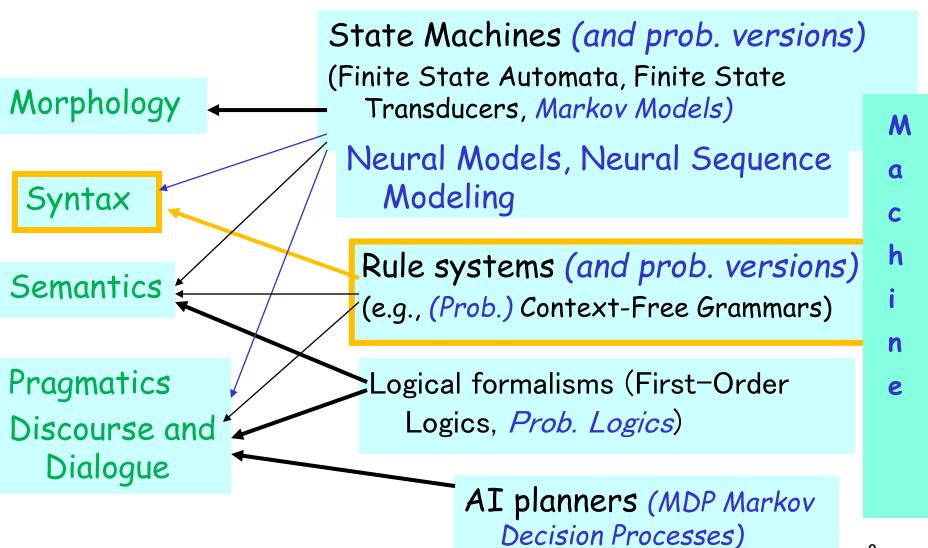
Intelligent Systems (AI-2)

Computer Science cpsc422, Lecture 27

Nov. 10, 2017

NLP: Knowledge-Formalisms Map (including probabilistic formalisms)



Lecture Overview

- Recap English Syntax and Parsing
- Key Problem with parsing: Ambiguity
- Probabilistic Context Free Grammars (PCFG)
- Treebanks and Grammar Learning

Key Constituents: Examples Hesa

NP -> De+ N

(Specifier) X (Complement)

· Noun phrases (NP)

- · (Det)
- N (PP)
 cat on the table

a cat

(PP)

Verb phrases (VP)

(Qual)

the

V (NP)

- never eat
- Prepositional phrases (PP). (Deg)
 P (NP)
 - almost in the net
- Adjective phrases(AP)

very happy about it

Sentences (5)

(NP) (-) (VP)

a mouse

(Deg)

-- ate iŧ

Context Free Grammar (CFG)

- 4-tuple (non-term., term., productions, start)
- (N, Σ , P, S)
- P is a set of rules $A \rightarrow \alpha$; $A \in \mathbb{N}$, $\alpha \in (\Sigma \cup \mathbb{N})^*$

