Constituency Parsing

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Slides adapted from Dan Klein, Dan Jurafsky, Chris Manning, Michael Collins, Luke Zettlemoyer, Yejin Choi, and Slav Petrov
Overview

• The constituency parsing problem
• CKY parsing
  – Chomsky Normal Form
• The Penn Treebank
Constituency (Phrase Structure) Trees

- Phrase structure organizes words into nested constituents

Diagram:

```
N | V
Fed raises  N | N
interest rates
```
Constituency (Phrase Structure) Trees

- Phrase structure organizes words into nested constituents
- Linguists can, and do, argue about details
Constituency Tests

• **Distribution:** a constituent behaves as a unit that can appear in different places:
  – John talked to the children about drugs.
  – John talked [to the children] [about drugs].
  – John talked [about drugs] [to the children].
  – *John talked drugs to the children about
Constituency Tests

• **Substitution/expansion/pro-forms:**
  – I sat near the table
  – I sat [on the box/right on top of the box/there].
Constituency Tests

• Distribution / movement / dislocation
• Substitution by pro-form
  – he, she, it, they, ...
• Question / answer
• Deletion
• Conjunction / coordination
Constituency (Phrase Structure) Trees

- Phrase structure organizes words into nested constituents
- Linguists can, and do, argue about details
- Lots of ambiguity

new art critics write reviews with computers
Context-Free Grammars (CFG)

- Writing parsing rules:
  - $N \rightarrow \text{Fed}$
  - $V \rightarrow \text{raises}$
  - $NP \rightarrow N$
  - $S \rightarrow NP \ VP$
  - $VP \rightarrow V \ NP$
  - $NP \rightarrow N \ N$
  - $NP \rightarrow NP \ PP$
  - $N \rightarrow \text{interest}$
  - $N \rightarrow \text{raises}$
Context-Free Grammars

- A context-free grammar is a tuple \(<N, \Sigma, S, R>\)
  - \(N\) : the set of non-terminals
    - Phrasal categories: S, NP, VP, ADJP, etc.
    - Parts-of-speech (pre-terminals): NN, JJ, DT, VB
  - \(\Sigma\) : the set of terminals (the words)
  - \(S\) : the start symbol
    - Often written as ROOT or TOP
    - \textit{Not} usually the sentence non-terminal \(S\) – why not?
  - \(R\) : the set of rules
    - Of the form \(X \rightarrow Y_1 Y_2 \ldots Y_n\), with \(X \in N, n \geq 0, Y_i \in (N \cup \Sigma)\)
    - Examples: \(S \rightarrow \text{NP } \text{VP}\), \(\text{VP } \rightarrow \text{VP } \text{CC } \text{VP}\)
    - Also called rewrites, productions, or local trees
### Example Grammar

\[ N = \{S, \text{NP}, \text{VP}, \text{PP}, \text{DT}, \text{Vi}, \text{Vt}, \text{NN}, \text{IN}\} \]

\[ S \rightarrow S \]

\[ \Sigma = \{\text{sleeps, saw, man, woman, telescope, the, with, in}\} \]

\[ R = \]

<table>
<thead>
<tr>
<th></th>
<th>NP</th>
<th>VP</th>
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<tbody>
<tr>
<td>S</td>
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<tr>
<td>VP</td>
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<td>Vi</td>
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<td>VP</td>
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<td>PP</td>
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<tbody>
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<td>sleeps</td>
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<td>Vt</td>
<td>⇒</td>
<td>saw</td>
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<tr>
<td>NN</td>
<td>⇒</td>
<td>man</td>
</tr>
<tr>
<td>NN</td>
<td>⇒</td>
<td>woman</td>
</tr>
<tr>
<td>NN</td>
<td>⇒</td>
<td>telescope</td>
</tr>
<tr>
<td>DT</td>
<td>⇒</td>
<td>the</td>
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<tr>
<td>IN</td>
<td>⇒</td>
<td>with</td>
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<tr>
<td>IN</td>
<td>⇒</td>
<td>in</td>
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</tbody>
</table>

*S=sentence, VP=verb phrase, NP=noun phrase, PP=prepositional phrase, DT=determiner, Vi=intransitive verb, Vt=transitive verb, NN=noun, IN=preposition*
\( R = \begin{array}{|c|c|c|}
\hline
S & \rightarrow & NP \quad VP \\
\hline
VP & \rightarrow & Vi \\
VP & \rightarrow & Vt \quad NP \\
VP & \rightarrow & VP \quad PP \\
NP & \rightarrow & DT \quad NN \\
NP & \rightarrow & NP \quad PP \\
PP & \rightarrow & IN \quad NP \\
\hline
\end{array} \)

**Example Parse**

The man sleeps

**Note:**
- S=sentence, VP=verb phrase, NP=noun phrase, PP=prepositional phrase,
- DT=determiner, Vi=intransitive verb, Vt=transitive verb, NN=noun, IN=preposition
Example Parse

\[ R = \begin{array}{c|cc}
  \text{S} & \Rightarrow & \text{NP} \quad \text{VP} \\
  \text{VP} & \Rightarrow & \text{Vi} \\
  \text{VP} & \Rightarrow & \text{Vt} \quad \text{NP} \\
  \text{VP} & \Rightarrow & \text{VP} \quad \text{PP} \\
  \text{NP} & \Rightarrow & \text{DT} \quad \text{NN} \\
  \text{NP} & \Rightarrow & \text{NP} \quad \text{PP} \\
  \text{PP} & \Rightarrow & \text{IN} \quad \text{NP} \\
\end{array} \]

Vi \Rightarrow \text{sleeps}
Vt \Rightarrow \text{saw}
NN \Rightarrow \text{man}
NN \Rightarrow \text{woman}
NN \Rightarrow \text{telescope}
DT \Rightarrow \text{the}
IN \Rightarrow \text{with}
IN \Rightarrow \text{in}

