- 0
 - f_{27} and f_{28} for 'brown' like for 'foxes'
 - f_{29} and $f_{2,10}$ for 'jumped' like for 'foxes; here $f_{2,10}$ is 1 (jumped has 'ed' as suffix)

An Aside: word vectors

- These features are opaquely represented in word vectors created from huge corpora
- Word vectors are vectors of numbers representing words
- It is not possible to tell which component in the word vector does what

Modelling Equations

$W: \wedge w_0 w_1 w_2 \dots w_{n-2} w_{n-1} w_n \cdot$ $T: \wedge t_0 t_1 t_2 \dots t_{n-2} t_{n-1} t_n \cdot$

$$P(T) = \prod_{i=0}^{n+1} [P(t_i \mid F_i)]$$

$$P(t_i = t \mid F_i) = \frac{e^{\sum_{j=1,k} \lambda_j f_{ij}}}{\sum_{t' \in S} e^{\sum_{j=1,k} \lambda_j f_{ij}(t')}}$$

Maximum Entropy Markov Model (MEMM)

S : set of tags.

The sequence probability of a tag sequence T is the product of $P(t_i/F_i)$, i varying over the positions.

Beam Search Based Decoding

- ***^ The brown foxes jumped .***
- Let us assume the following tags for the purpose of the discussion:
 - D- determiner like 'the'
 - A- adjective like 'brown'
 - N- noun like 'foxes', 'fence'
 - V- verb like 'jumped'
- Let the decoder start at the state '^' which denotes start of the sentence.

Step-1

- \wedge ***The brown foxes jumped .***
- The word '*the*' is encountered. First there are 4 next states possible corresponding to 4 tags, giving rise to 4 possible paths:
 - $\wedge D$ $-P_1$
 - $\wedge A$ $-P_2$
 - $\wedge N$ $-P_3$
 - $\wedge V$ $-P_4$

Commit to Beam Width

- Beam width is an integer which denotes how many of the possibilities should be kept *open*.
- Let the beam width be 2.
 - **This means that out of all the paths obtained so far we retain only the top 2 in terms of their probability scores.**
- We will assume that the actual linguistically viable sub-sequence appears amongst the top two choices.
 - ‘The’ is a determiner and we get the two highest probability paths for “^ The” as P_1 and P_3 .

Step-2

- \wedge *The **brown** foxes jumped .*
- '*brown*' is the next word. P_1 and P_3 are extended as
- $\wedge D D$ $-P_{11}$
- $\wedge D A$ $-P_{12}$
- $\wedge D N$ $-P_{13}$
- $\wedge D V$ $-P_{14}$
- $\wedge N D$ $-P_{31}$
- $\wedge N A$ $-P_{32}$
- $\wedge N N$ $-P_{33}$
- $\wedge N V$ $-P_{34}$

Retain two paths

- Keep two possibilities corresponding to correct/almost-correct sub-sequences.
'*brown*' is an adjective, but can be noun too (e.g., "*the brown of his eyes*").

$\wedge D A$

$-P_{12}$

$\wedge D N$

$-P_{13}$

Step-3

- **^ *The brown foxes jumped .***
- Can be both noun and verb (verb: "*he was foxed by their guile*").
- From P_{12} and P_{13} , we will get 8 paths, but retain only two, as per the beam width.
- We assume only the paths coming from P_{12} survive with 'A' and 'N' extending the paths:

 $\wedge D A A$

-P₁₂₂ (this is a wrong path!)

^DAN

$-P_{123}$

Step-4

- \wedge *The brown foxes **jumped** .*
- Can be both a past participial adjective (“*the halted train*”) and a verb.
- Retaining only two top probability paths we get

\wedge *D A N A* $-P_{1232}$

\wedge *D A N V* $-P_{1234}$

Step-5

- ^ *The brown foxes **jumped** .*
- Can be both a past participial adjective (“*the halted train*”) and a verb.
- Retaining only two top probability paths we get

^ *D A N A*

-P₁₂₃₂

^ *D A N V*

-P₁₂₃₄

Step-6: Final Step

- ^ *The brown foxes jumped* .
- On encountering dot, the beam search stops.
- We assume we get the correct path probabilistically in the beam (width 2)
^ *D A N V* .

How to fix the beam width (1/2)

- English POS tagging with Penn POS tag set: approximately 40 tags
- Fine categories like NNS for plural NNP for proper noun, VAUX for auxiliary verb, VBD for past tense verb and so on.
- A word can have on an average at most 3 POSs recorded in the dictionary.

How to fix the beam width (2/2)

- Allow for 4 finer category POSs under each category and with support from a lexicon that records the broad category POSs,
- A practical beam width for POS tagging for English using Penn tagset could be 12 (=3 X 4). (think and justify)

Start of Parsing

Strong evidence of existence of structure is *structural ambiguity*

- Parsing of “Unlockable”

- *Un + lockable*

- *lock + able*

- Meaning: something that cannot be locked
(*this gate is unlockable- open and cannot be locked*)



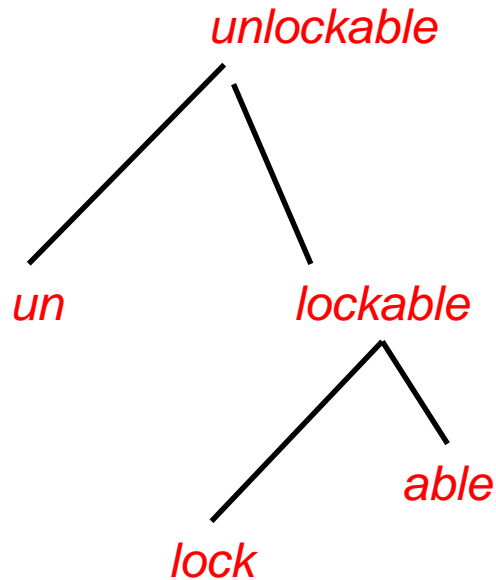
- *Unlock + able*

- *un + lock*

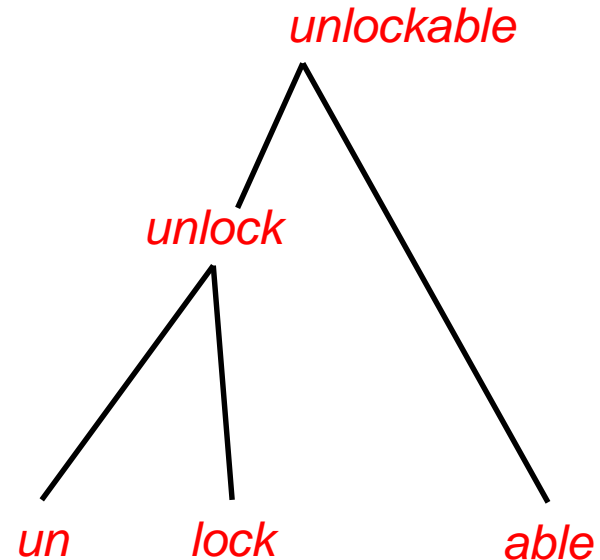
- Meaning: something that can be unlocked (*this gate is unlockable- shut with a lock and can be unlocked*)



Tree Structure: Morphotactics of “Unlockable”: two structures



something that cannot be locked
(“*this gate is unlockable*”- open
and cannot be locked)