$$N = \{XY\} = \{abc\} \quad P = X \rightarrow Xb$$

$$Y \rightarrow XX$$

$$X \rightarrow acY$$

$$X \rightarrow b$$

$$CPSC 422, Lecture 26$$

CFG Example

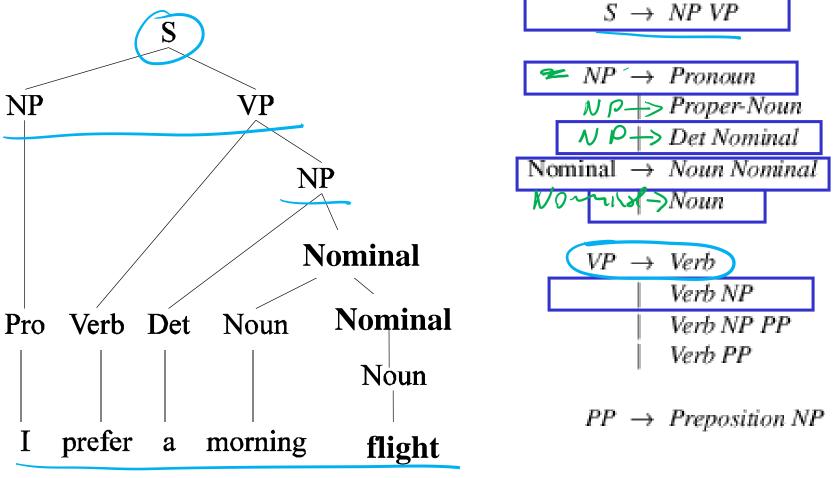
Grammar with example phrases

Lexicon

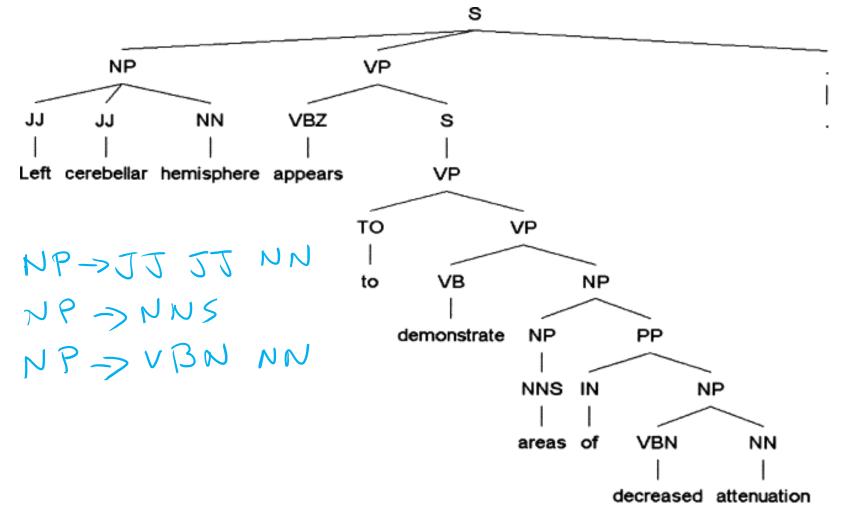
```
I + want a morning flight
      S \rightarrow NP VP
                                         NP
    NP \rightarrow Pronoun
    NP-+> Proper-Noun
                             Los Angeles
-> NP | Det Nominal
                             a + flight
Nominal → Noun Nominal
                            /morning + flight
         Noun
                             flights
     VP \rightarrow Verb
                             do
     Verb NP
                             want + a flight
            Verb NP PP
                             leave + Boston + in the morning
            Verb PP
                             leaving + on Thursday
     PP → Preposition NP
                             from + Los Angeles
```

```
Noun 
ightarrow flights \mid breeze \mid trip \mid morning \mid \dots
Verb 
ightarrow is \mid prefer \mid like \mid need \mid want \mid fly
Adjective 
ightarrow cheapest \mid non-stop \mid first \mid latest \mid other \mid direct \mid \dots
Pronoun 
ightarrow me \mid I \mid you \mid it \mid \dots
Proper-Noun 
ightarrow Alaska \mid Baltimore \mid Los Angeles \mid Chicago \mid United \mid American \mid \dots
Determiner 
ightarrow the \mid a \mid an \mid this \mid these \mid that \mid \dots
Preposition 
ightarrow from \mid to \mid on \mid near \mid \dots
Conjunction 
ightarrow and \mid or \mid but \mid \dots
```

Derivations as Trees



Example of relatively complex parse tree



Journal of the American Medical Informatics Association, 2005, Improved Identification of Noun Phrases in Clinical Radiology Reports Using a High-Performance Statistical Natural Language Parser Augmented with the UMLS Specialist Lexicon

Lecture Overview

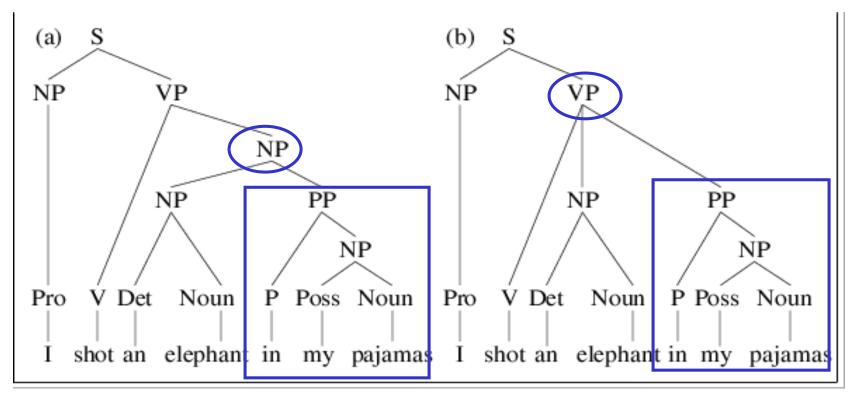
- Recap English Syntax and Parsing
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Structural Ambiguity (Ex. 1)

 $VP \rightarrow V NP ; NP \rightarrow NP PP$

VP -> V NP PP

"I shot an elephant in my pajamas"



