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Chapter 23(continued)

Natural Language for Communication

Phrase Structure Grammars

• Probabilistic context-free grammar (PCFG):

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- Context free: the left-hand side of the grammar consists of a single nonterminal symbol
- Probabilistic: the grammar assigns a probability to every string
- Lexicon: list of allowable words

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- Grammar: a collection of rules that defines a language as a set of allowable string of words
- Example: Fish people fish tanks

Backus–Naur Form (BNF)

Rule Prob θ_i	
$S \twoheadrightarrow NP VP$	θο
$NP \twoheadrightarrow NP \ NP$	θ_1
$N \rightarrow fish$	θ_{42}
$N \rightarrow people$	$\boldsymbol{\theta}_{43}$
$V \rightarrow fish$	$\boldsymbol{\theta}_{44}$

2

Phrase Structure Grammars (continued)

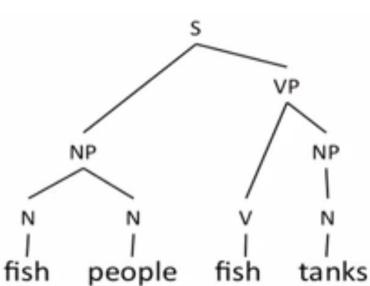
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PCFG

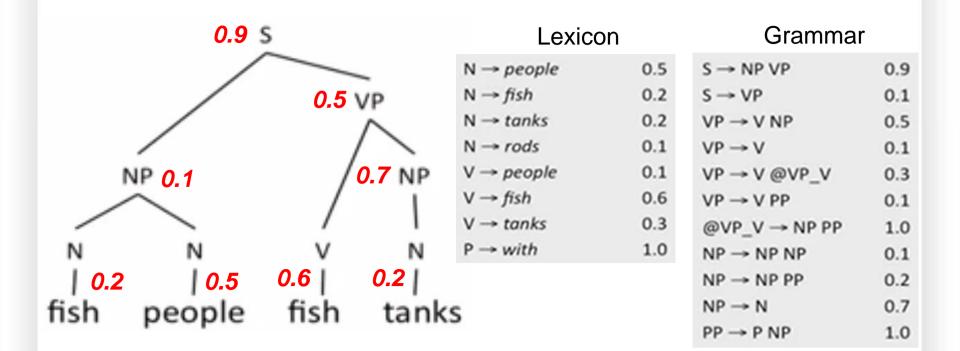
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Phrase Structure Grammars (continued)

Example: Fish people fish tanks

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Probability = 0.2 x 0.5 x 0.6 x 0.2 x 0.1 x 0.7 x 0.5 x 0.9

Parsing

- Objective: analyzing a string of words to uncover its phrase structure, given the lexicon and grammar.
 - The result of parsing is a parse tree
- Top-down parse and bottom-up parse
 - Naïve solutions: left-to-right or right-to-left parse

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- Example: The wumpus is dead

List of items	Rule
S	
NP VP	$S \rightarrow NP VP$
NP VP Adjective	$VP \rightarrow VP \ Adjective$
NP Verb Adjective	$VP \rightarrow Verb$
NP Verb dead	$Adjective \rightarrow dead$
NP is dead	$Verb \rightarrow is$
Article Noun is dead	$NP \rightarrow Article Noun$
Article wumpus is dead	$Noun \rightarrow$ wumpus
the wumpus is dead	Article \rightarrow the

Parsing (continued)

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Article wumpus is dead	$Noun \rightarrow$ wumpus
the wumpus is dead	$Article \rightarrow the$

- Efficient?
- Example:

Have the students in section 2 of Computer Science 101 take the exam. Have the students in section 2 of Computer Science 101 taken the exam?

Parsing (continued)

- Efficient solutions: chart parsers
 - Using dynamic programming
- CYK algorithm
 - A bottom-up chart parser:
 - (Named after its inventors, John Cocke, Daniel Younger, and Tadeo Kasami)
 - Input: lexicon, grammar and query strings.

