### PCFG Parsing, Evaluation, & Improvements

Ling 571
Deep Processing Techniques for NLP
January 24, 2011

#### Roadmap

- Parsing PCGFs:
  - Probabilistic CKY parsing
- Evaluation
  - Parseval
- Issues:
  - Positional and lexical independence assumptions
- Improvements:
  - Lexicalization: PLCFGs

### Parsing Problem for PCFGs

Select T such that:

$$\overset{\wedge}{T}(S) = \underset{Ts.t, S=yield(T)}{\operatorname{argmax}} P(T)$$

- String of words S is yield of parse tree over S
- Select tree that maximizes probability of parse
- Extend existing algorithms: CKY & Earley
  - Most modern PCFG parsers based on CKY
    - Augmented with probabilities

#### Probabilistic CKY

- Like regular CKY
  - Assume grammar in Chomsky Normal Form (CNF)
    - Productions:
      - A -> B C or A -> w
  - Represent input with indices b/t words
    - E.g., <sub>0</sub> Book <sub>1</sub> that <sub>2</sub> flight <sub>3</sub> through <sub>4</sub> Houston <sub>5</sub>
- For input string length n and non-terminals V
  - Cell[I,j,A] in (n+1)x(n+1)xV matrix contains
    - Probability that constituent A spans [i,j]

### Probabilistic CKY Algorithm

```
function PROBABILISTIC-CKY(words, grammar) returns most probable parse
                                                       and its probability
  for j \leftarrow from 1 to LENGTH(words) do
     for all \{A \mid A \rightarrow words[j] \in grammar\}
        table[j-1, j, A] \leftarrow P(A \rightarrow words[j])
     for i \leftarrow from j - 2 downto 0 do
         for k \leftarrow i+1 to j-1 do
                 for all \{A \mid A \rightarrow BC \in grammar,
                                 and table[i,k,B] > 0 and table[k,j,C] > 0
                        if (table[i,j,A] < P(A \rightarrow BC) \times table[i,k,B] \times table[k,j,C]) then
                            table[i,j,A] \leftarrow P(A \rightarrow BC) \times table[i,k,B] \times table[k,j,C]
                            back[i,j,A] \leftarrow \{k,B,C\}
     return BUILD_TREE(back[1, LENGTH(words), S]), table[1, LENGTH(words), S]
```

### PCKY Grammar Segment

S	$\rightarrow NP VP$	.80	Det	$\longrightarrow$	the	.40
NP	$\rightarrow$ <i>Det N</i>	.30	Det	$\longrightarrow$	a	.40
VP	$\rightarrow V NP$	.20	N	$\longrightarrow$	meal	.01
V	$\rightarrow$ includes	.05	N	$\rightarrow$	flight	.02

Det: 0.4		
[0,1]		

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[0,1]			
	N: 0.2		
	[1,2]		

Det: 0.4 [0,1]	NP: 0.3*0.4*0.2 =.0024 [0,2]		
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	N: 0.2 [1,2]		
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		[2,3]	

Det: 0.4	NP: 0.3*0.4*0.2		
[0,1]	=.0024 [0,2]		
	N: 0.2		
	[1,2]	[1,3]	
		V: 0.05	
		[2,3]	

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[0,1]	=.0024 [0,2]	[0,3]	
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	[1,2]	[1,3]	
		V: 0.05	
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Det: 0.4 [0,1]	NP: 0.3*0.4*0.2 =.0024 [0,2]	[0,3]		
	N: 0.2			
	[1,2]	[1,3]		
		V: 0.05		
		[2,3]		
			Det: 0.4	
			[3,4]	

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	[1,2]	[1,3]		
		V: 0.05		
		[2,3]	[2,4]	
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Det: 0.4 [0,1]	NP: 0.3*0.4*0.2 =.0024 [0,2]	[0,3]		
	N: 0.2 [1,2]	[1,3]	[1,4]	
	L-7-J	V: 0.05 [2,3]	[2,4]	
		L—, • J	Det: 0.4 [3,4]	