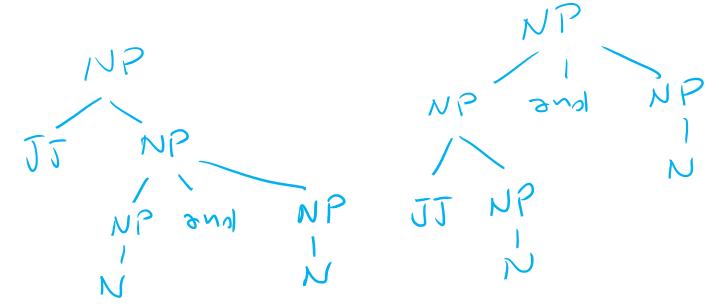
Structural Ambiguity (Ex.2)

"I saw Mary passing by cs2"

```
"I saw Mary passing by cs2"
(ROOT
                          (ROOT
 (5
                            (5
   (NP (PRP I))
                             (NP (PRP I))
   (VP (VBD saw)
                             (VP (VBD saw)
                                  (NP (NNP Mary))
     (5
      (NP (NNP Mary))
                                  (5
      (VP (VBG passing)
                                    (VP (VBG passing)
        (PP (IN by)
                                         (PP (IN by)
          (NP (NNP cs2)))))))
                                          (NP (NNP cs2)))))))
```

Structural Ambiguity (Ex. 3)

· Coordination "new student and profs"



Structural Ambiguity (Ex. 4)

· NP-bracketing "French language teacher"

Lecture Overview

- Recap English Syntax and Parsing
- Key Problem with parsing: Ambiguity
- Probabilistic Context Free Grammars (PCFG)
- Treebanks and Grammar Learning (acquiring the probabilities)
- Intro to Parsing PCFG

Probabilistic CFGs (PCFGs)

- GOAL: assign a probability to parse trees and to sentences
- · Each grammar rule is augmented with a conditional probability

· If these are all the rules for VP and .55

is the P(VP->Verb | VP)

VP -> Verb .55

VP -> Verb NP .40

VP -> Verb NP NP ??

What ?? should be ?

A. 1

B. 0

C. .05

D. None of the above

Probabilistic CFGs (PCFGs)

- GOAL: assign a probability to parse trees and to sentences
- · Each grammar rule is augmented with a conditional probability

· The expansions for a given non-terminal

sum to 1

VP -> Verb

VP -> Verb NP

VP -> Verb NP NP

.55 P(VP->Verb NP/VP) .40 P(VP->Verb NP/VP) .05 P(VP->Verb NPNP) VP)

Formal Def: 5-tuple $(N, \Sigma, P, \vec{S}, D)$

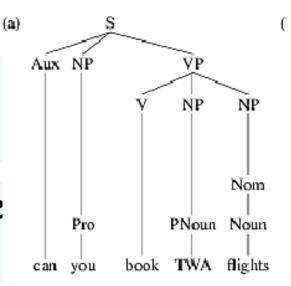
Sample PCFG

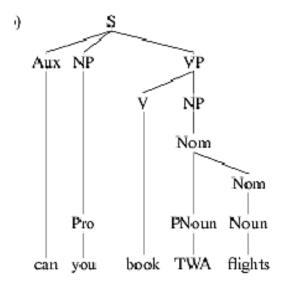
$S \rightarrow NP VP$	[.80]	$Det \rightarrow that [.05] \mid the [.80] \mid a$	[.15]
$S \rightarrow Aux NP VP$	[.15]	$Noun \rightarrow book$	[.10]
$S \rightarrow VP$	[.05]	$Noun \rightarrow flights$	[.50]
$NP \rightarrow Det Nom$	[.20]	$Noun \rightarrow meal$	[.40]
$NP \rightarrow Proper-Noun$	[.35]	$Verb \rightarrow book$	[.30]
$NP \rightarrow Nom$	[.05]	$Verb \rightarrow include$	[.30]
$NP \rightarrow Pronoun$	[.40]	Verb → want	[.40]
$Nom \rightarrow Noun$	[.75]	$Aux \rightarrow can$	[.40]
Nom → Noun Nom	[.20]	$Aux \rightarrow does$	[.30]
$Nom \rightarrow Proper-Noun Nom$	[.05]	$Aux \rightarrow do$	[.30]
$VP \rightarrow Verb$	[.55]	$Proper-Noun \rightarrow TWA$	[.40]
$VP \rightarrow Verb NP$	[.40]	$Proper-Noun \rightarrow Denver$	[.40]
$VP \rightarrow Verb NP NP$	[.05]	$Pronoun \rightarrow you[.40] \mid I[.60]$	

PCFGs are used to....

i⊧clicker.