The man sleeps

The man saw the woman with the telescope

S=sentence, VP=verb phrase, NP=noun phrase, PP=prepositional phrase, DT=determiner, Vi=intransitive verb, Vt=transitive verb, NN=noun, IN=preposition
A Context-Free Grammar for English

\[ R = \begin{array}{|c|c|c|} \hline \text{S} & \Rightarrow & \text{NP} \quad \text{VP} \\ \text{VP} & \Rightarrow & \text{Vi} \\ \text{VP} & \Rightarrow & \text{Vt} \quad \text{NP} \\ \text{VP} & \Rightarrow & \text{VP} \quad \text{PP} \\ \text{NP} & \Rightarrow & \text{DT} \quad \text{NN} \\ \text{NP} & \Rightarrow & \text{NP} \quad \text{PP} \\ \text{PP} & \Rightarrow & \text{IN} \quad \text{NP} \\ \text{Vi} & \Rightarrow & \text{sleeps} \\ \text{Vt} & \Rightarrow & \text{saw} \\ \text{NN} & \Rightarrow & \text{man} \\ \text{NN} & \Rightarrow & \text{woman} \\ \text{NN} & \Rightarrow & \text{telescope} \\ \text{DT} & \Rightarrow & \text{the} \\ \text{IN} & \Rightarrow & \text{with} \\ \text{IN} & \Rightarrow & \text{in} \\ \hline \end{array} \]

Note: S=sentence, VP=verb phrase, NP=noun phrase, PP=prepositional phrase, DT=determiner, Vi=intransitive verb, Vt=transitive verb, NN=noun, IN=preposition

Example Parse

\[ S \]
\[ \begin{array}{c} \text{NP} \quad \text{VP} \\ \text{DT} \quad \text{NN} \quad \text{Vi} \\ \text{The man sleeps} \\ \end{array} \]

\[ S \]
\[ \begin{array}{c} \text{VP} \quad \text{PP} \\ \text{Vt} \quad \text{NP} \\ \text{IN} \quad \text{NP} \\ \text{The man saw the woman with the telescope} \\ \end{array} \]
Headed Phrase Structure

• In NLP, CFG non-terminals often have internal structure
• Phrases are headed by particular word types with some modifiers:
  – VP → … VB* …
  – NP → … NN* …
  – ADJP → … JJ* …
  – ADVP → … RB* …
• This X-bar theory grammar (in a nutshell)
• This captures a dependency
Pre 1990 (“Classical”) NLP Parsing

- Wrote symbolic grammar (CFG or often richer) and lexicon
  
  \[
  \begin{align*}
  S & \rightarrow NP \ VP \\
  NP & \rightarrow (DT) \ NN \\
  NP & \rightarrow NN \ NNS \\
  NP & \rightarrow NNP \\
  VP & \rightarrow V \ NP \\
  NN & \rightarrow interest \\
  NNS & \rightarrow rates \\
  NNS & \rightarrow raises \\
  VBP & \rightarrow interest \\
  VBZ & \rightarrow rates
  \end{align*}
  \]

- Used grammar/proof systems to prove parses from words
- This scaled very badly and didn’t give coverage. For sentence:
  
  *Fed raises interest rates 0.5% in effort to control inflation*

  - Minimal grammar: 36 parses
  - Simple 10 rule grammar: 592 parses
  - Real-size broad-coverage grammar: millions of parses
Ambiguities: PP Attachment

The children ate the cake with a spoon.
Attachments

• I cleaned the dishes from dinner
• I cleaned the dishes with detergent
• I cleaned the dishes in my pajamas
• I cleaned the dishes in the sink
Syntactic Ambiguity I

- **Prepositional phrases:**
  They cooked the beans in the pot on the stove with handles.

- **Particle vs. preposition:**
  The puppy tore up the staircase.

- **Complement structures**
  The tourists objected to the guide that they couldn’t hear.
  She knows you like the back of her hand.

- **Gerund vs. participial adjective**
  Visiting relatives can be boring.
  Changing schedules frequently confused passengers.
Syntactic Ambiguity II

- **Modifier scope within NPs**
  impractical design requirements
  plastic cup holder

- **Multiple gap constructions**
  The chicken is ready to eat.
  The contractors are rich enough to sue.

- **Coordination scope:**
  Small rats and mice can squeeze into
  holes or cracks in the wall.
Classical NLP Parsing: The problem and its solution

- Categorical constraints can be added to grammars to limit unlikely/weird parses for sentences
  - But the attempt makes the grammars not robust
    - In traditional systems, commonly 30% of sentences in even an edited text would have *no* parse.
- A less constrained grammar can parse more sentences
  - But simple sentences end up with ever more parses with no way to choose between them
- We need mechanisms that allow us to find the most likely parse(s) for a sentence
  - Statistical parsing lets us work with very loose grammars that admit millions of parses for sentences but still quickly find the best parse(s)
The rise of annotated data: The Penn Treebank (PTB)

(S
 (NP-SBJ (DT The) (NN move))
 (VP (VBD followed)
   (NP
    (NP (DT a) (NN round))
    (PP (IN of)
     (NP
      (NP (JJ similar) (NNS increases))
      (PP (IN by)
       (NP (JJ other) (NNS lenders)))
      (PP (IN against)
       (NP (NNP Arizona) (JJ real) (NN estate) (NNS loans)))))))
 (. .))
(S-ADV
 (NP-SBJ (-NONE- *))
 (VP (VBG reflecting)
  (NP
   (NP (DT a) (VBG continuing) (NN decline))
   (PP-LOC (IN in)
    (NP (DT that) (NN market))))))
 (. .)))

[Marcus et al. 1993]
The rise of annotated data

• Starting off, building a treebank seems a lot slower and less useful than building a grammar

• But a treebank gives us many things
  – Reusability of the labor
    • Many parsers, POS taggers, etc.
    • Valuable resource for linguistics
  – Broad coverage
  – Frequencies and distributional information
  – A way to evaluate systems
## PTB Non-terminals