Det: 0.4 [0,1]	NP: 0.3*0.4*0.2 =.0024 [0,2]	[0,3]	[0,4]	
	N: 0.2			
	[1,2]	[1,3] V: 0.05	[1,4]	
		[2,3]	[2,4]	
			Det: 0.4	
			[3,4]	

Det: 0.4 [0,1]	NP: 0.3*0.4*0.02 =.0024 [0,2]	[0,3]	[0,4]	
	N: 0.2 [1,2]	[1,3]	[1,4]	
		V: 0.05		
		[2,3]	[2,4]	
			Det: 0.4	
			[3,4]	
				N: 0.01 [4,5]

0et: 0.4 0,1]	NP: 0.3*0.4*0.02 =.0024 [0,2]	[0,3]	[0,4]	
	N: 0.2 [1,2]	[1,3]	[1,4]	
		V: 0.05		
		[2,3]	[2,4]	
			Det: 0.4	NP: 0.3*0.4*0.01
			[3,4]	=0.0012 [3,5]
				N: 0.01 [4,5]

Det: 0.4 [0,1]	NP: 0.3*0.4*0.02 =.0024 [0,2]	[0,3]	[0,4]	
	N: 0.2 [1,2]	[1,3]	[1,4]	
		V: 0.05 [2,3]	[2,4]	VP: 0.2*0.05* 0.0012=0.0 00012 [2,5]
			Det: 0.4 [3,4]	NP: 0.3*0.4*0.01 =0.0012 [3,5]
				N: 0.01 [4,5]

Det: 0.4 [0,1]	NP: 0.3*0.4*0.02 =.0024 [0,2]	[0,3]	[0,4]	S: 0.000012* 0.0024 [0.5]
	N: 0.2 [1,2]	[1,3]	[1,4]	[1,5]
		V: 0.05 [2,3]	[2,4]	VP: 0.2*0.05* 0.0012=0.0 00012 [2,5]
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### Probabilistic Parser Development Paradigm

- Training:
  - (Large) Set of sentences with associated parses (Treebank)
    - E.g., Wall Street Journal section of Penn Treebank, sec 2-21
      - 39,830 sentences
    - Used to estimate rule probabilities

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      - 39,830 sentences
    - Used to estimate rule probabilities
- Development (dev):
  - (Small) Set of sentences with associated parses (WSJ, 22)
    - Used to tune/verify parser; check for overfitting, etc.
- Test:
  - (Small-med) Set of sentences w/parses (WSJ, 23)
    - 2416 sentences
  - Held out, used for final evaluation

- Assume a 'gold standard' set of parses for test set
- How can we tell how good the parser is?
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- How can we tell how good the parser is?
- How can we tell how good a parse is?
  - Maximally strict: identical to 'gold standard'
  - Partial credit:
    - Constituents in output match those in reference
      - Same start point, end point, non-terminal symbol

#### Parseval

- How can we compute parse score from constituents?
- Multiple measures:
  - Labeled recall (LR):
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- Multiple measures:
  - Labeled recall (LR):
    - # of correct constituents in hyp. parse
    - # of constituents in reference parse
  - Labeled precision (LP):
    - # of correct constituents in hyp. parse
    - # of total constituents in hyp. parse

### Parseval (cont'd)

- F-measure:
  - Combines precision and recall

$$F_{\beta} = \frac{(\beta^2 + 1)PR}{\beta^2 (P + R)}$$

• F1-measure: 
$$\beta = 1$$
  $F_1 = \frac{2PR}{(P+R)}$ 

- Crossing-brackets:
  - # of constituents where reference parse has bracketing ((A B) C) and hyp. has (A (B C))

- Gold standard
  - (S (NP (A a) ) (VP (B b) (NP (C c)) (PP (D d))))
- Hypothesis
  - (S (NP (A a)) (VP (B b) (NP (C c) (PP (D d)))))

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- LR: 4/5

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- LP: 4/5
- LR: 4/5
- F1: 4/5

## State-of-the-Art Parsing

- Parsers trained/tested on Wall Street Journal PTB
  - LR: 90%;
  - LP: 90%;
  - Crossing brackets: 1%
- Standard implementation of Parseval: evalb

### **Evaluation Issues**

Constituents?

