Natural Language Processing

Syntax and Parsing

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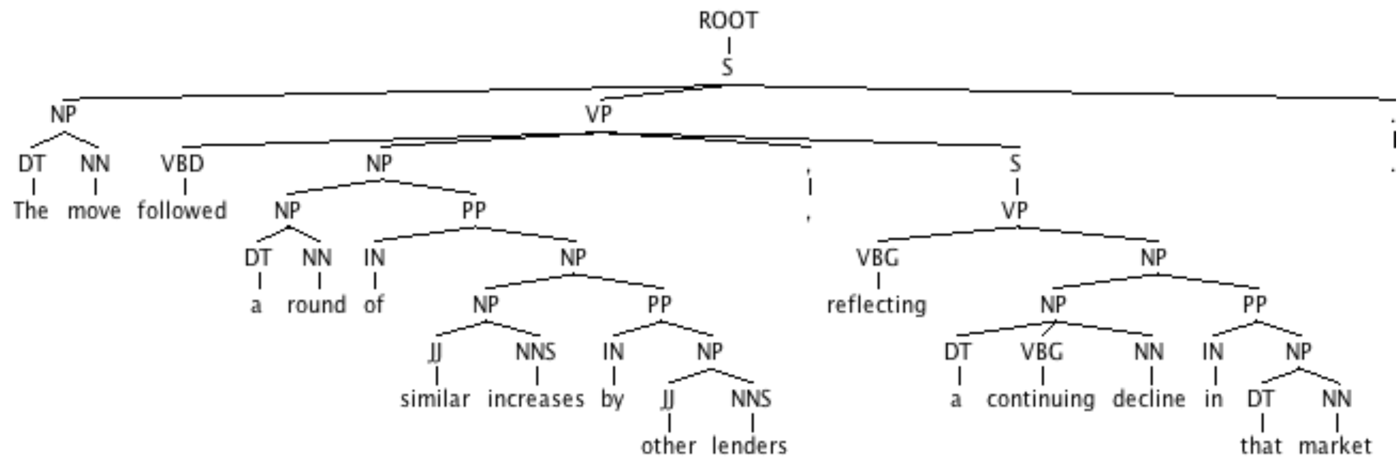
Syntax

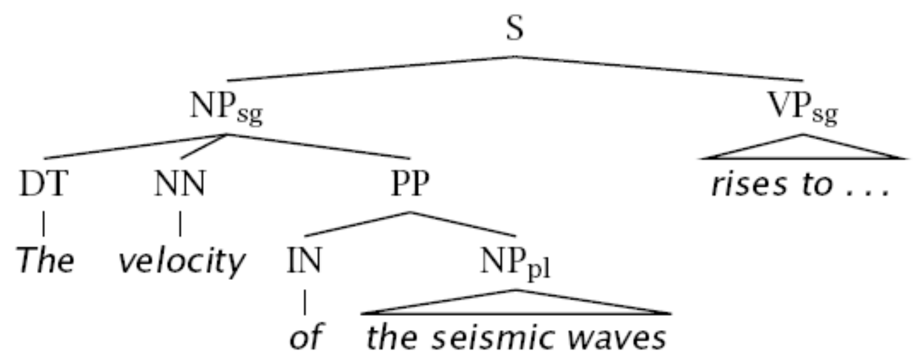
Parse Trees



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

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…

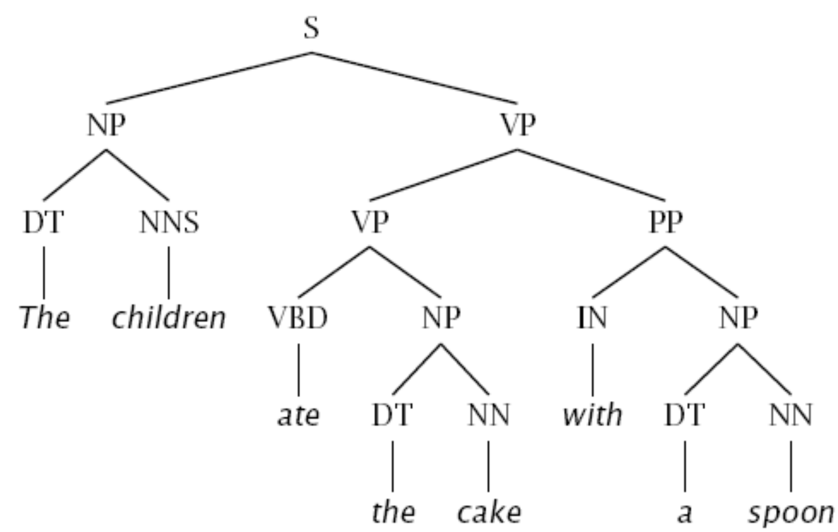


new art critics write reviews with computers

Constituency Tests

- How do we know what nodes go in the tree?

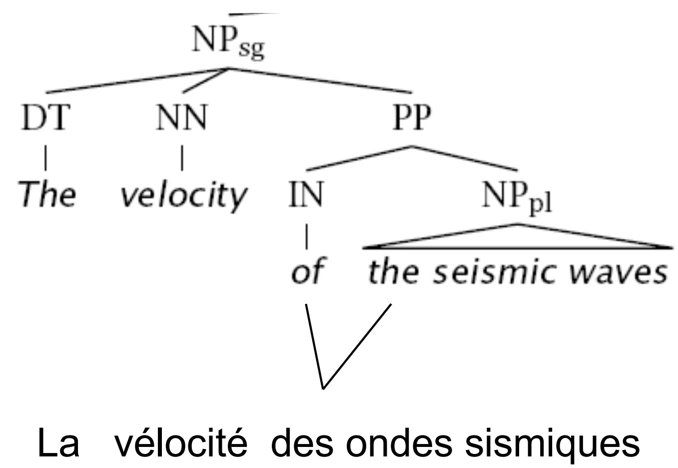
- Classic constituency tests:
  - Substitution by *proform*
  - Question answers
  - Semantic gounds
    - Coherence
    - Reference
    - Idioms
  - Dislocation
  - Conjunction



- Cross-linguistic arguments, too

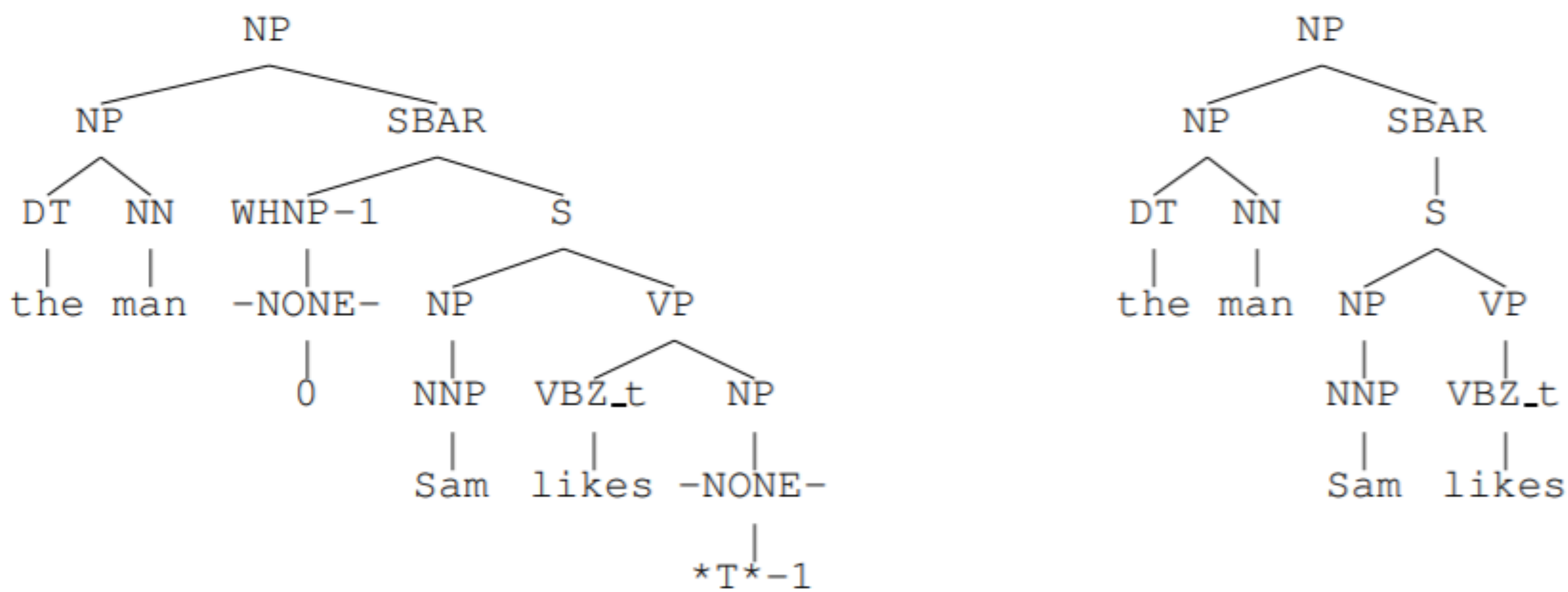
Conflicting Tests

- 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.

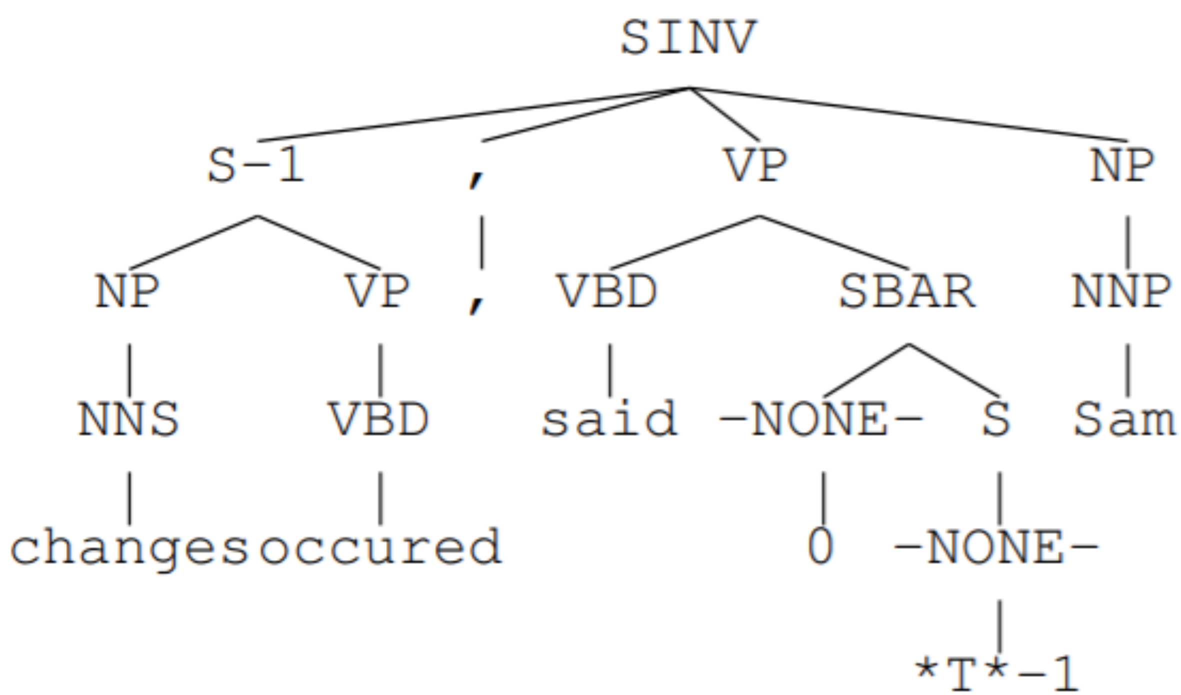


Questions from Last Time

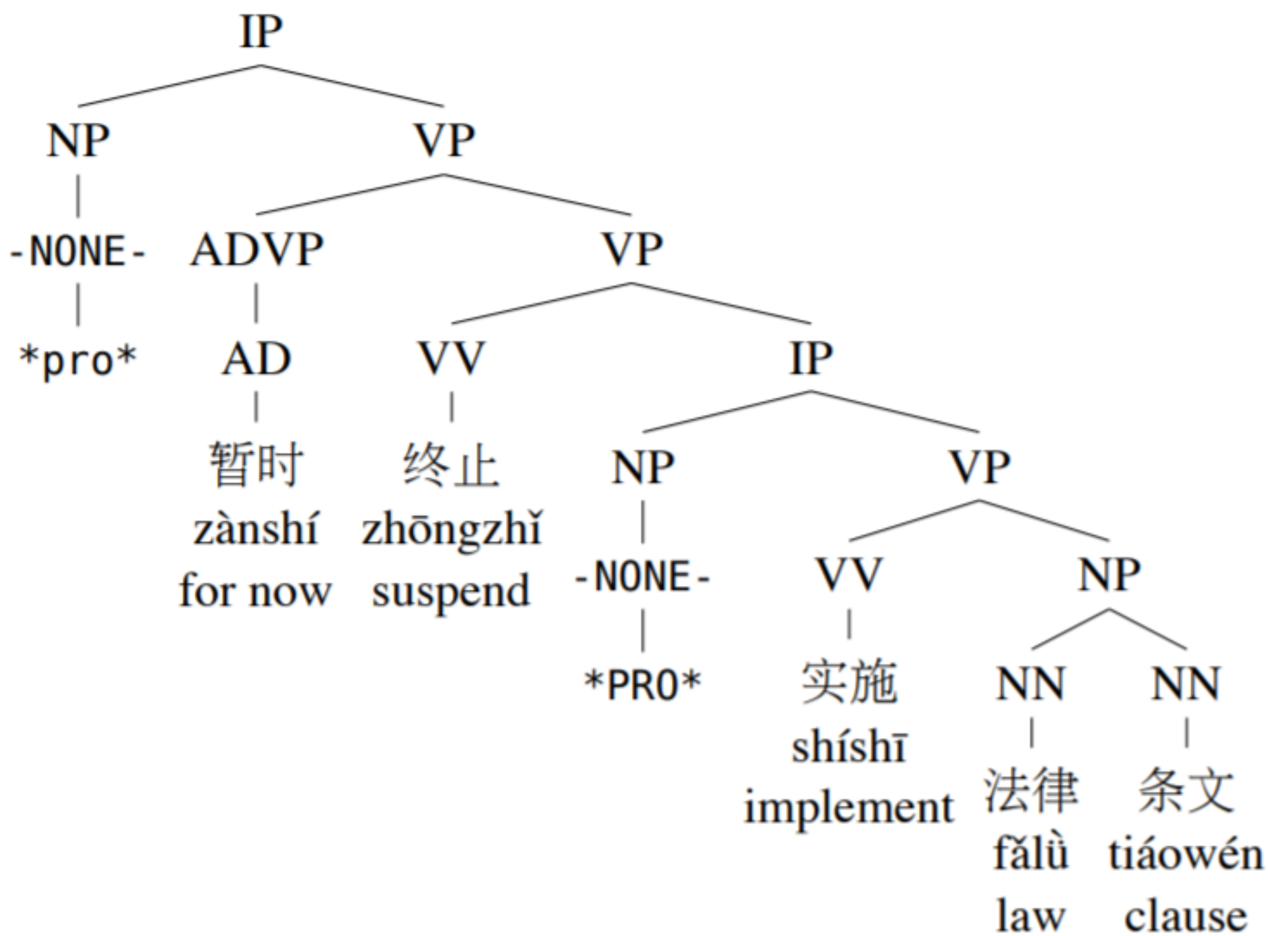
- Q: Do we model deep vs surface structure?