*Table 1.2.* The Penn Treebank syntactic tagset

<table>
<thead>
<tr>
<th>Tag</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADJP</td>
<td>Adjective phrase</td>
</tr>
<tr>
<td>ADVP</td>
<td>Adverb phrase</td>
</tr>
<tr>
<td>NP</td>
<td>Noun phrase</td>
</tr>
<tr>
<td>PP</td>
<td>Prepositional phrase</td>
</tr>
<tr>
<td>S</td>
<td>Simple declarative clause</td>
</tr>
<tr>
<td>SBAR</td>
<td>Subordinate clause</td>
</tr>
<tr>
<td>SBARQ</td>
<td>Direct question introduced by <em>wh</em>-element</td>
</tr>
<tr>
<td>SINV</td>
<td>Declarative sentence with subject-aux inversion</td>
</tr>
<tr>
<td>SQ</td>
<td>Yes/no questions and subconstituent of SBARQ excluding <em>wh</em>-element</td>
</tr>
<tr>
<td>VP</td>
<td>Verb phrase</td>
</tr>
<tr>
<td>WHADVP</td>
<td>Wh-adverb phrase</td>
</tr>
<tr>
<td>WHNP</td>
<td>Wh-noun phrase</td>
</tr>
<tr>
<td>WHPP</td>
<td>Wh-prepositional phrase</td>
</tr>
<tr>
<td>X</td>
<td>Constituent of unknown or uncertain category</td>
</tr>
<tr>
<td>*</td>
<td>“Understood” subject of infinitive or imperative</td>
</tr>
<tr>
<td>0</td>
<td>Zero variant of <em>that</em> in subordinate clauses</td>
</tr>
<tr>
<td>T</td>
<td>Trace of <em>wh</em>-Constituent</td>
</tr>
</tbody>
</table>

+ all POS tags
Non Local Phenomena

- Dislocation / gapping
  - Which book should Peter buy?
  - A debate arose which continued until the election.

- Binding
  - Reference
    - The IRS audits itself

- Control
  - I want to go
  - I want you to go
PTB Size

- Penn WSJ Treebank:
  - 50,000 annotated sentences
- Usual set-up:
  - 40,000 training
  - 2,400 test

An example tree:

```
Canadian Utilities had 1988 revenue of C$ 1.16 billion, mainly from its natural gas and electric utility businesses in Alberta, where the company serves about 800,000 customers.
```
Probabilistic Context-Free Grammars (PCFG)

• A context-free grammar is a tuple <N, Σ, S, R>
  – N: the set of non-terminals
    • Phrasal categories: S, NP, VP, ADJP, etc.
    • Parts-of-speech (pre-terminals): NN, JJ, DT, VB
  – Σ: the set of terminals (the words)
  – S: the start symbol
    • Often written as ROOT or TOP
    • Not usually the sentence non-terminal S
  – R: the set of rules
    • Of the form X → Y₁ Y₂ … Yₙ, with X ∈ N, n≥0, Yᵢ ∈ (N ∪ Σ)
    • Examples: S → NP VP, VP → VP CC VP
      • Also called rewrites, productions, or local trees

• A PCFG adds a distribution q:
  – Probability q(r) for each r ∈ R, such that for all X ∈ N:
    \[ \sum_{\alpha \to \beta \in R: \alpha = X} q(\alpha \to \beta) = 1 \]
### PCFG Example

<table>
<thead>
<tr>
<th>Production Rule</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>S $\Rightarrow$ NP VP</td>
<td>1.0</td>
</tr>
<tr>
<td>VP $\Rightarrow$ Vi</td>
<td>0.4</td>
</tr>
<tr>
<td>VP $\Rightarrow$ Vt NP</td>
<td>0.4</td>
</tr>
<tr>
<td>VP $\Rightarrow$ VP PP</td>
<td>0.2</td>
</tr>
<tr>
<td>NP $\Rightarrow$ DT NN</td>
<td>0.3</td>
</tr>
<tr>
<td>NP $\Rightarrow$ NP PP</td>
<td>0.7</td>
</tr>
<tr>
<td>PP $\Rightarrow$ P NP</td>
<td>1.0</td>
</tr>
<tr>
<td>Vi $\Rightarrow$ sleeps</td>
<td>1.0</td>
</tr>
<tr>
<td>Vt $\Rightarrow$ saw</td>
<td>1.0</td>
</tr>
<tr>
<td>NN $\Rightarrow$ man</td>
<td>0.7</td>
</tr>
<tr>
<td>NN $\Rightarrow$ woman</td>
<td>0.2</td>
</tr>
<tr>
<td>NN $\Rightarrow$ telescope</td>
<td>0.1</td>
</tr>
<tr>
<td>DT $\Rightarrow$ the</td>
<td>1.0</td>
</tr>
<tr>
<td>IN $\Rightarrow$ with</td>
<td>0.5</td>
</tr>
<tr>
<td>IN $\Rightarrow$ in</td>
<td>0.5</td>
</tr>
</tbody>
</table>

- **Probability of a tree** $t$ **with rules**

  $\alpha_1 \rightarrow \beta_1, \alpha_2 \rightarrow \beta_2, \ldots, \alpha_n \rightarrow \beta_n$

  is

  $$p(t) = \prod_{i=1}^{n} q(\alpha_i \rightarrow \beta_i)$$

  where $q(\alpha \rightarrow \beta)$ is the probability for rule $\alpha \rightarrow \beta$.  

**PCFG Example**

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<thead>
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<tr>
<td>S</td>
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<td>NN</td>
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<td>woman</td>
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<tr>
<td>NN</td>
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<td>telescope</td>
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<td>the</td>
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The man sleeps

The man saw the woman with the telescope
PCFG Example

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<tr>
<td>PP</td>
<td>⇒</td>
<td>P</td>
<td>NP</td>
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</tbody>
</table>

• Probability of a tree $t$ with rules $\alpha_1 \rightarrow \beta_1$, $\alpha_2 \rightarrow \beta_2$, ..., $\alpha_n \rightarrow \beta_n$ is $p(t) = \prod_{i=1}^{n} q(\alpha_i \rightarrow \beta_i)$ where $q(\alpha \rightarrow \beta)$ is the probability for rule $\alpha \rightarrow \beta$.

The man sleeps

$p(t_1) = 1.0 \times 0.3 \times 0.7 \times 0.4 \times 1.0$

The man saw the woman with the telescope

$p(t_2) = 1.0 \times 0.3 \times 1.0 \times 0.2 \times 0.4 \times 1.0 \times 0.5 \times 0.3 \times 1.0 \times 0.1$
Learning and Inference

• **Model**
  - The probability of a tree $t$ with $n$ rules $\alpha_i \rightarrow \beta_i$, $i = 1..n$
  
  $p(t) = \prod_{i=1}^{n} q(\alpha_i \rightarrow \beta_i)$

• **Learning**
  - Read the rules off of labeled sentences, use ML estimates for probabilities
  
  $q_{ML}(\alpha \rightarrow \beta) = \frac{\text{Count}(\alpha \rightarrow \beta)}{\text{Count}(\alpha)}$

  - and use all of our standard smoothing tricks!

