

Structural Ambiguity

How different parse trees may be produced from the same sentence or phrase

- ▶ Attachment ambiguity: where a constituent may attach to the rest of the tree
 - ▶ I saw a man with a telescope
- ▶ Coordination ambiguity: How to group the arguments of a conjunction
 - ▶ Spicy rice and apples
- ▶ *Disambiguation* relies on applying additional knowledge
 - ▶ Of language, e.g., what verbs and nouns or prepositions go together
 - ▶ Of the real world
 - ▶ Of the context, such as prior sentences or conversations

Jurafsky's Miniature Grammar, \mathcal{L}_1

Omitting the lexicon

S \rightarrow NP VP

S \rightarrow Auxiliary-Verb NP VP

S \rightarrow VP

NP \rightarrow Pronoun

NP \rightarrow Proper-Noun

NP \rightarrow Determiner Nominal

Nominal \rightarrow Noun

Nominal \rightarrow Nominal Noun

Nominal \rightarrow Nominal PP

VP \rightarrow Verb

VP \rightarrow Verb NP

VP \rightarrow Verb NP PP

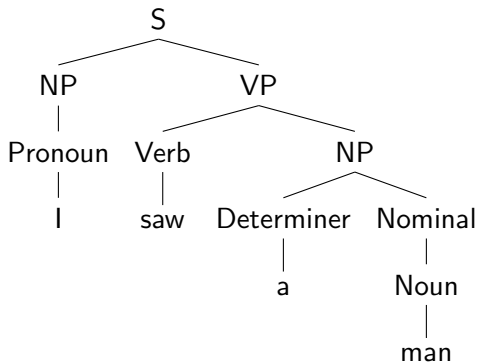
VP \rightarrow Verb PP

VP \rightarrow VP PP

PP \rightarrow Preposition NP

Attachment Ambiguity: Setting the Stage

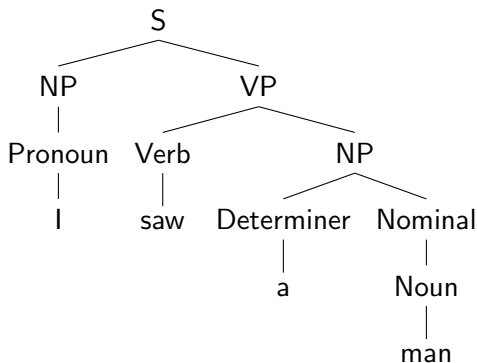
I saw a man



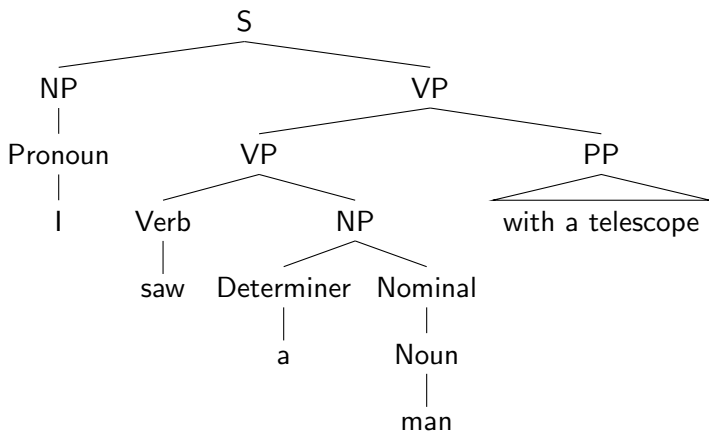
Attachment Ambiguity: Example

I saw a man with a telescope

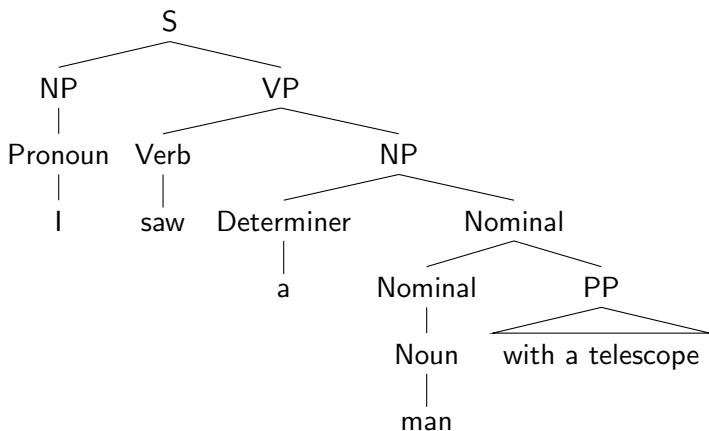
Modify the following tree for the above sentence



