Constituency Parsing

Natural Language Processing: Jordan Boyd-Graber
University of Maryland
INTRO / CHART PARSING

A More Grounded Syntax Theory

- A central question in linguistics is **how do we know when a sentence is grammatical**?
- Chomsky’s generative grammars attempted to mathematically formalize this question
- Linguistic phrases contained a universal, hierarchical structure formalized as parse trees

A More Grounded Syntax Theory

- A central question in linguistics is **how do we know when a sentence is grammatical**?
- Chomsky's generative grammars attempted to mathematically formalize this question
- Linguistic phrases contained a universal, hierarchical structure formalized as parse trees
- Today
    - A formalization
    - Foundation of all computational syntax
    - Learnable from data

Context Free Grammars

Definition

- N: finite set of non-terminal symbols
- Σ: finite set of terminal symbols
- R: productions of the form $X \rightarrow Y_1 \dots Y_n$, where $X \in N$, $Y \in (N \cup \Sigma)$
- S: a start symbol within N

Examples of non-terminals:

- np for "noun phrase"
- vp for "verb phrase"
- Often correspond to multiword syntactic abstractions

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Examples of terminals:

- *"dog"*
- *"play"*
- *"the"*

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Examples of productions:

- n $\longrightarrow$ "*dog*"
- np $\longrightarrow$ n
- np $\longrightarrow$ adj n

Context Free Grammars

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- S: a start symbol within N

In NLP applications, by convention we use S as the start symbol

Flexibility of CFG Productions

- Unary rules: nn $\longrightarrow$ "*man*"
- Mixing terminals and nonterminals on RHS:
  - np $\longrightarrow$ "*Congress*" Vt "*the*" "*pooch*"
  - np $\longrightarrow$ "*the*" nn
- Empty terminals
  - np $\longrightarrow \epsilon$
  - adj $\longrightarrow \epsilon$

Derivations

- A derivation is a sequence of strings $s_1 \dots s_T$ where
- $s_1 \equiv S$, the start symbol
- $s_T \in \Sigma^*$: i.e., the final string is only terminals
- $s_i, \forall i > 1$, is derived from s_{i-1} by replacing some non-terminal X in s_{i-1} and replacing it by some β, where $x \rightarrow \beta \in R$.

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- Example: parse tree

Example Derivation

Productions

s $\longrightarrow$ np vp	np $\longrightarrow$ Det nn	vp $\longrightarrow$ vz
vp $\longrightarrow$ AdvP vz	np $\longrightarrow$ AdjP nn	np $\longrightarrow$ pro
Det $\longrightarrow$ *"the"*	Det $\longrightarrow$ *"a"*	Det $\longrightarrow$ *"an"*
nn $\longrightarrow$ *"dot"*	nn $\longrightarrow$ *"cat"*	nn $\longrightarrow$ *"mouse"*
vz $\longrightarrow$ *"barked"*	vz $\longrightarrow$ *"ran"*	vz $\longrightarrow$ *"sat"*
$\vdots$	$\vdots$	$\vdots$

$s_1 =$

S

Example Derivation

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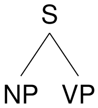
$\vdots$	$\vdots$	$\vdots$

$s_2 =$



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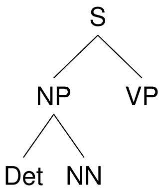
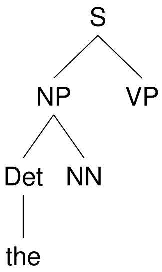
$s_3 =$



Productions

s → np vp	np → Det nn	vp → vz
vp → AdvP vz	np → AdjP nn	np → pro
Det → "*the*"	Det → "*a*"	Det → "*an*"
nn → "*dot*"	nn → "*cat*"	nn → "*mouse*"
vz → "*barked*"	vz → "*ran*"	vz → "*sat*"
⋮	⋮	⋮

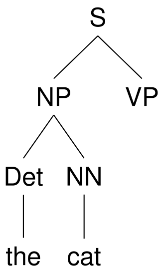
$s_4 =$



Productions

s → np vp	np → Det nn	vp → vz
vp → AdvP vz	np → AdjP nn	np → pro
Det → “*the*”	Det → “*a*”	Det → “*an*”
nn → “*dot*”	nn → “*cat*”	nn → “*mouse*”
vz → “*barked*”	vz → “*ran*”	vz → “*sat*”
⋮	⋮	⋮

$s_5 =$



Productions

s → np vp	np → Det nn	vp → vz
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Det → "*the*"	Det → "*a*"	Det → "*an*"
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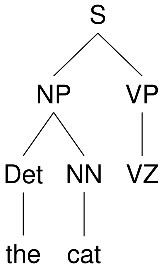
⋮	⋮	⋮