• **Inference**
  - For input sentence $s$, define $T(s)$ to be the set of trees whose *yield* is $s$ (whose leaves, read left to right, match the words in $s$)

  $t^*(s) = \arg \max_{t \in T(s)} p(t)$
The Constituency Parsing Problem

PCFG

Rule Prob $\theta_i$

$S \rightarrow NP\ VP\ \theta_0$

$NP \rightarrow NP\ NP\ \theta_1$

$N \rightarrow \text{fish}\ \theta_{42}$

$N \rightarrow \text{people}\ \theta_{43}$

$V \rightarrow \text{fish}\ \theta_{44}$

$\ldots$
A Recursive Parser

$$\text{bestScore}(X,i,j,s)$$

if \( j == i \)
   return \( q(X\rightarrow s[i]) \)
else
   return max \( q(X\rightarrow YZ) \) * 
       \( \text{bestScore}(Y,i,k,s) \) * 
       \( \text{bestScore}(Z,k+1,j,s) \)

• Will this parser work?
• Why or why not?
• Q: Remind you of anything? Can we adapt this to other models / inference tasks?
Cocke-Kasami-Younger (CKY) Constituency Parsing

fish people fish fish tanks
Cocke-Kasami-Younger (CKY) Constituency Parsing

```
S → NP VP 0.9
VP → V NP 0.5
VP → V @VP_V 0.3
VP → V PP 0.1
@VP_V → NP PP 1.0
NP → NP NP 0.1
NP → NP PP 0.2
PP → P NP 1.0
```
Cocke-Kasami-Younger (CKY) Constituency Parsing

- S → NP VP \(0.9\)
  - VP → V NP \(0.5\)
  - VP → V @VP_V \(0.3\)
  - @VP_V → NP PP \(1.0\)
- NP → NP NP \(0.1\)
- NP → NP PP \(0.2\)
- PP → P NP \(1.0\)

Diagram:

- **S**: 0.0189
- **NP**: 0.35
- **V**: 0.1
- **N**: 0.5
- **VP**: 0.06
- **NP**: 0.14
- **V**: 0.6
- **N**: 0.2

Words:
- people
- fish
Cocke-Kasami-Younger (CKY) Constituency Parsing

S  0.0189
NP 0.0098

NP 0.35
V  0.1
N  0.5

NP 0.14
V  0.6
N  0.2

VP 0.06

VP 0.06

S → NP VP  0.9
VP → V NP  0.5
VP → V @VP_V  0.3
VP → V PP  0.1
@VP_V → NP PP  1.0
NP → NP NP  0.1
NP → NP PP  0.2
PP → P NP  1.0
Cocke-Kasami-Younger (CKY) Constituency Parsing

S → NP VP 0.9
VP → V NP 0.5
VP → V @VP_V 0.3
VP → V PP 0.1
@VP_V → NP PP 1.0
NP → NP NP 0.1
NP → NP PP 0.2
PP → P NP 1.0
CKY Parsing

- **We will store:** score of the max parse of $x_i$ to $x_j$ with root non-terminal $X$
  \[ \pi(i, j, X) \]
- **So we can compute the most likely parse:**
  \[ \pi(1, n, S) = \arg \max_{t \in T_G(x)} \]
- **Via the recursion:**
  \[ \pi(i, j, X) = \]

- **With base case:**
  \[ \pi(i, i, X) = \]
The CKY Algorithm

- **Input**: a sentence $s = x_1 \ldots x_n$ and a PCFG $= \langle N, \Sigma, S, R, q \rangle$
- **Initialization**: For $i = 1 \ldots n$ and all $X$ in $N$
  $$\pi(i, i, X) = \begin{cases} q(X \rightarrow x_i) & \text{if } X \rightarrow x_i \in R \\ 0 & \text{otherwise} \end{cases}$$

  - For $l = 1 \ldots (n-1)$ [iterate all phrase lengths]
    - For $i = 1 \ldots (n-l)$ and $j = i+l$ [iterate all phrases of length $l$]
      - For all $X$ in $N$ [iterate all non-terminals]

  $$\pi(i, j, X) = \max_{X \rightarrow Y Z \in R, \atop s \in \{i \ldots (j-1)\}} (q(X \rightarrow Y Z) \times \pi(i, s, Y) \times \pi(s + 1, j, Z))$$
      - also, store back pointers

  $$bp(i, j, X) = \arg \max_{X \rightarrow Y Z \in R, \atop s \in \{i \ldots (j-1)\}} (q(X \rightarrow Y Z) \times \pi(i, s, Y) \times \pi(s + 1, j, Z))$$
Probabilistic CKY Parser

S → NP VP 
S → X1 VP 
X1 → Aux NP 
S → book | include | prefer 
0.01 0.004 0.006 
S → Verb NP 
S → VP PP 
NP → I | he | she | me 
0.1 0.02 0.02 0.06 
NP → Houston | NWA 
0.16 .04 
Det→ the | a | an 
0.6 0.1 0.05 
NP → Det Nominal 
0.6 
Nominal → book | flight | meal | money 
0.03 0.15 0.06 0.06 
Nominal → Nominal Nominal 
0.2 
Nominal → Nominal PP 
0.5 
Verb→ book | include | prefer 
0.5 0.04 0.06 
VP → Verb NP 
0.5 
VP → VP PP 
0.3 
Prep → through | to | from 
0.2 0.3 0.3 
PP → Prep NP 
1.0
Probabilistic CKY Parser

S → NP VP 0.8
S → X1 VP 0.1
X1 → Aux NP 1.0
S → book | include | prefer
   0.01 0.004 0.006
S → Verb NP 0.05
S → VP PP 0.03
NP → I | he | she | me
   0.1 0.02 0.02 0.06
NP → Houston | NWA
   0.16 .04
Det → the | a | an
   0.6 0.1 0.05
NP → Det Nominal 0.6
Nominal → book | flight | meal | money
   0.03 0.15 0.06 0.06
Nominal → Nominal Nominal 0.2
Nominal → Nominal PP 0.5
Verb → book | include | prefer
   0.5 0.04 0.06
VP → Verb NP 0.5
VP → VP PP 0.3
Prep → through | to | from
   0.2 0.3 0.3
PP → Prep NP 1.0
Probabilistic CKY Parser

\[
\begin{array}{c|c|c}
S &: .01, \\
  & \text{Verb}: .5 & \text{Nominal}: .03 \\
\hline
\text{None} & S &: .05 \times .5 \times .054 \\
  & = .00135 & \text{None} \\
\hline
\text{Det}: .6 & \text{NP}: .6 \times .6 \times .15 \\
  & = .054 & \text{None} \\
\hline
\text{Nominal}: .15 & \text{Nominal}: .6 \times .15 \times .032 \\
  & = .0024 & \text{None} \\
\hline
\text{Prep}: .2 & \text{PP}: 1 \times .2 \times .16 \\
  & = .032 & \text{NP}: .16 \\
\end{array}
\]

