Natural Language Processing

Parsing: PCFGs and Treebank Parsing

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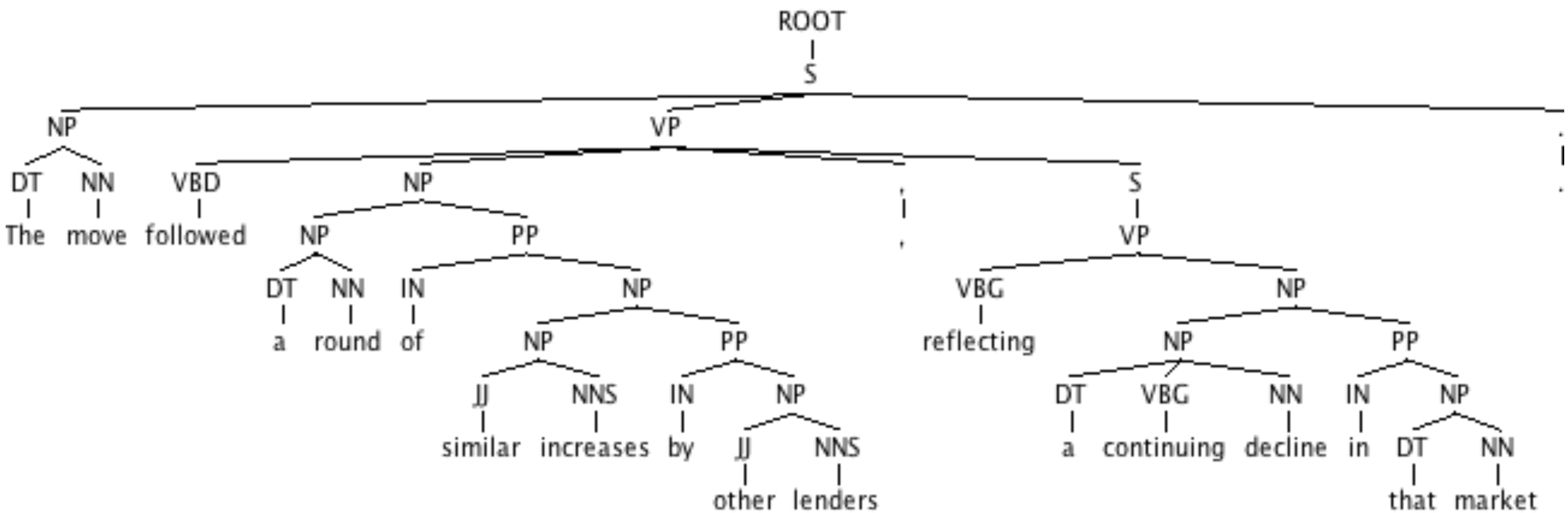
[Slides from Dan Klein, Michael Collins, and Ray Mooney]

Topics

- Parse Trees
- (Probabilistic) Context Free Grammars
  - Supervised learning
  - Parsing: most likely tree, marginal distributions
- Treebank Parsing (English, edited text)

Parse Trees



The move followed a round of similar increases by other lenders, reflecting a continuing decline in that market

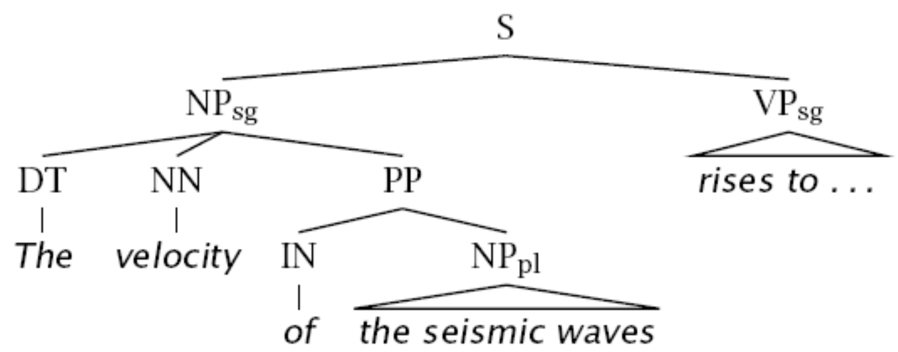
Penn Treebank Non-terminals

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

Phrase Structure Parsing

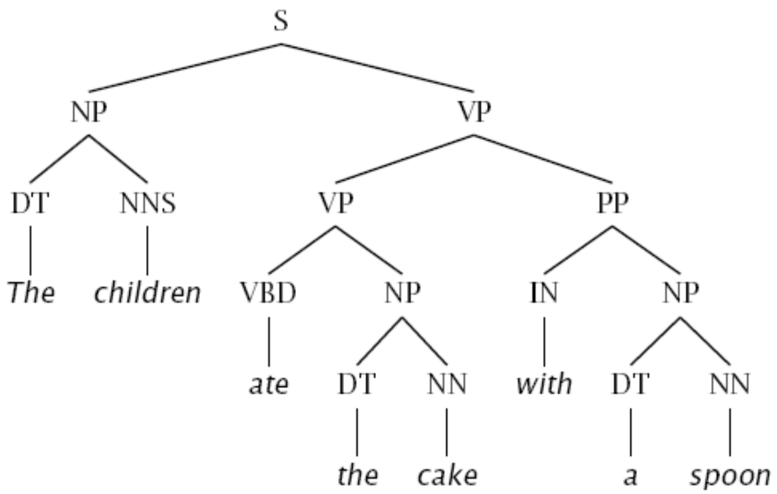
- Phrase structure parsing organizes syntax into constituents or brackets
- In general, this involves nested trees
- Linguists can, and do, argue about details
- Lots of ambiguity
- Not the only kind of syntax…



new art critics write reviews with computers

Constituency Tests

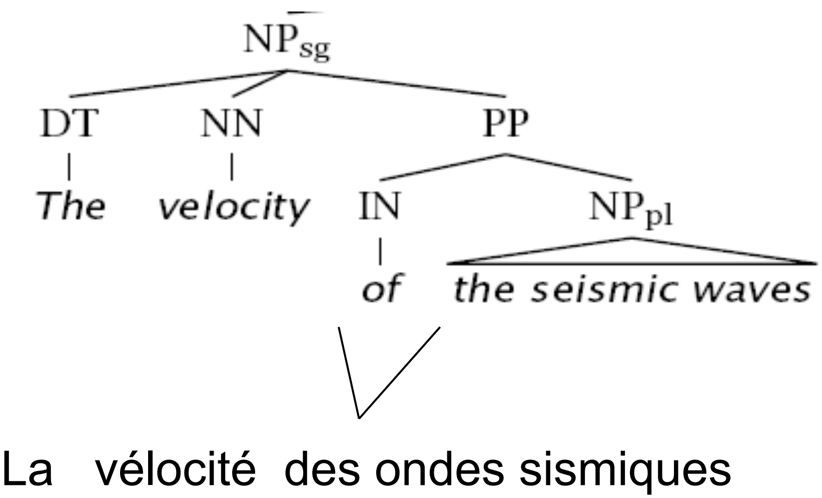
- How do we know what nodes go in the tree?
- Classic constituency tests:
  - Substitution by proform
    - he, she, it, they, ...
  - Question / answer
  - Deletion
  - Movement / dislocation
  - Conjunction / coordination



- Cross-linguistic arguments, too

Conflicting Tests

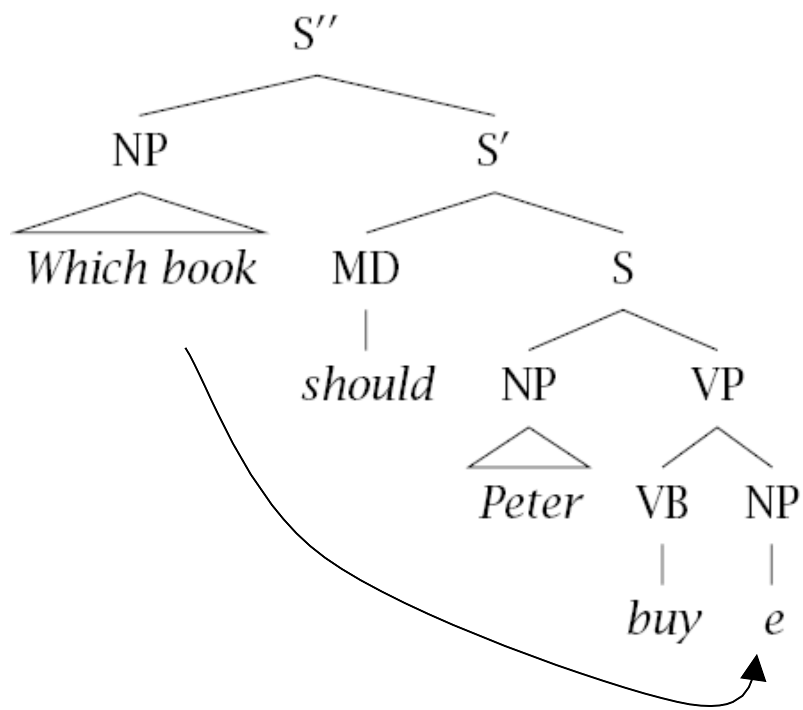
- Constituency isn't always clear
  - Units of transfer:
    - think about ~ penser à
    - talk about ~ hablar de
  - Phonological reduction:
    - I will go → I'll go
    - I want to go → I wanna go
    - a le centre → au centre
  - Coordination
    - He went to and came from the store.



Non-Local Phenomena

- Dislocation / gapping
  - Which book should Peter buy?
  - A debate arose which continued until the election.

- Binding
  - Reference
    - The IRS audits itself
  - Control
    - I want to go
    - I want you to go



Classical NLP: Parsing

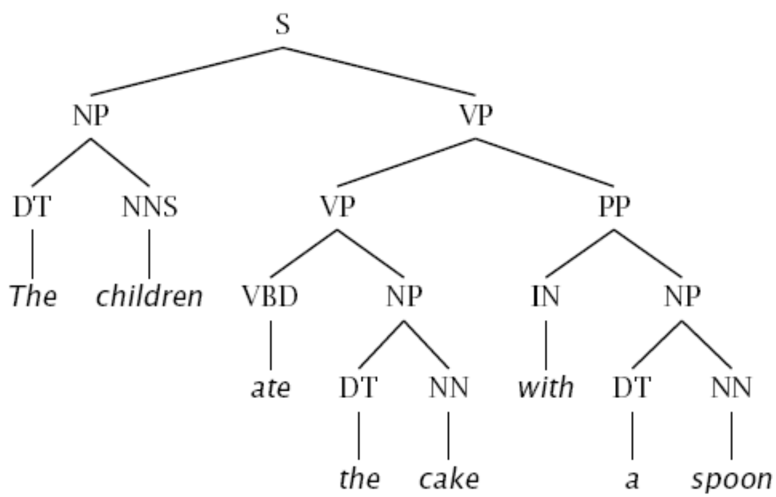
- Write symbolic or logical rules:

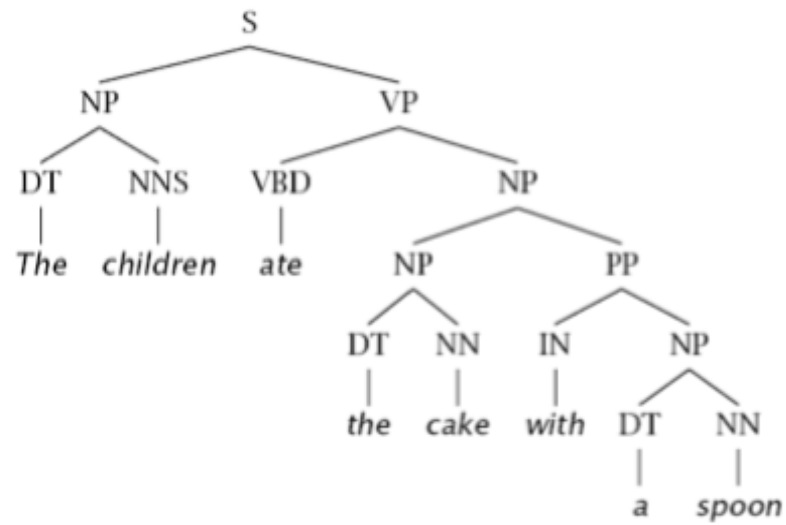
Grammar (CFG)		Lexicon
ROOT → S	NP → NP PP	NN → interest
S → NP VP	VP → VBP NP	NNS → raises
NP → DT NN	VP → VBP NP PP	VBP → interest
NP → NN NNS	PP → IN NP	VBZ → raises
		…

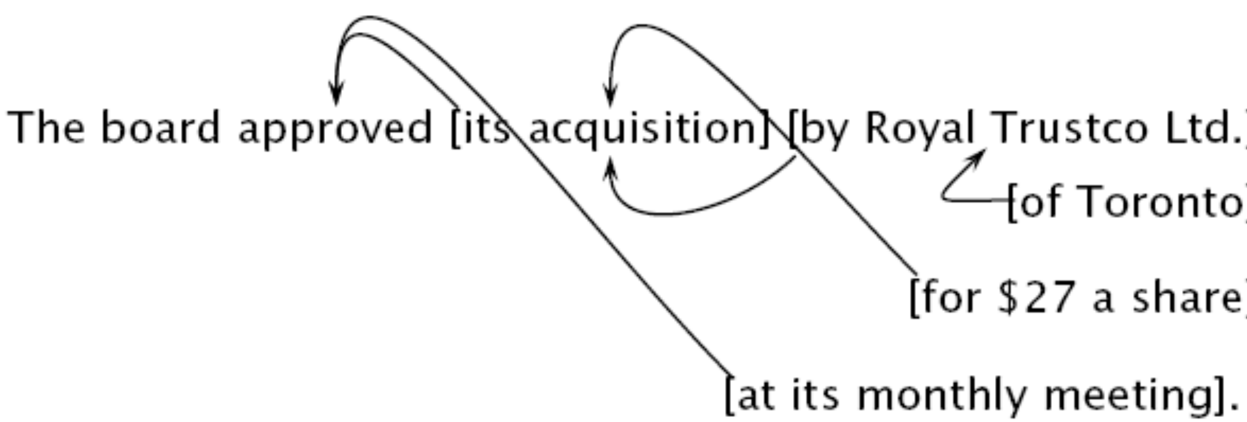
- Use deduction systems to prove parses from words
  - Minimal grammar on “Fed raises” sentence: 36 parses
  - Simple 10-rule grammar: 592 parses
  - Real-size grammar: many millions of parses
- This scaled very badly, didn’t yield broad-coverage tools

Ambiguities: PP Attachment

The children ate the cake with a spoon.







Attachments

- I cleaned the dishes from dinner
- I cleaned the dishes with detergent
- I cleaned the dishes in my pajamas
- I cleaned the dishes in the sink

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

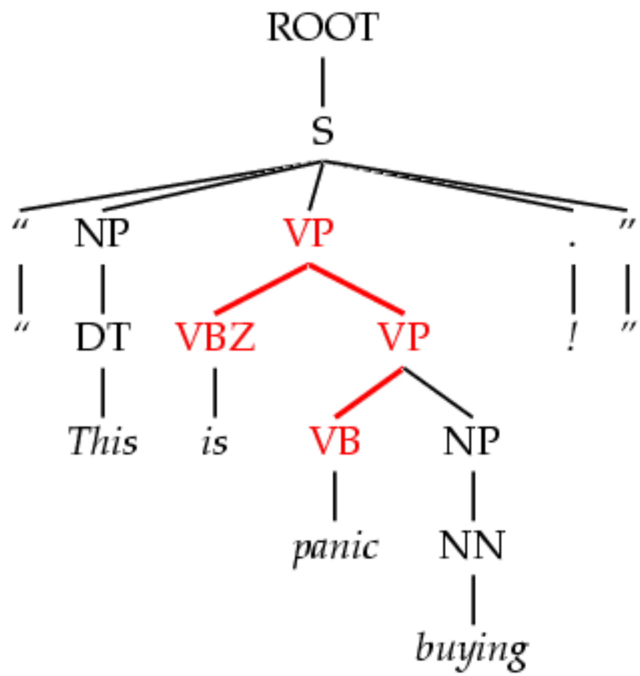
- Modifier scope within NPs
  impractical design requirements
  plastic cup holder
- Multiple gap constructions
  The chicken is ready to eat.
  The contractors are rich enough to sue.
- Coordination scope:
  Small rats and mice can squeeze into holes or cracks in the wall.

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

- A context-free grammar is a tuple <N, T, Σ , R>
  - N : the set of non-terminals
    - Phrasal categories: S, NP, VP, ADJP, etc.
    - Parts-of-speech (pre-terminals): NN, JJ, DT, VB
  - 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 $X \rightarrow Y_1\ Y_2\ \ldots\ Y_k$, with $X, Y_i \in N$
    - Examples: S → NP VP,   VP → VP CC VP
    - Also called rewrites, productions, or local trees

Example Grammar

N = {S, NP, VP, PP, DT, Vi, Vt, NN, IN}
S = S
Σ = {sleeps, saw, man, woman, telescope, the, with, in}

R =

S	$\Rightarrow$	NP	VP
VP	$\Rightarrow$	Vi	
VP	$\Rightarrow$	Vt	NP
VP	$\Rightarrow$	VP	PP
NP	$\Rightarrow$	DT	NN
NP	$\Rightarrow$	NP	PP
PP	$\Rightarrow$	IN	NP

Vi	$\Rightarrow$	sleeps
Vt	$\Rightarrow$	saw
NN	$\Rightarrow$	man
NN	$\Rightarrow$	woman
NN	$\Rightarrow$	telescope
DT	$\Rightarrow$	the
IN	$\Rightarrow$	with
IN	$\Rightarrow$	in

S=sentence, VP-verb phrase, NP=noun phrase, PP=prepositional phrase, DT=determiner, Vi=intransitive verb, Vt=transitive verb, NN=noun, IN=preposition

Example Parses

$R =$

S	$\Rightarrow$	NP	VP
VP	$\Rightarrow$	Vi	
VP	$\Rightarrow$	Vt	NP
VP	$\Rightarrow$	VP	PP
NP	$\Rightarrow$	DT	NN
NP	$\Rightarrow$	NP	PP
PP	$\Rightarrow$	IN	NP

Vi	$\Rightarrow$	sleeps
Vt	$\Rightarrow$	saw
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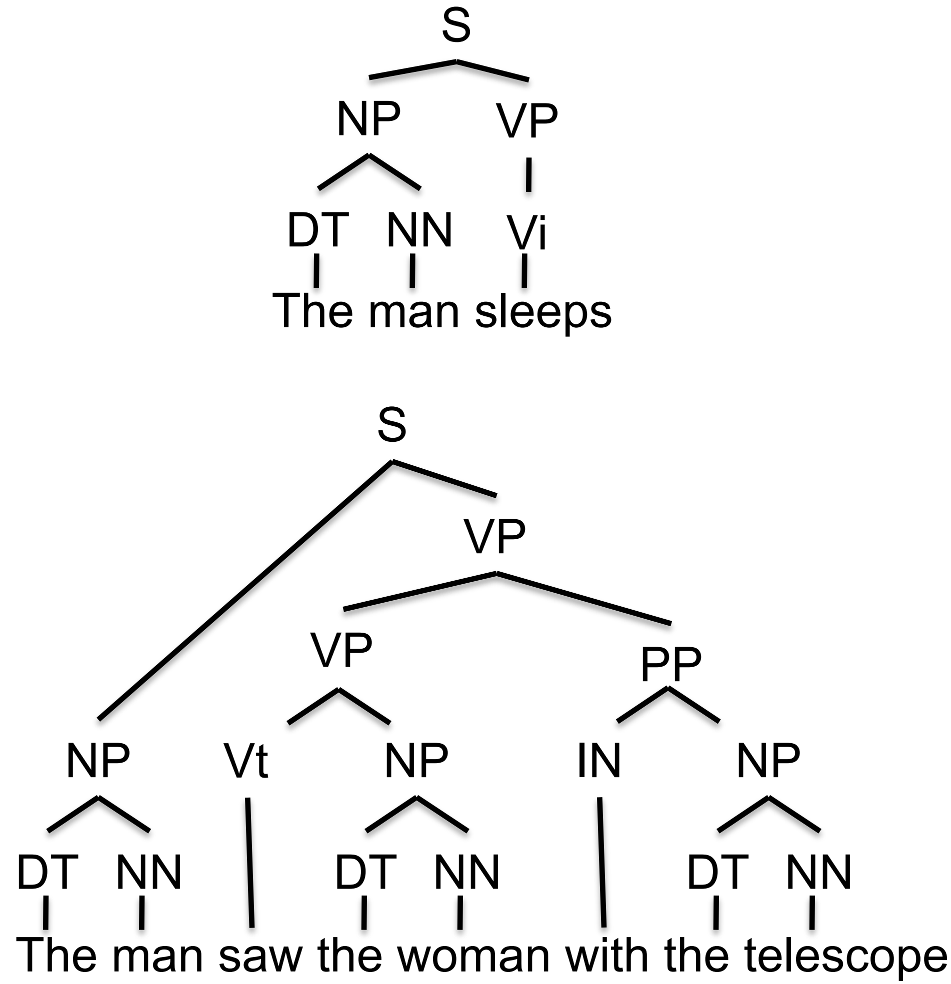

