

CS626: NLP, Speech and the Web

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Lecture 15, 17: Parsing Ambiguity,
Probabilistic Parsing, sample seminar

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(16th lecture was on UNL by Avishek)

Dealing With Structural Ambiguity

- Multiple parses for a sentence
 - The man saw the boy with a telescope.
 - The man saw the mountain with a telescope.
 - The man saw the boy with the ponytail.

At the level of syntax, all these sentences are ambiguous. But semantics can disambiguate 2nd & 3rd sentence.

Prepositional Phrase (PP) Attachment Problem

$V - NP_1 - P - NP_2$

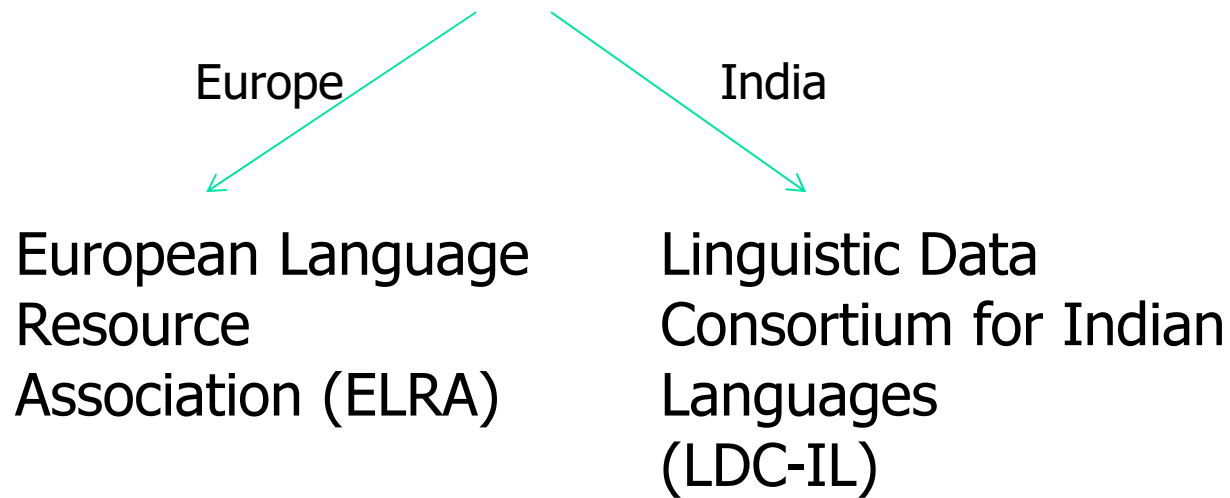
(Here P means preposition)

NP_2 attaches to NP_1 ?

or NP_2 attaches to V ?

- Xerox Parsers
 - XLE Parser (Freely available)
 - XIP Parser (expensive)

Linguistic Data Consortium (LDC at UPenn)