Pick most probable parse
The CKY Algorithm

- **Input:** a sentence $s = x_1 \ldots x_n$ and a PCFG $= \langle N, \Sigma, S, R, q \rangle$
- **Initialization:** For $i = 1 \ldots n$ and all $X$ in $N$
  \[
  \pi(i, i, X) = \begin{cases} 
    q(X \rightarrow x_i) & \text{if } X \rightarrow x_i \in R \\
    0 & \text{otherwise}
  \end{cases}
  \]
- For $l = 1 \ldots (n-1)$ [iterate all phrase lengths]
  - For $i = 1 \ldots (n-l)$ and $j = i+l$ [iterate all phrases of length $l$]
    - For all $X$ in $N$ [iterate all non-terminals]
      \[
      \pi(i, j, X) = \max_{X \rightarrow YZ \in R, \atop s \in \{ i \ldots (j-1) \}} (q(X \rightarrow YZ) \times \pi(i, s, Y) \times \pi(s + 1, j, Z))
      \]
- also, store back pointers
  \[
  bp(i, j, X) = \arg \max_{X \rightarrow YZ \in R, \atop s \in \{ i \ldots (j-1) \}} (q(X \rightarrow YZ) \times \pi(i, s, Y) \times \pi(s + 1, j, Z))
  \]
Time: Theory

• For each length (\(<= n\))
  – For each i (\(<= n\))
    • For each split point k
      – For each rule \(X \rightarrow Y Z\)
        » Do constant work

• Total time: \(|\text{rules}| \times n^3\)
Time: Practice

- Parsing with the vanilla treebank grammar:
  - Why’s it worse in practice?
    - Longer sentences “unlock” more of the grammar
    - All kinds of systems issues don’t scale

~ 20K Rules
(not an optimized parser!)

Observed exponent:
3.6
The CKY Algorithm

- **Input:** a sentence $s = x_1 \ldots x_n$ and a PCFG $= \langle N, \Sigma, S, R, q \rangle$
- **Initialization:** For $i = 1 \ldots n$ and all $X$ in $N$
  $$\pi(i, i, X) = \begin{cases} q(X \to x_i) & \text{if } X \to x_i \in R \\ 0 & \text{otherwise} \end{cases}$$

- For $l = 1 \ldots (n-1)$  
  - For $i = 1 \ldots (n-l)$ and $j = i+l$  
    - For all $X$ in $N$  
      - [iterate all non-terminals]
        $$\pi(i, j, X) = \max_{X \to YZ \in R, s \in \{i \ldots (j-1)\}} (q(X \to YZ) \times \pi(i, s, Y) \times \pi(s + 1, j, Z))$$
      - also, store back pointers
        $$bp(i, j, X) = \arg \max_{X \to YZ \in R, s \in \{i \ldots (j-1)\}} (q(X \to YZ) \times \pi(i, s, Y) \times \pi(s + 1, j, Z))$$

- Figure 6: The CKY parsing algorithm.

This is a natural definition: the only way that we can have a tree. The algorithm is “bottom-up”, in the sense that it will...
Memory

• How much memory does this require?
  – Have to store the score cache
  – Cache size:
    • $|\text{symbols}| \times n^2$ doubles

• Pruning: Beams
  – score$[X][i][j]$ can get too large (when?)
  – Can keep beams (truncated maps score$[i][j]$)
    which only store the best few scores for the span $[i,j]$ – Exact?

• Pruning: Coarse-to-Fine
  – Use a smaller grammar to rule out most $X[i,j]$
Let’s parse with CKY!

• Any problem?
Chomsky Normal Form

- All rules are of the form $X \rightarrow YZ$ or $X \rightarrow w$
  - $X, Y, Z \in N$ and $w \in T$
- A transformation to this form doesn’t change the weak generative capacity of a CFG
  - That is, it recognizes the same language
    - But maybe with different trees
- Empties and unaries are removed recursively
- n-ary rules are divided by introducing new nonterminals ($n > 2$)
Special Case: Unary Rules

• Chomsky normal form (CNF):
  – All rules of the form $X \rightarrow YZ$ or $X \rightarrow w$
  – Makes parsing easier!

• Can also allow unary rules
  – All rules of the form $X \rightarrow YZ$, $X \rightarrow Y$, or $X \rightarrow w$
  – Conversion to/from the normal form is easier
  – Q: How does this change CKY?
  – WARNING: Watch for unary cycles…
CKY with Unary Rules

- **Input:** a sentence \( s = x_1 \ldots x_n \) and a PCFG = \( \langle N, \Sigma, S, R, q \rangle \)

- **Initialization:** For \( i = 1 \ldots n \):
  - **Step 1:** for all \( X \) in \( N \):
    \[
    \pi(i, i, X) = \begin{cases} 
    q(X \to x_i) & \text{if } X \to x_i \in R \\
    0 & \text{otherwise}
    \end{cases}
    \]
  - **Step 2:** for all \( X \) in \( N \):
    \[
    \pi_U(i, i, X) = \max_{X \to Y \in R} (q(X \to Y) \times \pi(i, i, Y))
    \]

- For \( l = 1 \ldots (n-1) \) [iterate all phrase lengths]
  - For \( i = 1 \ldots (n-l) \) and \( j = i+l \) [iterate all phrases of length \( l \)]
    - **Step 1:** (Binary)
      - For all \( X \) in \( N \) [iterate all non-terminals]
        \[
        \pi_B(i, j, X) = \max_{X \to Y Z \in R, s \in \{i \ldots (j-1)\}} (q(X \to Y) \times \pi_B(i, s, Y) \times \pi_B(s+1, j, Z))
        \]
    - **Step 2:** (Unary)
      - For all \( X \) in \( N \) [iterate all non-terminals]
        \[
        \pi_U(i, j, X) = \max_{X \to Y \in R} (q(X \to Y) \times \pi_B(i, j, X))
        \]

