Intelligent Systems (AI-2)

Computer Science cpsc422, Lecture 27

March, 24, 2021

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....

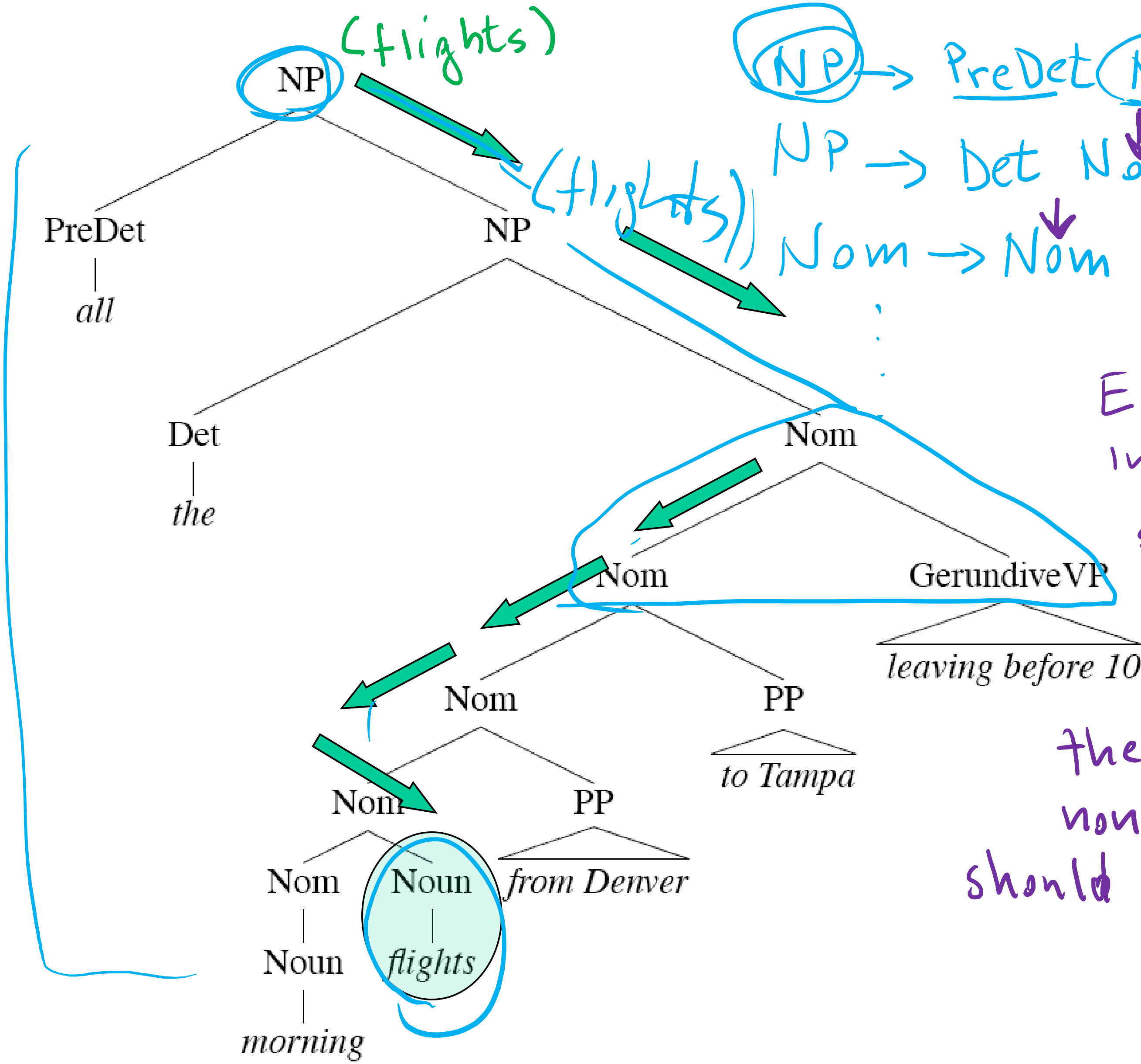
- **Estimate Prob. of parse tree**

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

- **Estimate Prob. to sentences**

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

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:**

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

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Probabilistic Parsing:

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

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

Probabilistic CKY Algorithm

Ney, 1991
Collins, 1999

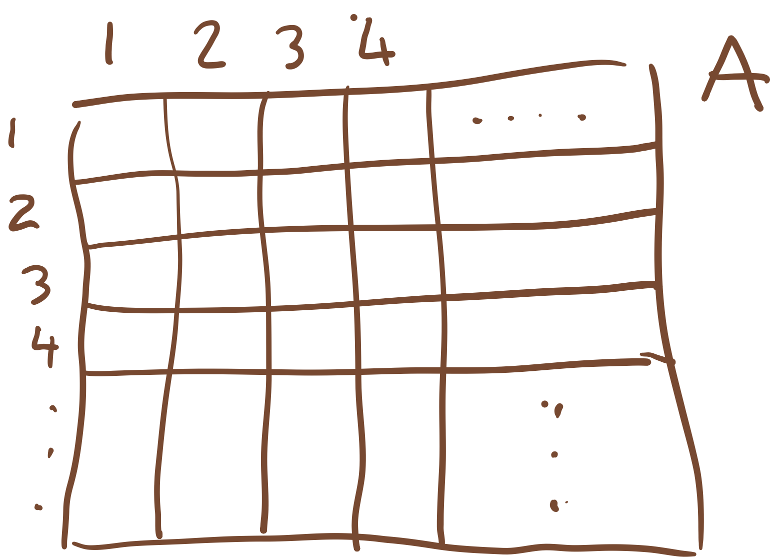
CYK (Cocke-Kasami-Younger) algorithm

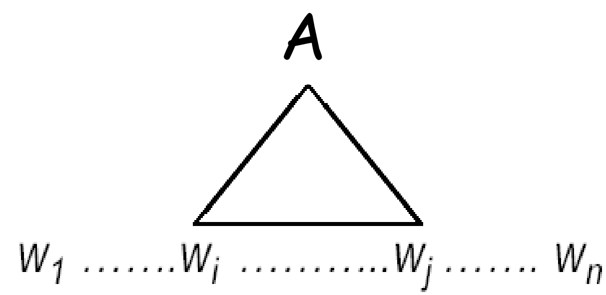
- A **bottom-up** parser using dynamic programming
- Assume the PCFG is in Chomsky normal form (CNF)
  - Non-terminal can be rewritten either as two Non-terminals or as a Terminal

