

Parsing

Kevin Duh

Intro to NLP, Fall 2019

Refresher

- Recall the Random Sentence Generator the CFG lectures and homework

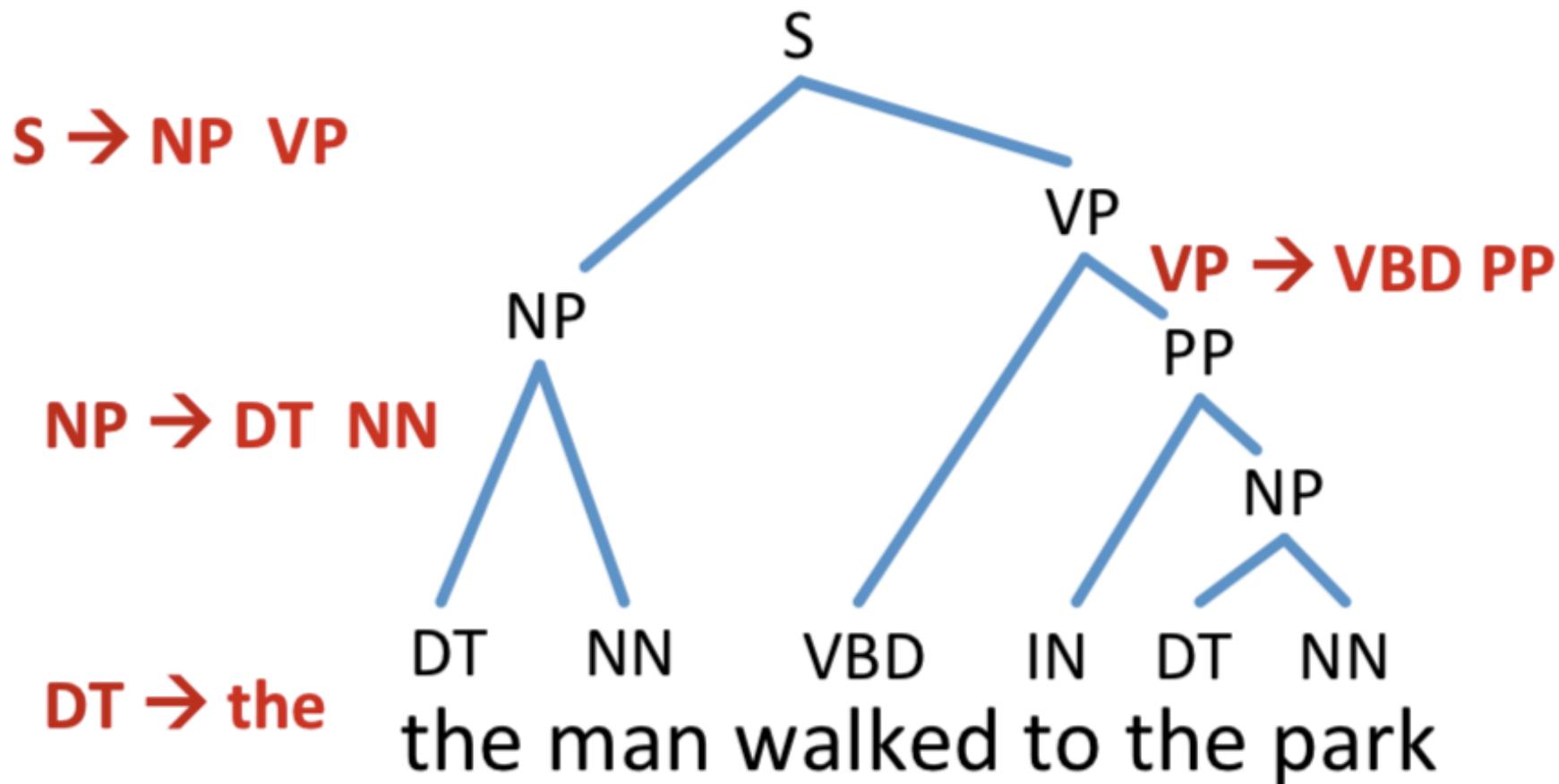
S symbol



CFG rule application

Sentence

Example Sentence and Parse Tree



What is parsing?

- Parsing: given Sentence, find a legal (or most probable) parse tree (with S as root)

S symbol



CFG rule application

Sentence

Top-Down Parsing (v1)

- Run Random Sentence Generator until we get the sentence we want

S symbol

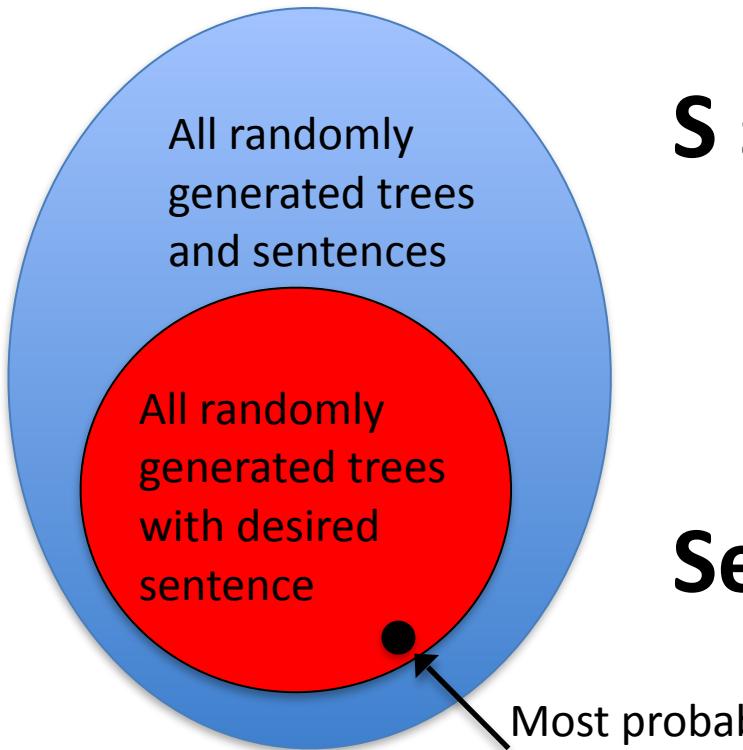


CFG rule application

Sentence

Top-Down Parsing (v1)

- Run Random Sentence Generator until we get the sentence we want



S symbol



CFG rule application

Sentence

Most probable
tree (if PCFG)

Bottom-Up Parsing (v1)

Book that flight

Noun Det Noun
Book that flight
Verb Det Noun
Book that flight

Nominal
Noun Det Noun
Book that flight

Nominal
Verb Det Noun
Book that flight

NP
Nominal
Noun Det Noun
Book that flight

VP
Verb Det Noun
Book that flight

NP
Verb Det Noun
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VP
Verb Det Noun
Book that flight

VP
Verb Det Noun
Book that flight

From: Jurafsky & Martin (2009),
Speech and Language Processing,
2nd ed., Pearson Education

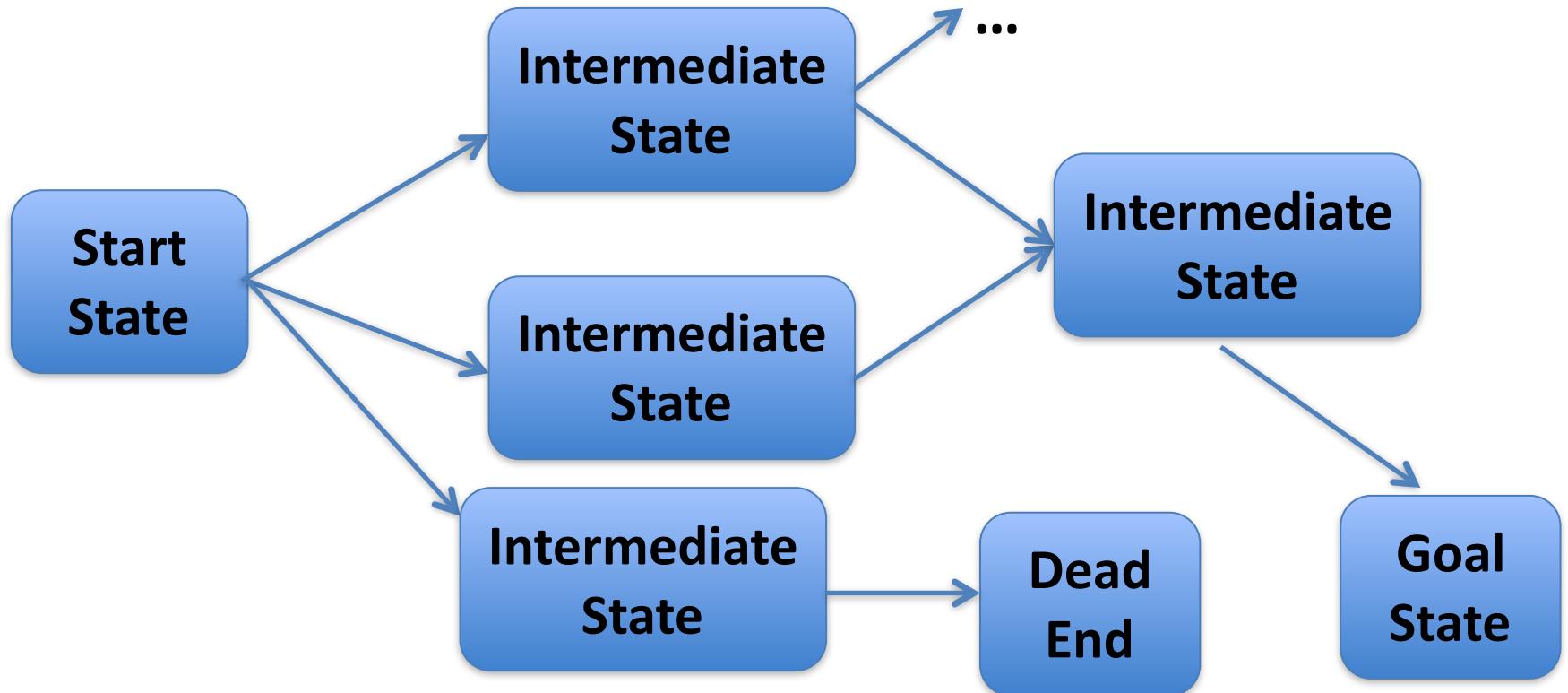
Overview

- Constituency Parsing
 - Parsing as Search; Dynamic Programming
 - CKY Algorithm
- Treebanks and Evaluation
- Dependency Parsing
 - Definitions
 - Eisner Algorithm