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- Constituents?
  - Other grammar formalisms
    - LFG, Dependency structure, ...
    - Require conversion to PTB format

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- Constituents?
  - Other grammar formalisms
    - LFG, Dependency structure, ...
    - Require conversion to PTB format
  - Extrinsic evaluation
    - How well does this match semantics, etc?

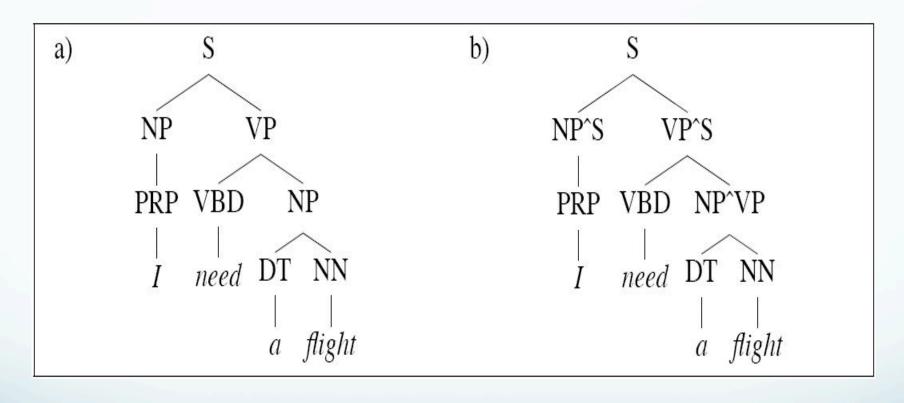
#### Parser Issues

- PCFGs make many (unwarranted) independence assumptions
  - Structural Dependency
    - NP -> Pronoun: much more likely in subject position
  - Lexical Dependency
    - Verb subcategorization
    - Coordination ambiguity

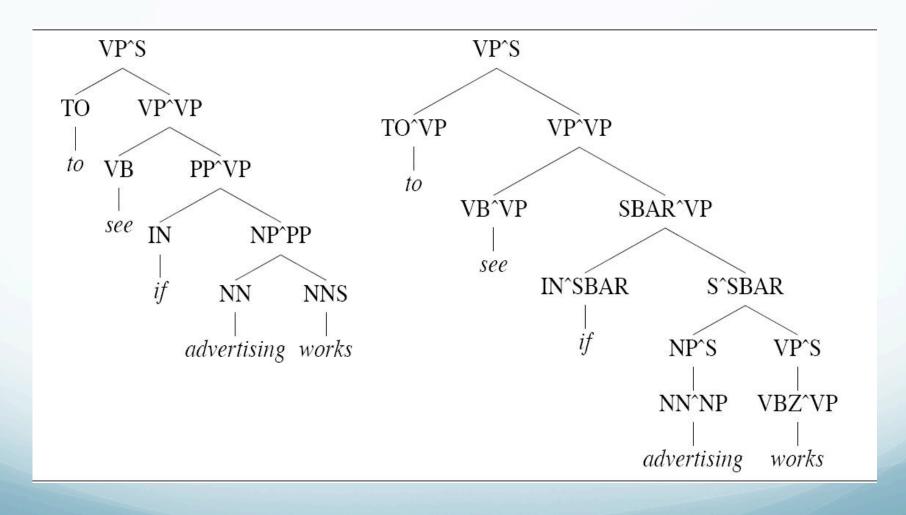
# Improving PCFGs: Structural Dependencies

- How can we capture Subject/Object asymmetry?
  - E.g., NP<sub>subj</sub>-> Pron vs NP<sub>Obj</sub>->Pron
- Parent annotation:
  - Annotate each node with parent in parse tree
    - E.g., NP^S vs NP^VP
    - Also annotate pre-terminals:
      - RB^ADVP vs RB^VP
      - IN^SBAR vs IN^PP
- Can also split rules on other conditions