- · Estimate Prob. of parse tree
 - A. Sum of the probs of all the rules applied
 - B. Product of the probs of all the rules applied
 - · Estimate Prob. of a sentence
 - A. Sum of the probs of all the parse trees
 - B. Product of the probs of all the parse trees





PCFGs are used to....

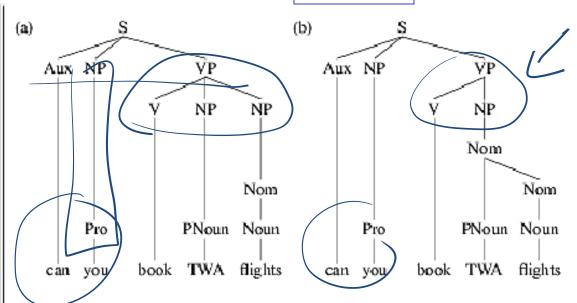
· Estimate Prob. of parse tree

· Estimate Prob. to sentences

Example

$$P(Tree^a) = .15 * .4 * ... = 1.5 \times 10^{-6}$$

$$P(Tree^b) = .15 * .4 * ... = 1.7 \times 10^{-6}$$



$$P("Can you....") = 1.7 \times 10^{-6} + 1.5 \times 10^{-6} = 3.2 \times 10^{-6}$$

		Rı	ıl es-	P		R	ules	P	
	S	\rightarrow	Aux NP VP	.15	S	\rightarrow	Aux NP VP	.15	
	NP	\rightarrow	Pro	.40	NP	\rightarrow	Pro	.40	<i>~</i> . <i>~</i>
>	VP	\rightarrow	V NP NP	.05	VP	\rightarrow	V NP	.40	- (5)
	NP	\rightarrow	Nom	.05	NP	\rightarrow	Nom	.05	
	NP	\rightarrow	PNoun	.35	Nom	\rightarrow	PNoun Nom	.05	
	Nom	\rightarrow	Noun	.75	Nom	\rightarrow	Noun	.75	
	Aux	$\boldsymbol{\rightarrow}$	Can	.40	Aux	\rightarrow	Can	.40	
-	NP	\rightarrow	Pro	.40	-NP	\rightarrow	Pro	.40	
	Pro	\rightarrow	you	.40	Pro	\rightarrow	you	.40	
	Verb	\rightarrow	book	.30	Verb	\rightarrow	book	.30	
	PNoun	\rightarrow	TWA	.40	Pnoun	\rightarrow	TWA	.40	
	Noun	\rightarrow	flights	.50	Noun	\rightarrow	flights	.50	

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- Treebanks and Grammar Learning (acquiring the probabilities)

Treebanks

- DEF. corpora in which each sentence has been paired with a parse tree
- · These are generally created
 - Parse collection with parser
 - human annotators revise each parse
- Requires detailed annotation guidelines
 - POS tagset
 - Grammar
 - instructions for how to deal with particular grammatical constructions.

Penn Treebank

Penn TreeBank is a widely used treebank.

 Most well known is the Wall Street Journal section of the Penn TreeBank.

■1 M wordsfrom the 1987-1989 Wall StreetJournal.

```
(VP (MD would)
  (VP (VB have)
                      5 -> NP VP
      (NP-SBJ (-NONE- *-1) )
      (VP (TO to)
        (VP (VB wait)
          (SBAR-TMP (IN until)
            (S
              (NP-SBJ (PRP we) )
              (VP (VBP have)
                (VP (VBN collected)
                  (PP-CLR (IN on)
                    (NP (DT those)(NNS assets))))))))))))))
 SBJ (PRP he) )
 (VBD said)
   (-NONE - *T*-2
```

Treebank Grammars

- Such grammars tend to contain lots of rules....
- For example, the Penn Treebank has 4500 different rules for VPs! Among them...