Top-Down vs. Bottom-Up

- Bottom-Up:
 - Doesn't waste time generating trees that don't get our desired sentence
- Top-Down:
 - Doesn't waste time generating trees that don't get to S symbol at the end

Parsing as a Search Problem



Many methods! Take an AI class. We'll focus on class of algorithms based on Dynamic Programming

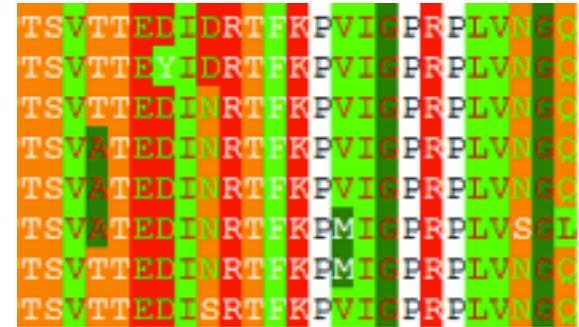
Successful algorithms based on Dynamic Programming



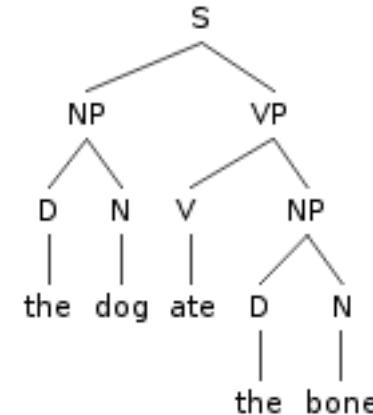
Viterbi Algorithm
for Digital Communications



Bellman-Ford Algorithm
for Shortest Path on Graphs



Needleman-Wunsch Algorithm
for Biological Sequence Alignment



Cocke-Younger-Kasami Algorithm
for parsing of language

What is Dynamic Programming

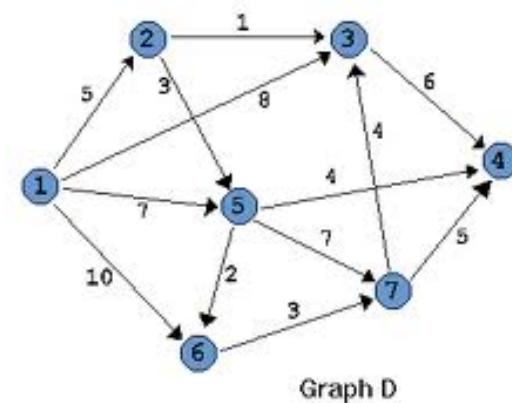
- A strategy for solving problems by
 - dividing into overlapping sub-problems, and
 - re-using sub-problem solutions

What is Dynamic Programming

- A strategy for solving problems by
 - dividing into overlapping sub-problems, and
 - re-using sub-problem solutions
- Can be thought as intelligent “brute-force”:
 - Try all possible solutions without actually trying all possible solutions

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CKY Algorithm for Parsing Trees

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- Assume Chomsky Normal Form (CNF)

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- Rules must be
 - RHS has 2 non-terminals: $A \rightarrow B C$
 - RHS has 1 terminal: $A \rightarrow w$

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- Bottom-up parsing

CKY Algorithm for Parsing Trees

- Assume Chomsky Normal Form (CNF)
- Rules must be
 - RHS has 2 non-terminals: $A \rightarrow B C$
 - RHS has 1 terminal: $A \rightarrow w$
- Bottom-up parsing
- Use an efficient data structure to store partial parsing sub-problem solutions

Conversion of any grammar to CNF

\mathcal{L}_1 Grammar	\mathcal{L}_1 in CNF
$S \rightarrow NP VP$	$S \rightarrow NP VP$
$S \rightarrow Aux NP VP$	$S \rightarrow X1 VP$ $X1 \rightarrow Aux NP$
$S \rightarrow VP$	$S \rightarrow book include prefer$ $S \rightarrow Verb NP$ $S \rightarrow X2 PP$ $S \rightarrow Verb PP$ $S \rightarrow VP PP$
$NP \rightarrow Pronoun$	$NP \rightarrow I she me$
$NP \rightarrow Proper-Noun$	$NP \rightarrow TWA Houston$
$NP \rightarrow Det Nominal$	$NP \rightarrow Det Nominal$
$Nominal \rightarrow Noun$	$Nominal \rightarrow book flight meal money$
$Nominal \rightarrow Nominal Noun$	$Nominal \rightarrow Nominal Noun$
$Nominal \rightarrow Nominal PP$	$Nominal \rightarrow Nominal PP$
$VP \rightarrow Verb$	$VP \rightarrow book include prefer$
$VP \rightarrow Verb NP$	$VP \rightarrow Verb NP$
$VP \rightarrow Verb NP PP$	$VP \rightarrow X2 PP$ $X2 \rightarrow Verb NP$
$VP \rightarrow Verb PP$	$VP \rightarrow Verb PP$
$VP \rightarrow VP PP$	$VP \rightarrow VP PP$
$PP \rightarrow Preposition NP$	$PP \rightarrow Preposition NP$

Intuition

- 2-dim matrix encoding of solutions
- Each non-terminal above POS has exactly 2 children
- For each $[i,j]$ span, there must be a position $i < k < j$ that splits it into two constituents

Book	the	flight	through	Houston
S, VP, Verb Nominal, Noun [0,1]		S,VP,X2 [0,3]		S, VP [0,5]
Det [1,2]	NP [1,3]			NP [1,5]
	Nominal, Noun [2,3]			Nominal [2,5]
		Prep [3,4]	PP [3,5]	
				NP, Proper- Noun [4,5]

Example: Parsing “Book the flight through Houston”

- $_0 \text{ Book } _1 \text{ the } _2 \text{ flight } _3 \text{ through } _4 \text{ Houston } _5$
- $[0,1] = \text{parse for: “Book”}$
- $[1,2] = \text{parse for: “the”}$
- $[2,3] = \text{parse for: “flight”}$
- $[0,2] = \text{parse for: “Book the”}$
- $[1,3] = \text{parse for: “the flight”}$
- $[0,3] = \text{parse for: “Book the flight”}$
- $[0,5] = \text{parse for sentence}$

<i>Book</i>	<i>the</i>	<i>flight</i>	<i>through</i>	<i>Houston</i>
S, VP, Verb Nominal, Noun [0,1]	[0,2]	S,VP,X2 [0,3]	[0,4]	S, VP [0,5]
Det [1,2]	NP [1,3]			NP [1,5]
Nominal, Noun [2,3]		[1,4]		Nominal [1,5]
Prep [3,4]		[2,4]	[2,5]	PP [3,5]
NP, Proper- Noun [4,5]				

Example: Parsing “Book the flight through Houston”

<i>Book</i>	<i>the</i>	<i>flight</i>	<i>through</i>	<i>Houston</i>
S, VP, Verb Nominal, Noun [0,1]	[0,2]	S,VP,X2 [0,3]	[0,4]	S, VP [0,5]
Det [1,2]	NP [1,3]			NP [1,5]
	Nominal, Noun [2,3]			Nominal [2,5]
	Prep [3,4]	PP [3,5]		
		NP, Proper- Noun [4,5]		

```
function CKY-PARSE(words, grammar) returns table
```

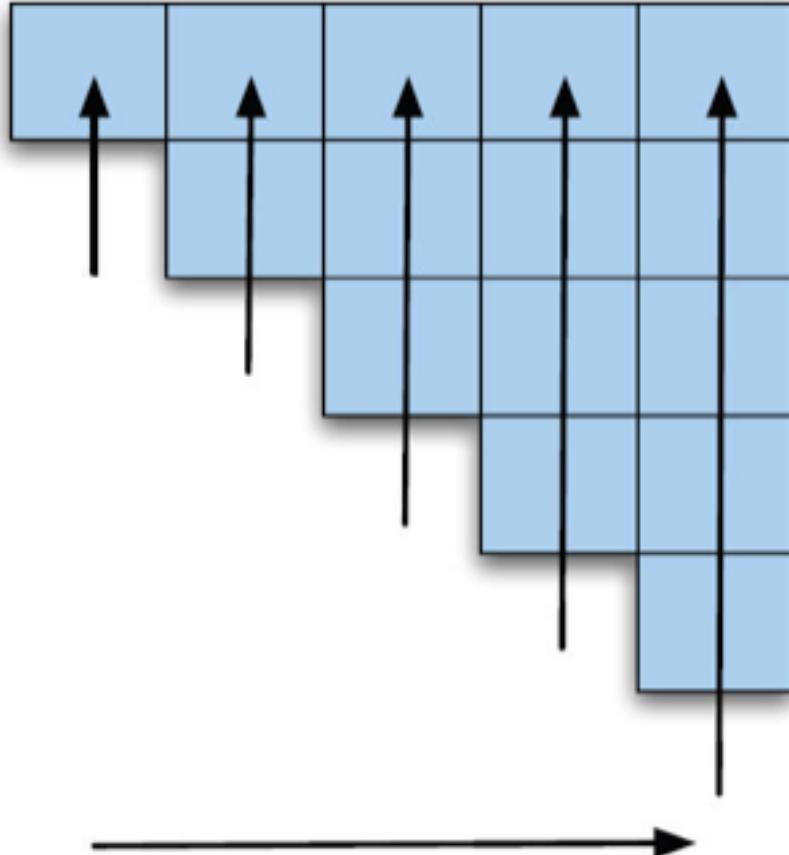
```
for j ← from 1 to LENGTH(words) do
```

```
    table[j − 1, j] ← {A | A → w[j] ∈ grammar}
```

```
    for i ← from j − 2 downto 0 do
```

```
        for k ← i + 1 to j − 1 do
```