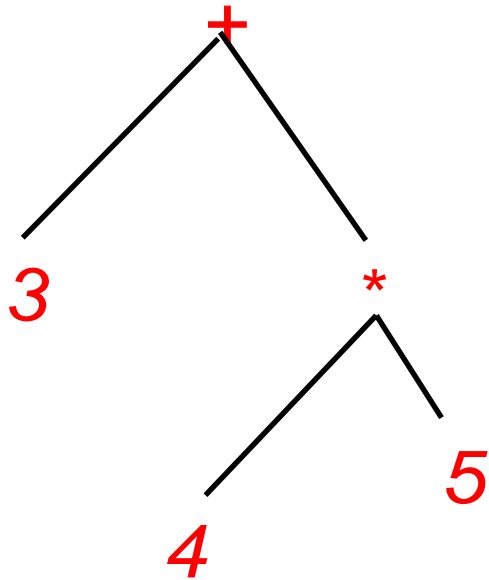


Something that can be unlocked (“*this gate is unlockable*”- shut with a lock,
but can be unlocked)

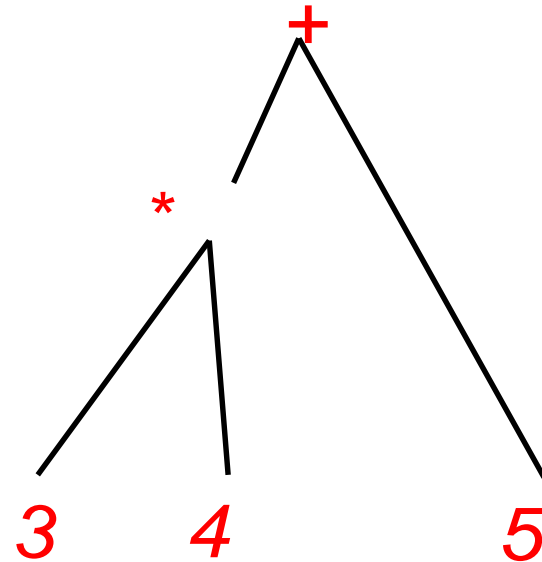


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Trees frequently used: Arithmetic Expressions



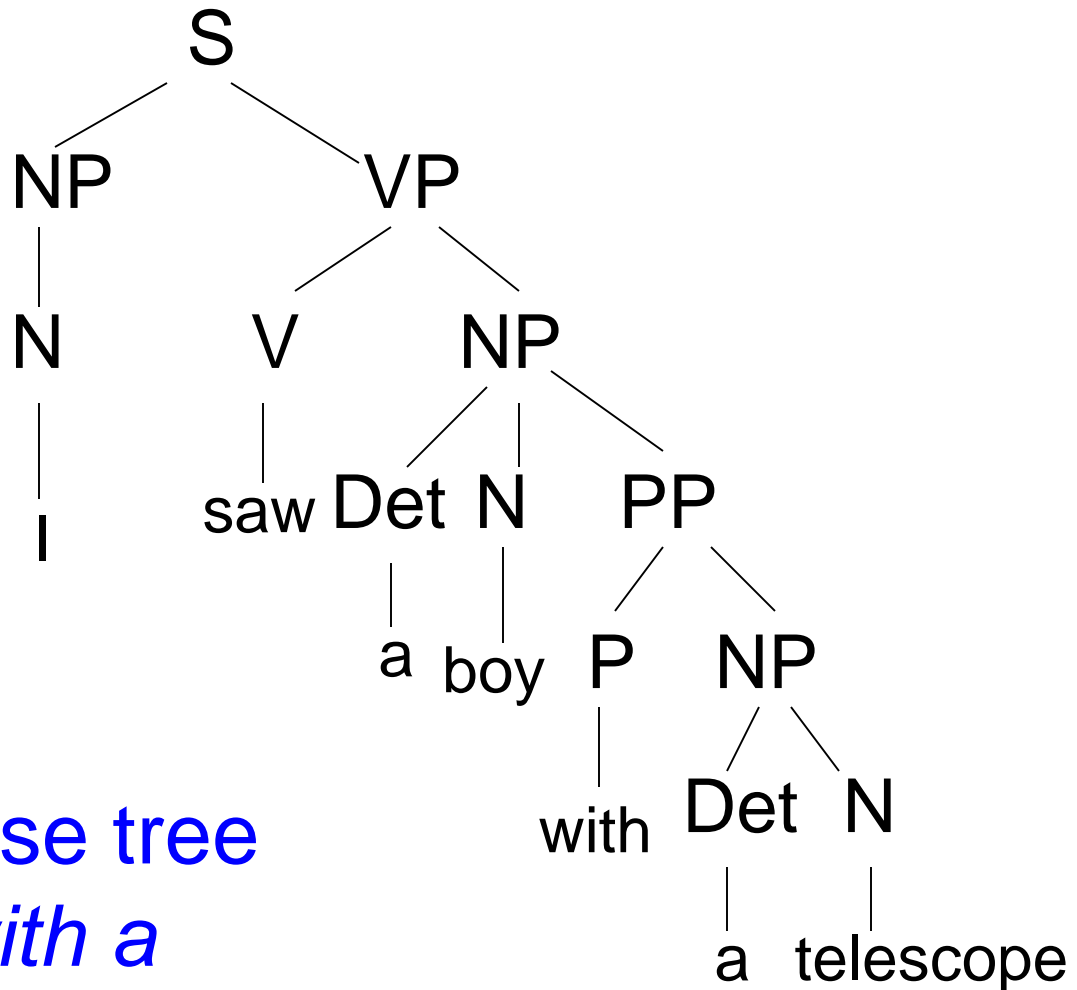
$$3 + 4 * 5 = 23$$



$$3 * 4 + 5 = 17$$

Trees are devices to represent constituents and their interactions to form bigger constituents