Probabilistic CKY Algorithm

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 $w_i \ldots w_j$





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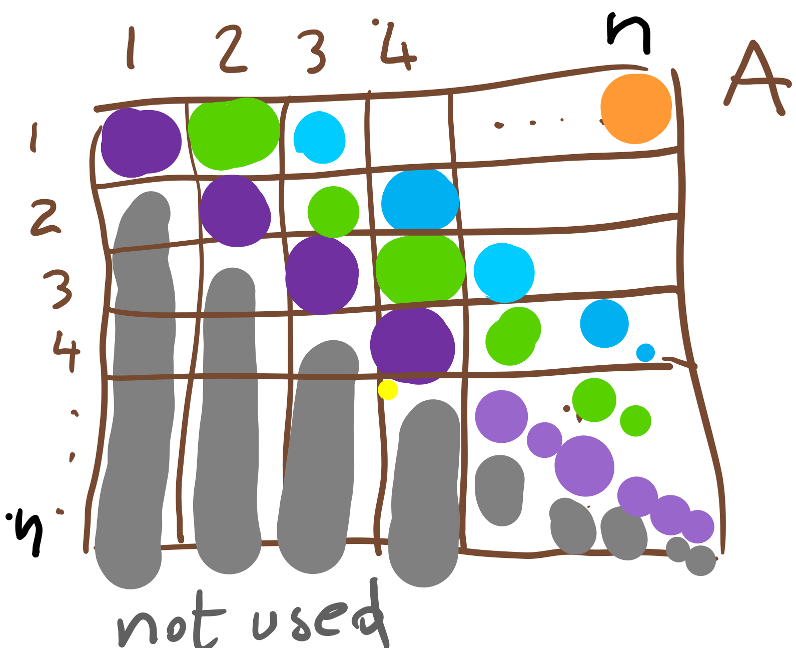
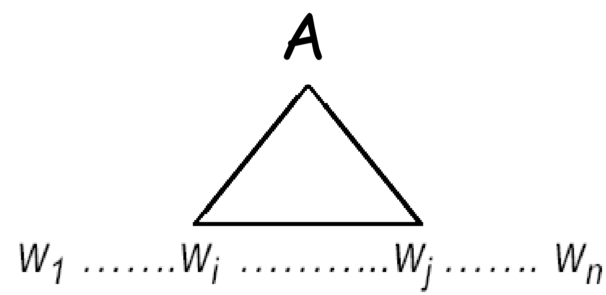




spanning one word
spanning two words
spanning three words
spanning n words

CKY: Base Case

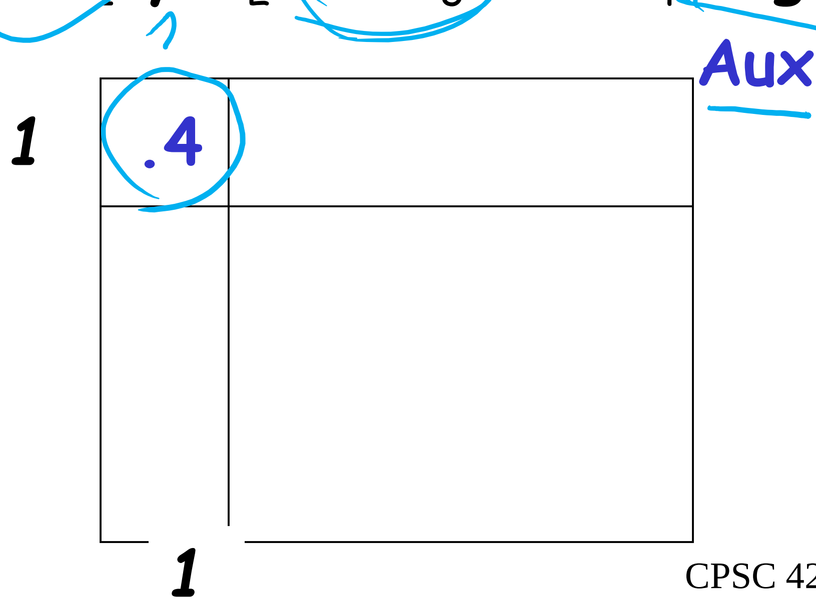
Fill out the table entries by induction: **Base case**

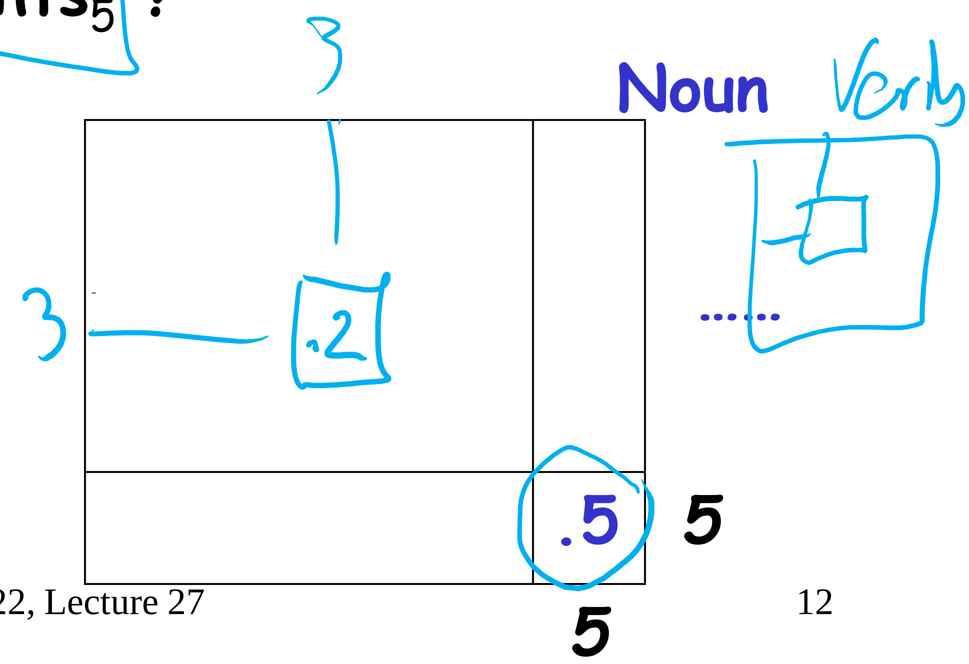
- Consider the input strings of length one (i.e., each individual word w_i)
- Since the grammar is in CNF: $A \overset{*}{\Rightarrow} w_i$ iff $A \rightarrow w_i$
- So $\mu[i, i, A] = P(A \rightarrow w_i)$

Noun → book .2

Aux → "Can" .4

"Can_1 you_2 book_3 TWA_4 flights_5 ?"





