CSE 517
Natural Language Processing
Winter 2019

Parsing (Trees)

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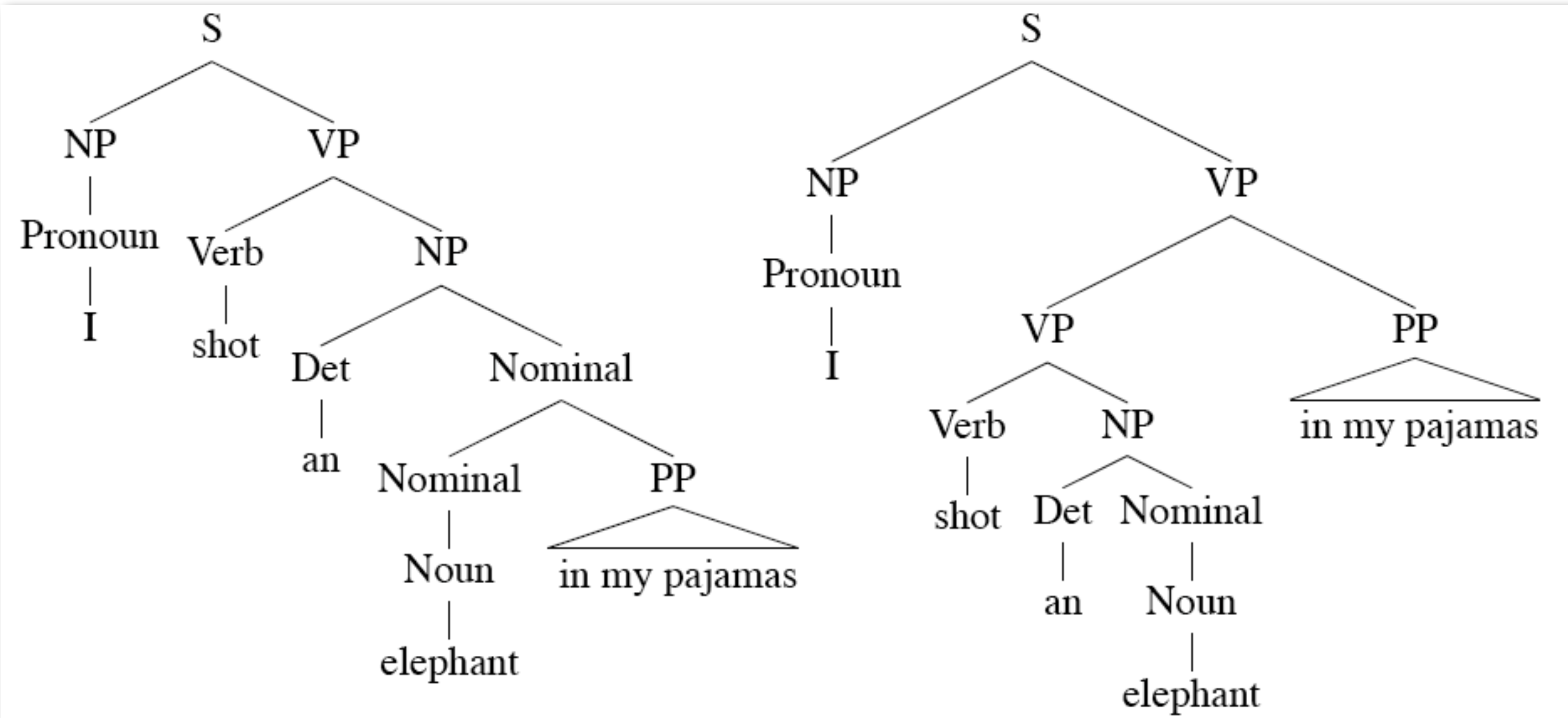
[Slides from Dan Klein, Michael Collins, Luke Zettlemoyer and Ray Mooney]

Ambiguities

I shot [an elephant] [in my pajamas]



Examples from J&M

Syntactic Ambiguities I

- Prepositional phrases:
  They cooked the beans in the pot on the stove with handles.
- Particle vs. preposition:
  The puppy tore up the staircase.
- Complement structures
  The tourists objected to the guide that they couldn't hear.
  She knows you like the back of her hand.
- Gerund vs. participial adjective
  Visiting relatives can be boring.
  Changing schedules frequently confused passengers.

Syntactic Ambiguities II

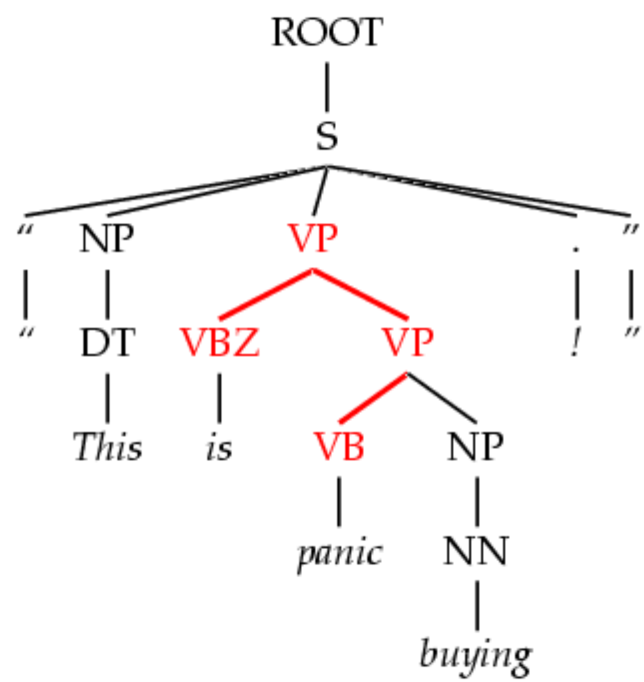
- Modifier scope within NPs
  impractical design requirements
  plastic cup holder
- Multiple gap constructions
  The chicken is ready to eat.
  The contractors are rich enough to sue.
- Coordination scope:
  Small rats and mice can squeeze into holes or cracks in the wall.

Dark Ambiguities

- *Dark ambiguities*: most analyses are shockingly bad (meaning, they don't have an interpretation you can get your mind around)

This analysis corresponds to the correct parse of

"This will panic buyers ! "



- Unknown words and new usages
- Solution: We need mechanisms to focus attention on the best ones, probabilistic techniques do this

Probabilistic
Context Free Grammars

Probabilistic Context-Free Grammars

- A context-free grammar is a tuple <*N*, Σ, *S*, *R*>
  - *N* : the set of non-terminals
    - Phrasal categories: S, NP, VP, ADJP, etc.
    - Parts-of-speech (pre-terminals): NN, JJ, DT, VB, etc.
  - Σ : the set of terminals (the words)
  - *S* : the start symbol
    - Often written as ROOT or TOP
    - *Not* usually the sentence non-terminal S
  - *R* : the set of rules
    - Of the form $X \rightarrow Y_1\ Y_2 \ldots Y_n$, with $X \in N$, $n \geq 0$, $Y_i \in (N \cup \Sigma)$
    - Examples: $S \rightarrow NP\ VP$, $VP \rightarrow VP\ CC\ VP$
- A PCFG adds a distribution q:
  - Probability q(r) for each $r \in R$, such that for all $X \in N$:

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

PCFG Example

S	$\Rightarrow$	NP	VP	1.0
VP	$\Rightarrow$	Vi		0.4
VP	$\Rightarrow$	Vt	NP	0.4
VP	$\Rightarrow$	VP	PP	0.2
NP	$\Rightarrow$	DT	NN	0.3
NP	$\Rightarrow$	NP	PP	0.7
PP	$\Rightarrow$	P	NP	1.0

Vi	$\Rightarrow$	sleeps	1.0
Vt	$\Rightarrow$	saw	1.0
NN	$\Rightarrow$	man	0.7
NN	$\Rightarrow$	woman	0.2
NN	$\Rightarrow$	telescope	0.1
DT	$\Rightarrow$	the	1.0
IN	$\Rightarrow$	with	0.5
IN	$\Rightarrow$	in	0.5

- Probability of a tree t with rules

$$\alpha_1 \rightarrow \beta_1, \alpha_2 \rightarrow \beta_2, \ldots, \alpha_n \rightarrow \beta_n$$

is

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

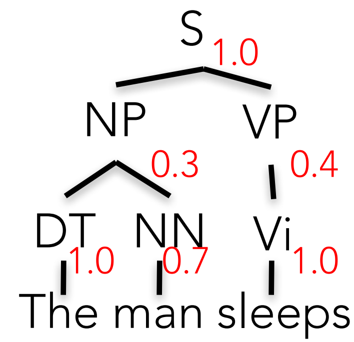
where $q(\alpha \rightarrow \beta)$ is the probability for rule $\alpha \rightarrow \beta$.

PCFG Example

S	$\Rightarrow$	NP	VP	1.0
VP	$\Rightarrow$	Vi		0.4
VP	$\Rightarrow$	Vt	NP	0.4
VP	$\Rightarrow$	VP	PP	0.2
NP	$\Rightarrow$	DT	NN	0.3
NP	$\Rightarrow$	NP	PP	0.7
PP	$\Rightarrow$	P	NP	1.0

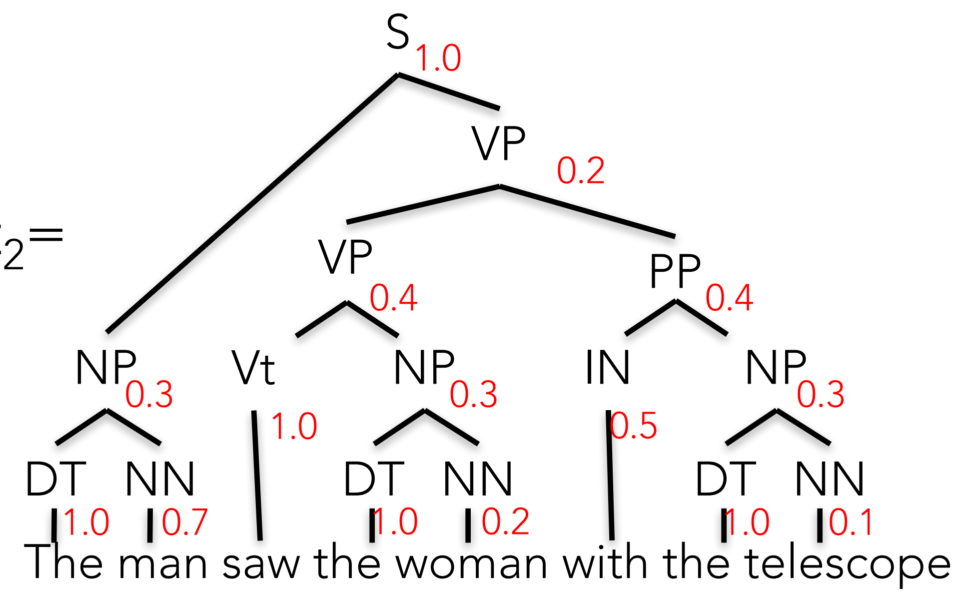
Vi	$\Rightarrow$	sleeps	1.0
Vt	$\Rightarrow$	saw	1.0
NN	$\Rightarrow$	man	0.7
NN	$\Rightarrow$	woman	0.2
NN	$\Rightarrow$	telescope	0.1
DT	$\Rightarrow$	the	1.0
IN	$\Rightarrow$	with	0.5
IN	$\Rightarrow$	in	0.5

$t_1=$



$p(t_1)=1.0*0.3*1.0*0.7*0.4*1.0$

$t_2=$



$p(t_s)=1.8*0.3*1.0*0.7*0.2*0.4*1.0*0.3*1.0*0.2*0.4*0.5*0.3*1.0*0.1$

PCFGs: Learning and Inference

- Model
  - The probability of a tree t with n rules $\alpha_i \rightarrow \beta_i$, i = 1..n

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

- Learning
  - Read the rules off of labeled sentences, use ML estimates for probabilities

$$q_{ML}(\alpha \rightarrow \beta) = \frac{\text{Count}(\alpha \rightarrow \beta)}{\text{Count}(\alpha)}$$

  - and use all of our standard smoothing tricks!