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

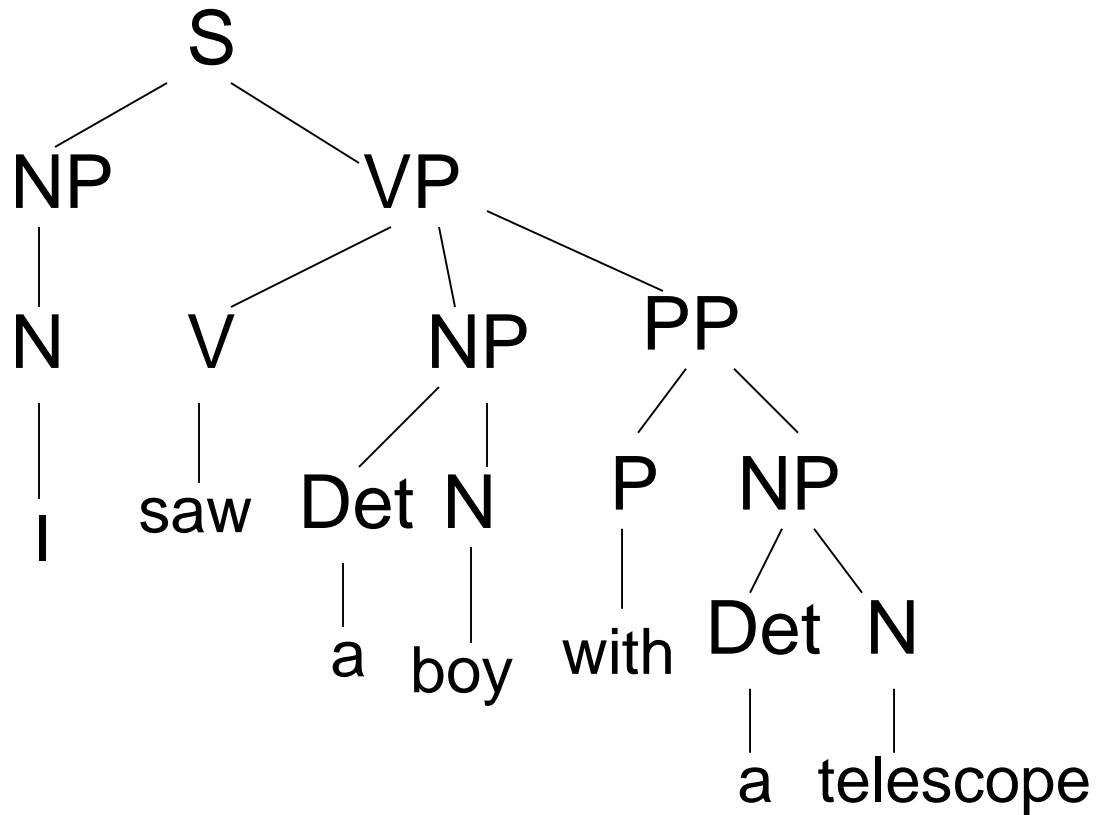


Constituency parse tree
of *"I saw a boy with a
telescope"*

Foundation of Constituency Tree

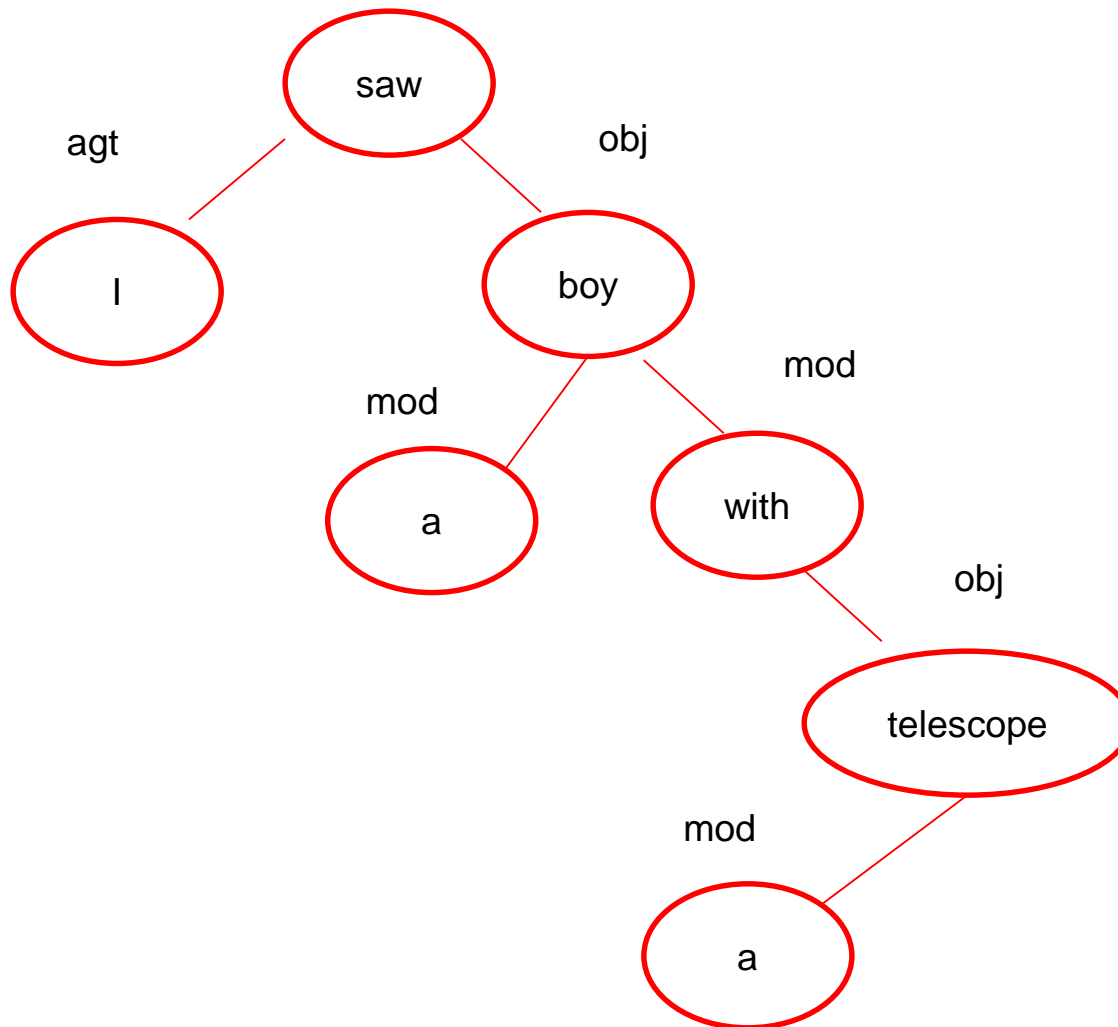
- Parent child relation means parent is constituted of child(ren)
- If there are multiple children, i.e., multiple constituents, one of them is the head and others are modifiers
- Thus given $VP \rightarrow V NP$, VP is constituted of V and NP
- V is the head and NP the modifier for the VP