$s_6 =$



Productions

s → np vp	np → Det nn	vp → vz
vp → AdvP vz	np → AdjP nn	np → pro
Det → "*the*"	Det → "*a*"	Det → "*an*"
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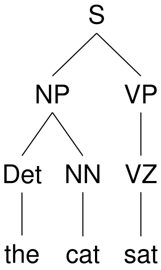
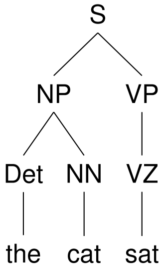
⋮	⋮	⋮

$s_7 =$



$S_7 =$

Example Derivation



Ambiguous Yields

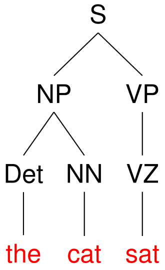
The **yield** of a parse tree is the collection of terminals produced by the parse tree. Given a yield s.

Parsing / Decoding

Given, a yield s and a grammar G, determine the set of parse trees that could have produced that sequence of terminals: $T_G(s)$.

$S_7 =$

Example Derivation



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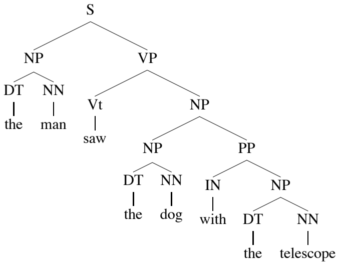
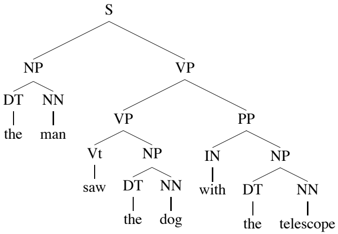
Ambiguity

Example sentence: “The man saw the dog with the telescope”

- Grammatical: $T_G(s) > 0$
- Ambiguous: $T_G(s) > 1$





- Which should we prefer?

Ambiguity

Example sentence: “The man saw the dog with the telescope”

- Grammatical: $T_G(s) > 0$
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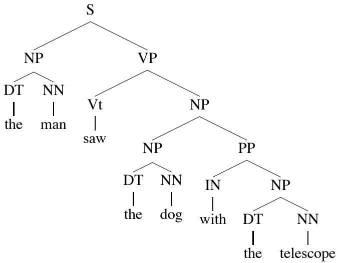
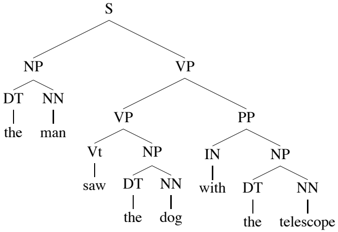




- Which should we prefer?
- One is more probable than the other
- Add probabilities!

Goals

- What we want is a probability distribution over possible parse trees $t \in T_G(s)$

$$\forall t, p(t) \geq 0 \qquad \sum_{t \in T_G(s)} p(t) = 1 \tag{1}$$

- Rest of this lecture:
  - How do we define the function $p(t)$ (paramterization)
  - How do we learn $p(t)$ from data (estimation)
  - Given a sentence, how do we find the possible parse trees (parsing / decoding)

Parametrization

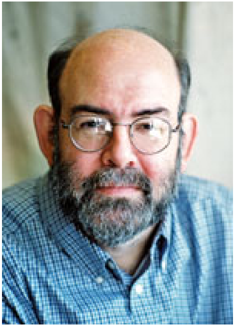
- For every production $\alpha \rightarrow \beta$, we assume we have a function $q(\alpha \rightarrow \beta)$
- We consider it a **conditional probability** of β (LHS) being derived from α (RHS)

$$\sum_{\alpha \rightarrow \beta \in R : \alpha = X} q(\alpha \rightarrow \beta) = 1 \tag{2}$$

- The total probability of a tree $t \equiv \{\alpha_1 \rightarrow \beta_1 \ldots \alpha_n \rightarrow \beta_n\}$ is

$$p(t) = \prod_{i=1}^{n} q(\alpha_i \rightarrow \beta_i) \tag{3}$$

Estimation

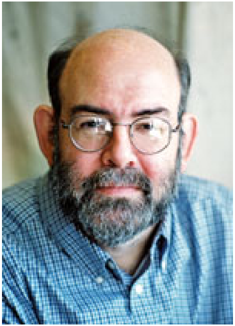


- Get a bunch of grad students to make parse trees for a million sentences
- Mitch Markus: Penn Treebank (Wall Street Journal)
- To compute the conditional probability of a rule,

$$q(\text{np} \rightarrow \text{Det} \quad \text{adj} \quad \text{nn}) \approx \frac{\text{Count}(\text{np} \rightarrow \text{Det} \quad \text{adj} \quad \text{nn})}{\text{Count}(\text{np})}$$

- Where “Count” is the number of times that derivation appears in the sentences

Estimation



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- Where "Count" is the number of times that derivation appears in the sentences
- Why no smoothing?