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    - Of the form $X \rightarrow Y_1\ Y_2 \ldots Y_k$, with $X, Y_i \in N$
    - Examples: $S \rightarrow NP\ VP$, $VP \rightarrow VP\ CC\ VP$
    - Also called rewrites, productions, or local trees
- A PCFG adds:
  - A top-down production probability per rule $P(X \rightarrow Y_1\ Y_2 \ldots Y_k)$

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
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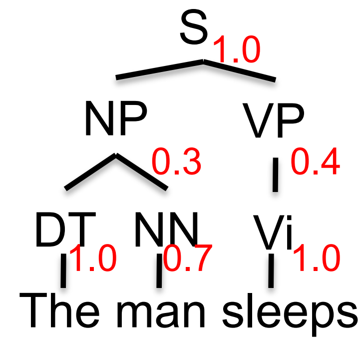
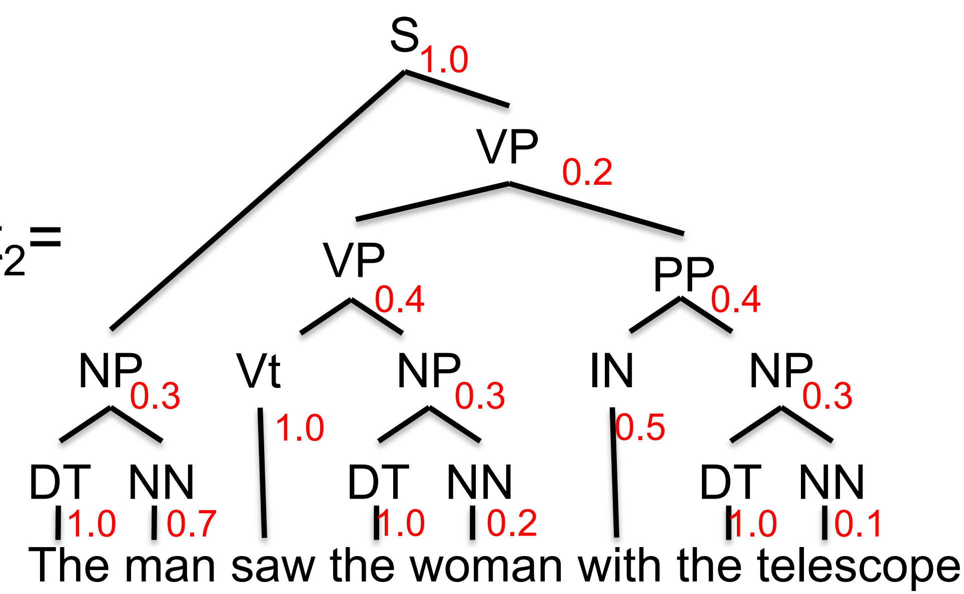
DT	$\Rightarrow$	the	1.0
IN	$\Rightarrow$	with	0.5
IN	$\Rightarrow$	in	0.5

$t_1=$



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

$t_2=$



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

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

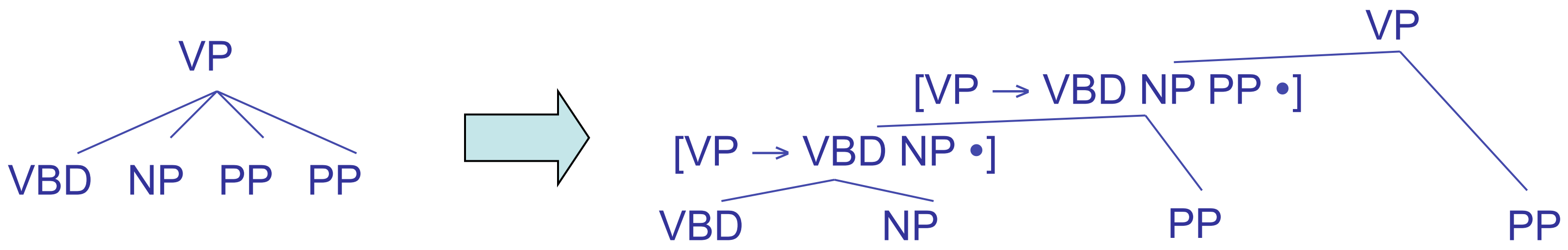
$$q_{ML}(\alpha \rightarrow \beta) = \frac{\mathsf{Count}(\alpha \rightarrow \beta)}{\mathsf{Count}(\alpha)}$$

  - 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)

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

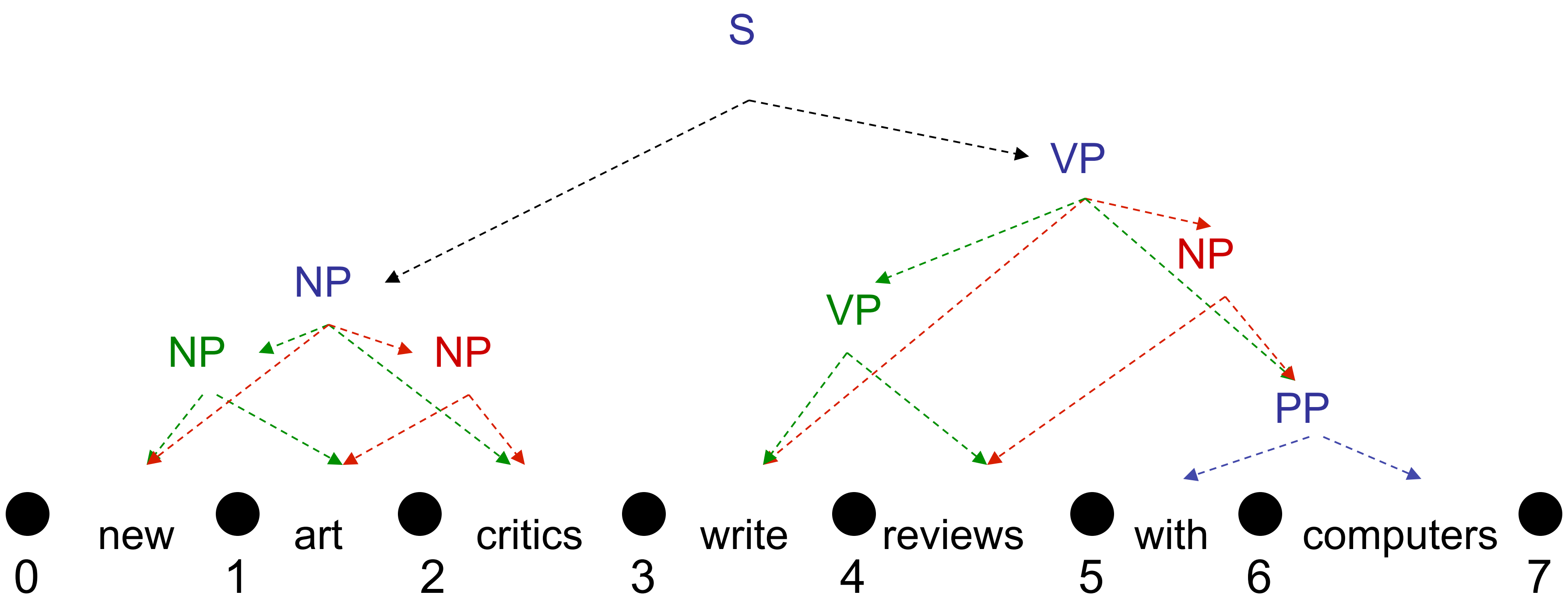
Chomsky Normal Form

- Chomsky normal form:
  - All rules of the form $X \rightarrow Y\ Z$ or $X \rightarrow w$
  - 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!

The Parsing Problem



A Recursive Parser

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

- Will this parser work?
- Why or why not?
- Memory/time requirements?
- Q: Remind you of anything? Can we adapt this to other models / inference tasks?

A Memoized Parser

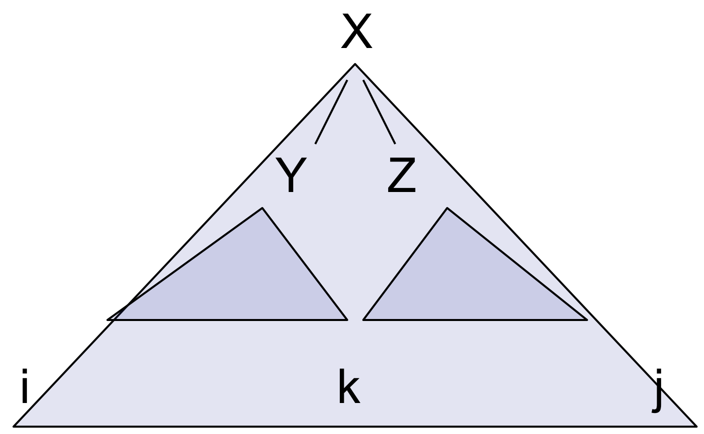
- One small change:

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

A Bottom-Up Parser (CKY)

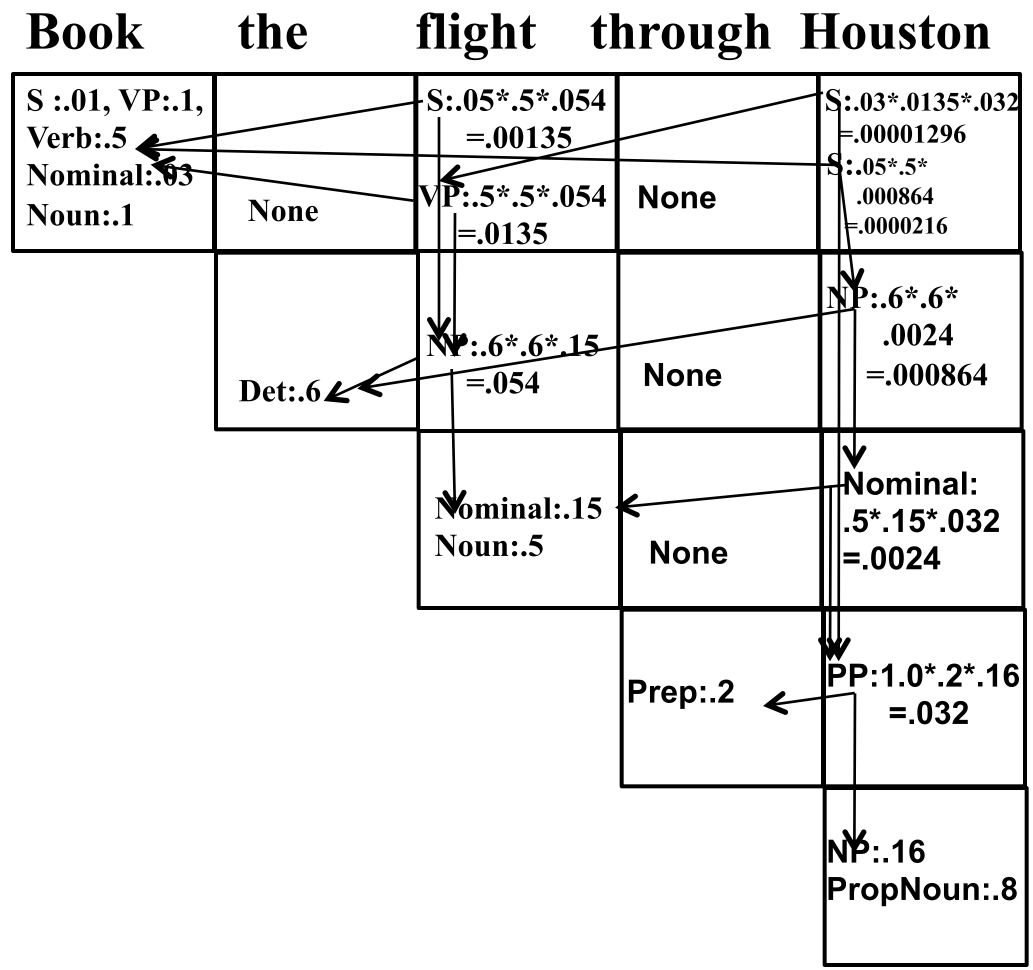
- Can also organize things bottom-up

```
bestScore(s)
  for (i : [0,n-1])
    for (X : tags[s[i]])
      score[X][i][i+1] =
          tagScore(X,s[i])
  for (diff : [2,n])
    for (i : [0,n-diff])
      j = i + diff
      for (X->YZ : rule)
        for (k : [i+1, j-1])
          score[X][i][j] = max      score[X][i][j],
                           k,X->YZ   score(X->YZ) *
                                     score[Y][i][k] *
                                     score[Z][k][j]
```



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**	
NP → Det Nominal	0.6
Nominal → book | flight | meal | money **0.03 0.15 0.06 0.06**	
Nominal → Nominal Noun	0.2
Nominal → Nominal PP	0.5
VP → book | include | prefer **0.1 0.04 0.06**	
VP → Verb NP	0.5
VP → VP PP	0.3
PP → Prep NP	1.0



Probabilistic CKY Parser

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	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 Noun:.5	None	Nominal: .5*.15*.032 =.0024
			Prep:.2	PP:1.0*.2*.16 =.032
				NP:.16 PropNoun:.8

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

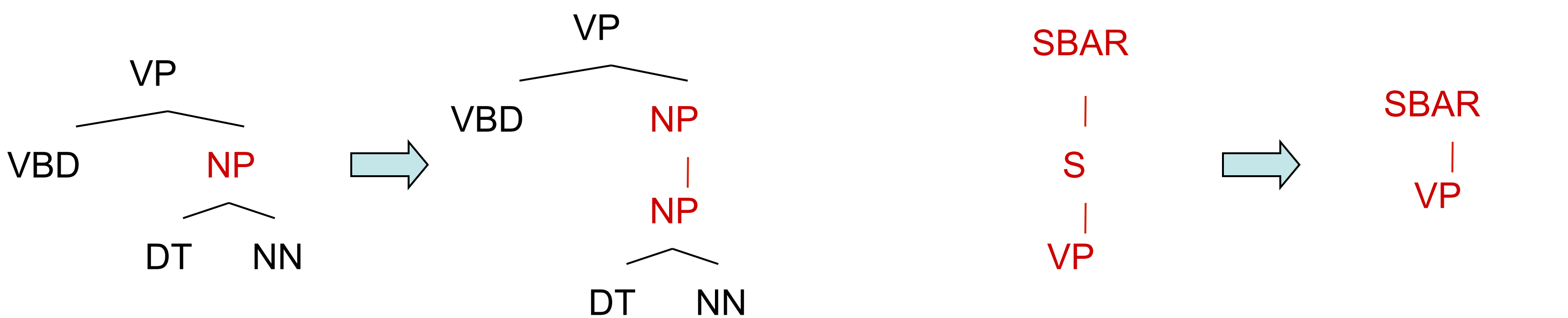
Unary Rules

- Unary rules?

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

CNF + Unary Closure

- We need unaries to be non-cyclic
  - Can address by pre-calculating the unary closure
  - Rather than having zero or more unaries, always have exactly one



  - Alternate unary and binary layers
  - Reconstruct unary chains afterwards

Alternating Layers

```
bestScoreB(X,i,j,s)
    return max         score(X->YZ) *
         k,X->YZ             bestScoreU(Y,i,k) *
                             bestScoreU(Z,k,j)


bestScoreU(X,i,j,s)
  if (j = i+1)
      return tagScore(X,s[i])
  else
      return max   score(X->Y) *
             X->Y       bestScoreB(Y,i,j)
```

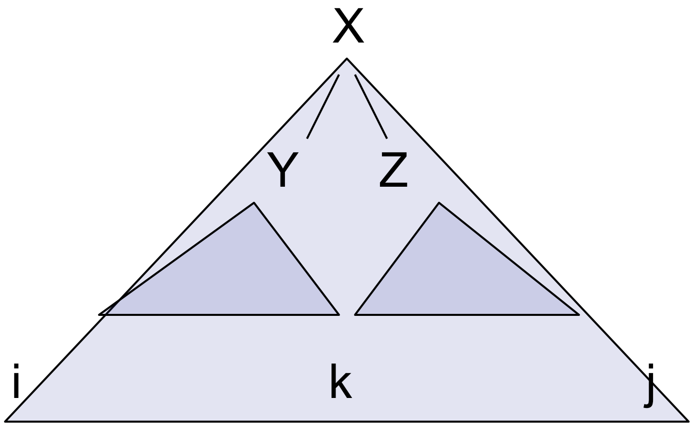
Memory

- How much memory does this require?
  - Have to store the score cache
  - Cache size: |symbols|*n^2 doubles
  - For the plain treebank grammar:
    - X ~ 20K, n = 40, double ~ 8 bytes = ~ 256MB
    - Big, but workable.
- Pruning: Beams
  - score[X][i][j] can get too large (when?)
  - Can keep beams (truncated maps score[i][j]) which only store the best few 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?