Sample PCFG

S → *NP VP*	[.80]	$Det \rightarrow that\ [.05] \mid the\ [.80] \mid a\ [.15]$	
S → *Aux NP VP*	[.15]	*Noun* → *book*	[.10]
S → *VP*	[.05]	*Noun* → *flights*	[.50]
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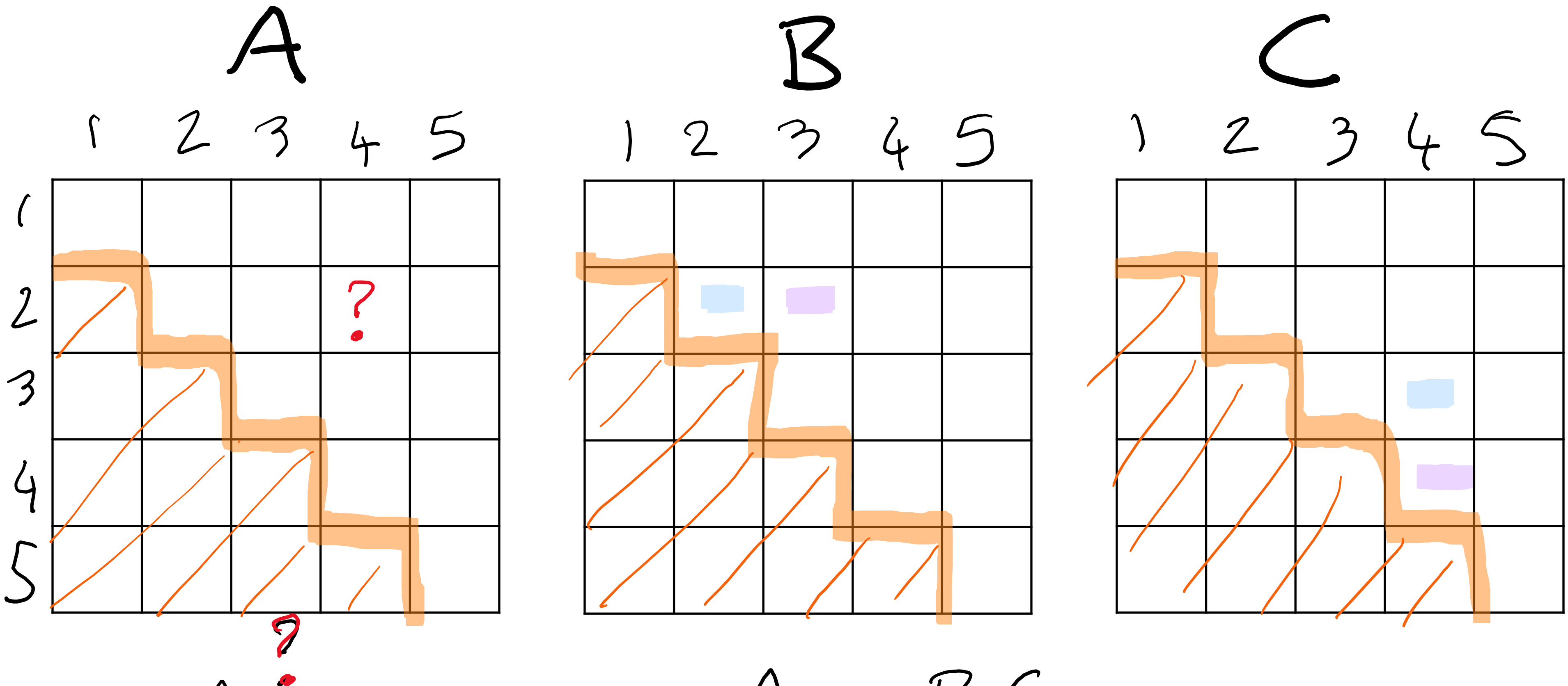
VP → *Verb*	[.55]	*Proper-Noun* → *TWA*	[.40]
VP → *Verb NP*	[.40]	*Proper-Noun* → *Denver*	[.40]
VP → *Verb NP NP*	[.05]	$Pronoun \rightarrow you\ [.40] \mid I\ [.60]$	



$A \Rightarrow w_{24}$

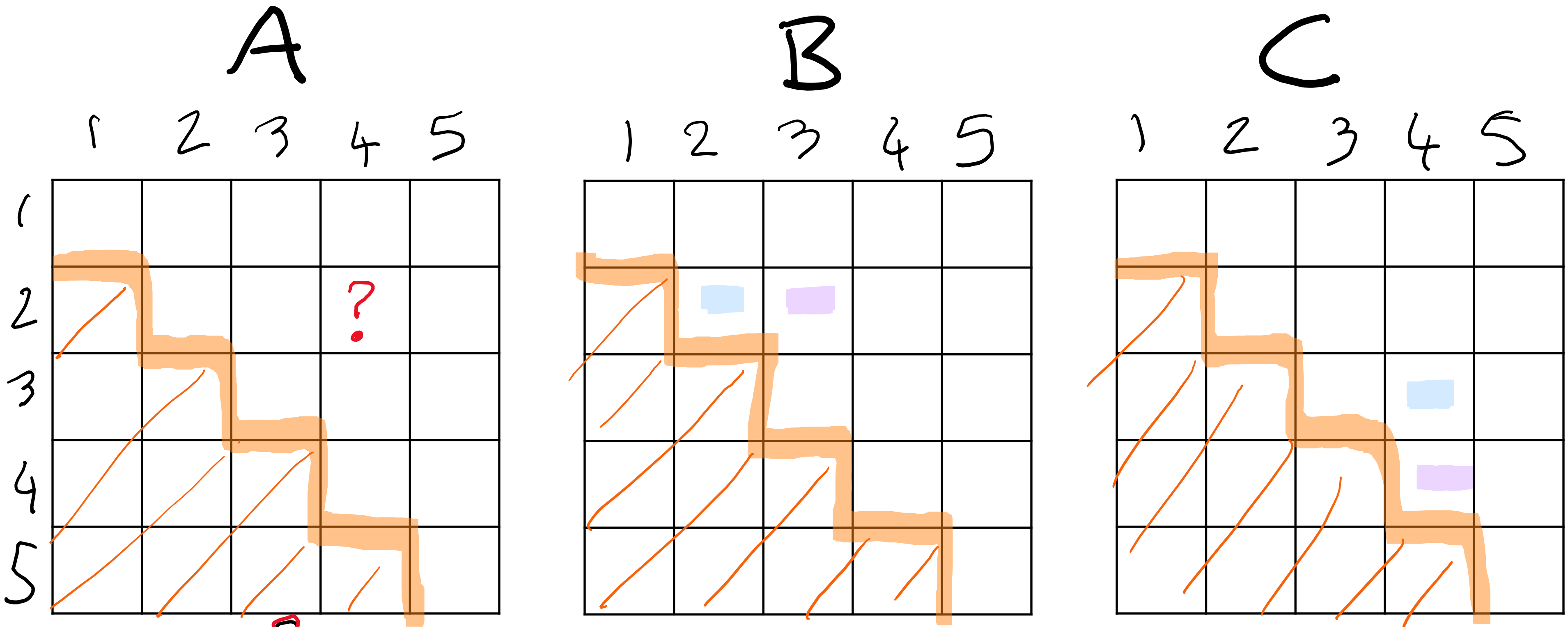
$w_1 \, w_2 \, w_3 \, w_4 \, w_5$

$A \to BC$

either $B \Rightarrow w_2$ $\quad C \Rightarrow w_3 w_4$

or $B \Rightarrow w_2 w_3$ $\quad C \Rightarrow w_4$

e.g. prob. of first one $= P(A \to BC) * M(2,2,B) * M(3,4,C)$



?

