Statistical NLP
Spring 2009

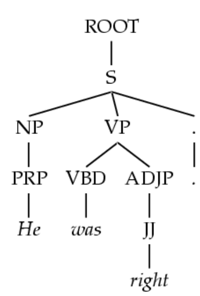
Lecture 15: PCFGs

Dan Klein – UC Berkeley

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

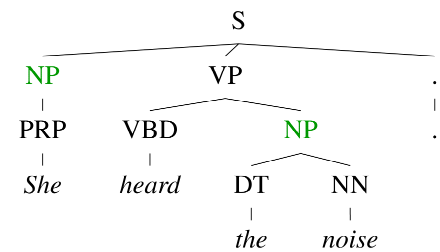
NP → PRP 1

VP → VBD ADJP 1

…..

Model	*F1*
Baseline	72.0

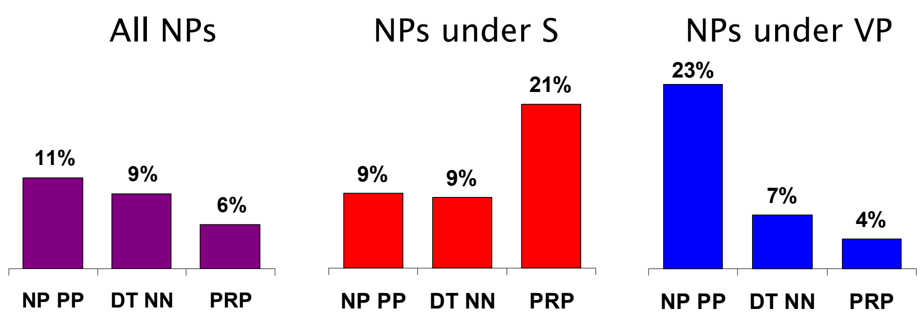
Conditional Independence?



- 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

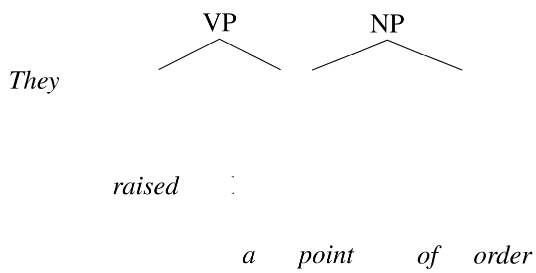
- Independence assumptions are often too strong.



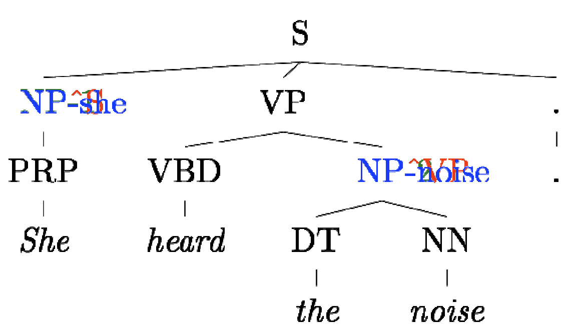
- Example: the expansion of an NP is highly dependent on the parent of the NP (i.e., subjects vs. objects).
- Also: the subject and object expansions are correlated!

Grammar Refinement

- Example: PP attachment

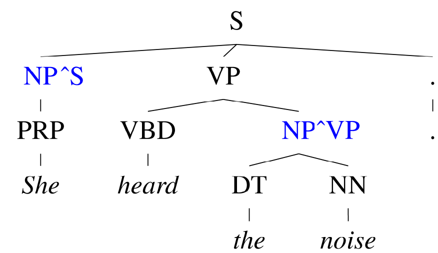


Grammar Refinement



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

The Game of Designing a Grammar



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

Typical Experimental Setup

- Corpus: Penn Treebank, WSJ

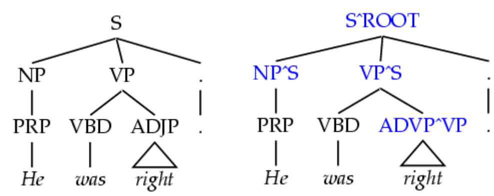
Training:	sections	02-21
Development:	section	22 (here, first 20 files)
Test:	section	23

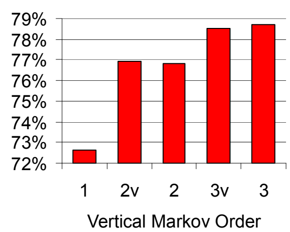
- Accuracy – F1: harmonic mean of per-node labeled precision and recall.
- Here: also size – number of symbols in grammar.
  - Passive / complete symbols: NP, NP^S
  - Active / incomplete symbols: NP $\rightarrow$ NP CC •