- Inference
  - For input sentence s, define T(s) to be the set of trees whole yield is s (whole leaves, read left to right, match the words in s)

$$t^*(s) = \arg\max_{t \in \mathcal{T}(s)} p(t)$$

Dynamic Programming

- We will store: score of the max parse of x_i to x_j with root non-terminal X

$$\pi(i, j, X)$$

- So we can compute the most likely parse:

$$\pi(1, n, S) = \max_{t \in \mathcal{T}_G(s)} p(t)$$

- Via the recursion:

$$\pi(i, j, X) = \max_{\substack{X \to YZ \in R, \\ s \in \{i \ldots (j-1)\}}} \left(q(X \to YZ) \times \pi(i, s, Y) \times \pi(s+1, j, Z) \right)$$

- With base case:

$$\pi(i, i, X) = \begin{cases} q(X \to x_i) & \text{if } X \to x_i \in R \\ 0 & \text{otherwise} \end{cases}$$

The CKY Algorithm

- Input: a sentence s = x_1 .. x_n and a PCFG = <N, Σ ,S, R, q>
- Initialization: For i = 1 … n and all X in N

$$\pi(i,i,X) = \begin{cases} q(X \rightarrow x_i) & \text{if } X \rightarrow x_i \in R \\ 0 & \text{otherwise} \end{cases}$$

- For l = 1 … (n-1) [iterate all phrase lengths]
  - For i = 1 … (n-l) and j = i+l [iterate all phrases of length l]
    - For all X in N [iterate all non-terminals]

$$\pi(i,j,X) = \max_{\substack{X \rightarrow YZ \in R, \\ s \in \{i \ldots (j-1)\}}} \left(q(X \rightarrow YZ) \times \pi(i,s,Y) \times \pi(s+1,j,Z) \right)$$

    - also, store back pointers

$$bp(i,j,X) = \arg \max_{\substack{X \rightarrow YZ \in R, \\ s \in \{i \ldots (j-1)\}}} \left(q(X \rightarrow YZ) \times \pi(i,s,Y) \times \pi(s+1,j,Z) \right)$$

Probabilistic CKY Parser

S → NP VP	0.8
S → X1 VP	0.1
X1 → Aux NP	1.0
S → book | include | prefer **0.01 0.004 0.006**	
S → Verb NP	0.05
S → VP PP	0.03
NP → I | he | she | me **0.1 0.02 0.02 0.06**	
NP → Houston | NWA **0.16 .04**	
Det→ the | a | an **0.6 0.1 0.05**	
NP → Det Nominal	0.6
Nominal → book | flight | meal | money **0.03 0.15 0.06 0.06**	
Nominal → Nominal Nominal	0.2
Nominal → Nominal PP	0.5
Verb→ book | include | prefer **0.5 0.04 0.06**	
VP → Verb NP	0.5
VP → VP PP	0.3
Prep → through | to | from **0.2 0.3 0.3**	
PP → Prep NP	1.0

Book	**the**	**flight**	**through**	**Houston**
S :.01, **Verb:.5** **Nominal:.03**	**None**	**S:.05*.5*.054** **=.00135** **VP:.5*.5*.054** **=.0135**	None	**S:.03*.0135*.032** **=.00001296** **S:.05*.5*** **.000864** **=.0000216**
	Det:.6	**NP:.6*.6*.15** **=.054**	None	**NP:.6*.6*** **.0024** **=.000864**
		Nominal:.15	None	Nominal: .5*.15*.032 =.0024
			Prep:.2	PP:1.0*.2*.16 =.032
				NP:.16

Probabilistic CKY Parser

Book	the	flight	through	Houston
S :.01, Verb:.5 Nominal:.03	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135	None	S:.0000216
	Det:.6	NP:.6*.6*.15 =.054	None	NP:.6*.6* .0024 =.000864
		Nominal:.15	None	Nominal: .5*.15*.032 =.0024
			Prep:.2	PP:1.0*.2*.16 =.032
				NP:.16

Parse Tree #1

Pick most probable parse, i.e. take max to combine probabilities of multiple derivations of each constituent in each cell.

Probabilistic CKY Parser

Book	the	flight	through	Houston
S :.01, Verb:.5 Nominal:.03	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135	None	S: 00001296 S:.0000216
	Det:.6	NP:.6*.6*.15 =.054	None	NP:.6*.6* .0024 =.000864
		Nominal:.15	None	Nominal: .5*.15*.032 =.0024
			Prep:.2	PP:1.0*.2*.16 =.032
				NP:.16

Parse Tree #2

Pick most probable parse, i.e. take max to combine probabilities of multiple derivations of each constituent in each cell.

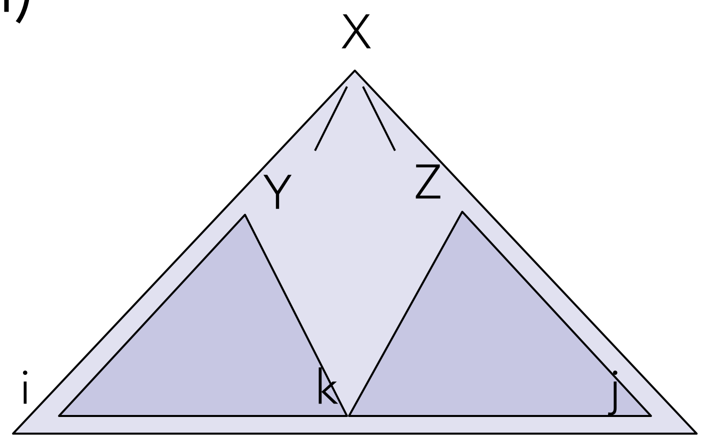
Memory

- How much memory does this require?
  - Have to store the score cache
  - Cache size: |symbols|*n^2
- Pruning: Beam Search
  - score[X][i][j] can get too large (when?)
  - Can keep beams (truncated maps score[i][j]) which only store the best K scores for the span [i,j]
- Pruning: Coarse-to-Fine
  - Use a smaller grammar to rule out most X[i,j]
  - Much more on this later…

Time: Theory

- How much time will it take to parse?

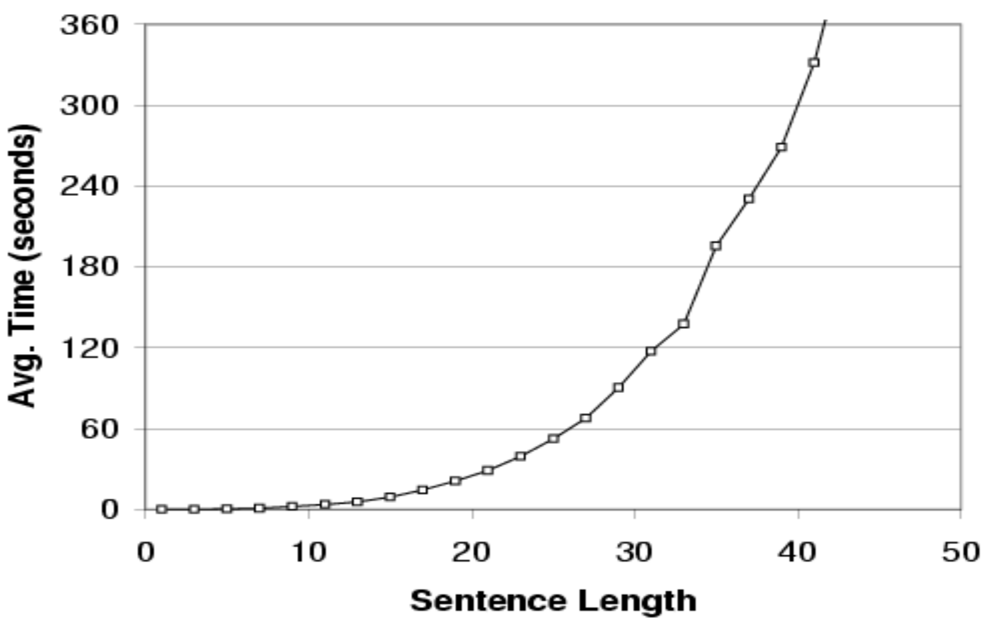
  - For each diff (:= j – i) (<= n)
    - For each i (<= n)
      - For each rule X → Y Z
        - For each split point k
          Do constant work



- Total time: |rules|*n^3
- Something like 5 sec for an unoptimized parse of a 20-word sentences

Time: Practice

- Parsing with the vanilla treebank grammar:



~ 20K Rules

(not an optimized parser!)

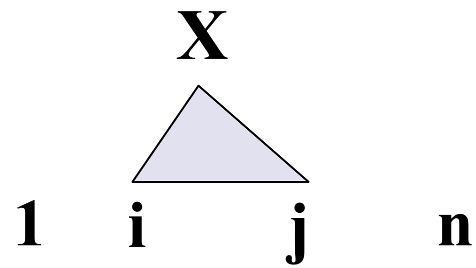
Observed exponent: 3.6

- Why's it worse in practice?
  - Longer sentences "unlock" more of the grammar
  - All kinds of systems issues don't scale

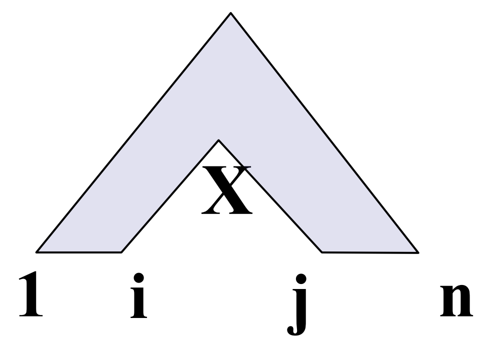
Other Dynamic Programs

Can also compute other quantities:

- Best Inside: score of the max parse of w_i to w_j with root non-terminal X

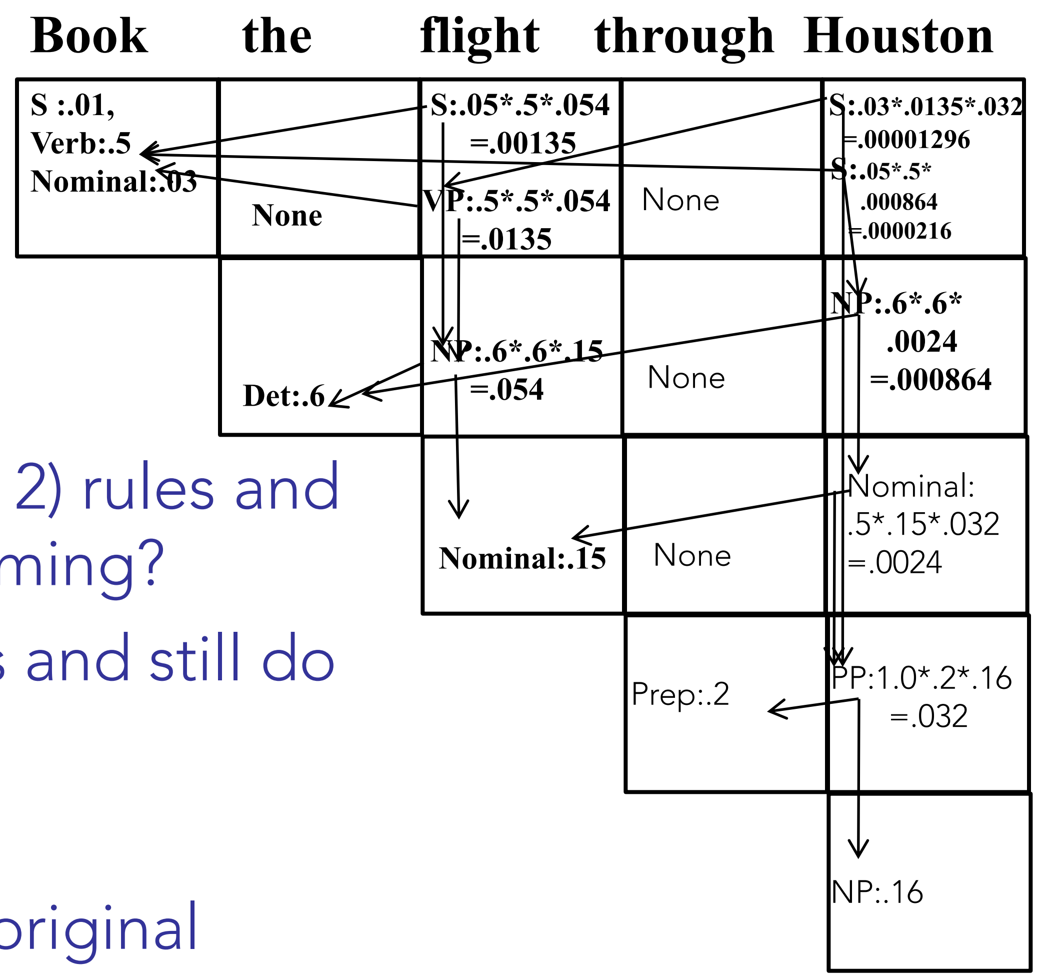


- Best Outside: score of the max parse of w_0 to w_n with a gap from w_i to w_j rooted with non-terminal X
  - see notes for derivation, it is a bit more complicated



- Sum Inside/Outside: Do sums instead of maxes

Why Chomsky Normal Form?



Inference:

- Can we keep N-ary (N > 2) rules and still do dynamic programming?
- Can we keep unary rules and still do dynamic programming?