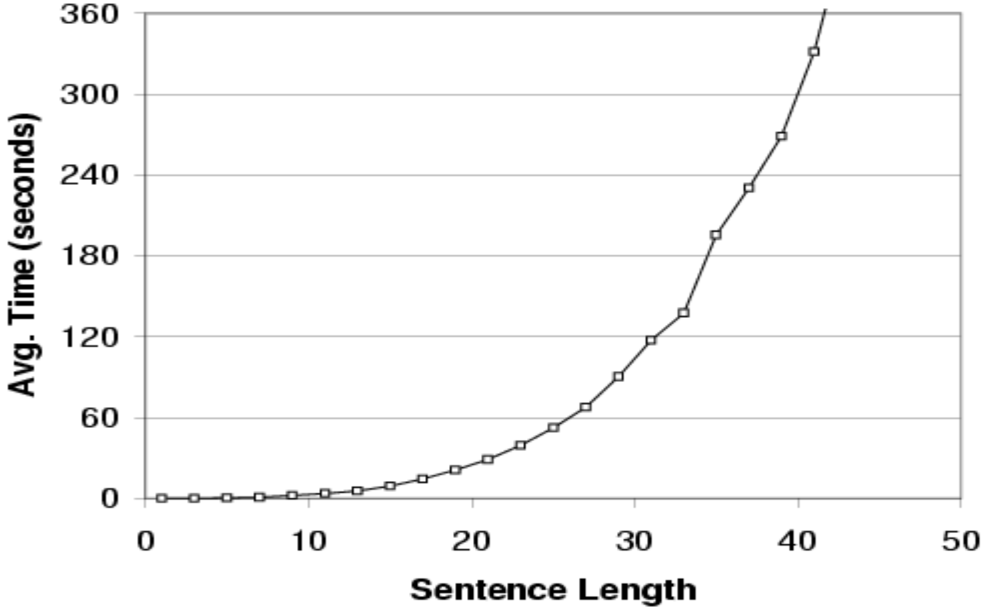
  - For each diff (<= n)
    - For each i (<= n)
      - For each rule X → Y Z
        - For each split point k
          Do constant work



- 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

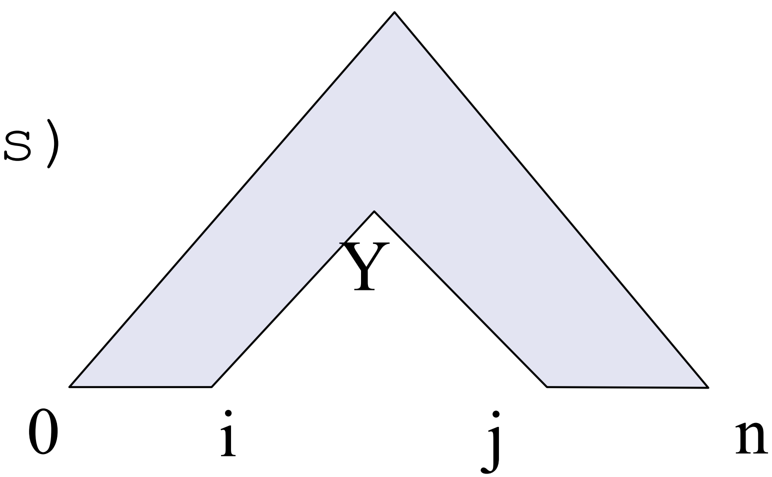
- Why's it worse in practice?
  - Longer sentences "unlock" more of the grammar
  - All kinds of systems issues don't scale

Best Outside Scores

Want to compute the best parse missing a specific word span:

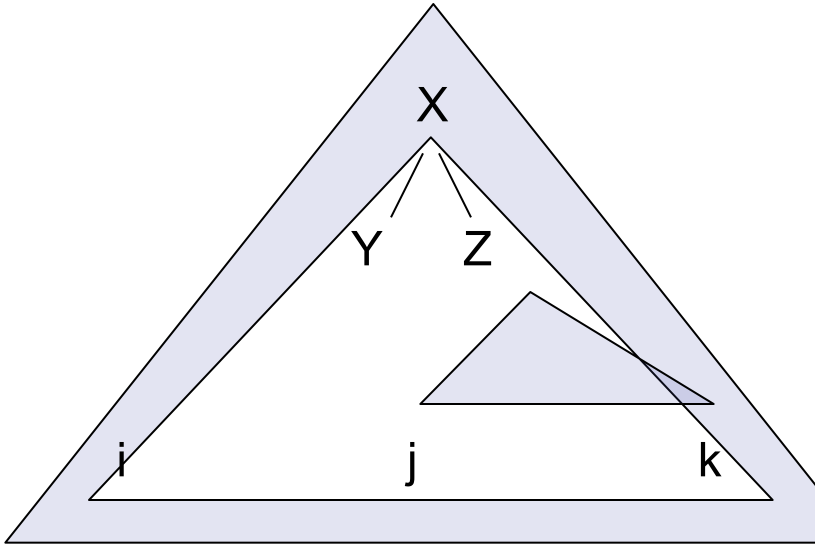
- Tree rooted at Y from words s[i:j] is left unspecified
- this is the "opposite" of the `bestScore` / inside score

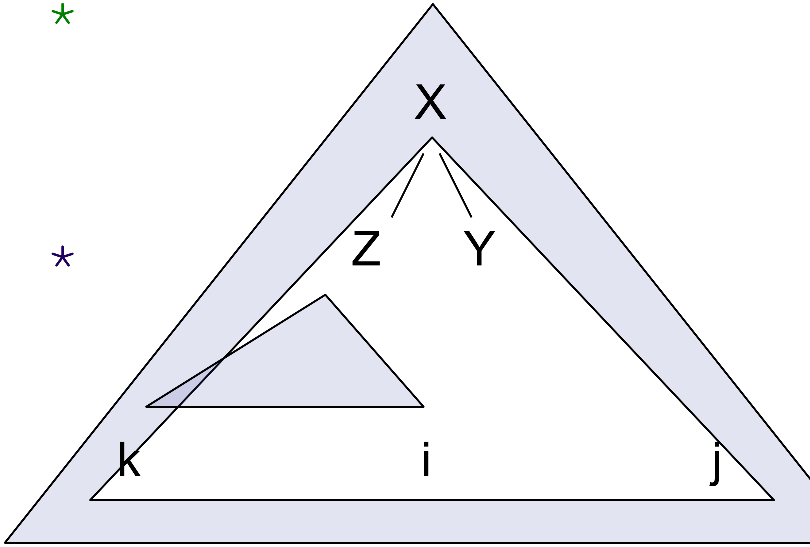
`bestOutside(Y,i,j,s)`



Best Outside Scores

```
bestOutside(Y,i,j,s)
 if (i==0 && j==n)
   return 1.0
 else
   return max
    max      score(X->YZ) *
  k,X->YZ
              bestOutside(X,i,k,s) *
              bestScore(Z,j,k,s)
    max      score(X->ZY) *
  k,X->ZY
              bestOutside(X,k,j,s) *
              bestScore(Z,k,i,s)
```





Efficient CKY

- Lots of tricks to make CKY efficient
  - Most of them are little engineering details:
    - E.g., first choose k, then enumerate through the Y:[i,k] which are non-zero, then loop through rules by left child.
    - Optimal layout of the dynamic program depends on grammar, input, even system details.
  - Another kind is more critical:
    - Many X:[i,j] can be suppressed on the basis of the input string
    - We'll see this next class as figures-of-merit or A* heuristics

Agenda-Based Parsing

- Agenda-based parsing is like graph search (but over a hypergraph)
- Concepts:
  - Numbering: we number fenceposts between words
  - "Edges" or items: spans with labels, e.g. PP[3,5], represent the sets of trees over those words rooted at that label (cf. search states)
  - A chart: records edges we've expanded (cf. closed set)
  - An agenda: a queue which holds edges (cf. a fringe or open set)

Word Items

- Building an item for the first time is called discovery. Items go into the agenda on discovery.
- To initialize, we discover all word items (with score 1.0).

AGENDA

critics[0,1], write[1,2], reviews[2,3], with[3,4], computers[4,5]

CHART [EMPTY]

0 1 2 3 4 5

critics write reviews with computers

Unary Projection

- When we pop a word item, the lexicon tells us the tag item successors (and scores) which go on the agenda

critics[0,1]	write[1,2]	reviews[2,3]	with[3,4]	computers[4,5]
NNS[0,1]	VBP[1,2]	NNS[2,3]	IN[3,4]	NNS[4,5]

critics write reviews with computers

Item Successors

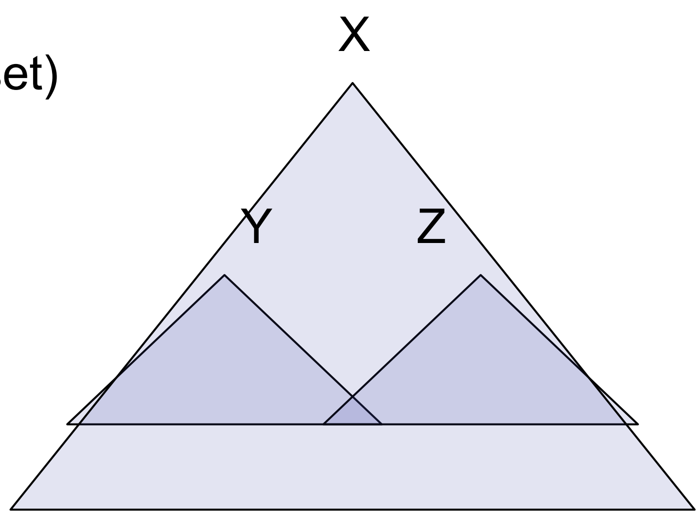
- When we pop items off of the agenda:
  - Graph successors: unary projections (NNS → critics, NP → NNS)

$$Y[i,j] \text{ with } X \rightarrow Y \text{ forms } X[i,j]$$

  - Hypergraph successors: combine with items already in our chart

$$Y[i,j] \text{ and } Z[j,k] \text{ with } X \rightarrow Y\ Z \text{ form } X[i,k]$$

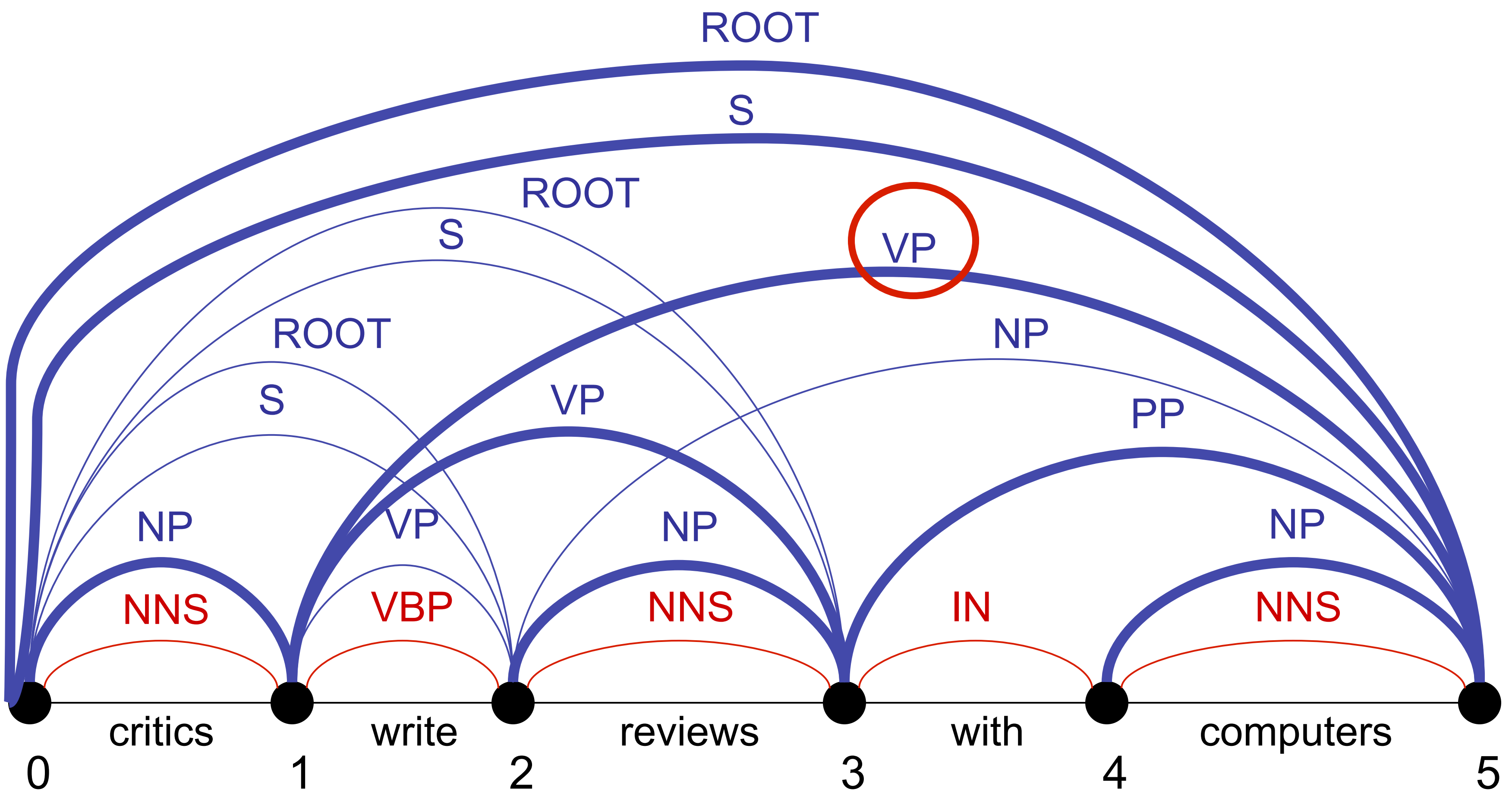
  - Enqueue / promote resulting items (if not in chart already)
  - Record backtraces as appropriate
  - Stick the popped edge in the chart (closed set)
- Queries a chart must support:
  - Is edge X:[i,j] in the chart? (What score?)
  - What edges with label Y end at position j?
  - What edges with label Z start at position i?



An Example

NNS[0,1] VBP[1,2] NNS[2,3] IN[3,4] NNS[3,4] NP[0,1] VP[1,2] NP[2,3] NP[4,5] S[0,2]

VP[1,3] PP[3,5] ROOT[0,2] S[0,3] VP[1,5] NP[2,5] ROOT[0,3] S[0,5] ROOT[0,5]



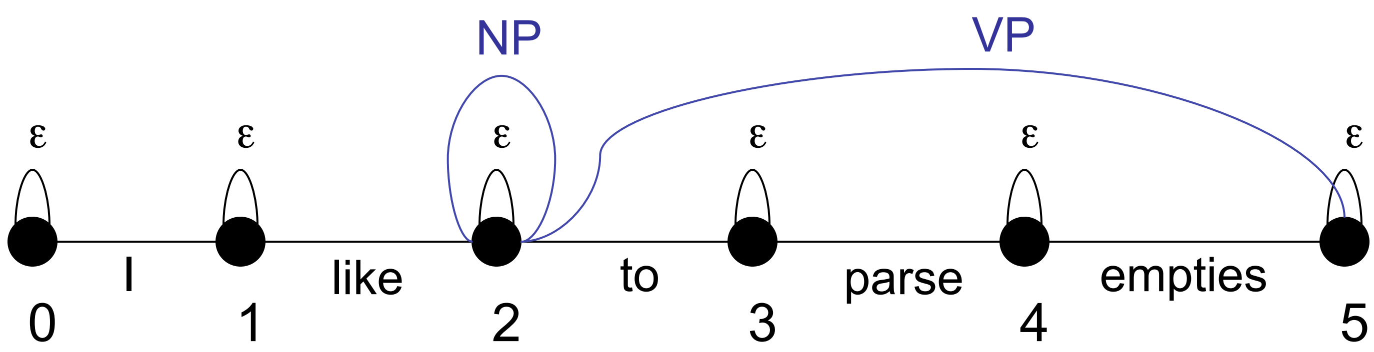
Empty Elements

- Sometimes we want to posit nodes in a parse tree that don't contain any pronounced words:

I want you to parse this sentence

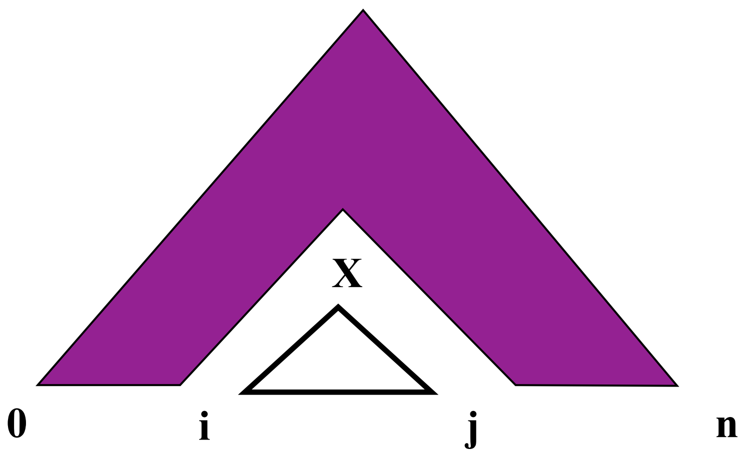
I want [   ] to parse this sentence

- These are easy to add to a chart parser!
  - For each position i, add the "word" edge ε:[i,i]
  - Add rules like NP → ε to the grammar
  - That's it!



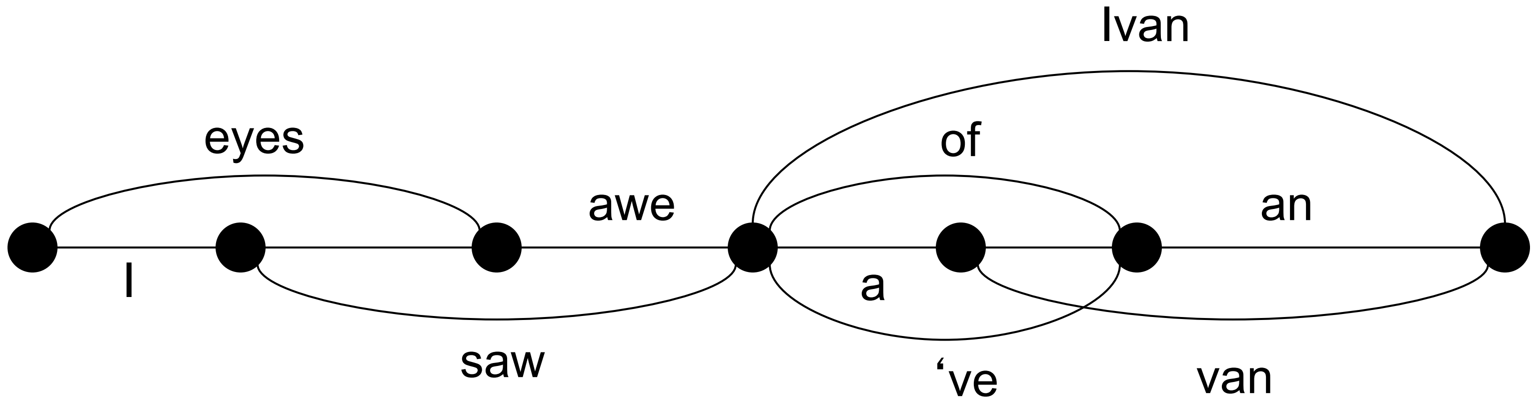
UCS / A*

- With weighted edges, order matters
  - Must expand optimal parse from bottom up (subparses first)
  - CKY does this by processing smaller spans before larger ones
  - UCS pops items off the agenda in order of decreasing Viterbi score
  - A* search also well defined
- You can also speed up the search without sacrificing optimality
  - Can select which items to process first
  - Can do with any "figure of merit" [Charniak 98]
  - If your figure-of-merit is a valid A* heuristic, no loss of optimiality [Klein and Manning 03]



(Speech) Lattices

- There was nothing magical about words spanning exactly one position.
- When working with speech, we generally don't know how many words there are, or where they break.
- We can represent the possibilities as a lattice and parse these just as easily.

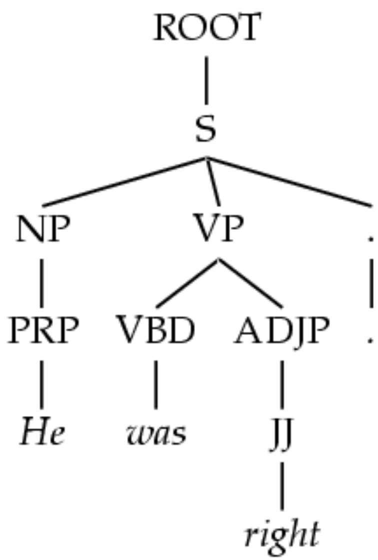


Treebank Sentences

```
( (S (NP-SBJ The move)
     (VP followed
         (NP (NP a round)
             (PP of
                 (NP (NP similar increases)
                     (PP by
                         (NP other lenders))
                     (PP against
                         (NP Arizona real estate loans)))))
         ,
         (S-ADV (NP-SBJ *)
                (VP reflecting
                    (NP (NP a continuing decline)
                        (PP-LOC in
                                (NP that market))))))
     .))
```

Treebank Grammars

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



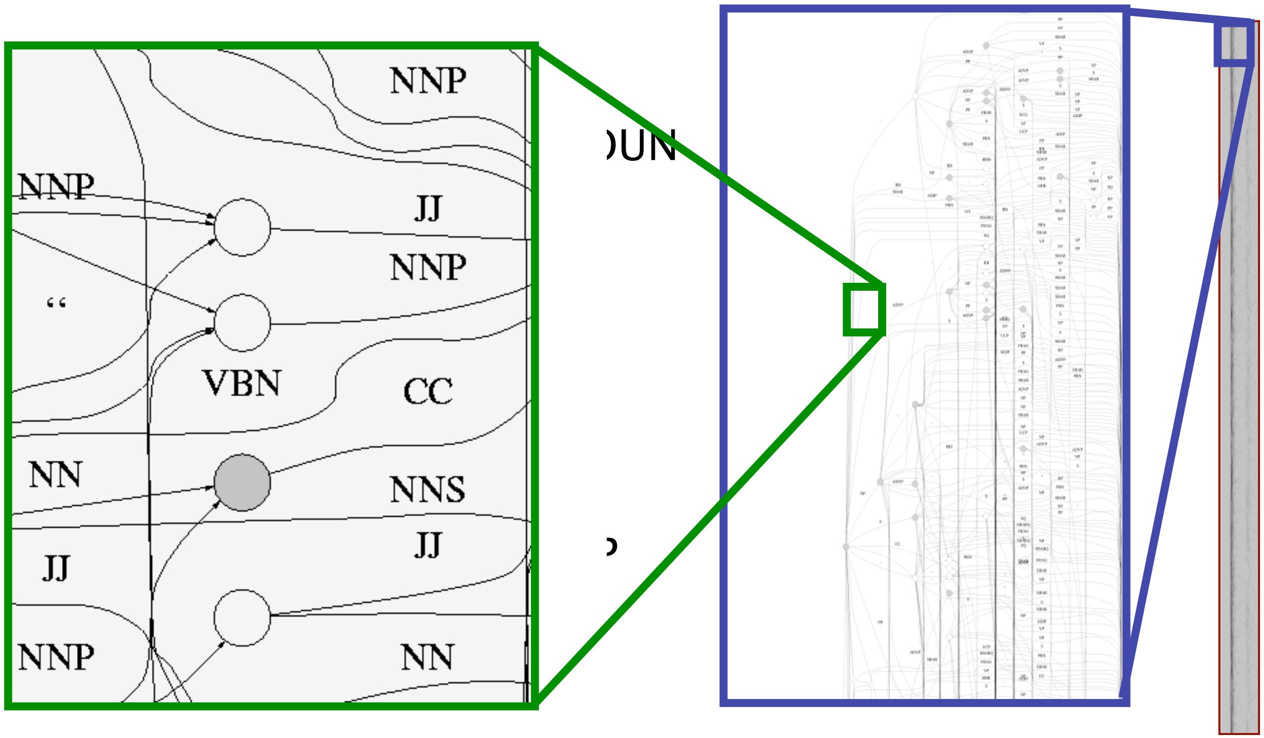
ROOT → S	1
S → NP VP .	1
NP → PRP	1
VP → VBD ADJP	1
…..	