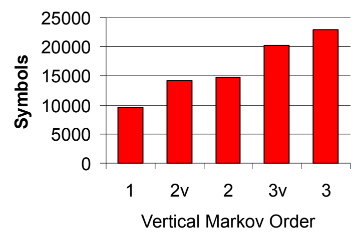
Vertical Markovization

- Vertical Markov order: rewrites depend on past k ancestor nodes.
  (cf. parent annotation)

Order 1 | Order 2

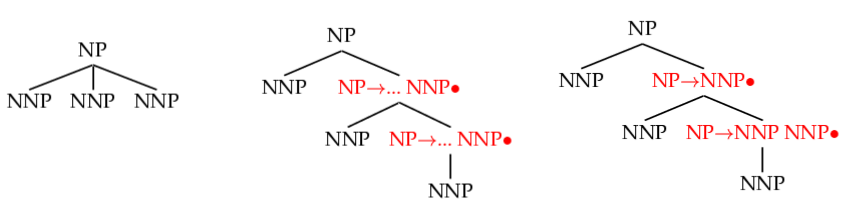


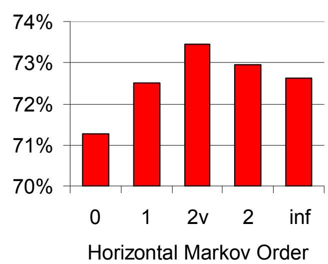


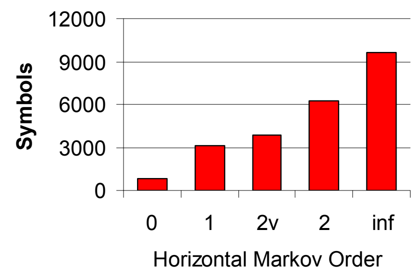


Horizontal Markovization

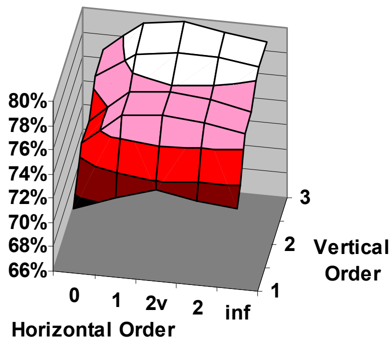
Order 1 | Order ∞

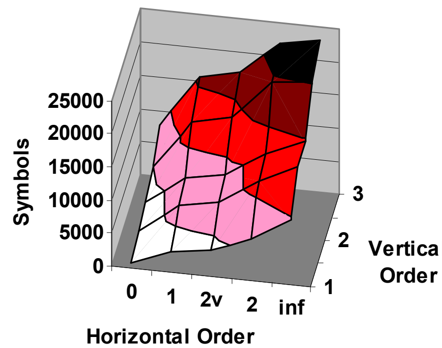






Vertical and Horizontal



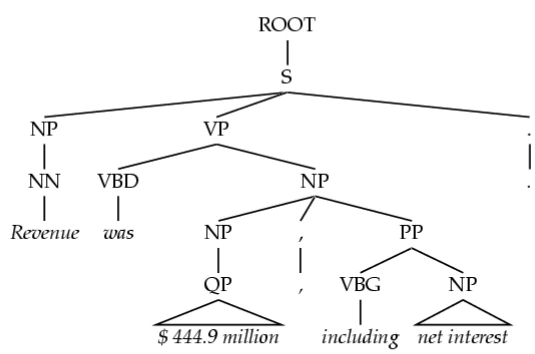


- Examples:
  - Raw treebank: v=1, h=∞
  - Johnson 98: v=2, h=∞
  - Collins 99: v=2, h=2
  - Best F1: v=3, h=2v

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

Unary Splits

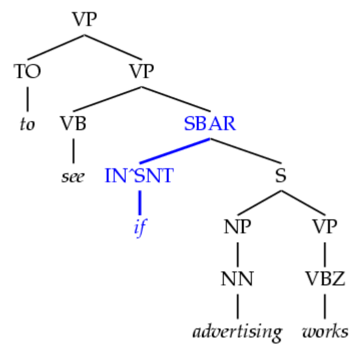
- Problem: unary rewrites used to transmute categories so a high-probability rule can be used.
- Solution: Mark unary rewrite sites with -U



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.



