# Intelligent Systems (AI-2)

## Computer Science cpsc422, Lecture 28

## Nov, 18, 2015

# Lecture Overview

- **Recap Probabilistic Context Free Grammars (PCFG)**
- CKY parsing for PCFG (only key steps)
- PCFG in practice: Modeling Structural and Lexical Dependencies

# Sample PCFG

| | | | |
|---|---|---|---|
| $S \rightarrow NP\ VP$ | [.80] | $Det \rightarrow that$ [.05] \| $the$ [.80] \| $a$ [.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] |
| $NP \rightarrow Proper\text{-}Noun$ | [.35] | $Verb \rightarrow book$ | [.30] |
| $NP \rightarrow Nom$ | [.05] | $Verb \rightarrow include$ | [.30] |
| $NP \rightarrow Pronoun$ | [.40] | $Verb \rightarrow want$ | [.40] |
| $Nom \rightarrow Noun$ | [.75] | $Aux \rightarrow can$ | [.40] |
| $Nom \rightarrow Noun\ Nom$ | [.20] | $Aux \rightarrow does$ | [.30] |
| $Nom \rightarrow Proper\text{-}Noun\ Nom$ | [.05] | $Aux \rightarrow do$ | [.30] |
| $VP \rightarrow Verb$ | [.55] | $Proper\text{-}Noun \rightarrow TWA$ | [.40] |
| $VP \rightarrow Verb\ NP$ | [.40] | $Proper\text{-}Noun \rightarrow Denver$ | [.40] |
| $VP \rightarrow Verb\ NP\ NP$ | [.05] | $Pronoun \rightarrow you$ [.40] \| $I$ [.60] | |