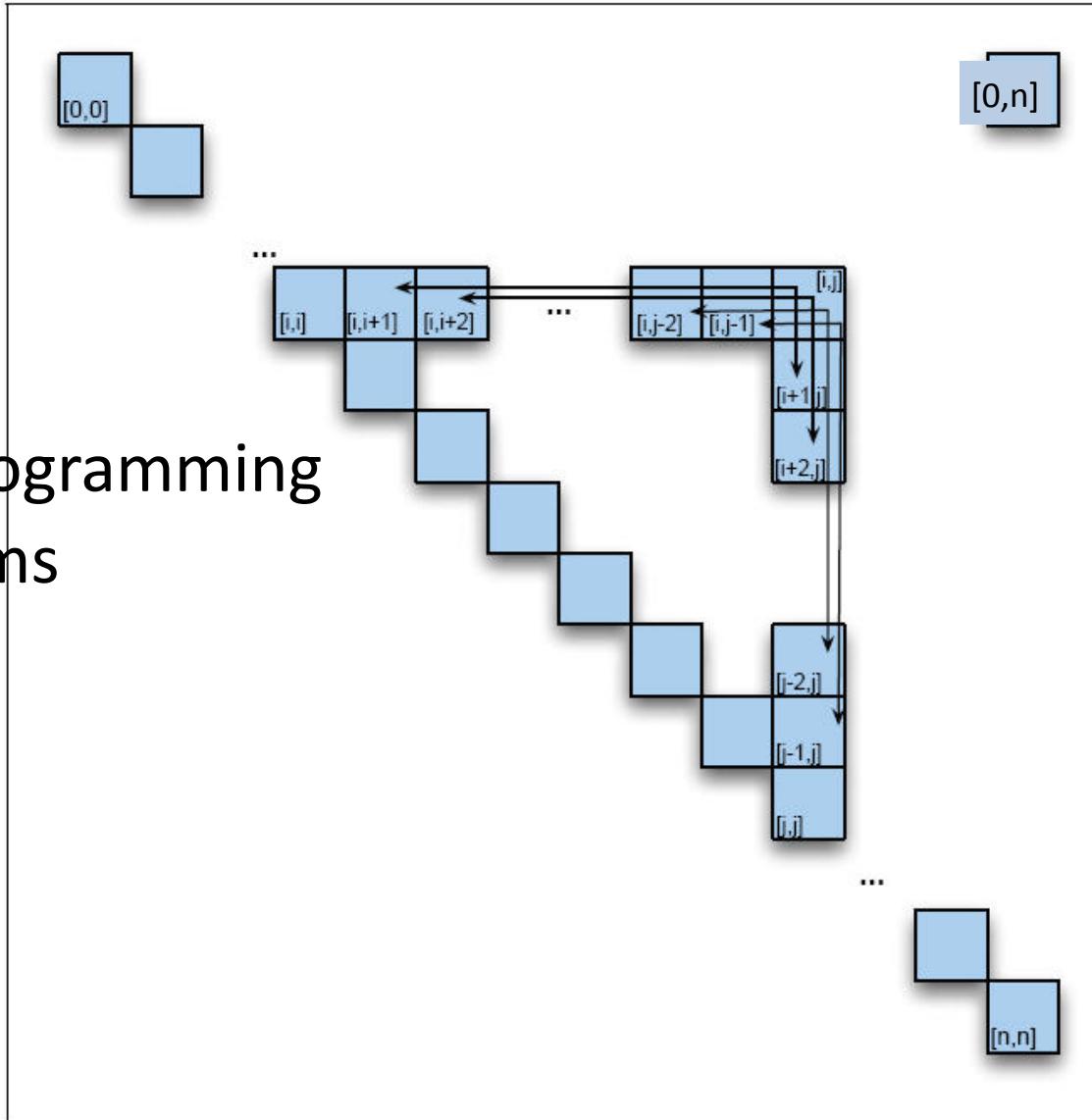
```
            table[i, j] ← table[i, j] ∪  
                {A | A → BC ∈ grammar,  
                 B ∈ table[i, k],  
                 C ∈ table[k, j]}
```



Note: this finds all valid trees.

*Think about how to modify this
to find the most probable tree*

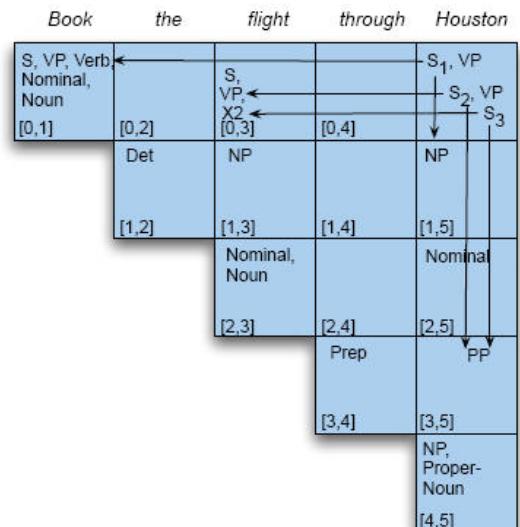
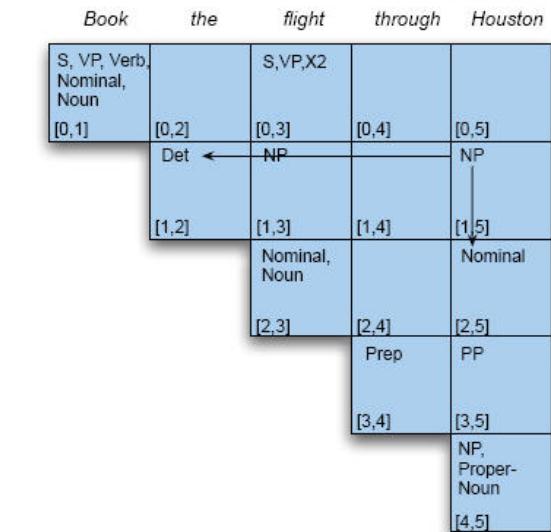
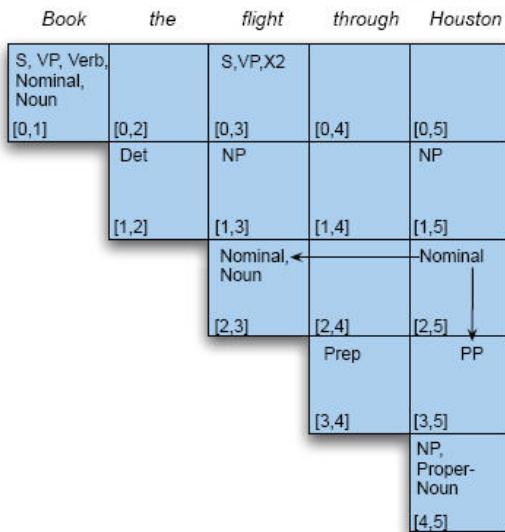
Dynamic Programming Sub-Problems



From: Jurafsky & Martin (2009), Speech and
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\mathcal{L}_1 in CNF

$S \rightarrow NP VP$
 $S \rightarrow X1 VP$
 $X1 \rightarrow Aux NP$
 $S \rightarrow book \mid include \mid prefer$
 $S \rightarrow Verb NP$
 $S \rightarrow X2 PP$
 $S \rightarrow Verb PP$
 $S \rightarrow VP PP$
 $NP \rightarrow I \mid she \mid me$
 $NP \rightarrow TWA \mid Houston$
 $NP \rightarrow Det Nominal$
 $Nominal \rightarrow book \mid flight \mid meal \mid money$
 $Nominal \rightarrow Nominal Noun$
 $Nominal \rightarrow Nominal PP$
 $VP \rightarrow book \mid include \mid prefer$
 $VP \rightarrow Verb NP$
 $VP \rightarrow X2 PP$
 $X2 \rightarrow Verb NP$
 $VP \rightarrow Verb PP$
 $VP \rightarrow VP PP$
 $PP \rightarrow Preposition NP$



- CKY Exercise- Parse this sentence: **fruit flies like a banana**
- Grammar:
 - $S \rightarrow NP\ VP$
 - $NP \rightarrow Adj\ Noun$
 - $NP \rightarrow Det\ Noun$
 - $VP \rightarrow Verb\ NP$
 - $VP \rightarrow Verb\ PP$
 - $PP \rightarrow Prep\ NP$
 - $Adj \rightarrow fruit$
 - $Noun \rightarrow fruit$
 - $NP \rightarrow fruit$
 - $Noun \rightarrow flies$
 - $Verb \rightarrow flies$
 - $Verb \rightarrow like$
 - $Prep \rightarrow like$
 - $Det \rightarrow a$
 - $Noun \rightarrow banana$

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Treebank

- Treebank: A corpus of parsed sentences
- Penn Treebank
 - 40k sentences, mostly from Wall Street Journal