Parse Trees for a Structurally Ambiguous Sentence

Let the grammar be –

$S \rightarrow NP VP$

$NP \rightarrow DT N \mid DT N PP$

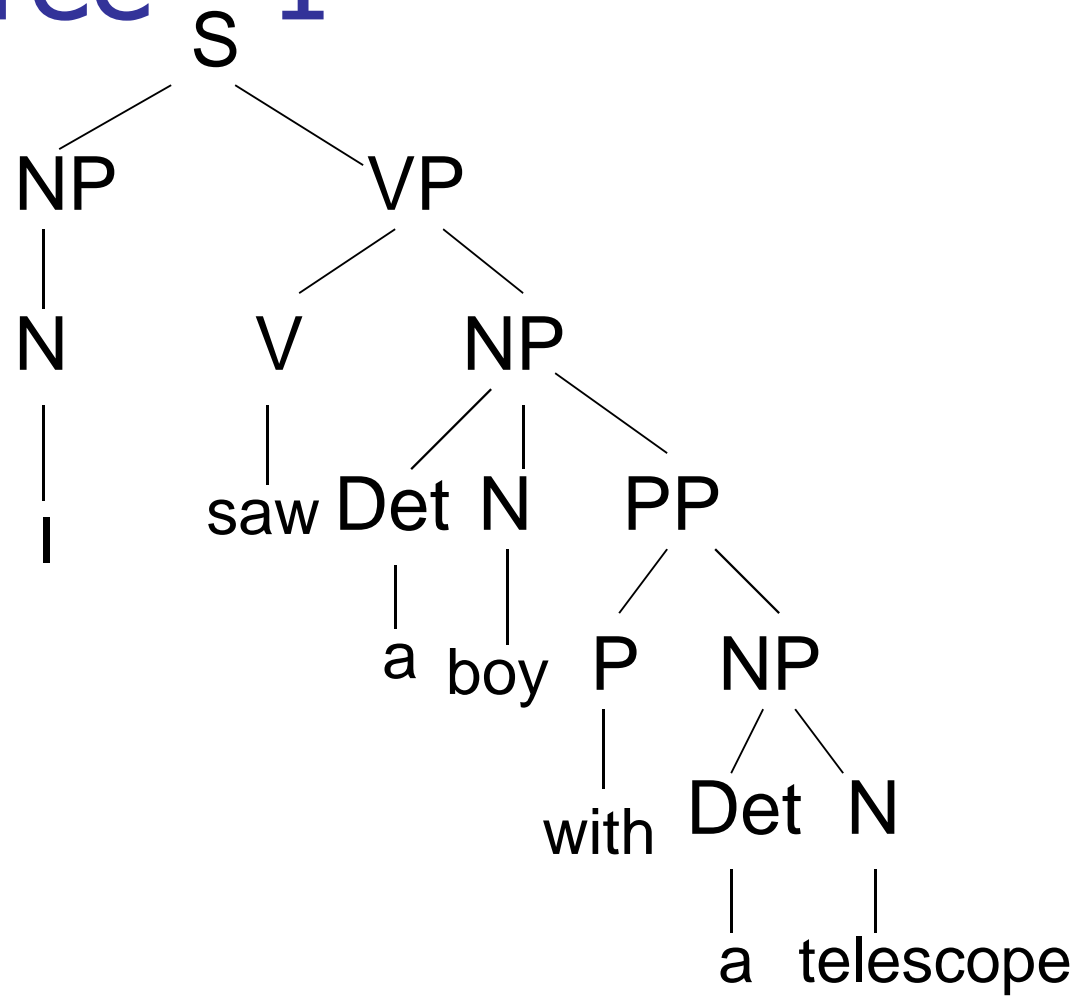
$PP \rightarrow P NP$

$VP \rightarrow V NP PP \mid V NP$

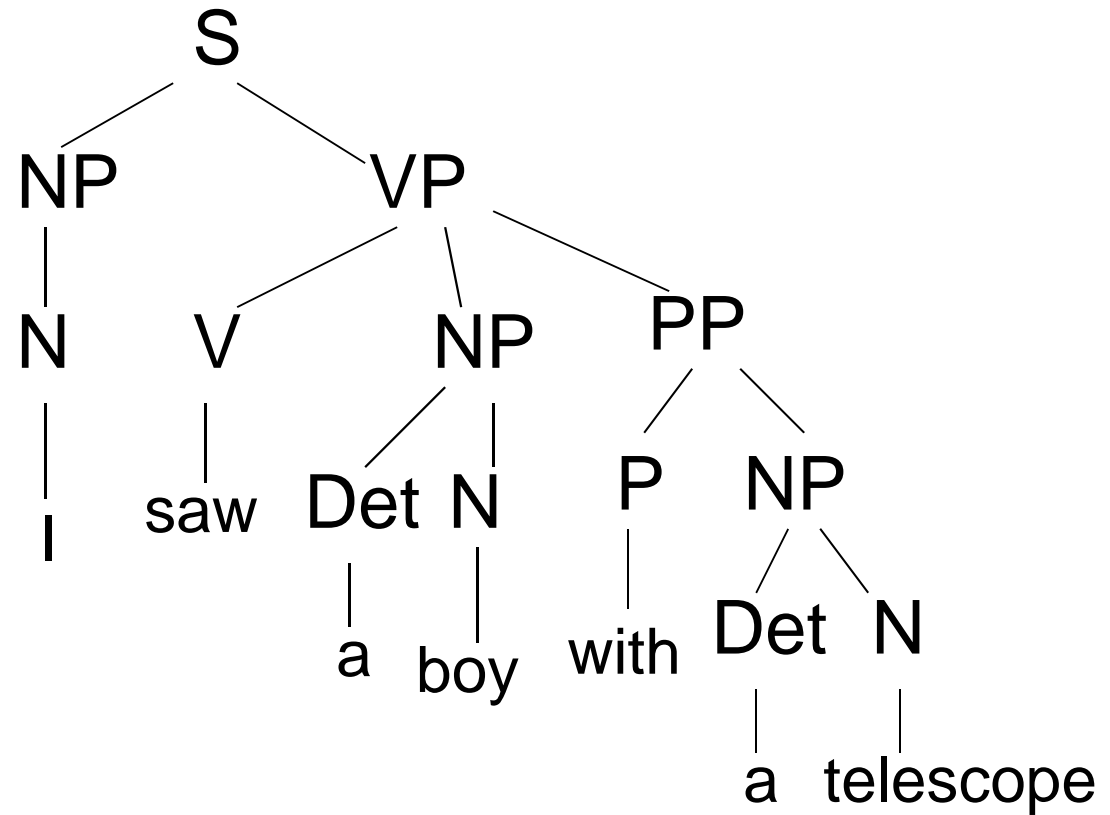
For the sentence,

“I saw a boy with a telescope”

Parse Tree - 1



Parse Tree -2



Parsing Structural Ambiguity

Parsing for Structurally Ambiguous Sentences

- Sentence "I saw a boy with a telescope"
- Grammar:
 - S → NP VP
 - NP → ART N | ART N PP | PRON
 - VP → V NP PP | V NP
 - ART → a | an | the
 - N → boy | telescope
 - PRON → I
 - V → saw

Ambiguous Parses

- Two possible parses:
 - PP attached with Verb (i.e. *I used a telescope to see*)
 - (S (NP (PRON "I")) (VP (V "saw") (NP ((ART "a") (N "boy")) (PP (P "with") (NP (ART "a") (N "telescope"))))))))
 - PP attached with Noun (i.e. *boy had a telescope*)
 - (S (NP (PRON "I")) (VP (V "saw") (NP ((ART "a") (N "boy") (PP (P "with") (NP (ART "a") (N "telescope"))))))))

Top Down Parse

	State	Backup State	Action	Comments
1	((S) 1)	–	–	Use S → NP VP
2	((NP VP) 1)	–	–	Use NP → ART N ART N PP PRON
3	((ART N VP) 1)	(a) ((ART N PP VP) 1) (b) ((PRON VP) 1)	–	ART does not match "I", backup state (b) used
3 B	((PRON VP) 1)	–	–	
4	((VP) 2)	–	Consumed "I"	
5	((V NP PP) 2)	((V NP) 2)	–	Verb Attachment Rule used
6	((NP PP) 3)	–	Consumed "saw"	

Top Down Parse

	State	Backup State	Action	Comments
1	((S) 1)	–	–	Use S → NP VP
2	((NP VP) 1)	–	–	Use NP → ART N ART N PP PRON
3	((ART N VP) 1)	(a) ((ART N PP VP) 1) (b) ((PRON VP) 1)	–	ART does not match "I", backup state (b) used
3 B	((PRON VP) 1)	–	–	
4	((VP) 2)	–	Consumed "I"	
5	((V NP PP) 2)	((V NP) 2)	–	Verb Attachment Rule used
6	((NP PP) 3)	–	Consumed "saw"	
7	((ART N PP) 3)	(a) ((ART N PP PP) 3) (b) ((PRON PP) 3)		

Top Down Parse

	State	Backup State	Action	Comments
1	((S) 1)	–	–	Use S → NP VP
2	((NP VP) 1)	–	–	Use NP → ART N ART N PP PRON
3	((ART N VP) 1)	(a) ((ART N PP VP) 1) (b) ((PRON VP) 1)	–	ART does not match "I", backup state (b) used
3 B	((PRON VP) 1)	–	–	
4	((VP) 2)	–	Consumed "I"	
5	((V NP PP) 2)	((V NP) 2)	–	Verb Attachment Rule used
6	((NP PP) 3)	–	Consumed "saw"	
7	((ART N PP) 3)	(a) ((ART N PP PP) 3) (b) ((PRON PP) 3)		
8	((N PP) 4)	–	Consumed "a"	