Learning:

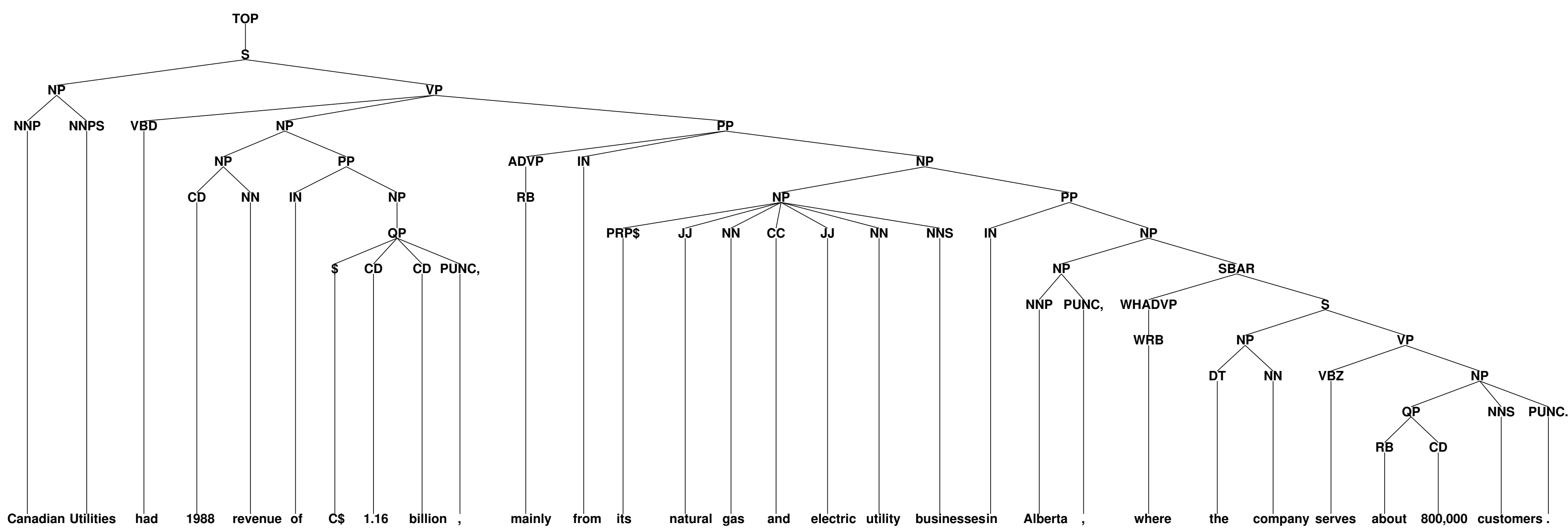
- Can we reconstruct the original trees?

Treebanks

The Penn Treebank: Size

- Penn WSJ Treebank = 50,000 sentences with associated trees
- Usual set-up: 40,000 training sentences, 2400 test sentences

An example tree:



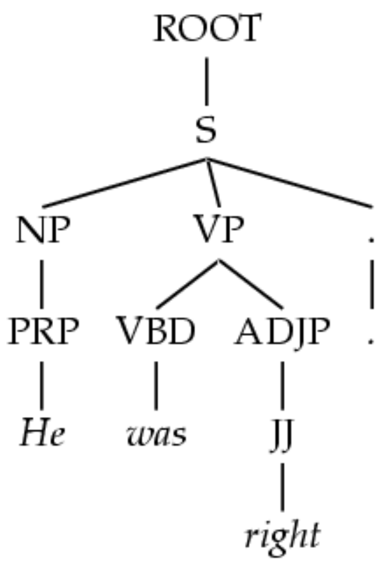
Penn Treebank Non-terminals

Table 1.2. The Penn Treebank syntactic tagset

ADJP	Adjective phrase
ADVP	Adverb phrase
NP	Noun phrase
PP	Prepositional phrase
S	Simple declarative clause
SBAR	Subordinate clause
SBARQ	Direct question introduced by *wh*-element
SINV	Declarative sentence with subject-aux inversion
SQ	Yes/no questions and subconstituent of SBARQ excluding *wh*-element
VP	Verb phrase
WHADVP	Wh-adverb phrase
WHNP	Wh-noun phrase
WHPP	Wh-prepositional phrase
X	Constituent of unknown or uncertain category
*	"Understood" subject of infinitive or imperative
0	Zero variant of *that* in subordinate clauses
T	Trace of wh-Constituent

Treebank Grammars

- Need a PCFG for broad coverage parsing.
- Can take a grammar right off the trees (doesn't work well):



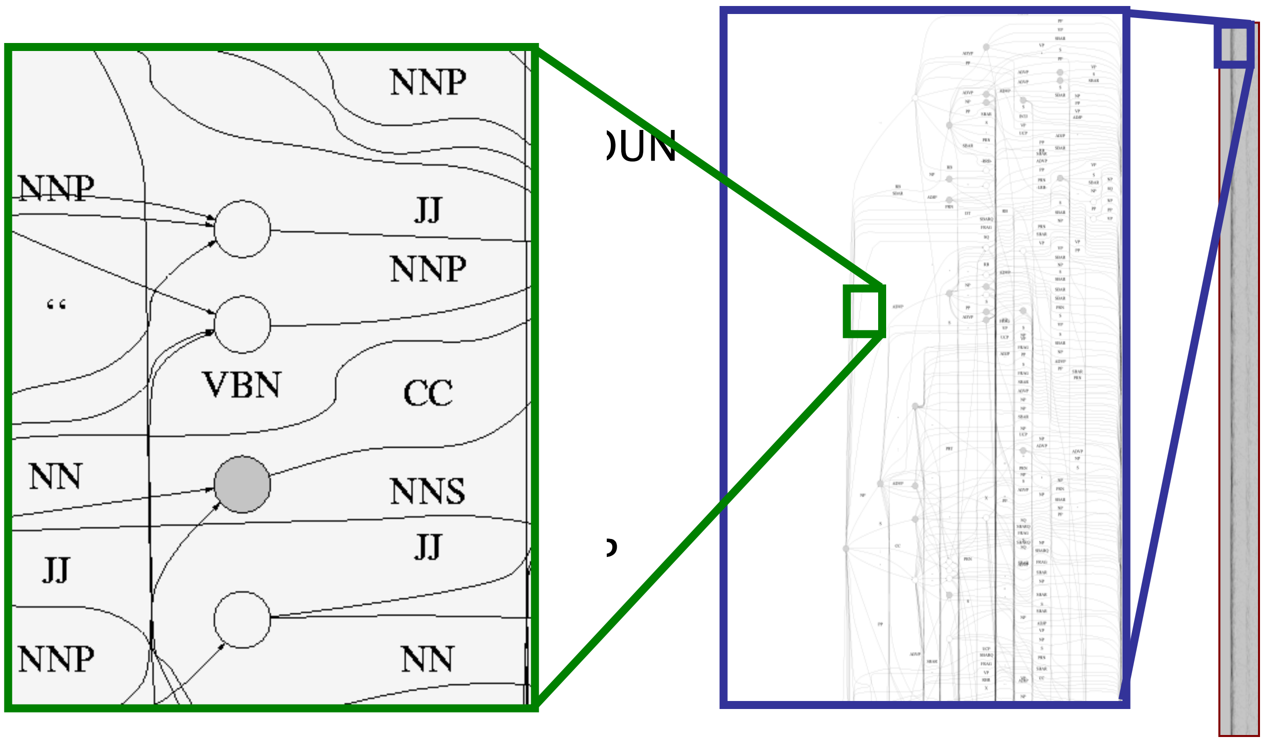
ROOT → S	1
S → NP VP .	1
NP → PRP	1
VP → VBD ADJP	1
…..	

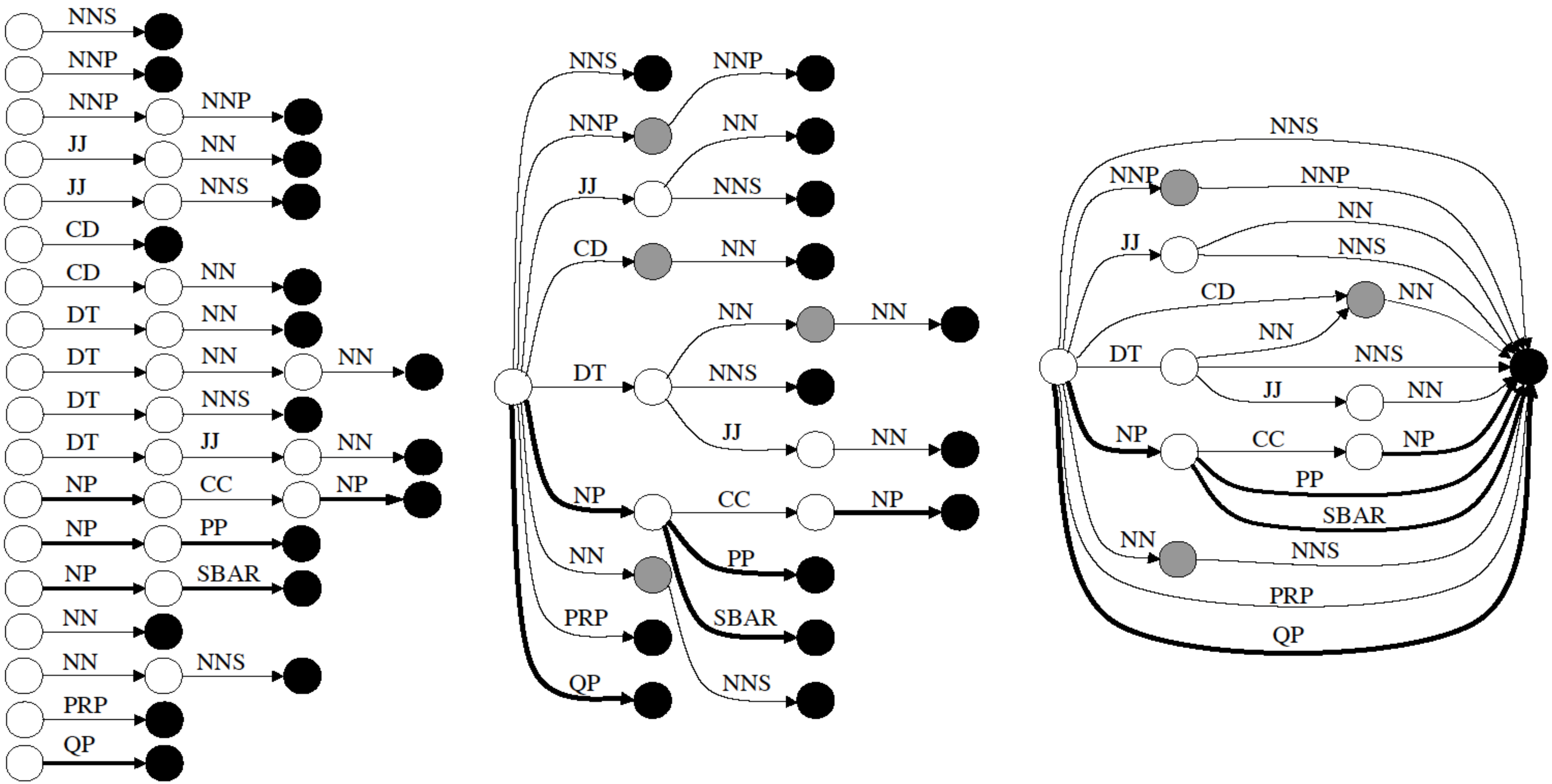
- Better results by enriching the grammar (e.g., lexicalization).
- Can also get reasonable parsers without lexicalization.

Treebank Grammar Scale

- Treebank grammars can be enormous
  - As FSAs, the raw grammar has ~10K states, excluding the lexicon
  - Better parsers usually make the grammars larger, not smaller

NP:





LIST TRIE Min FSA

Grammar encodings: Non-black states are active, non-white states are accepting, and bold transitions are phrasal. FSAs for a subset of the rules for the category NP.

Typical Experimental Setup

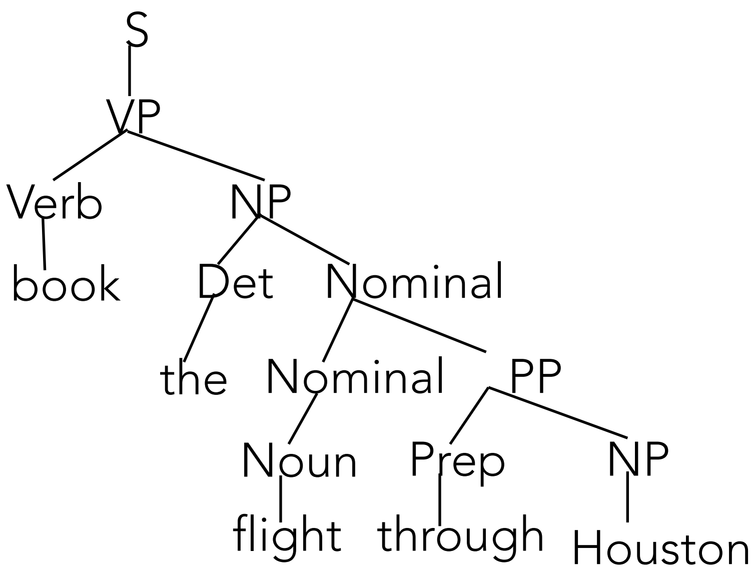
- Corpus: Penn Treebank, WSJ

Training:	sections	02-21
Development:	section	22 (here, first 20 files)
Test:	section	23

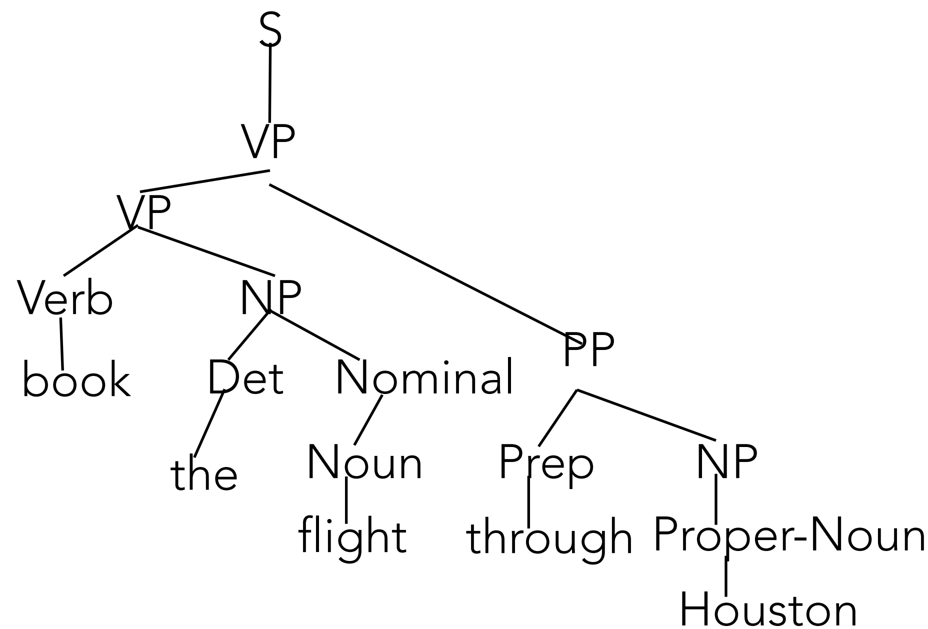
- Accuracy – F1: harmonic mean of per-node labeled precision and recall.
- Here: also size – number of symbols in grammar.
  - Passive / complete symbols: NP, NP^S
  - Active / incomplete symbols: NP → NP CC •

How to Evaluate?