- 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:



Typical Experimental Setup

- Corpus: Penn Treebank, WSJ

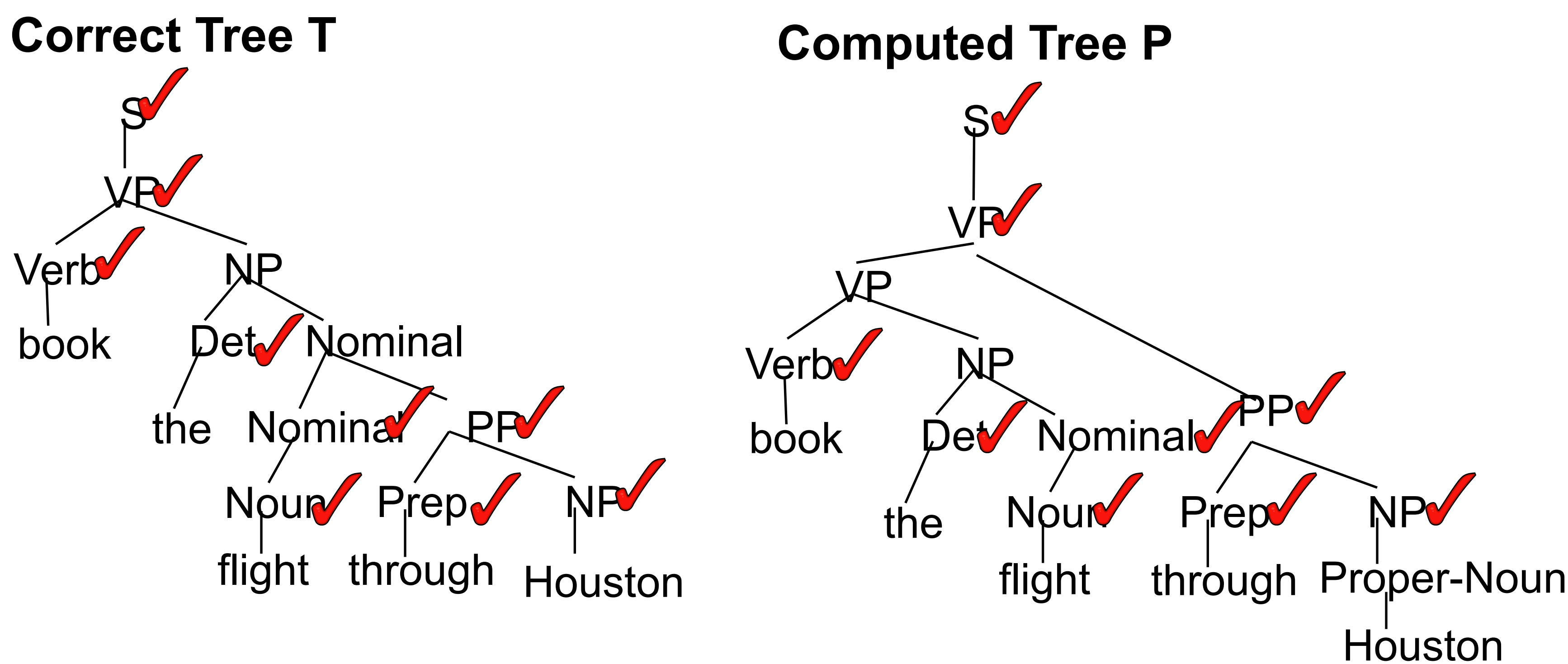
Training:	sections	02-21
Development:	section	22 (here, first 20 files)
Test:	section	23

- 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 •

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)

PARSEVAL Example



Constituents: 11

Constituents: 12

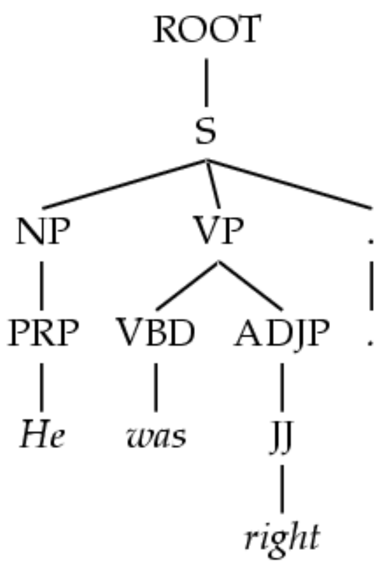
Correct Constituents: 10

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

Treebank PCFGs

[Charniak 96]

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

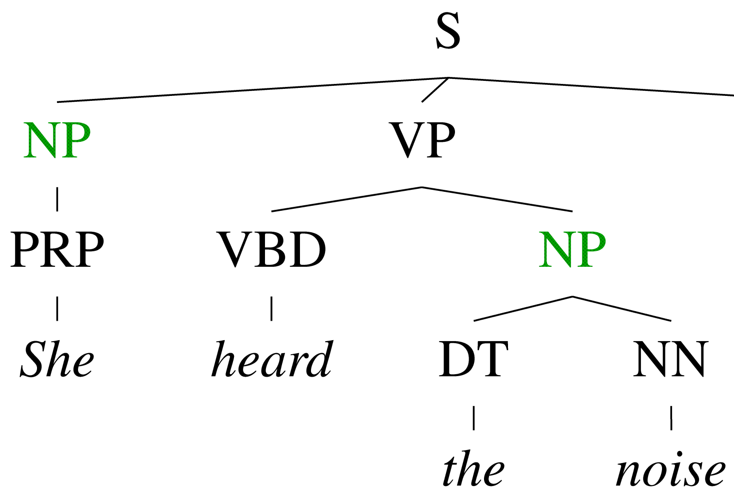


ROOT → S	1
S → NP VP .	1
NP → PRP	1
VP → VBD ADJP	1

…..

Model	F1
Baseline	72.0

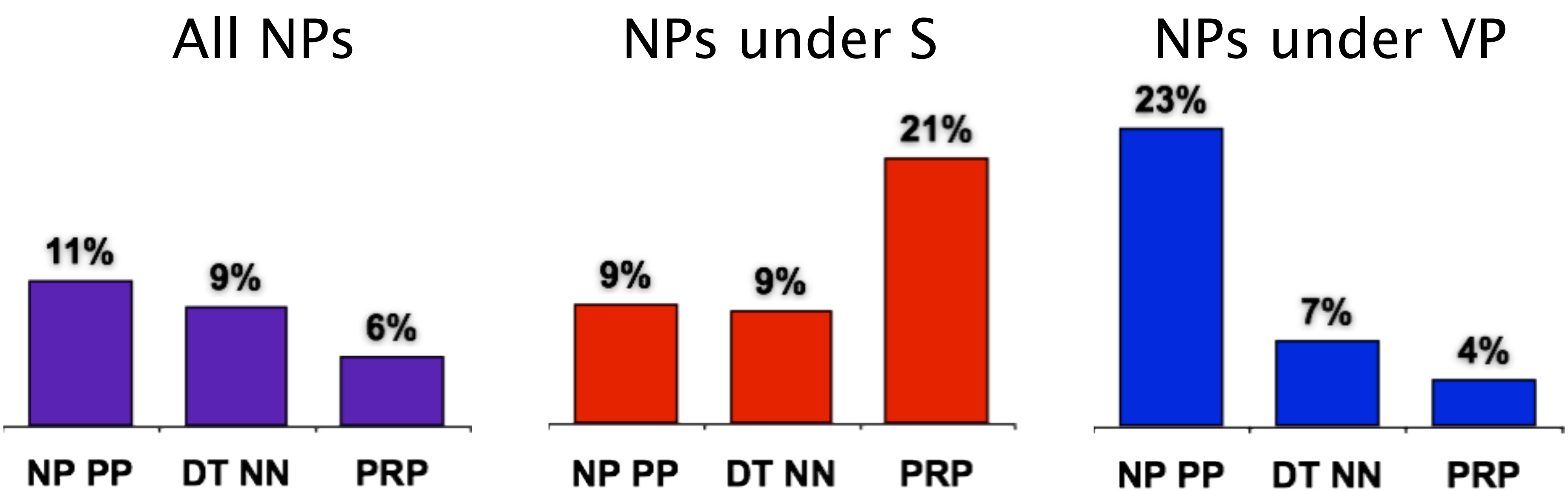
Conditional Independence?



- 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

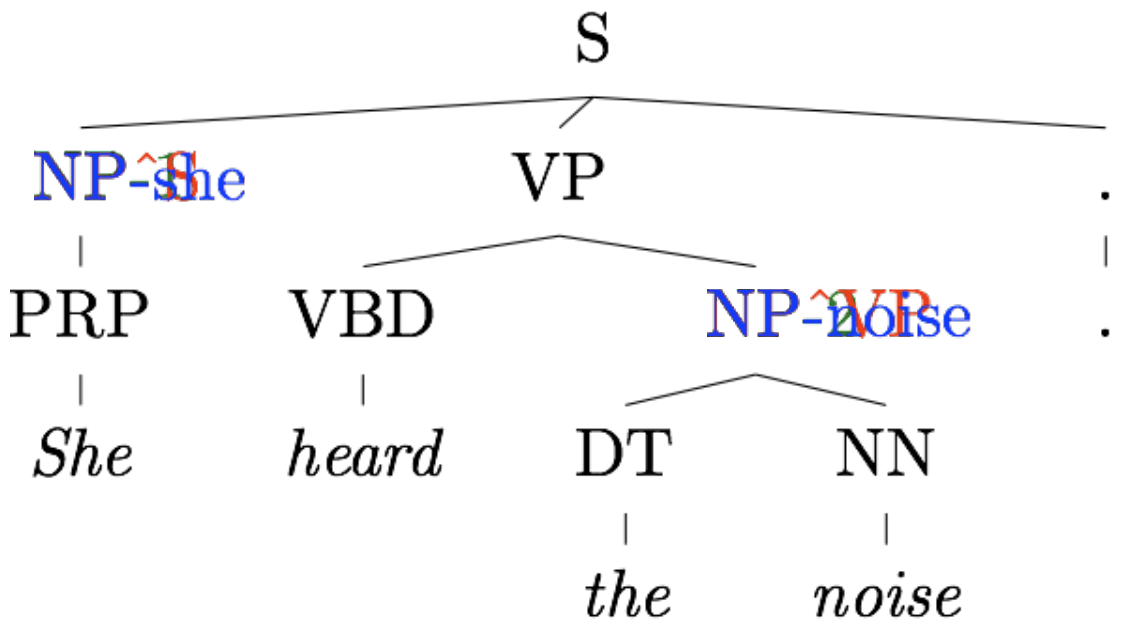
Non-Independence

- Independence assumptions are often too strong.



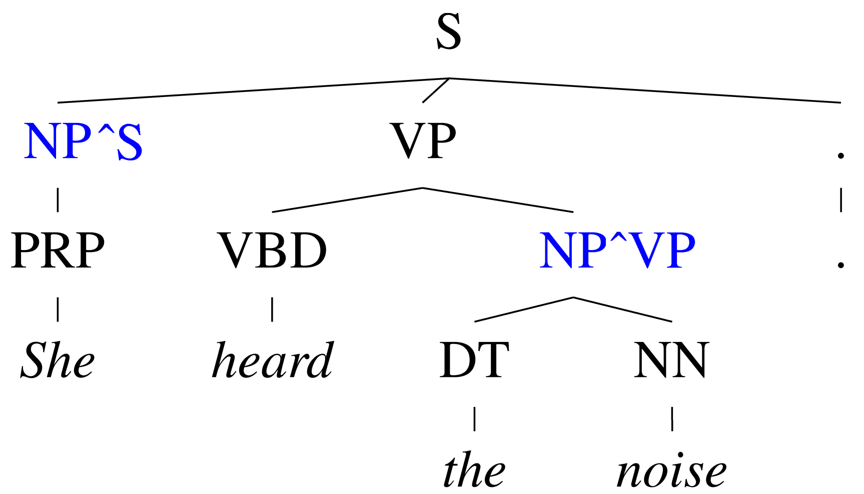
- Example: the expansion of an NP is highly dependent on the parent of the NP (i.e., subjects vs. objects).
- Also: the subject and object expansions are correlated!

Grammar Refinement



- Structure Annotation [Johnson ’98, Klein&Manning ’03]
- Lexicalization [Collins ’99, Charniak ’00]
- Latent Variables [Matsuzaki et al. 05, Petrov et al. ’06]

The Game of Designing a Grammar



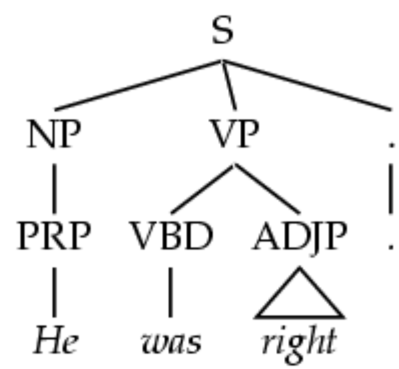
- Annotation refines base treebank symbols to improve statistical fit of the grammar
- Structural annotation

Vertical Markovization

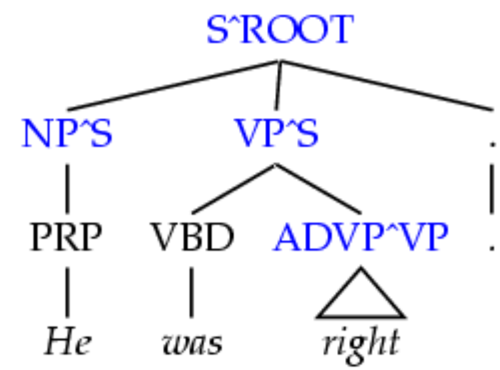
- Vertical Markov order: rewrites depend on past k ancestor nodes.

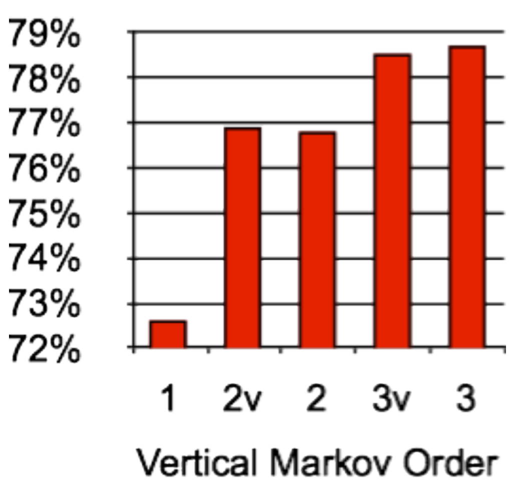
  (cf. parent annotation)