$A \Rightarrow w_{24}$

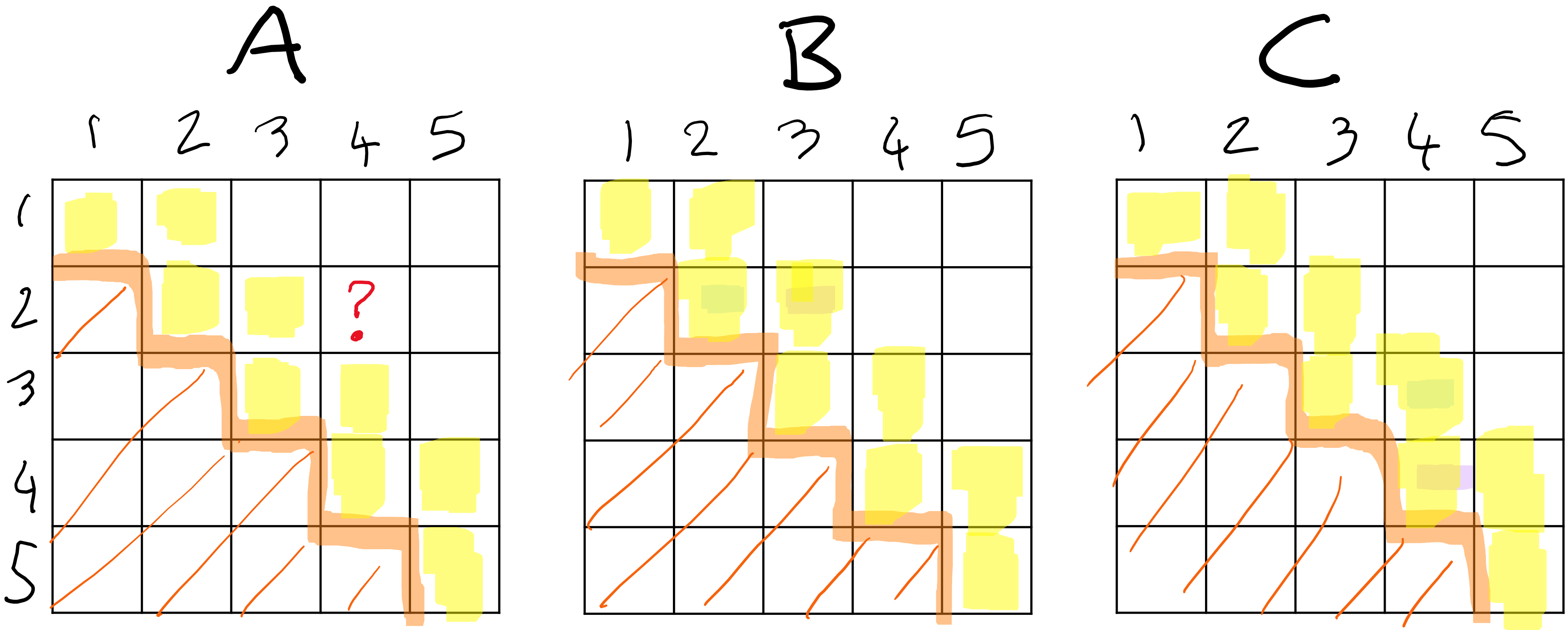
$w_1 \; w_2 \; w_3 \; w_4 \; w_5$

$A \rightarrow BC$

either $B \Rightarrow w_2 \quad C \Rightarrow w_3 w_4$

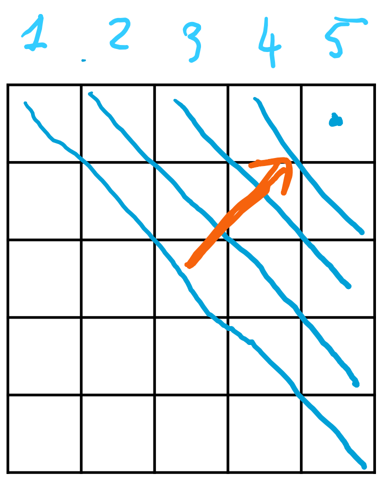
or $B \Rightarrow w_2 w_3 \quad C \Rightarrow w_4$

e.g. prob. of second one $= \underline{P(A \rightarrow BC)} * \mu(2,3,B) * \mu(4,4,C)$



Key idea: to compute the value of a cell **?** I can find the needed values in lower diagonals

So CKY just fills the diagonals one at the time, with each diagonal representing subsequences of increasing length

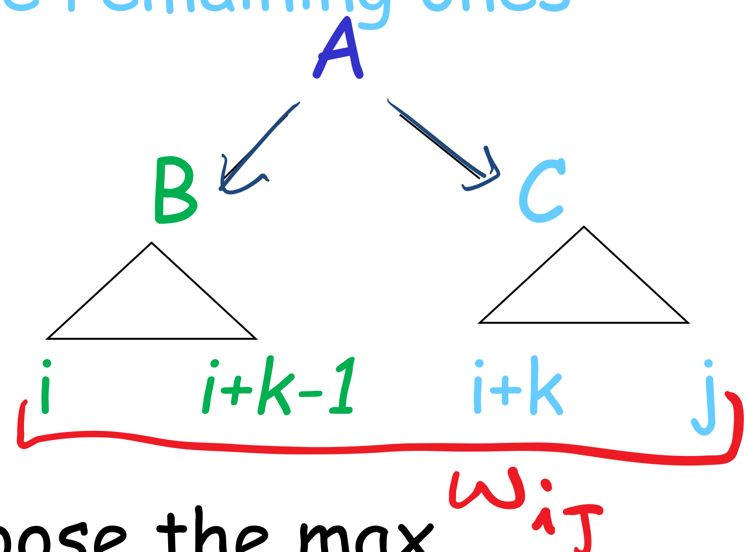


CKY: Recursive Case

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*)



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

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

$A \Rightarrow BC \quad A \Rightarrow BB$

w_{ij} $\quad A \Rightarrow AB \quad A \Rightarrow CB$ …

CKY: Termination

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

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

		5	
1		1.7×10^{-6}	S
5			

CKY: Termination

iclicker

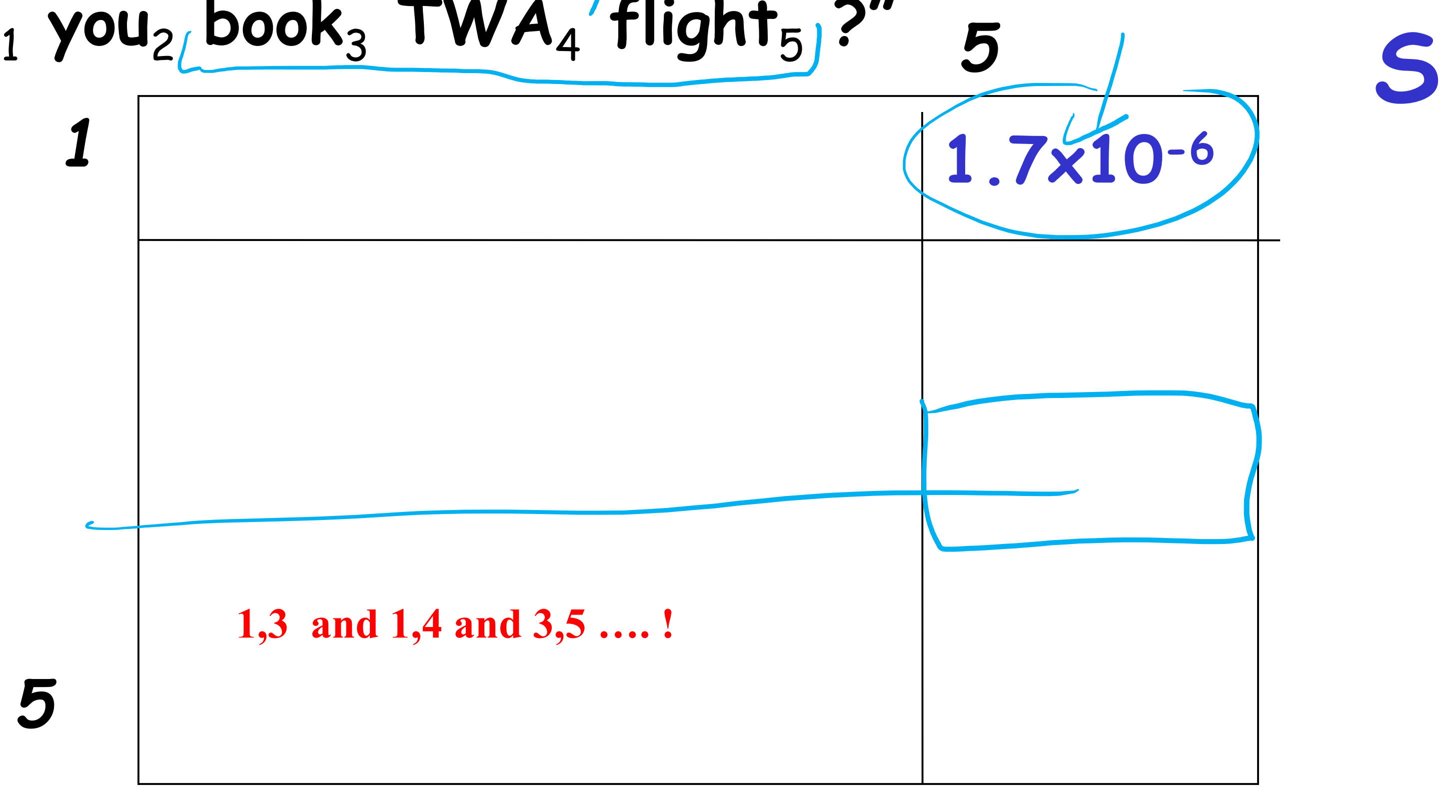
Any other entry in this matrix for S?