# PCFGs are used to....

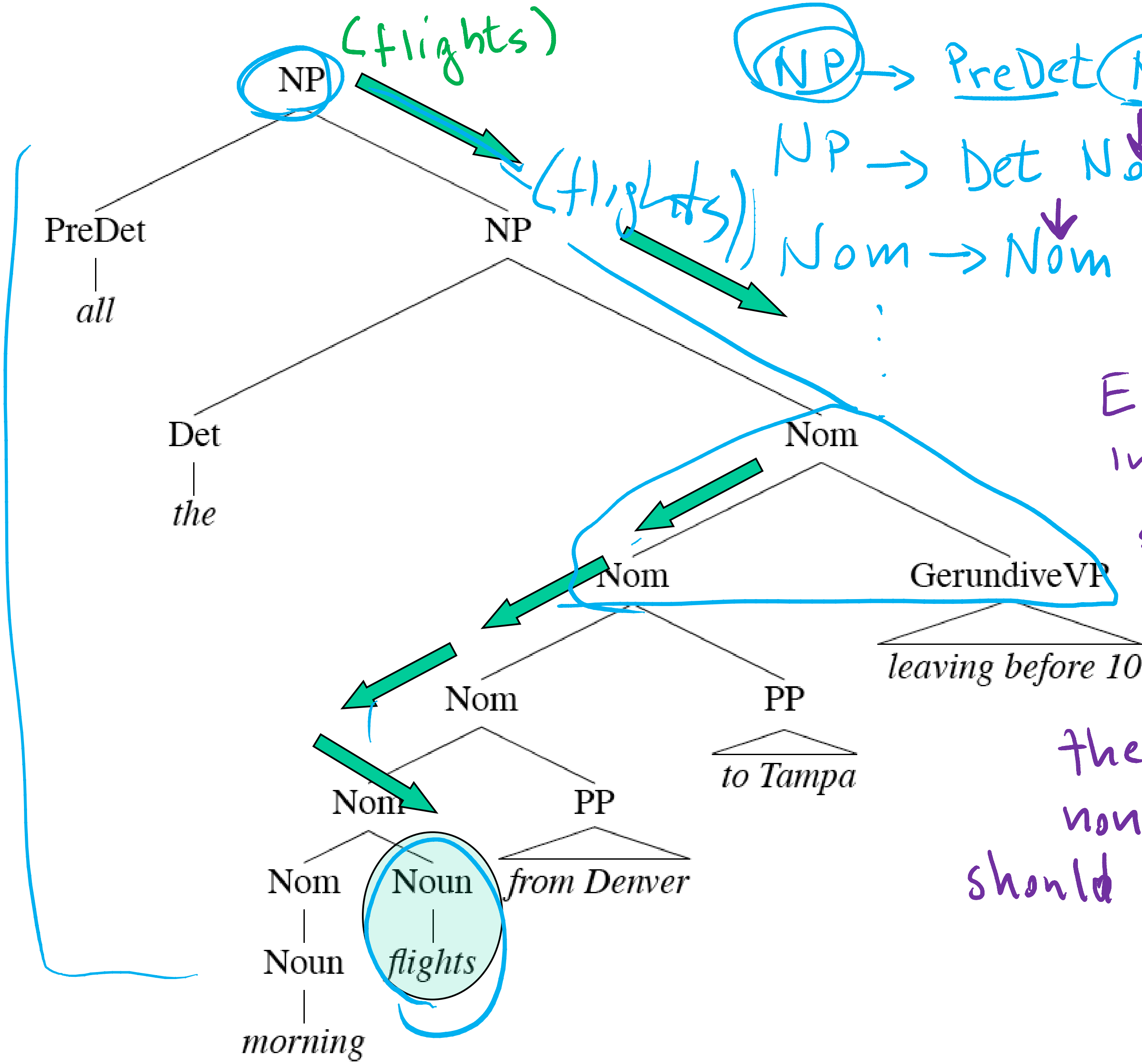
- **Estimate Prob. of parse tree**

$$P(Tree) = \prod_{node \in Tree} P(\text{expansion for node})$$

- **Estimate Prob. to sentences**

$$P(Sentence) = \sum_{Trees \in \text{Parse Trees of Sentence}} P(Tree)$$

# Head of a Phrase




NP → PreDet NP

NP → Det Nom

Nom → Nom GerundiveVP

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

# 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:**

$$P(A \to \alpha \mid A) = \frac{count(A \to \alpha)}{\sum_{\forall \gamma} count(A \to \gamma)} = \frac{count(A \to \alpha)}{count(A)}$$

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# Probabilistic Parsing:

- (Restricted) Task is to find the max probability tree for an input

$$\hat{Tree}(Sentence) = \operatorname*{argmax}_{Tree \in Parse\text{-}trees(Sentence)} P(Tree)$$

# Probabilistic CKY Algorithm

**Ney, 1991**
**Collins, 1999**

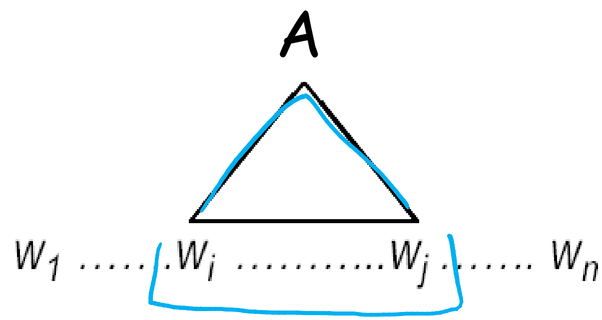
CYK (Cocke-Kasami-Younger) algorithm

- A **bottom-up** parser using dynamic programming
- Assume the PCFG is in Chomsky normal form (CNF)

$A \to BC \quad A \to w$

Definitions

- $w_1 \ldots w_n$ an input string composed of $n$ words
- $w_{ij}$ a string of words from word $i$ to word $j$
- $\mu[i, j, A]$ : a table entry holds the maximum probability for a constituent with non-terminal $A$ spanning words $w_i \ldots w_j$



# CKY: Base Case

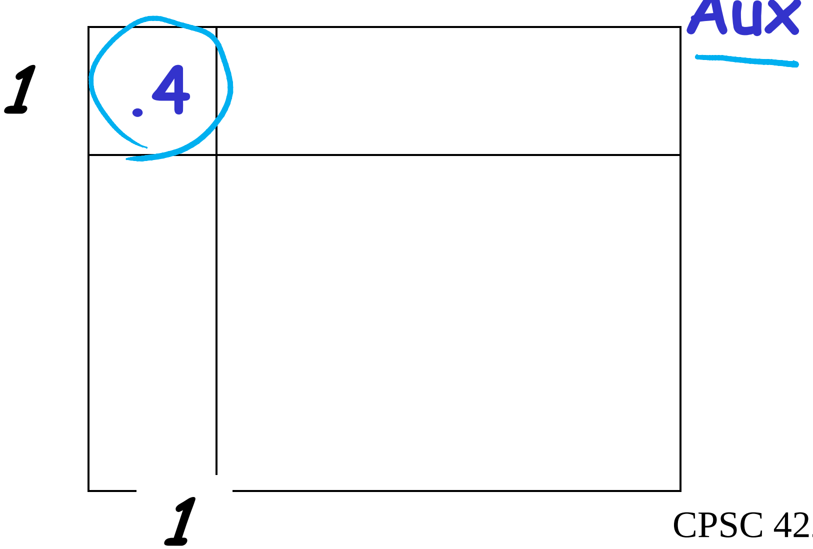
Fill out the table entries by induction: **Base case**