Must always have one and exactly one unary rule!
Unary Closure

- Rather than zero or more unaries, always exactly one
- Calculate closure $\text{Close}(R)$ for unary rules in $R$
  - Add $X \rightarrow Y$ if there exists a rule chain $X \rightarrow Z_1, Z_1 \rightarrow Z_2, \ldots, Z_k \rightarrow Y$ with $q(X \rightarrow Y) = q(X \rightarrow Z_1) \cdot q(Z_1 \rightarrow Z_2) \cdot \ldots \cdot q(Z_k \rightarrow Y)$
  - Add $X \rightarrow X$ with $q(X \rightarrow X) = 1$ for all $X$ in $N$

- In CKY and chart: Alternate unary and binary layers
- Reconstruct unary chains afterwards (with extra marking)
Other Chart Computations

- Max inside score
  - Score of the max parse of $x_i$ to $x_j$ with root $X$
    \[ \pi(i, j, X) \]
  - Marginalize over internal structure
- Max outside score
- Sum inside/outside
Other Chart Computations

- Max inside score
- Max outside score
  - Score of max parse of the complete span with a gap between i and j
  - Details in notes
- Sum inside/outside
Other Chart Computations

- Max inside score
- Max outside score
- Sum inside/outside
  - Do sums instead of maxes
Just Like Sequences

• Locally normalized:
  – Generative
  – MaxEnt
• Globally normalized:
  – CRFs
• Additive, un-normalized:
  – Perceptron
Treebank Parsing

(S
  (NP-SBJ (DT The) (NN move))
  (VP (VBD followed)
    (NP
      (NP (DT a) (NN round))
      (PP (IN of)
        (NP
          (NP (JJ similar) (NNS increases))
          (PP (IN by)
            (NP (JJ other) (NNS lenders)))
          (PP (IN against)
            (NP (NNP Arizona) (JJ real) (NN estate) (NNS loans))))))
  (, ,))
(S-ADV
  (NP-SBJ (-NONE- *))
  (VP (VBG reflecting)
    (NP
      (NP (DT a) (VBG continuing) (NN decline))
      (PP-LOC (IN in)
        (NP (DT that) (NN market)))))))

[Marcus et al. 1993]
Treebank Grammars

• Need a PCFG for broad coverage parsing.
• Can take a grammar right off the trees:

```
ROOT → S   1
S → NP VP  .  1
NP → PRP   1
VP → VBD ADJP 1
  ...  
```

```
ROOT
  |  
  S
    |  
  NP   VP
    |  
  PRP  VBD ADJP
    |  
  He was JJ
    |  
    right
```
Typical Experimental Setup

• The Penn Treebank is divided into sections:
  – Training: sections 2-18
  – Development: section 22 (also 0-1 and 24)
  – Testing: section 23

• Evaluation?
Evaluating Constituency Parsing

Gold standard brackets:  

S-(0:11), NP-(0:2), VP-(2:9), VP-(3:9), NP-(4:6), PP-(6-9), NP-(7,9), NP-(9:10)

```
S
  NP
    NNS
    NNS
      VBD 
        VP
          VBG
            NP
              IN
                NP
                  PP
                    NP
                        NN
                        11
          10
          yesterday

NP
  NNS
  0 Sales
  2 executives
  1 were

VP
  VBG
    3 examining

VP
  NP
    DT
      4 the
        NP
          IN
            NP
              JJ
                NN
                  7 great
                    8 care
                      9 yesterday
```

Candidate brackets:  

S-(0:11), NP-(0:2), VP-(2:10), VP-(3:10), NP-(4:6), PP-(6-10), NP-(7,10)

```
S
  NP
    NNS
    NNS
      VBD 
        VP
          VBG
            NP
              IN
                NP
                  PP
                    NP
                        NN
                        11
          10
          yesterday

NP
  NNS
  0 Sales
  2 executives
  1 were

VP
  VBG
    3 examining

VP
  NP
    DT
      4 the
        NP
          IN
            NP
              JJ
                NN
                  7 great
                    8 care
                      9 yesterday
```
Evaluating Constituency Parsing

• Recall:
  – Recall = (# correct constituents in candidate) / (# constituents in gold)

• Precision:
  – Precision = (# correct constituents in candidate) / (# constituents in candidate)

• Labeled Precision and labeled recall require getting the non-terminal label on the constituent node correct to count as correct.

• F1 is the harmonic mean of precision and recall.
  – F1 = (2 * Precision * Recall) / (Precision + Recall)
Evaluating Constituency Parsing

Gold standard brackets:
S-(0:11), NP-(0:2), VP-(2:9), VP-(3:9), NP-(4:6), PP-(6-9), NP-(7,9), NP-(9:10)

Candidate brackets:
S-(0:11), NP-(0:2), VP-(2:10), VP-(3:10), NP-(4:6), PP-(6-10), NP-(7,10)

• Precision: \( \frac{3}{7} = 42.9\% \)
• Recall: \( \frac{3}{8} = 37.5\% \)
• F1: \( 40\% \)
• Also, tagging accuracy: \( \frac{11}{11} = 100\% \)
How Good are PCFGs?

- Robust
  - Usually admit everything, but with low probability
- Partial solution for grammar ambiguity
  - A PCFG gives some idea of the plausibility of a parse
  - But not so good because the independence assumptions are too strong
- Give a probabilistic language model
  - But in the simple case it performs worse than a trigram model
- The problem seems to be that PCFGs lack the lexicalization of a trigram model

Penn WSJ parsing performance:
~ 73% F1
The man saw the woman with the hat.
Extra Slides
Chomsky Normal Form

• All rules are of the form $X \rightarrow Y Z$ or $X \rightarrow w$
  – $X, Y, Z \in N$ and $w \in T$
• A transformation to this form doesn’t change the weak generative capacity of a CFG
  – That is, it recognizes the same language
    • But maybe with different trees
• Empties and unaries are removed recursively
• n-ary rules are divided by introducing new nonterminals ($n > 2$)
Example: Before Binarization

```
ROOT
  S
    NP
    N
    people
    V
    fish
    NP
    N
    tanks
    PP
    P
    with
    NP
    N
    rods
```
Example: After Binarization

(ROOT
  S
    NP
    VP
      @VP_V
        NP
        PP
          NP
        N
        P
          NP
        N
      V
        N
        N
        P
      fish
      tanks
      with
      rods
    people)
A Phrase Structure Grammar