Constituency Parse Tree -2

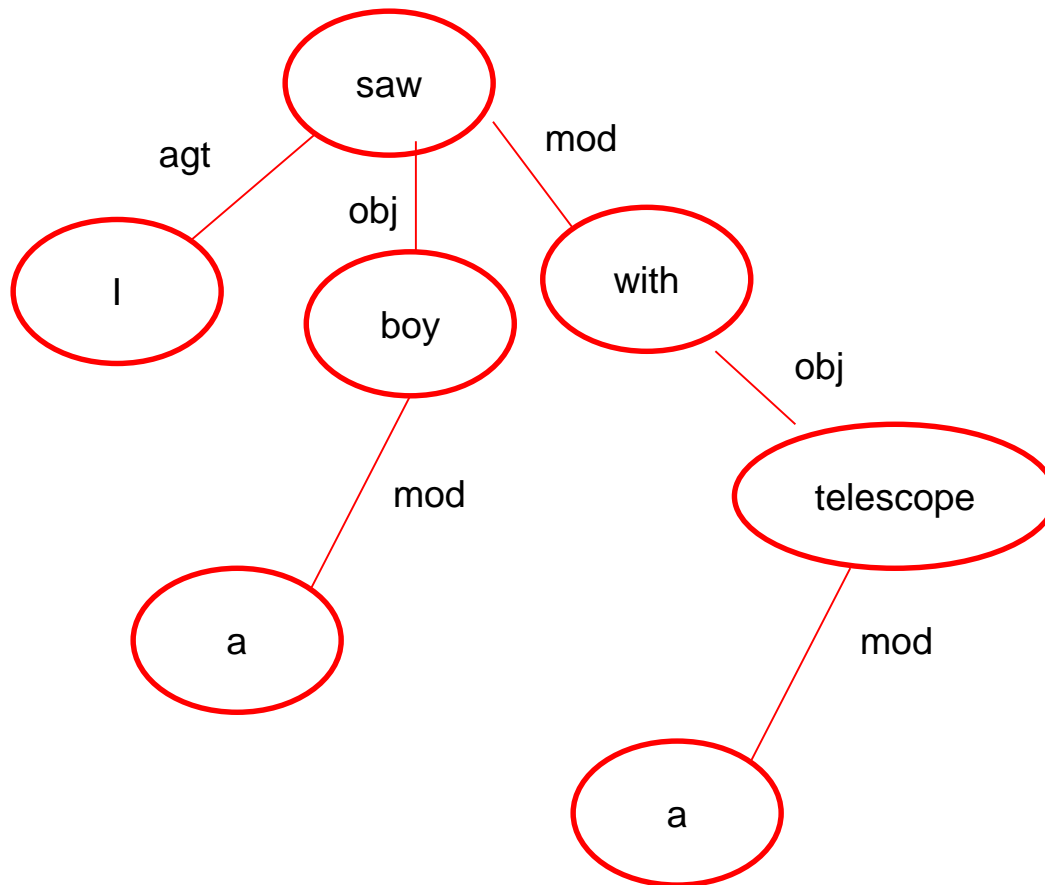


I saw a boy with a telescope

Dependency Parse Tree - 1



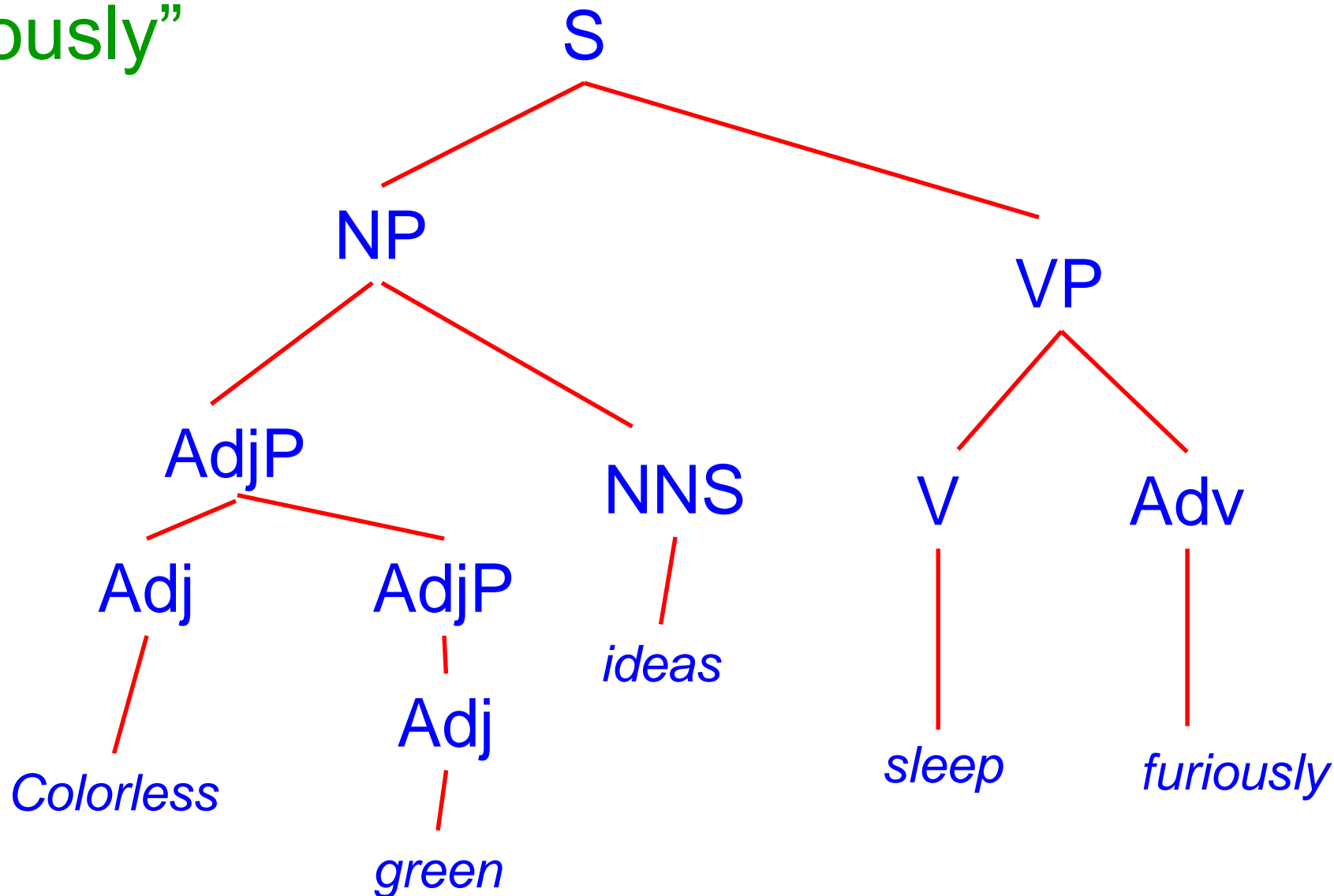
Dependency Parse Tree - 2



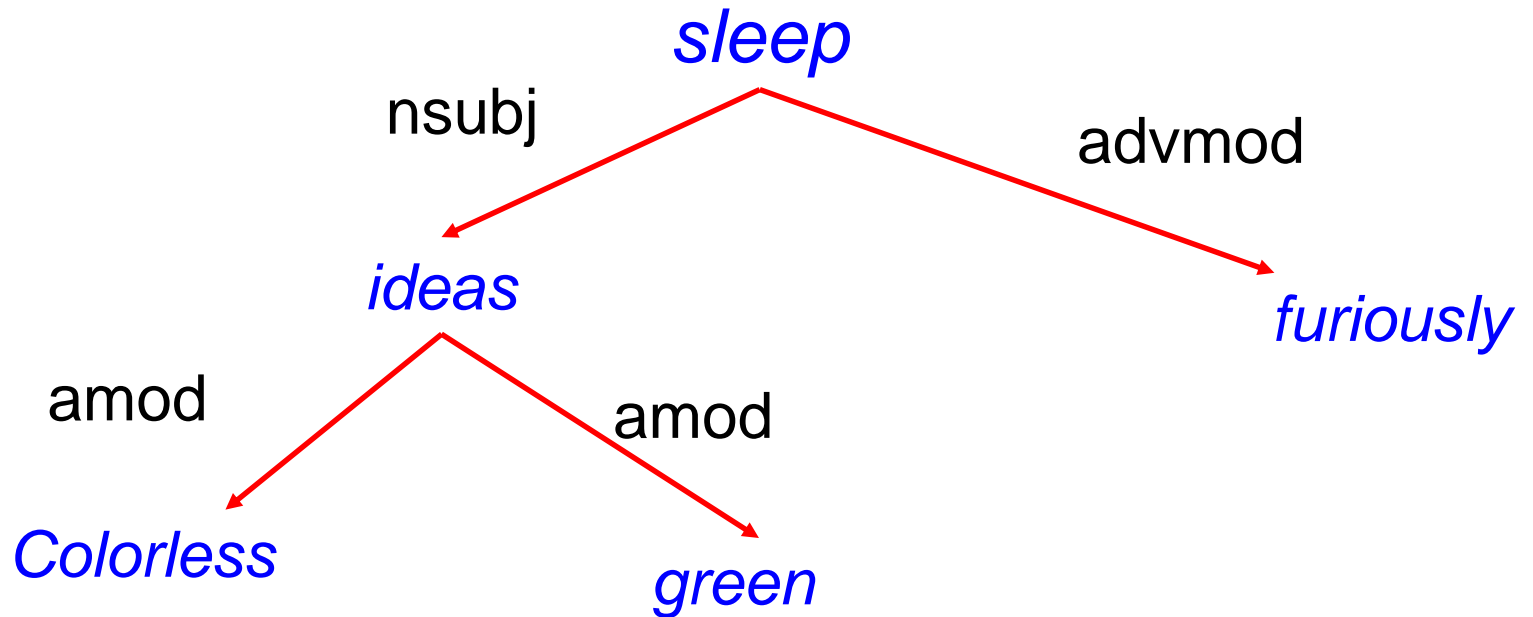
Foundation of Dependency Tree (DT)

- 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 furiously”



Dependency parse tree of “Colorless...”: Head Modifier Relations



Syntax-Semantics

- Syntax and semantics influence each other
- However, they can be independent too- as in the “*colourless green ideas...*” sentence
- Consistent with neurolinguistics- Broca’s and Wernicke’s areas

Broca's Area: wikipedia



- “Patients with lesions in Broca's area exhibit agrammatical speech production; they also show inability to use syntactic information to determine the meaning of sentences.”