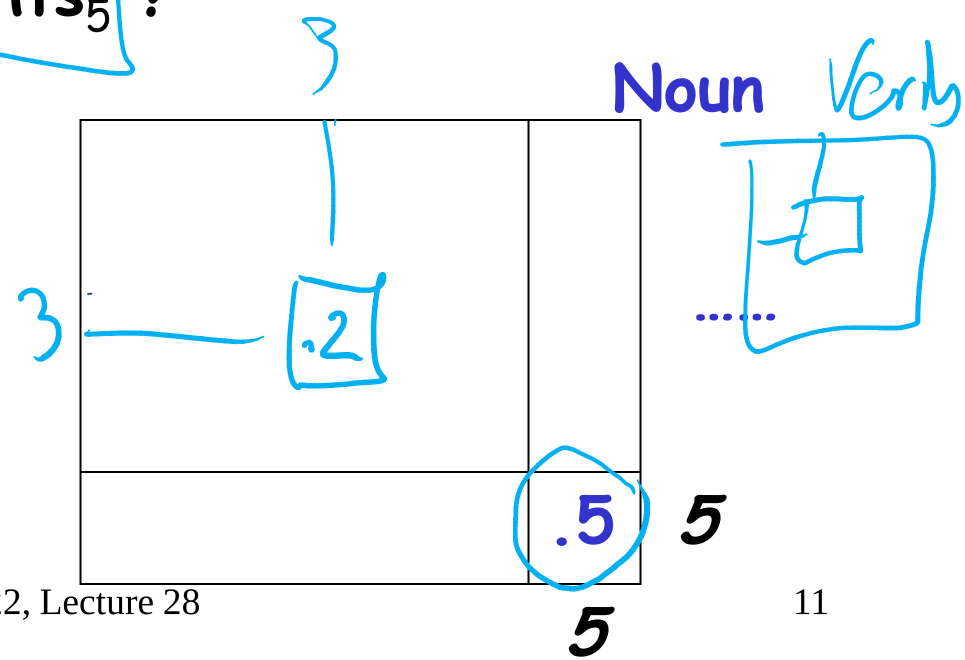
- Consider the input strings of length one (i.e., each individual word $w_i$)
- Since the grammar is in CNF: $A \stackrel{*}{\Rightarrow} w_i$ iff $A \rightarrow w_i$
- So $\mu[i, i, A] = P(A \rightarrow w_i)$

Noun → book .3

Aux → "Can" .4

**"Can$_1$ you$_2$ book$_3$ TWA$_4$ flights$_5$ ?"**



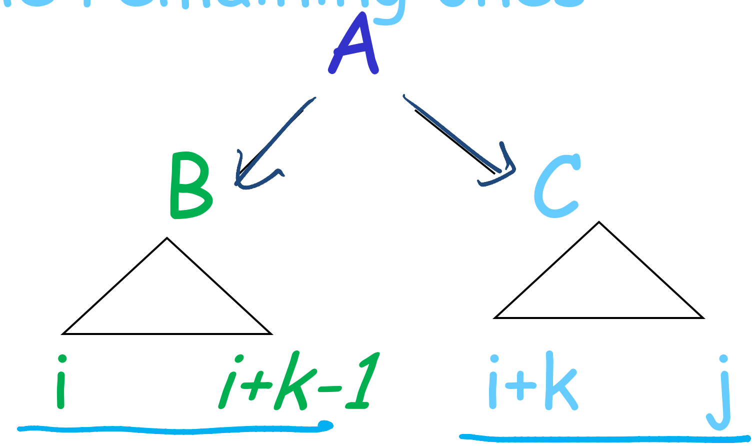



# CKY: Recursive Case

**Recursive case**

- For strings of words of length = 2, 3 . . . n

  $A \overset{*}{\Rightarrow} w_{ij}$ iff there is at least one rule $A \rightarrow BC$ where B derives the first *k* words (between i and *i+k-1* ) and C derives the remaining ones (between i+k and *j*)