Top Down Parse

	State	Backup State	Action	Comments
1	((S) 1)	–	–	Use S → NP VP
2	((NP VP) 1)	–	–	Use NP → ART N ART N PP PRON
3	((ART N VP) 1)	(a) ((ART N PP VP) 1) (b) ((PRON VP) 1)	–	ART does not match "I", backup state (b) used
3 B	((PRON VP) 1)	–	–	
4	((VP) 2)	–	Consumed "I"	
5	((V NP PP) 2)	((V NP) 2)	–	Verb Attachment Rule used
6	((NP PP) 3)	–	Consumed "saw"	
7	((ART N PP) 3)	(a) ((ART N PP PP) 3) (b) ((PRON PP) 3)		
8	((N PP) 4)	–	Consumed "a"	
9	((DD) 5)	–	Consumed	

Top Down Parse

	State	Backup State	Action	Comments
1	((S) 1)	–	–	Use S → NP VP
2	((NP VP) 1)	–	–	Use NP → ART N ART N PP PRON
3	((ART N VP) 1)	(a) ((ART N PP VP) 1) (b) ((PRON VP) 1)	–	ART does not match "I", backup state (b) used
3 B	((PRON VP) 1)	–	–	
4	((VP) 2)	–	Consumed "I"	
5	((V NP PP) 2)	((V NP) 2)	–	Verb Attachment Rule used
6	((NP PP) 3)	–	Consumed "saw"	
7	((ART N PP) 3)	(a) ((ART N PP PP) 3) (b) ((PRON PP) 3)		
8	((N PP) 4)	–	Consumed "a"	
9	((DD) 5)	–	Consumed	

Top Down Parse

	State	Backup State	Action	Comments
1	((S) 1)	–	–	Use S → NP VP
...
7	((ART N PP) 3)	(a) ((ART N PP PP) 3) (b) ((PRON PP) 3)		
8	((N PP) 4)	–	Consumed "a"	
9	((PP) 5)	–	Consumed "boy"	
10	((P NP) 5)	–	–	
11	((NP) 6)	–	Consumed "with"	

Top Down Parse

	State	Backup State	Action	Comments
1	((S) 1)	–	–	Use S → NP VP
...
7	((ART N PP) 3)	(a) ((ART N PP PP) 3) (b) ((PRON PP) 3)		
8	((N PP) 4)	–	Consumed "a"	
9	((PP) 5)	–	Consumed "boy"	
10	((P NP) 5)	–	–	
11	((NP) 6)	–	Consumed "with"	
12	((ART N) 6)	(a) ((ART N PP) 6) (b) ((PRON) 6)	–	

Top Down Parse

	State	Backup State	Action	Comments
1	((S) 1)	–	–	Use S → NP VP
...
7	((ART N PP) 3)	(a) ((ART N PP PP) 3) (b) ((PRON PP) 3)		
8	((N PP) 4)	–	Consumed "a"	
9	((PP) 5)	–	Consumed "boy"	
10	((P NP) 5)	–	–	
11	((NP) 6)	–	Consumed "with"	
12	((ART N) 6)	(a) ((ART N PP) 6) (b) ((PRON) 6)	–	
13	((N) 7)	–	Consumed "a"	

Top Down Parse

	State	Backup State	Action	Comments
1	((S) 1)	–	–	Use S → NP VP
...
7	((ART N PP) 3)	(a) ((ART N PP PP) 3) (b) ((PRON PP) 3)		
8	((N PP) 4)	–	Consumed "a"	
9	((PP) 5)	–	Consumed "boy"	
10	((P NP) 5)	–	–	
11	((NP) 6)	–	Consumed "with"	
12	((ART N) 6)	(a) ((ART N PP) 6) (b) ((PRON) 6)	–	
13	((N) 7)	–	Consumed "a"	
14	((–) 8)	–	Consume "telescope" Finish Parsing	

Top Down Parsing - Observations

- Top down parsing gave us the Verb Attachment Parse Tree (i.e., *I used a telescope*)
- To obtain the alternate parse tree, the backup state in step 5 will have to be invoked
- Is there an efficient way to obtain all parses ?

Bottom Up Parse

1 I 2 saw 3 a 4 boy 5 with 6 a 7 telescope 8

Colour Scheme :

- Blue for Normal Parse
- Green for Verb Attachment Parse
- Purple for Noun Attachment Parse
- Red for Invalid Parse