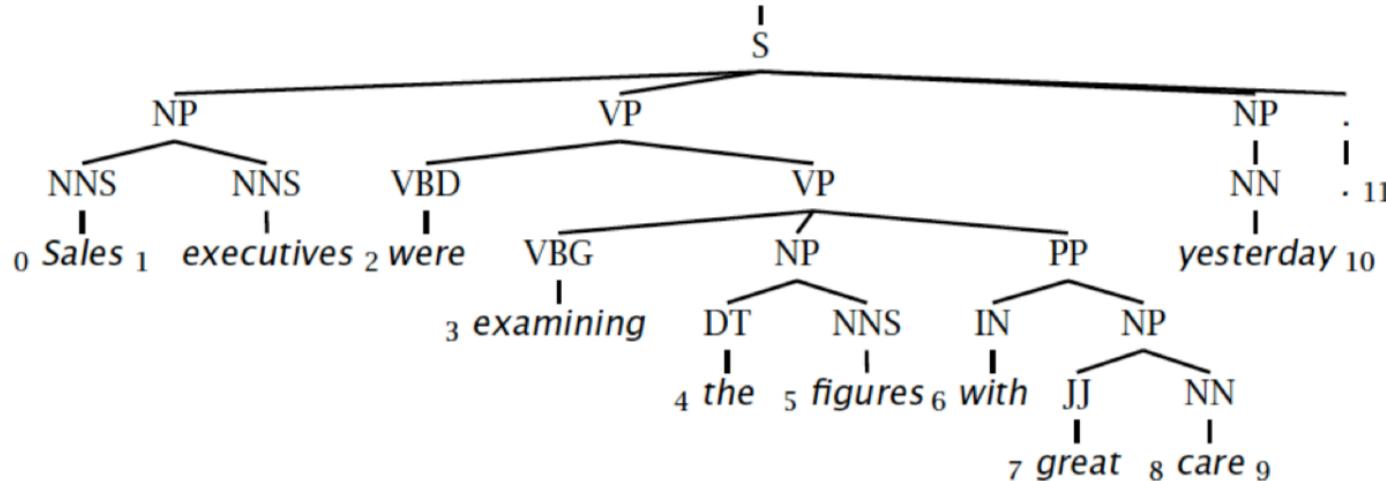
```
(S
  (SBAR-PRP
    (IN Because)
    (S
      (S
        (NP-SBJ (DT the) (NNP CD))
        (VP
          (VBD had)
          (NP
            (NP (DT an) (JJ effective) (NN yield))
            (PP (IN of) (NP (CD 13.4) (NN %))))
          (SBAR-TMP
            (WHADVP-4 (WRB when)))
          (S
            (NP-SBJ-1 (PRP it))
            (VP
              (VBD was)
              (VP
                (VBN issued)
                (NP (-NONE- *-1))
                (PP-TMP (IN in) (NP (CD 1984)))
                (ADVP-TMP (-NONE- *T*-4)))))))
        ...
      )
    )
  )
)
```

How to get probabilities for PCFG

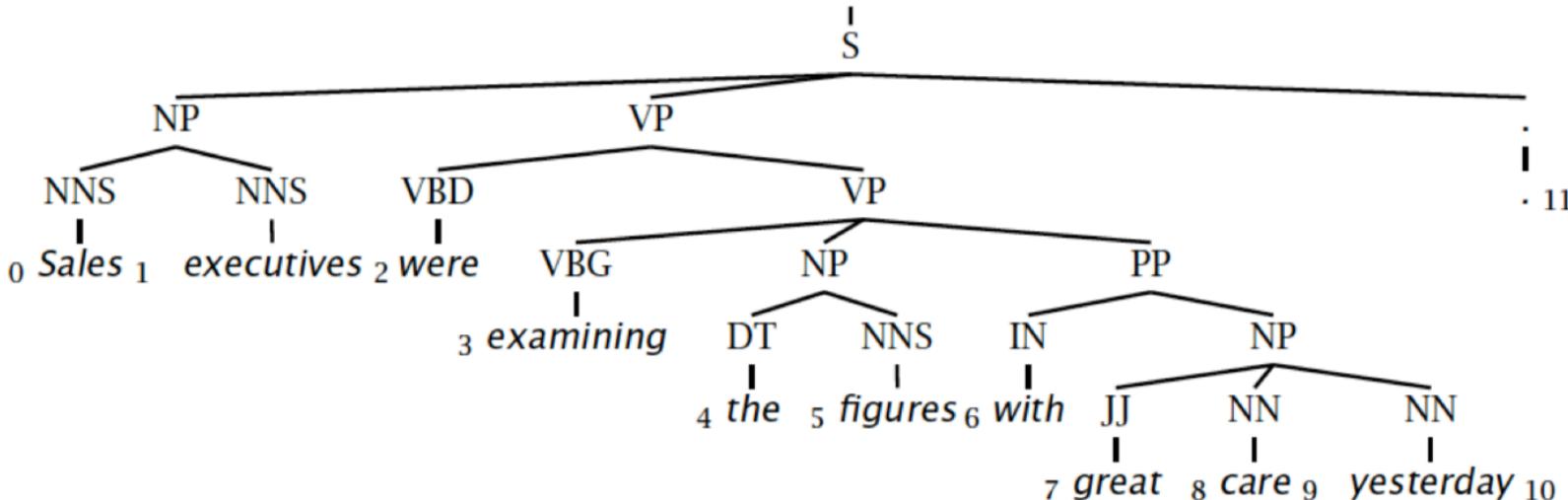
- One method: Count rules from a treebank
- $P(S \rightarrow NP\ VP) = \text{count}(S \rightarrow NP\ VP) / \text{count}(S)$
- We can apply various smoothing techniques
- Large research literature:
 - How to get best PCFG from treebank?
 - What if we don't have a treebank?

Evaluating Parse Results

Gold standard brackets: **S-(0:11), NP-(0:2), VP-(2:9), VP-(3:9), NP-(4:6), PP-(6:9), NP-(7,9), NP-(9:10)**



Candidate brackets: **S-(0:11), NP-(0:2), VP-(2:10), VP-(3:10), NP-(4:6), PP-(6-10), NP-(7,10)**



Evaluating Parse Results

Gold standard brackets:

S-(0:11), NP-(0:2), VP-(2:9), VP-(3:9), NP-(4:6), PP-(6-9), NP-(7,9), NP-(9:10)

Candidate brackets:

S-(0:11), NP-(0:2), VP-(2:10), VP-(3:10), NP-(4:6), PP-(6-10), NP-(7,10)

Recall = # correct candidate constituents / # gold constituents
= 3/8 = 37.5%

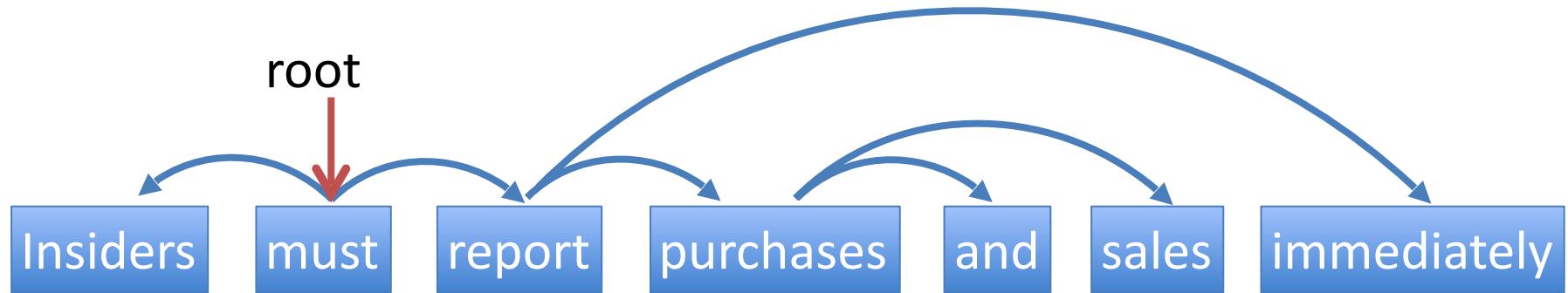
Precision = # correct candidate constituents / # constituents in candidate
= 3/7 = 42.9%

F1 = (2*precision*recall)/(precision+recall) i.e. harmonic mean
= 40%

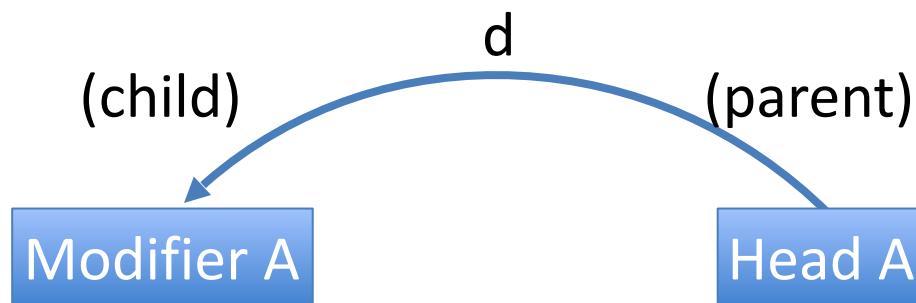
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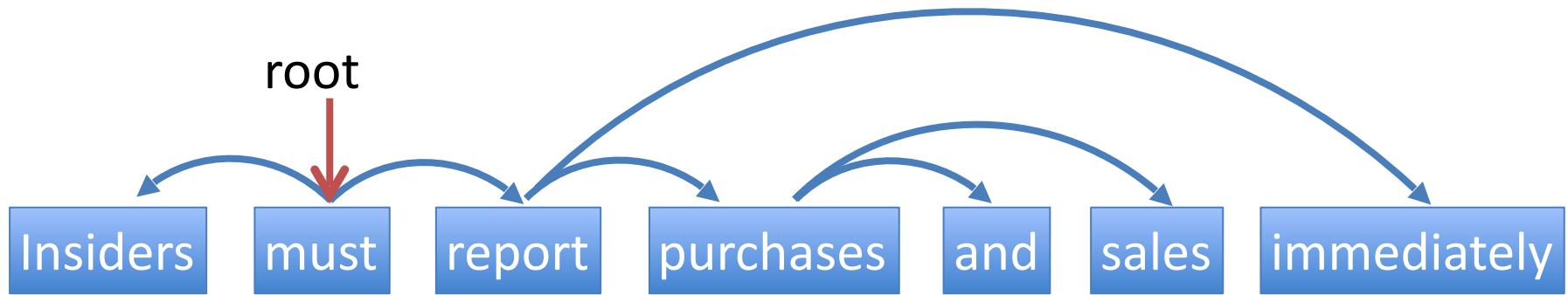
Dependency Tree