- $\mu[i, j, A] = \mu[i, i+k-1, B] * \mu[i+k, j, C] * P(A \rightarrow BC)$

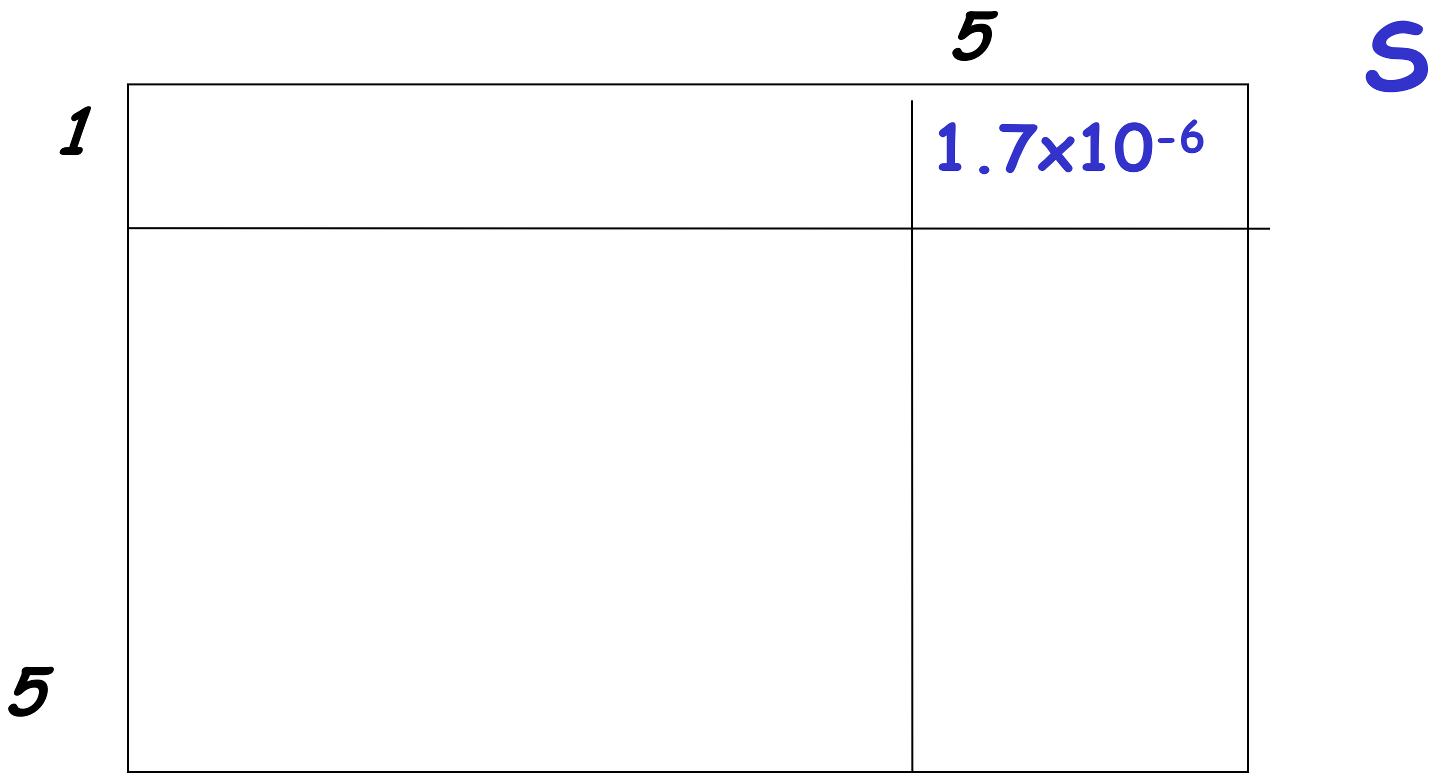
$w_{ij}$

- (for each non-terminal)Choose the max among all possibilities

# CKY: Termination

The max prob parse will be $\mu[1, n, S]$

"Can$_1$ you$_2$ book$_3$ TWA$_4$ flight$_5$ ?"



# CKY: Termination

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Any other entry in this matrix for S?

A. Yes

B. No

C. Cannot Tell

"Can$_1$ you$_2$ book$_3$ TWA$_4$ flight$_5$ ?"