Bottom Up Parse

I saw a boy with a telescope

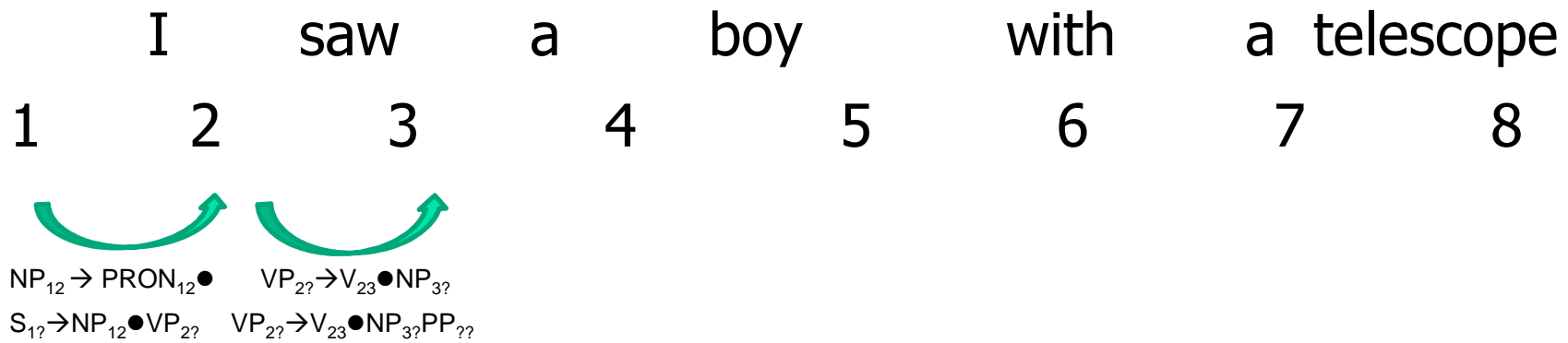
1 2 3 4 5 6 7 8



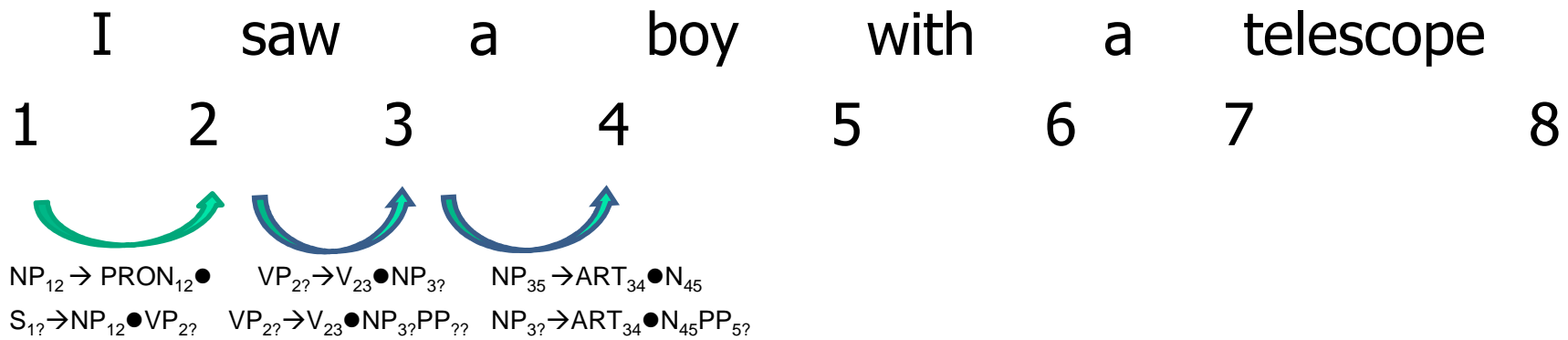
$NP_{12} \rightarrow PRON_{12} \bullet$

$S_{1?} \rightarrow NP_{12} \bullet VP_{2?}$

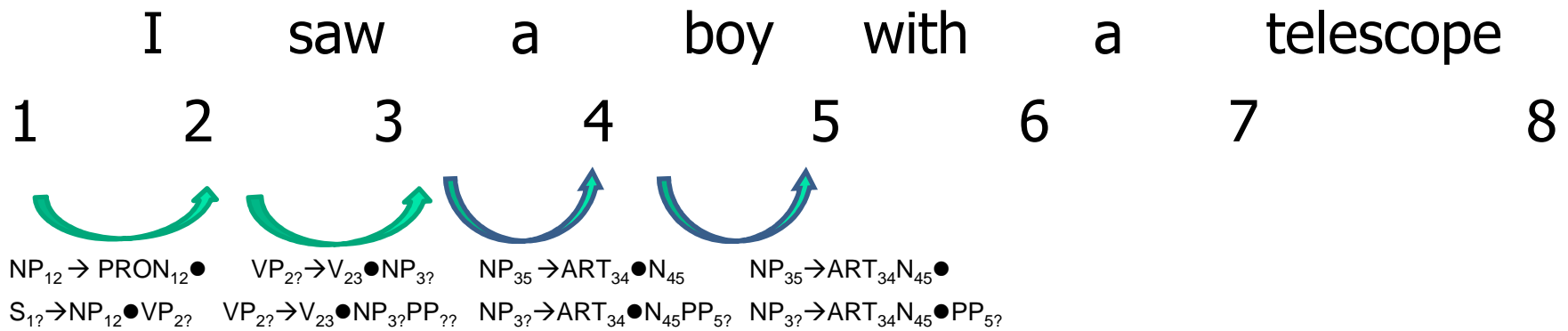
Bottom Up Parse



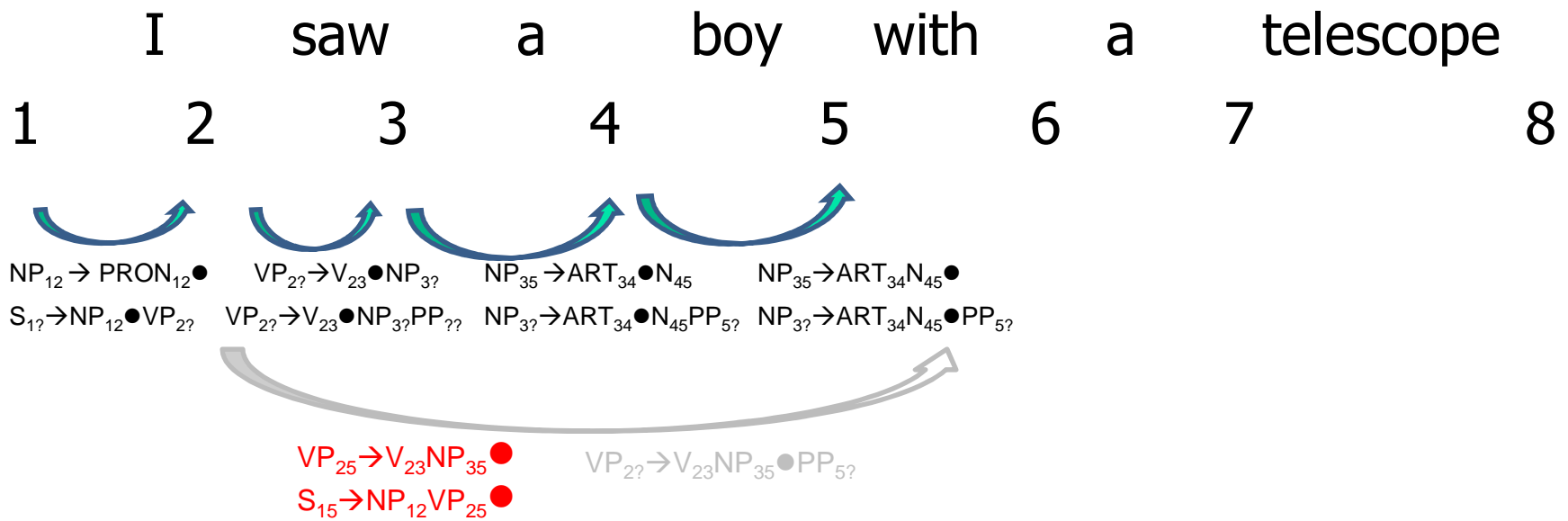
Bottom Up Parse



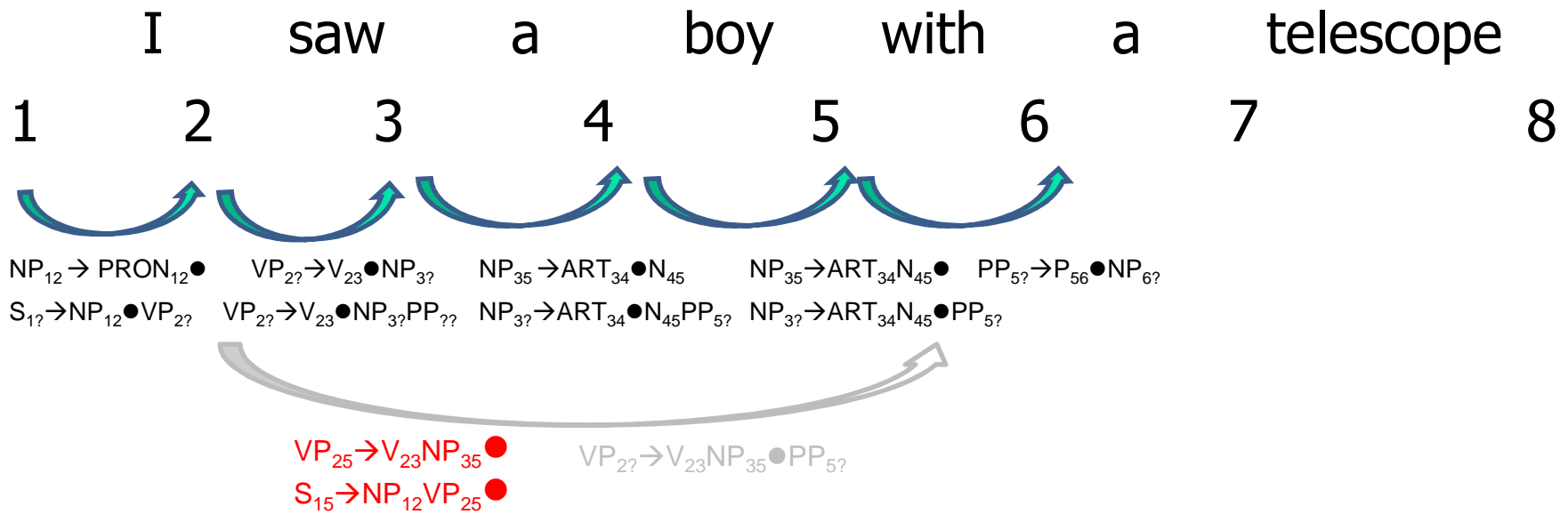
Bottom Up Parse



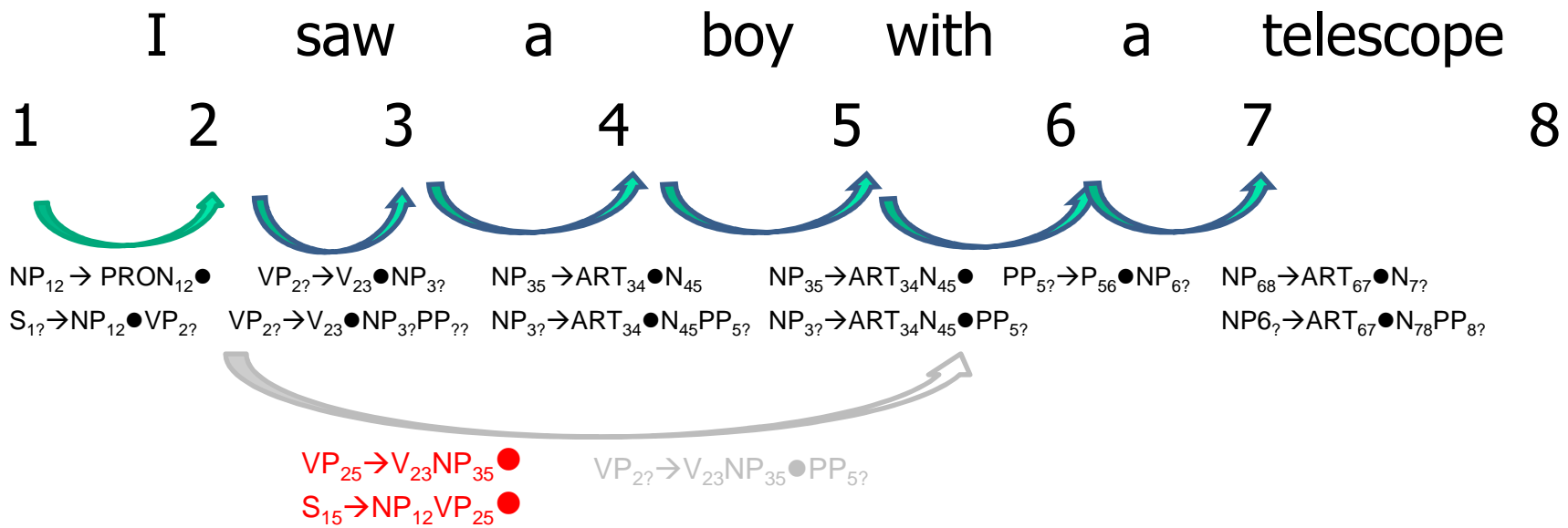
Bottom Up Parse



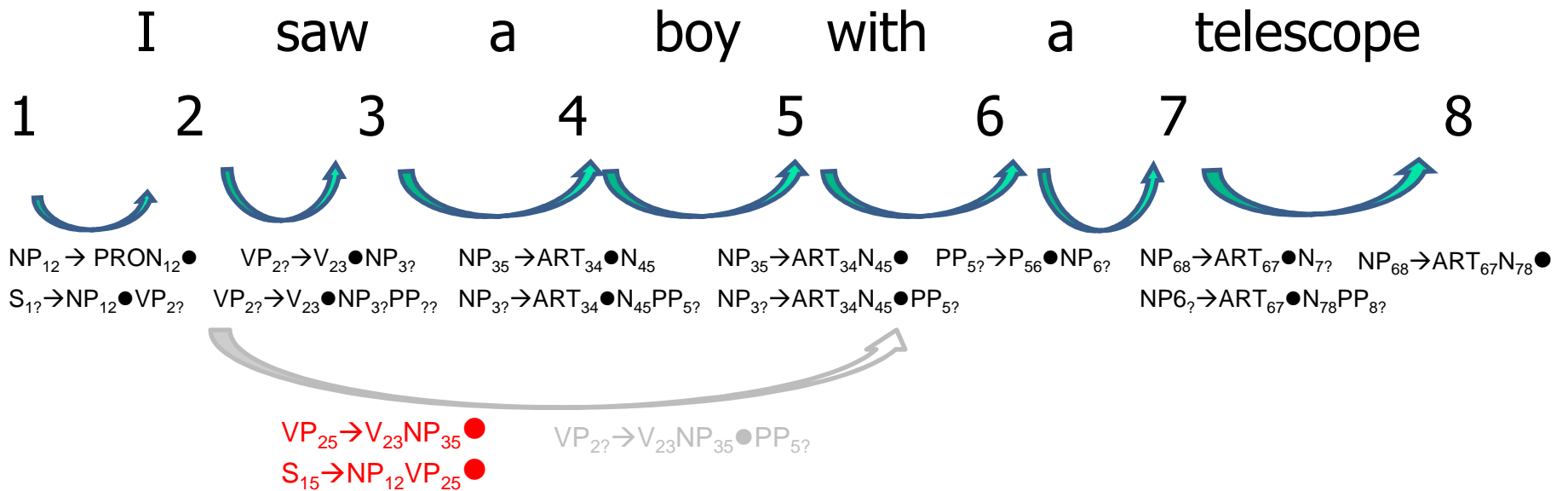
Bottom Up Parse



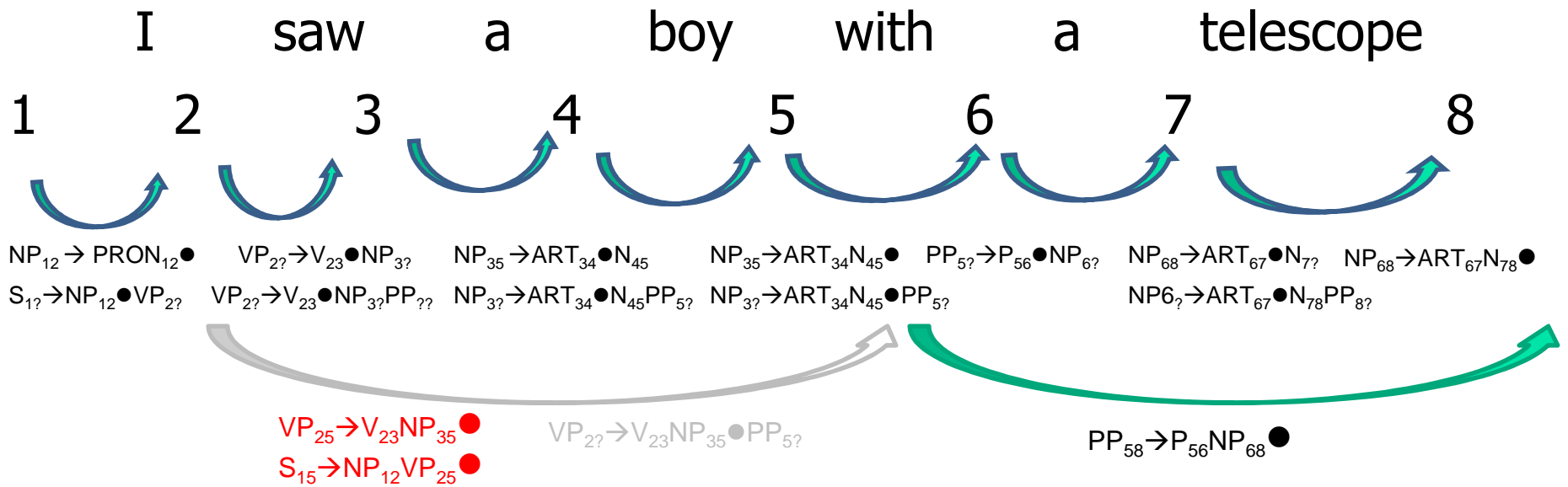
Bottom Up Parse



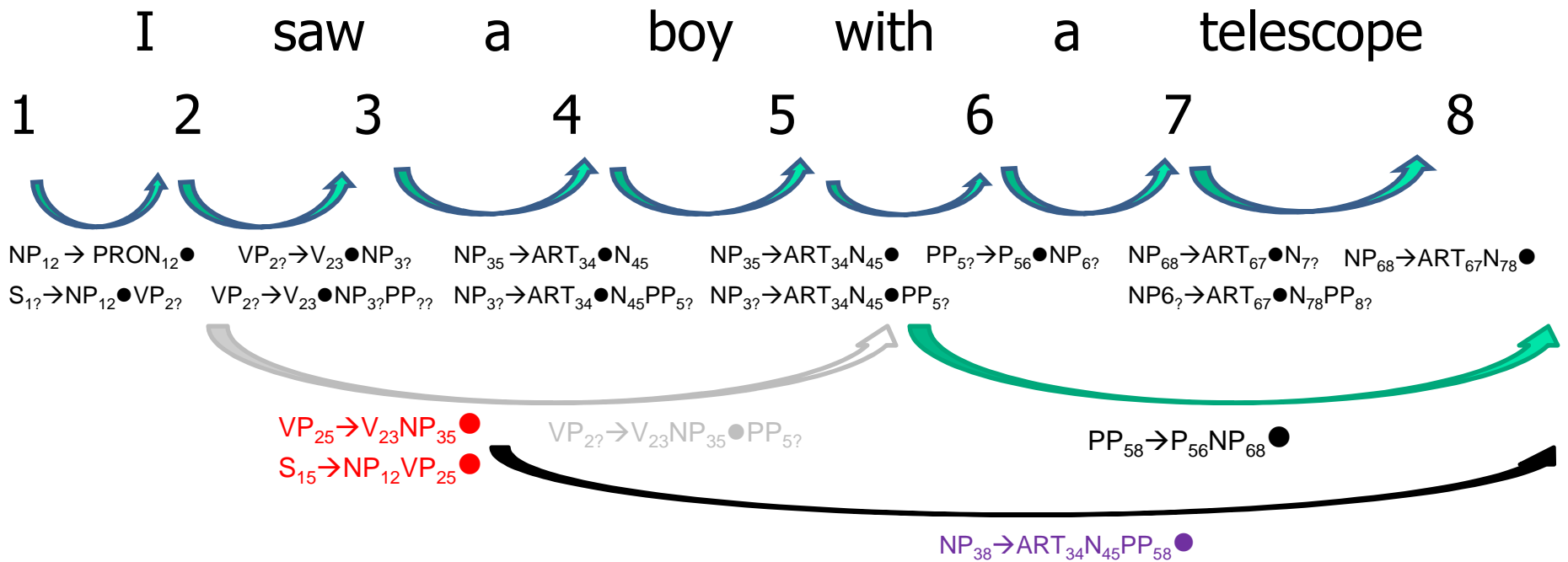
Bottom Up Parse



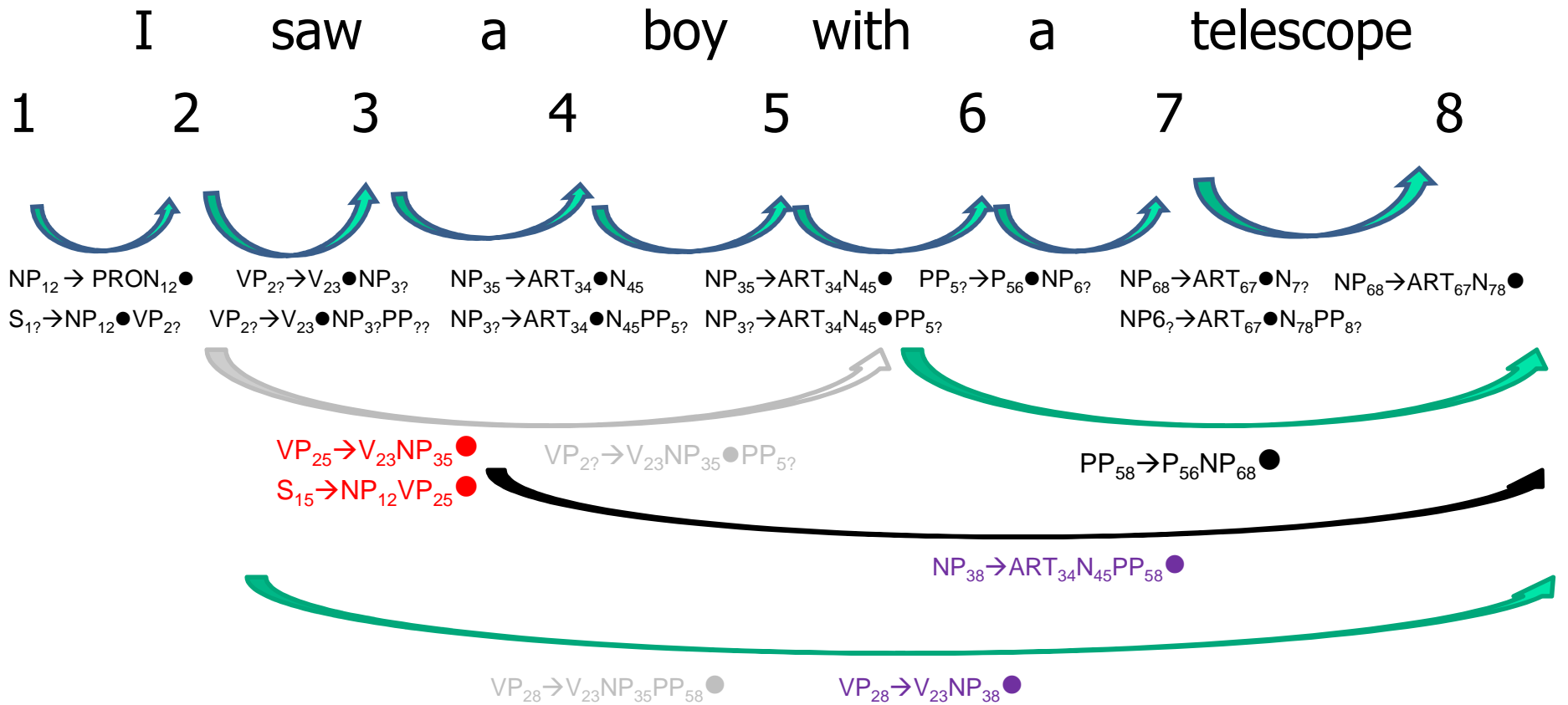
Bottom Up Parse



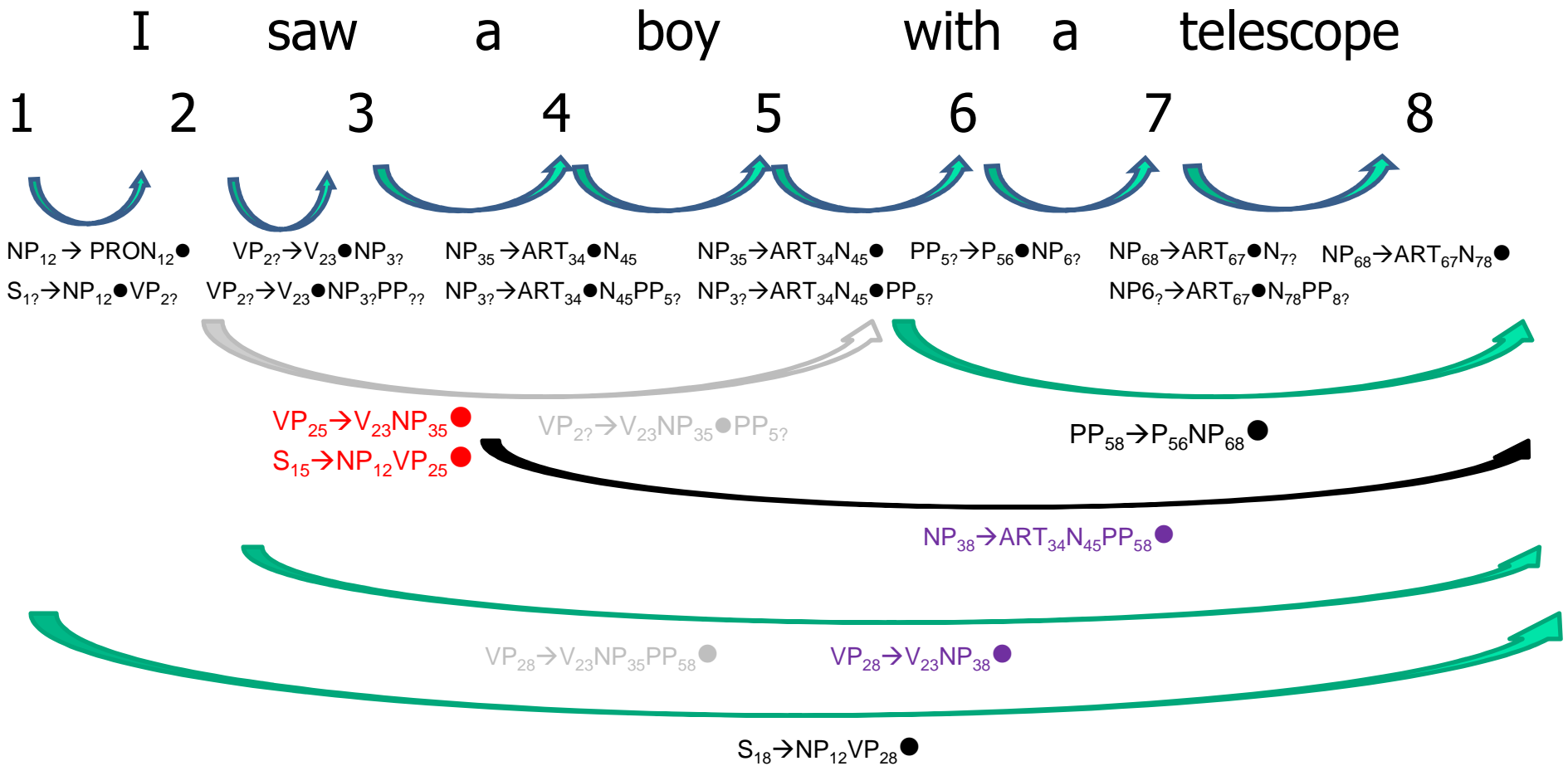
Bottom Up Parse



Bottom Up Parse



Bottom Up Parse



Bottom Up Parsing - Observations