Attachment Ambiguity: 1

I saw a man with a telescope

Attachment Ambiguity: 2

I saw a man with a telescope

Simple Coordination Productions

Add these to the earlier grammar

NP \rightarrow NP Conjunction NP

Nominal \rightarrow Nominal Conjunction Nominal

VP \rightarrow VP Conjunction VP

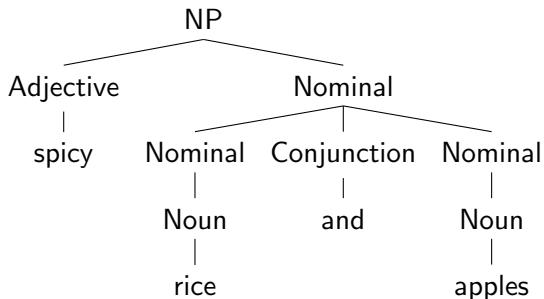
PP \rightarrow PP Conjunction PP

Also, for adjectives include

NP \rightarrow Adjective Nominal

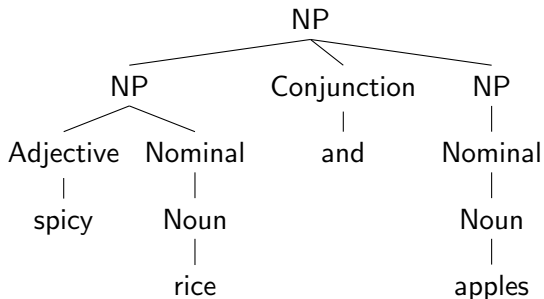
Coordination Ambiguity: 1

Spicy rice and apples



Coordination Ambiguity: 2

Spicy rice and apples



Sentences in Practice

A. A. Milne, Winnie the Pooh

Eeyore's take on writing

“This writing business. Pencils and what-not. Over-rated, if you ask me. Silly stuff. Nothing in it.”

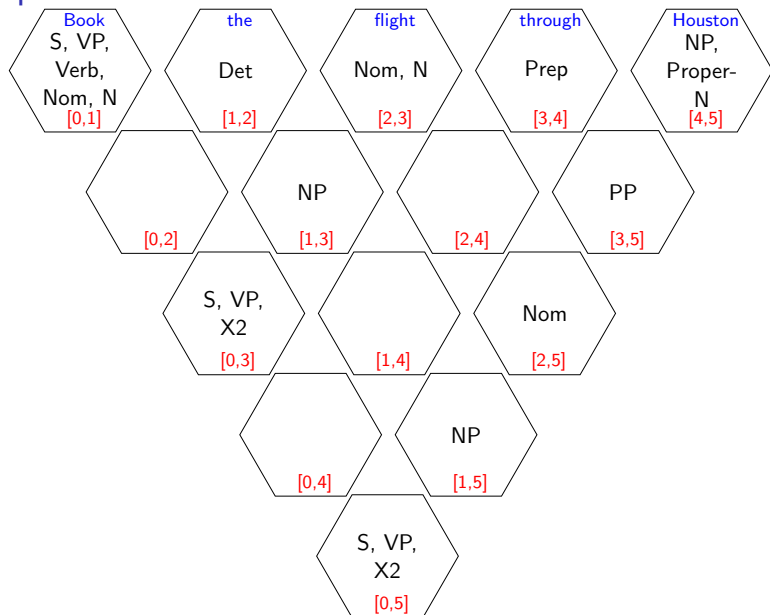
- ▶ Five sentences
- ▶ Do you identify verbs in them?
- ▶ What grammar would generate these sentences?