A. Yes

B. No

C. Cannot Tell

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

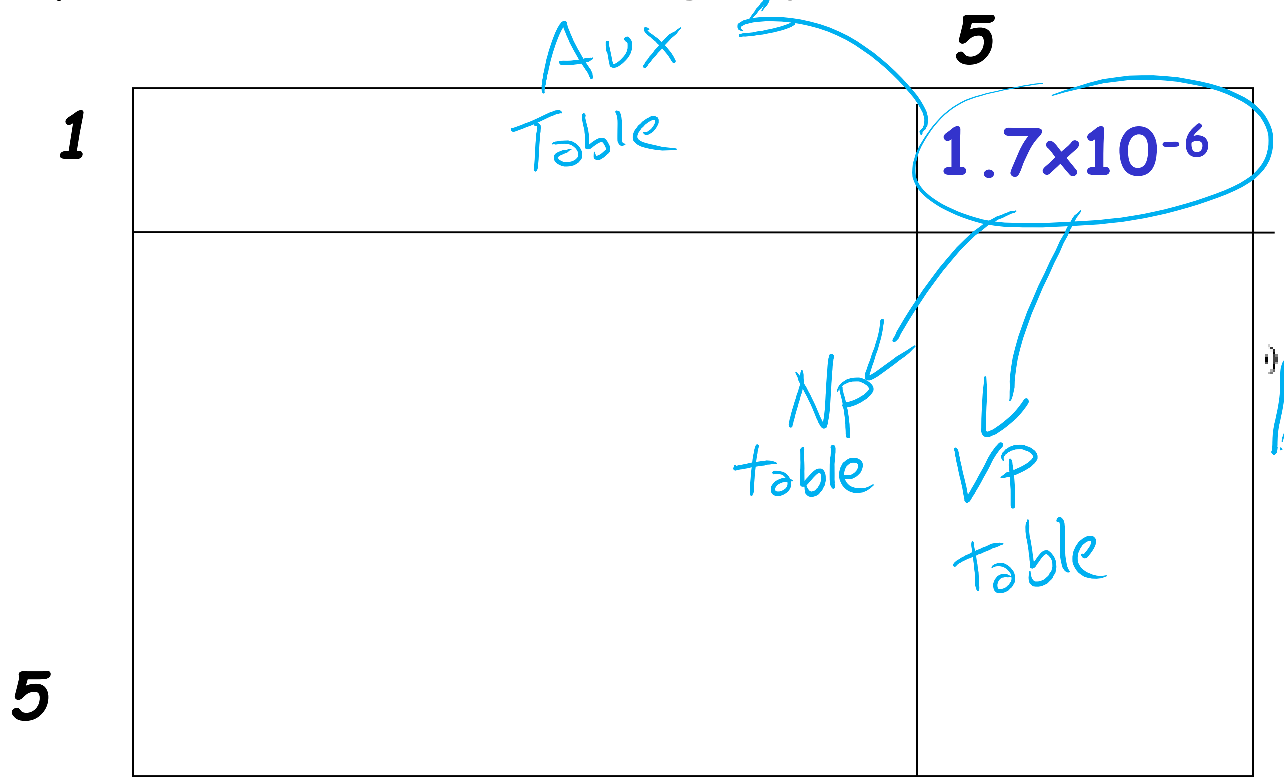


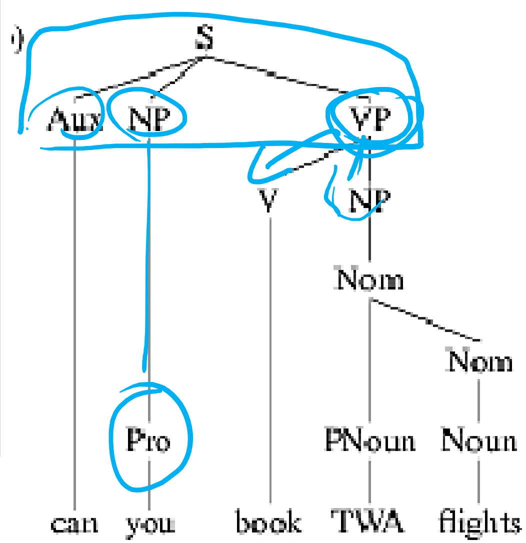
CKY: anything missing?

The parse tree!!

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

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





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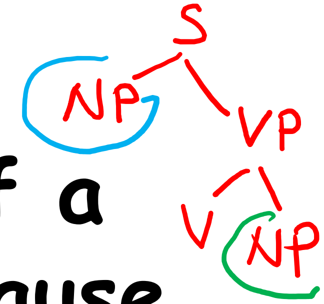
- **PCFG in practice: Modeling Structural and Lexical Dependencies**

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 (vs. object) of a sentence tends to be a <u>pronoun</u> because

- Subject tends to realize the topic of a sentence
- Topic is usually old information (expressed in previous sentences)
- Pronouns are usually used to refer to old information

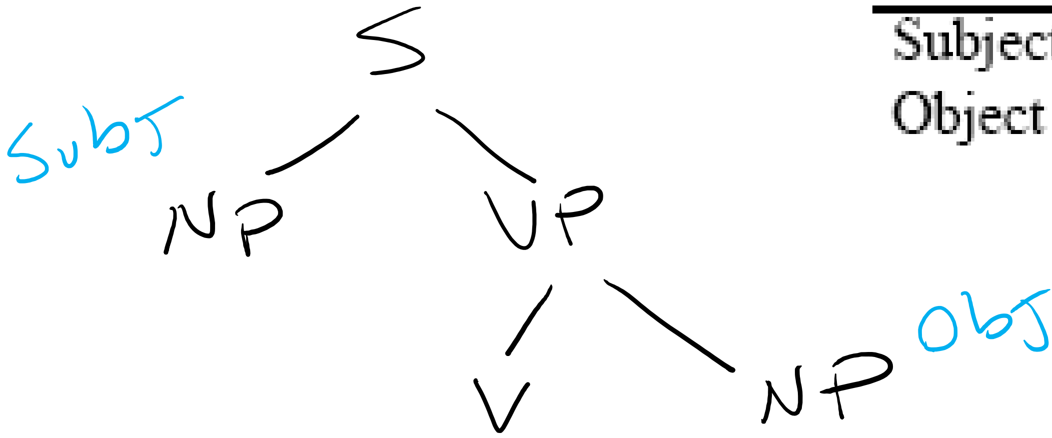
Mary bought a new book for her trip. She didn't like the first chapter. So she decided to watch a movie.