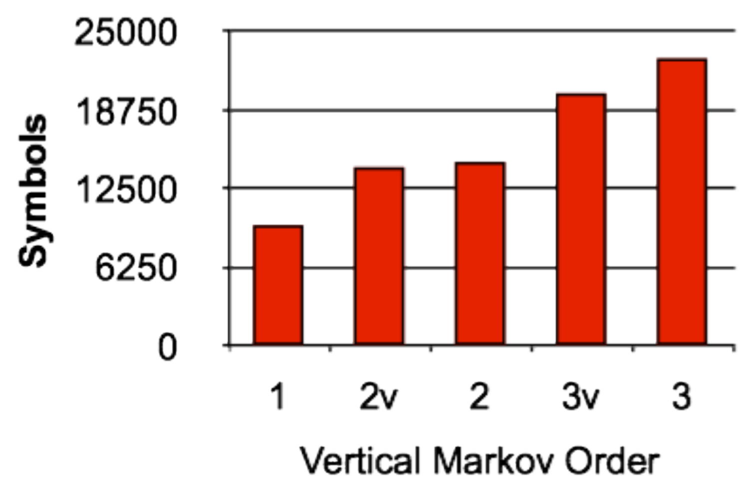
Order 1



Order 2

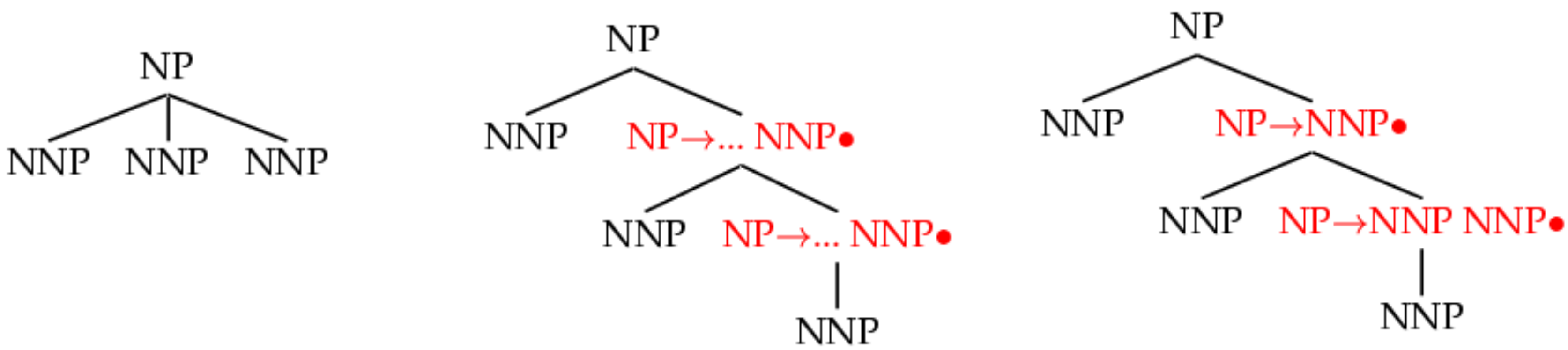


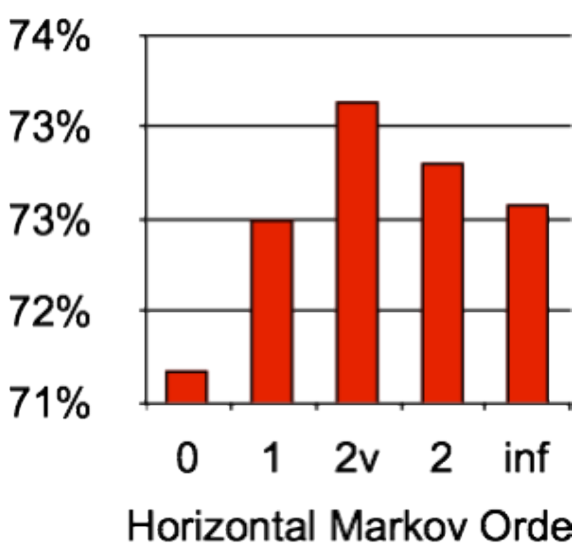


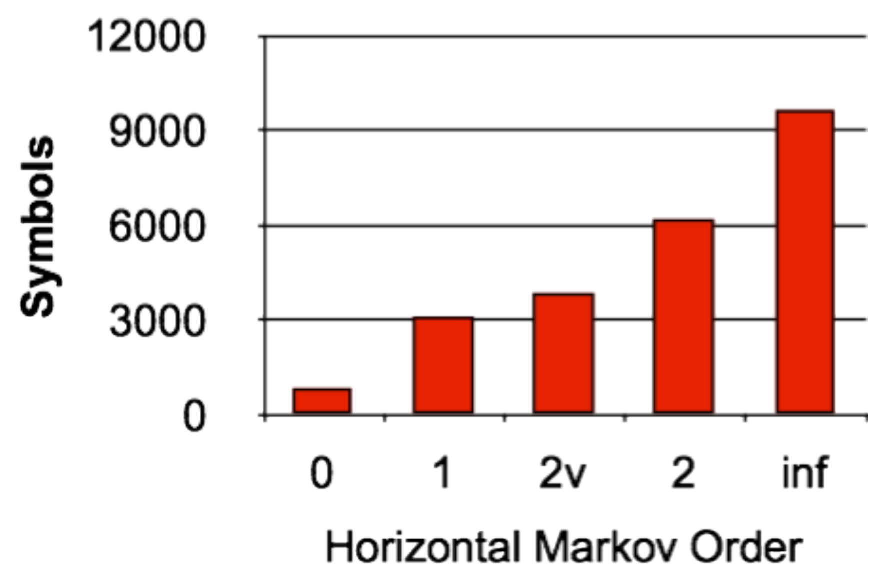


Horizontal Markovization

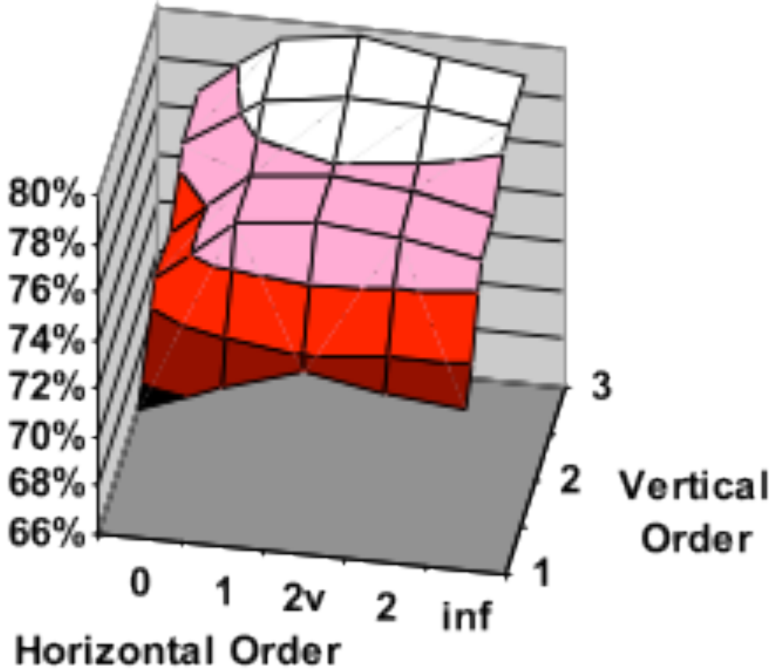
Order 1 Order ∞

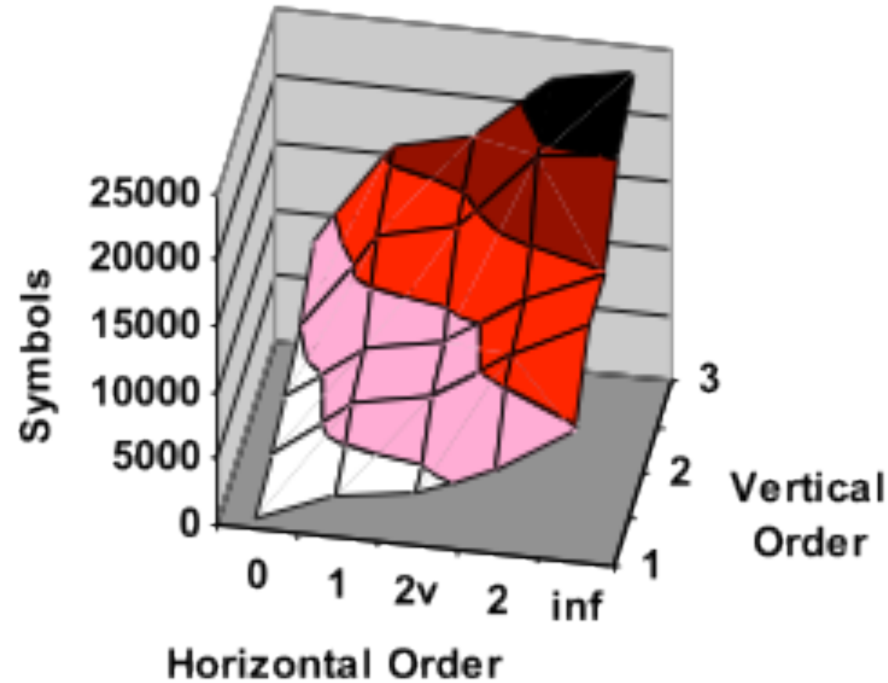






Vertical and Horizontal



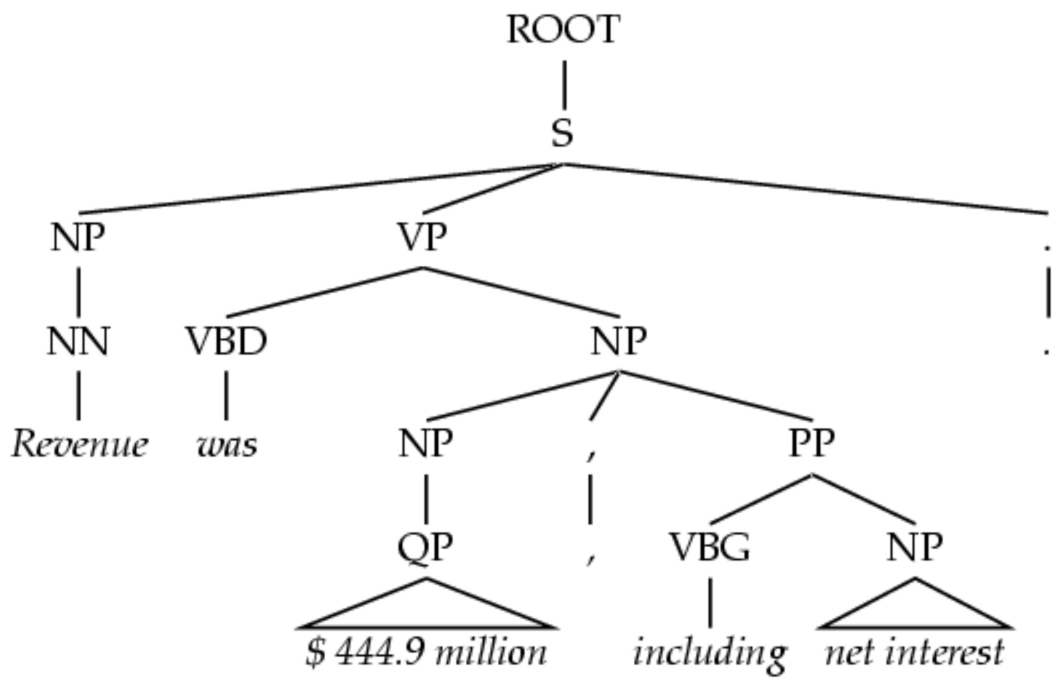


- Examples:
  - Raw treebank: v=1, h=∞
  - Johnson 98: v=2, h=∞
  - Collins 99: v=2, h=2
  - Best F1: v=3, h=2v

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

Unary Splits

- Problem: unary rewrites used to transmute categories so a high-probability rule can be used.

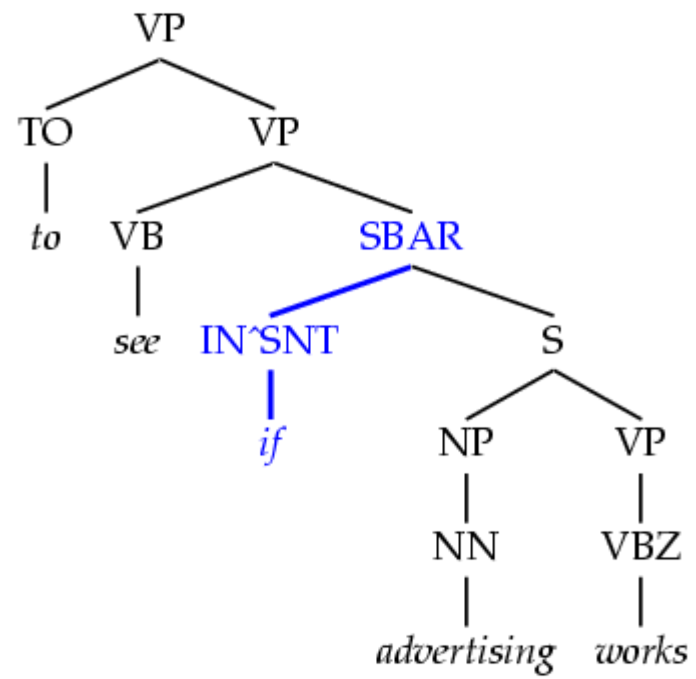


- Solution: Mark unary rewrite sites with -U

Annotation	F1	Size
Base	77.8	7.5K
UNARY	78.3	8.0K

Tag Splits

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



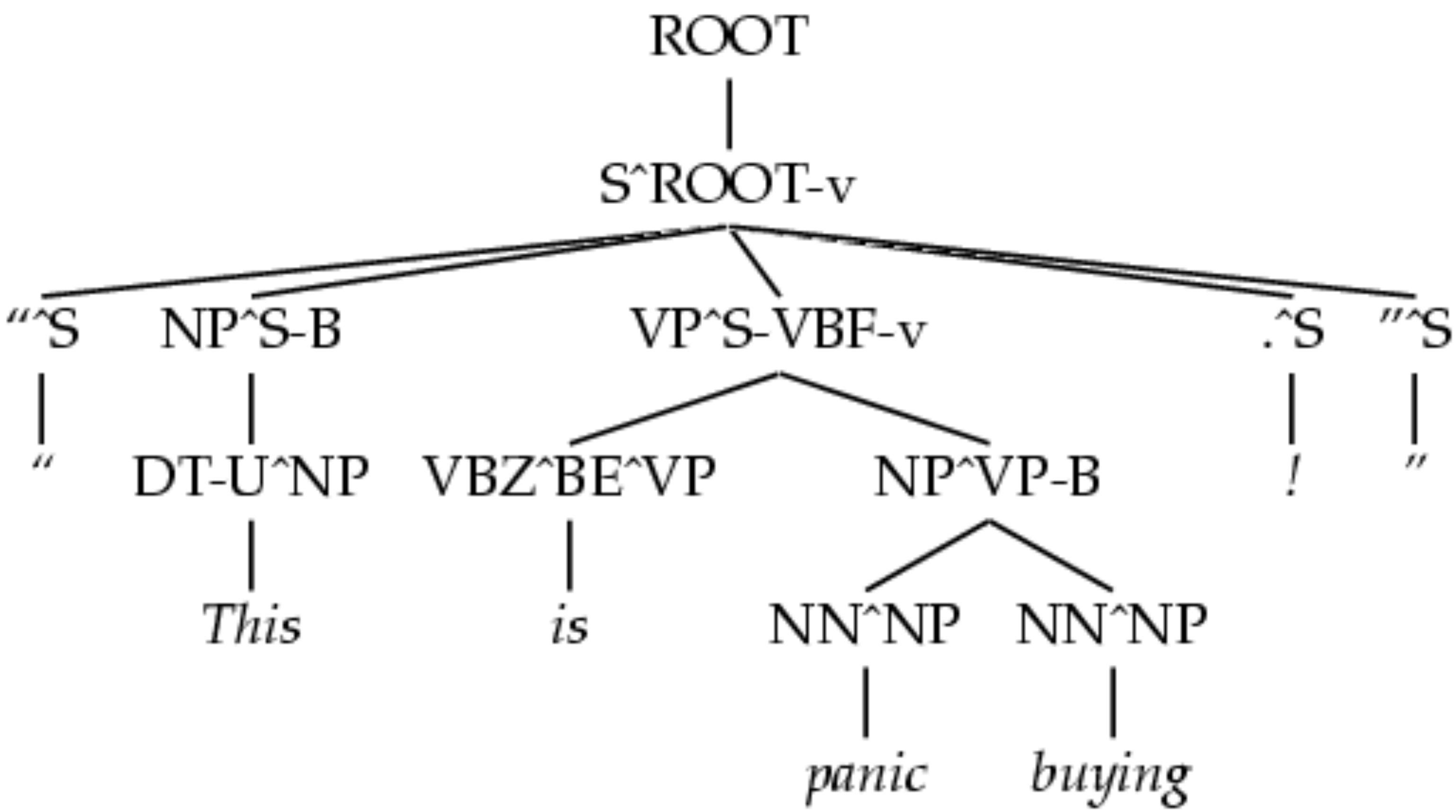
Annotation	F1	Size
Previous	78.3	8.0K
SPLIT-IN	80.3	8.1K

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

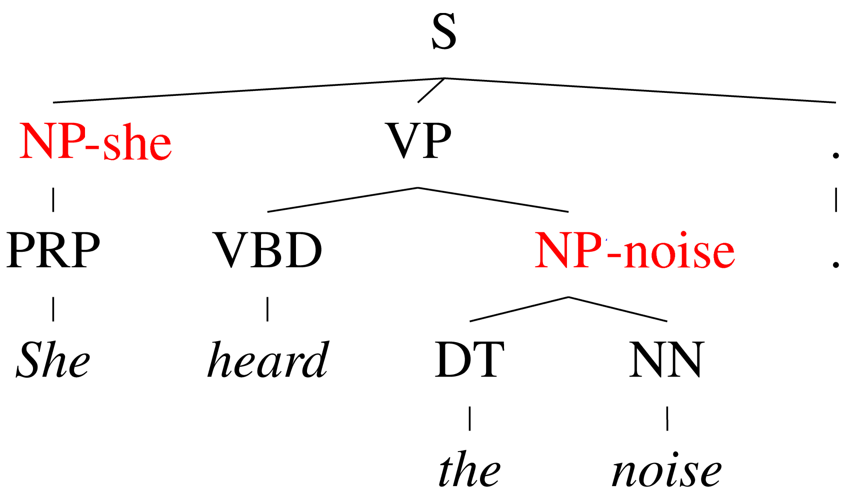


Some Test Set Results

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

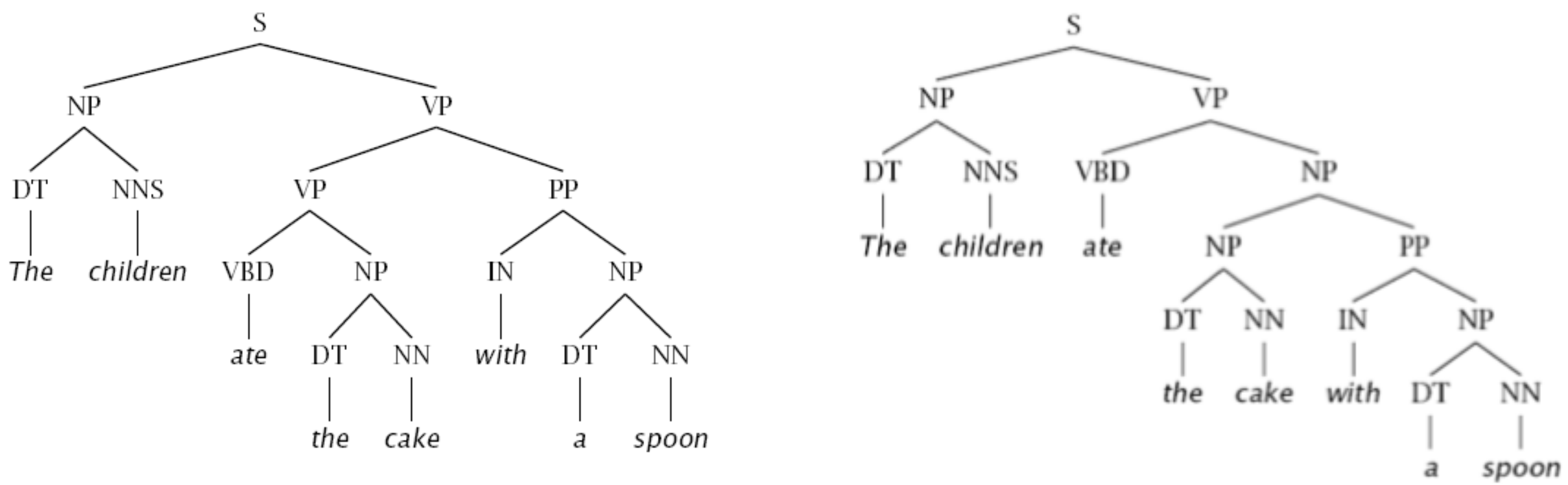
- Beats “first generation” lexicalized parsers.
- Lots of room to improve – more complex models next.

The Game of Designing a Grammar



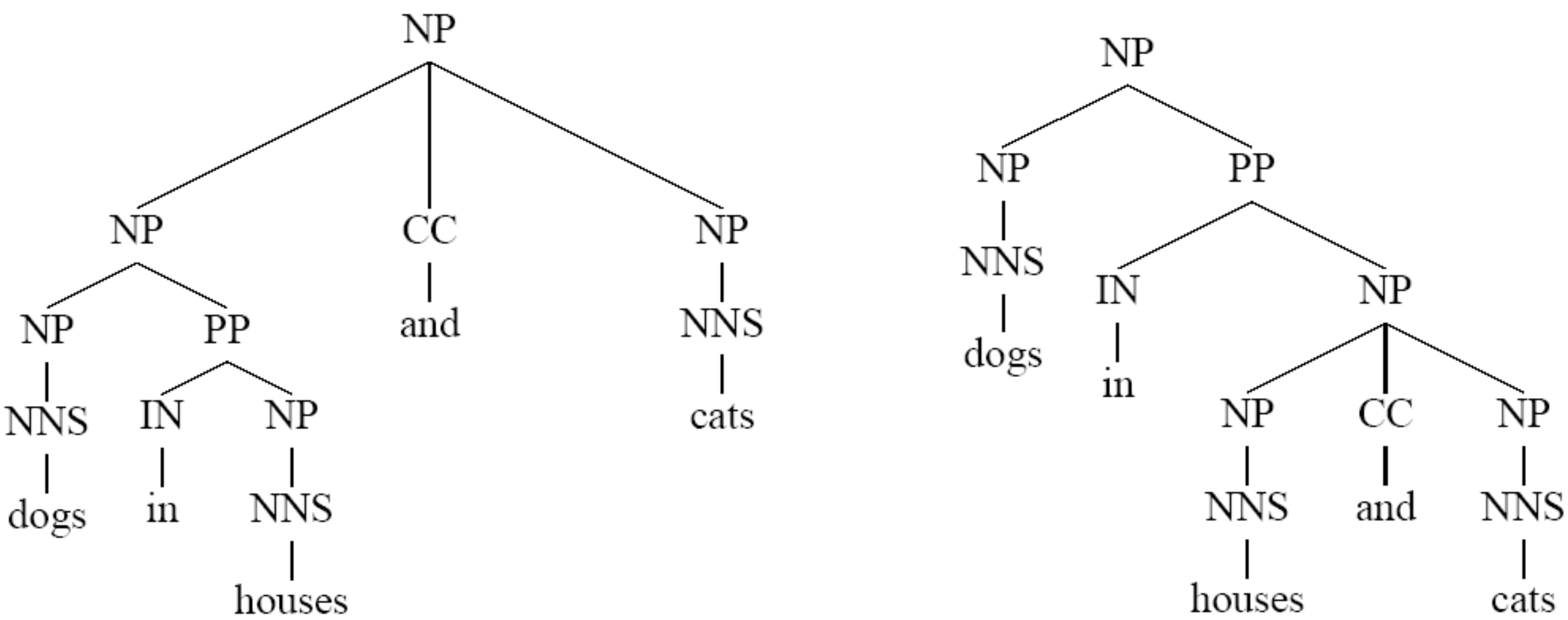
- Annotation refines base treebank symbols to improve statistical fit of the grammar
- Structural annotation [Johnson ’98, Klein and Manning 03]
- Head lexicalization [Collins ’99, Charniak ’00]

Problems with PCFGs



- If we do no annotation, these trees differ only in one rule:
  - VP → VP PP
  - NP → NP PP
- Parse will go one way or the other, regardless of words
- We addressed this in one way with unlexicalized grammars (how?)
- Lexicalization allows us to be sensitive to specific words

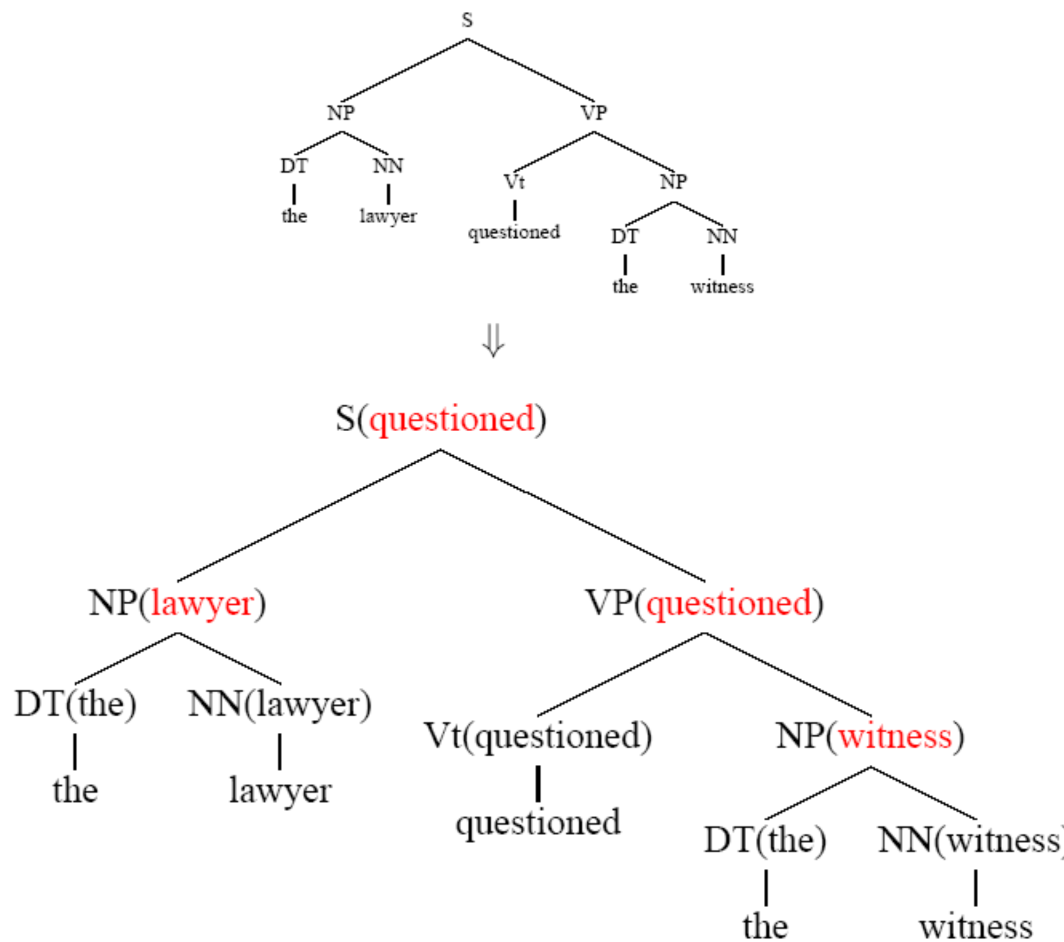
Problems with PCFGs



- What's different between basic PCFG scores here?
- What (lexical) correlations need to be scored?