5

S

1

$1.7\times10^{-6}$

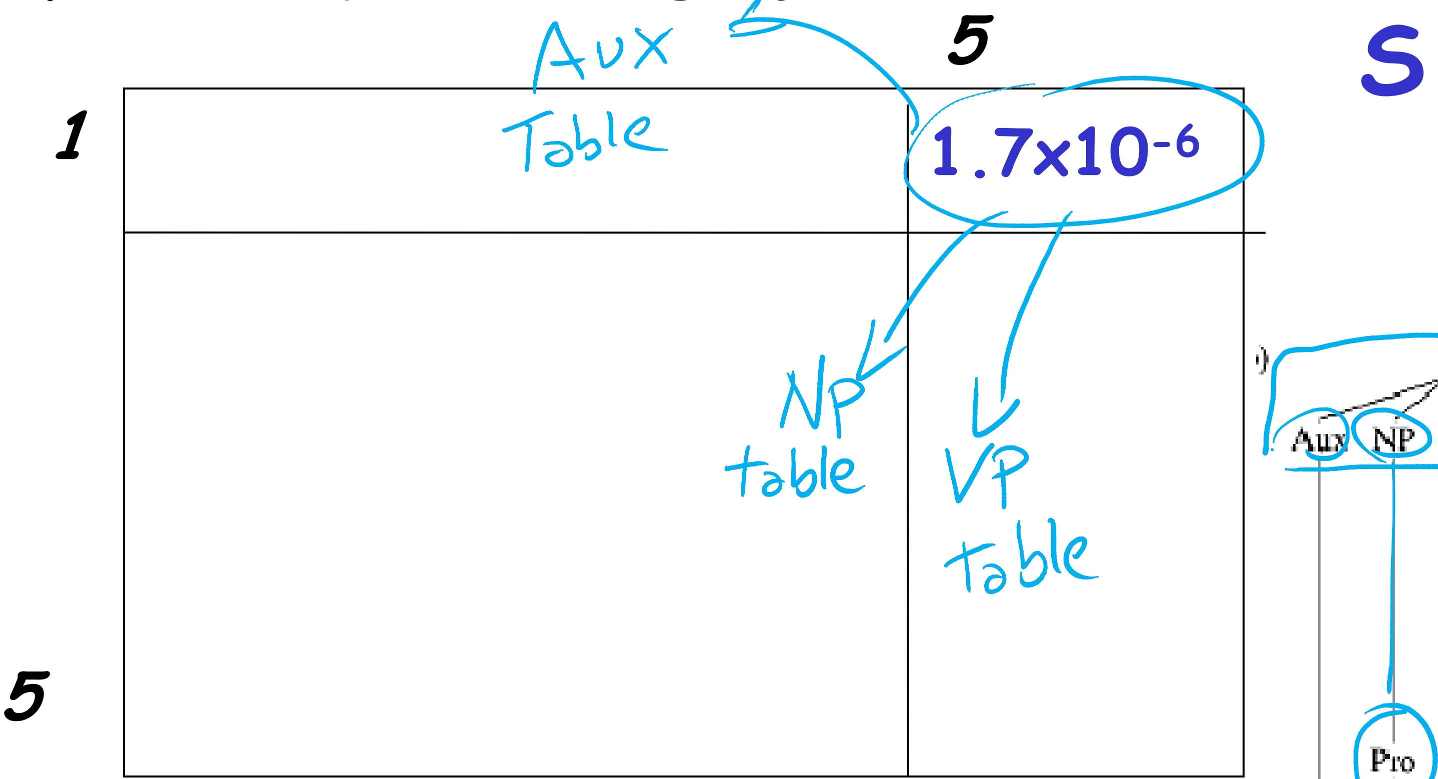
5

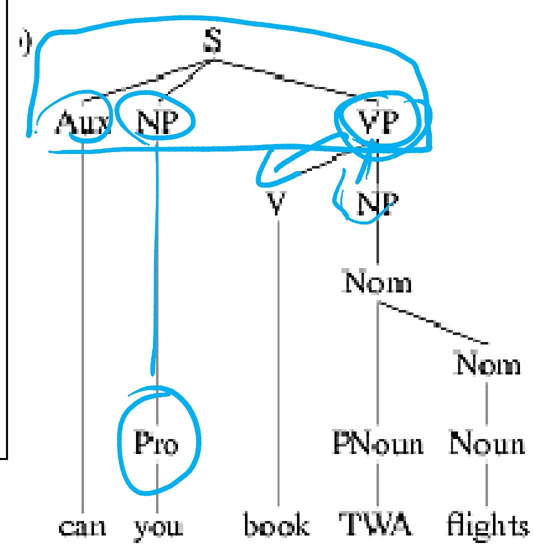
# CKY: anything missing?

The parse tree !!

The max prob parse will be $\mu[1, 4, S]$

**"Can$_1$ you$_2$ book$_3$ TWA$_4$ flight$_5$ ?"**



# Lecture Overview

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- **PCFG in practice: Modeling Structural and Lexical Dependencies**

# Problems with PCFGs

- Most current PCFG models are not vanilla PCFGs
  - Usually augmented in some way
- Vanilla PCFGs assume independence of non-terminal expansions
- But statistical analysis shows this is not a valid assumption
  - Structural and lexical dependencies

# Structural Dependencies: Problem

E.g. Syntactic **subject** of a sentence tends to be a **pronoun**

- Subject tends to realize "old information"
- *"Mary bought a new book for her trip. She didn't like the first chapter. So she decided to watch a movie."*

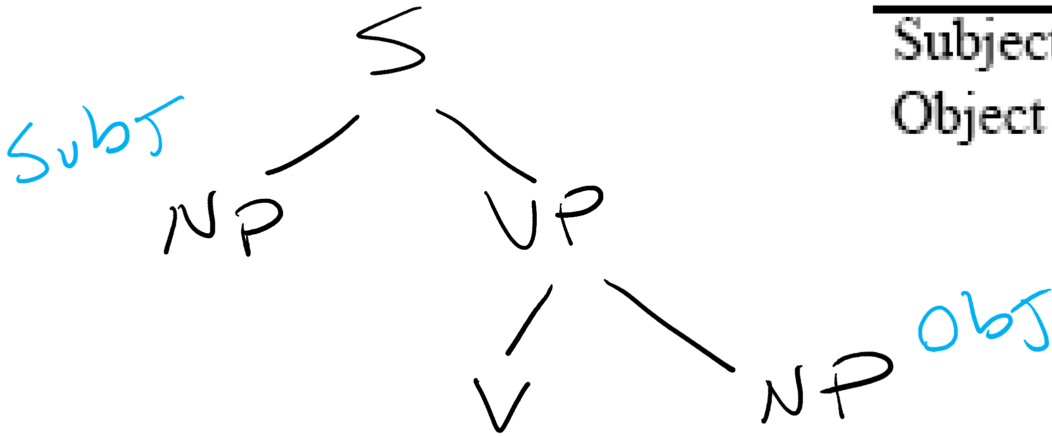
In *Switchboard corpus*:

| | Pronoun | Non-Pronoun |
|---|---|---|
| Subject | 91% | 9% |
| Object | 34% | 66% |