In *Switchboard corpus*:

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

All data
Pronoun 62.5%
Non-Pronoun 37.5%

How would you address this problem?



	Pronoun	Non-Pronoun
Subject	91%	9%
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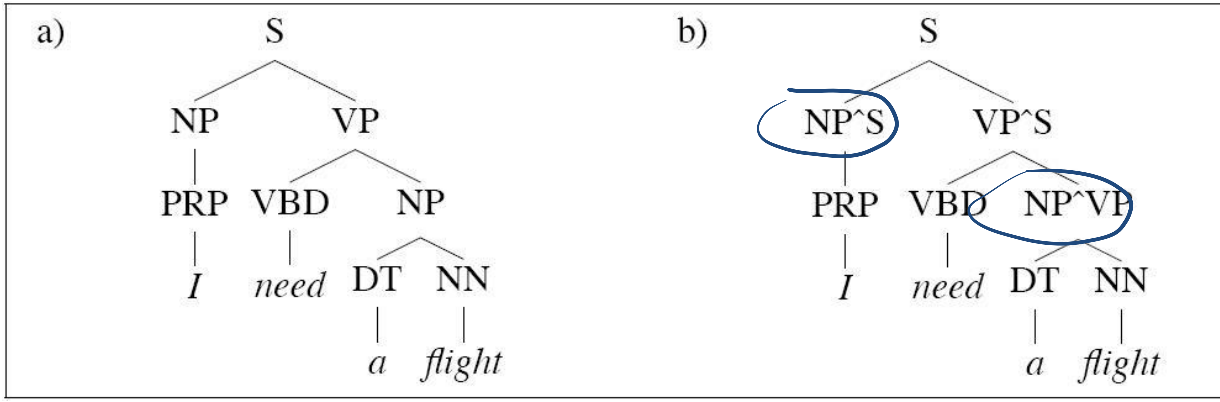
Structural Dependencies: Solution

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

	Verb			
Local tree	*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%

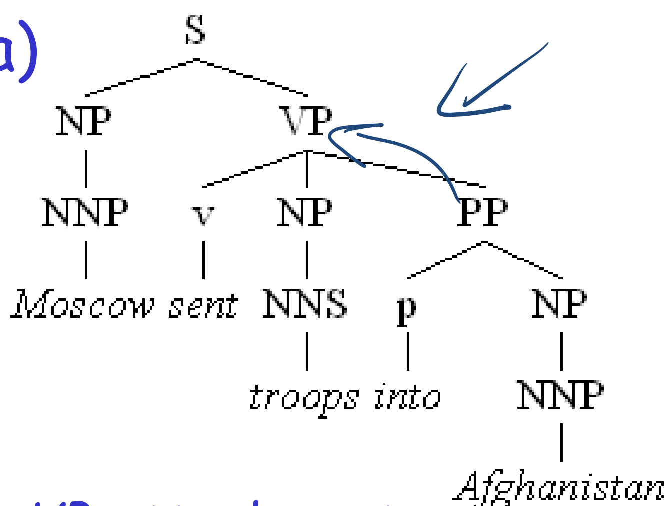
Table 12.2 Frequency of common subcategorization frames (local trees expanding VP) for selected verbs. The data show that the rule used to expand VP is highly dependent on the lexical identity of the verb. The counts ignore distinctions in verbal form tags. Phrase names are as in table 12.1, and tags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

SBAR = subordinate clause

Lexical Dependencies: Problem

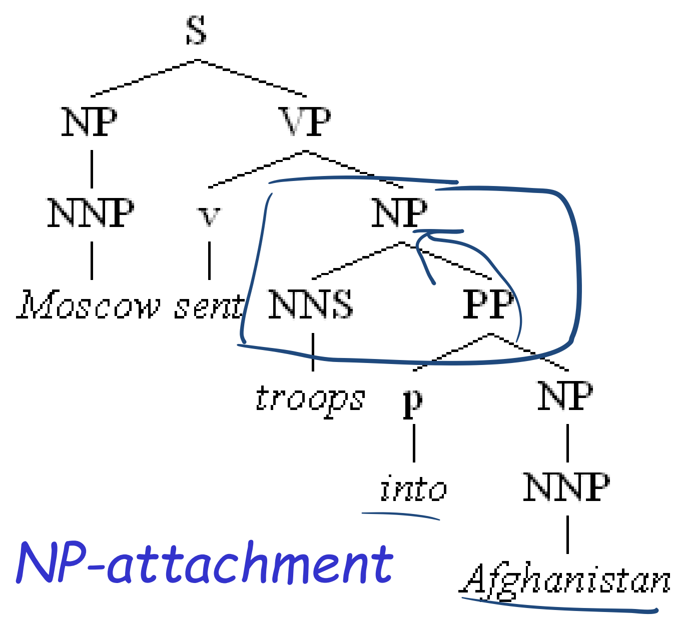
Two parse trees for the sentence
"Moscow sent troops into Afghanistan"

(a)



VP-attachment

(b)



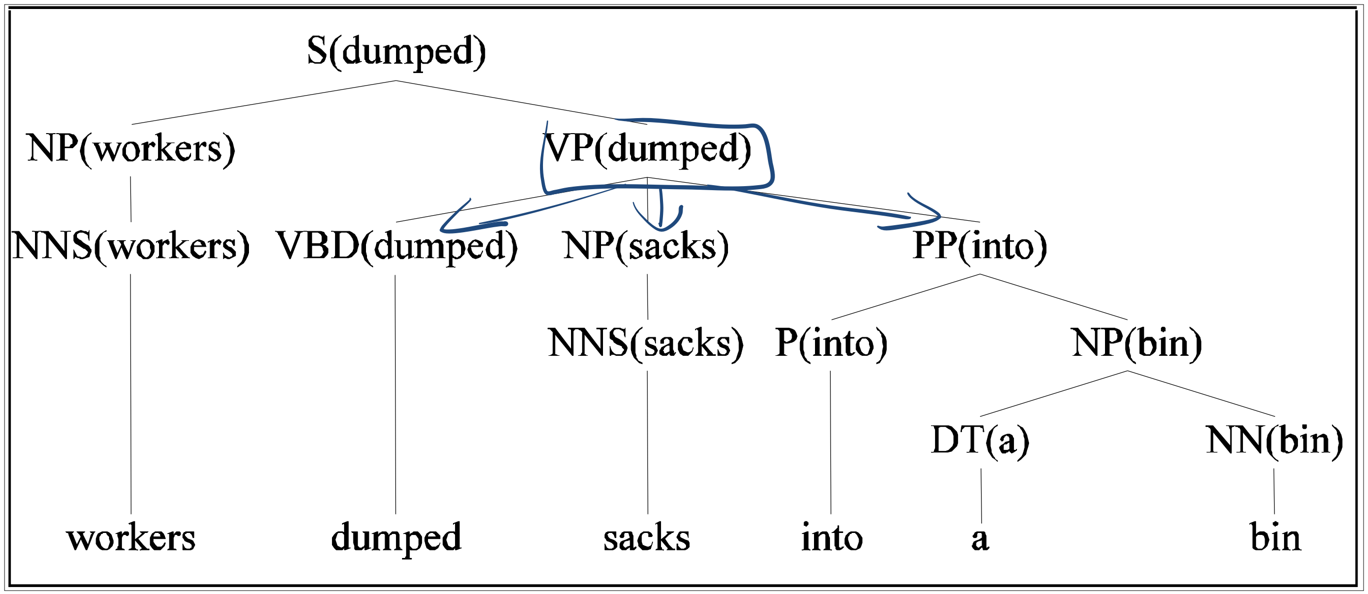
NP-attachment

Typically NP-attachment more frequent than VP-attachment

VP → V NP
VP → V NP PP

VP(send) → V NP
VP(send) → V NP PP ← higher prob!