Lexicalized Trees

- Add “headwords” to each phrasal node
  - Headship not in (most) treebanks
  - Usually use 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



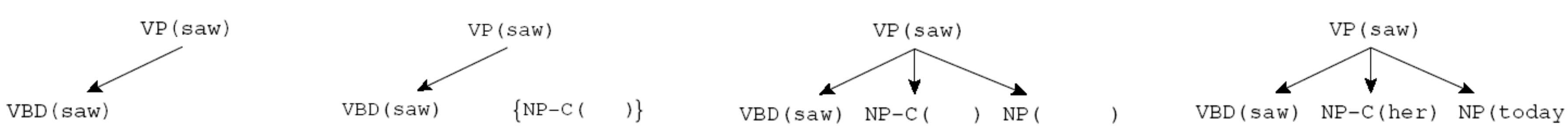
Lexicalized PCFGs?

- Problem: we now have to estimate probabilities like

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

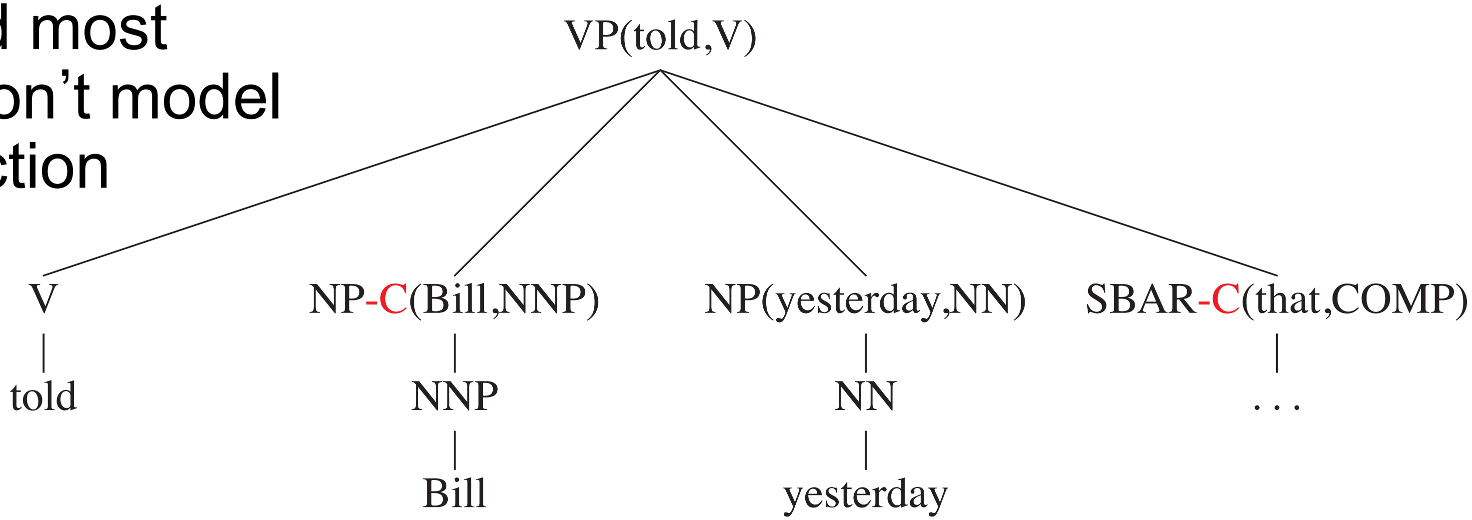
- Never going to get these atomically off of a treebank

- Solution: break up derivation into smaller steps



Complement / Adjunct Distinction

- *warning* - can be tricky, and most parsers don’t model the distinction

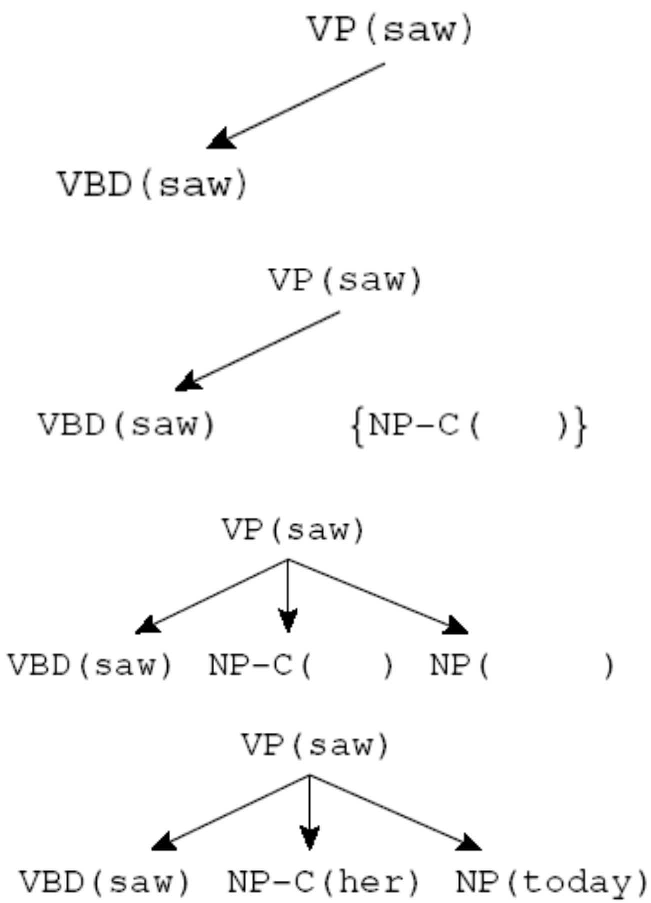


- Complement: defines a property/argument (often obligatory), ex: [capitol [of Rome]]
- Adjunct: modifies / describes something (always optional), ex: [quickly ran]
- A Test for Adjuncts: [X Y] --> can claim X and Y
  - [they ran and it happened quickly] vs. [capitol and it was of Rome]

[Collins 99]

Lexical Derivation Steps

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



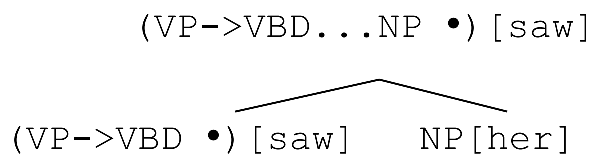
Step 1: Choose a head tag and word

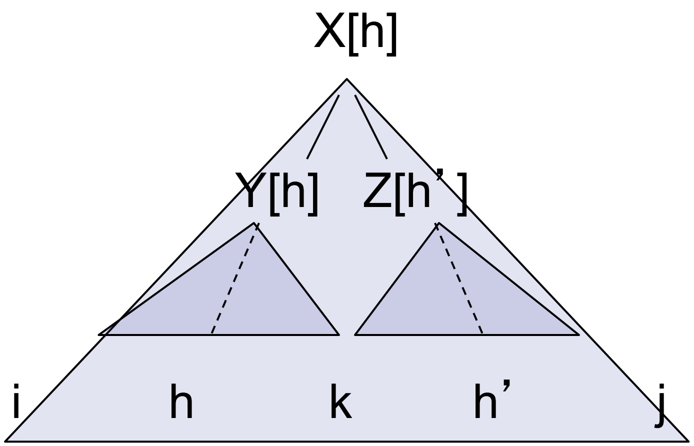
Step 2: Choose a complement bag

Step 3: Generate children (incl. adjuncts)