[Example: Johnson 02]



[Example: Johnson 02]

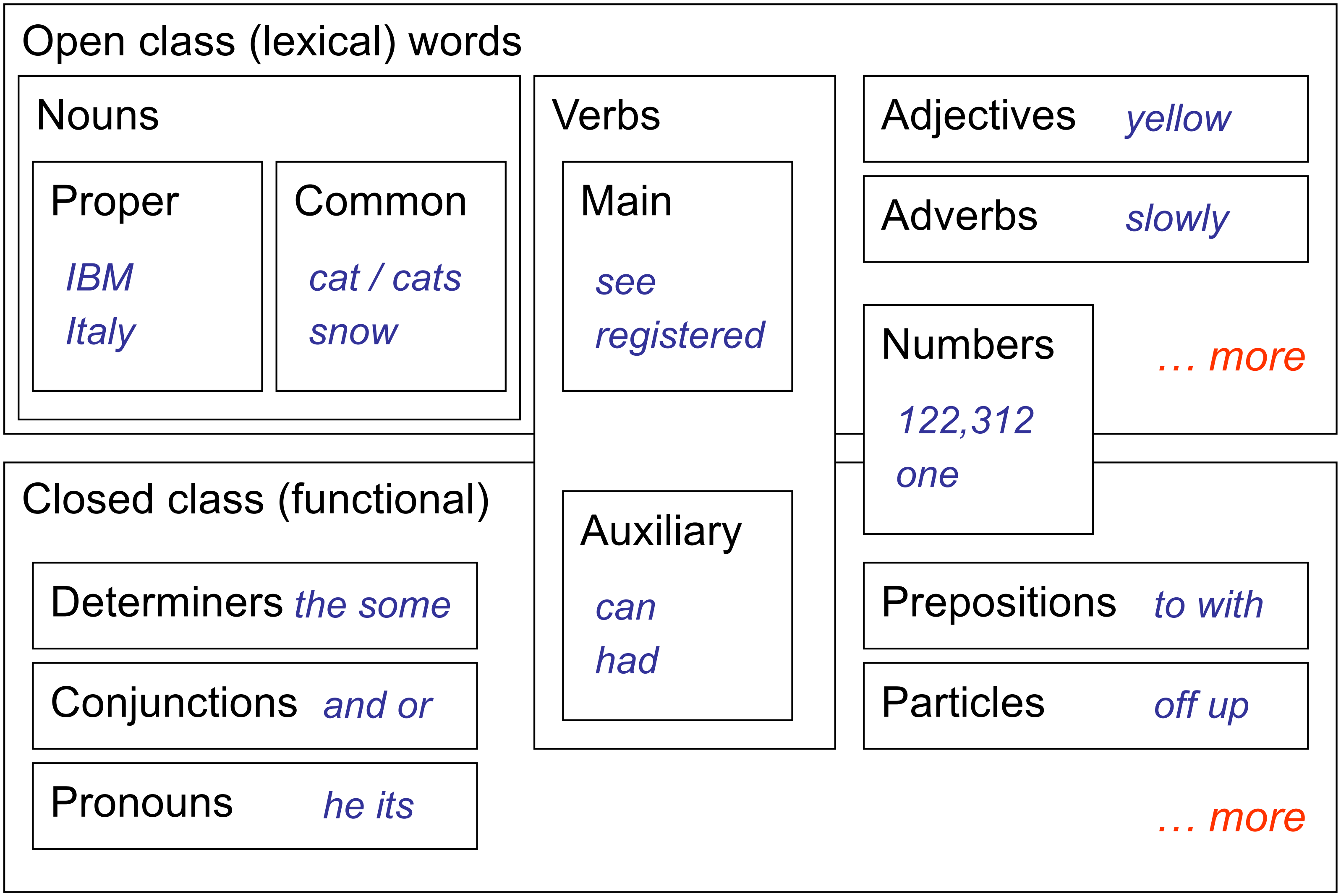


[Example: Cai et al 11]

Ambiguities

Parts-of-Speech (English)

- One basic kind of linguistic structure: syntactic word classes



Part-of-Speech Ambiguity

- Words can have multiple parts of speech

VBD		VB			
VBN	VBZ	VBP	VBZ		
NNP	NNS	NN	NNS	CD	NN
Fed	raises	interest	rates	0.5	percent

Mrs./NNP Shaefer/NNP never/RB got/VBD **around/RP** to/TO joining/VBG

All/DT we/PRP gotta/VBN do/VB is/VBZ go/VB **around/IN** the/DT corner/NN

Chateau/NNP Petrus/NNP costs/VBZ **around/RB** 250/CD

- Two basic sources of constraint:
  - Grammatical environment
  - Identity of the current word
- Many more possible features:
  - Suffixes, capitalization, name databases (gazetteers), etc…

Why POS Tagging?

- Useful in and of itself (more than you'd think)
  - Text-to-speech: record, lead
  - Lemmatization: saw[v] $\rightarrow$ see, saw[n] $\rightarrow$ saw
  - Quick-and-dirty NP-chunk detection: grep {JJ | NN}* {NN | NNS}

- Useful as a pre-processing step for parsing
  - Less tag ambiguity means fewer parses
  - However, some tag choices are better decided by parsers

```
                                  IN
DT   NNP     NN   VBD VBN  RP  NN       NNS
The Georgia branch had taken on loan commitments …

                              VDN
DT   NN   IN   NN      VBD  NNS    VBD
The average of interbank offered rates plummeted …
```

Classical NLP: Parsing

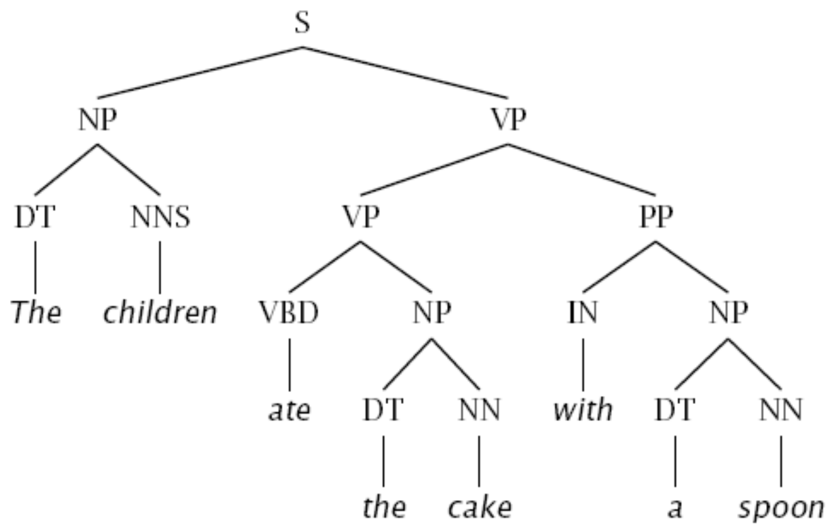
- Write symbolic or logical rules:

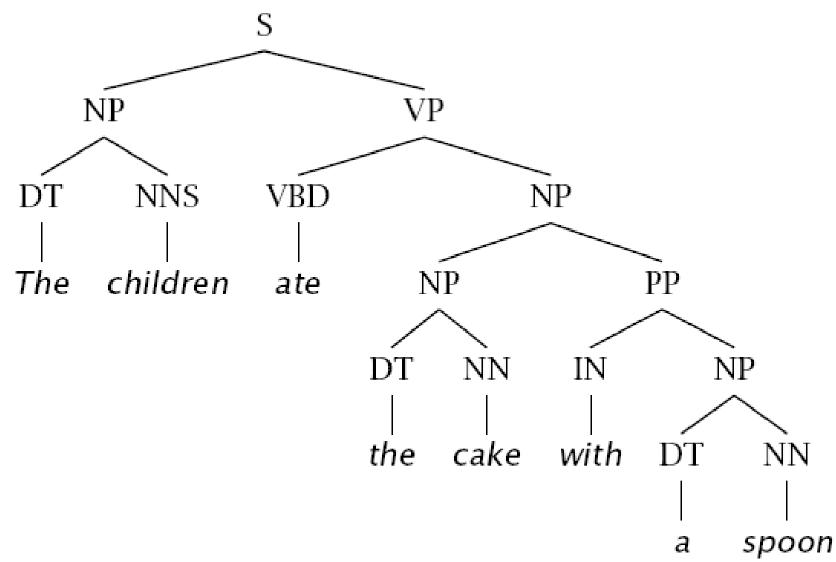
Grammar (CFG)		Lexicon
ROOT → S	NP → NP PP	NN → interest
S → NP VP	VP → VBP NP	NNS → raises
NP → DT NN	VP → VBP NP PP	VBP → interest
NP → NN NNS	PP → IN NP	VBZ → raises
		…

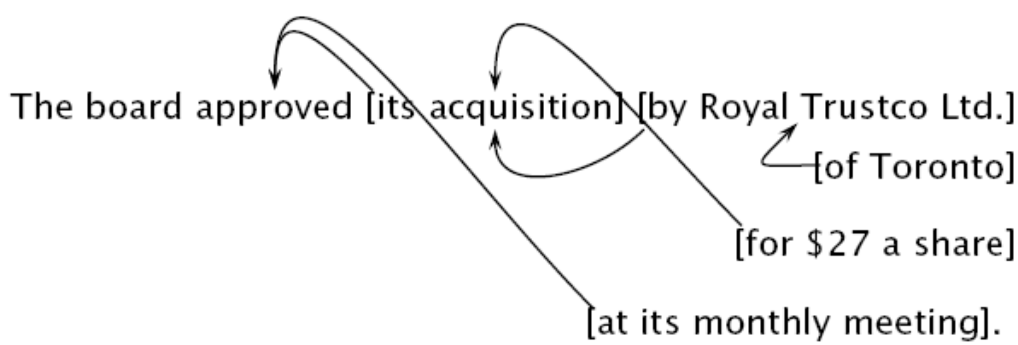
- Use deduction systems to prove parses from words
  - Minimal grammar on “Fed raises” sentence: 36 parses
  - Simple 10-rule grammar: 592 parses
  - Real-size grammar: many millions of parses

- This scaled very badly, didn’t yield broad-coverage tools

Ambiguities: PP Attachment







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.

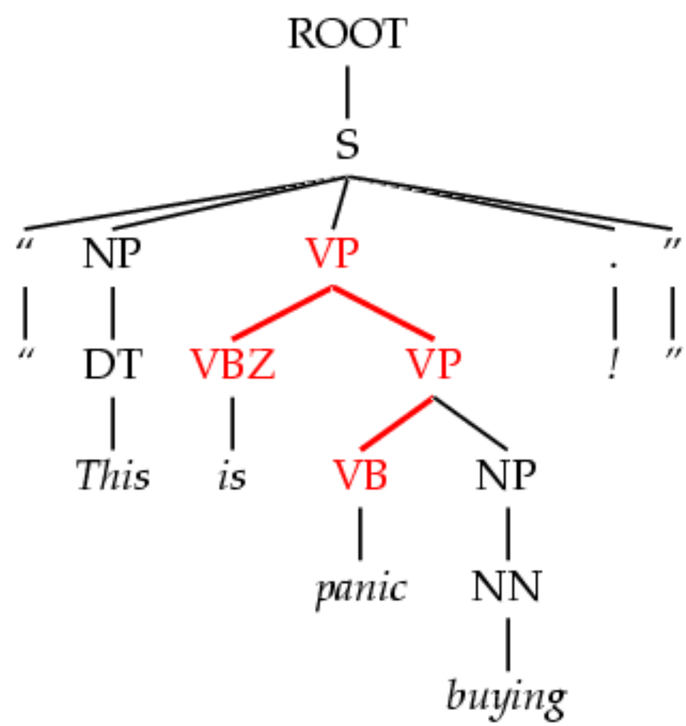
- Coordination scope:
  Small rats and mice can squeeze into holes or cracks in the wall.

Dark Ambiguities

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

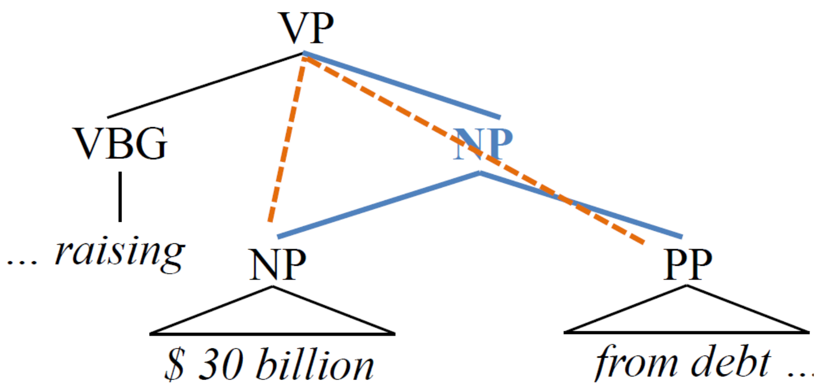
This analysis corresponds to the correct parse of

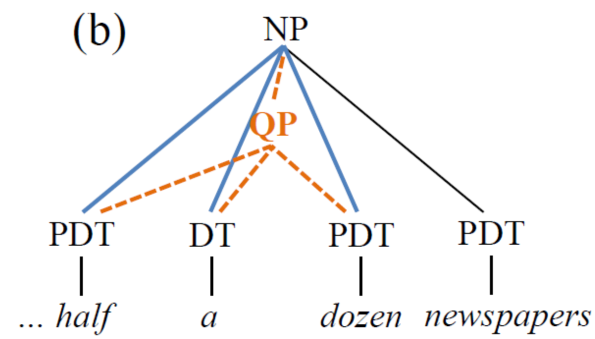
"This will panic buyers ! "

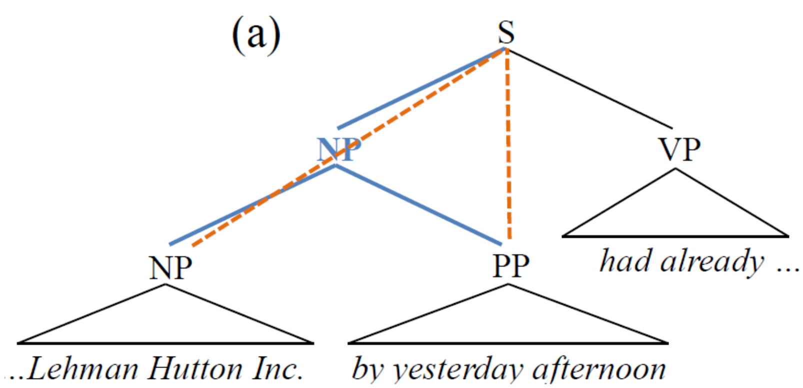


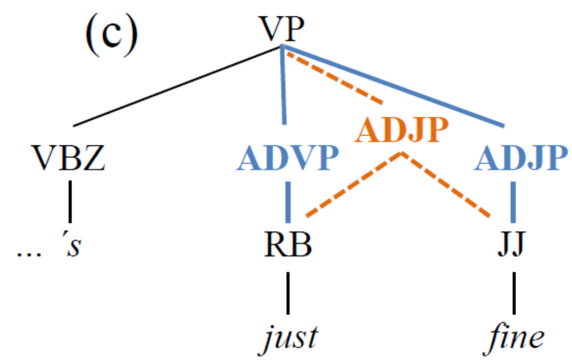
- Unknown words and new usages
- Solution: We need mechanisms to focus attention on the best ones, probabilistic techniques do this

Ambiguities as Trees









PCFGs

Probabilistic Context-Free Grammars

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

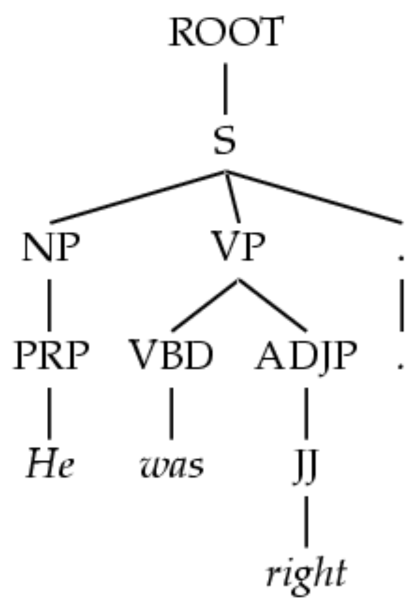
- A PCFG adds:
  - A top-down production probability per rule $P(Y_1\ Y_2 \ldots Y_k \mid X)$

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):

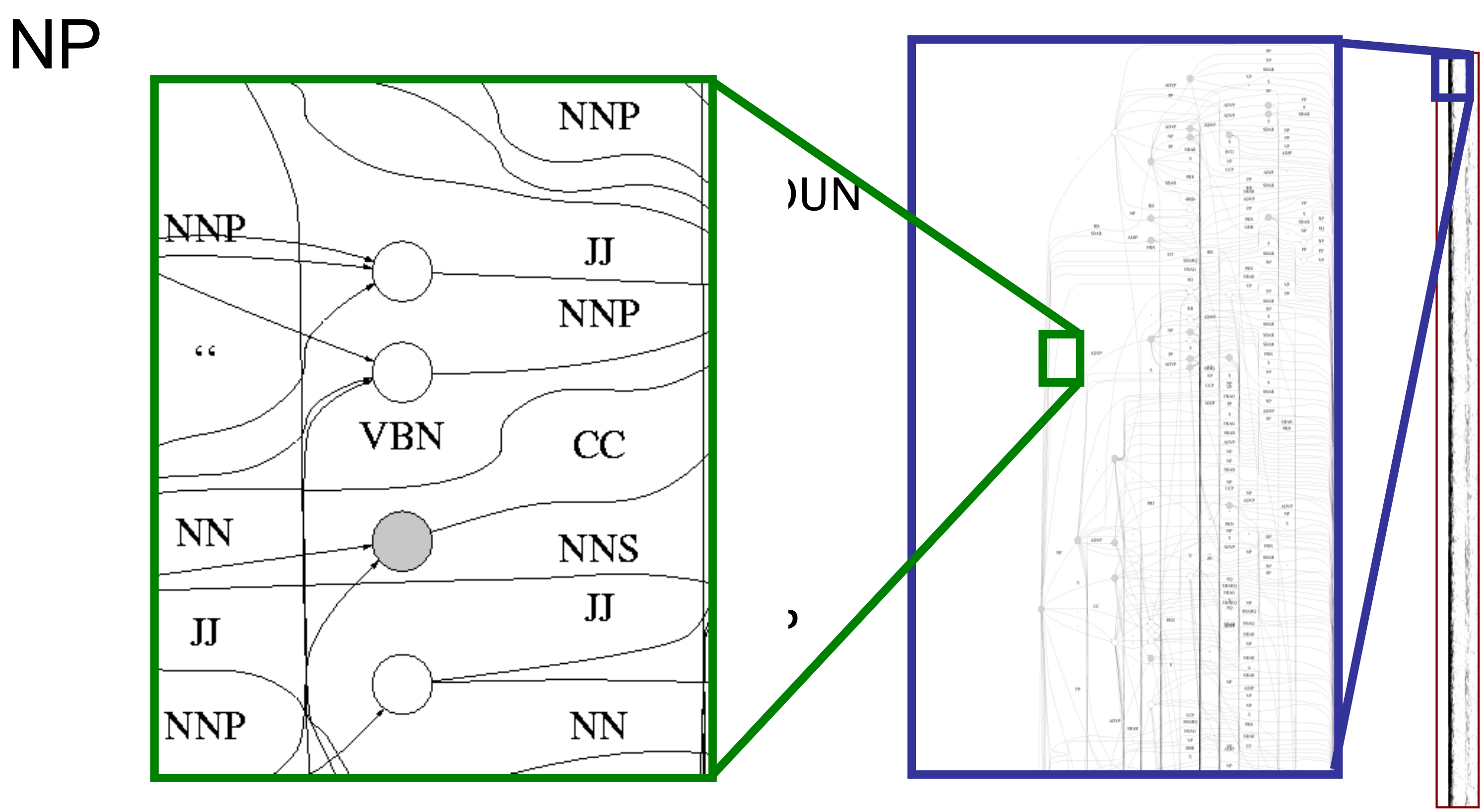


ROOT $\rightarrow$ S	1
S $\rightarrow$ NP VP .	1
NP $\rightarrow$ PRP	1
VP $\rightarrow$ VBD ADJP	1
…..	