All data

| Pronoun | Non-Pronoun |
|---|---|
| 62.5 % | 37.5 % |

# How would you address this problem?

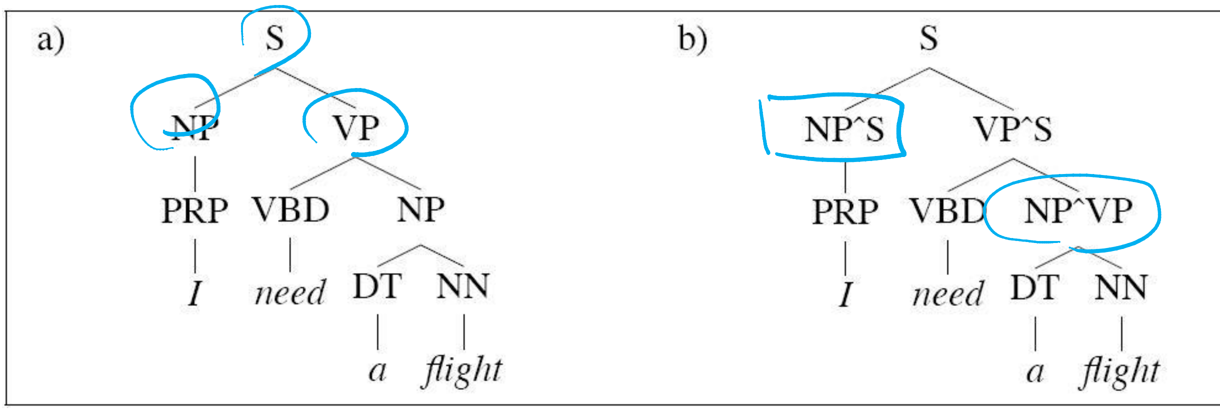



| | Pronoun | Non-Pronoun |
|---|---|---|
| Subject | 91% | 9% |
| Object | 34% | 66% |

# Structural Dependencies: Solution

Split non-terminal. E.g., NPsubject and NPobject

**Parent Annotation:**




Hand-write rules for more complex struct. dependencies

Splitting problems?

- Automatic/Optimal split – Split and Merge algorithm [Petrov et al. 2006- COLING/ACL]

# Lexical Dependencies: Problem

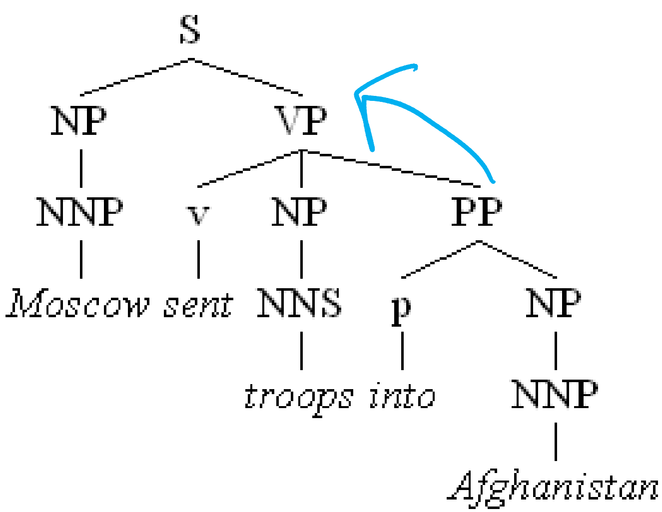
| Local tree | Verb *come* | *take* | *think* | *want* |
|---|---|---|---|---|
| VP → V | 9.5% | 2.6% | 4.6% | 5.7% |
| VP → V NP | 1.1% | 32.1% | 0.2% | 13.9% |
| VP → V PP | 34.5% | 3.1% | 7.1% | 0.3% |
| VP → V SBAR | 6.6% | 0.3% | 73.0% | 0.2% |
| VP → V S | 2.2% | 1.3% | 4.8% | 70.8% |
| VP → V NP S | 0.1% | 5.7% | 0.0% | 0.3% |
| VP → V PRT NP | 0.3% | 5.8% | 0.0% | 0.0% |
| VP → V PRT PP | 6.1% | 1.5% | 0.2% | 0.0% |

**Table 12.2** Frequency of common subcategorization frames (local trees expanding VP) for selected verbs. The data show that the rule used to expand VP is highly dependent on the lexical identity of the verb. The counts ignore distinctions in verbal form tags. Phrase names are as in table 12.1, and tags are Penn Treebank tags (tables 4.5 and 4.6).