Attribute grammar for Lexicalized PCFG : each non-terminal is annotated with its lexical head… many more rules!



(Collins 1999)

- We used to have rules like
  VP -> V NP PP

- Now we have much more specific rules like
  VP(dumped)-> V(dumped) NP(sacks) PP(into)

PCFG Parsing State of the art(~2010)

Parser	F1 ≤ 40 words (sentence length)	F1 all words (no limit on sentence length)
Klein & Manning unlexicalized 2003 (hand crafted "states")	86.3	85.7
Matsuzaki et al. simple EM latent states 2005	86.7	86.1
Charniak generative, lexicalized ("maxent inspired") 2000	90.1	89.5
Petrov and Klein NAACL 2007	90.6	90.1
Charniak & Johnson discriminative reranker 2005	92.0	91.4
Fossum & Knight 2009 combining constituent parsers "O + ☆"		92.4

From C. Manning (Stanford NLP)

Parser	Training Set	WSJ 22	WSJ 23
baseline LSTM+D	WSJ only	< 70	< 70
LSTM+A+D	WSJ only	88.7	88.3
LSTM+A+D ensemble	WSJ only	90.7	90.5
baseline LSTM	BerkeleyParser corpus	91.0	90.5
LSTM+A	high-confidence corpus	93.3	92.5
LSTM+A ensemble	high-confidence corpus	**93.5**	**92.8**
Petrov et al. (2006) [12]	WSJ only	91.1	90.4
Zhu et al. (2013) [13]	WSJ only	N/A	90.4
Petrov et al. (2010) ensemble [14]	WSJ only	92.5	91.8
Zhu et al. (2013) [13]	semi-supervised	N/A	91.3
Huang & Harper (2009) [15]	semi-supervised	N/A	91.3
McClosky et al. (2006) [16]	semi-supervised	92.4	92.1
Huang & Harper (2010) ensemble [17]	semi-supervised	92.8	92.4

Neural

Table 1: F1 scores of various parsers on the development and test set. See text for discussion.

Grammar as a Foreign Language

Computation and Language [cs.CL] Published 24 Dec 2014
Updated 9 Jun 2015

O. Vinyals, L. Kaiser, T. Koo, S. Petrov, I. Sutskever, G. Hinton *Google*

Fast and Accurate Shift-Reduce Constituent Parsing by Muhua Zhu, Yue Zhang, Wenliang Chen, Min Zhang and Jingbo Zhu (ACL - 2013)

Very recent paper (NAACL 2018)

(not required for 422)

What's Going On in Neural Constituency Parsers? An Analysis,

D.Gaddy, M. Stern, D. Klein, Computer Science ., Univ. of California, Berkeley

- Abstractly, our model consists of a single scoring function ***s(i, j, l)*** that assigns a real-valued score to every label ***l*** for each ***span(i, j)*** in an input sentence.
- We take the set of available labels to be the collection of **all non-terminals** … in the training data,
- To build up to spans, we first run a **bidirectional LSTM** over the sequence of word representations for an input sentence
- we implement the label scoring function by feeding the span representation through a one **layer feedforward network** whose output dimensionality equals the number of possible labels
- …. we can still employ a **CKY-style algorithm** for efficient globally optimal inference …..
- "We find that our model implicitly learns to encode much of the same information that was explicitly provided by grammars and lexicons in the past, indicating that this scaffolding can largely be subsumed by powerful general-purpose neural machinery
- Also this one does **(92.08 F1 on PTB)**

CKY/PCFG Beyond syntax……. Discourse Parsing….. And Dialog

- **CKY Probabilistic parsing Paper in Reading**

- **Conversation Trees: A Grammar Model for Topic Structure in Forums, Annie Louis and Shay B. Cohen, EMNLP 2015. [corpus]**

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

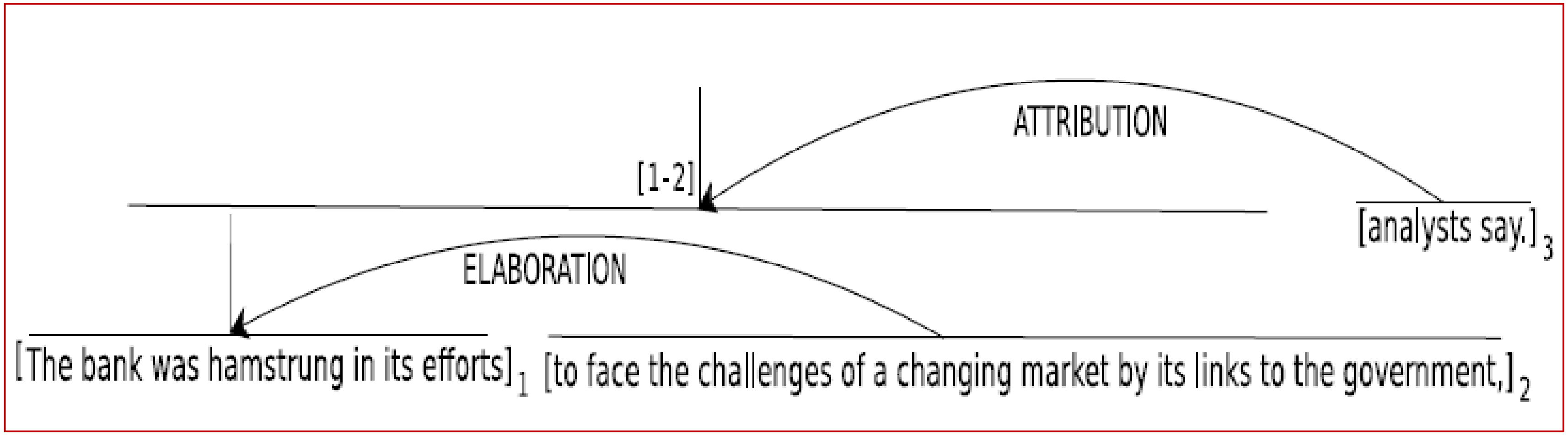
to face the challenges of a changing market by its links to the government,

2

analysts say.

3

Discourse Parsing



422 big picture

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 Fri

- **We will start Markov Logics**

1.5	$\forall x\ Smokes(x) \Rightarrow Cancer(x)$
1.1	$\forall x, y\ Friends(x, y) \Rightarrow \left(Smokes(x) \Leftrightarrow Smokes(y)\right)$

Assignment-3 due on Mon 29th
Assignment-4 will be out on the same day

NOT REQUIRED !