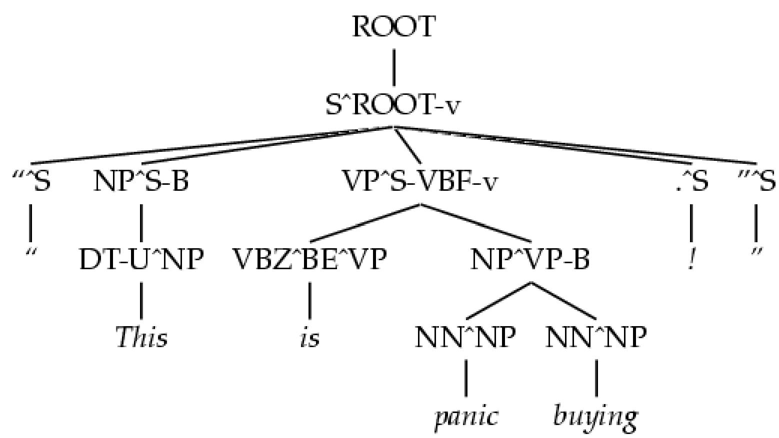
Annotation	F1	Size
Previous	78.3	8.0K
SPLIT-IN	80.3	8.1K

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

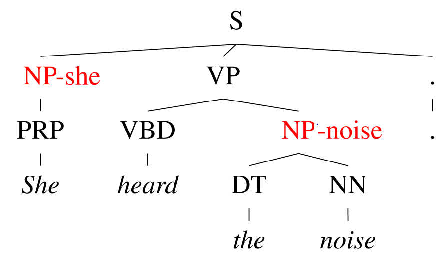


Some Test Set Results

Parser	LP	LR	**F1**	CB	0 CB
Magerman 95	84.9	84.6	**84.7**	1.26	56.6
Collins 96	86.3	85.8	**86.0**	1.14	59.9
Unlexicalized	86.9	85.7	**86.3**	1.10	60.3
Charniak 97	87.4	87.5	**87.4**	1.00	62.1
Collins 99	88.7	88.6	**88.6**	0.90	67.1

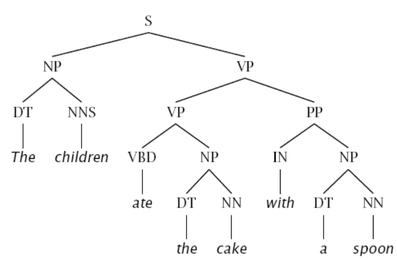
- Beats “first generation” lexicalized parsers.
- Lots of room to improve – more complex models next.

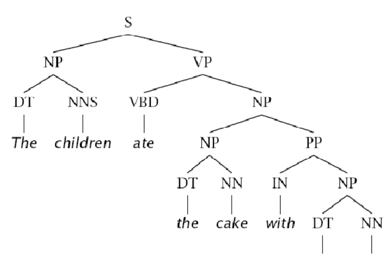
The Game of Designing a Grammar



- 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]

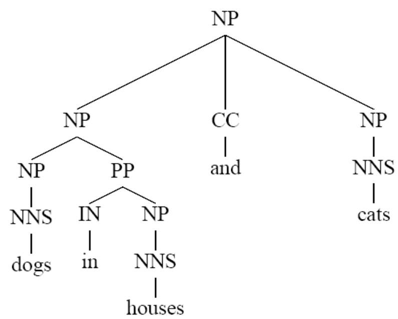
Problems with PCFGs

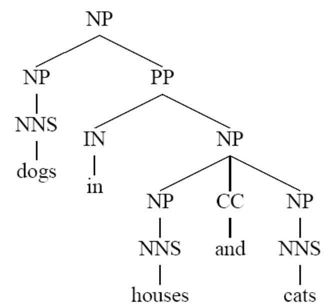




- If we do no annotation, these trees differ only in one rule:
  - VP → VP PP
  - NP → NP PP
- Parse will go one way or the other, regardless of words
- We addressed this in one way with unlexicalized grammars (how?)
- Lexicalization allows us to be sensitive to specific words

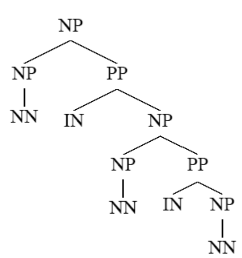
Problems with PCFGs

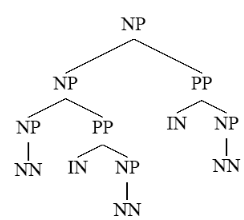




- What's different between basic PCFG scores here?
- What (lexical) correlations need to be scored?