- Both Noun Attachment and Verb Attachment Parses obtained by simply systematically applying the rules
- Numbers in subscript help in verifying the parse and getting chunks from the parse

Exercise

For the sentence,

“The man saw the boy with a telescope”
& the grammar given previously,
compare the performance of top-down,
bottom-up & top-down chart parsing.

Start of Probabilistic Parsing

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]]]]]]]

[.]

Noisy Channel Modeling



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

Corpus

- A collection of text called *corpus*, is used for collecting various language data
- With annotation: more information, but manual labor intensive
- Practice: *label automatically; correct manually*
- The famous *Brown Corpus* contains 1 million tagged words.
- **Switchboard:** very famous corpora 2400 conversations, 543 speakers, many US dialects, annotated with orthography and phonetics

Discriminative vs. Generative Model

$$W^* = \underset{W}{\operatorname{argmax}} (P(W/SS))$$

Discriminative
Model

Generative
Model

Compute directly from
 $P(W/SS)$

Compute from
 $P(W).P(SS/W)$

Language Models

- N-grams: sequence of n consecutive words/characters
- Probabilistic / Stochastic Context Free Grammars:
 - Simple probabilistic models capable of handling recursion
 - A CFG with probabilities attached to rules
 - Rule probabilities → how likely is it that a particular rewrite rule is used?

PCFGs

- Why PCFGs?
 - Intuitive probabilistic models for tree-structured languages
 - Algorithms are extensions of HMM algorithms
 - Better than the n-gram model for language modeling.

Data driven parsing is tied up with what is seen in the training data

- “*Stand right walk left.*” Often a message on the airport escalators.