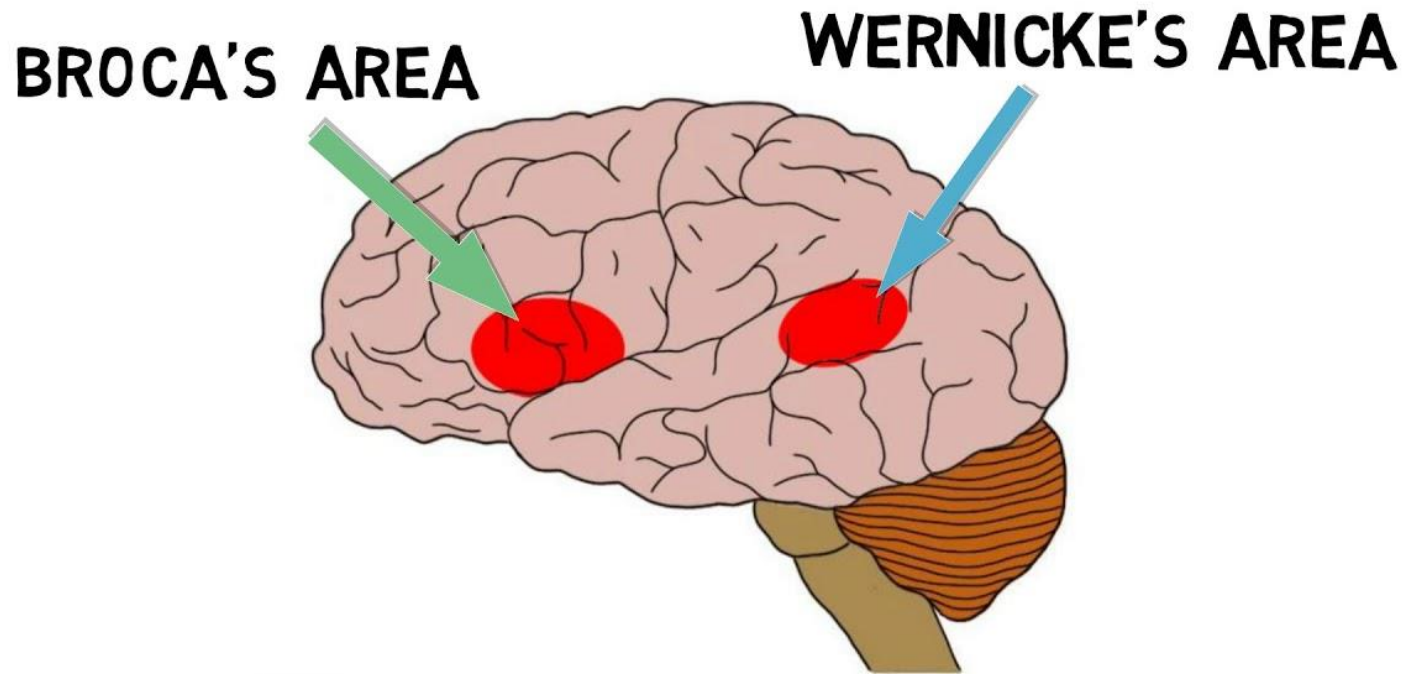
Broca's area damage (1/2) (Wikipedia)

- Agrammatical speech production
- Disconnected speech
- Mainly loss of function words and affixes
- Uses **telegraphic** speech
 - “*I eat rice spoon*” → *I eat rice with spoon*
 - “*Many boy play football yesterday*” → *Many boys played football yesterday*

Broca's Area Damage (2/2)

- Cannot use syntax to arrive at precise meaning
- No difference between
 - *Visit to the President vs.*
 - *Visit by the President*

Wernicke's Area (Wikipedia)



WERNICKE-GES



Wernicke's Area Damage

- “Damage caused to Wernicke's area results in receptive, fluent aphasia. This means that the person with aphasia will be able to fluently connect words, but the phrases will lack meaning”.
 - *The pink elephant sang and the blue stone danced*

Grammar Rules

A segment of English

- $S \rightarrow NP VP$
- $NP \rightarrow DT NN$
- $NP \rightarrow NNS$
- $NP \rightarrow NP PP$
- $PP \rightarrow P NP$
- $VP \rightarrow VP PP$
- $VP \rightarrow VBD NP$
- $DT \rightarrow \text{the}$
- $NN \rightarrow \text{gunman}$
- $NN \rightarrow \text{building}$
- $VBD \rightarrow \text{sprayed}$
- $NNS \rightarrow \text{bullets}$

CYK Parsing: Start with (0,1)

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

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

CYK: Keep filling diagonals

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

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



CYK: Try getting higher level structures

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

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

CYK: Diagonal continues

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

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

CYK (cont...)

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7 *.*

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

CYK (cont...)

0 *The* 1 *aunman* 2 *spraved* 3 *the* 4 *buildina* 5 *with* 6 *bullets* 7.

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



CYK (cont...)

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

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

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

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

CYK (cont...)

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

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 (cont...)

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

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!

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

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	-----	-----	-----	-----	-----	-----	



CYK (cont...)

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

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 (cont...)

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.

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	-----	-----	-----	-----	-----	-----	

[illegible]

CYK (cont...)

0 The 1 gunman 2 sprayed 3 the 4 building 5 with 6 bullets 7.

[illegible]

CYK (cont...)

0 The 1 gunman 2 sprayed 3 the 4 building 5 with 6 bullets 7.

[illegible]

CYK (cont...)

0 The 1 gunman 2 sprayed 3 the 4 building 5 with 6 bullets 7.

[illegible]

[illegible]

0 The 1 gunman 2 sprayed 3 the 4 building 5 with 6 bullets 7.

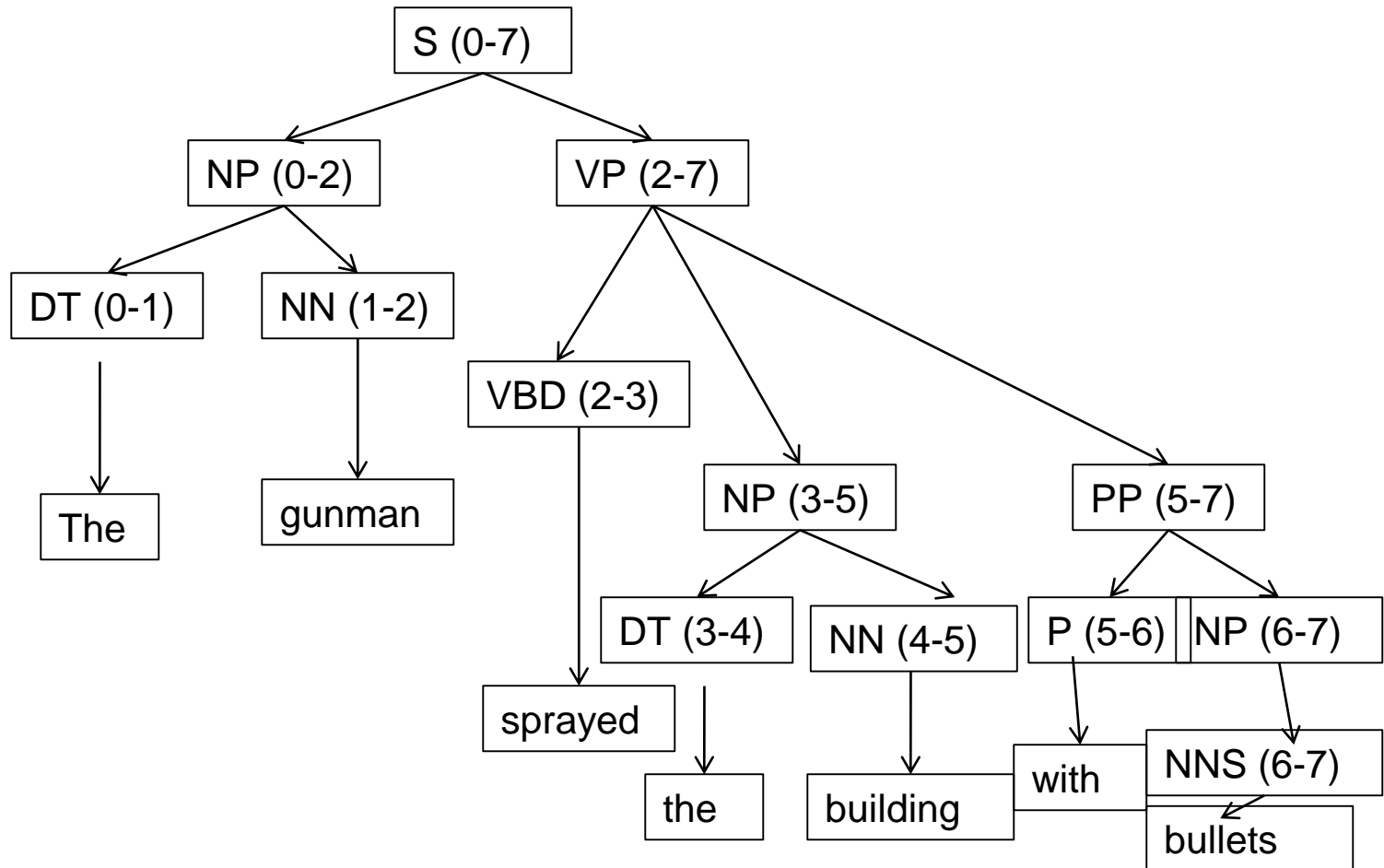
[illegible]