Dynamic Programming

- Like for dependency parsing, we build a chart to consider all possible subtrees
- First, however, we'll just consider whether a sentence is grammatical or not
- Build up a chart with all possible derivations of spans
- Then see entry with start symbol over the entire sentence: those are all grammatical parses

CYK Algorithm (deterministic)

Assumptions

Assumes binary grammar (not too difficult to extend) and no recursive rules

Given sentence $\vec{w}$ of length N, grammar (N, Σ, R, S)
Initialize array $C[s,t,n]$ as array of booleans, all false ($\perp$)

CYK Algorithm (deterministic)

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Initialize array $C[s,t,n]$ as array of booleans, all false ($\perp$)
for $i = 0 \ldots N$ **do**
  for For each production $r_j \equiv N_a \longrightarrow w_i$ **do**
    set $C[i,i,a] \leftarrow \top$

CYK Algorithm (deterministic)

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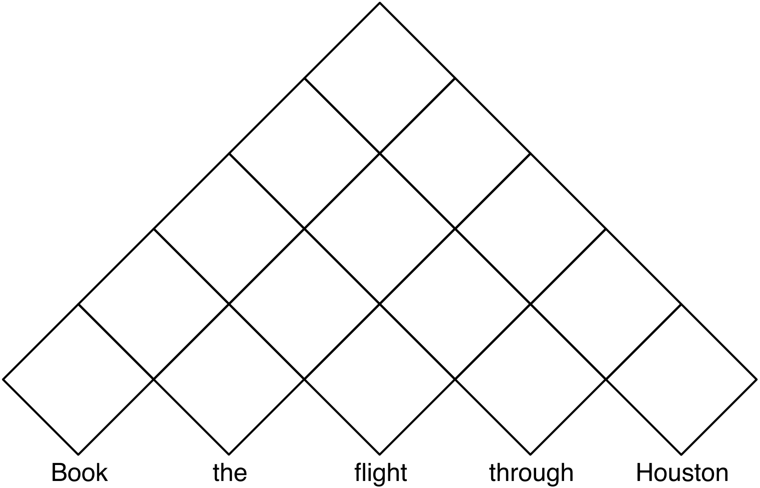
Initialize array $C[s, t, n]$ as array of booleans, all false $(\perp)$
for $i = 0 \ldots N$ **do**
  for For each production $r_j \equiv N_a \longrightarrow w_i$ **do**
    set $C[i, i, a] \leftarrow \top$
for $l = 2 \ldots n$ (length of span) **do**
  for $s = 1 \ldots N - l + 1$ (start of span) **do**
    for $k = 1 \ldots l - 1$ (pivot within span) **do**
      for each production $r \equiv \alpha \longrightarrow \beta\gamma$ **do**
        if $\neg C[s, s + l, \alpha]$ **then**
          $C[s, s + l, \alpha] \leftarrow C[s, s + k - 1, \beta] \wedge C[s + k, s + l, \gamma]$

Chart Parsing



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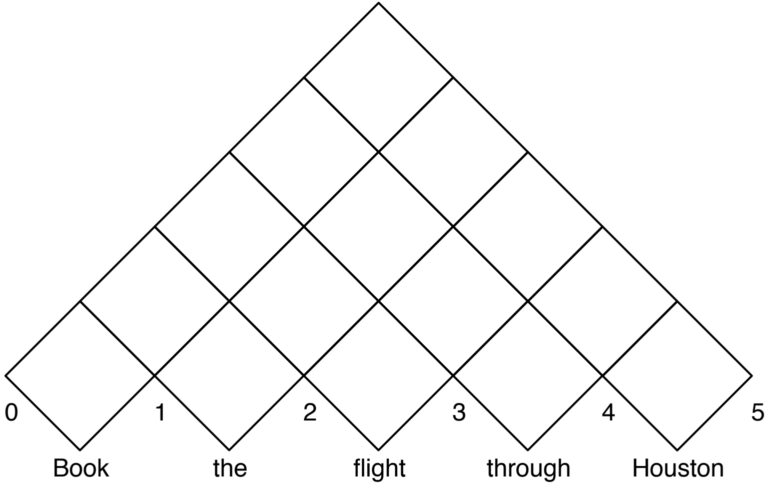

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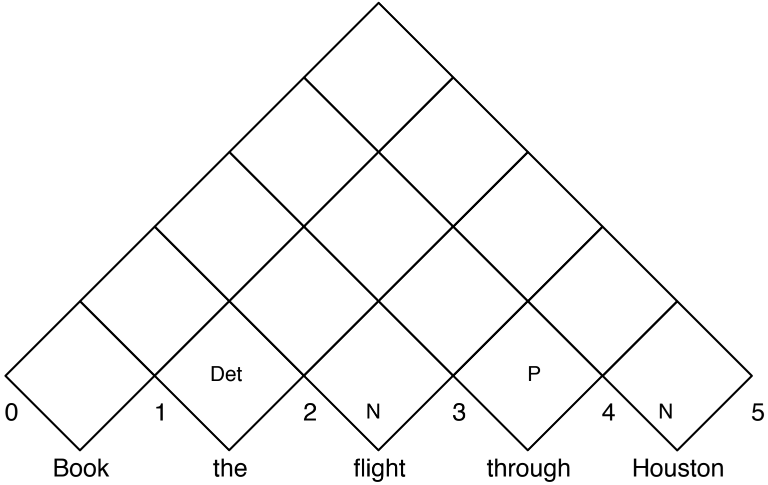