Problems with PCFGs



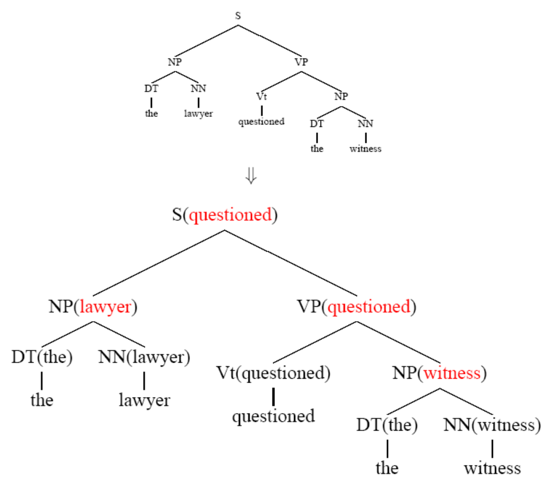


president of a company in Africa

- Another example of PCFG indifference
  - Left structure far more common
  - How to model this?
  - Really structural: "chicken with potatoes with gravy"
  - Lexical parsers model this effect, but not by virtue of being lexical

Lexicalized Trees

- Add "headwords" 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

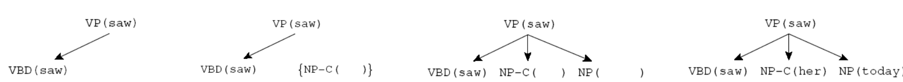


Lexicalized PCFGs?

- Problem: we now have to estimate probabilities like

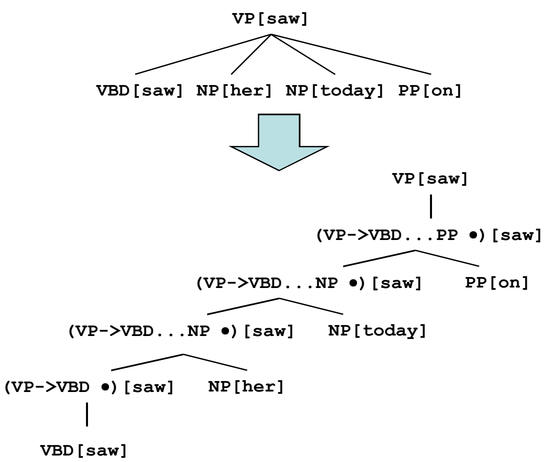
```
VP(saw) -> VBD(saw) NP-C(her) NP(today)
```

- Never going to get these atomically off of a treebank
- Solution: break up derivation into smaller steps



Lexical Derivation Steps

- Derivation of a local tree [simplified Charniak 97]



Still have to smooth with mono- and non-lexical backoffs

$$\overbrace{\qquad\qquad\qquad\qquad\qquad\qquad}$$

$$P(\texttt{STOP}|\texttt{VBD}[saw], \texttt{VP}, \texttt{PP})$$

$$P(\texttt{PP}[on]|\texttt{VBD}[saw], \texttt{VP}, \texttt{NP})$$

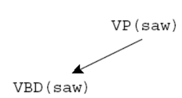
$$P(\texttt{NP}[today]|\texttt{VBD}[saw], \texttt{VP}, \texttt{NP})$$

$$P(\texttt{NP}[her]|\texttt{VBD}[saw], \texttt{VP}, \texttt{START})$$

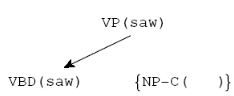
$$P(\texttt{VBD}[saw]|\texttt{VP}[saw])$$

Lexical Derivation Steps

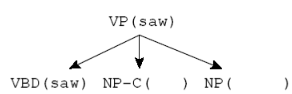
- Another derivation of a local tree [Collins 99]



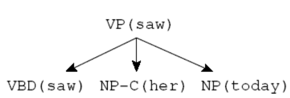
Choose a head tag and word



Choose a complement bag



Generate children (incl. adjuncts)