Represents head and modifier relationship



Dependency Parsing



- Input: Sentence (Word sequence)

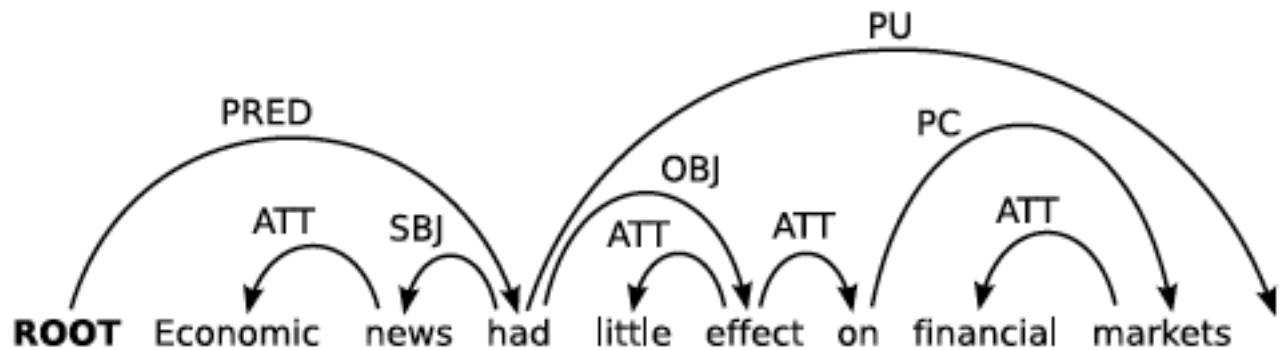
$$S = \{w_1, \dots, w_n\}$$

- Output: Dependency

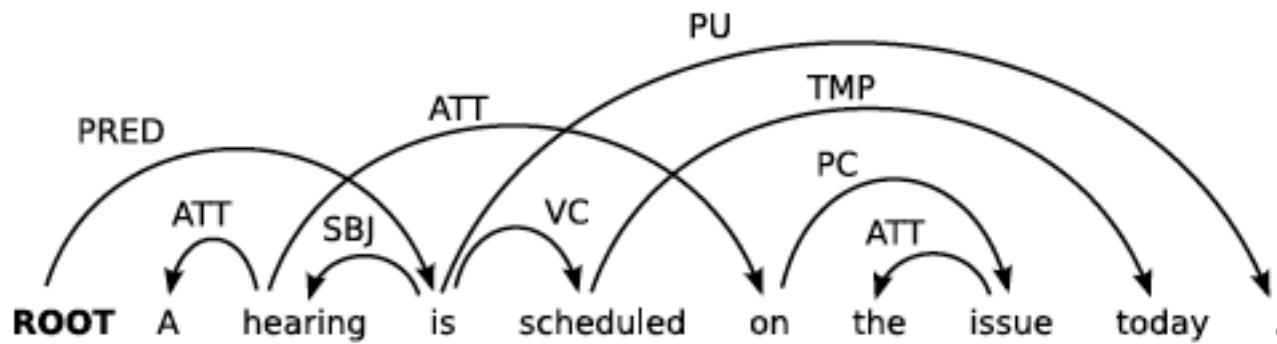
$$D = \{d_1, \dots, d_n\}$$

- All elements are acyclic, connected

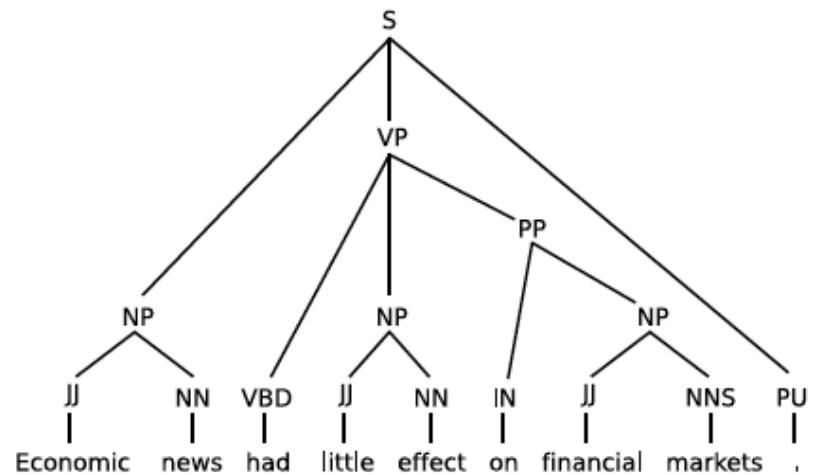
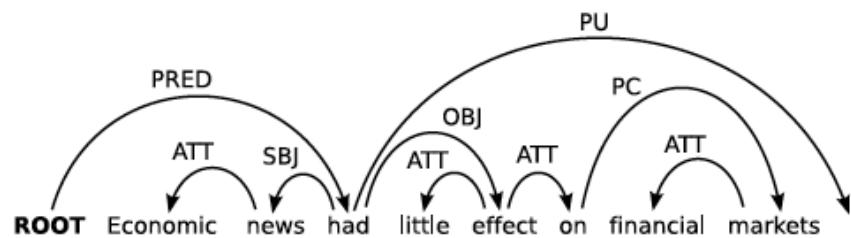
Projective Dependency Trees: no crossings



Non-Projective Dependency Trees



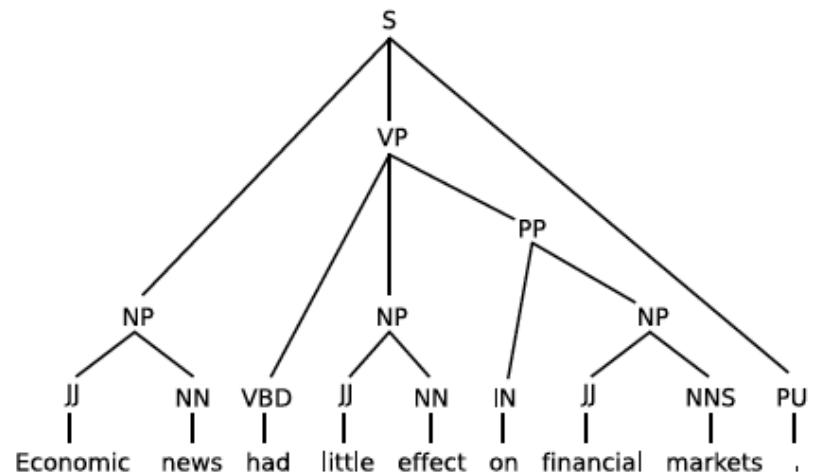
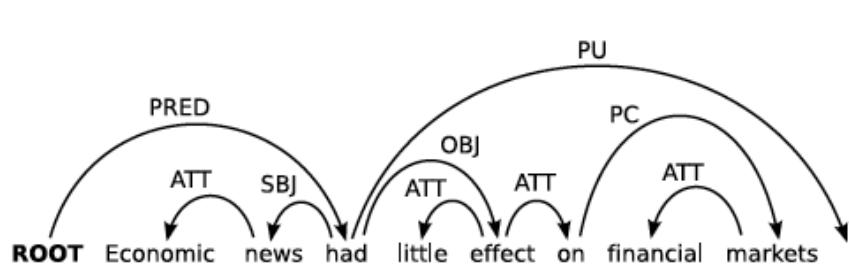
Dependency vs Constituency



From: Kubler, McDonald, Nivre (2009). Dependency Parsing.
Synthesis Lectures in HLT, Morgan & Claypool

Dependency vs Constituency

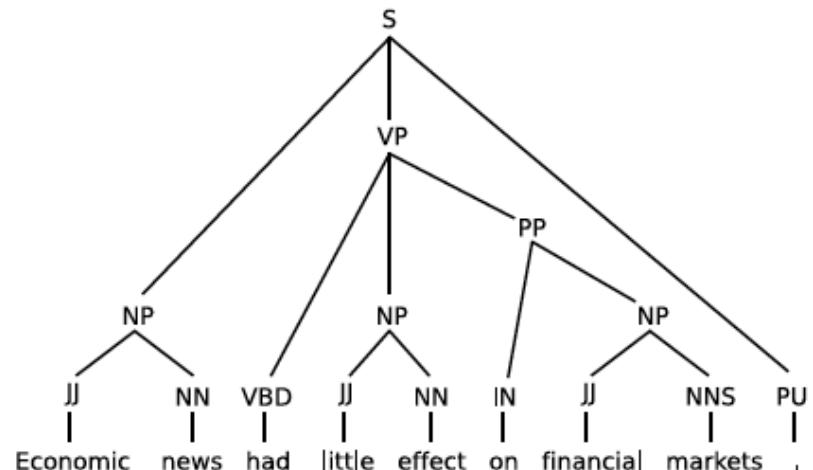
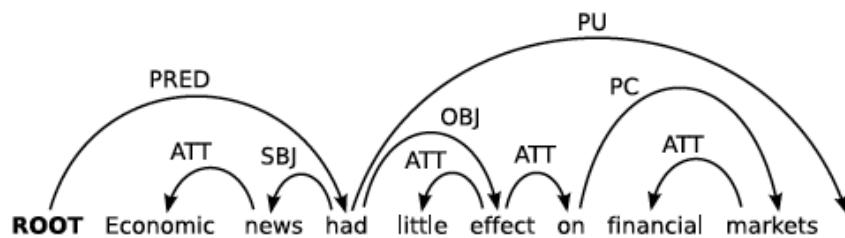
- Different ways to think about syntax
 - E.g. free word order in Czech