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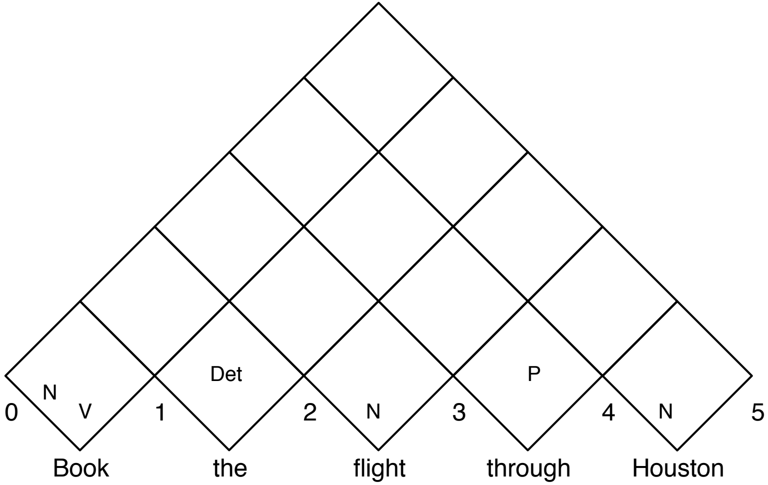

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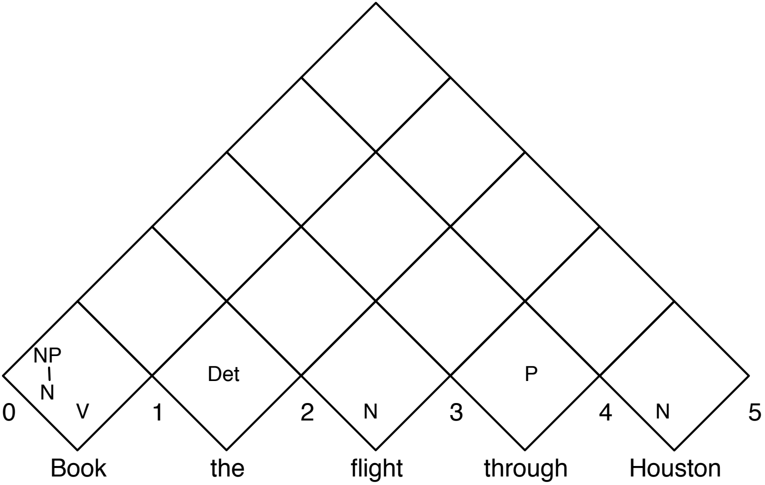

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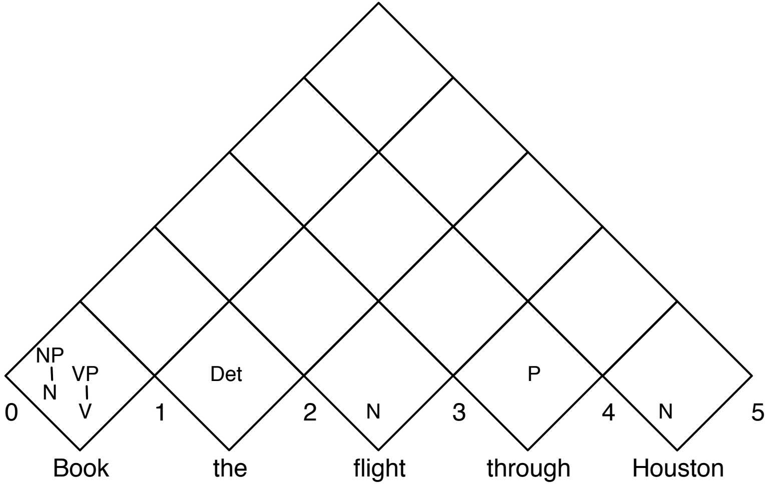