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

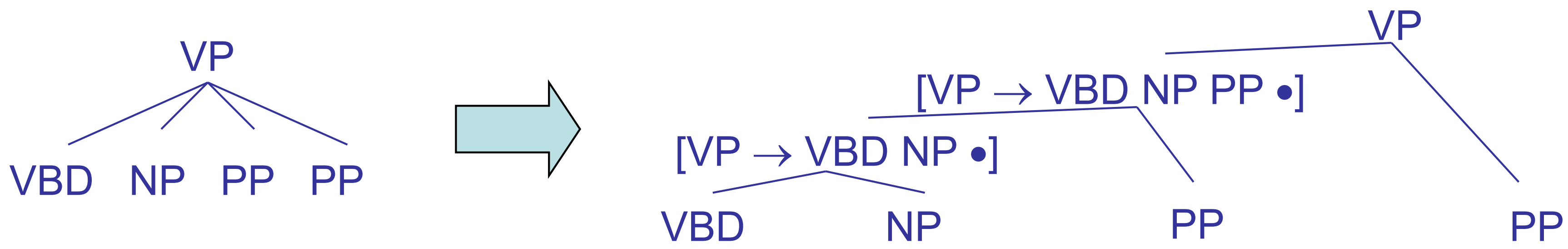
Treebank Grammar Scale

- 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



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!

CKY Parsing

A Recursive Parser

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

- Will this parser work?
- Why or why not?
- Memory requirements?

A Memoized Parser

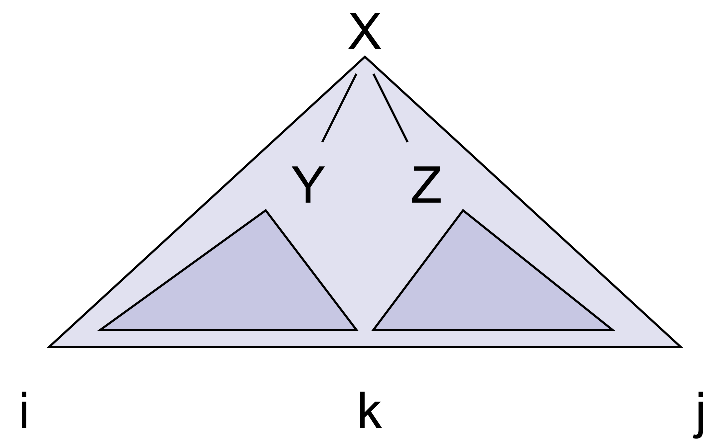
- One small change:

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



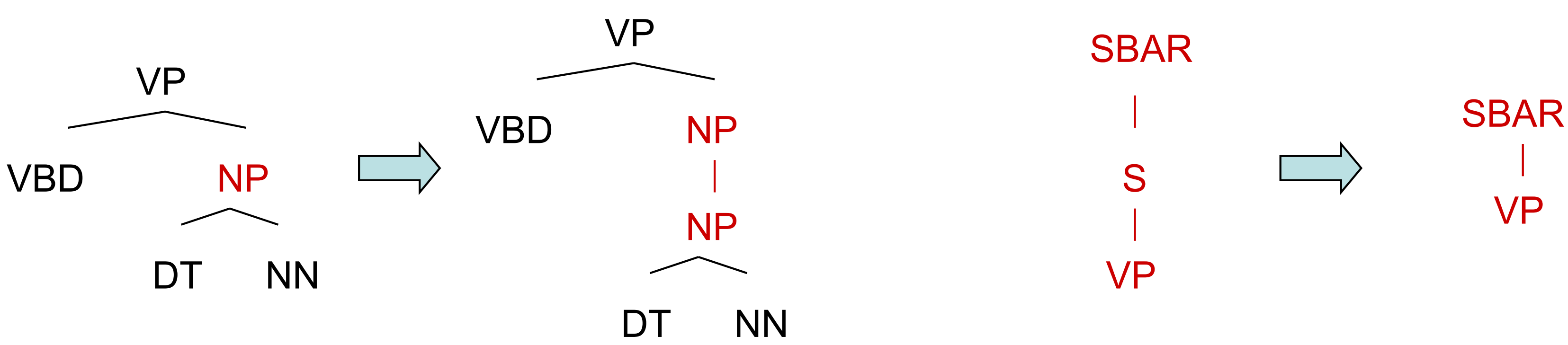
Unary Rules

- Unary rules?