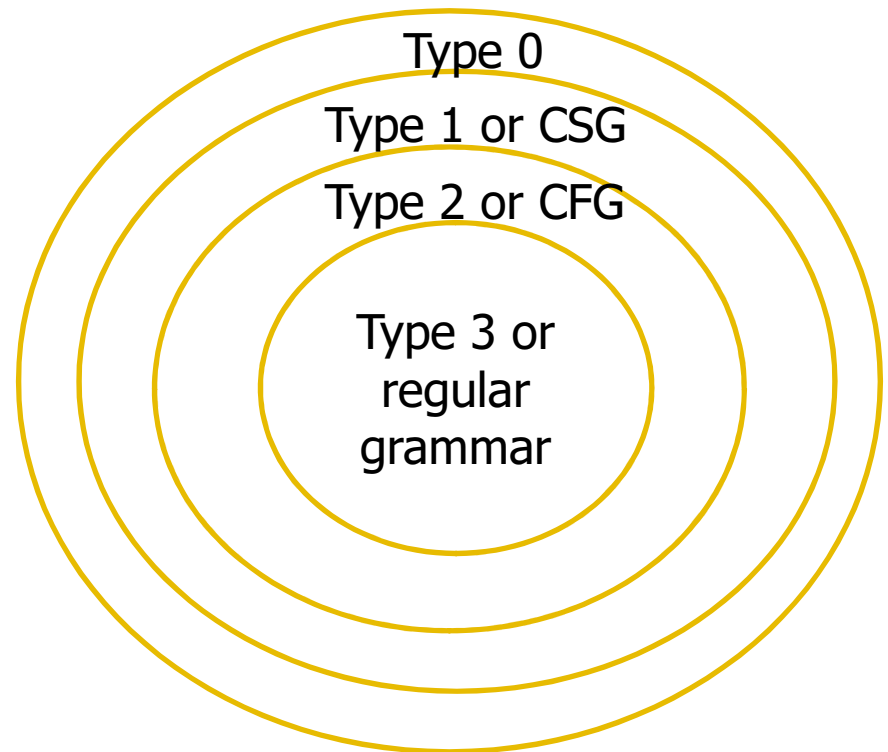


- “Walk left” can come from :- “*After climbing , we realized the walk left was still considerable.*”
- “Stand right” can come from: - “*The stand right though it seemed at that time, does not stand the scrutiny now.*”
- Then the given sentence “Stand right walk left” will never be parsed correctly.

Chomski Hierarchy

Properties of the hierarchy:-

- *The containment is proper.*
- *Grammar is not learnable even for the lowest type from positive examples alone.*



$Type\ 0 \supset Type\ 1 \supset Type\ 2 \supset Type\ 3$

Rationalism vs Empiricism

- Scientific paper : - “*The pendulum swings back*” by Ken Church.
- Every 20 years there is a shift from rationalism to empiricism.
- AI approaches are of two types:-
 - Rational (Theory and model driven e.g. Brill Tagger; humans decide the templates)
 - Empirical (Data driven e.g. HMM)
- Is it possible to classify probabilistic CFG into any of these categories?
 - Very difficult to answer.
 - Anything that comes purely from brain can be put into the category of “rationalism”.
- There is no pure rationalism or pure empiricism

Laws of machine learning

- “Learning from vacuum (zero knowledge) is impossible”.
- “Inductive bias decides what to learn”.
 - *In case of POS tagger , bias is that we assume the tagger to be a HMM model.*

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

$$\forall i \sum_j P(N^i \rightarrow \zeta^j) = 1$$

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

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

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

- $P(\text{NP} \rightarrow \text{DT NN}) = 0.2$
 - 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