Step 4: Recursively derive children

Lexicalized CKY

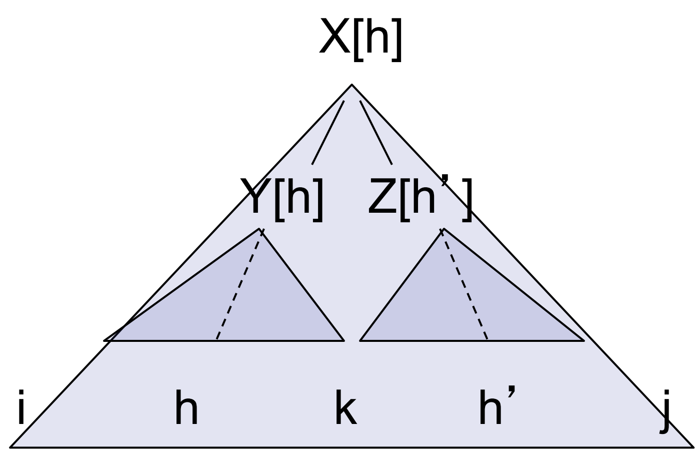





```
bestScore(X,i,j,h)
  if (j = i+1)
    return tagScore(X,s[i])
  else
    return
      max        max     score(X[h]->Y[h] Z[h']) *
      k,h',               bestScore(Y,i,k,h) *
      X->YZ               bestScore(Z,k,j,h')
                 max     score(X[h]->Y[h'] Z[h]) *
      k,h,           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

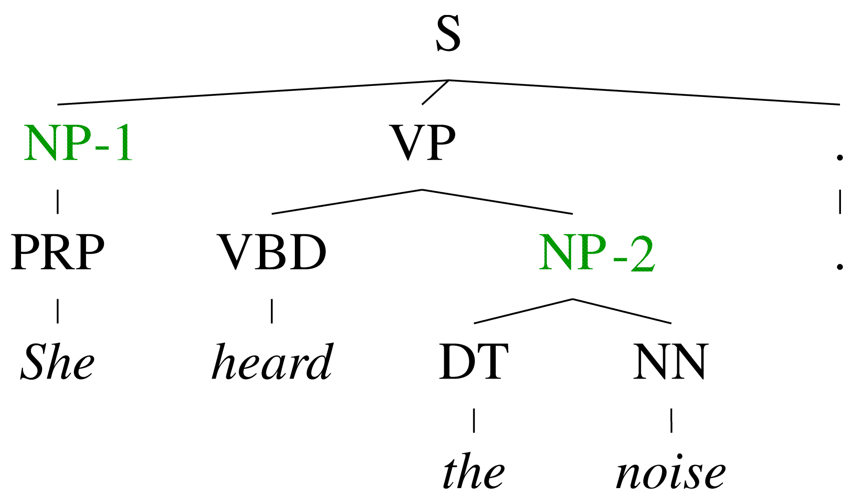
Pruning with Beams

- The Collins parser prunes with per-cell beams [Collins 99]
  - Essentially, run the $O(n^5)$ CKY
  - Remember only a few hypotheses for each span <i,j>.
  - 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)

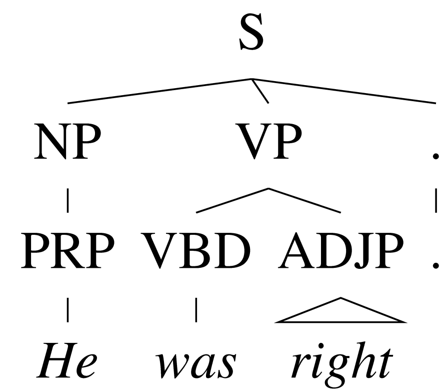
The Game of Designing a Grammar



- Annotation refines base treebank symbols to improve statistical fit of the grammar
- Parent annotation [Johnson ’98]
- Head lexicalization [Collins ’99, Charniak ’00]
- Automatic clustering?

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

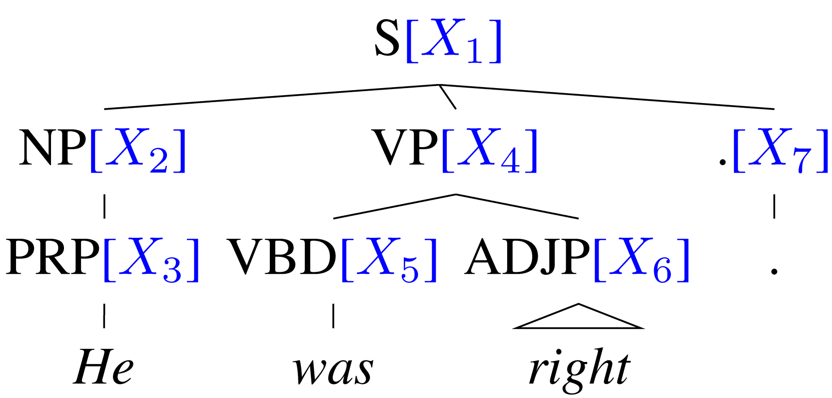


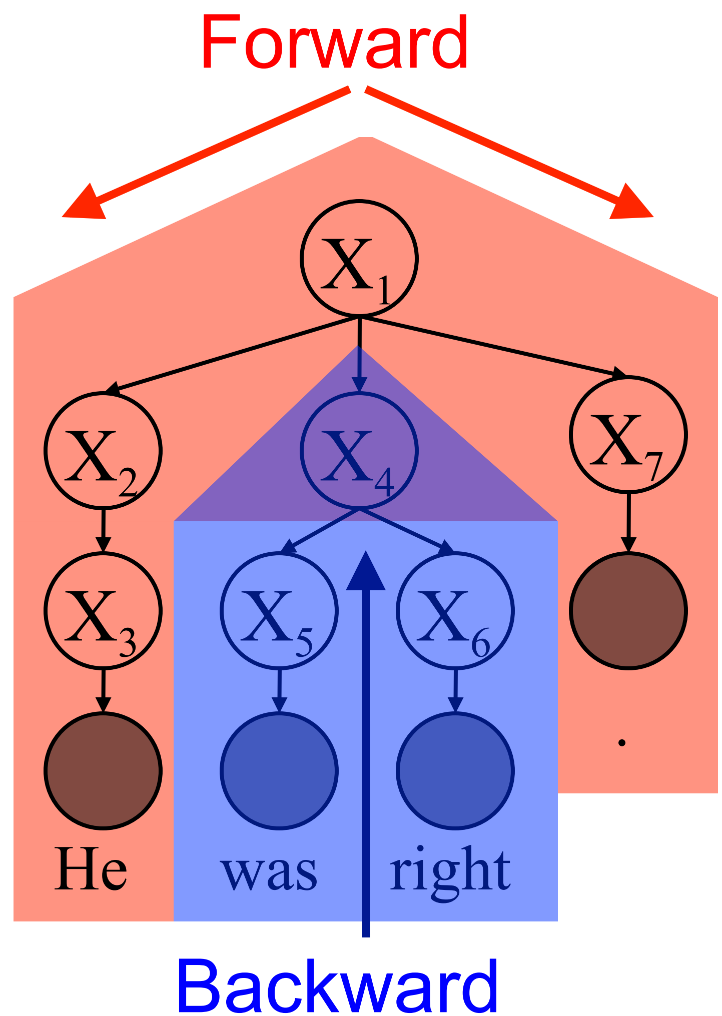
Model	F1
Naïve Treebank Grammar	72.6
Klein & Manning ’03	86.3
Collins 99	88.6

Learning Latent Annotations

Latent Annotations:

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





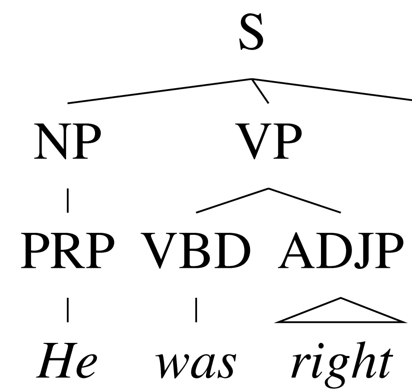
Can learn with EM: like Forward-Backward for HMMs.

Automatic Annotation Induction

- Advantages:
  - Automatically learned:

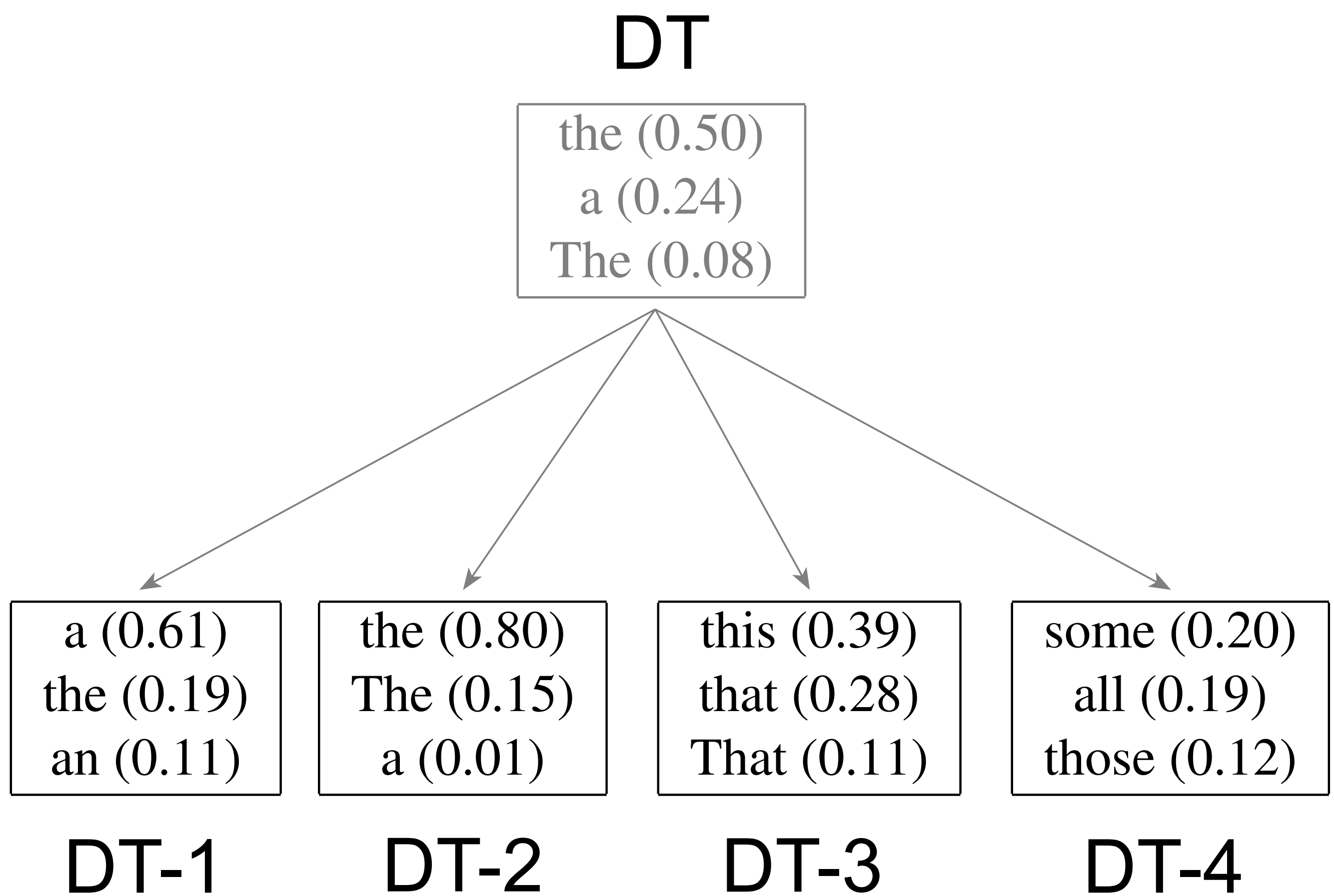
    Label all nodes with latent variables.

    Same number k of subcategories for all categories.
- Disadvantages:
  - Grammar gets too large
  - Most categories are oversplit while others are undersplit.



Model	F1
Klein & Manning '03	86.3
Matsuzaki et al. '05	86.7

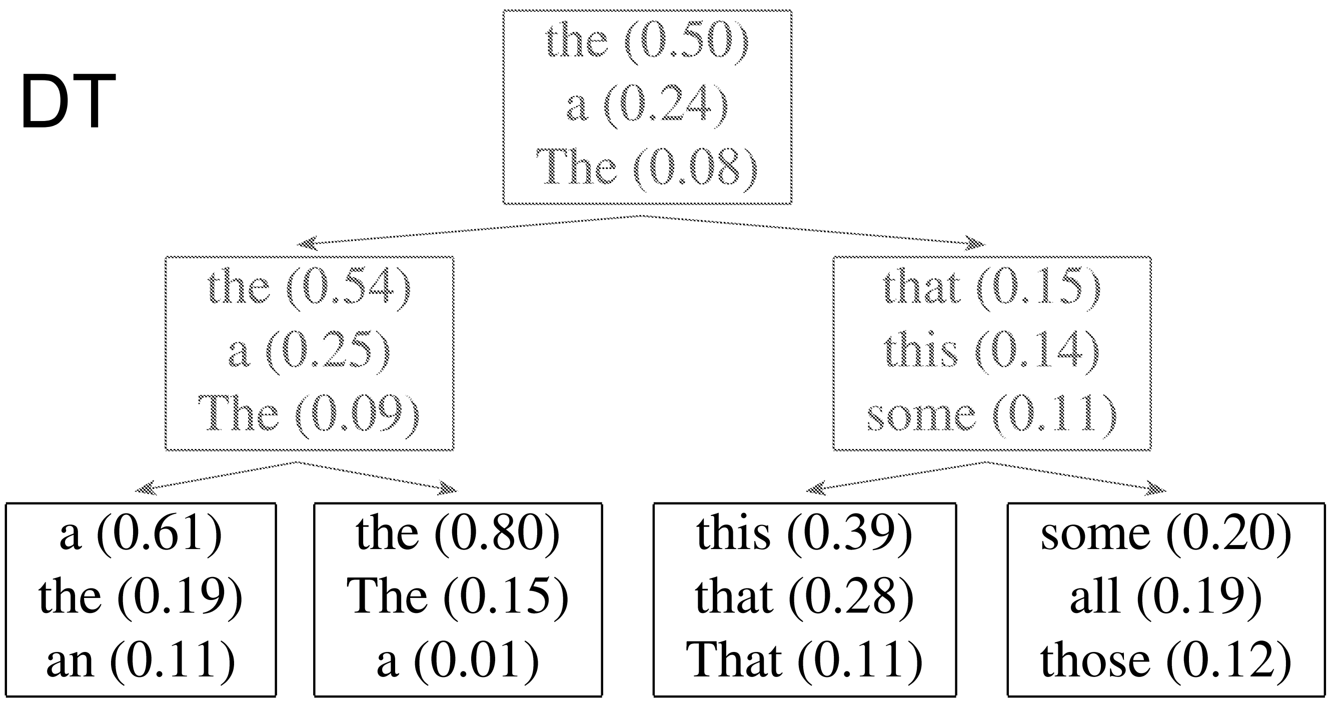
Refinement of the DT tag



Hierarchical refinement

- Repeatedly learn more fine-grained subcategories
- start with two (per non-terminal), then keep splitting
- initialize each EM run with the output of the last

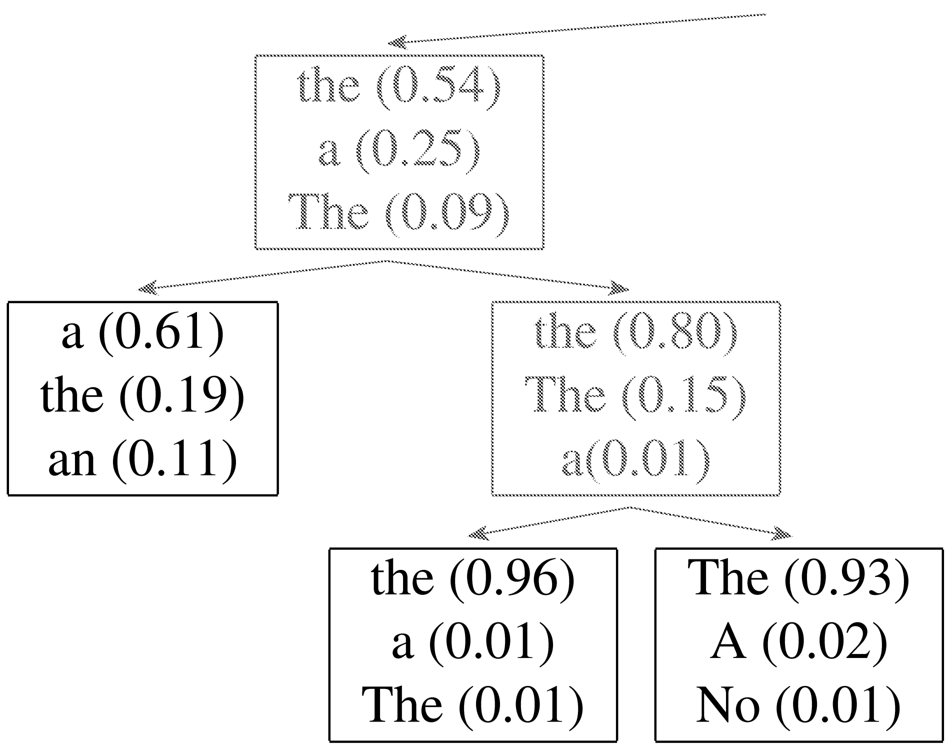
DT



[Petrov et al. 06]

Adaptive Splitting

- Want to split complex categories more
- Idea: split everything, roll back splits which were least useful

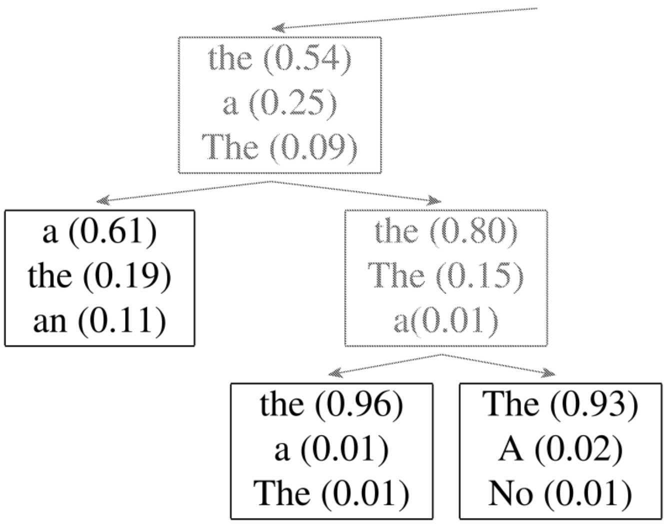


Adaptive Splitting

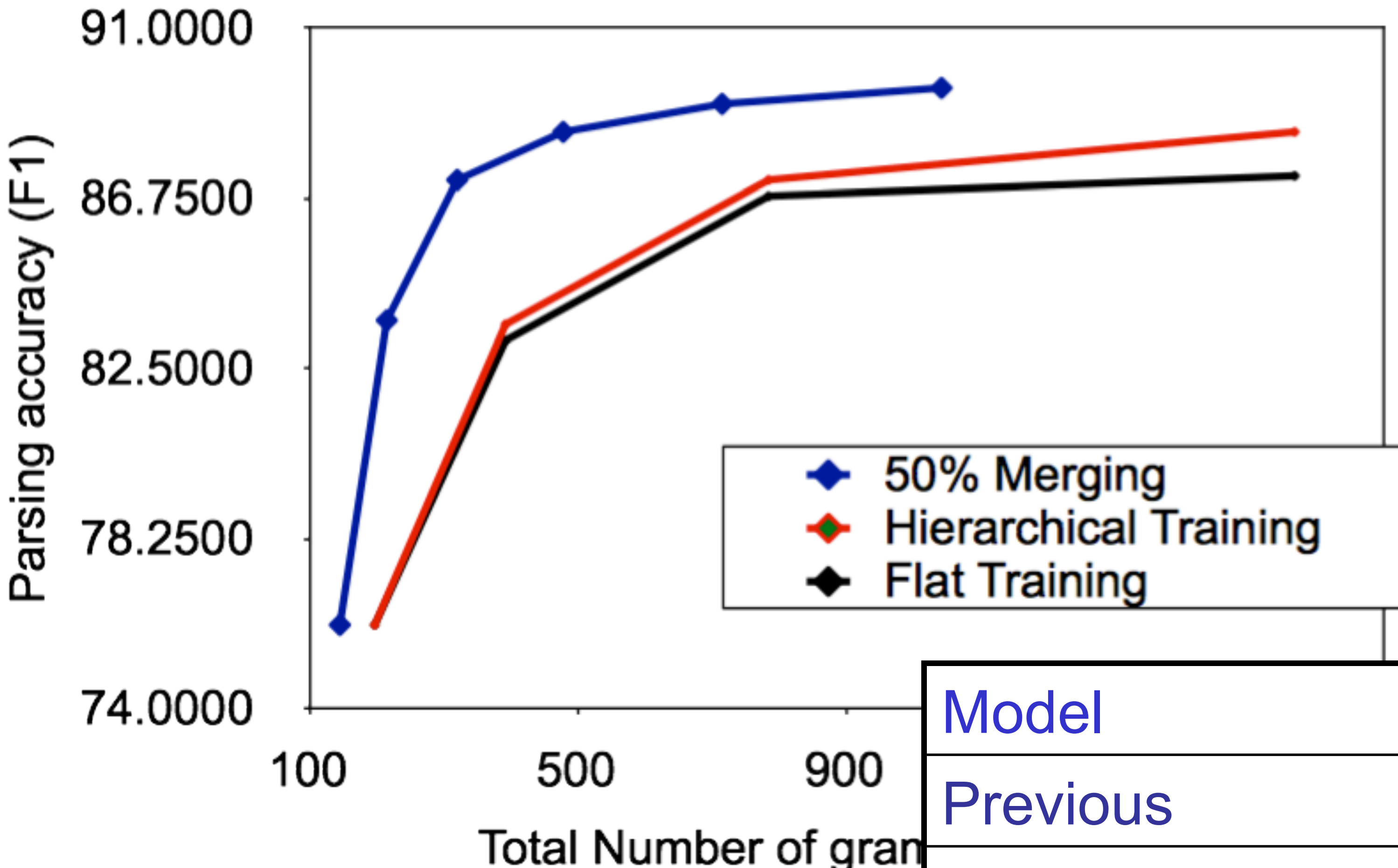
- Evaluate loss in likelihood from removing each split =

$$\frac{\text{Data likelihood with split reversed}}{\text{Data likelihood with split}}$$

- No loss in accuracy when 50% of the splits are reversed.

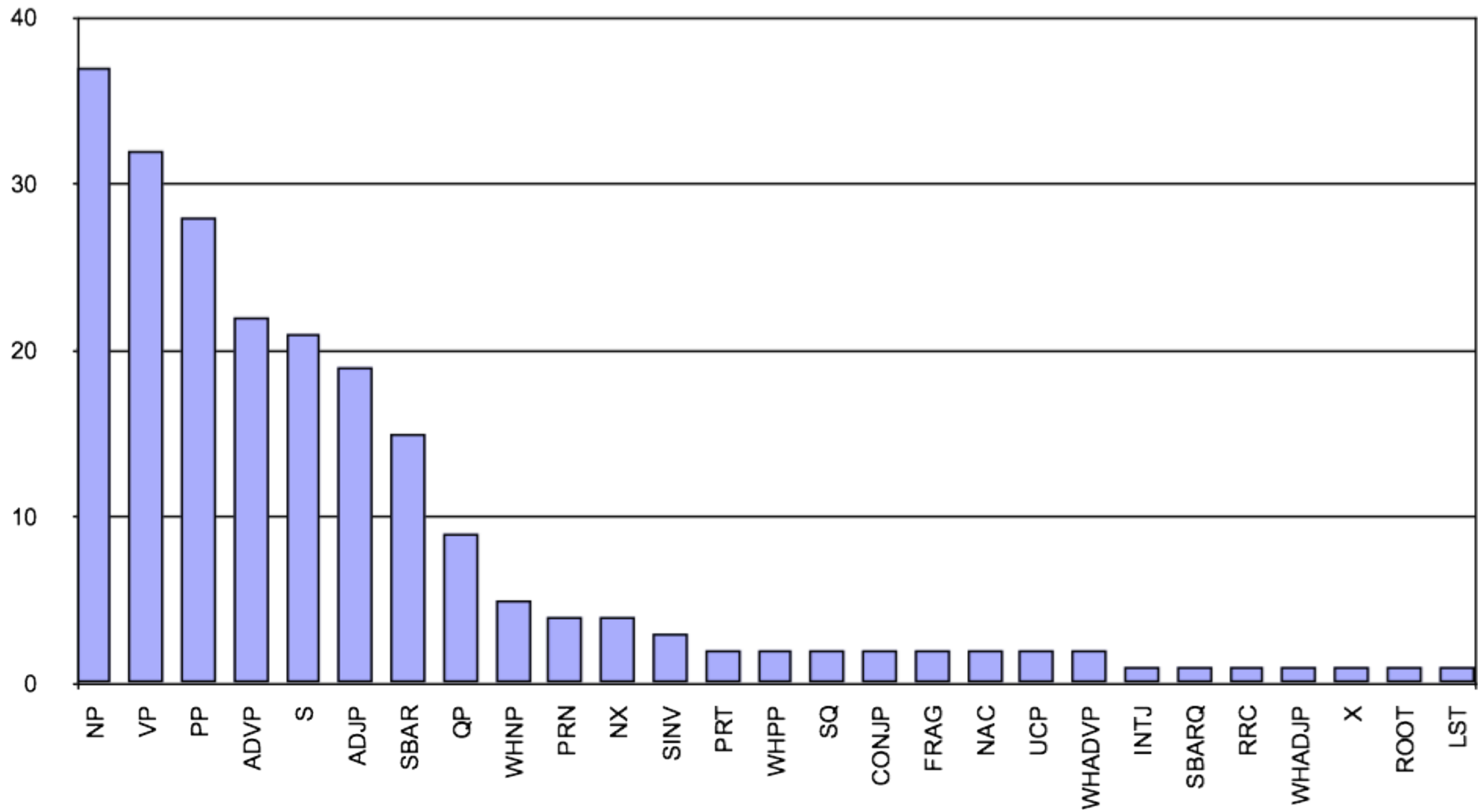


Adaptive Splitting Results

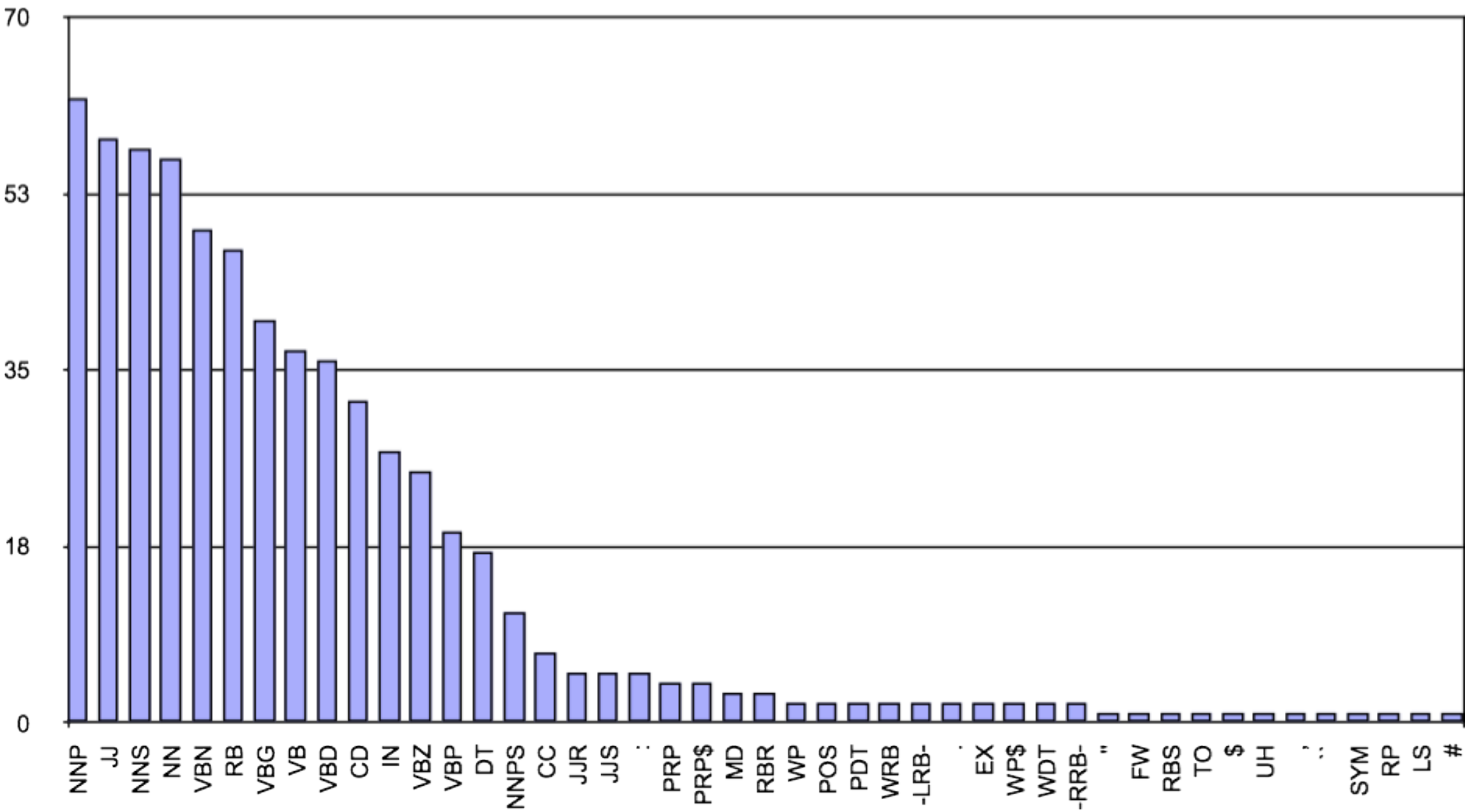