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

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

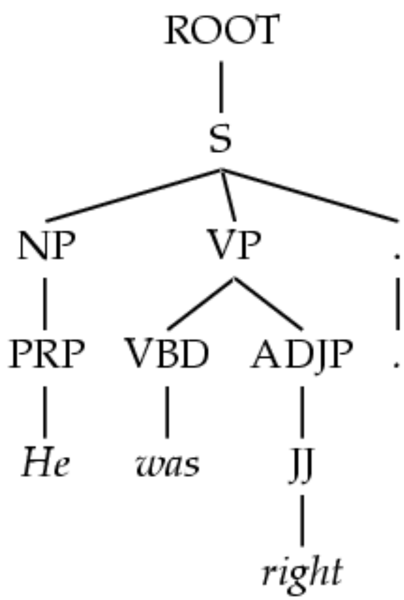
```
bestScoreB(X,i,j,s)
      return max max score(X->YZ) *
                      bestScoreU(Y,i,k) *
                      bestScoreU(Z,k,j)


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

Learning PCFGs

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

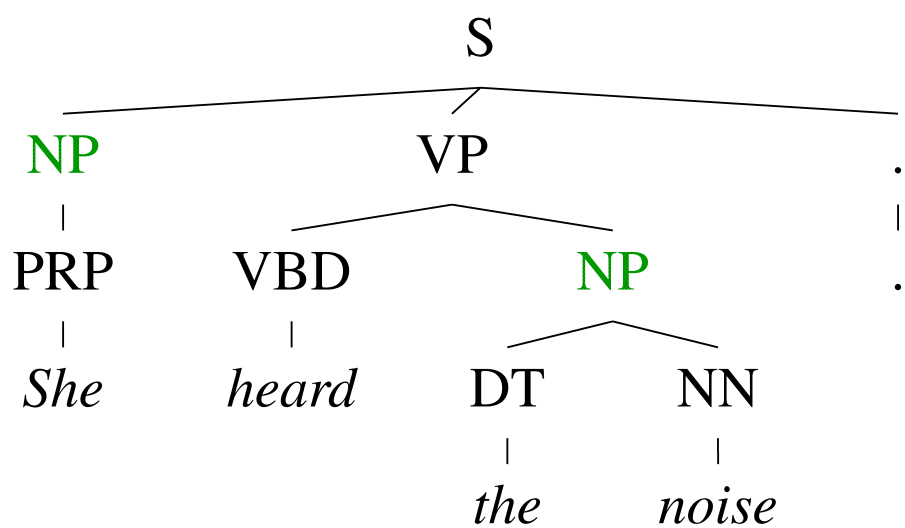
NP → PRP 1

VP → VBD ADJP 1

.....

Model	*F1*
Baseline	72.0

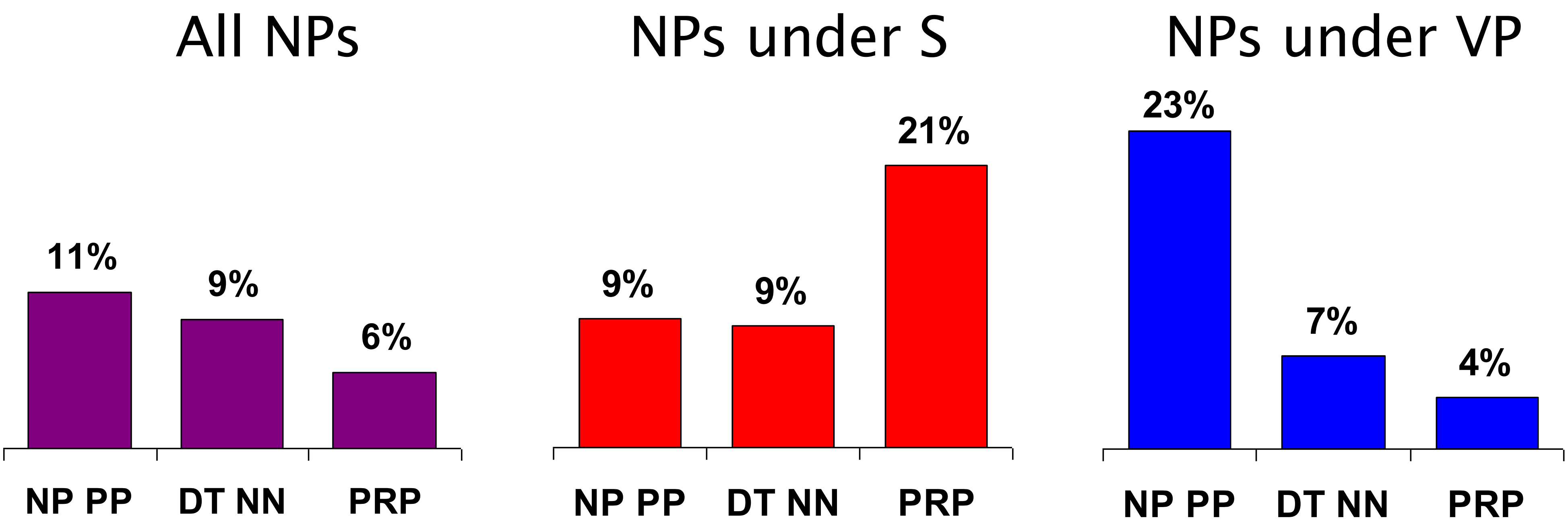
Conditional Independence?



- 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

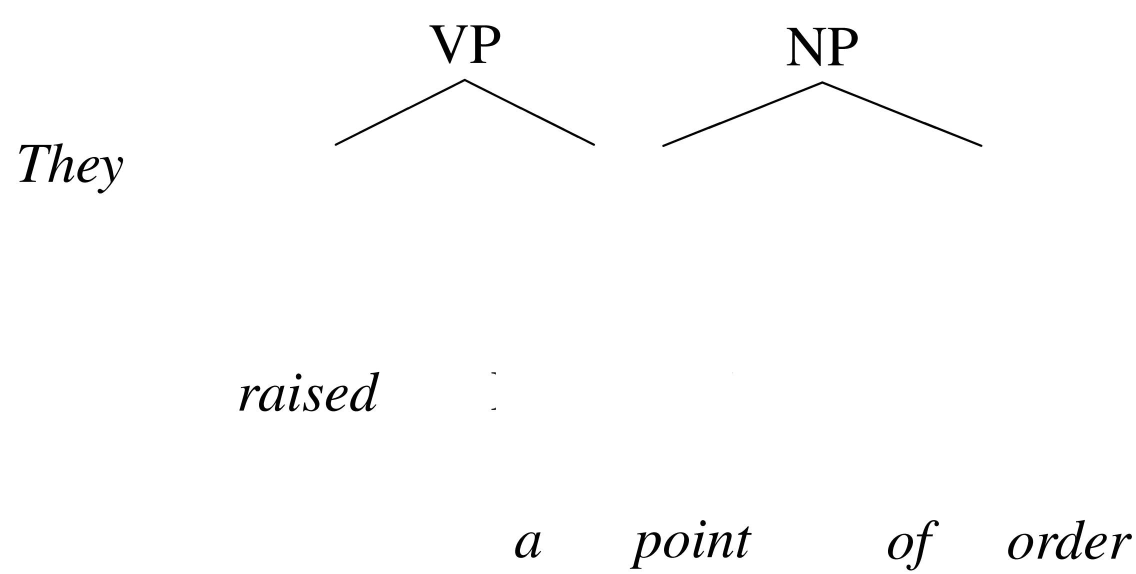
- Independence assumptions are often too strong.



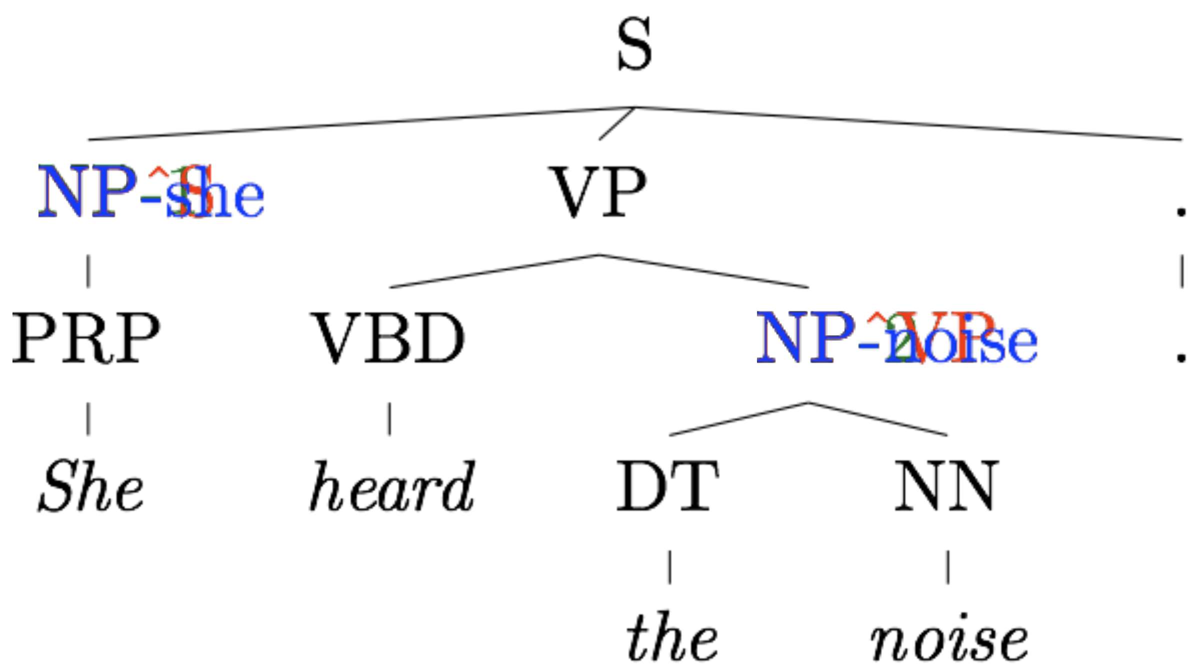
- Example: the expansion of an NP is highly dependent on the parent of the NP (i.e., subjects vs. objects).
- Also: the subject and object expansions are correlated!

Grammar Refinement

- Example: PP attachment



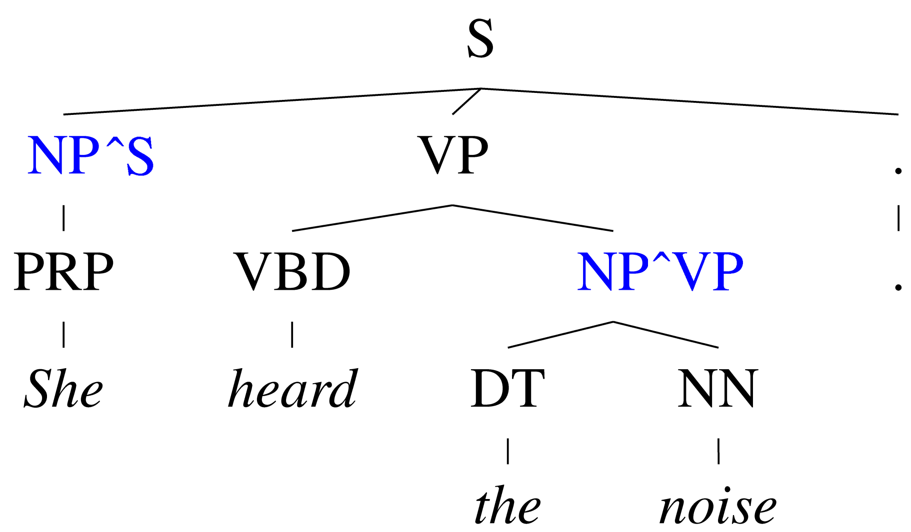
Grammar Refinement



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

Structural Annotation

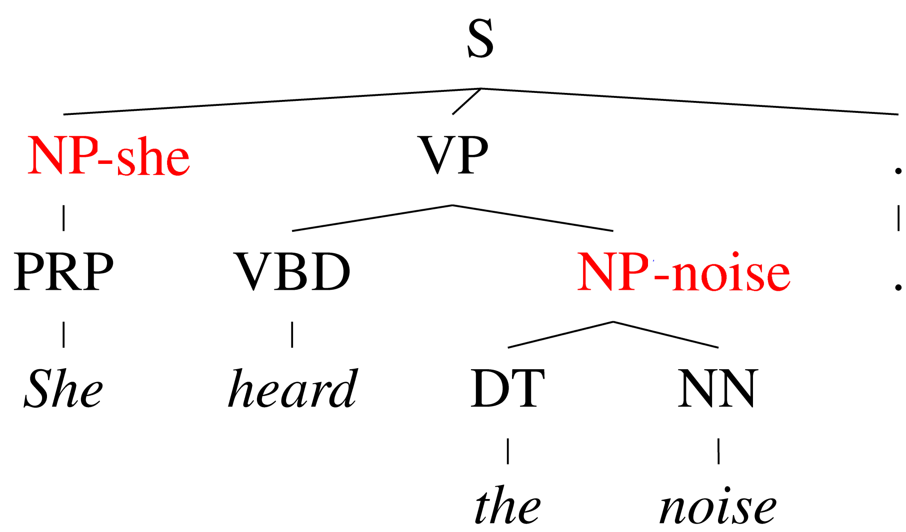
The Game of Designing a Grammar



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

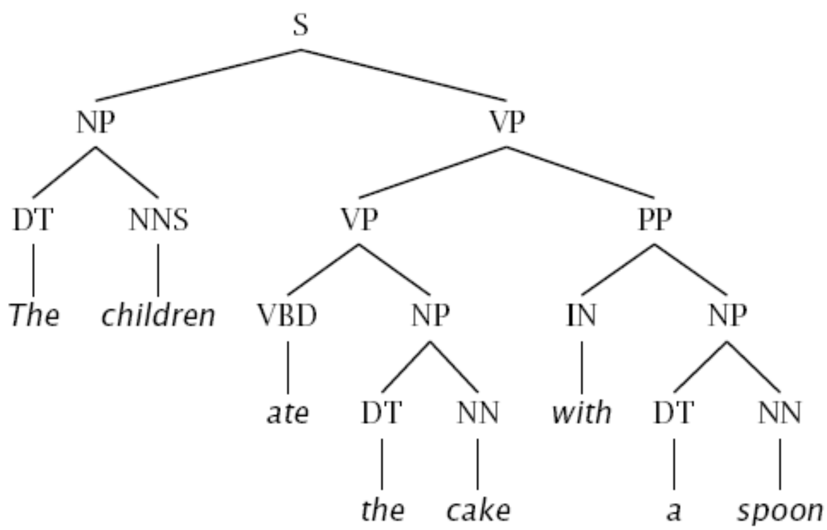
Lexicalization

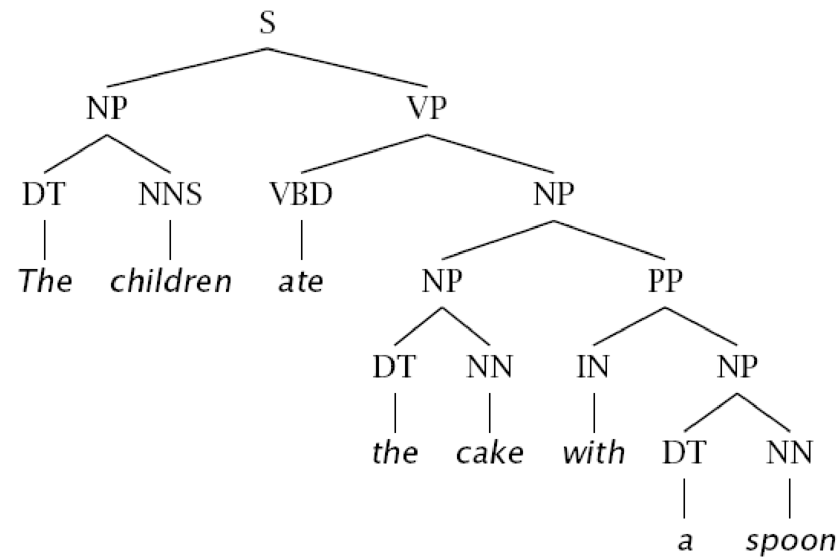
The Game of Designing a Grammar



- 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]

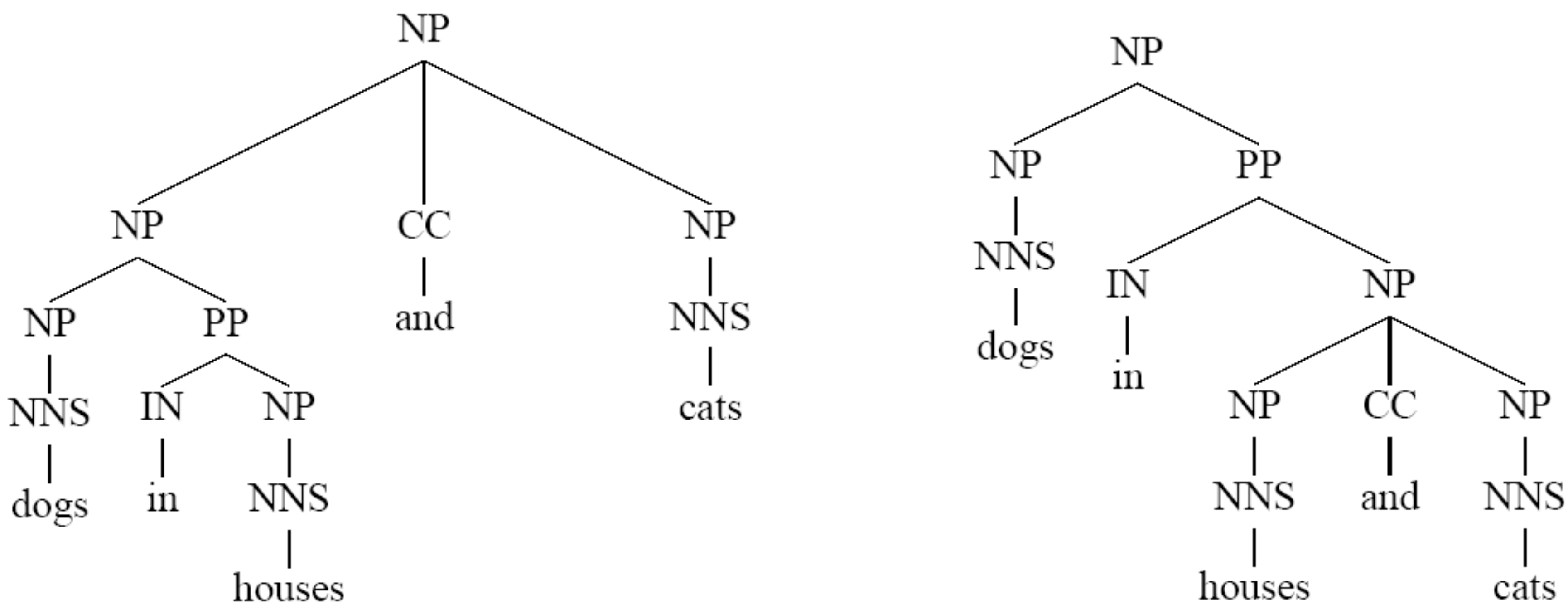
Problems with PCFGs





- If we do no annotation, these trees differ only in one rule:
  - VP $\rightarrow$ VP PP
  - NP $\rightarrow$ 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

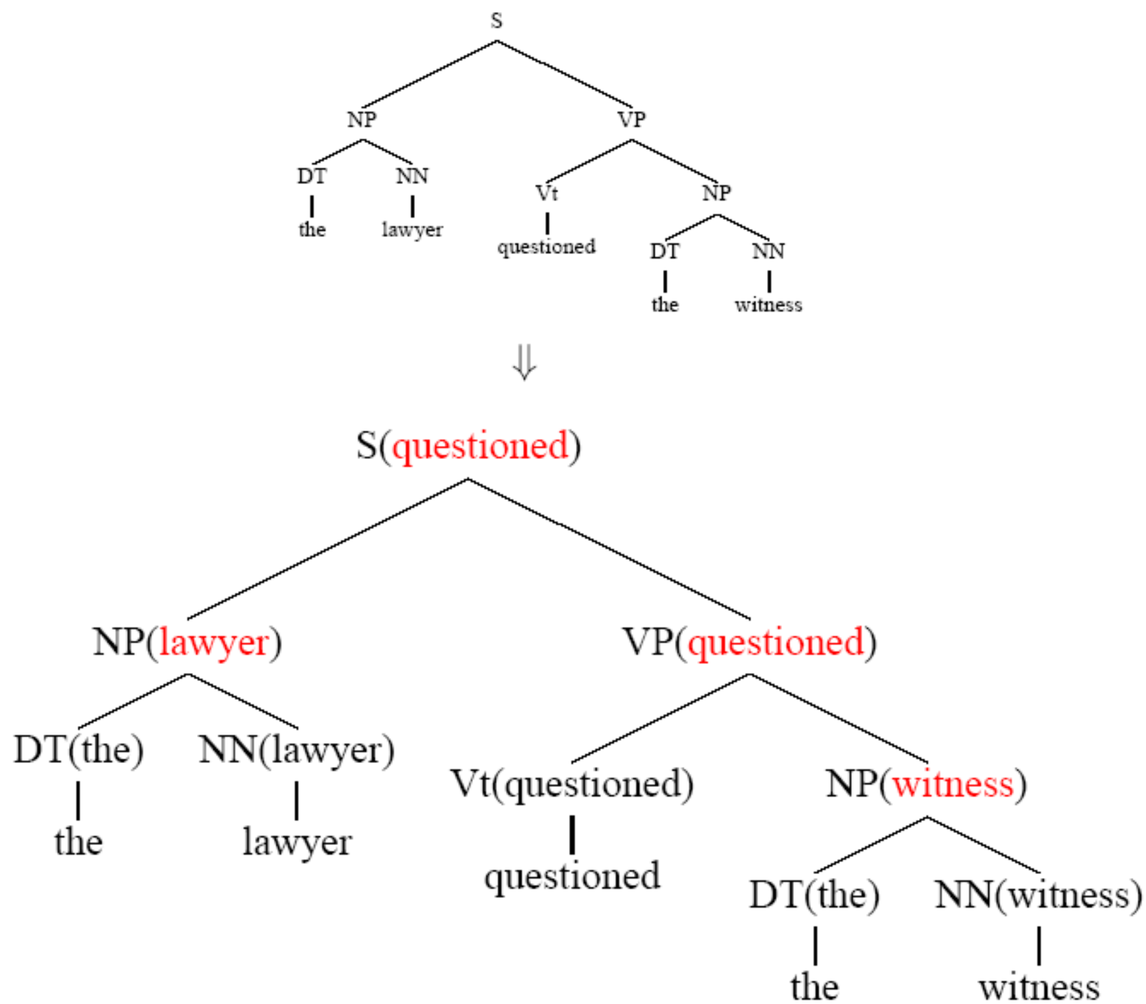
Problems with PCFGs



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

Lexicalized Trees

- Add "head words" to each phrasal node
  - Syntactic vs. semantic heads
  - 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



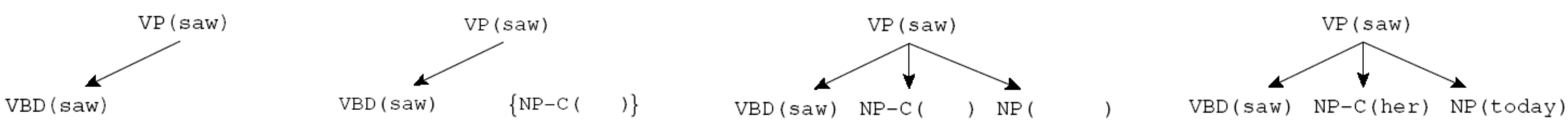
Lexicalized PCFGs?

- Problem: we now have to estimate probabilities like

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

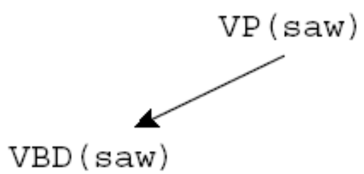
- Never going to get these atomically off of a treebank

- Solution: break up derivation into smaller steps

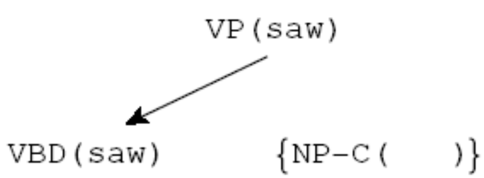


Lexical Derivation Steps

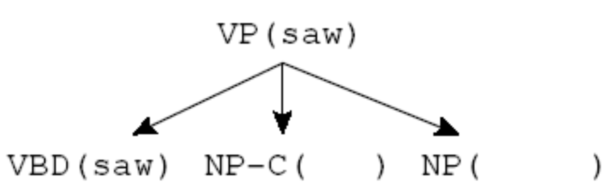
- A derivation of a local tree [Collins 99]



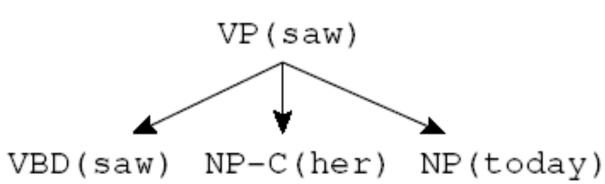
Choose a head tag and word



Choose a complement bag

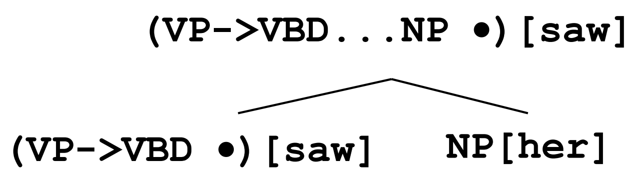


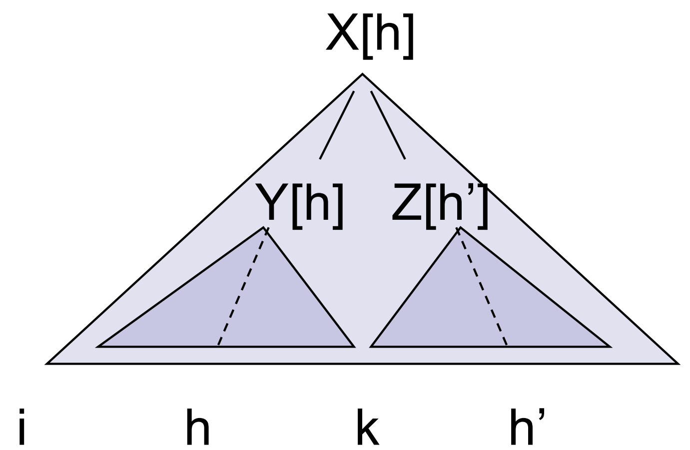
Generate children (incl. adjuncts)



Recursively derive children

Lexicalized CKY





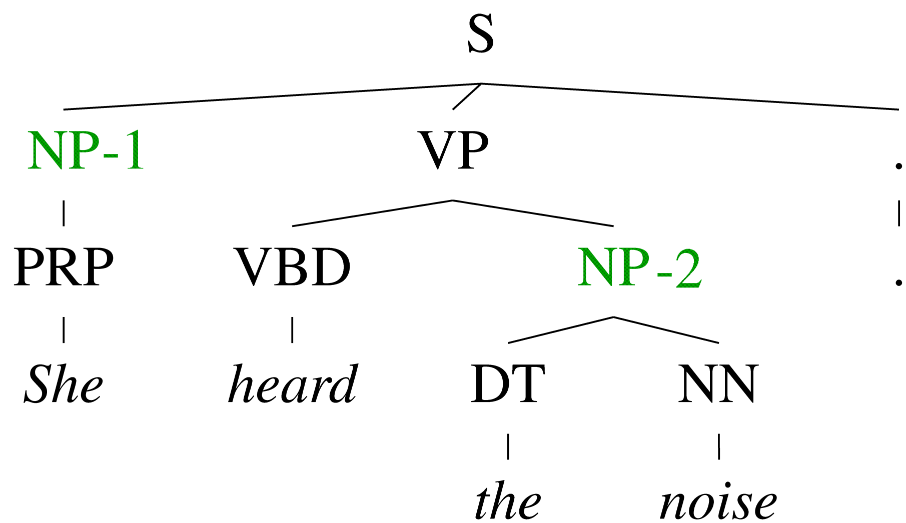

```
bestScore(X,i,j,h)
  if (j = i+1)
    return tagScore(X,s[i])
  else
    return
      max        max        score(X[h]->Y[h] Z[h']) *
         k,h',X->YZ          bestScore(Y,i,k,h) *
                             bestScore(Z,k,j,h')
                 max        score(X[h]->Y[h'] Z[h]) *
         k,h',X->YZ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

Results

- Some results
  - Collins 99 – 88.6 F1 (generative lexical)
  - Charniak and Johnson 05 – 89.7 / 91.3 F1 (generative lexical / reranked)
  - Petrov et al 06 – 90.7 F1 (generative unlexical)
  - McClosky et al 06 – 92.1 F1 (gen + rerank + self-train)
- However
  - Bilexical counts rarely make a difference (why?)
  - Gildea 01 – Removing bilexical counts costs < 0.5 F1

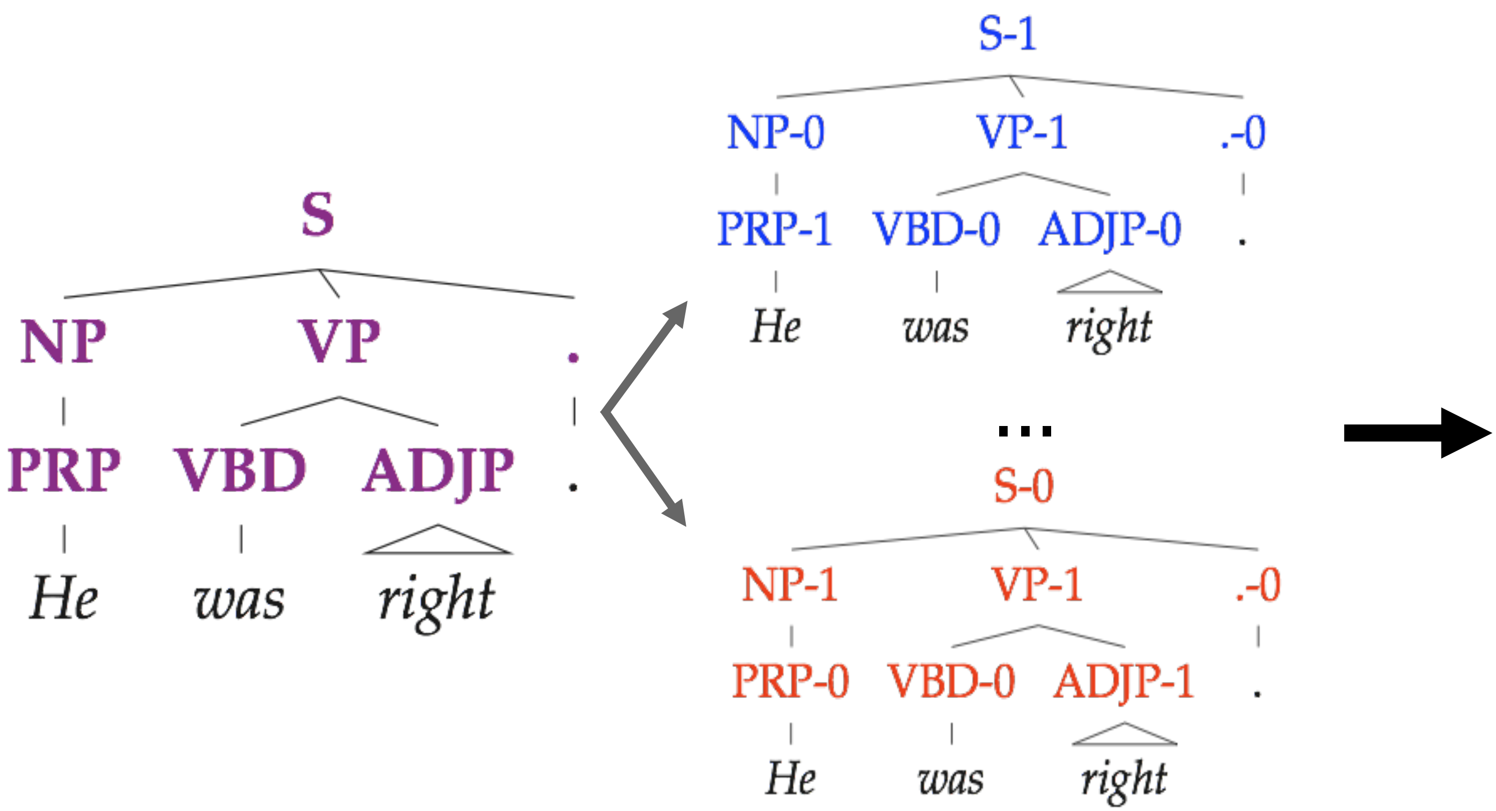
Latent Variable PCFGs

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?