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Dependency vs Constituency

- Different ways to think about syntax
 - E.g. free word order in Czech
- Different applications need different formalisms

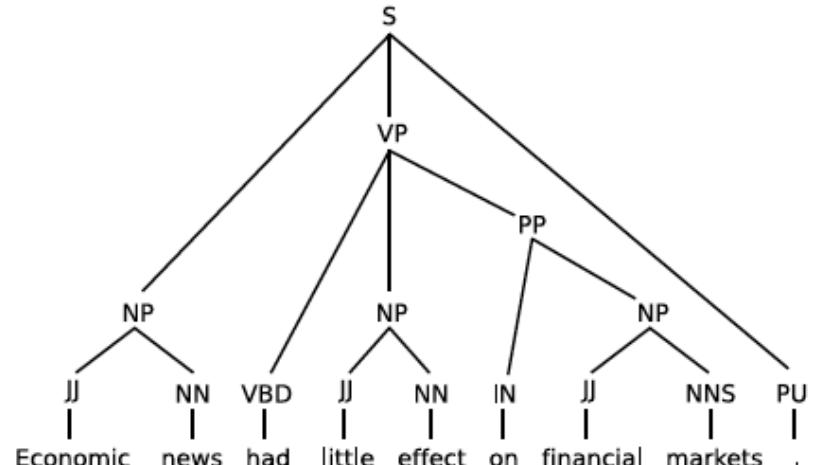
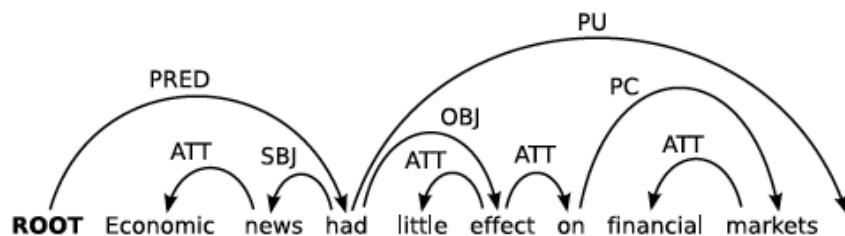


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Dependency vs Constituency

- Different ways to think about syntax
 - E.g. free word order in Czech
- Different applications need different formalisms
- Linguistic tradition based on language
 - E. Practical concerns:
 - Dependency treebanks might be easier to annotate
 - Constituency-Dependency conversion possible



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The Eisner Algorithm

- A Bottom-Up Dynamic Program

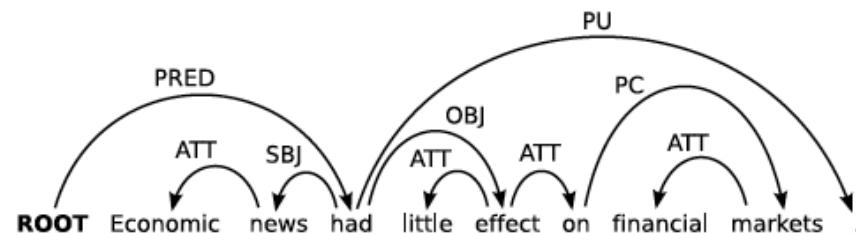


Rules

$$\text{Sub Tree} = \square + \triangle$$

$$\text{Dependency} = \triangle + \triangle$$

$$\triangle \triangle = \text{word} \\ (\text{as atomic tree})$$

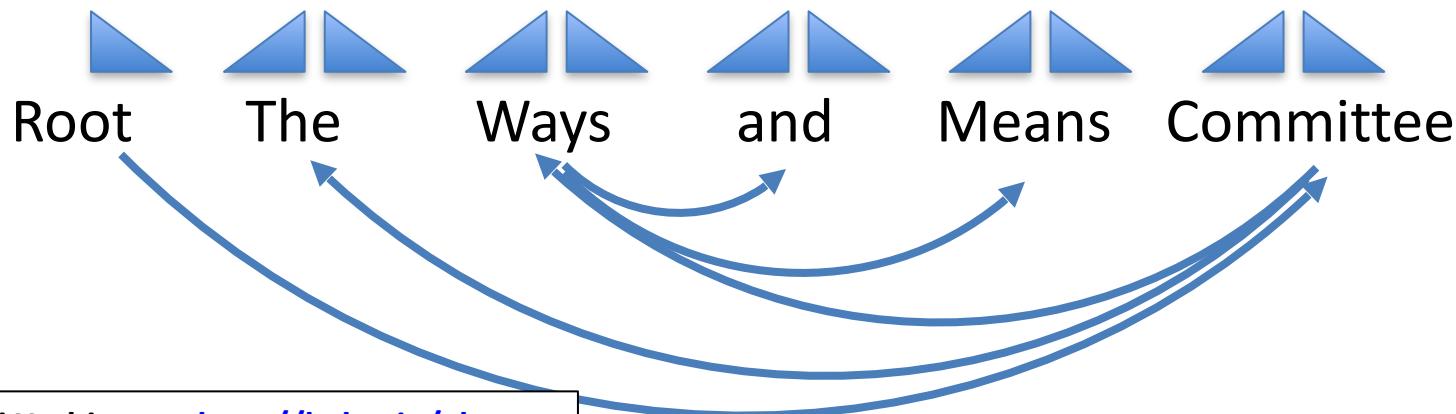


The Eisner Algorithm

Sub Tree =  + 

Dependency =  + 

 = word
(as atomic tree)