- Output: a parse tree
- Three major steps:
 - Assign lexicons
 - Compute probability of adjacent phrases
 - Solve grammar conflict by selecting the most probable phrases

Parsing (continued)

- CYK algorithm
 - Three major steps:
 - Assign lexicons
 - Compute probability of adjacent phrases

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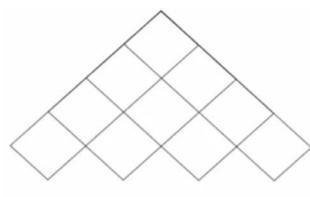
• Solve grammar conflict by selecting the most probable phrases

```
function CYK-PARSE(words, grammar) returns P, a table of probabilities
N \leftarrow \text{LENGTH}(words)
M \leftarrow the number of nonterminal symbols in grammar
P \leftarrow an array of size [M, N, N], initially all 0
/ * Insert lexical rules for each word */
                                                    Assign lexicons
for i = 1 to N do
   for each rule of form (X \rightarrow words_i [p]) do
     P[X, i, 1] \leftarrow p
/* Combine first and second parts of right-hand sides of rules, from short to long */
for length = 2 to N do
   for start = 1 to N - length + 1 do
     for len1 = 1 to N - 1 do
        len2 \leftarrow length - len1 Solve grammar conflict
        for each rule of the form (X \rightarrow Y Z [p]) do
          P[X, start, length] \leftarrow MAX(P[X, start, length]),
                             P[Y, start, len1] \times P[Z, start + len1, len2] \times p)
return P
                            Compute probability of adjacent phrases
```

Parsing (continued)

• Example: Fish people fish tanks

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fish people fish tanks

0	fish	1	people	2	fish	3	tanks	4
1								
2								
3								
4								

Lexicon		
$N \rightarrow people$	0.5	s -
N → fish	0.2	s -
$N \rightarrow tanks$	0.2	VP
$N \rightarrow rods$	0.1	VP
$V \rightarrow people$	0.1	VP
$V \rightarrow fish$	0.6	VP
$V \rightarrow tanks$	0.3	@1
$P \rightarrow with$	1.0	NP

Grammar	
$S \to NP \; VP$	0.9
$S \rightarrow VP$	0.1
$VP \rightarrow V NP$	0.5
$VP\toV$	0.1
$VP \rightarrow V @VP_V$	0.3
$VP \rightarrow V PP$	0.1
$@VP_V \rightarrow NP PP$	1.0
$NP \rightarrow NP NP$	0.1
$NP \rightarrow NP PP$	0.2
$NP \rightarrow N$	0.7
$PP \rightarrow P NP$	1.0

Parsing (continued)

• Example: by Dr. Christopher Manning from Stanford



CKY Parsing

A worked example



Augmented Parsing Methods

Lexicalized PCFGs

- BNF notation for grammars too restrictive

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- Augmented grammar

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- adding logical inference
- to construct sentence semantics

 \mathcal{E}_1 : $S \rightarrow NP_S VP \mid \dots$ $NP_S \rightarrow Pronoun_S \mid Name \mid Noun \mid \dots$ $NP_{O} \rightarrow Pronoun_{O} \mid Name \mid Noun \mid \dots$ $VP \rightarrow VP NP_O \mid \dots$ $PP \rightarrow Prep NP_{O}$ $Pronoun_S \rightarrow \mathbf{I} \mid \mathbf{you} \mid \mathbf{he} \mid \mathbf{she} \mid \mathbf{it} \mid \dots$ $Pronoun_O \rightarrow \mathbf{me} \mid \mathbf{you} \mid \mathbf{him} \mid \mathbf{her} \mid \mathbf{it} \mid \dots$. . . $S(head) \rightarrow NP(Sbj, pn, h) VP(pn, head) \mid \dots$ \mathcal{E}_2 : $NP(c, pn, head) \rightarrow Pronoun(c, pn, head) \mid Noun(c, pn, head) \mid \dots$ $VP(pn, head) \rightarrow VP(pn, head) NP(Obj, p, h) \mid \dots$ $PP(head) \rightarrow Prep(head) NP(Obj, pn, h)$ $Pronoun(Sbj, 1S, \mathbf{I}) \rightarrow \mathbf{I}$ $Pronoun(Sbj, 1P, we) \rightarrow we$ $Pronoun(Obj, 1S, \mathbf{me}) \rightarrow \mathbf{me}$ $Pronoun(Obj, 3P, \text{them}) \rightarrow \text{them}$