# Lexical Dependencies: Problem

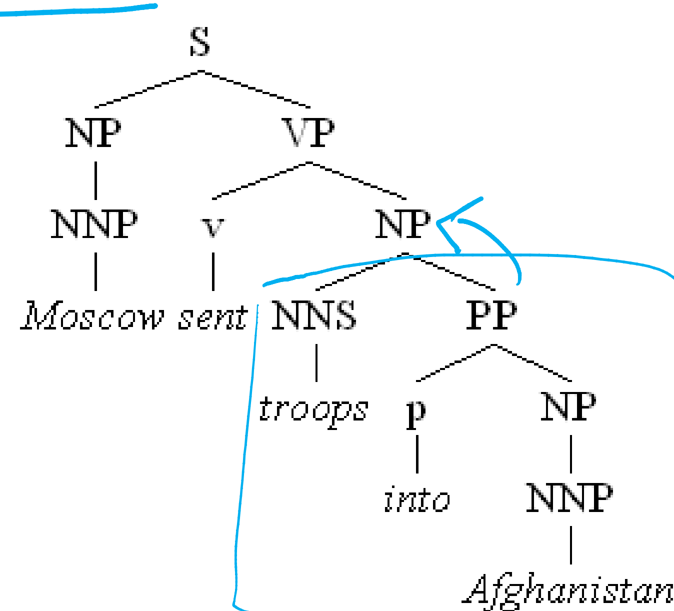
Two parse trees for the sentence
*"Moscow sent troops into Afghanistan"*

(a)




*VP-attachment*

(b)




*NP-attachment*

Typically NP-attachment more frequent than VP-attachment

# Lexical Dependencies: Solution

- **Add lexical dependencies to the scheme…**
  - **Infiltrate the influence of particular words into the probabilities of the rules**

**All the words?**

(a) - P(VP -> V NP PP | VP = "sent troops into Afg.")

(b) - P(VP -> V NP | VP = "sent troops into Afg.")

A. Good Idea

B. Bad Idea

C. Cannot Tell

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# Lexical Dependencies: Solution

- **Add lexical dependencies to the scheme…**
  - **Infiltrate the influence of particular words into the probabilities of the rules**
  - **All the words?**

(a) - P(VP -> V NP PP | VP = "sent troops into Afg.")

(b) - P(VP -> V NP | VP = "sent troops into Afg.")

Not likely to have significant counts in any treebank!

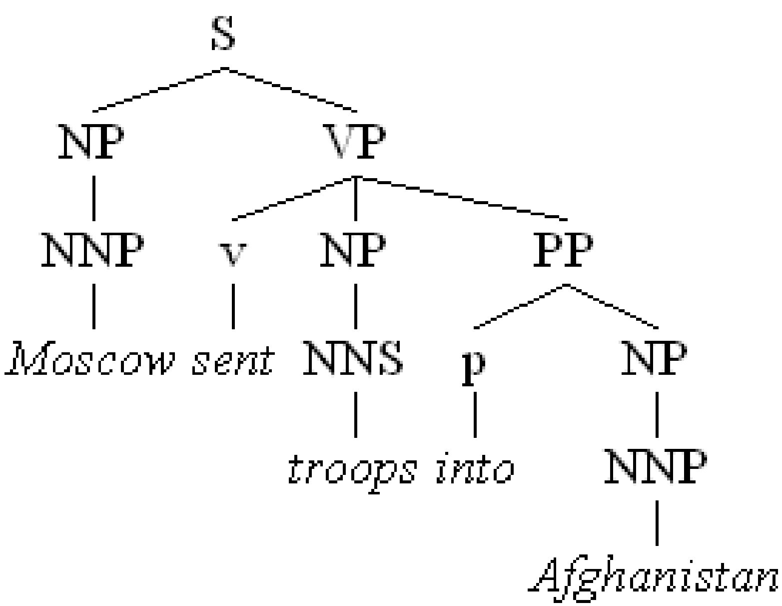
A. Good Idea

B. Bad Idea

C. Cannot Tell

# Use only the Heads

- To do that we're going to make use of the notion of the head of a phrase
  - The head of an NP is its noun
  - The head of a VP is its verb
  - The head of a PP is its preposition



# More specific rules

- We used to have rule r
  - VP -> V NP PP    P(r|VP)
    - That's the count of this rule divided by the number of VPs in a treebank
- Now we have rule r
  - VP(h(VP))-> V(h(VP)) NP PP    P(r | VP, h(VP))
  
  e.g. - VP(sent)-> V(sent) NP PP    P(r | VP, *sent*)

What is the estimate for P(r | VP, *sent*) ?