Latent Variable Grammars



Grammar G

$S_0 \rightarrow NP_0\ VP_0$?
$S_0 \rightarrow NP_1\ VP_0$?
$S_0 \rightarrow NP_0\ VP_1$?
$S_0 \rightarrow NP_1\ VP_1$?
$S_1 \rightarrow NP_0\ VP_0$?
...
$S_1 \rightarrow NP_1\ VP_1$?
...
$NP_0 \rightarrow PRP_0$?
$NP_0 \rightarrow PRP_1$?
...

Lexicon

$PRP_0 \rightarrow$ She ?
$PRP_1 \rightarrow$ She ?
...
$VBD_0 \rightarrow$ was ?
$VBD_1 \rightarrow$ was ?
$VBD_2 \rightarrow$ was ?
...

Parse Tree T
Sentence w

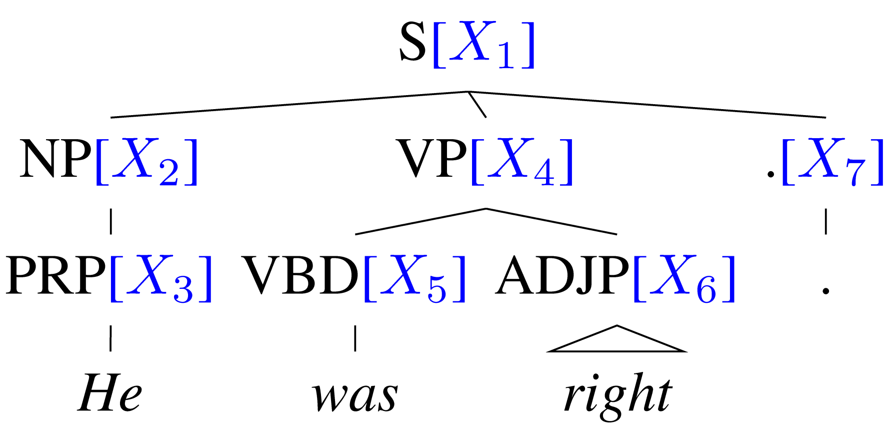
Derivations $t : T$

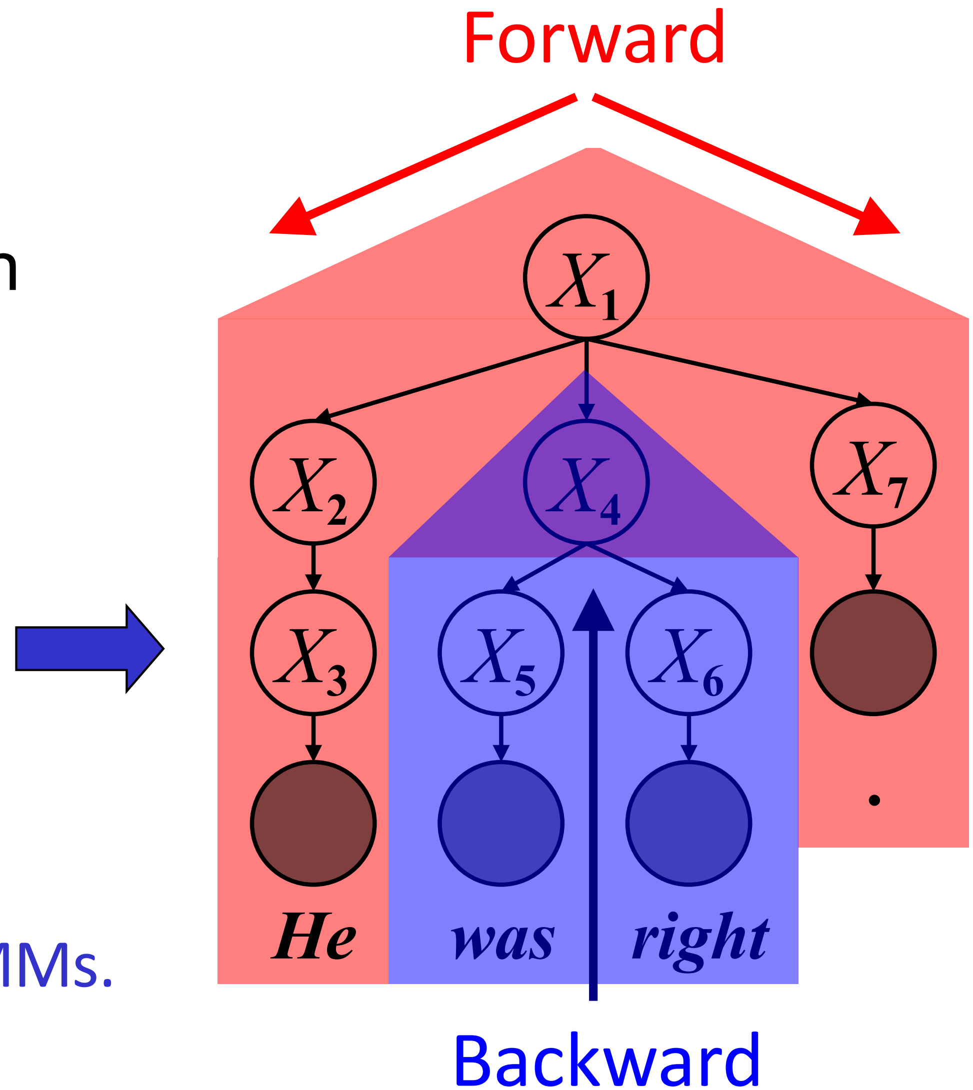
Parameters θ

Learning Latent Annotations

EM algorithm:

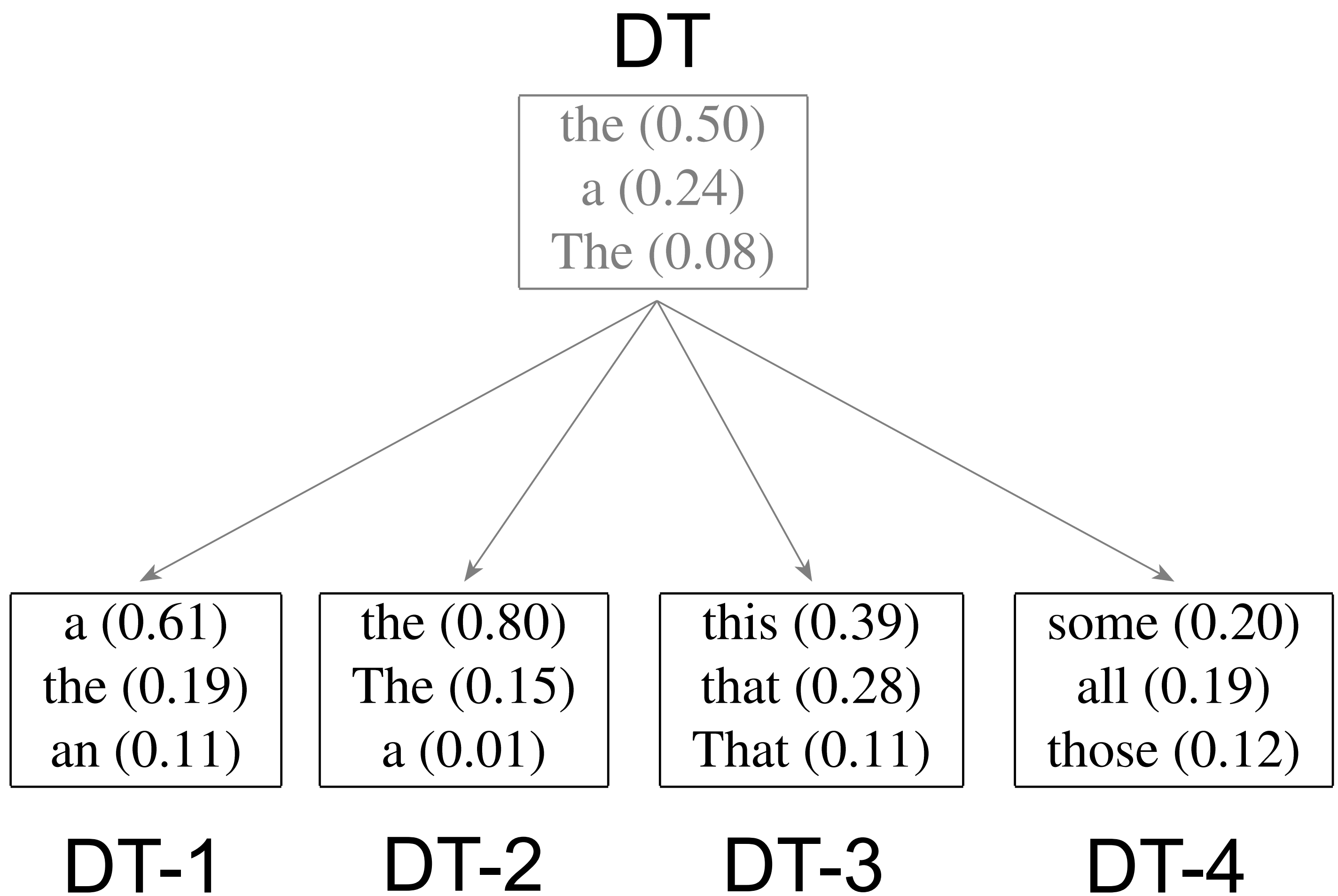
- Brackets are known
- Base categories are known
- Only induce subcategories



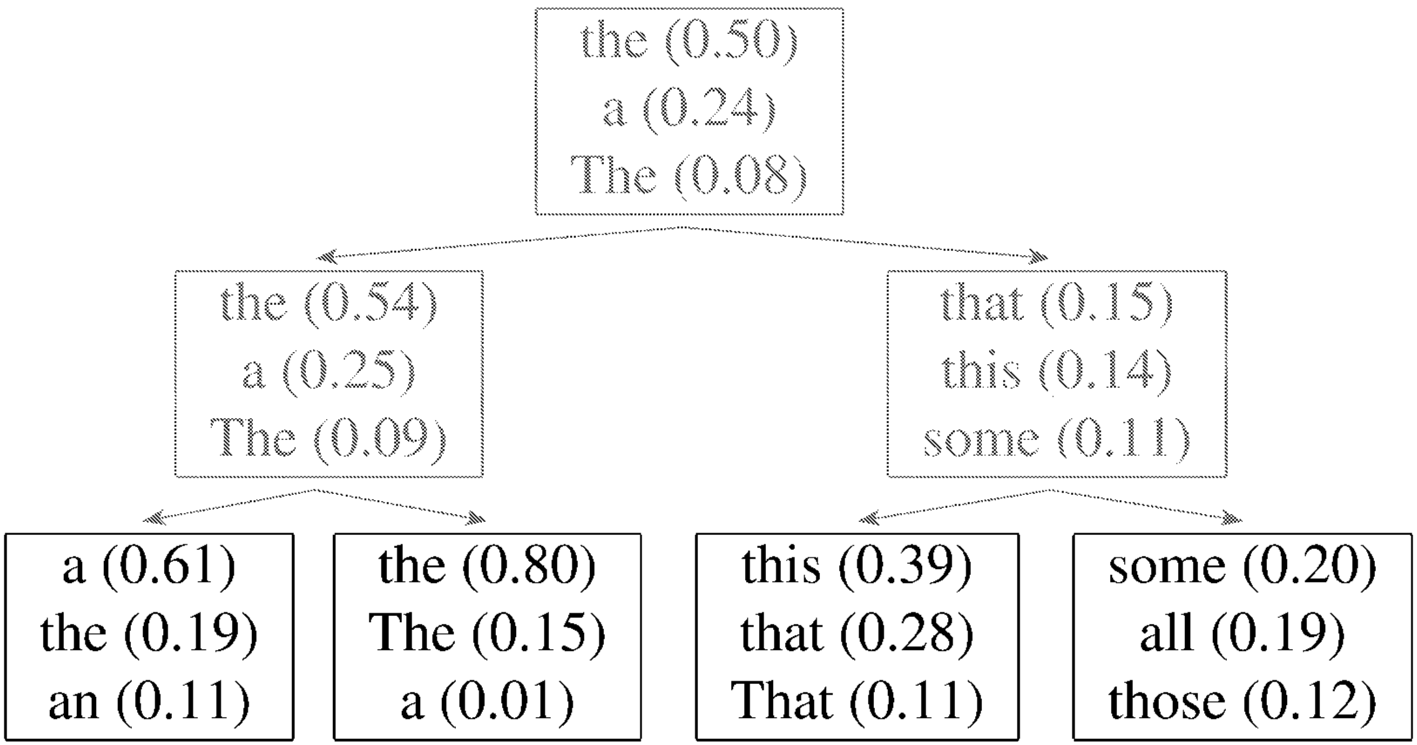


Just like Forward-Backward for HMMs.