S → NP VP
VP → V NP
VP → V NP PP
NP → NP NP
NP → NP PP
NP → N
NP → e
PP → P NP

N → people
N → fish
N → tanks
N → rods
V → people
V → fish
V → tanks
P → with
Chomsky Normal Form

Step 1: Remove epsilon rules

\[
\begin{align*}
S & \rightarrow NP \ VP \\
VP & \rightarrow V \ NP \\
VP & \rightarrow V \ NP \ PP \\
NP & \rightarrow NP \ NP \\
NP & \rightarrow NP \ PP \\
NP & \rightarrow N \\
NP & \rightarrow e \\
PP & \rightarrow P \ NP \\
N & \rightarrow people \\
N & \rightarrow fish \\
N & \rightarrow tanks \\
N & \rightarrow rods \\
V & \rightarrow people \\
V & \rightarrow fish \\
V & \rightarrow tanks \\
P & \rightarrow with
\end{align*}
\]
Chomsky Normal Form

Step 1: Remove epsilon rules

S → NP VP
VP → V NP
VP → V NP PP
NP → NP NP
NP → NP PP
NP → N
NP → e
PP → P NP

N → people
N → fish
N → tanks
N → rods
V → people
V → fish
V → tanks
P → with
Chomsky Normal Form

Step 1: Remove epsilon rules

$$S \rightarrow NP \ VP$$  \hspace{1cm}  $$N \rightarrow \text{people}$$
$$VP \rightarrow V \ NP$$  \hspace{1cm}  $$N \rightarrow \text{fish}$$
$$VP \rightarrow V \ NP \ PP$$  \hspace{1cm}  $$N \rightarrow \text{tanks}$$
$$NP \rightarrow NP \ NP$$  \hspace{1cm}  $$N \rightarrow \text{rods}$$
$$NP \rightarrow NP \ PP$$  \hspace{1cm}  $$V \rightarrow \text{people}$$
$$NP \rightarrow N$$  \hspace{1cm}  $$V \rightarrow \text{fish}$$
$$NP \rightarrow e$$  \hspace{1cm}  $$V \rightarrow \text{tanks}$$
$$PP \rightarrow P \ NP$$  \hspace{1cm}  $$P \rightarrow \text{with}$$

Recognizing the same language?  
For every rule with NP, create a unary rule
Chomsky Normal Form

Step 1: Remove epsilon rules

S → NP VP
S → VP
VP → V NP
VP → V
VP → V NP PP
VP → V PP
NP → NP NP
NP → NP
NP → NP PP
NP → PP
NP → N
PP → P NP
PP → P

N → people
N → fish
N → tanks
N → rods
V → people
V → fish
V → tanks
P → with
Chomsky Normal Form

Step 2: Remove unary rules

\[
\begin{align*}
S &\rightarrow NP \ VP \\
S &\rightarrow \ VP \\
VP &\rightarrow V \ NP \\
VP &\rightarrow V \\
VP &\rightarrow V \ NP \ PP \\
VP &\rightarrow V \ PP \\
NP &\rightarrow NP \ NP \\
NP &\rightarrow NP \\
NP &\rightarrow NP \ PP \\
NP &\rightarrow PP \\
NP &\rightarrow N \\
PP &\rightarrow P \ NP \\
PP &\rightarrow P \\
\end{align*}
\]

\[
\begin{align*}
N &\rightarrow people \\
N &\rightarrow fish \\
N &\rightarrow tanks \\
N &\rightarrow rods \\
V &\rightarrow people \\
V &\rightarrow fish \\
V &\rightarrow tanks \\
P &\rightarrow with \\
\end{align*}
\]
Chomsky Normal Form

Step 2: Remove unary rules

S \rightarrow NP \ VP
S \rightarrow VP
VP \rightarrow V \ NP
VP \rightarrow V
VP \rightarrow V \ NP \ PP
VP \rightarrow V \ PP
NP \rightarrow NP \ NP
NP \rightarrow NP
NP \rightarrow NP \ PP
NP \rightarrow PP
NP \rightarrow N
PP \rightarrow P \ NP
PP \rightarrow P

N \rightarrow people
N \rightarrow fish
N \rightarrow tanks
N \rightarrow rods
V \rightarrow people
V \rightarrow fish
V \rightarrow tanks
P \rightarrow with
Chomsky Normal Form

Step 2: Remove unary rules

S → NP VP
S → VP
VP → V NP
VP → V
VP → V NP PP
VP → V PP
NP → NP NP
NP → NP
NP → NP PP
NP → PP
NP → N
PP → P NP
PP → P

N → people
N → fish
N → tanks
N → rods
V → people
V → fish
V → tanks
P → with

Recognizing the same language?
Work your way down to propagate
Chomsky Normal Form

Step 2: Remove unary rules

S → NP VP
S → VP
VP → V NP
VP → V
VP → V NP PP
VP → V PP
NP → NP NP
NP → NP
NP → NP PP
NP → PP
NP → N
PP → P NP
PP → P

N → *people*
N → *fish*
N → *tanks*
N → *rods*
V → *people*
V → *fish*
V → *tanks*
P → *with*

Recognizing the same language? Work your way down to propagate
Chomsky Normal Form

Step 2: Remove unary rules

S → NP VP
VP → V NP
S → V NP
VP → V
S → V
VP → V NP PP
S → V NP PP
VP → V PP
S → V PP
NP → NP NP
NP → NP
NP → NP PP
NP → PP
NP → N
PP → P NP
PP → P

Just added a unary rule!
Need to apply until they are all gone

N → people
N → fish
N → tanks
N → rods
V → people
V → fish
V → tanks
P → with
Chomsky Normal Form

Step 2: Remove unary rules

S → NP VP
VP → V NP
S → V NP
VP → V
S → V

VP → V NP PP
S → V NP PP
VP → V PP
S → V PP
NP → NP NP
NP → NP
NP → NP PP
NP → PP
NP → N
PP → P NP
PP → P

N → people
N → fish
N → tanks
N → rods
V → people
V → fish
V → tanks
P → with

Just added a unary rule! Need to apply until they are all gone.
Chomsky Normal Form