How many times was this rule used with *sent*, divided by the number of VPs that *sent* appears in total

For each verb reflect probabilities like the ones in slide 21

# NLP Practical Goal for FOL (and Prob. Parsing) the ultimate Web question-answering system?

**Map NL queries into FOPC so that answers can be effectively computed**

- *What African countries are not on the Mediterranean Sea?*

$$\exists c\ Country(c) \wedge \neg Borders(c, Med.Sea) \wedge In(c, Africa)$$

- *Was 2007 the first El Nino year after 2001?*

$$ElNino(2007) \wedge \neg \exists y\ Year(y) \wedge After(y, 2001) \wedge Before(y, 2007) \wedge ElNino(y)$$

NL query → parsing → synt. tree → λ calculus → "FOPC" query → applied KB

into KB ← IExtraction ← Web

NER

Relation identification & Extraction

# Beyond syntax……. Discourse parsing…..

- **CKY Probabilistic parsing Paper on Fri.**

# Beyond NLP……. Planning…..

- Li, N., Cushing, W., Kambhampati, S., & Yoon, S. (2012). Learning probabilistic hierarchical task networks as probabilistic context-free grammars to capture user preferences. ACM Transactions on Intelligent Systems and Technology. (CMU+Arizona State)

# Discovering Discourse Structure: Computational Tasks

*The bank was hamstrung in its efforts to face the challenges of a changing market by its links to the government, analysts say.*

**Discourse Segmentation**

*The bank was hamstrung in its efforts*

1

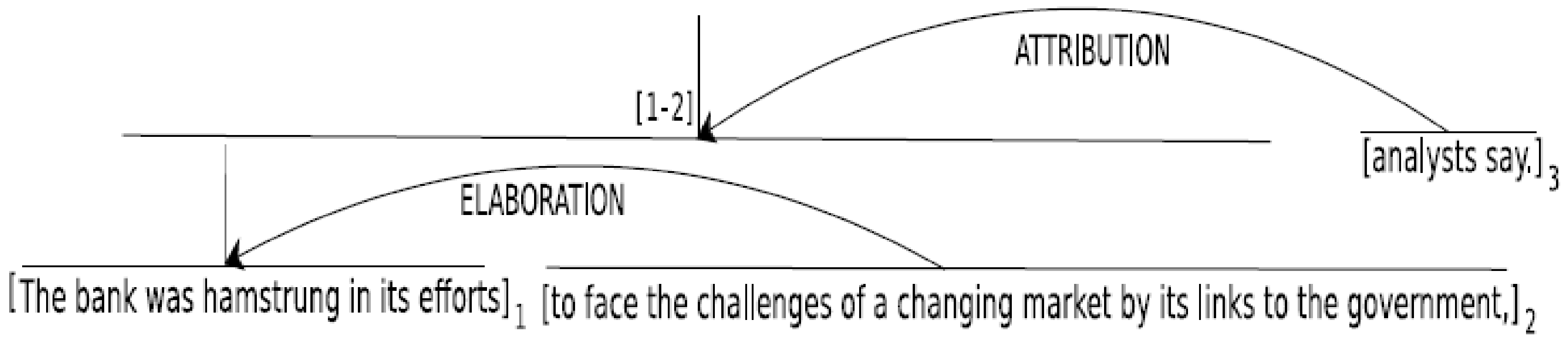
*to face the challenges of a changing market by its links to the government,*

2

*analysts say.*

3

**Discourse Parsing**



# 422 big picture: Where are we?

StarAI (statistical relational AI)

Hybrid: Det +Sto

*Prob CFG*

*Prob Relational Models*

*Markov Logics*

Deterministic | Stochastic

Query

*Logics*

*First Order Logics*

*Ontologies*

- Full Resolution
- SAT

*Belief Nets*

Approx. : Gibbs

*Markov Chains and HMMs*

Forward, Viterbi….

Approx. : Particle Filtering

*Undirected Graphical Models*

*Markov Networks*

*Conditional Random Fields*

Planning

*Markov Decision Processes and*

*Partially Observable MDP*

- Value Iteration
- Approx. Inference

*Reinforcement Learning*

*Applications of AI*

*Representation*

Reasoning Technique

# Learning Goals for today's class

**You can:**

- Describe the key steps of CKY probabilistic parsing
- Motivate introduction of structural and lexical dependencies
- Describe how to deal with these dependencies within the PCFG framework

# Next class on Mon: paper discussion

- Portions of Journal of Computational Linguistics paper (Just accepted!) only sections 1, 3 and 4 are mandatory
- CODRA: A Novel Discriminative Framework for Rhetorical Analysis

## Assignment-3 due on Fri
## Assignment-4 will be out on the same day