Model	F1
Previous	88.4
With 50% Merging	89.5

Number of Phrasal Subcategories



Number of Lexical Subcategories



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

Learned Splits

- Proper Nouns (NNP):

NNP-14	Oct.	Nov.	Sept.
NNP-12	John	Robert	James
NNP-2	J.	E.	L.
NNP-1	Bush	Noriega	Peters
NNP-15	New	San	Wall
NNP-3	York	Francisco	Street

- Personal pronouns (PRP):

PRP-0	It	He	I
PRP-1	it	he	they
PRP-2	it	them	him

Learned Splits

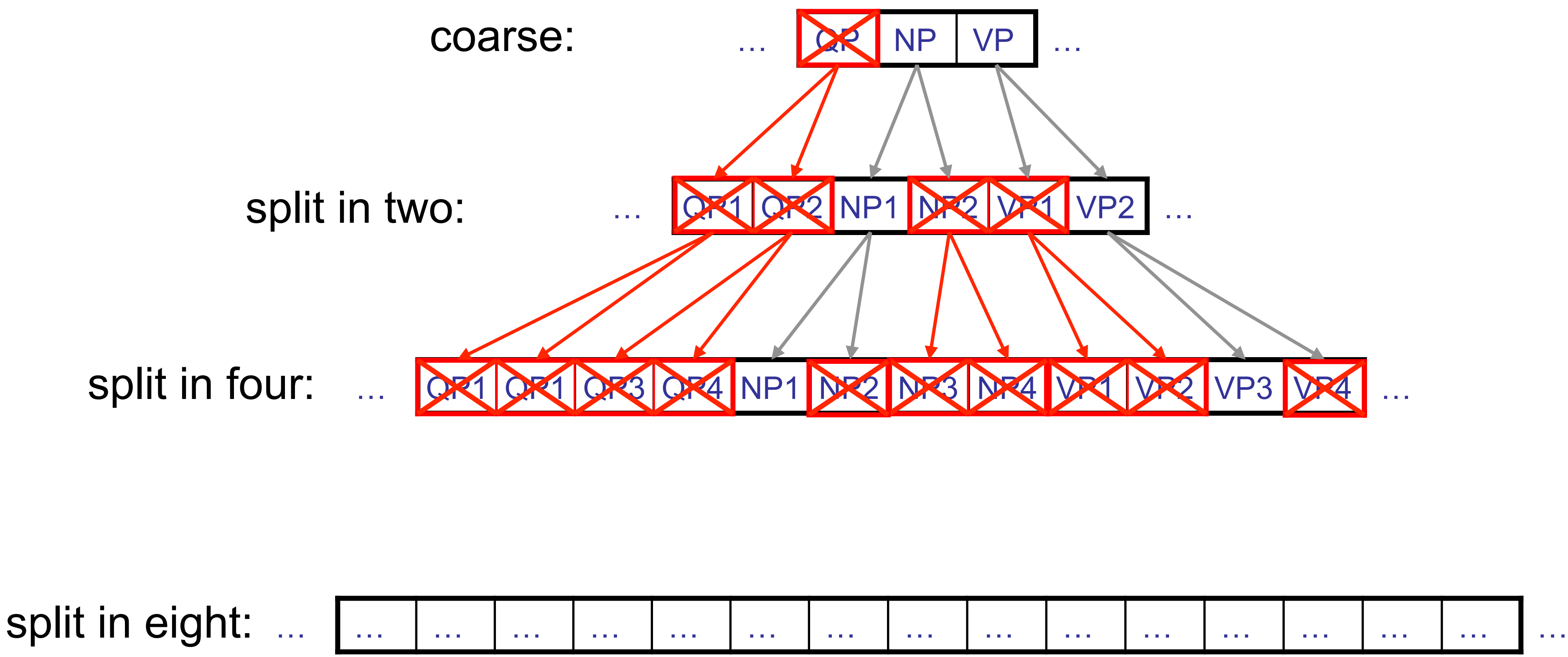
- Relative adverbs (RBR):

RBR-0	further	lower	higher
RBR-1	more	less	More
RBR-2	earlier	Earlier	later

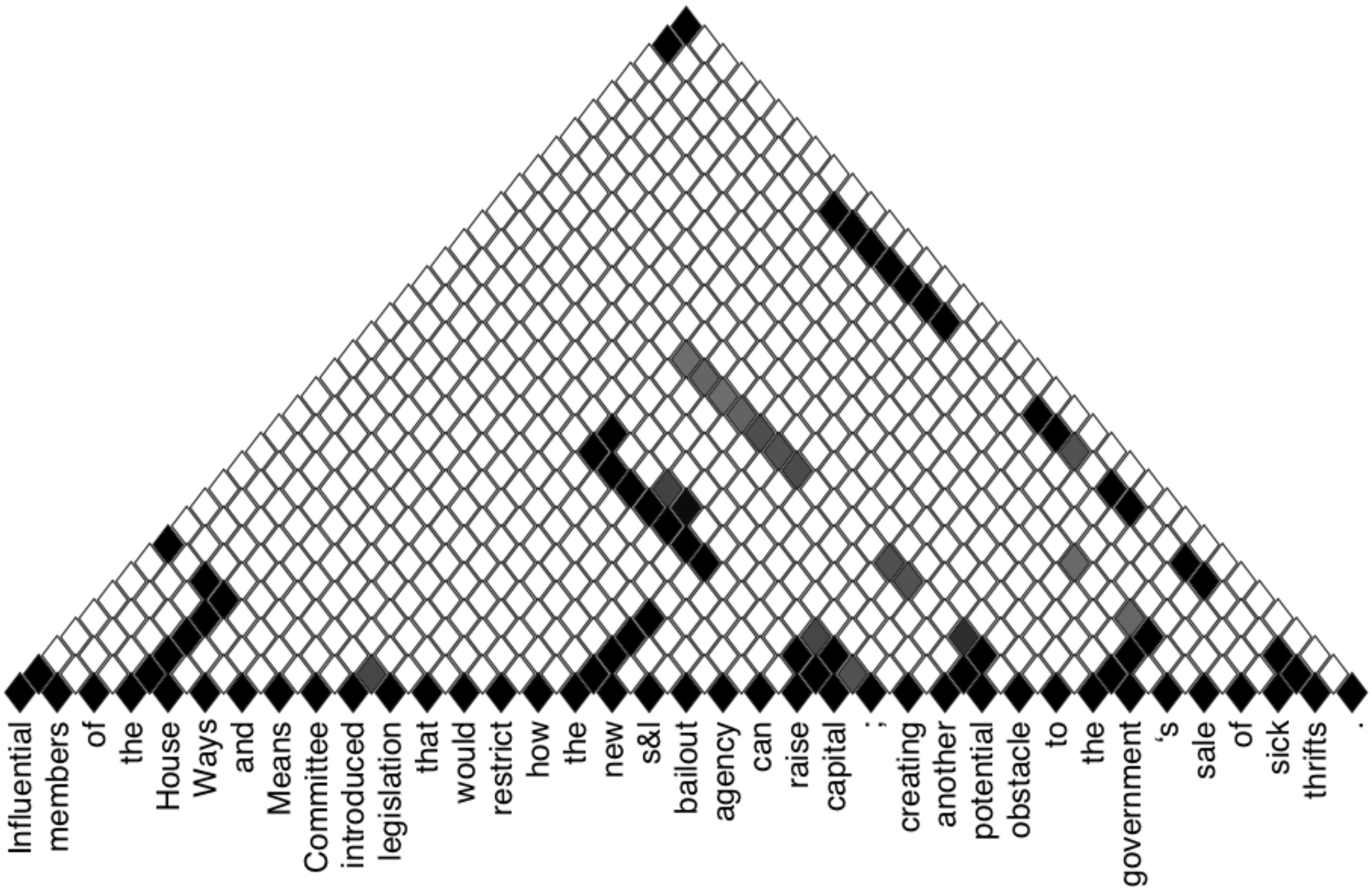
- Cardinal Numbers (CD):

CD-7	one	two	Three
CD-4	1989	1990	1988
CD-11	million	billion	trillion
CD-0	1	50	100
CD-3	1	30	31
CD-9	78	58	34

Hierarchical Pruning



Bracket Posteriors



1621 min

111 min

35 min

15 min
(no search error)

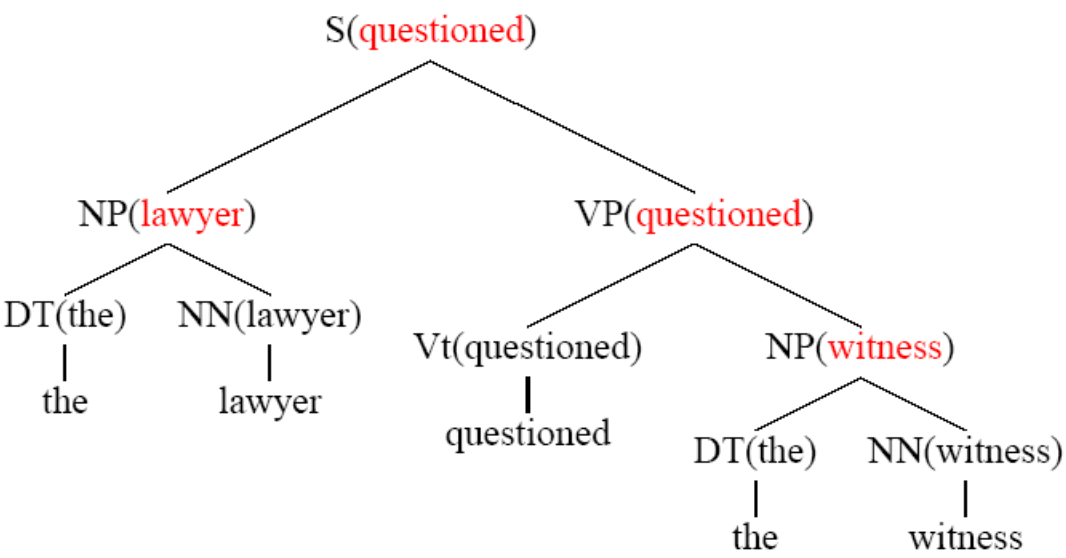
Final Results (Accuracy)

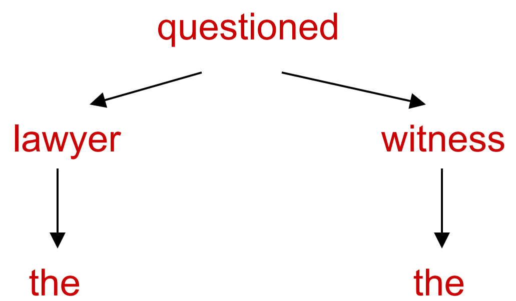
		≤ 40 words F1	all F1
ENG	Charniak&Johnson '05 (generative)	90.1	89.6
	Split / Merge	**90.6**	**90.1**
GER	Dubey '05	76.3	-
	Split / Merge	**80.8**	**80.1**
CHN	Chiang et al. '02	80.0	76.6
	Split / Merge	**86.3**	**83.4**

Still higher numbers from reranking / self-training methods

Dependency Parsing

- Lexicalized parsers can be seen as producing *dependency trees*

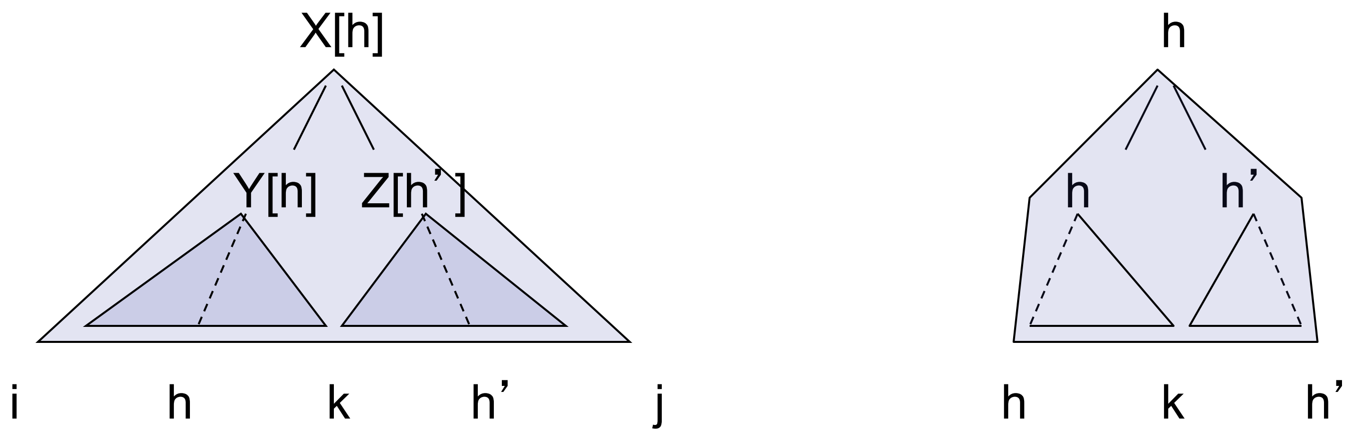




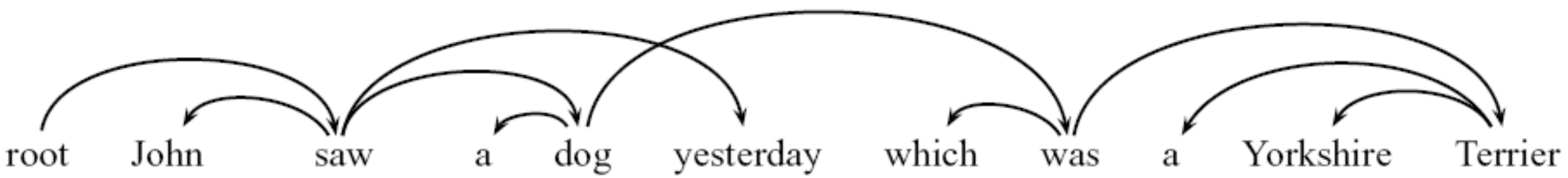
- Each local binary tree corresponds to an attachment in the dependency graph

Dependency Parsing

- Pure dependency parsing is only cubic [Eisner 99]

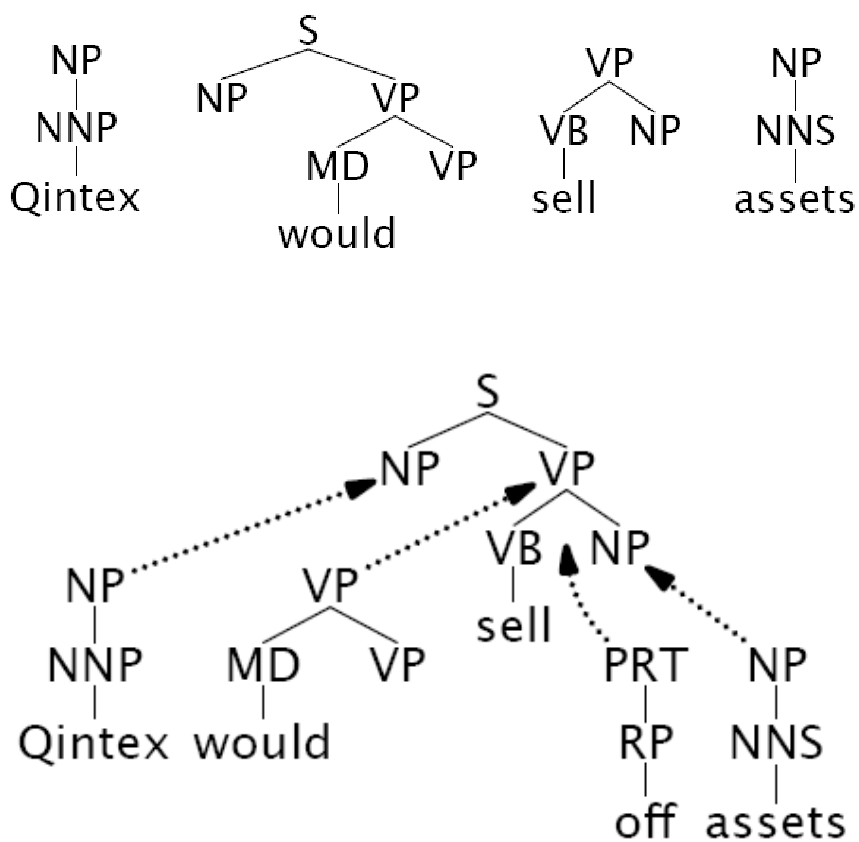


- Some work on *non-projective* dependencies
  - Common in, e.g. Czech parsing
  - Can do with MST algorithms [McDonald and Pereira 05]

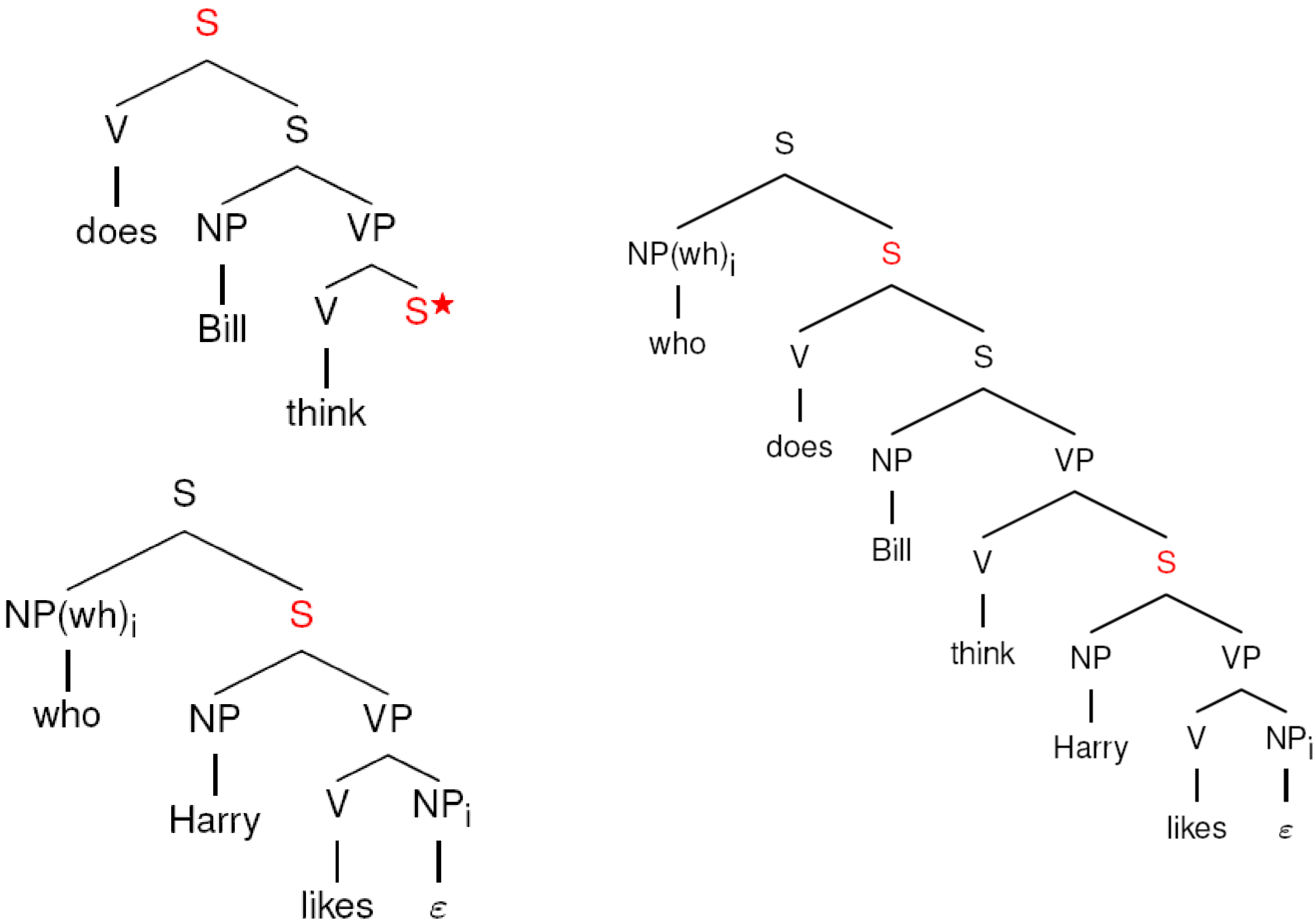


Tree-adjoining grammars

- Start with *local trees*
- Can insert structure with *adjunction* operators
- Mildly context-sensitive
- Models long-distance dependencies naturally
- … as well as other weird stuff that CFGs don't capture well (e.g. cross-serial dependencies)



TAG: Long Distance



CCG Parsing

- Combinatory Categorial Grammar
  - Fully (mono-) lexicalized grammar
  - Categories encode argument sequences
  - Very closely related to the lambda calculus (more later)
  - Can have spurious ambiguities (why?)

$$\textit{John} \vdash \mathsf{NP}$$

$$\textit{shares} \vdash \mathsf{NP}$$

$$\textit{buys} \vdash (\mathsf{S}\backslash\mathsf{NP})/\mathsf{NP}$$

$$\textit{sleeps} \vdash \mathsf{S}\backslash\mathsf{NP}$$

$$\textit{well} \vdash (\mathsf{S}\backslash\mathsf{NP})\backslash(\mathsf{S}\backslash\mathsf{NP})$$