Step 2: Remove unary rules

<table>
<thead>
<tr>
<th>Grammar</th>
<th>Symbol</th>
<th>Rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>S →</td>
<td>NP VP</td>
<td></td>
</tr>
<tr>
<td>VP →</td>
<td>V NP</td>
<td></td>
</tr>
<tr>
<td>S →</td>
<td>V NP</td>
<td></td>
</tr>
<tr>
<td>VP →</td>
<td>V</td>
<td></td>
</tr>
<tr>
<td>VP →</td>
<td>V NP PP</td>
<td></td>
</tr>
<tr>
<td>S →</td>
<td>V NP PP</td>
<td></td>
</tr>
<tr>
<td>VP →</td>
<td>V PP</td>
<td></td>
</tr>
<tr>
<td>S →</td>
<td>V PP</td>
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<tr>
<td>NP →</td>
<td>NP NP</td>
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<td>N →</td>
<td>people</td>
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<tr>
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<td>fish</td>
<td></td>
</tr>
<tr>
<td>N →</td>
<td>tanks</td>
<td></td>
</tr>
<tr>
<td>N →</td>
<td>rods</td>
<td></td>
</tr>
<tr>
<td>V →</td>
<td>people</td>
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</tr>
<tr>
<td>V →</td>
<td>fish</td>
<td></td>
</tr>
<tr>
<td>V →</td>
<td>tanks</td>
<td></td>
</tr>
<tr>
<td>P →</td>
<td>with</td>
<td></td>
</tr>
</tbody>
</table>
Chomsky Normal Form

Step 2: Remove unary rules

S → NP VP
VP → V NP
S → V NP
VP → V NP PP
VP → V PP
S → V PP
NP → NP NP
NP → NP
NP → NP PP
NP → PP
NP → N
PP → P NP
PP → P

N → people
N → fish
N → tanks
N → rods
V → people
V → fish
V → tanks
P → with
Chomsky Normal Form

Step 2: Remove unary rules

S → NP VP
VP → V NP
S → V NP
VP → V NP PP
S → V NP PP
VP → V PP
S → V PP
NP → NP NP
NP → NP
NP → NP PP
NP → PP
NP → N
PP → P NP
PP → P

N → people
N → fish
N → tanks
N → rods
V → people
V → fish
V → tanks
P → with
Chomsky Normal Form

Step 2: Remove unary rules

S → NP VP
VP → V NP
S → V NP
VP → V NP PP
S → V NP PP
VP → V PP
S → V PP
NP → NP NP
NP → NP PP
NP → PP
NP → N
PP → P NP
PP → P

N → people
N → fish
N → tanks
N → rods
V → people
V → fish
V → tanks
P → with

Recognizing the same language?
Yes!
Chomsky Normal Form

Step 2: Remove unary rules

S → NP VP
VP → V NP
S → V NP
VP → V NP PP
S → V NP PP
VP → V PP
S → V PP
NP → NP NP
NP → NP PP
NP → PP
NP → N
PP → P NP
PP → P

Only place N appears
So can get rid of it altogether

N → people
N → fish
N → tanks
N → rods
V → people
V → fish
V → tanks
P → with
Chomsky Normal Form

Step 2: Remove unary rules

S → NP VP
VP → V NP
S → V NP
VP → V NP PP
S → V NP PP
VP → V PP
S → V PP
NP → NP NP
NP → NP PP
NP → PP
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NP → people
NP → fish
NP → tanks
NP → rods
V → people
V → fish
V → tanks
P → with
Chomsky Normal Form

Step 2: Remove unary rules

S → NP VP
VP → V NP
S → V NP
VP → V NP PP
S → V NP PP
VP → V PP
S → V PP
NP → NP NP
NP → NP PP
NP → PP
PP → P NP
PP → P

NP → people
NP → fish
NP → tanks
NP → rods
V → people
V → fish
V → tanks
P → with
Chomsky Normal Form

Step 2: Binarize

S → NP VP
VP → V NP
S → V NP
VP → V NP PP
S → V NP PP
VP → V PP
S → V PP
NP → NP NP
NP → NP PP
NP → P NP
PP → P NP

NP → people
NP → fish
NP → tanks
NP → rods
V → people
S → people
VP → people
V → fish
S → fish
VP → fish
V → tanks
S → tanks
VP → tanks
P → with
PP → with
Chomsky Normal Form

Step 2: Binarize

S → NP VP
VP → V NP
S → V NP
VP → V NP PP
S → V NP PP
VP → V PP
S → V PP
NP → NP NP
NP → NP PP
NP → P NP
PP → P NP

NP → people
VP → fish
NP → tanks
VP → rods
V → people
S → people
VP → people
V → fish
S → fish
VP → fish
V → tanks
S → tanks
VP → tanks
P → with
PP → with
Chomsky Normal Form

Step 2: Binarize

S → NP VP
VP → V NP
S → V NP
VP → V @VP_V
@VP_V → NP PP
S → V @S_V
@S_V → NP PP
VP → V PP
S → V PP
NP → NP NP
NP → NP PP
NP → P NP
PP → P NP

NP → people
NP → fish
NP → tanks
NP → rods
V → people
S → people
VP → people
V → fish
S → fish
VP → fish
V → tanks
S → tanks
VP → tanks
P → with
PP → with
Chomsky Normal Form: Source

S → NP VP
VP → V NP
VP → V NP PP
NP → NP NP
NP → NP PP
NP → N
NP → e
PP → P NP

N → people
N → fish
N → tanks
N → rods
V → people
V → fish
V → tanks
P → with
Chomsky Normal Form

S → NP VP
VP → V NP
S → V NP
VP → V @VP_V
@VP_V → NP PP
S → V @S_V
@S_V → NP PP
VP → V PP
S → V PP
NP → NP NP
NP → NP PP
NP → P NP
PP → P NP

NP → people
NP → fish
NP → tanks
NP → rods
V → people
S → people
VP → people
V → fish
S → fish
VP → fish
V → tanks
S → tanks
VP → tanks
P → with
PP → with
Chomsky Normal Form

- You should think of this as a transformation for efficient parsing
- With some extra book-keeping in symbol names, you can even reconstruct the same trees with a detransform
- In practice full Chomsky Normal Form is a pain
  - Reconstructing n-aries is easy
  - Reconstructing unaries/empties is trickier

- **Binarization** is crucial for cubic time CFG parsing

- The rest isn’t necessary; it just makes the algorithms cleaner and a bit quicker
Treebank: empties and unaries

PTB Tree  NoFuncTags  NoEmptyes  High  Low  NoUnaries