Correct Tree T

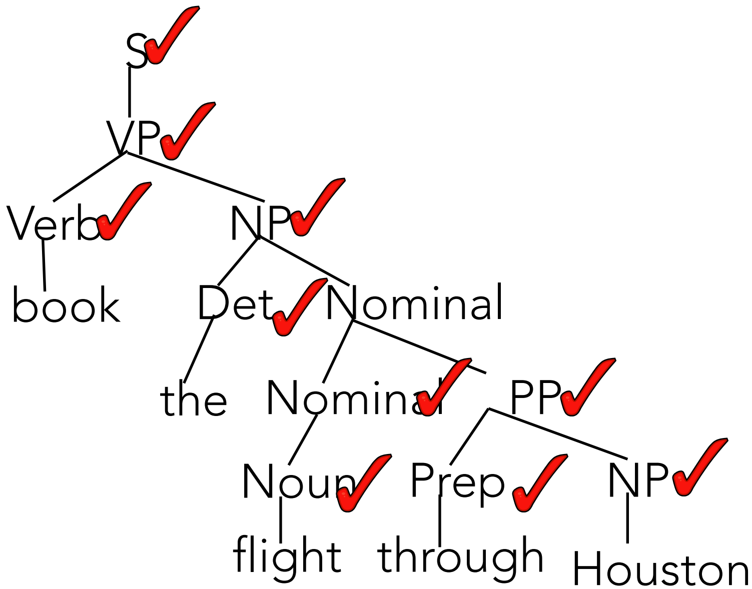


Computed Tree P

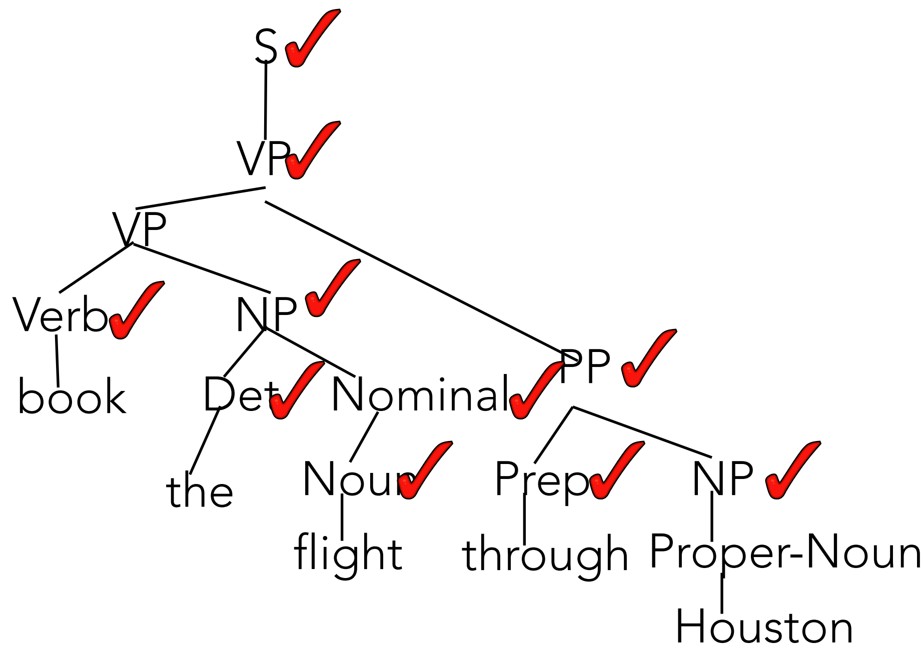


PARSEVAL Example

Correct Tree T



Computed Tree P



Constituents: 11

Constituents: 12

Correct Constituents: 10

Recall = 10/11= 90.9% Precision = 10/12=83.3% F_1 = 87.4%

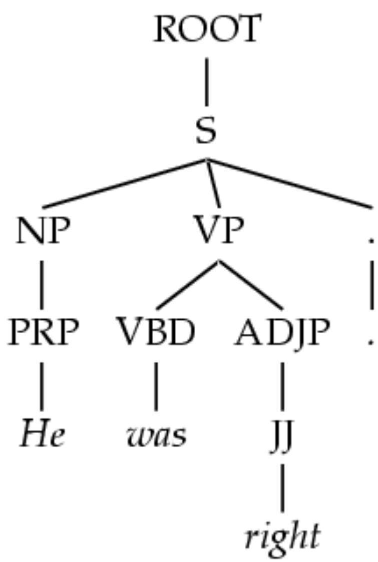
Evaluation Metric

- PARSEVAL metrics measure the fraction of the constituents that match between the computed and human parse trees. If P is the system's parse tree and T is the human parse tree (the "gold standard"):
  - Recall = (# correct constituents in P) / (# constituents in T)
  - Precision = (# correct constituents in P) / (# constituents in P)
- Labeled Precision and labeled recall require getting the non-terminal label on the constituent node correct to count as correct.
- F1 is the harmonic mean of precision and recall.
  - F1= (2 * Precision * Recall) / (Precision + Recall)

Performance with Vanilla PCFGs

[Charniak 96]

- Use PCFGs for broad coverage parsing
- Take the grammar right off the trees



ROOT → S	1
S → NP VP .	1
NP → PRP	1
VP → VBD ADJP	1

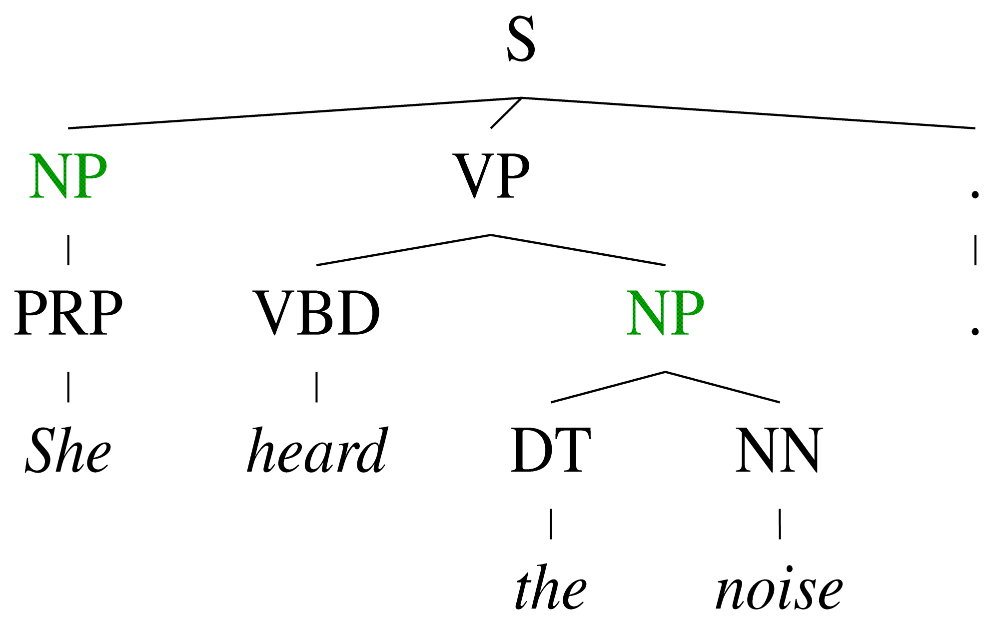
.....

Model	*F1*
Baseline	72.0

Grammar Refinements

1. Markovization

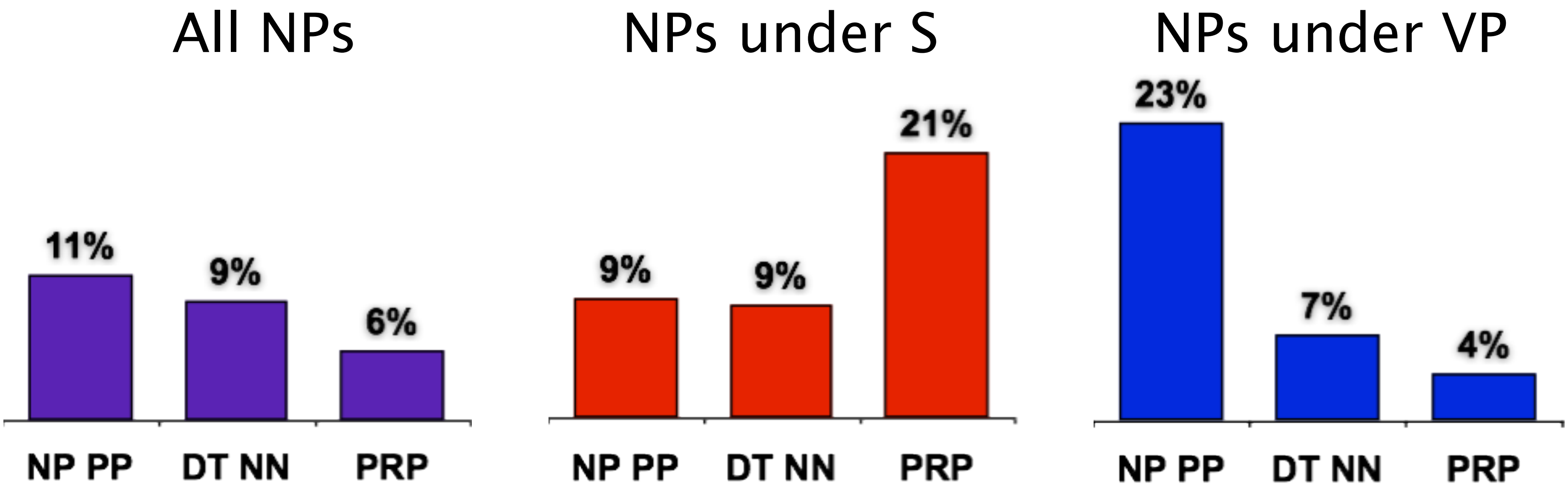
Conditional Independence?



- Not every NP expansion can fill every NP slot
  - A grammar with symbols like "NP" won't be context-free
  - Statistically, conditional independence too strong

Non-Independence

- Independence assumptions are often too strong.



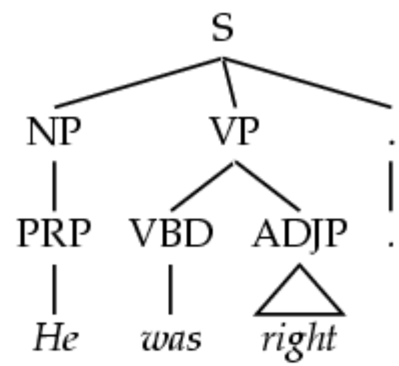
- Example: the expansion of an NP is highly dependent on the parent of the NP (i.e., subjects vs. objects).
- Also: the subject and object expansions are correlated!

Vertical Markovization

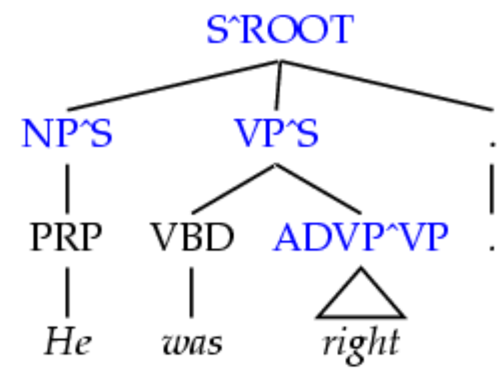
- Vertical Markov order: rewrites depend on past k ancestor nodes.