CYK: Extracting the Parse Tree

- The parse tree is obtained by keeping back pointers.

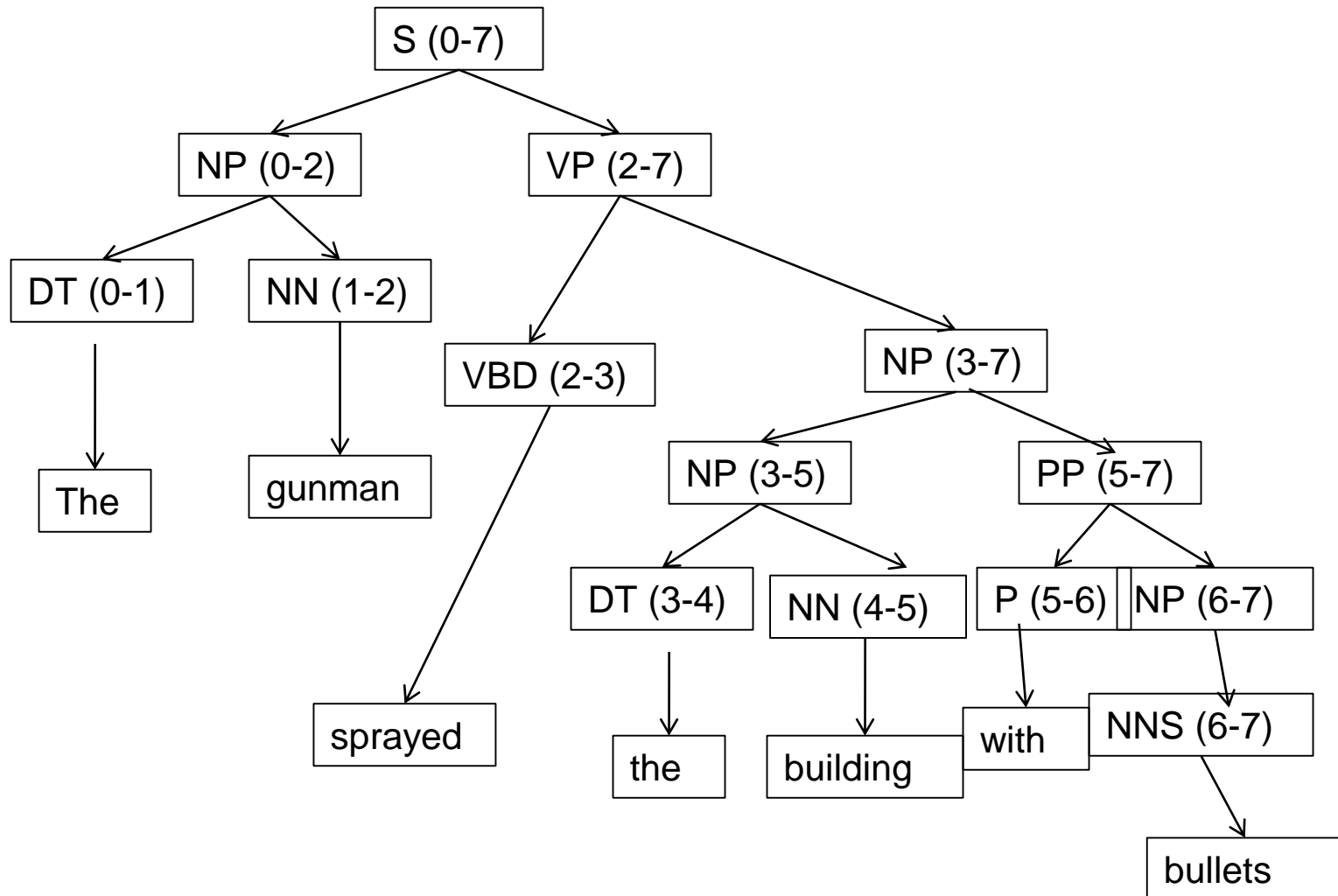
Parse Tree #1

0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.



Parse Tree #2

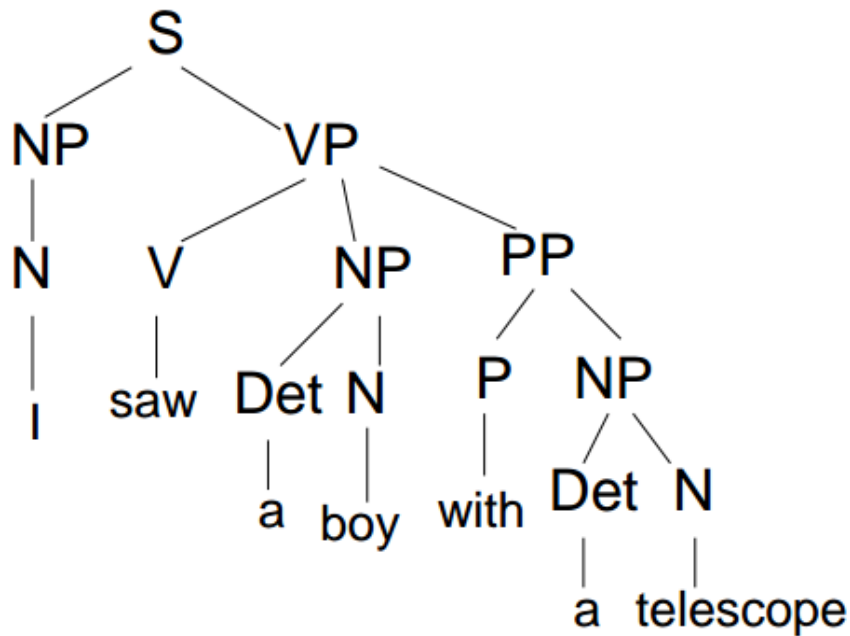
0 *The* 1 *gunman* 2 *sprayed* 3 *the* 4 *building* 5 *with* 6 *bullets* 7.