Very recent paper (NAACL 2018)

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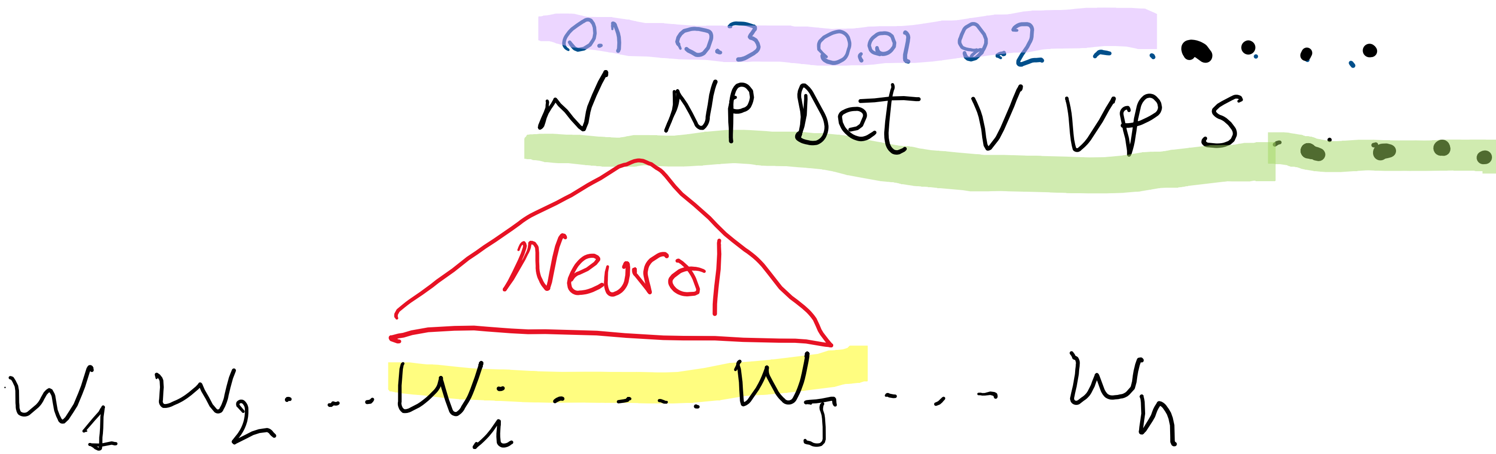

You know the terminology and the methods !
You should be able to understand most of this !

Very recent paper (NAACL 2018)

- To build up to spans, we first run a bidirectional LSTM over the sequence of word representations for an input sentence

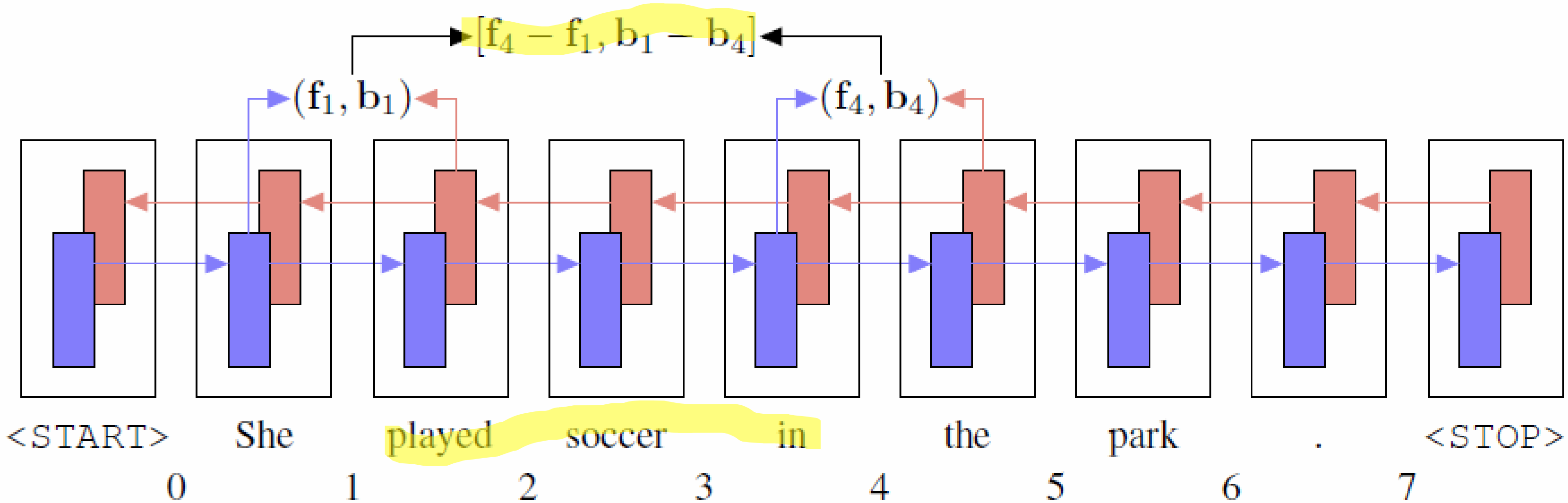

Figure 1: Span representations are computed by running a bidirectional LSTM over the input sentence and taking differences of the output vectors at the two endpoints. Here we illustrate the process for the span $(1, 4)$ corresponding to "played soccer in" in the example sentence.

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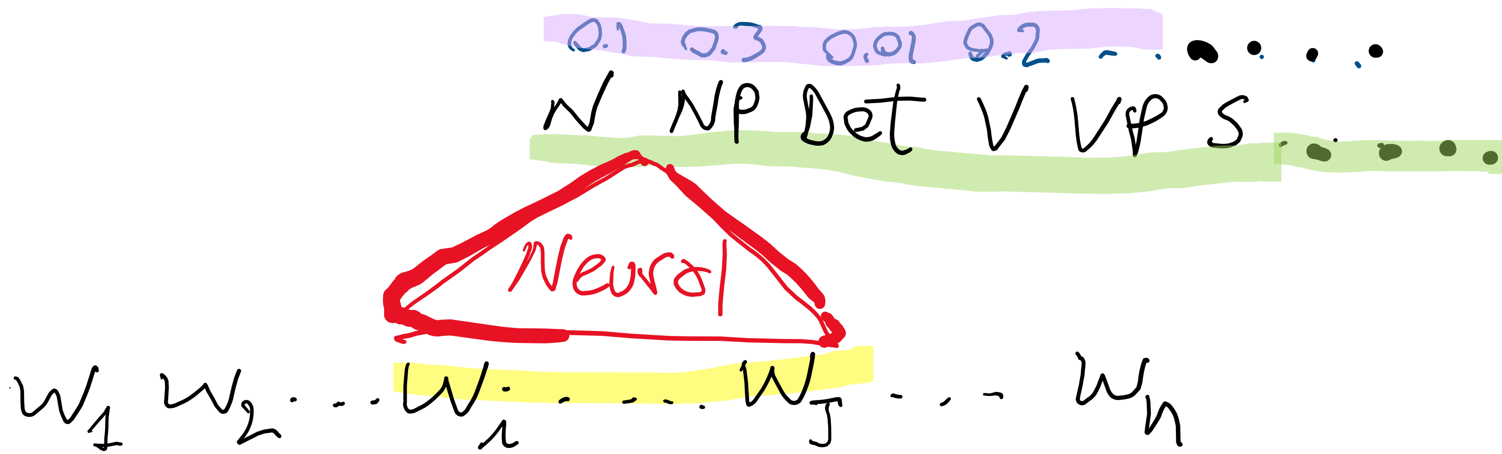
Very recent paper (NAACL 2018)



- we implement the label scoring function by feeding the span representation through a one **layer feedforward network** whose output dimensionality equals the number of possible labels
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