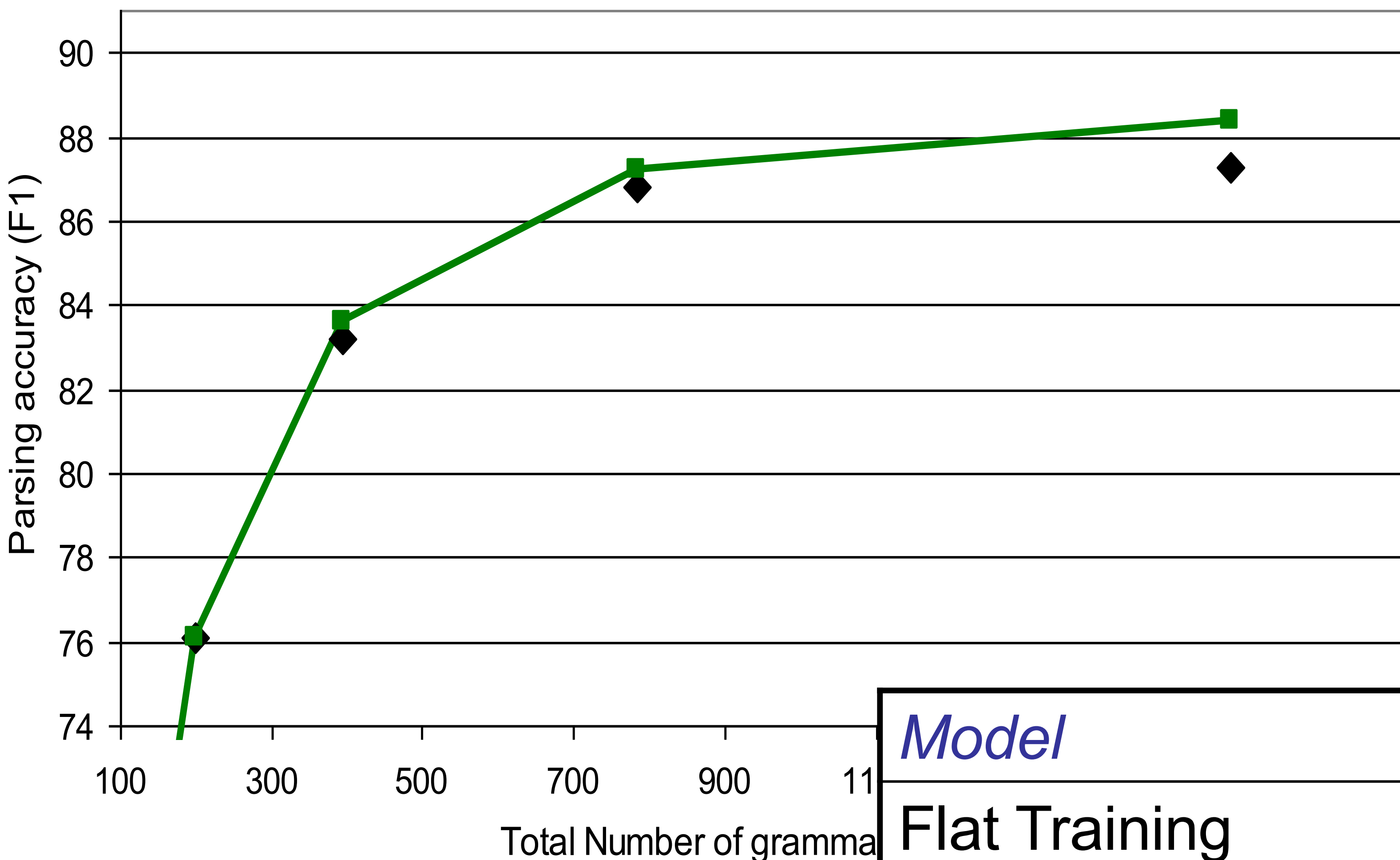
Refinement of the DT tag



Hierarchical refinement



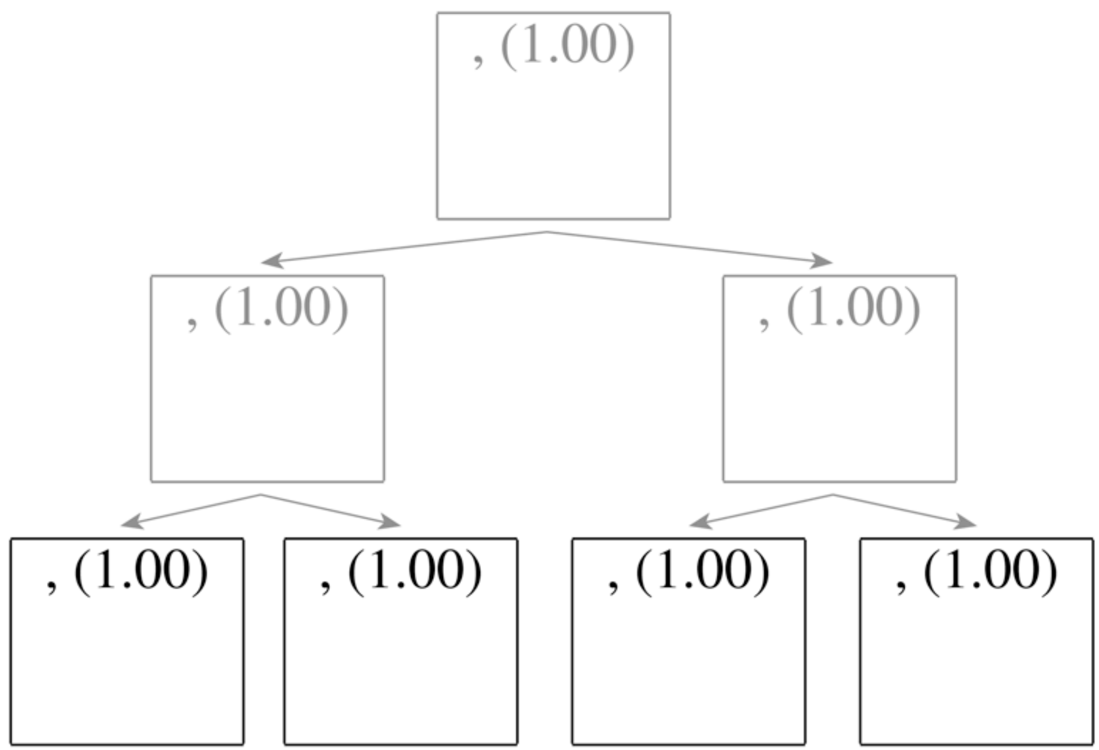
Hierarchical Estimation Results



Model	*F1*
Flat Training	87.3
Hierarchical Training	88.4

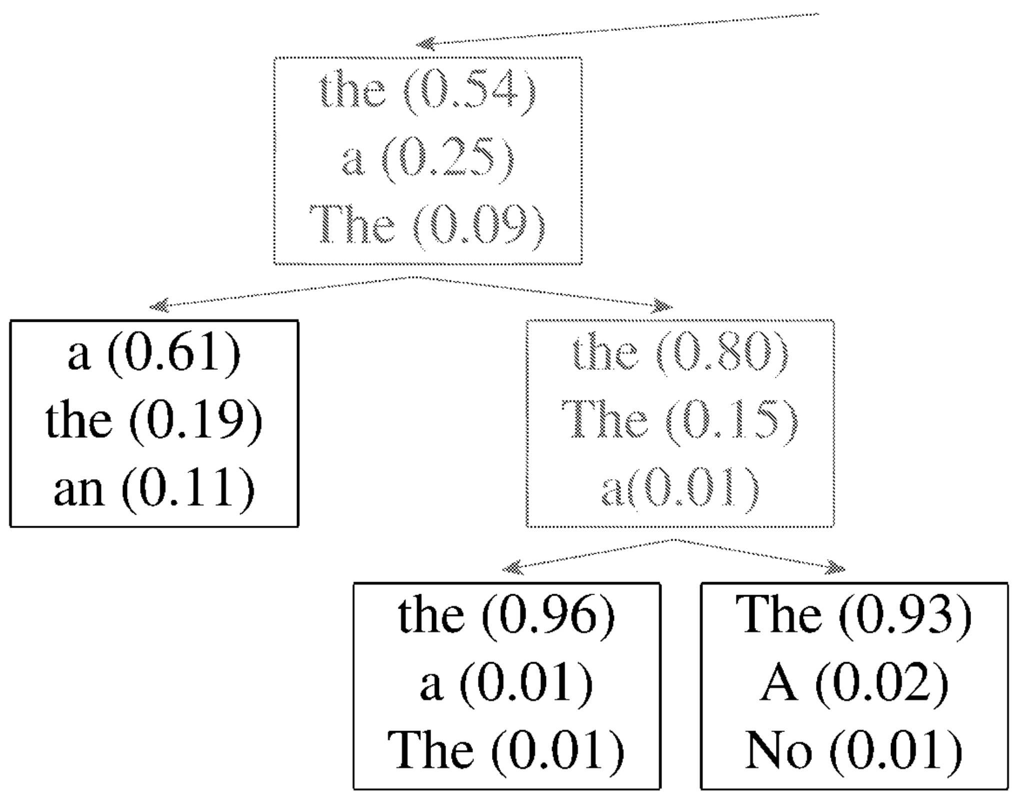
Refinement of the , tag

- Splitting all categories equally is wasteful:

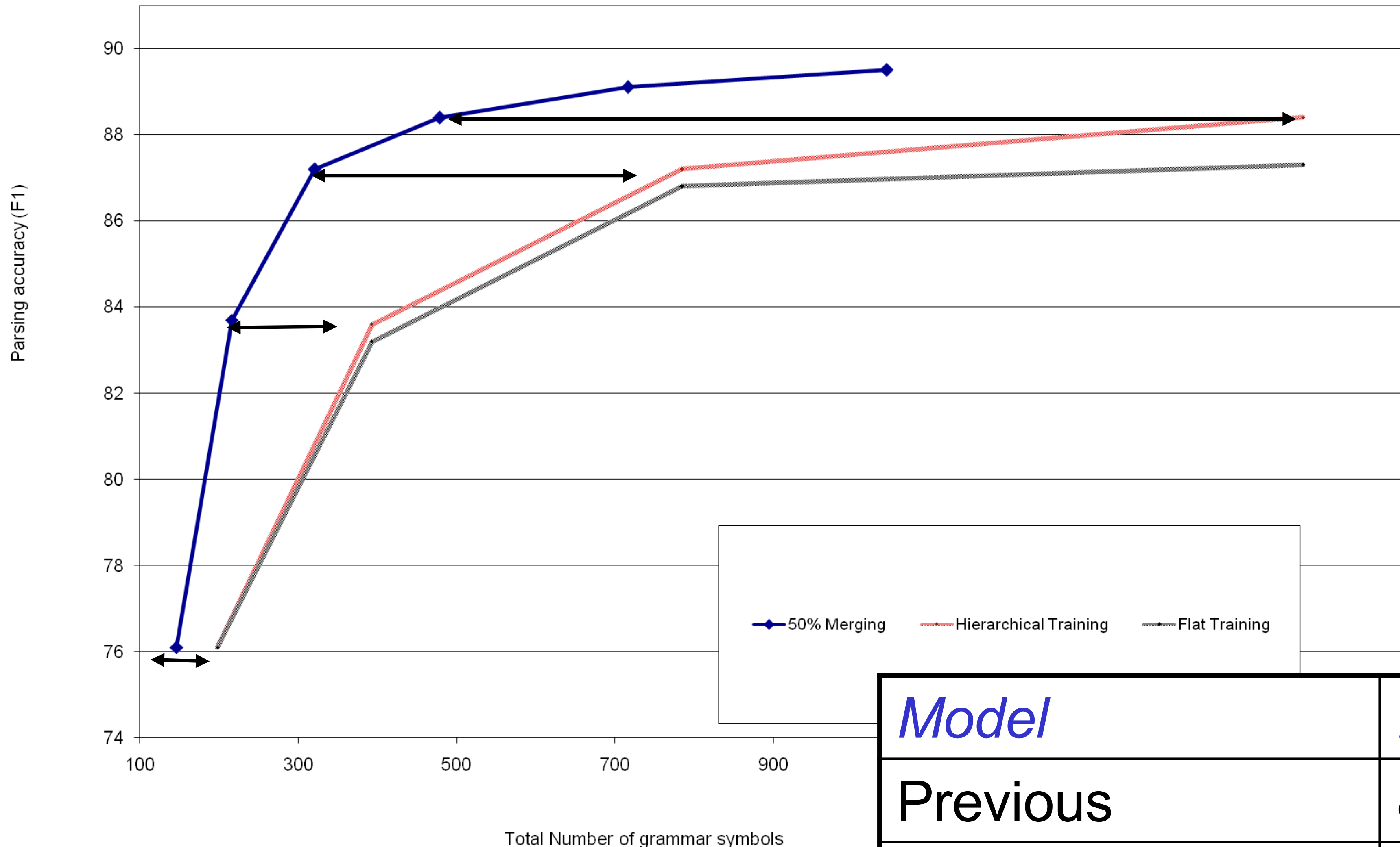


Adaptive Splitting

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

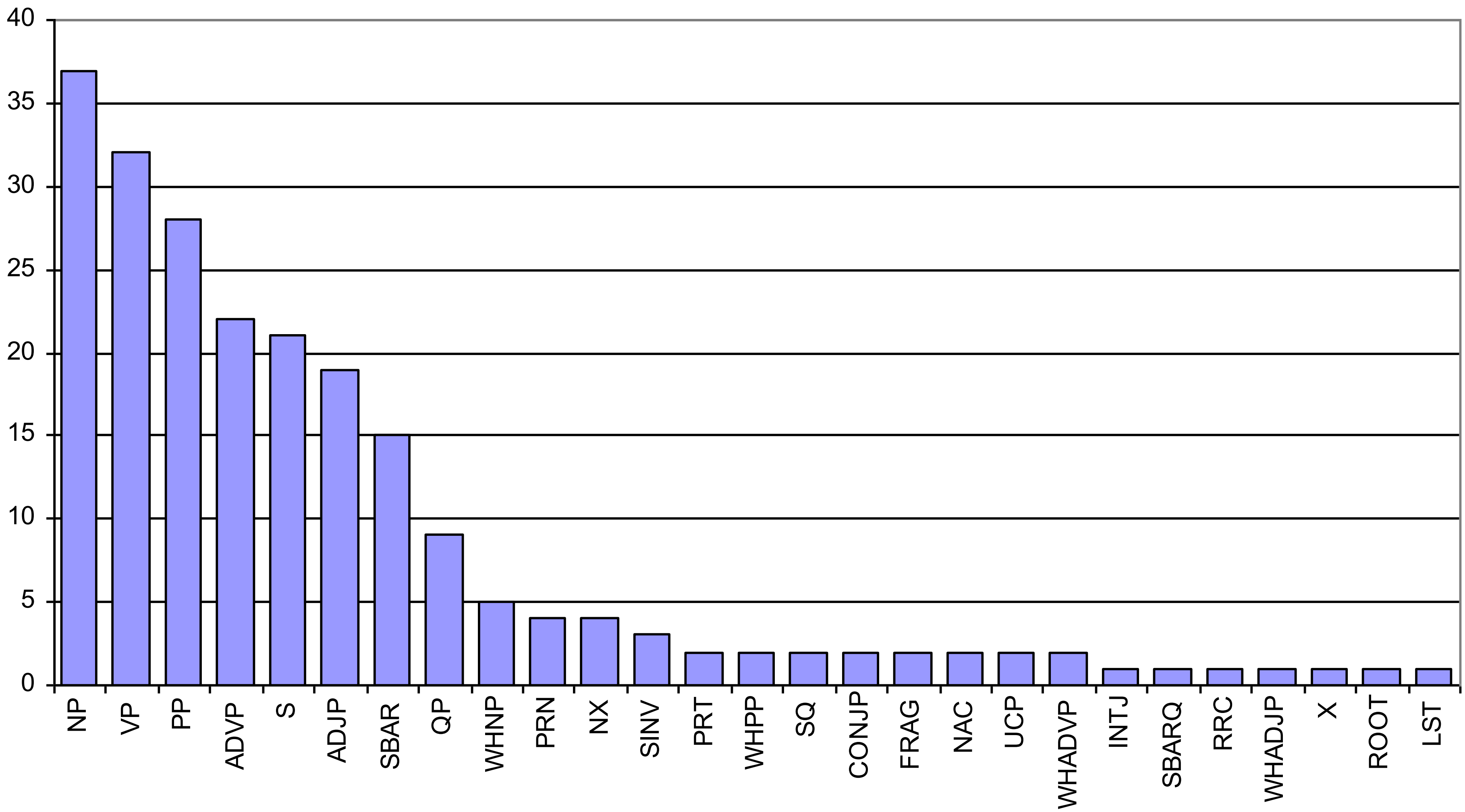


Adaptive Splitting Results

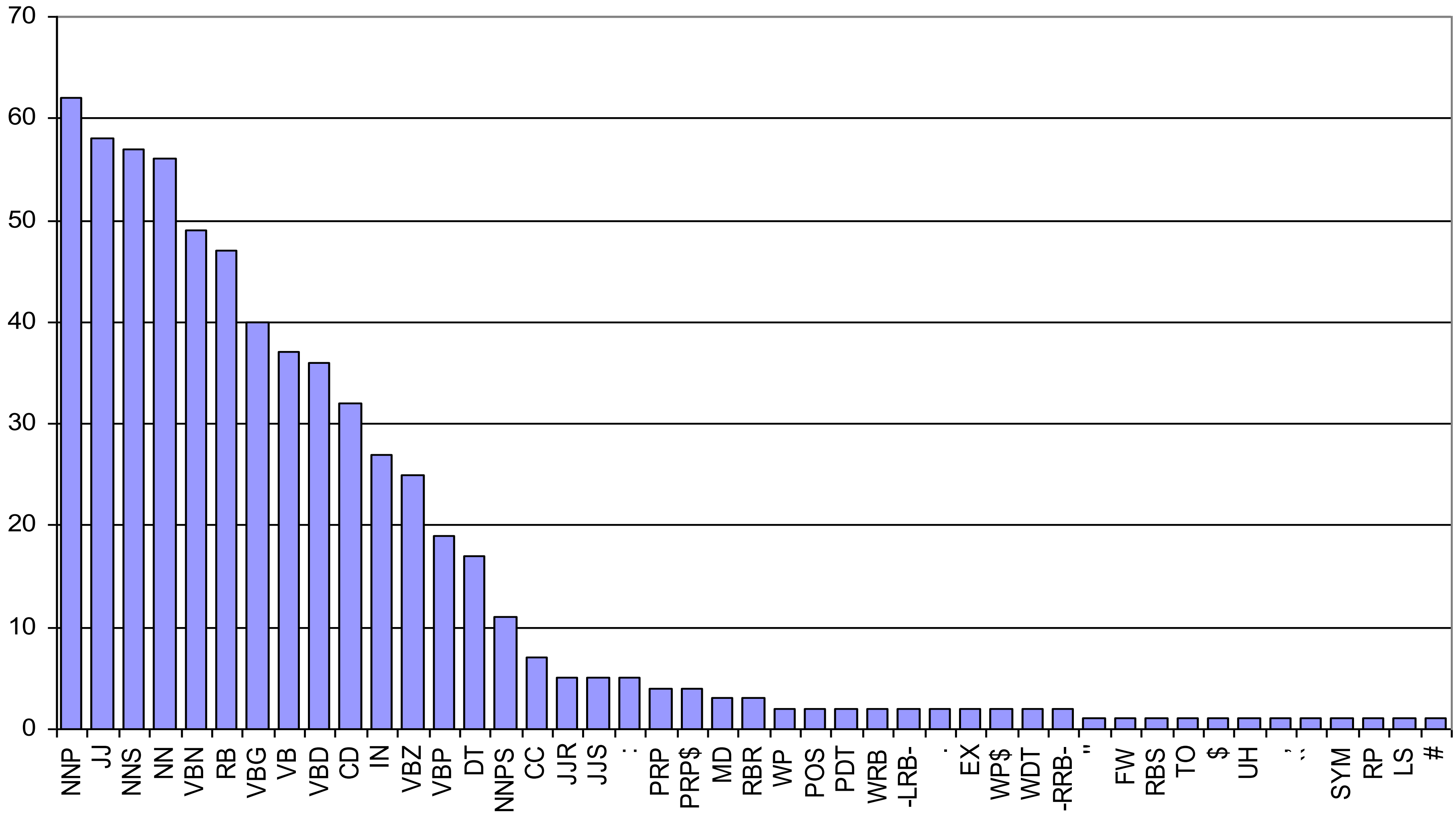


Model	F1
Previous	88.4
With 50% Merging	89.5

Number of Phrasal Subcategories



Number of Lexical Subcategories



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):