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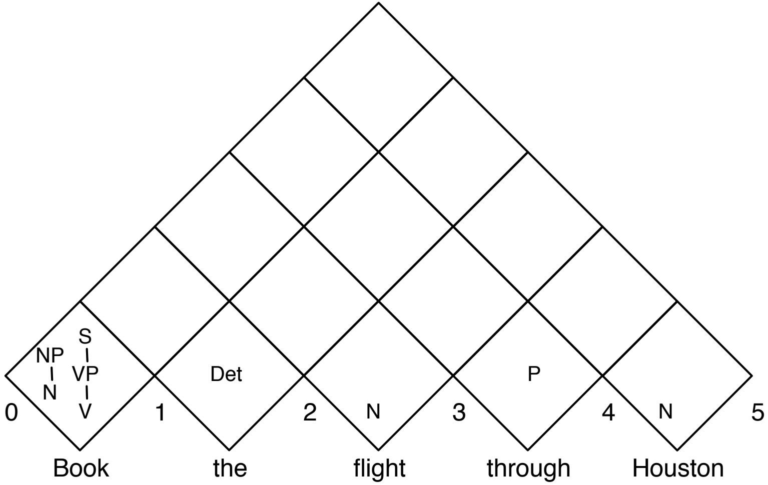

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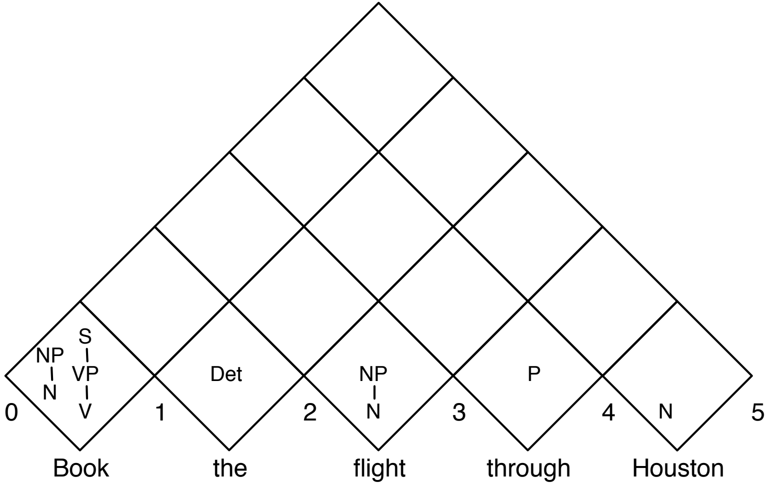

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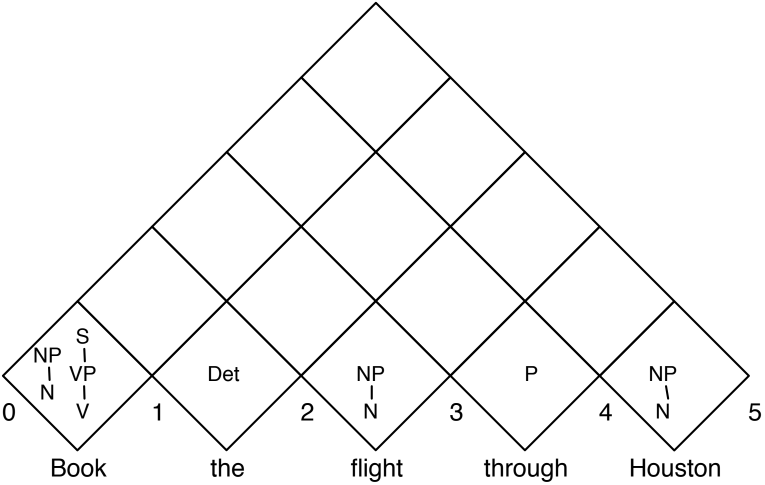

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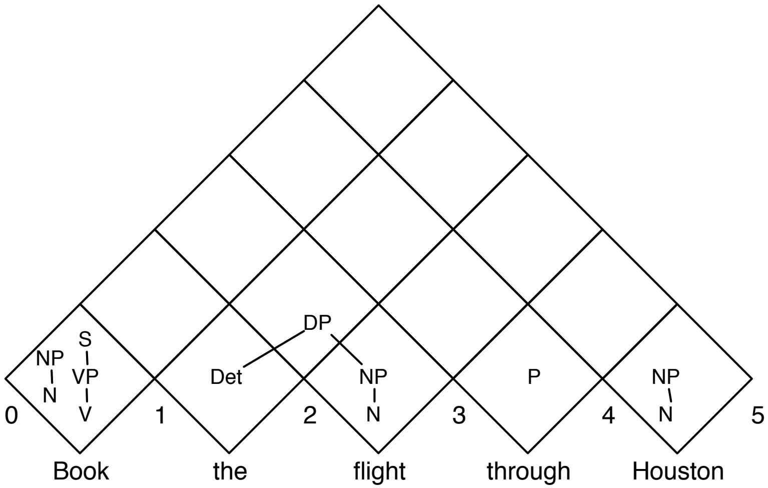