Parsing with a Context-Free Grammar

Cocke-Kasami-Younger (CKY) algorithm

- ▶ Apply dynamic programming
 - ▶ Build up solutions incrementally
 - ▶ Reusing them in larger solutions
- ▶ Convert to Chomsky Normal Form
- ▶ Each constituent is based on
 - ▶ A single terminal
 - ▶ Two nonterminals (constituents)
- ▶ Compute and store all possible constituents for each cell in a matrix
 - ▶ Allow duplicates to accommodate ambiguity
 - ▶ Store provenance of each value
- ▶ When we arrive at a cell the cells it relies upon are already computed
- ▶ The nonterminal in the final cell represents the constituent for the entire input (if any)
- ▶ Reconstruct parse tree from the provenance

Example of a CKY Parse



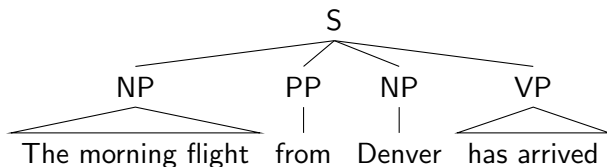
Improving CKY for Practical Use

- ▶ Generalize to arbitrary grammars (not just Chomsky Normal Form)
 - ▶ Ensures parses produced reflect grammarians' intuitions
- ▶ In statistical parsing, accommodate probabilities to
 - ▶ Select likelier parses
 - ▶ Avoid exponentially many parses

Partial or Shallow Parsing

Applicable when we don't need a complete parse to produce a valuable product

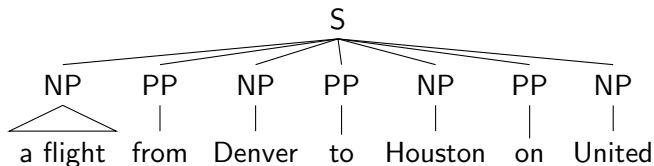
- ▶ Produce flat trees
 - ▶ Avoid decisions about nesting and ambiguity that a full parser must contend with
- ▶ *Chunking*: Identify constituents for nonoverlapping segments
- ▶ Exclude hierarchical structure (i.e., slightly above POS tagging)
 - ▶ [Pro I] [V saw] [NP a man] [PP with a telescope]



Identifying Base Phrases

Alternative to chunking

- ▶ A base phrase (some variation in definitions)
 - ▶ Doesn't (recursively) contain constituents of the same type
 - ▶ Includes the headword and any prehead modifiers (or any post-head material)
 - ▶ Excludes post-head modifiers (to avoid attachment ambiguity)
 - ▶ Can be difficult to use as a result since boundaries are less clear
 - ▶ Can yield outcomes where an NP or PP may contain nothing other than its head



Machine Learning for Chunking

An application of sequence learning

- ▶ Introduce $2n + 1$ tags (given n chunk types)
 - ▶ B_k : Beginning of chunk type k
 - ▶ I_k : Inside of chunk type k
 - ▶ O : Outside of all chunk types
 - ▶ No need for end of a chunk since the beginning of the next (or end of sentence) indicates its end
- ▶ Example of IOB chunking

I	saw	a	man	with	a	telescope
B_{NP}	B_{VP}	B_{NP}	I_{NP}	B_{PP}	I_{PP}	I_{PP}
$[NP]I$	$[VP]saw$	$[NP]a$	man	$[PP]with$	a	$telescope$
- ▶ Training data: from existing treebanks
 - ▶ Identify head words of a constituent
 - ▶ Include head and prehead words within the constituent
 - ▶ Exclude post-head words

Evaluation Metrics for Chunking

- ▶ Correct chunk: whose tag (label) and segment are correct
- ▶ Metrics adopted from information retrieval

$$\text{Precision, } P = \frac{\text{Number of correct chunks identified}}{\text{Number of chunks identified}}$$

$$\text{Recall, } R = \frac{\text{Number of correct chunks identified}}{\text{Number of (correct) chunks existing}}$$

$$\text{F-measure, } F_{\beta} = \frac{(\beta^2 + 1)PR}{\beta^2 P + R}$$

$$F_1, F_1 = \frac{2PR}{P + R}$$

- ▶ F-measure trades off precision and recall
 - ▶ F_1 gives equal importance to precision and recall