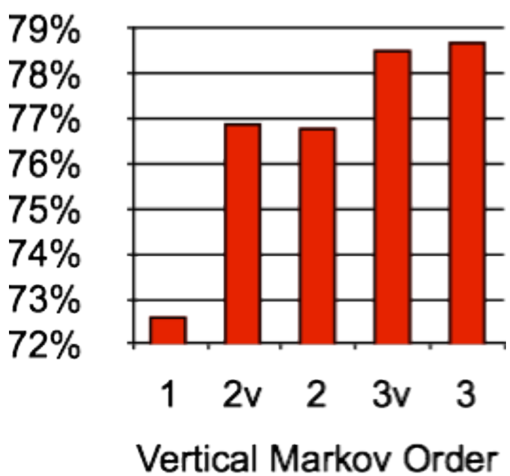
  (cf. parent annotation)

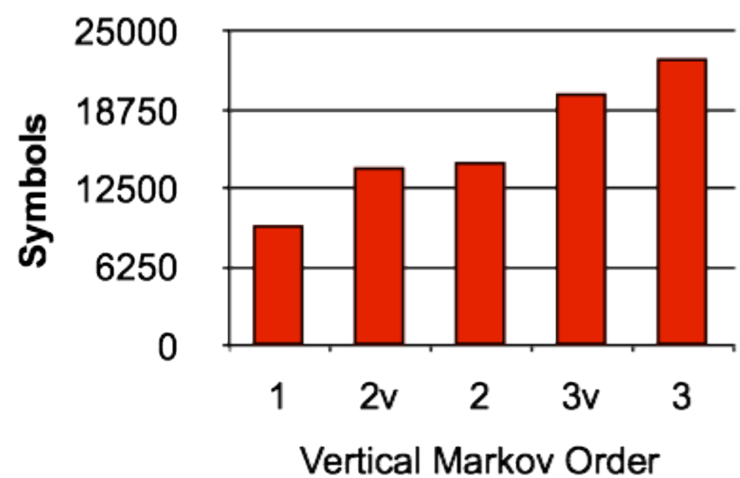
Order 1



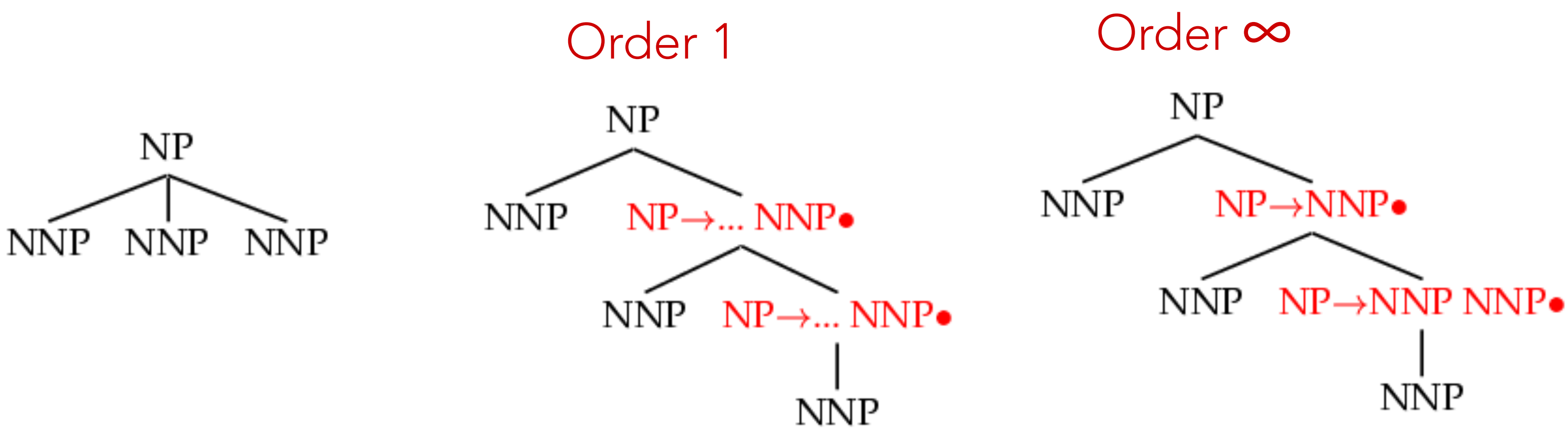
Order 2

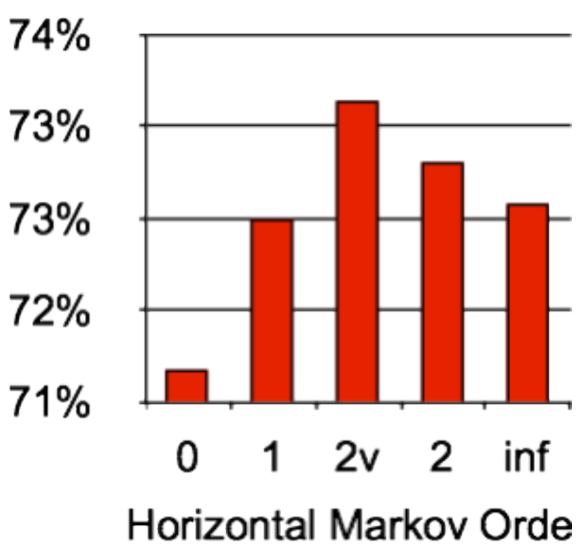


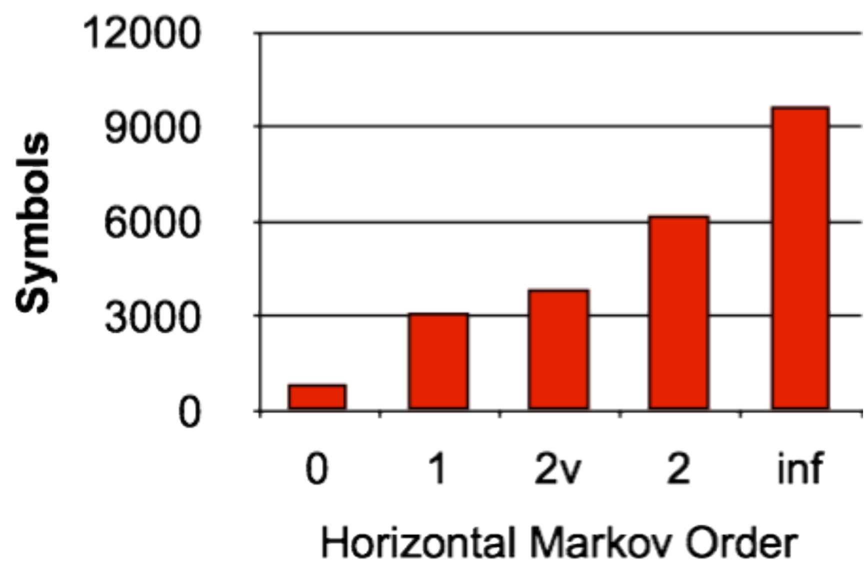




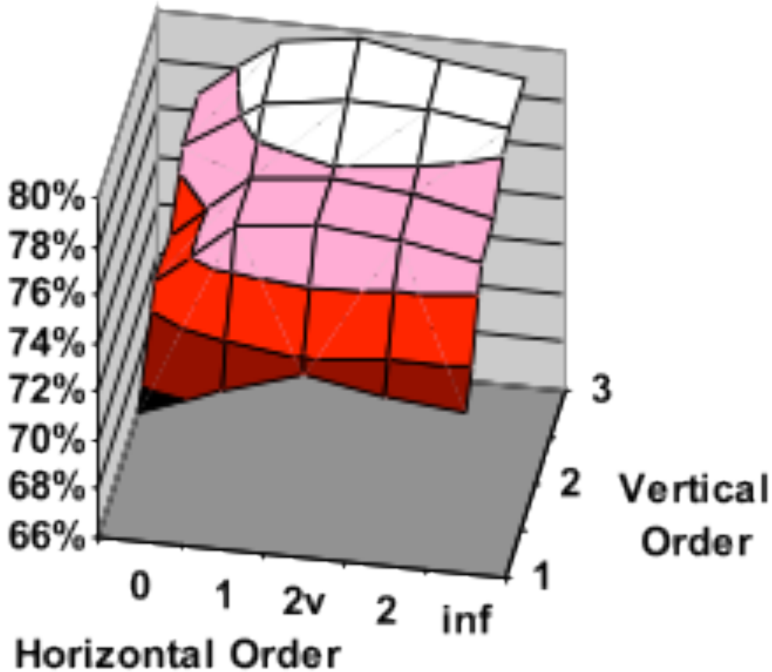
Horizontal Markovization

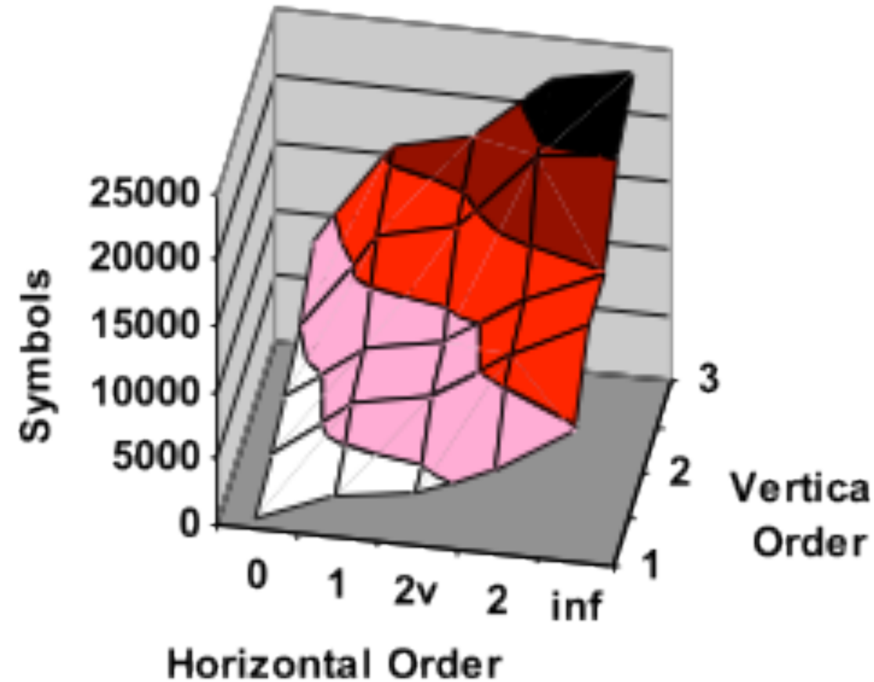






Vertical and Horizontal





Model	F1	Size
v=h=2v	77.8	7.5K

Unlexicalized PCFG Grammar Size

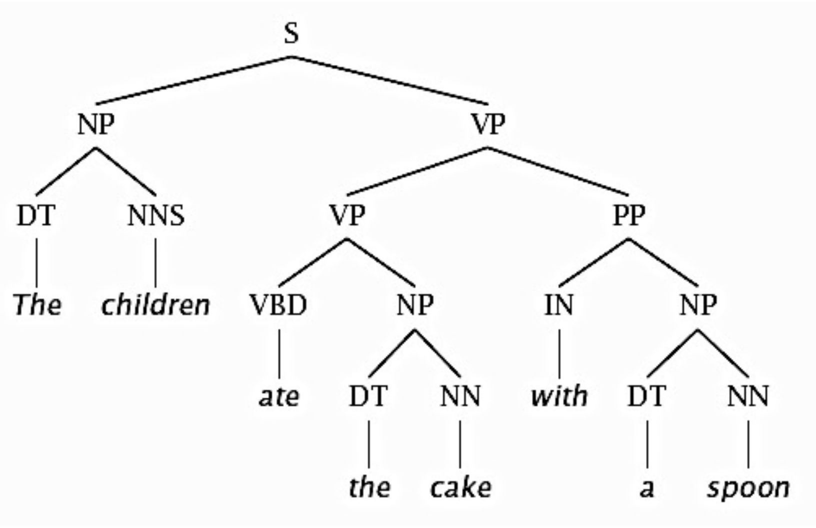
Vertical Order		Horizontal Markov Order $h = 0$	$h = 1$	$h \leq 2$	$h = 2$	$h = \infty$
$v = 1$	No annotation	71.27 (854)	72.5 (3119)	73.46 (3863)	72.96 (6207)	72.62 (9657)
$v \leq 2$	Sel. Parents	74.75 (2285)	77.42 (6564)	77.77 (7619)	77.50 (11398)	76.91 (14247)
$v = 2$	All Parents	74.68 (2984)	77.42 (7312)	77.81 (8367)	77.50 (12132)	76.81 (14666)
$v \leq 3$	Sel. GParents	76.50 (4943)	78.59 (12374)	79.07 (13627)	78.97 (19545)	78.54 (20123)
$v = 3$	All GParents	76.74 (7797)	79.18 (15740)	79.74 (16994)	79.07 (22886)	78.72 (22002)

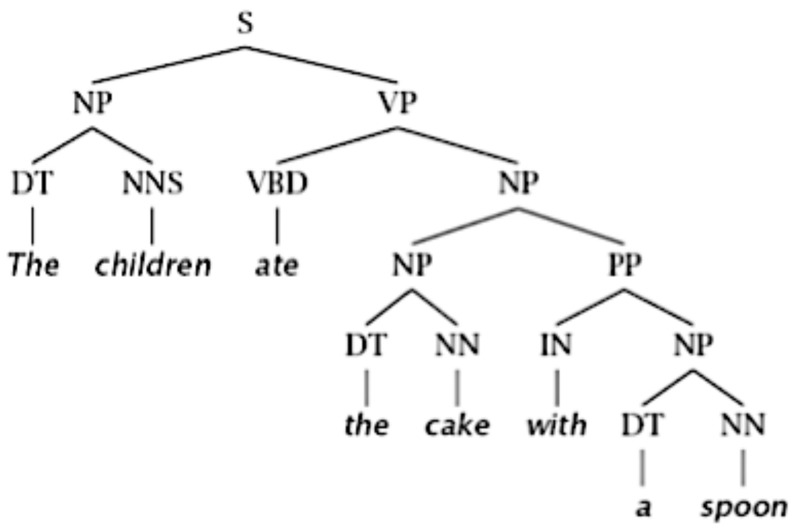
Figure 2: Markovizations: F_1 and grammar size.