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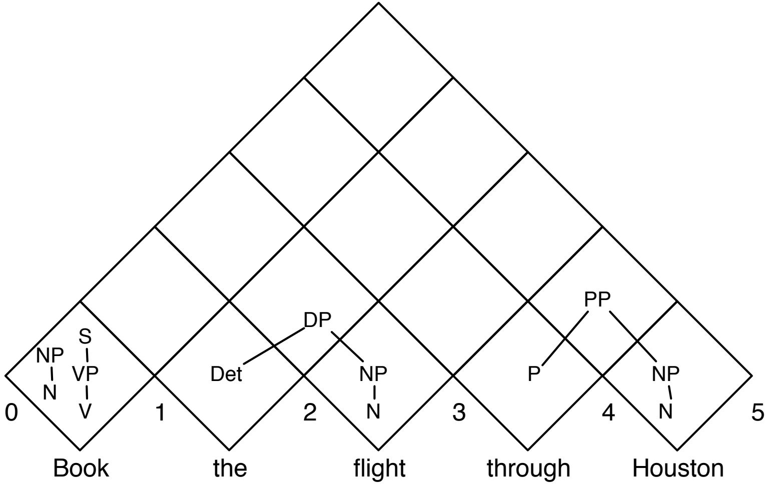

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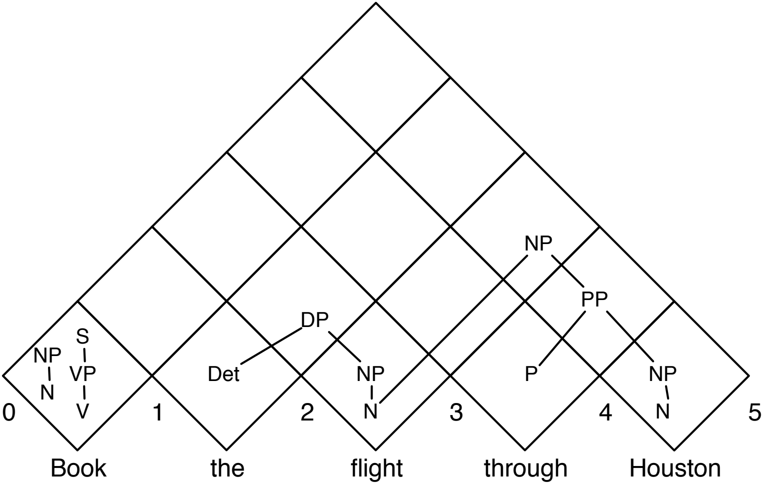

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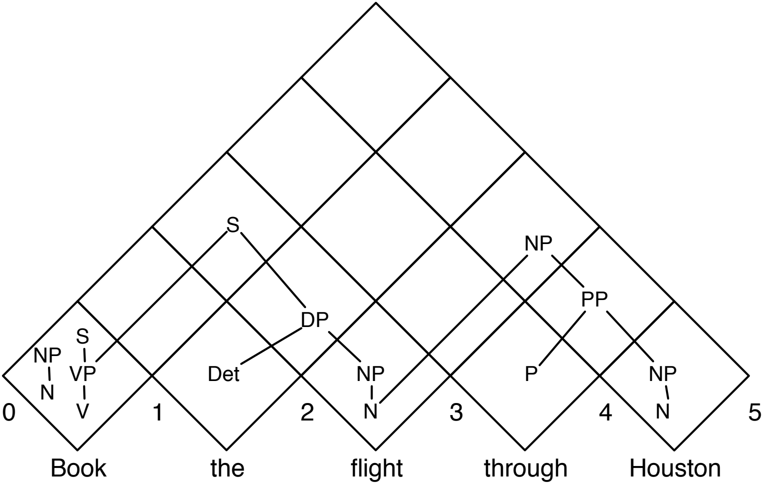

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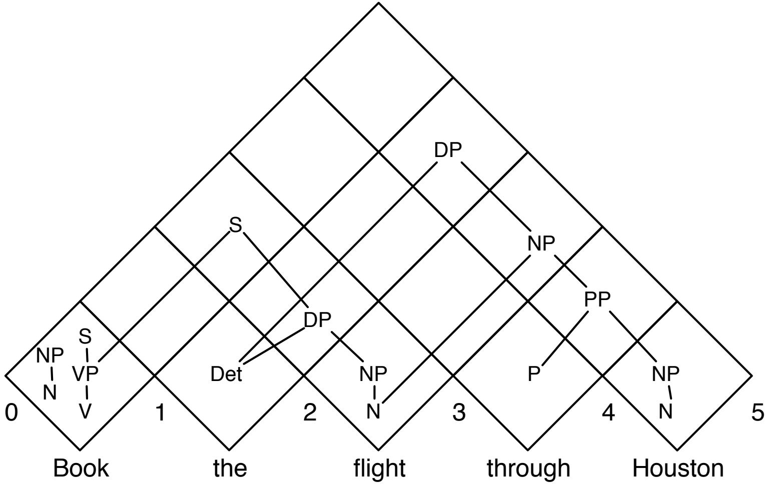