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

Probabilistic parsing

Noisy Channel Modeling



$$\begin{aligned} T^* &= \underset{T}{\operatorname{argmax}} [P(T|S)] \\ &= \underset{T}{\operatorname{argmax}} [P(T).P(S|T)] \\ &= \underset{T}{\operatorname{argmax}} [P(T)], \text{ since given the parse the} \\ &\quad \text{sentence is completely} \\ &\quad \text{determined and } P(S|T)=1 \end{aligned}$$

Example of Sentence labeling: Parsing

[S₁[S[S[VP[VB Come][NP[NNP July]]]]]

[,]

[CC and]

[S [NP [DT the] [JJ IIT] [NN campus]]

[VP [AUX is]

[ADJP [JJ abuzz]

[PP[IN with]

[NP[ADJP [JJ new] [CC and] [VBG returning]]

[NNS students]]]]]]

[.]]]

Formal Definition of PCFG

- A PCFG consists of
 - A set of terminals $\{w_k\}$, $k = 1, \dots, V$
 $\{w_k\} = \{\text{child, teddy, bear, played...}\}$
 - A set of non-terminals $\{N_i\}$, $i = 1, \dots, n$
 $\{N_i\} = \{\text{NP, VP, DT...}\}$
 - A designated start symbol N^1
 - A set of rules $\{N^i \rightarrow \zeta^j\}$, where ζ^j is a sequence of terminals & non-terminals
 $\text{NP} \rightarrow \text{DT NN}$
 - A corresponding set of rule probabilities

Rule Probabilities

- Rule probabilities are such that for the same non terminal all production rules sum to 1.

E.g., $P(\text{NP} \rightarrow \text{DT NN}) = 0.2$

$P(\text{NP} \rightarrow \text{NNS}) = 0.5$

$P(\text{NP} \rightarrow \text{NP PP}) = 0.3$

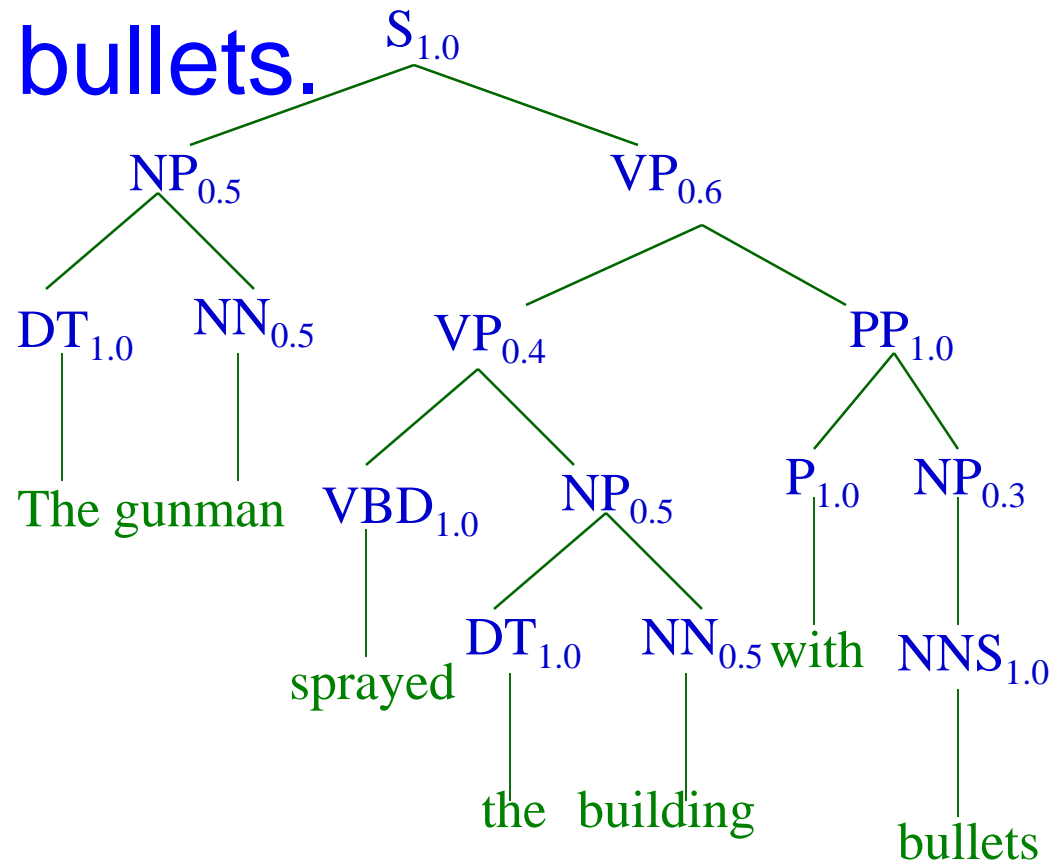
- $P(\text{NP} \rightarrow \text{DT NN}) = 0.2$
 - Means 20 % of the training data parses use the rule $\text{NP} \rightarrow \text{DT NN}$

Probabilistic Context Free Grammars

- $S \rightarrow NP VP$ 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

Example Parse t_1

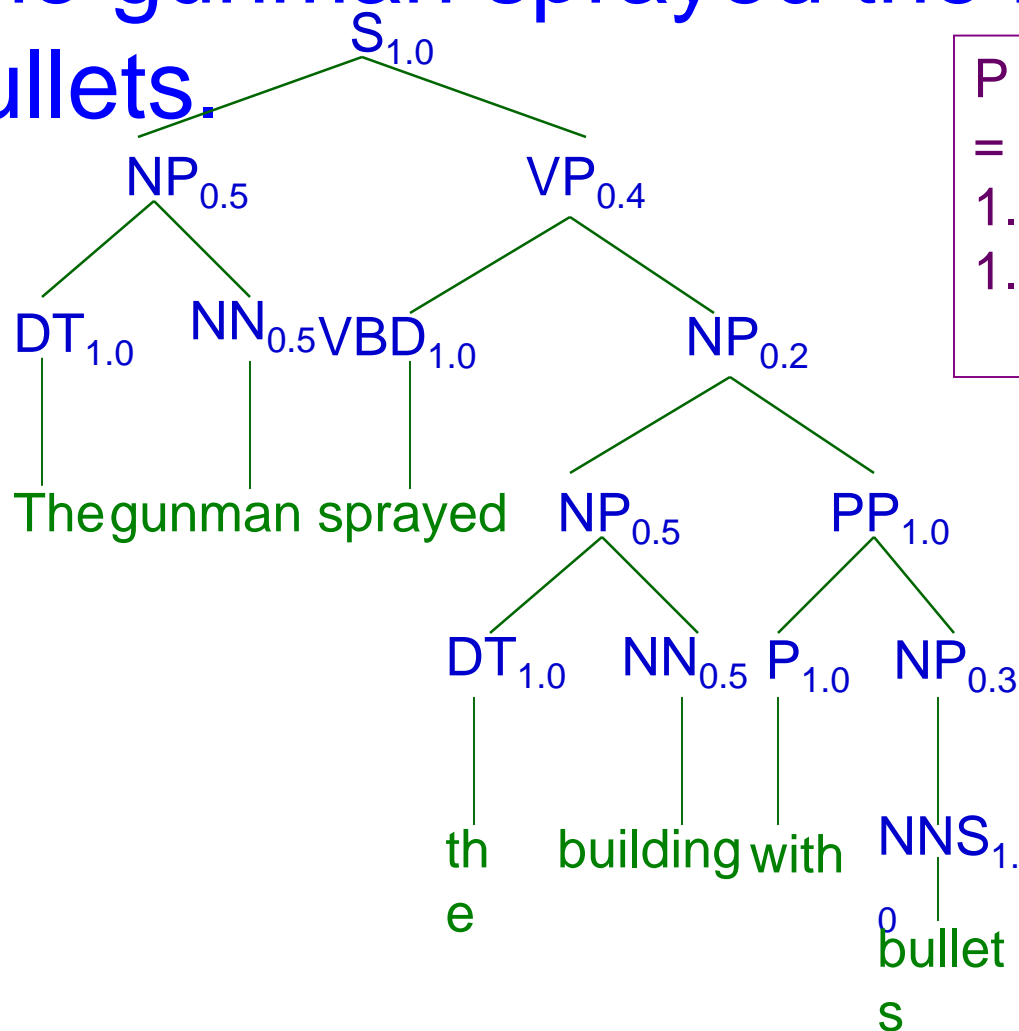
- The gunman sprayed the building with bullets.



$$\begin{aligned}
 P(t_1) &= 1.0 * \\
 &0.5 * 1.0 * 0.5 * 0.6 * 0.4 * 1.0 \\
 &* 0.5 * 1.0 * 0.5 * 1.0 * 1.0 * \\
 &0.3 * 1.0 \\
 &= 0.00225
 \end{aligned}$$

Another Parse t_2

- The gunman sprayed the building with bullets.