. . .

Real human languages provide many problems for NLP

- Ambiguity
- Anaphora
- Indexicality
- Vagueness
- Discourse structure
- Metonymy
- Metaphor
- Noncompositionality

Real language

- Real human languages provide many problems for NLP
 - Ambiguity: can be lexical (polysemy), syntactic, semantic, referential

I ate spaghetti with meatballs

Real language

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 - Ambiguity: can be lexical (polysemy), syntactic, semantic, referential

I ate spaghetti with meatballs salad

Real language

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 - Ambiguity: can be lexical (polysemy), syntactic, semantic, referential

I ate spaghetti with meatballs salad abandon

Real language

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I ate spaghetti with meatballs salad abandon a fork

Real language

- Real human languages provide many problems for NLP
 - Ambiguity: can be lexical (polysemy), syntactic, semantic, referential

I ate spaghetti with meatballs salad abandon a fork a friend

Real human languages provide many problems for NLP

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- Ambiguity
- Anaphora: using pronouns to refer back to entities already introduced in the text

After Mary proposed to John, they found a preacher and got married.

Real human languages provide many problems for NLP

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- Ambiguity
- Anaphora: using pronouns to refer back to entities already introduced in the text

After Mary proposed to John, **they** found a preacher and got married. For the honeymoon, **they** went to Hawaii

Real human languages provide many problems for NLP

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- Ambiguity
- Anaphora: using pronouns to refer back to entities already introduced in the text

After Mary proposed to John, <u>they</u> found a preacher and got married. For the honeymoon, <u>they</u> went to Hawaii Mary saw a ring through the window and asked John for <u>it</u>

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- Ambiguity
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After Mary proposed to John, <u>they</u> found a preacher and got married. For the honeymoon, <u>they</u> went to Hawaii Mary saw a ring through the window and asked John for <u>it</u> Mary threw a rock at the window and broke <u>it</u>

Real human languages provide many problems for NLP

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- Ambiguity
- Anaphora
- Indexicality: indexical sentences refer to utterance situation (place, time, S/H, etc.)

lam over here

Why did **you** do **<u>that</u>**?

- Real human languages provide many problems for NLP
 - Ambiguity
 - Anaphora
 - Indexicality
 - Vagueness
 - Discourse structure
 - Metonymy: using one noun phrase to stand for another

I've read **Shakespeare**

Chrysler announced record profits

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The ham sandwich on Table 4 wants another beer

Real human languages provide many problems for NLP

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- Ambiguity
- Anaphora
- Indexicality
- Vagueness
- Discourse structure
- Metonymy
- Metaphor: "Non-literal" usage of words and phrases

I've tried killing the process but it won't die. Its parent keeps it alive

- Real human languages provide many problems for NLP
 - Ambiguity
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 - Indexicality
 - Vagueness
 - Discourse structure
 - Metonymy
 - Metaphor
 - Noncompositionality

basketball shoesred bookbaby shoesred penalligator shoesred hairdesigner shoesred herringbrake shoesred herring

Real human languages provide many problems for NLP

- Ambiguity
- Anaphora
- Indexicality
- Vagueness
- Discourse structure
- Metonymy
- Metaphor
- Noncompositionality
- Interpreting natural language using computer agents is challenging and still an open problem (but we are doing better)