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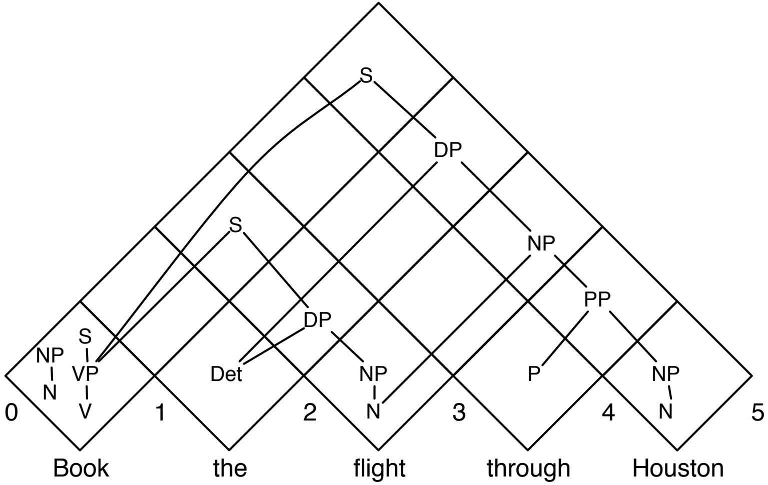

Complexity?

- Chart has n^2 cells

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- Times the number of productions $|G|$

Complexity?

- Chart has n^2 cells
- Each cell has n options
- Times the number of productions $|G|$
- Thus, $O(n^3|G|)$

How to deal with PCFG ambiguity

- In addition to keeping track of non-terminals in cell, also include **max** probability of forming non-terminal from sub-trees

$$C[s,s+k,\alpha] \leftarrow \max(C[s,s+k,\alpha], C[s,s+l-1,\beta] \cdot C[s+l,s+k,\gamma])$$

- The score associated with S in the top of the chart is the best overall parse-tree (**given the yield**)

Recap

- Hierarchical syntax model: context free grammar
- Probabilistic interpretation: learn from data to solve ambiguity
- In class (next time):
  - Work through example to resolve ambiguity
  - Scoring a sentence

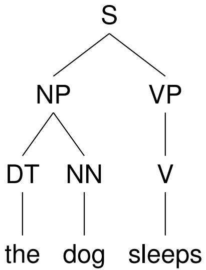
A pcfg

Assume the following grammar

s	⟶	np	vp	1.0	v	⟶	sleeps	0.4
vp	⟶	v	np	0.7	v	⟶	saw	0.6
vp	⟶	vp	pp	0.2	nn	⟶	man	0.1
vp	⟶	v		0.1	nn	⟶	woman	0.1
np	⟶	dt	nn	0.2	nn	⟶	telescope	0.3
np	⟶	np	pp	0.8	nn	⟶	dog	0.5
pp	⟶	p	np	1.0	dt	⟶	the	1.0
					p	⟶	with	0.6
					p	⟶	in	0.4

Evaluating the probability of a sentence

What is the probability of the parse



Evaluating the probability of a sentence

$$\underbrace{1.0}_{\text{det} \longrightarrow \text{the}} \cdot \underbrace{0.5}_{\text{n} \longrightarrow \text{dog}} \cdot \underbrace{1.0}_{\text{v} \longrightarrow \text{sleeps}} \cdot \underbrace{0.1}_{\text{vp} \longrightarrow \text{v}} \cdot \underbrace{0.2}_{\text{np} \longrightarrow \text{dt n}} \cdot \underbrace{1.0}_{\text{s} \longrightarrow \text{np vp}} = 0.002$$

Span 0

1. $C[8,8,\text{nn}] = \ln(0.3) = -1.2$
2. $C[7,7,\text{dt}] = \ln(1.0) = 0.0$
3. $C[6,6,\text{p}] = \ln(0.6) = -0.51$
4. $C[5,5,\text{nn}] = \ln(0.5) = -0.69$
5. $C[4,4,\text{dt}] = \ln(1.0) = 0.0$
6. $C[3,3,\text{v}] = \ln(0.6) = -.51$
7. $C[3,3,\text{vp}] = \ln(0.6) + \ln(0.1) = -2.8$
8. $C[2,2,\text{nn}] = \ln(0.1) = -2.3$
9. $C[1,1,\text{dt}] = \ln(1.0) = 0.0$

Span 1

1. $C[1,2,\text{np}] = \underbrace{0.0}_{\text{C[1,1,DT]}} + \ln(\underbrace{-2.3}_{\text{C[2,2,NN]}}) + \ln(\underbrace{0.2}_{\text{np} \rightarrow \text{dt n}}) = -2.3 + -1.6 = -3.9$