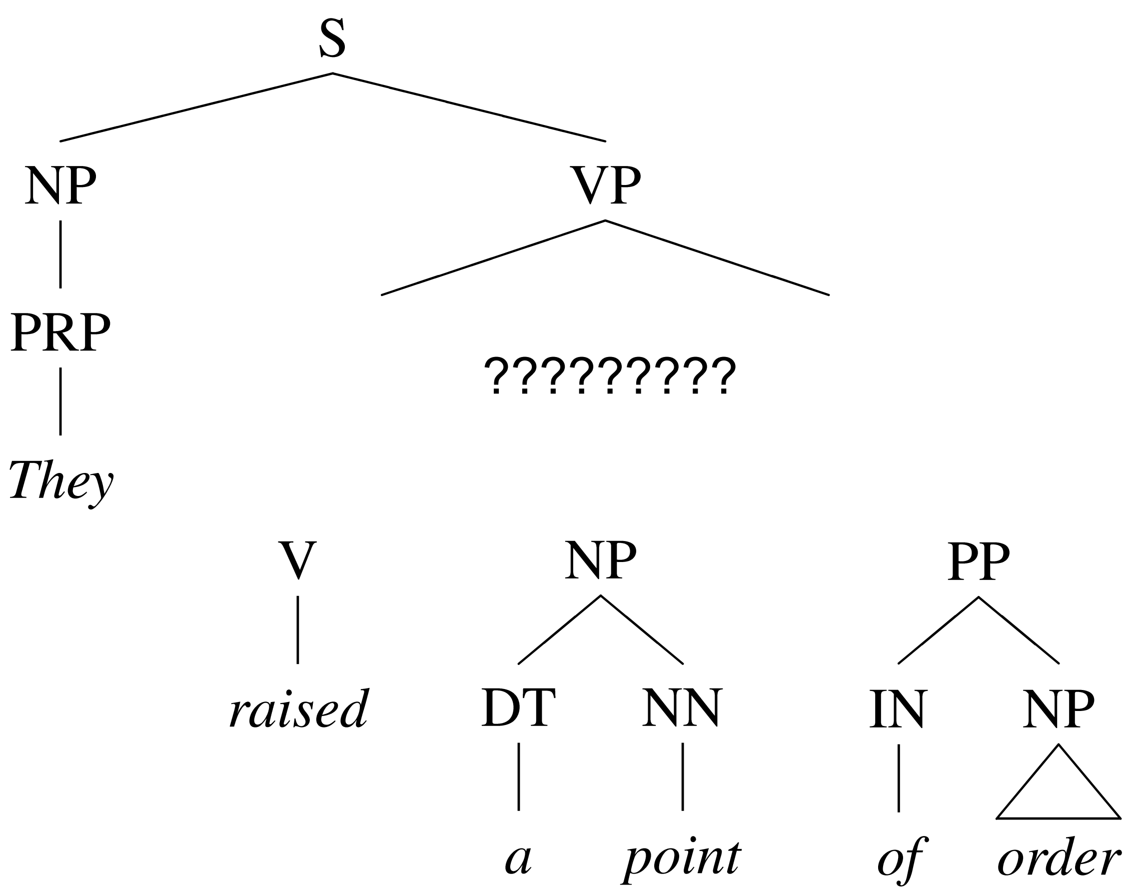
RBR-0	further	lower	higher
RBR-1	more	less	More
RBR-2	earlier	Earlier	later

- Cardinal Numbers (CD):

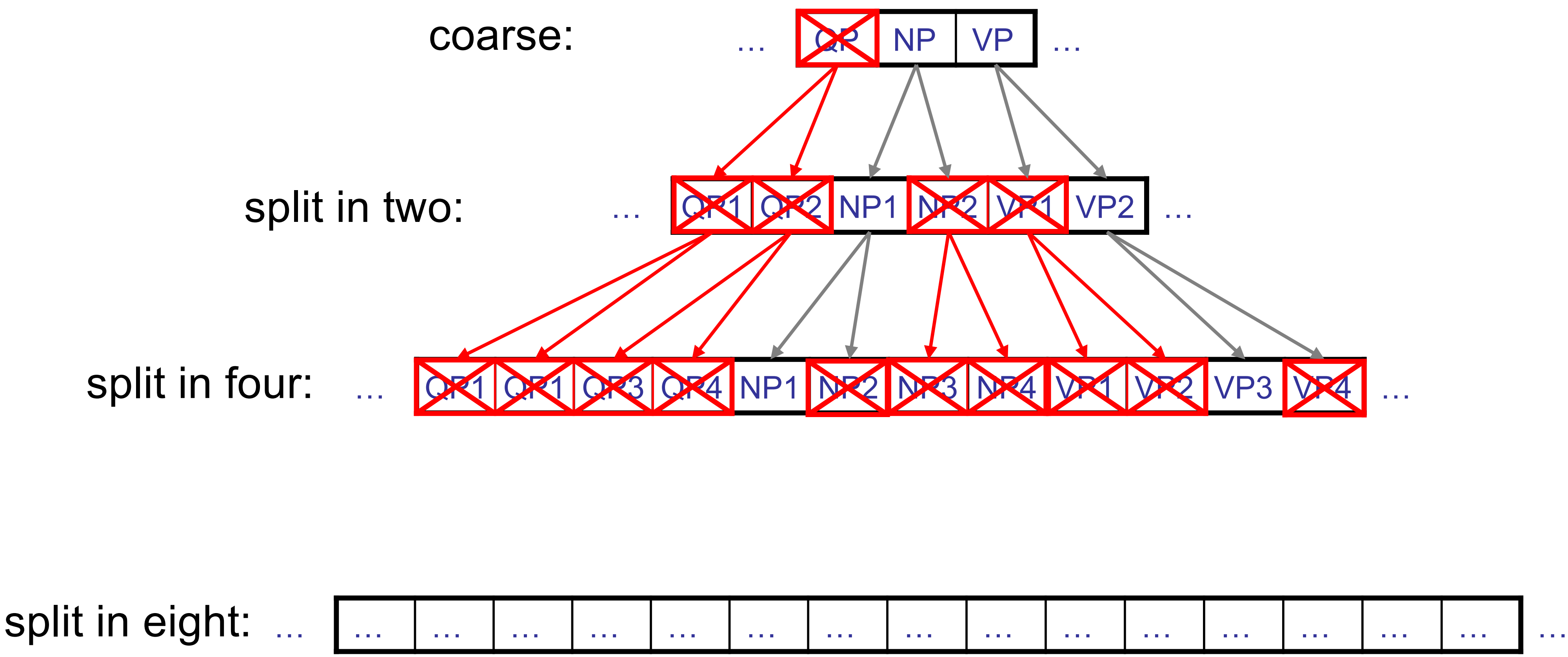
CD-7	one	two	Three
CD-4	1989	1990	1988
CD-11	million	billion	trillion
CD-0	1	50	100
CD-3	1	30	31
CD-9	78	58	34

Coarse-to-Fine Inference

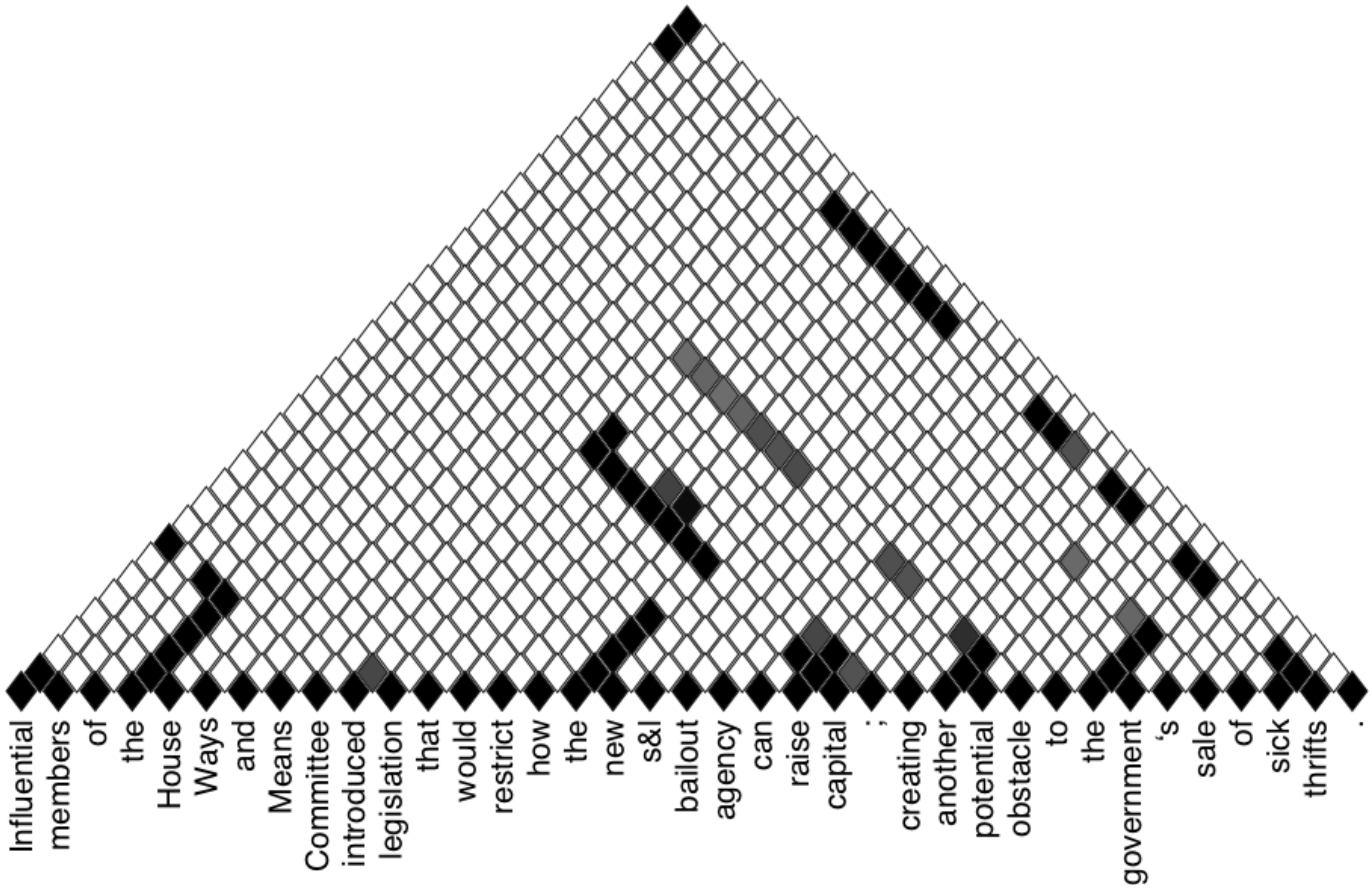
- Example: PP attachment



Hierarchical Pruning



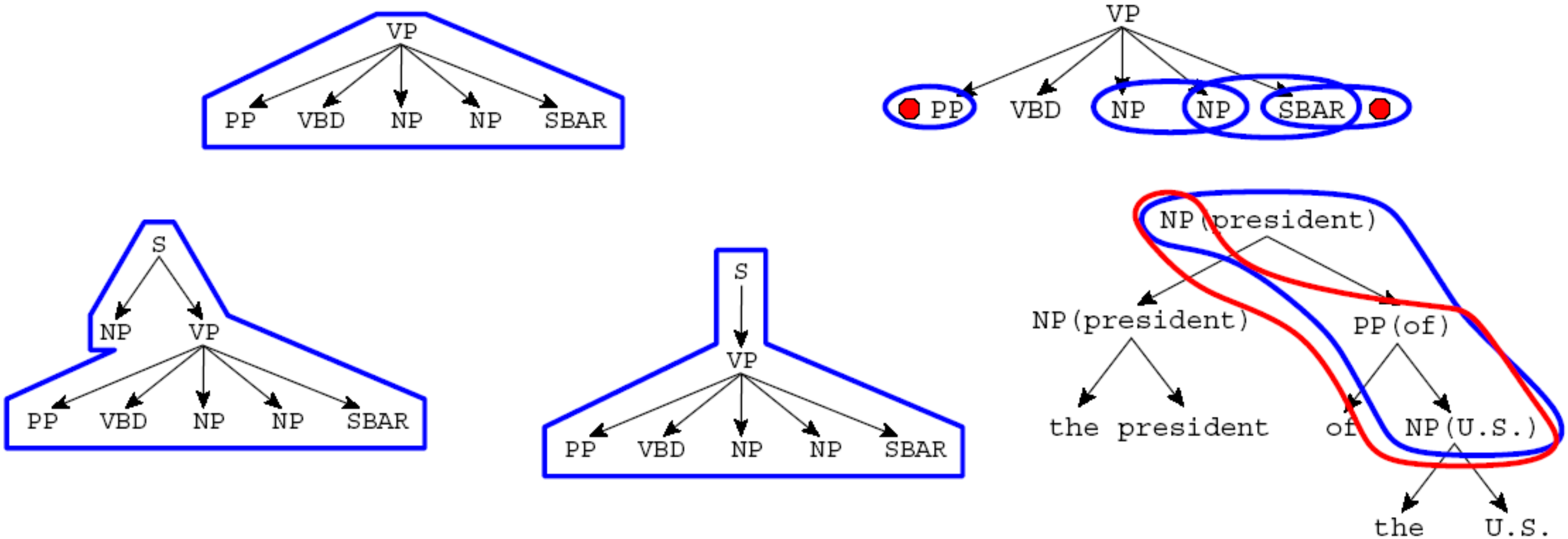
Bracket Posteriors



Other Syntactic Models

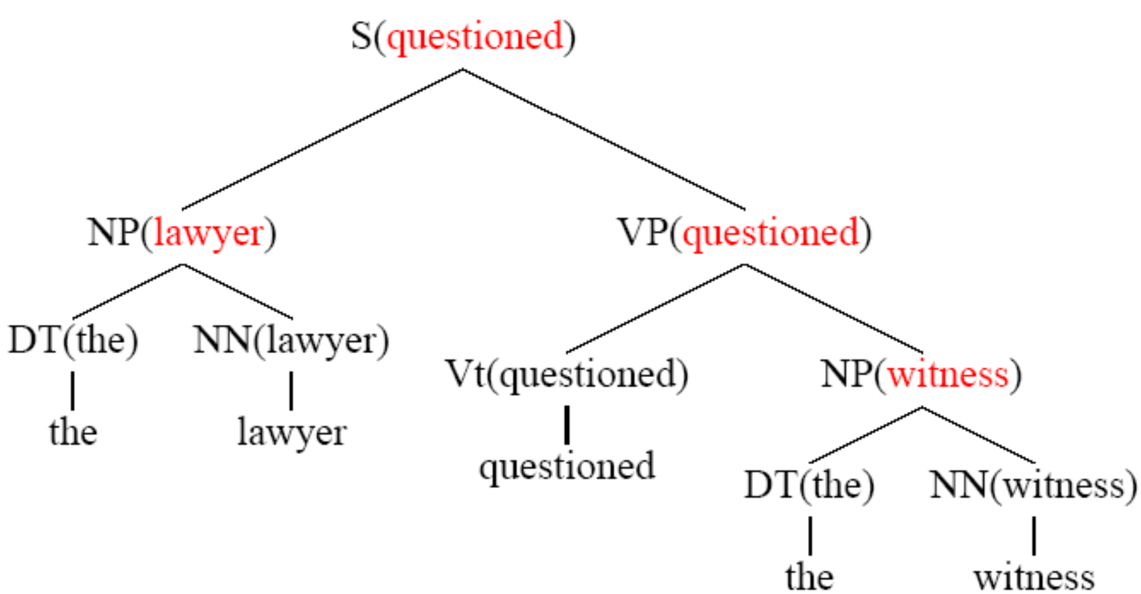
Parse Reranking

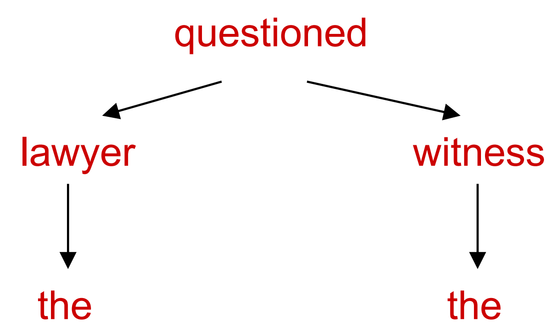
- Assume the number of parses is very small
- We can represent each parse T as a feature vector φ(T)
  - Typically, all local rules are features
  - Also non-local features, like how right-branching the overall tree is
  - [Charniak and Johnson 05] gives a rich set of features



Dependency Parsing

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

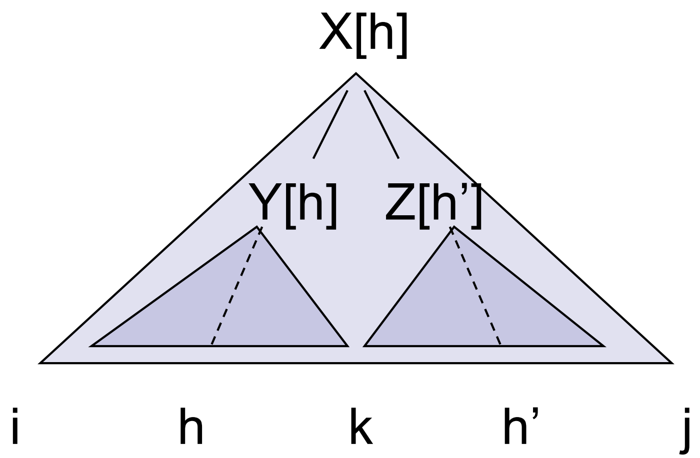


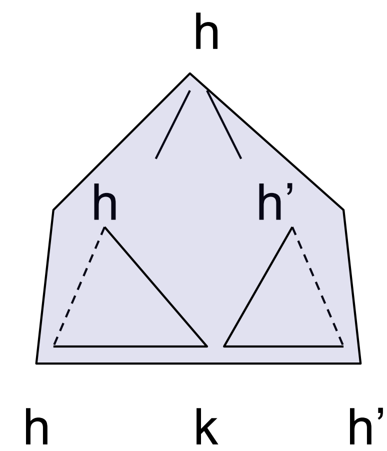


- Each local binary tree corresponds to an attachment in the dependency graph

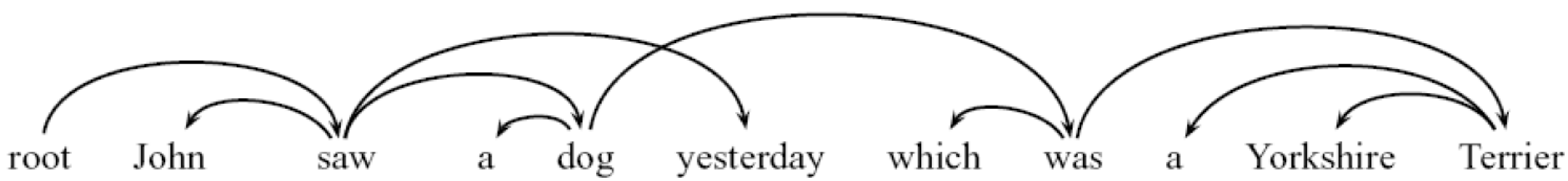
Dependency Parsing

- Pure dependency parsing is only cubic [Eisner 99]