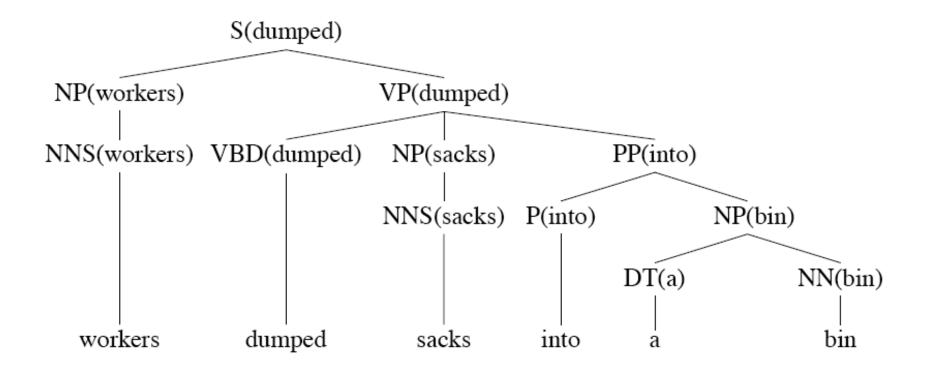
```
egin{array}{llll} VP & 
ightarrow & VBD & PP & PP \ VP & 
ightarrow & VBD & PP & PP & PP \ VP & 
ightarrow & VBD & PP & PP & PP \ VP & 
ightarrow & VBD & PP & PP & PP \ \end{array}
```

Heads in Trees

- Finding heads in treebank trees is a task that arises frequently in many applications.
 - Particularly important in statistical parsing

 We can visualize this task by annotating the nodes of a parse tree with the heads of each corresponding node.

Lexically Decorated Tree

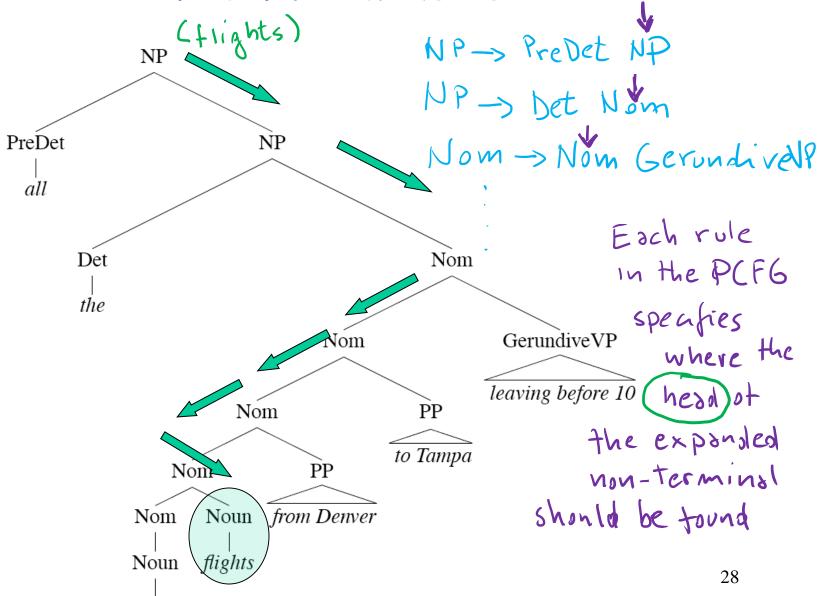


Head Finding

 The standard way to do head finding is to use a simple set of tree traversal rules specific to each non-terminal in the grammar.

 Each rule in the PCFG specifies where the head of the expanded non-terminal should be found

Noun Phrases



morning

Acquiring Grammars and Probabilities

Manually parsed text corpora (e.g., PennTreebank)

• Grammar: read it off the parse trees Ex: if an NP contains an ART, ADJ, and NOUN then we create the rule NP -> ART ADJ NOUN.

· Probabilities:

$$P(A \to \alpha | A) = \frac{\text{count}(A \to \alpha)}{\text{count}(A \to \beta)} = \frac{\text{count}(A \to \alpha)}{\text{count}(A)}$$

Ex: if the NP -> ART ADJ NOUN rule is used 50 times and all NP rules are used 5000 times, then the rule's probability is ... \mathcal{P}

Example

if you look at all the porse trees in the bank you find three rules for MP

- ONP-SART ADJ NOUN
- 2 NP -> NOUN
- 3) NP-> PRONOUN

$$P(0|NP) = \frac{50}{5000} = .01$$

 $P(2|NP) = \frac{4000}{5000} = .8$
 $P(3|NP) = \frac{950}{5000} = .17$

How many times
50
4000

5000 total #
of NP
expansions

Learning Goals for today's class

You can:

- Provide a formal definition of a PCFG
- Apply a PCFG to compute the probability of a parse tree of a sentence as well as the probability of a sentence
- Describe the content of a treebank
- Describe the process to identify a head of a syntactic constituent
- Compute the probability distribution of a PCFG from a treebank

Next class on Wed

- Parsing Probabilistic CFG: CKY parsing
- PCFG in practice: Modeling Structural and Lexical Dependencies

Assignment-3 due on Nov 20 (last year took students 8-18 hours)

Assignment-4 will be out on the same day