Grammar Refinements

2. Lexicalization

Problems with PCFGs

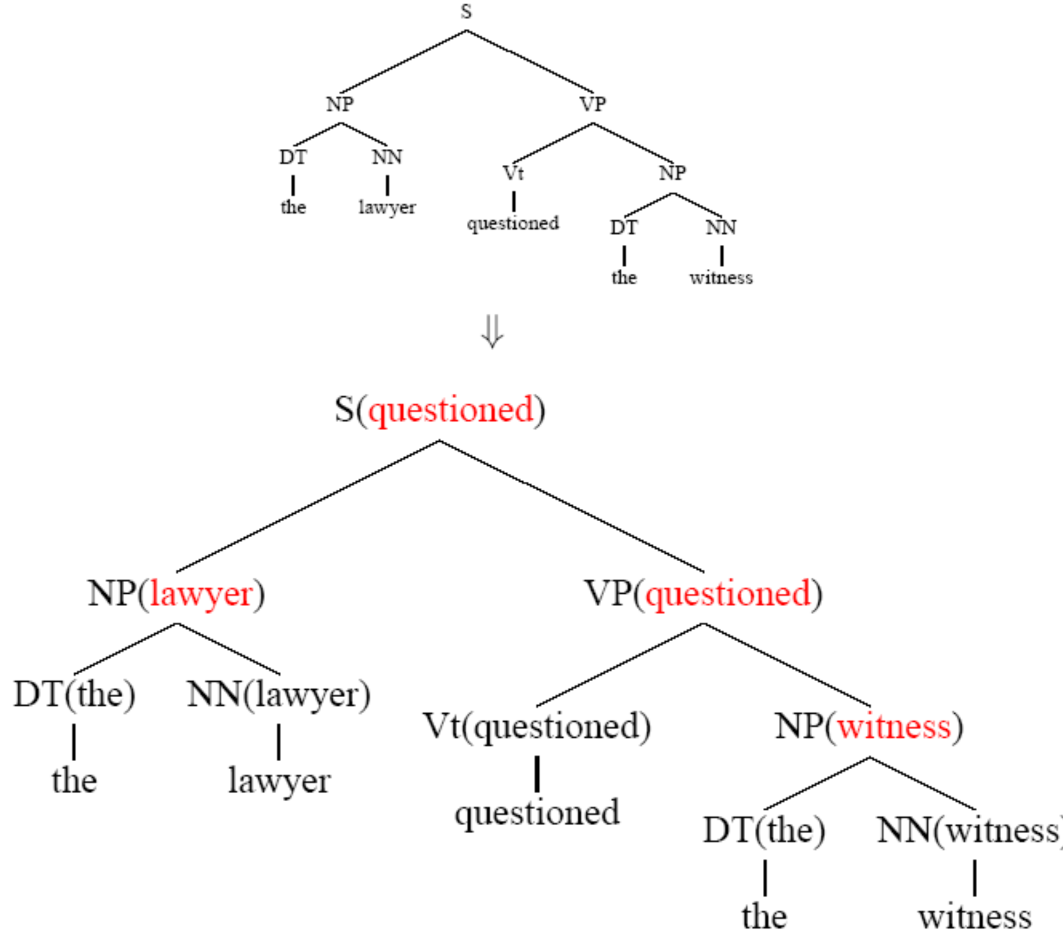




- These trees differ only in one rule:
  - VP → VP PP
  - NP → NP PP
- Lexicalization allows us to be sensitive to specific words

Lexicalize Trees!

- Add "headwords" to each phrasal node
  - Headship not in (most) treebanks
  - Usually *use (handwritten) head rules*, e.g.:
    - NP:
      - Take leftmost NP
      - Take rightmost N*
      - Take rightmost JJ
      - Take right child
    - VP:
      - Take leftmost VB*
      - Take leftmost VP
      - Take left child



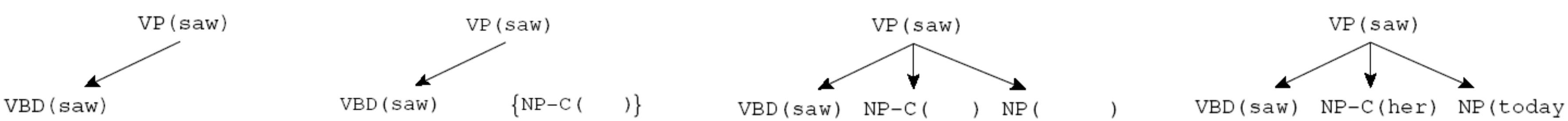
Lexicalized PCFGs?

- Problem: we now have to estimate probabilities like

```
VP(saw) -> VBD(saw) NP-C(her) NP(today)
```

- Never going to get these atomically off of a treebank

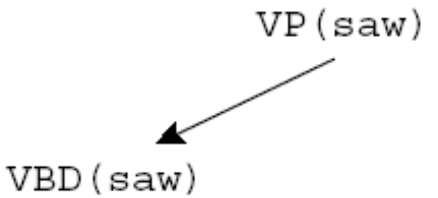
- Solution: break up derivation into smaller steps



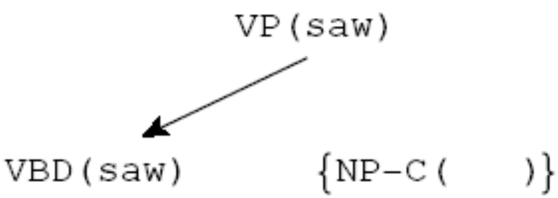
Lexical Derivation Steps

[Collins 99]

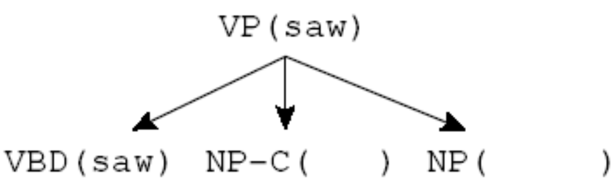
- Main idea: define a linguistically-motivated Markov process for generating children given the parent



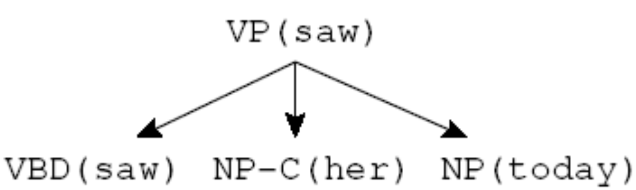
Step 1: Choose a head tag and word



Step 2: Choose a complement bag

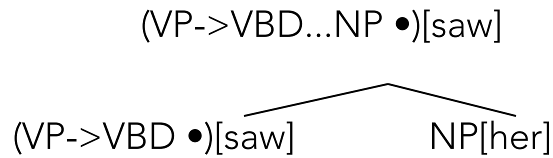


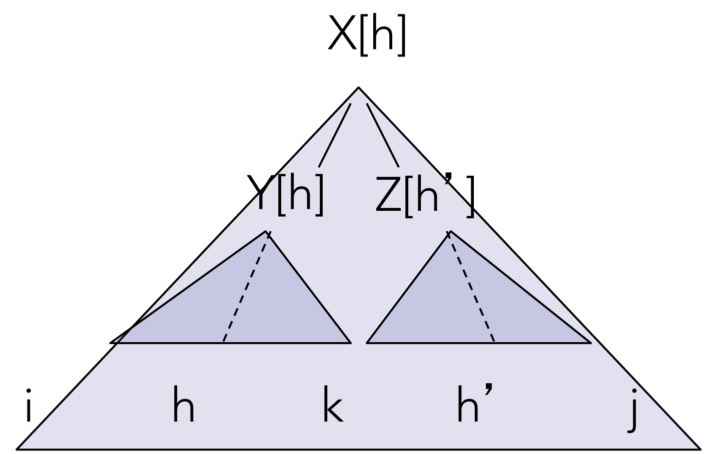
Step 3: Generate children (incl. adjuncts)



Step 4: Recursively derive children

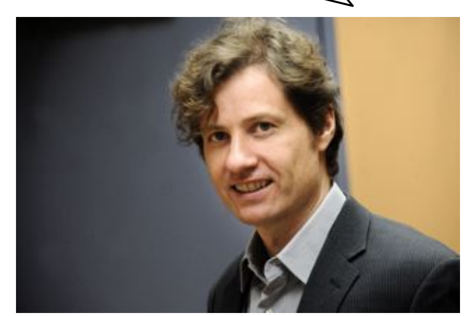
Lexicalized CKY





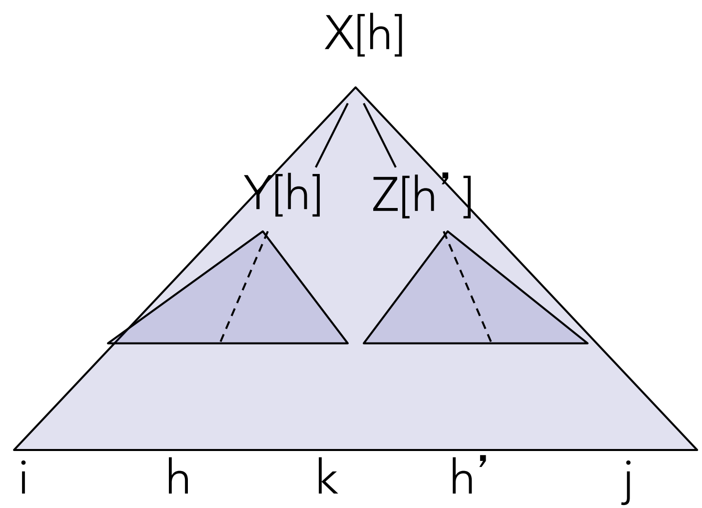

```
bestScore(i,j,X, h)
  if (j = i)
    return tagScore(X,s[i])
  else
    return
      max    max    score(X[h]->Y[h] Z[h']) *
       k,h',        bestScore(i,k,Y, h) *
       X->YZ        bestScore(k+1,j,Z, h')
             max    score(X[h]->Y[h'] Z[h]) *
       k,h',        bestScore(i,k,Y, h') *
       X->YZ        bestScore(k+1,j,Z, h)
```

still cubic time?