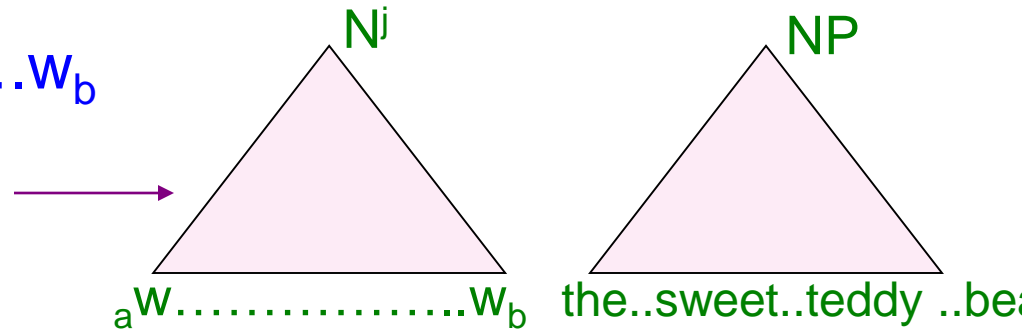


$$\begin{aligned}
 P(t_2) &= 1.0 * 0.5 * 1.0 * 0.5 * 0.4 * \\
 &1.0 * 0.2 * 0.5 * 1.0 * 0.5 * \\
 &1.0 * 1.0 * 0.3 * 1.0 \\
 &= 0.0015
 \end{aligned}$$

Probability of a sentence

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

- w_{ab} – subsequence $a w \dots w_b$
- N^j dominates $a w \dots w_b$
or $\text{yield}(N^j) = a w \dots w_b$



Probability of a sentence = $P(w_{0,l})$ (0 is the index before the first word and l the index after the last word. All other indices are between words)

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

$$= \sum_t (P(t) \cdot (P(w_{0,l} | t)))$$

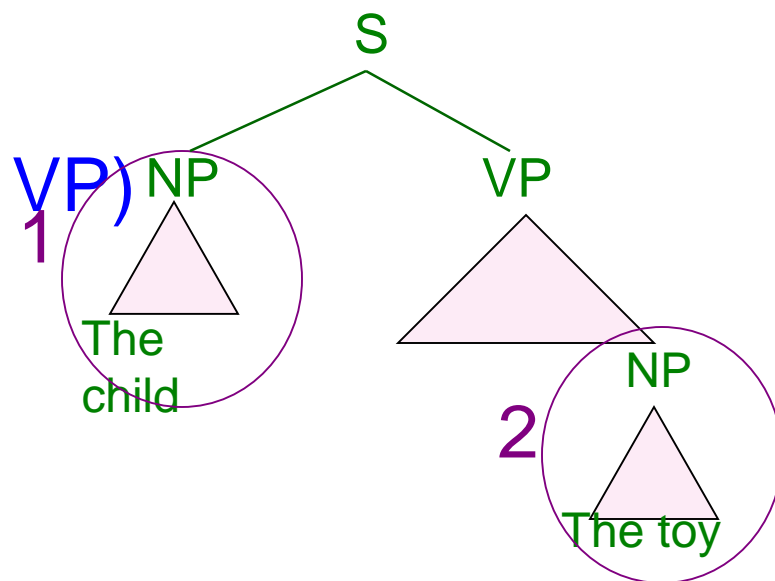
$$= \sum_t P(t) \cdot 1$$

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

Where t is a parse tree of the sentence

Assumptions of the PCFG model

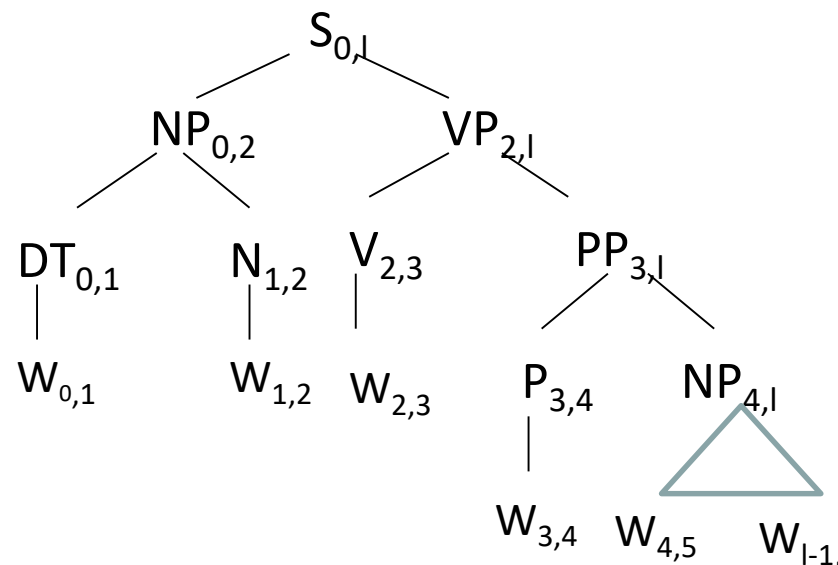
- Place invariance :
 $P(\text{NP} \rightarrow \text{DT NN})$ is same in locations 1 and 2
- Context-free :
 $P(\text{NP} \rightarrow \text{DT NN} \mid \text{anything outside "The child"})$
 $= P(\text{NP} \rightarrow \text{DT NN})$
- Ancestor free : At 2,
 $P(\text{NP} \rightarrow \text{DT NN} \mid \text{its ancestor is VP})$
 $= P(\text{NP} \rightarrow \text{DT NN})$



Probability of a parse tree

- *Domination* : We say N_j dominates from k to l , symbolized as $N_j^i_{k,l}$, if $W_{k,l}$ is derived from N_j
- $P(\text{tree} \mid \text{sentence}) = P(\text{tree} \mid S_{1,l})$
 where $S_{0,l}$ means that the start symbol S dominates the word sequence $W_{0,l}$
- $P(t \mid s)$ approximately equals joint probability of constituent non-terminals dominating the sentence fragments (next slide)

Probability of a parse tree (cont.)



$$P(t|s) = P(t | S_{0,1})$$

$$= P(NP_{0,2}, DT_{0,1}, w_{0,1}, N_{1,2}, w_{1,2}, VP_{2,1}, V_{2,3}, w_{2,3}, PP_{3,1}, P_{3,4}, w_{3,4}, NP_{4,1}, w_{4,5} | S_{0,1})$$

$$= P(NP_{0,2}, VP_{2,1} | S_{0,1}) * P(DT_{0,1}, N_{1,2} | NP_{0,2}) * P(w_{0,1} | DT_{0,1}) * P(w_{1,2} | N_{1,2}) * P(V_{2,3}, PP_{3,1} | VP_{2,1}) * P(w_{2,3} | V_{2,3}) * P(P_{3,4}, NP_{4,1} | PP_{3,1}) * P(w_{3,4} | P_{3,4}) * P(w_{4,5} | NP_{4,1})$$

(Using Chain Rule, Context Freeness and Ancestor Freeness)