Span 1

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2. $C[4,5,\text{np}] = \underbrace{0.0}_{\text{C[4,4,DT]}} + \underbrace{-.69}_{\text{C[5,5,NN]}} + \ln(\underbrace{0.2}_{\text{np} \longrightarrow \text{dt n}}) = -0.69 + -1.6 = -2.3$

Span 1

1. $C[1,2,np] = \underbrace{0.0}_{\text{C[1,1,DT]}} + \ln(\underbrace{-2.3}_{\text{C[2,2,NN]}}) + \ln(\underbrace{0.2}_{\text{np} \rightarrow \text{dt n}}) = -2.3 + -1.6 = -3.9$

2. $C[4,5,np] = \underbrace{0.0}_{\text{C[4,4,DT]}} + \underbrace{-.69}_{\text{C[5,5,NN]}} + \ln(\underbrace{0.2}_{\text{np} \rightarrow \text{dt n}}) = -0.69 + -1.6 = -2.3$

3. $C[7,8,np] = \underbrace{0.0}_{\text{C[7,7,DT]}} + \underbrace{-1.2}_{\text{C[8,8,NN]}} + \ln(\underbrace{0.2}_{\text{np} \rightarrow \text{dt n}}) = -1.2 + -1.6 = -2.8$

Span 2

1. $C[1,3,\mathrm{s}] = \underbrace{-3.9}_{\text{C[1,2,NP]}} + \underbrace{-2.8}_{\text{C[3,3,VP]}} + \ln(\underbrace{1.0}_{\text{s} \rightarrow \text{np vp}}) = -6.7$

Span 2

1. $C[1,3,s] = \underbrace{-3.9}_{\text{C[1,2,NP]}} + \underbrace{-2.8}_{\text{C[3,3,VP]}} + \ln(\underbrace{1.0}_{\text{s} \rightarrow \text{np vp}}) = -6.7$
2. $C[3,5,vp] = \underbrace{-0.5}_{\text{C[3,3,V]}} + \underbrace{-2.3}_{\text{C[4,5,NP]}} + \ln(\underbrace{0.7}_{\text{vp} \rightarrow \text{v np}}) = -2.8 - 0.36 = -3.2$

Span 2

1. $C[1,3,\text{s}] = \underbrace{-3.9}_{\text{C[1,2,NP]}} + \underbrace{-2.8}_{\text{C[3,3,VP]}} + \ln(\underbrace{1.0}_{\text{s} \rightarrow \text{np vp}}) = -6.7$
2. $C[3,5,\text{vp}] = \underbrace{-0.5}_{\text{C[3,3,V]}} + \underbrace{-2.3}_{\text{C[4,5,NP]}} + \ln(\underbrace{0.7}_{\text{vp} \rightarrow \text{v np}}) = -2.8 - 0.36 = -3.2$
3. $C[6,8,\text{pp}] = \underbrace{-0.51}_{\text{C[6,6,P]}} + \underbrace{-2.8}_{\text{C[7,8,NP]}} + \ln(\underbrace{1.0}_{\text{pp} \rightarrow \text{p np}}) = -3.3 + -1.6 = -3.3$

Span 4

1. $C[1,5,\mathrm{s}] = \underbrace{-3.9}_{\text{C[1,2,NP]}} + \underbrace{-3.2}_{\text{C[3,5,VP]}} + \ln(\underbrace{1.0}_{\text{s} \rightarrow \text{np vp}}) = -7.1$

Span 4

1. $C[1,5,\text{s}] = \underbrace{-3.9}_{\text{C[1,2,NP]}} + \underbrace{-3.2}_{\text{C[3,5,VP]}} + \ln(\underbrace{1.0}_{\text{s} \rightarrow \text{np vp}}) = -7.1$
2. $C[4,8,\text{np}] = \underbrace{-2.3}_{\text{C[4,5,NP]}} + \underbrace{-3.3}_{\text{C[6,8,PP]}} + \ln(\underbrace{0.8}_{\text{np} \rightarrow \text{np pp}}) = -5.6 + -0.2 = -5.8$

Span 5

$$C[3,8,\mathrm{vp}] = \max(\tag{4}$$

$$\underbrace{-3.2}_{\text{C[3,5,VP]}} + \underbrace{-3.3}_{\text{C[6,8,PP]}} + \underbrace{-1.6}_{\text{vp} \rightarrow \text{vp pp}} , \tag{5}$$

$$\underbrace{-0.5}_{\text{C[3,3,V]}} + \underbrace{-5.8}_{\text{C[4,8,NP]}} + \underbrace{-.36}_{\text{vp} \rightarrow \text{v np}}) \tag{6}$$

$$= \max(-8.1, -6.7) = -6.7 \tag{7}$$

Span 7

1. $C[1,8,\mathrm{s}] = \underbrace{-3.9}_{\text{C[1,2,NP]}} + \underbrace{-6.7}_{\text{C[3,8,VP]}} = -10.6$