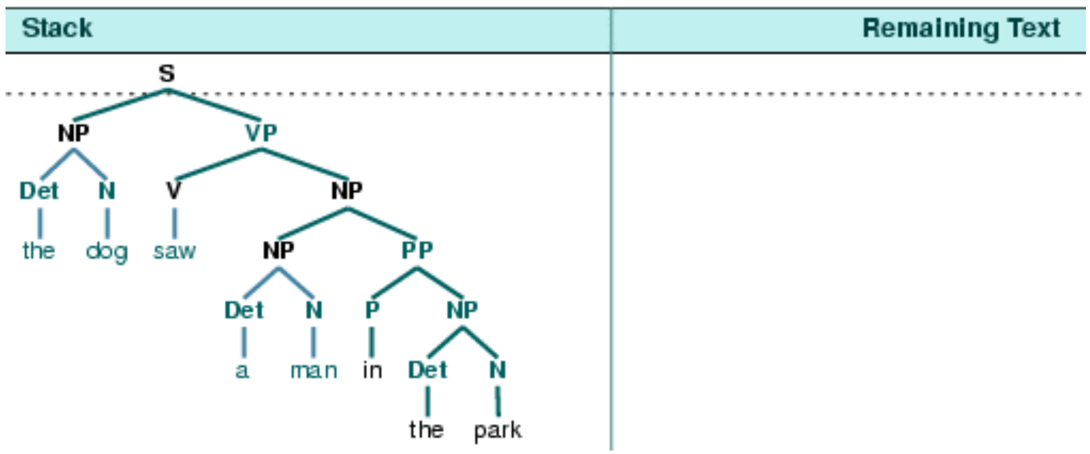


- Some work on *non-projective* dependencies
  - Common in, e.g. Czech parsing
  - Can do with MST algorithms [McDonald and Pereira 05]



Shift-Reduce Parsers

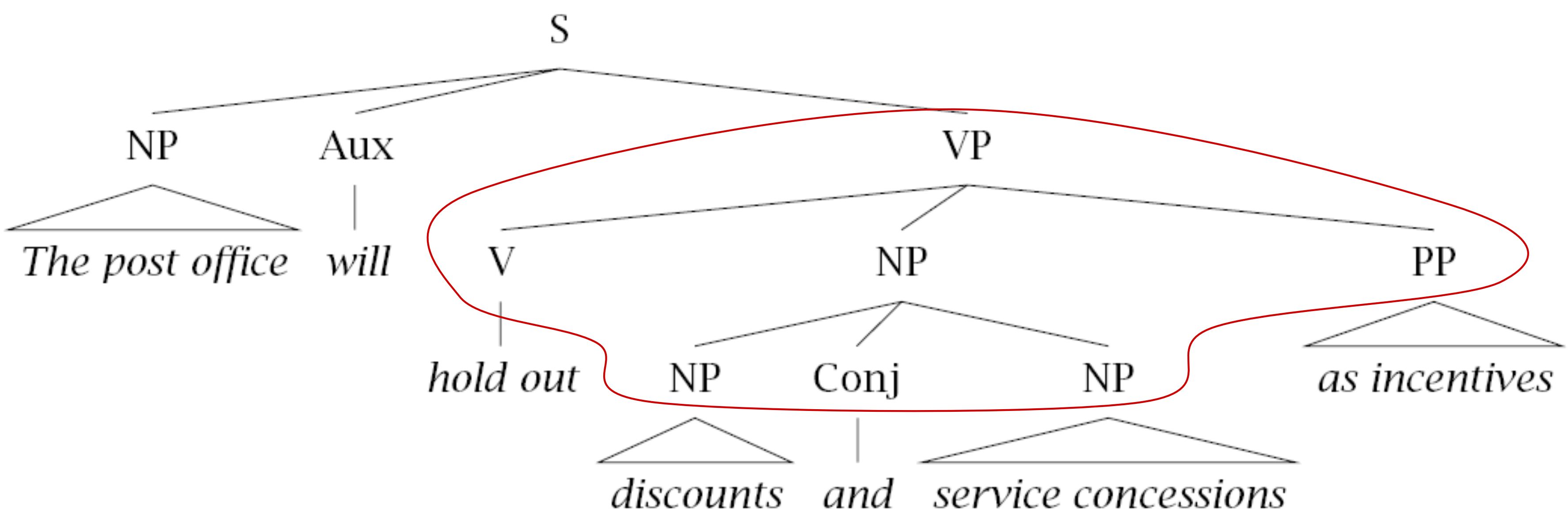
- Another way to derive a tree:



- Parsing
  - No useful dynamic programming search
  - Can still use beam search [Ratnaparkhi 97]

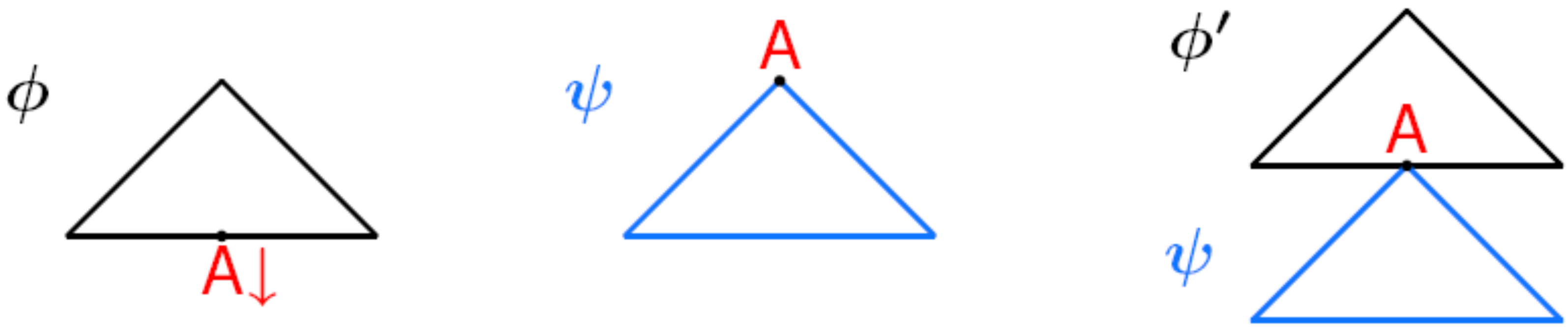
Data-oriented parsing:

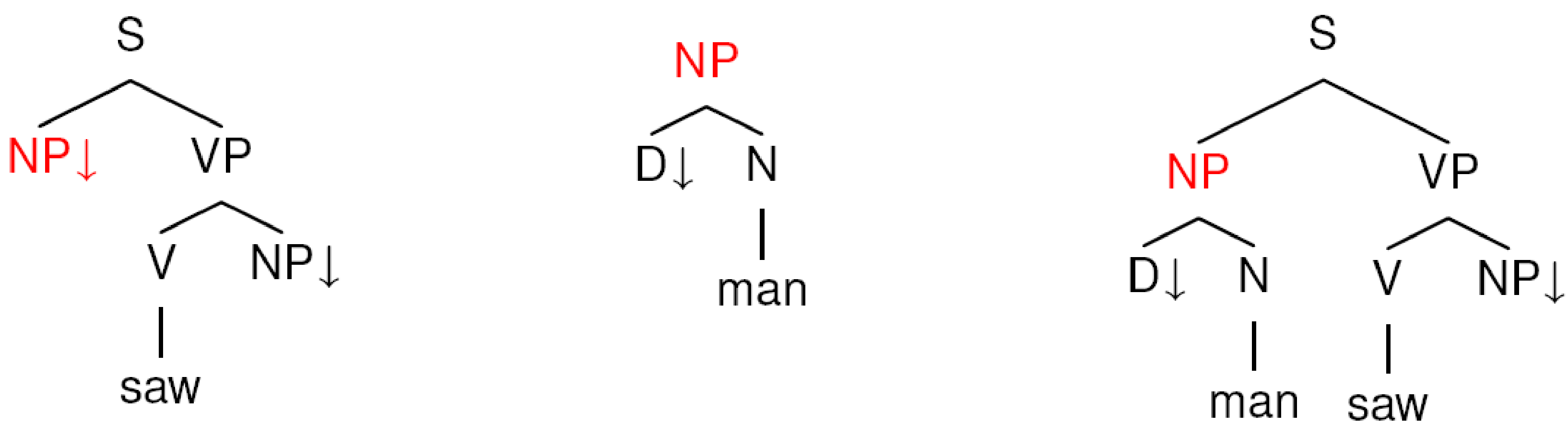
- Rewrite large (possibly lexicalized) subtrees in a single step



- Formally, a *tree-insertion grammar*
- Derivational ambiguity whether subtrees were generated atomically or compositionally
- Most probable *parse* is NP-complete

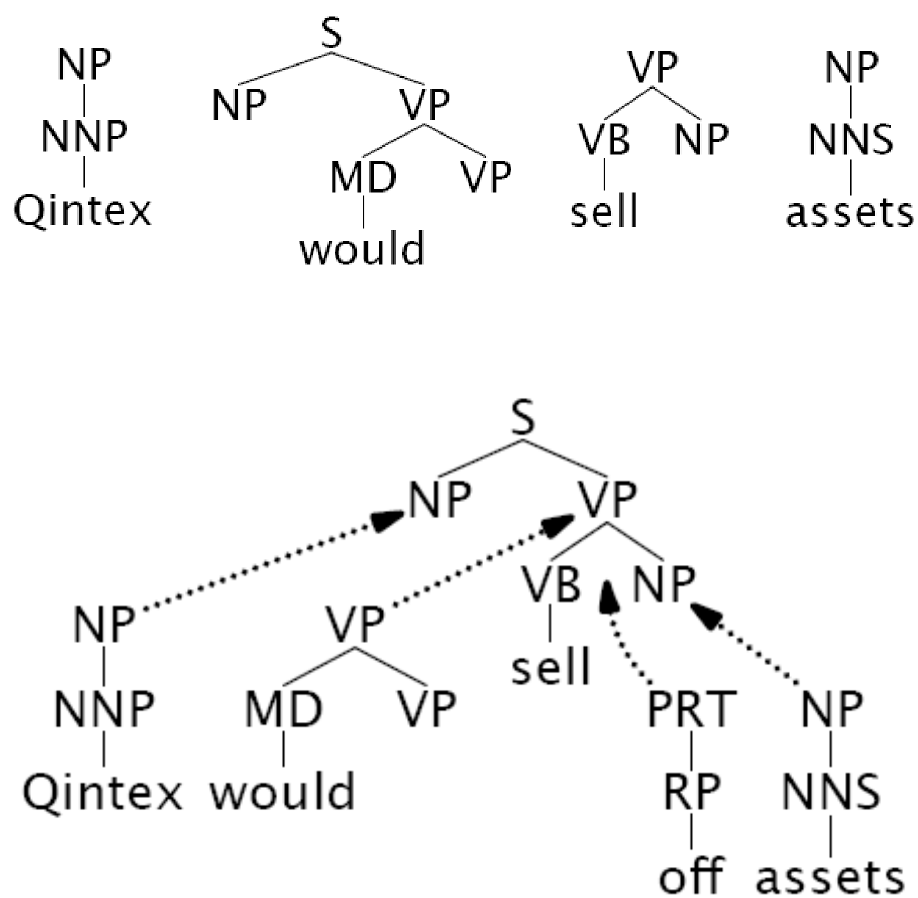
TIG: Insertion



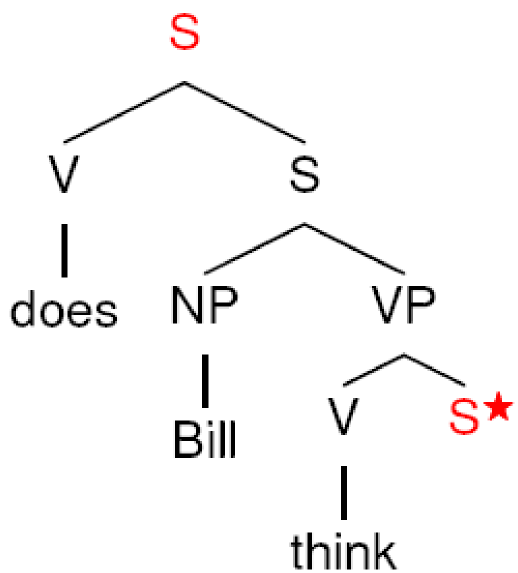


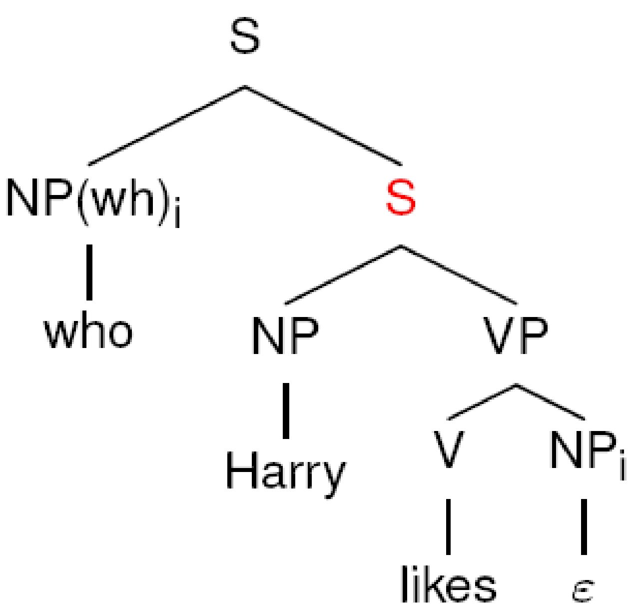
Tree-adjoining grammars

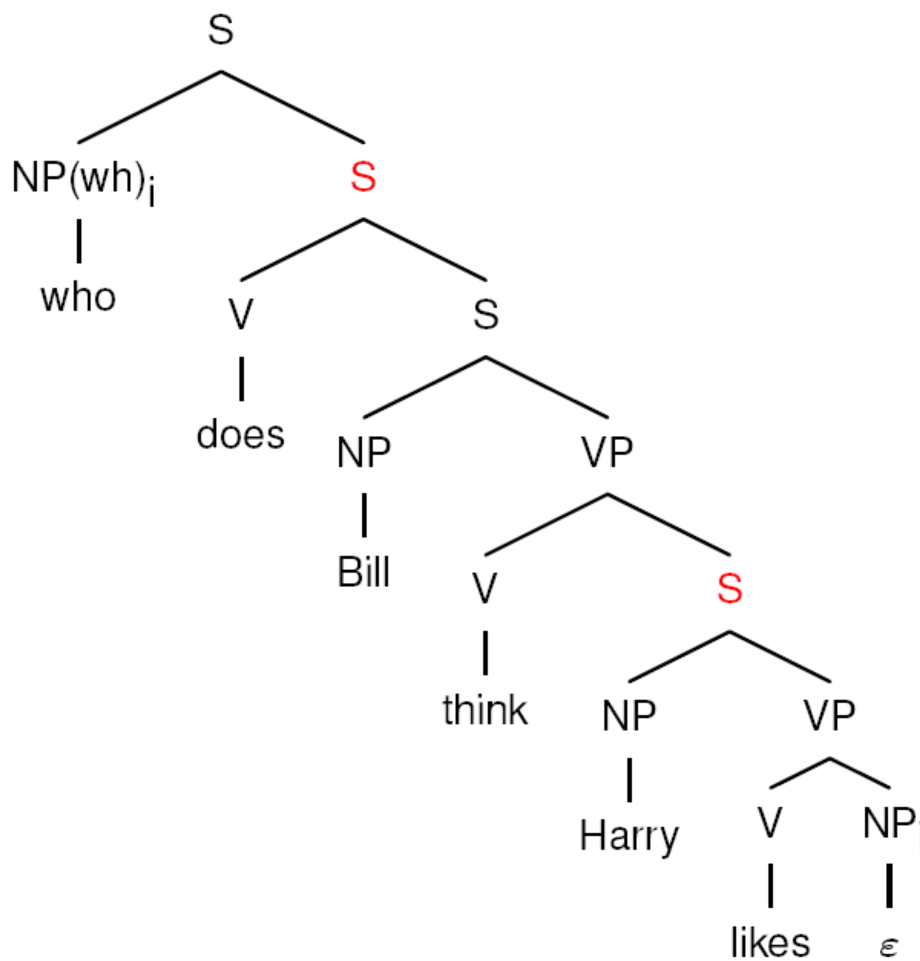
- Start with *local trees*
- Can insert structure with *adjunction* operators
- Mildly context-sensitive
- Models long-distance dependencies naturally
- … as well as other weird stuff that CFGs don't capture well (e.g. cross-serial dependencies)



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?)

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

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

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

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

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