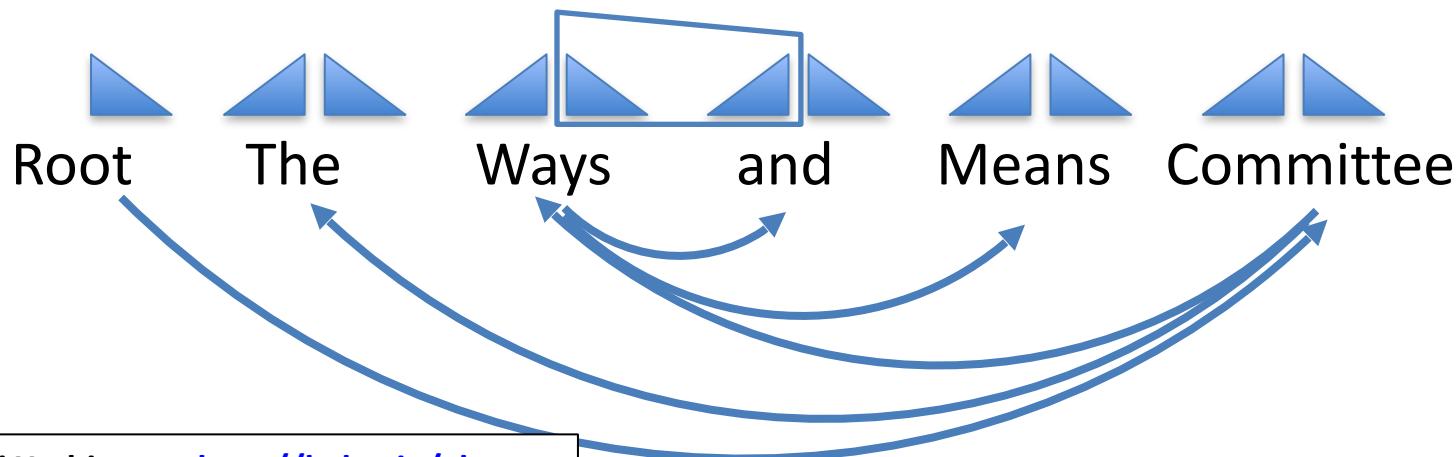


The Eisner Algorithm

Sub Tree =  + 

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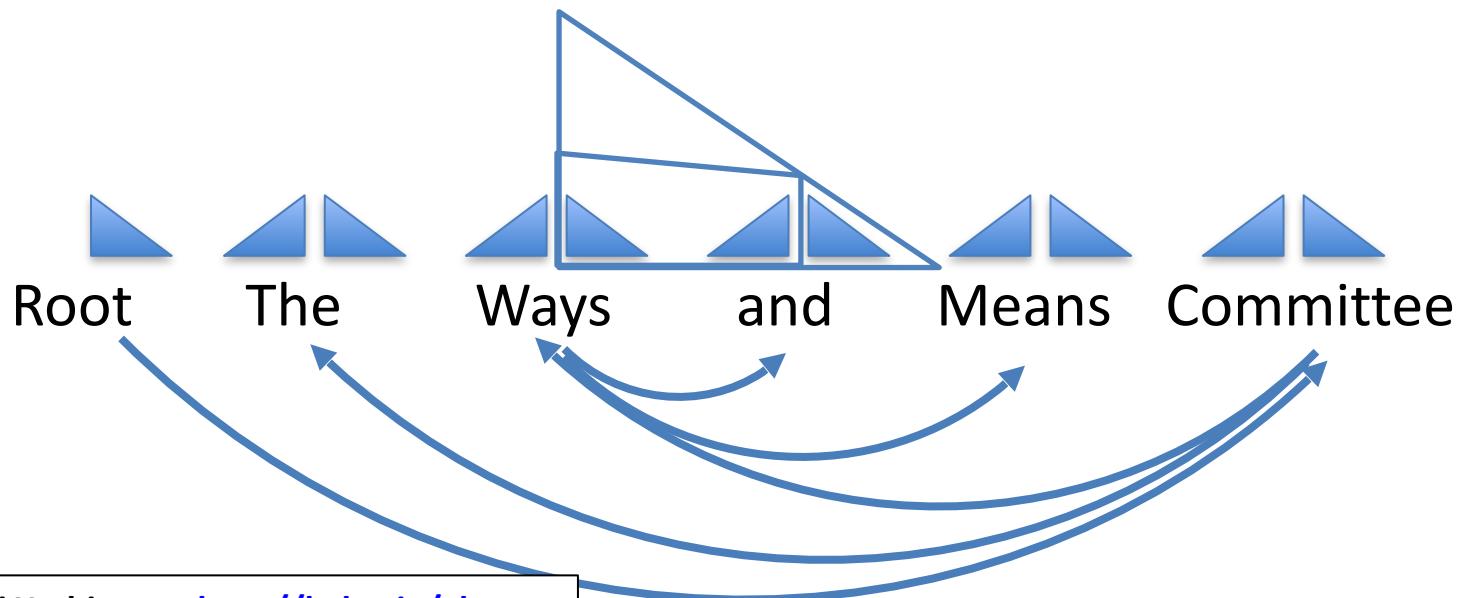


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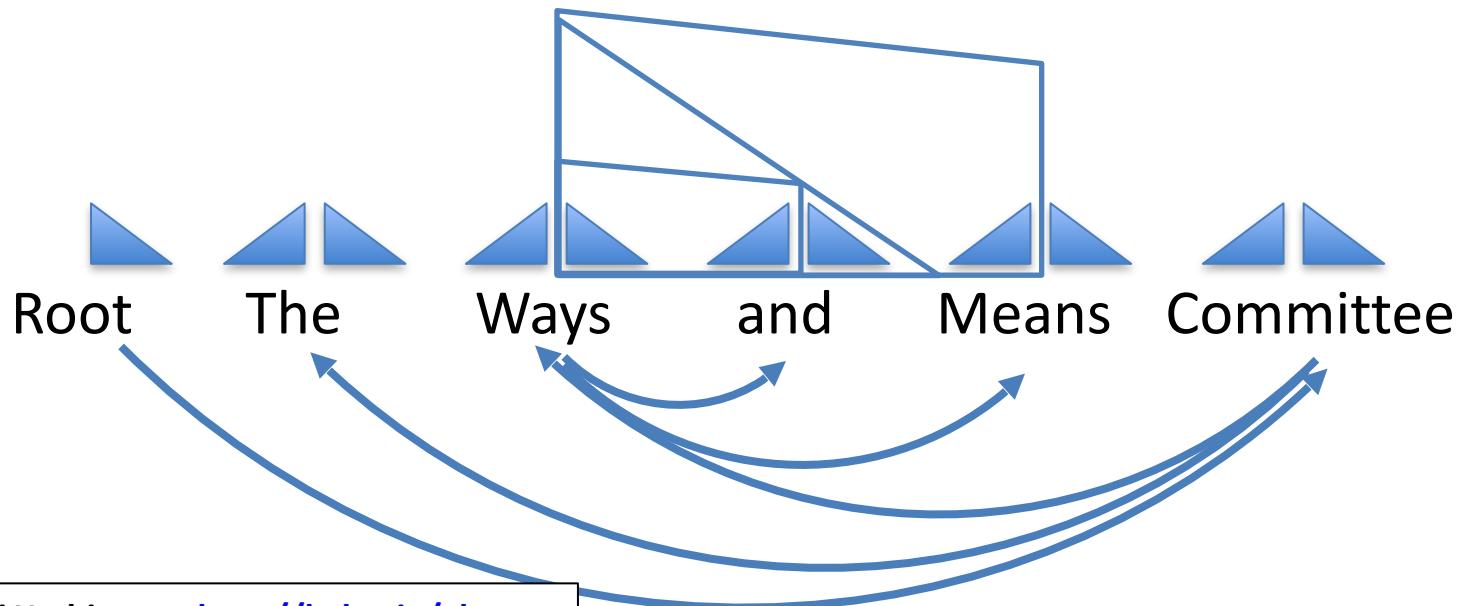


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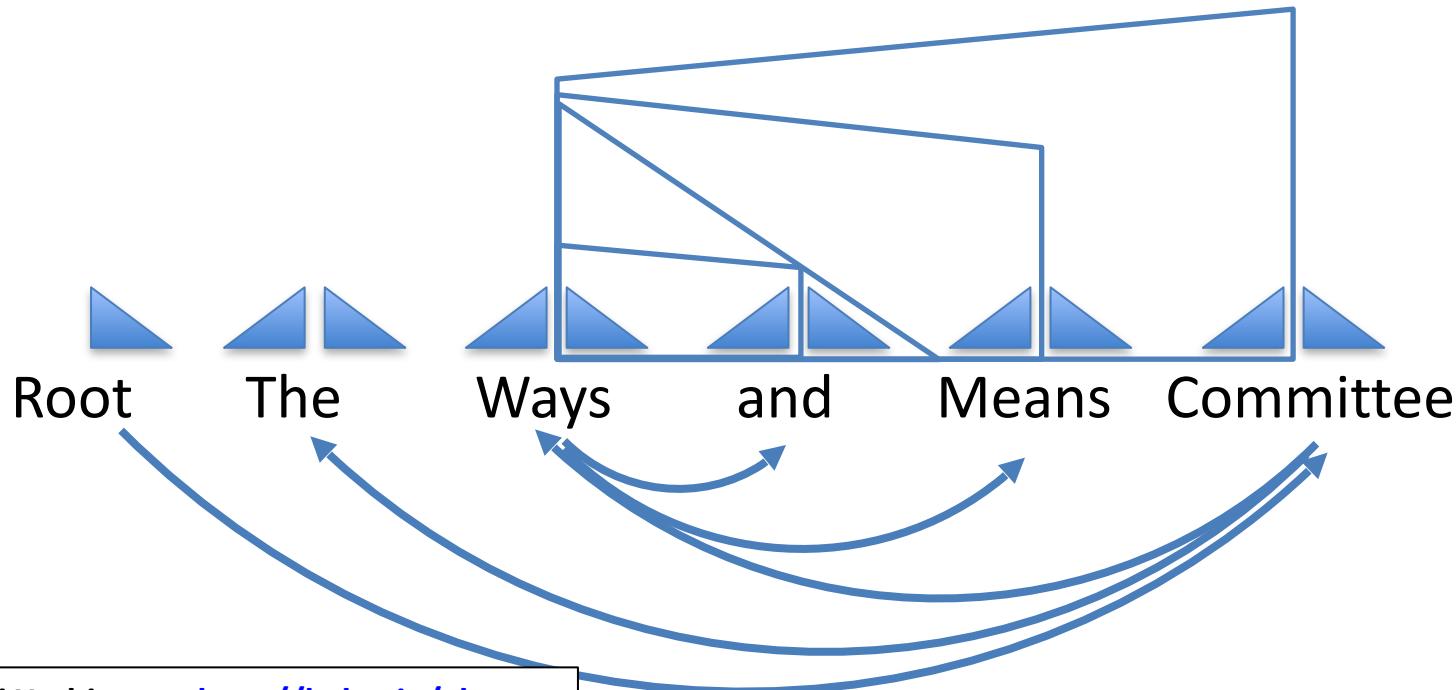


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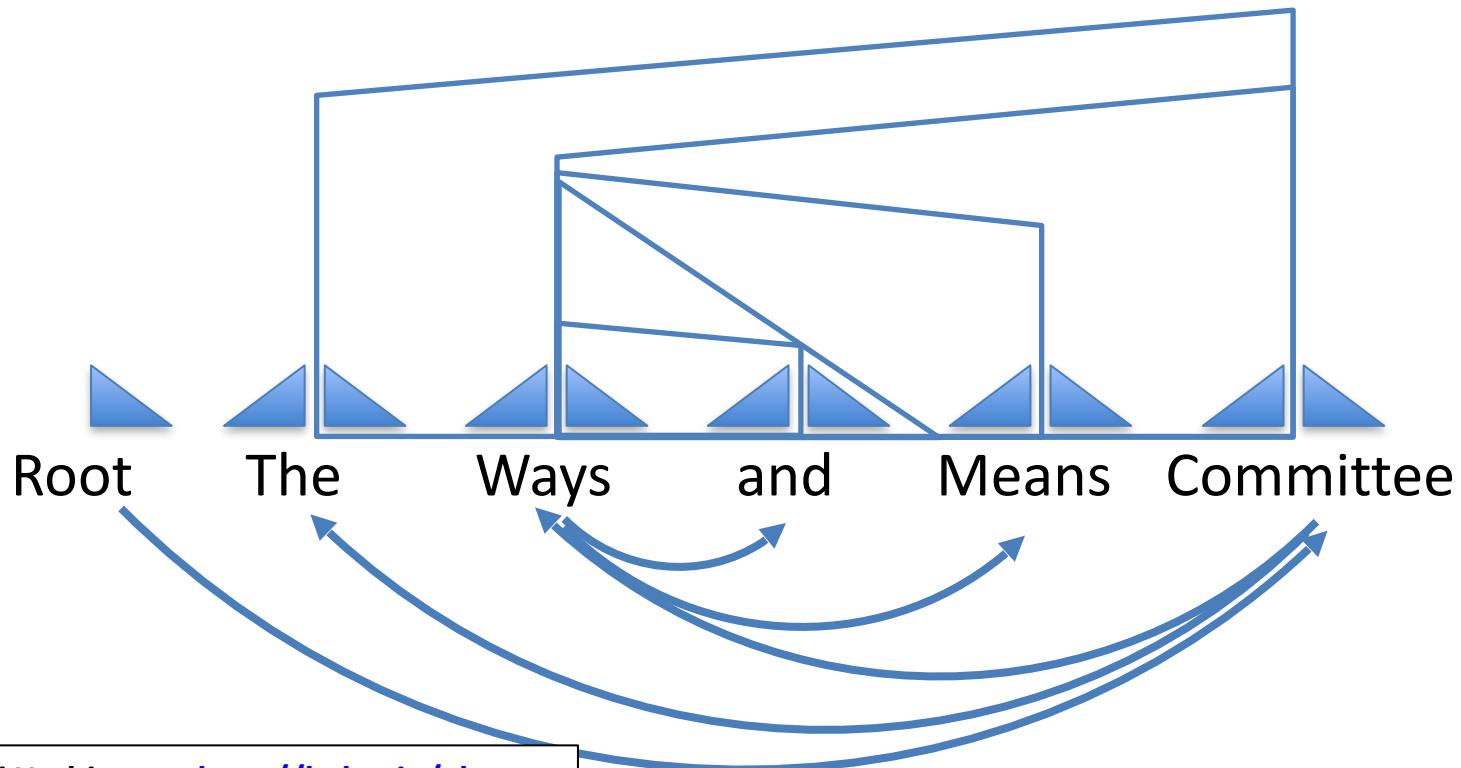