Pruning with Beams

- The Collins parser prunes with per-cell beams [Collins 99]
  - Essentially, run the $O(n^5)$ CKY
  - If we keep K hypotheses at each span, then we do at most $O(nK^2)$ work per span (why?)
  - Keeps things more or less cubic



- Also: certain spans are forbidden entirely on the basis of punctuation (crucial for speed)

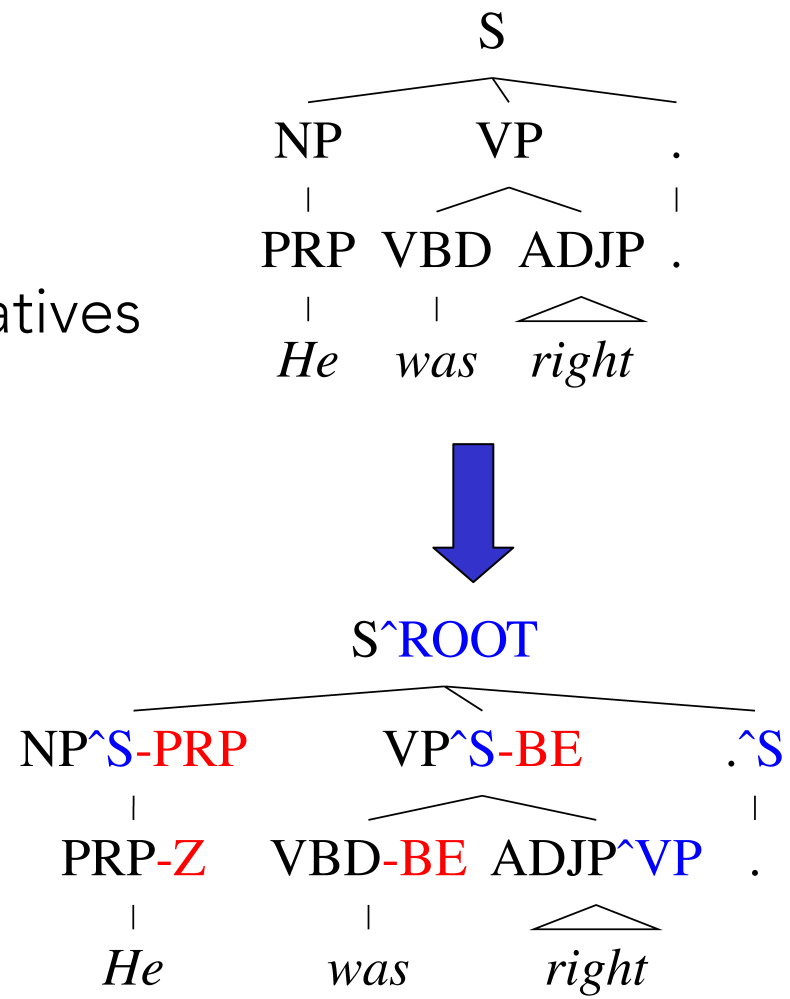
Model	*F1*
Naïve Treebank Grammar	72.6
Klein & Manning '03	86.3
Collins 99	88.6

Grammar Refinements

3. Using Latent Sub-categories

Manual Annotation

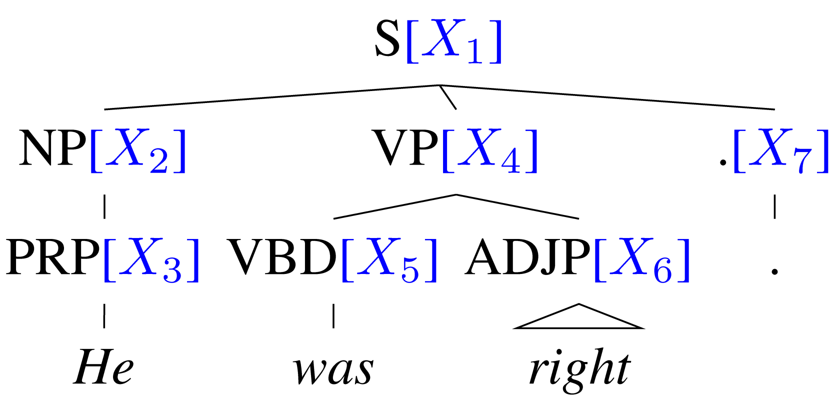
- Manually split categories
  - NP: subject vs object
  - DT: determiners vs demonstratives
  - IN: sentential vs prepositional
- Advantages:
  - Fairly compact grammar
  - Linguistic motivations
- Disadvantages:
  - Performance leveled out
  - Manually annotated

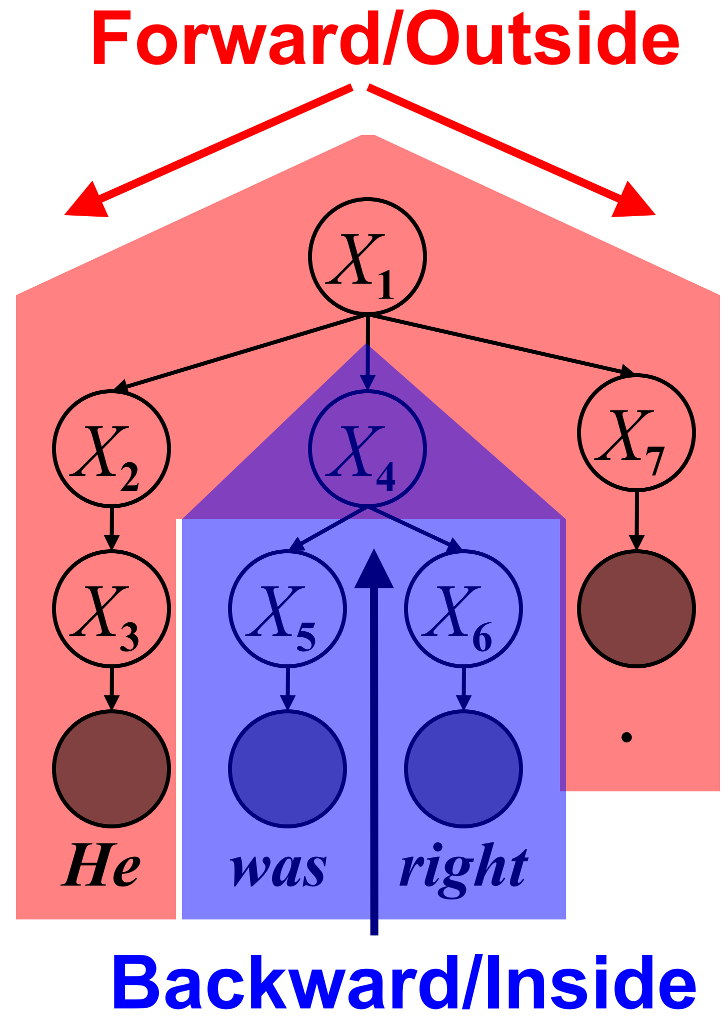


Learning Latent Annotations

Latent Annotations:

- Brackets are known
- Base categories are known
- Hidden variables for subcategories





Can learn with EM: like Forward-Backward for HMMs.

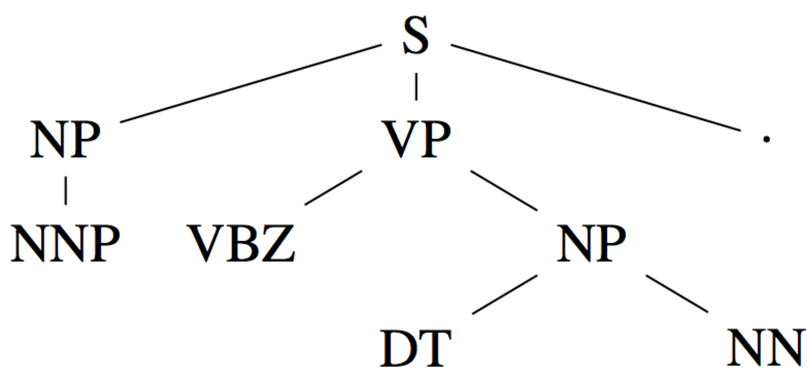
Final Results

Parser	*F1 ≤ 40 words*	*F1 all words*
Klein & Manning '03	86.3	85.7
Matsuzaki et al. '05	86.7	86.1
Collins '99	88.6	88.2
Charniak & Johnson '05	90.1	89.6
Petrov et. al. 06	**90.2**	**89.7**

"Grammar as Foreign Language" (deep learning)

Vinyals et al., 2015

John has a dog ➔



John has a dog ➔

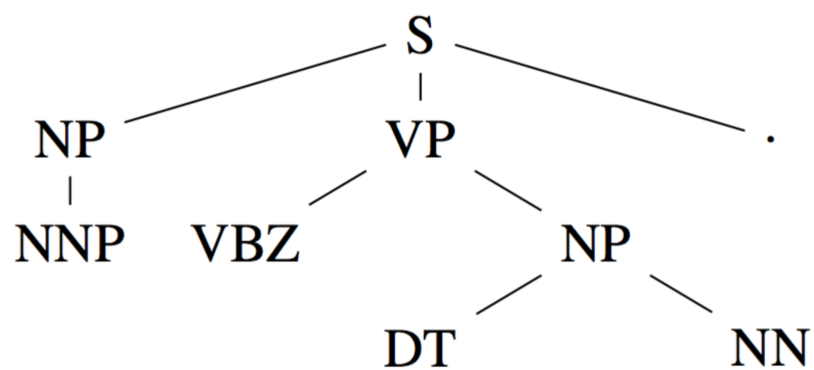
$$\text{(S (NP NNP)}_{\text{NP}}\text{ (VP VBZ (NP DT NN)}_{\text{NP}}\text{)}_{\text{VP}}\text{ .)}_{\text{S}}$$

- Linearize a tree into a sequence
- Then parsing problem becomes similar to machine translation
  - Input: sequence
  - Output: sequence (of different length)
- Encoder-decoder LSTMs (Long short-term memory networks)

“Grammar as Foreign Language” (deep learning)

Vinyals et al., 2015

John has a dog ➔



John has a dog ➔

$$\text{(S (NP NNP)}_{\text{NP}}\text{ (VP VBZ (NP DT NN)}_{\text{NP}}\text{)}_{\text{VP}}\text{ .)}_{\text{S}}$$

- Penn treebank (~40K sentences) is too small to train LSTMs
- Create a larger training set with 11M sentences automatically parsed by two state-of-the-art parsers (and keep only those sentences for which two parsers agreed)

“Grammar as Foreign Language” (deep learning)

Vinyals et al., 2015

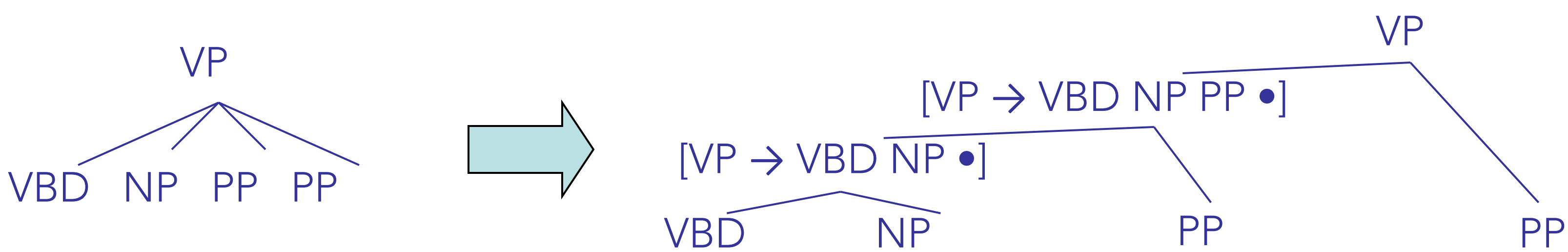
Parser	Training Set	WSJ 22	WSJ 23
baseline LSTM+D	WSJ only	< 70	< 70
LSTM+A+D	WSJ only	88.7	88.3
LSTM+A+D ensemble	WSJ only	90.7	90.5
baseline LSTM	BerkeleyParser corpus	91.0	90.5
LSTM+A	high-confidence corpus	93.3	92.5
LSTM+A ensemble	high-confidence corpus	**93.5**	**92.8**
Petrov et al. (2006) [12]	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

Supplementary Topics

I. CNF Conversion

Chomsky Normal Form

- Chomsky normal form:
  - All rules of the form X → Y Z or X → w
  - In principle, this is no limitation on the space of (P)CFGs
    - N-ary rules introduce new non-terminals



    - Unaries / empties are "promoted"
  - In practice it's kind of a pain:
    - Reconstructing n-aries is easy
    - Reconstructing unaries is trickier
    - The straightforward transformations don't preserve tree scores
  - Makes parsing algorithms simpler!

Original Grammar

CNF Conversion Example

S → NP VP	0.8
S → Aux NP VP	0.1
S → VP	0.1
NP → Pronoun	0.2
NP → Proper-Noun	0.2
NP → Det Nominal	0.6
Nominal → Noun	0.3
Nominal → Nominal Noun	0.2
Nominal → Nominal PP	0.5
VP → Verb	0.2
VP → Verb NP	0.5
VP → VP PP	0.3
PP → Prep NP	1.0

Lexicon:

Noun → book | flight | meal | money
0.1 0.5 0.2 0.2

Verb → book | include | prefer
0.5 0.2 0.3

Det → the | a | that | this
0.6 0.2 0.1 0.1

Pronoun → I | he | she | me
0.5 0.1 0.1 0.3

Proper-Noun → Houston | NWA
0.8 0.2

Aux → does
1.0

Prep → from | to | on | near | through
0.25 0.25 0.1 0.2 0.2

Original Grammar		Chomsky Normal Form	
S → NP VP	0.8	S → NP VP	0.8
S → Aux NP VP	0.1	S → X1 VP	0.1
		X1 → Aux NP	1.0
S → VP	0.1		
NP → Pronoun	0.2		
NP → Proper-Noun	0.2		
NP → Det Nominal	0.6		
Nominal → Noun	0.3		
Nominal → Nominal Noun	0.2		
Nominal → Nominal PP	0.5		
VP → Verb	0.2		
VP → Verb NP	0.5		
VP → VP PP	0.3		
PP → Prep NP	1.0		

Lexicon (See previous slide for full list) :

Noun → book | flight | meal | money
0.1 0.5 0.2 0.2

Verb → book | include | prefer
0.5 0.2 0.3

Original Grammar

S → NP VP 0.8
S → Aux NP VP 0.1

S → VP 0.1

NP → Pronoun 0.2

NP → Proper-Noun 0.2

NP → Det Nominal 0.6
Nominal → Noun 0.3

Nominal → Nominal Noun 0.2
Nominal → Nominal PP 0.5
VP → Verb 0.2

VP → Verb NP 0.5
VP → VP PP 0.3
PP → Prep NP 1.0

Lexicon (See previous slide for full list) :
Noun → book | flight | meal | money
0.1 0.5 0.2 0.2
Verb → book | include | prefer
0.5 0.2 0.3