#### Parent Annotaation



# Parent Annotation: Pre-terminals



#### Parent Annotaation

- Advantages:
  - Captures structural dependency in grammars

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- Disadvantages:
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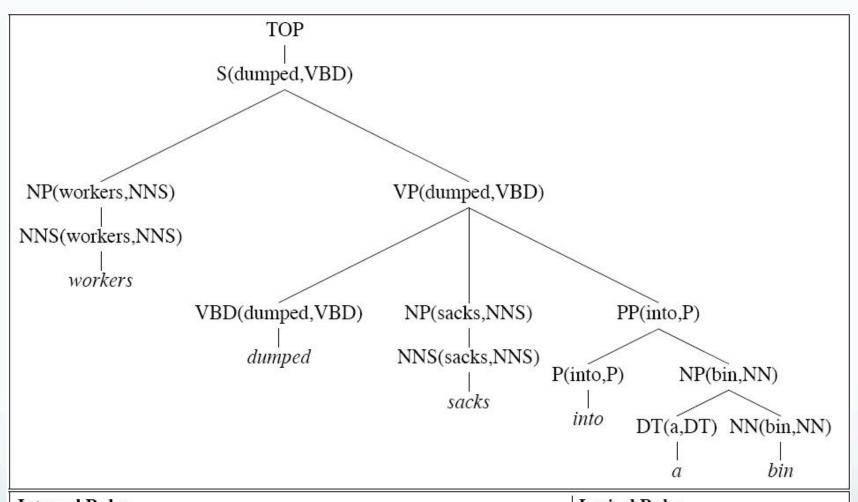
- Advantages:
  - Captures structural dependency in grammars
- Disadvantages:
  - Increases number of rules in grammar
  - Decreases amount of training per rule
    - Strategies to search for optimal # of rules

# Improving PCFGs: Lexical Dependencies

- Lexicalized rules:
  - Best known parsers: Collins, Charniak parsers
  - Each non-terminal annotated with its lexical head
    - E.g. verb with verb phrase, noun with noun phrase
  - Each rule must identify RHS element as head
    - Heads propagate up tree
  - Conceptually like adding 1 rule per head value
    - VP(dumped) -> VBD(dumped)NP(sacks)PP(into)
    - VP(dumped) -> VBD(dumped)NP(cats)PP(into)

#### Lexicalized PCFGs

- Also, add head tag to non-terminals
  - Head tag: Part-of-speech tag of head word
    - VP(dumped) -> VBD(dumped)NP(sacks)PP(into)
    - VP(dumped,VBD) -> VBD(dumped,VBD)NP(sacks,NNS) PP(into,IN)
- Two types of rules:
  - Lexical rules: pre-terminal -> word
    - Deterministic, probability 1
  - Internal rules: all other expansions
    - Must estimate probabilities



Internal Rules				Lexical Rules		
TOP	$\rightarrow$	S(dumped, VBD)		NNS(workers,NNS)	$ \to $	workers
S(dumped, VBD)	$\rightarrow$	NP(workers,NNS)	VP(dumped,VBD)	VBD(dumped, VBD)	$ \to $	dumped
NP(workers,NNS)	$\longrightarrow$	NNS(workers,NNS)		NNS(sacks,NNS)	$\rightarrow$	sacks
VP(dumped, VBD)	$\rightarrow$	VBD(dumped, VBD)	NP(sacks,NNS) PP(into,P)	P(into,P)	$\rightarrow$	into
PP(into,P)	$\rightarrow$	P(into,P)	NP(bin,NN)	DT(a,DT)	$\rightarrow$	a
NP(bin,NN)	$\rightarrow$	DT(a,DT)	NN(bin,NN)	NN(bin,NN)	$\rightarrow$	bin

# PLCFGs

• Issue:

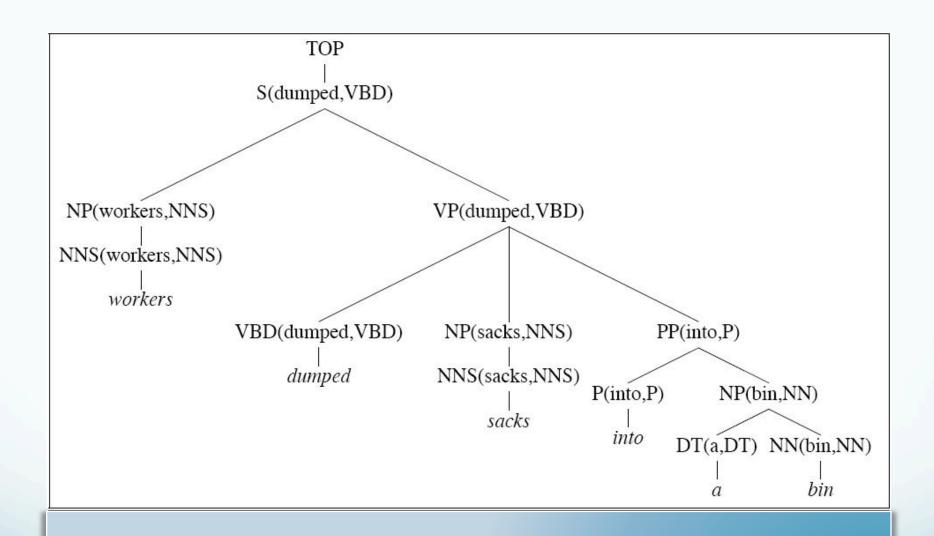
## **PLCFGs**

- Issue: Too many rules
  - No way to find corpus with enough examples

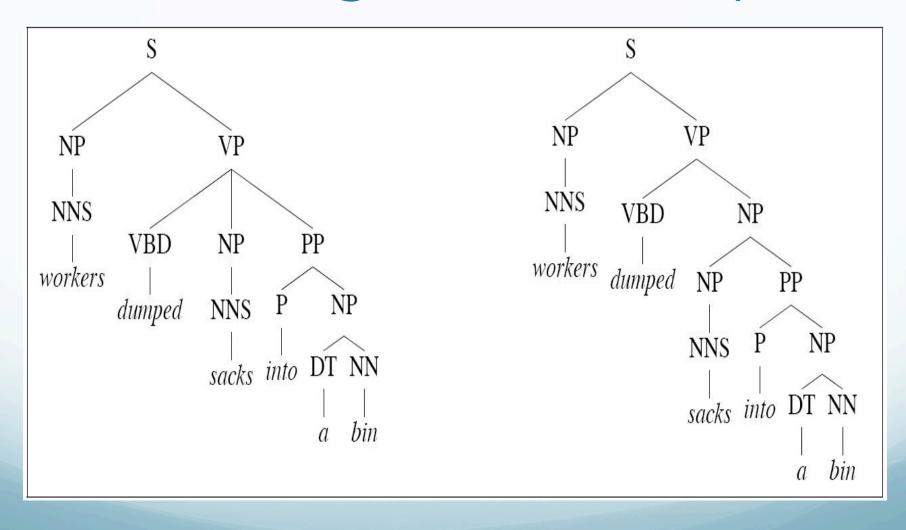
#### **PLCFGs**

- Issue: Too many rules
  - No way to find corpus with enough examples
- (Partial) Solution: Independence assumed
  - Condition rule on
    - Category of LHS, head
  - Condition head on
    - Category of LHS and parent's head

$$P(T,S) = \prod_{n \in T} p(r(n) | n, h(n)) * p(h(n) | n, h(m(n)))$$



# Disambiguation Example



## Disambiguation Example

$$P(VP \to VBDNPPP | VP, dumped)$$

$$= \frac{C(VP(dumped) \to VBDNPP)}{\sum_{\beta} C(VP(dumped) \to \beta)}$$

$$= 6/9 = 0.67$$

$$p(VP \to VBDNP \mid VP, dumped)$$

$$= \frac{C(VP(dumped) \to VBDNP)}{\sum_{\beta} C(VP(dumped) \to \beta)}$$

$$= 0/9 = 0$$

$$p(in | PP, dumped)$$

$$= \frac{C(X(dumped) \rightarrow ...PP(in)..)}{\sum_{\beta} C(X(dumped) \rightarrow ...PP...)}$$

$$= 2/9 = 0.22$$

$$p(in | PP, sacks)$$

$$= \frac{C(X(sacks) \rightarrow ...PP(in)...)}{\sum_{\beta} C(X(sacks) \rightarrow ...PP...)}$$

$$= 0/0$$