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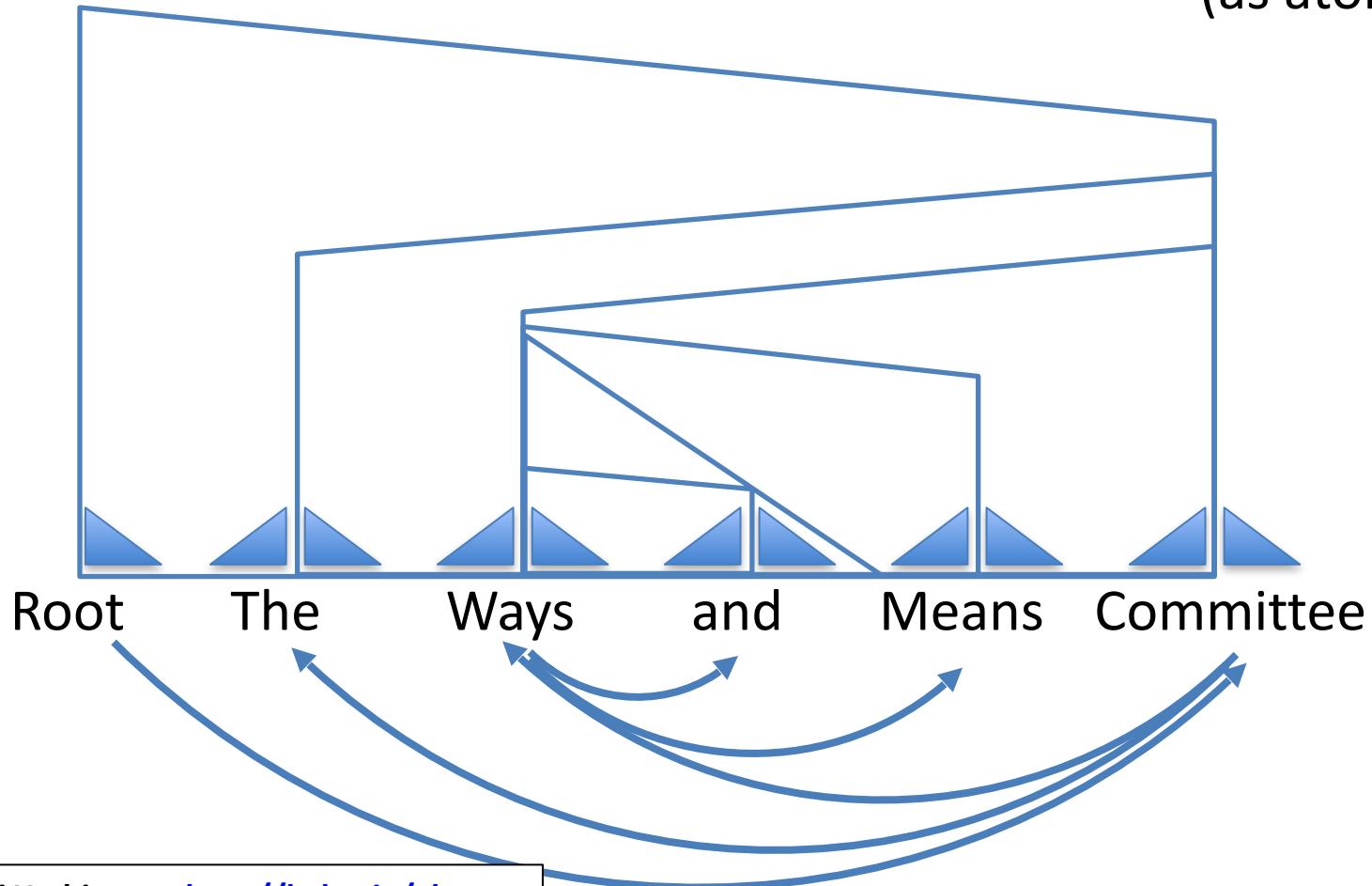


The Eisner Algorithm

Sub Tree =  + 

Dependency =  + 

 = word
(as atomic tree)



CKY Table: C[start][end][rule]

for k: 1..n

for s: 1..n

t = s+k

if t>n then break

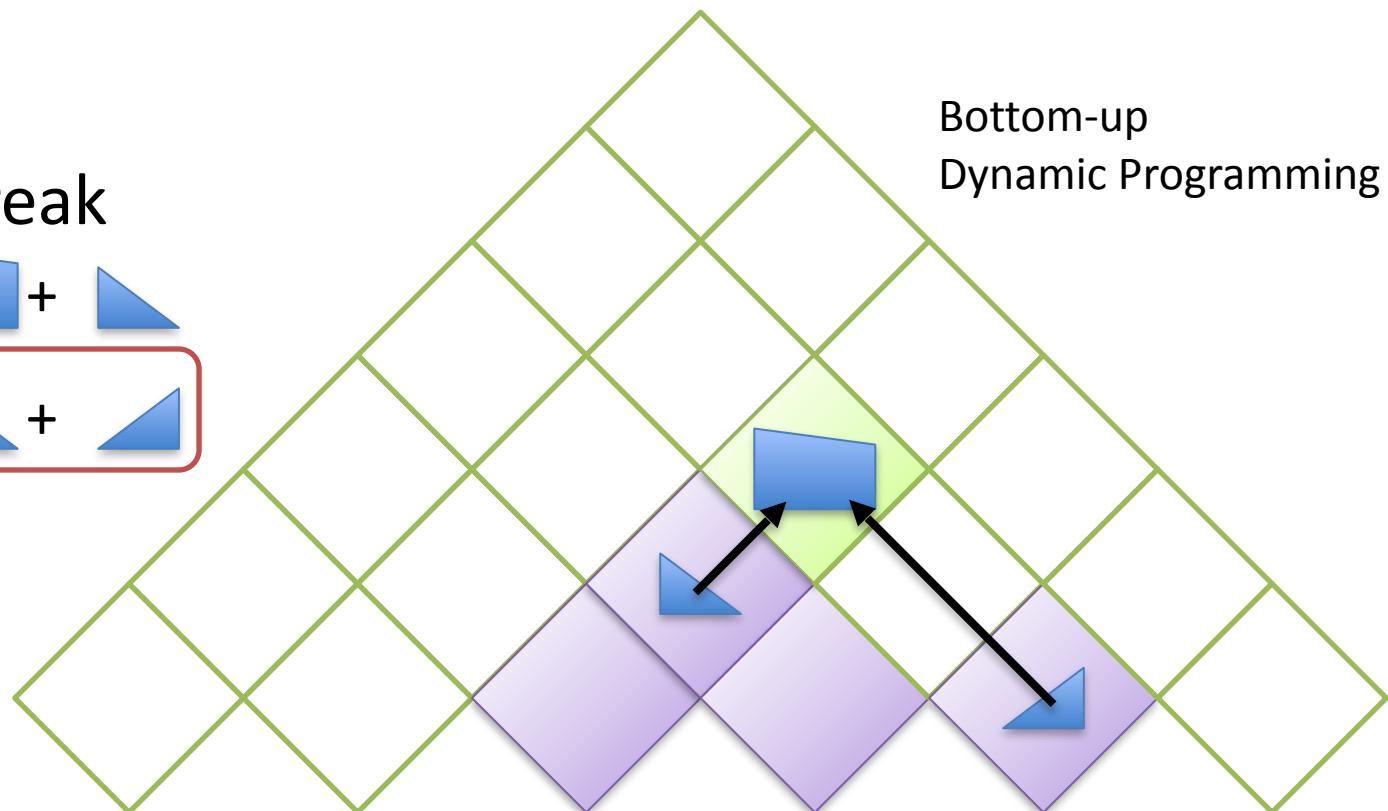
$$\begin{array}{c} \text{triangle} \\ = \quad \square + \triangle \\ \boxed{\square} = \triangle + \triangle \\ \vdots \end{array}$$

end for

end for

Eisner algorithm extends CKY

Bottom-up
Dynamic Programming



Root

The

Ways

and

Means

Committee

$-s \rightarrow$

$-t \rightarrow$

$\leftarrow \quad k \quad \rightarrow$

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Recurring Theme!