Chomsky Normal Form

S → NP VP 0.8
S → X1 VP 0.1
X1 → Aux NP 1.0
S → book | include | prefer

S → Verb NP
S → VP PP

Original Grammar		Chomsky Normal Form	
S → NP VP	0.8	S → NP VP	0.8
S → Aux NP VP	0.1	S → X1 VP	0.1
		X1 → Aux NP	1.0
S → VP	0.1	S → book | include | prefer 0.01 0.004 0.006	
		S → Verb NP	0.05
		S → VP PP	0.03
NP → Pronoun	0.2	NP → I | he | she | me 0.1 0.02 0.02 0.06	
NP → Proper-Noun	0.2	NP → Houston | NWA 0.16 .04	
NP → Det Nominal	0.6	NP → Det Nominal	0.6
Nominal → Noun	0.3	Nominal → book | flight | meal | money 0.03 0.15 0.06 0.06	
Nominal → Nominal Noun	0.2	Nominal → Nominal Noun	0.2
Nominal → Nominal PP	0.5	Nominal → Nominal PP	0.5
VP → Verb	0.2	VP → book | include | prefer 0.1 0.04 0.06	
VP → Verb NP	0.5	VP → Verb NP	0.5
VP → VP PP	0.3	VP → VP PP	0.3
PP → Prep NP	1.0	PP → Prep NP	1.0

Lexicon (See previous slide for full list) :

Noun → book | flight | meal | money
0.1 0.5 0.2 0.2

Verb → book | include | prefer
0.5 0.2 0.3

Advanced Topics

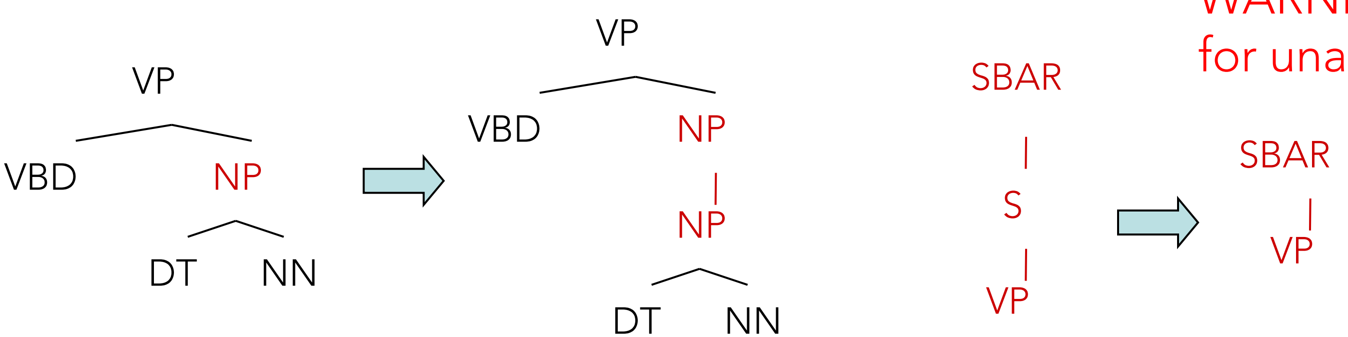
I. CKY with Unary Rules

CNF + Unary Closure

We need unaries to be non-cyclic

- Calculate *closure Close(R) for unary rules in R*
  - Add X→Y if there exists a rule chain $X \rightarrow Z_1$, $Z_1 \rightarrow Z_2, \ldots, Z_k \rightarrow Y$ with $q(X \rightarrow Y$ $= q(X \rightarrow Z_1) * q(Z_1 \rightarrow Z_2) * \ldots * q(Z_k \rightarrow Y)$
  - If no unary rule exist for X, add X→X with $q(X \rightarrow X)=1$ for all X in N

WARNING: Watch out for unary cycles!



- Rather than zero or more unaries, always exactly one
- Alternate unary and binary layers
- What about X→Y with different unary paths (and scores)?

The CKY Algorithm

- Input: a sentence s = x_1 .. x_n and a PCFG = <N, Σ ,S, R, q>
- Initialization: For i = 1 … n and all X in N

$$\pi(i,i,X) = \begin{cases} q(X \rightarrow x_i) & \text{if } X \rightarrow x_i \in R \\ 0 & \text{otherwise} \end{cases}$$

- For l = 1 … (n-1) [iterate all phrase lengths]
  - For i = 1 … (n-l) and j = i+l [iterate all phrases of length l]
    - For all X in N [iterate all non-terminals]

$$\pi(i,j,X) = \max_{\substack{X \rightarrow YZ \in R, \\ s \in \{i \ldots (j-1)\}}} \left(q(X \rightarrow YZ) \times \pi(i,s,Y) \times \pi(s+1,j,Z) \right)$$

    - also, store back pointers

$$bp(i,j,X) = \arg \max_{\substack{X \rightarrow YZ \in R, \\ s \in \{i \ldots (j-1)\}}} \left(q(X \rightarrow YZ) \times \pi(i,s,Y) \times \pi(s+1,j,Z) \right)$$

CKY with Unary Closure

- Input: a sentence s = x_1 .. x_n and a PCFG = <*N, Σ ,S, R, q*>
- Initialization: For i = 1 … n:
  - Step 1: for all X in N:

$$\pi(i,i,X) = \begin{cases} q(X \rightarrow x_i) & \text{if } X \rightarrow x_i \in R \\ 0 & \text{otherwise} \end{cases}$$

  - Step 2: for all X in N:

$$\pi_U(i,i,X) = \max_{X \rightarrow Y \in Close(R)} (q(X \rightarrow Y) \times \pi(i,i,Y))$$

- For l = 1 … (n-1) [iterate all phrase lengths]
  - For i = 1 … (n-l) and j = i+l [iterate all phrases of length l]
    - Step 1: (Binary)
      - For all X in N [iterate all non-terminals]

$$\pi_B(i,j,X) = \max_{X \rightarrow YZ \in R, s \in \{i \ldots (j-1)\}} (q(X \rightarrow YZ) \times \pi_U(i,s,Y) \times \pi_U(s+1,j,Z))$$

    - Step 2: (Unary)
      - For all X in N [iterate all non-terminals]

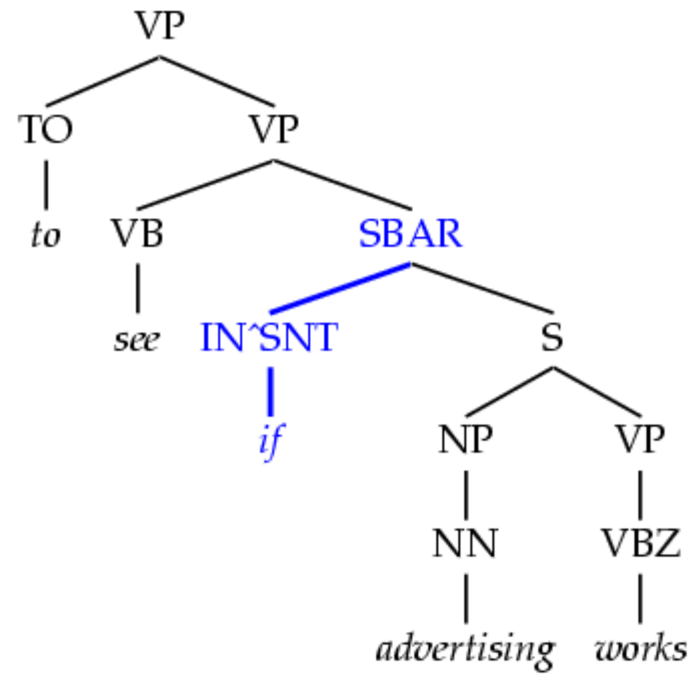
$$\pi_U(i,j,X) = \max_{X \rightarrow Y \in Close(R)} (q(X \rightarrow Y) \times \pi_B(i,j,Y))$$

Advanced Topics

2. Grammar Refinements :Tag Splits

Tag Splits

- Problem: Treebank tags are too coarse.
- Example: Sentential, PP, and other prepositions are all marked IN.
- Partial Solution:
  - Subdivide the IN tag.



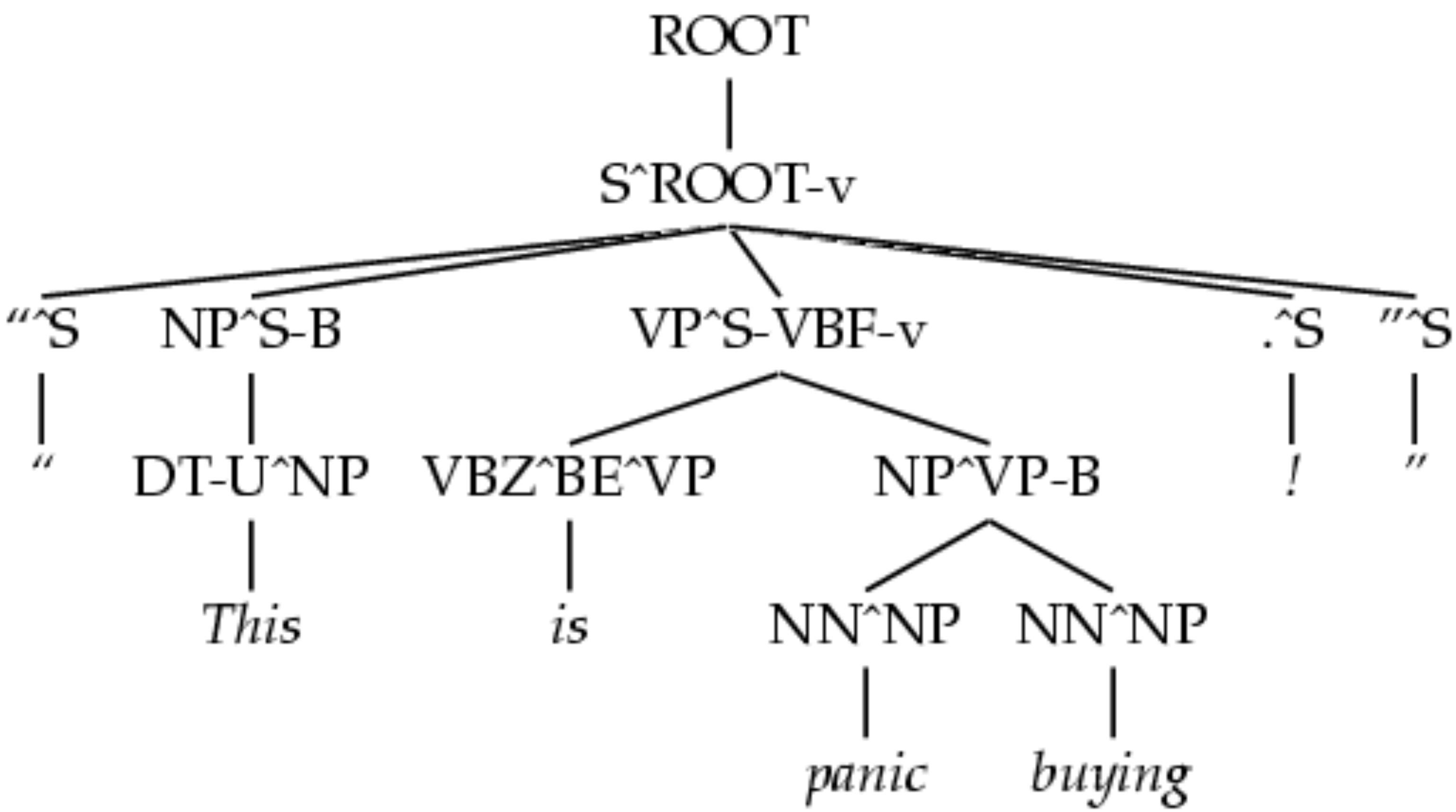
Annotation	F1	Size
v=h=2v	78.3	8.0K
SPLIT-IN	80.3	8.1K

Other Tag Splits

- UNARY-DT: mark demonstratives as DT^U ("the X" vs. "those")
- UNARY-RB: mark phrasal adverbs as RB^U ("quickly" vs. "very")
- TAG-PA: mark tags with non-canonical parents ("not" is an RB^VP)
- SPLIT-AUX: mark auxiliary verbs with –AUX [cf. Charniak 97]
- SPLIT-CC: separate "but" and "&" from other conjunctions
- SPLIT-%: "%" gets its own tag.

F1	Size
80.4	8.1K
80.5	8.1K
81.2	8.5K
81.6	9.0K
81.7	9.1K
81.8	9.3K

A Fully Annotated (Unlex) Tree



Some Test Set Results

Parser	LP	LR	**F1**
Magerman 95	84.9	84.6	**84.7**
Collins 96	86.3	85.8	**86.0**
Unlexicalized	86.9	85.7	**86.3**
Charniak 97	87.4	87.5	**87.4**
Collins 99	88.7	88.6	**88.6**

- Beats "first generation" lexicalized parsers.
- Lots of room to improve – more complex models next.