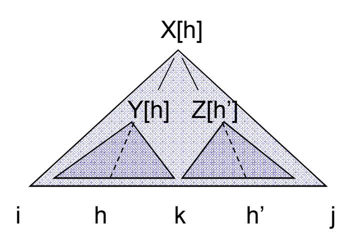
Recursively derive children

Naïve Lexicalized Parsing

- Can, in principle, use CKY on lexicalized PCFGs
  - $O(Rn^3)$ time and $O(Sn^2)$ memory
  - But $R = rV^2$ and $S = sV$
  - Result is completely impractical (why?)
  - Memory: 10K rules * 50K words * (40 words)^2 * 8 bytes ≈ 6TB
- Can modify CKY to exploit lexical sparsity
  - Lexicalized symbols are a base grammar symbol and a pointer into the input sentence, not any arbitrary word
  - Result: $O(rn^5)$ time, $O(sn^3)$
  - Memory: 10K rules * (40 words)^3 * 8 bytes ≈ 5GB

Lexicalized CKY

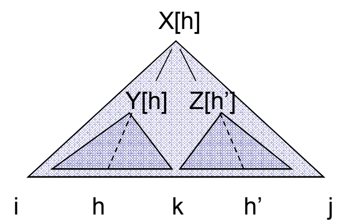
```
        (VP->VBD...NP •)[saw]
(VP->VBD •)[saw]      NP[her]
```

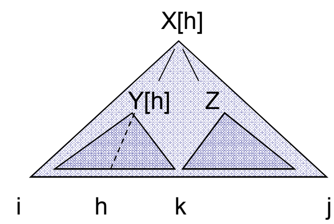



```
bestScore(X,i,j,h)
  if (j = i+1)
    return tagScore(X,s[i])
  else
    return
      max   max  score(X[h]->Y[h] Z[h']) *
         k,h',X->YZ
                 bestScore(Y,i,k,h) *
                 bestScore(Z,k,j,h')
            max  score(X[h]->Y[h'] Z[h]) *
         k,h',X->YZ
               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

Quartic Parsing

- Turns out, you can do (a little) better [Eisner 99]

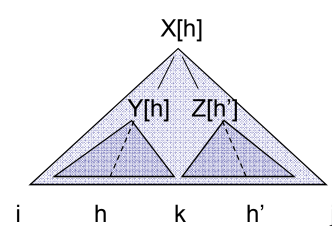




- Gives an $O(n^4)$ algorithm
- Still prohibitive in practice if not pruned

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



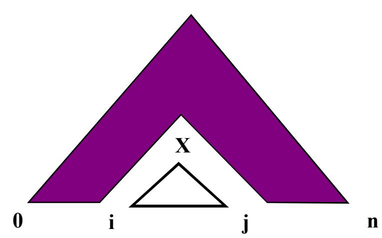
- Also: certain spans are forbidden entirely on the basis of punctuation (crucial for speed)

Pruning with a PCFG

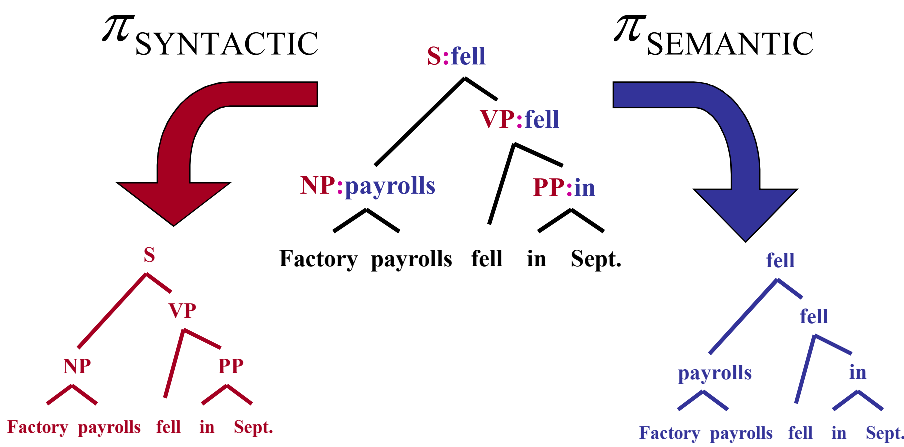
- The Charniak parser prunes using a two-pass approach [Charniak 97+]
  - First, parse with the base grammar
  - For each X:[i,j] calculate P(X|i,j,s)
    - This isn't trivial, and there are clever speed ups
  - Second, do the full $O(n^5)$ CKY
    - Skip any X :[i,j] which had low (say, < 0.0001) posterior
  - Avoids almost all work in the second phase!
- Charniak et al 06: can use more passes
- Petrov et al 07: can use many more passes

Pruning with A*

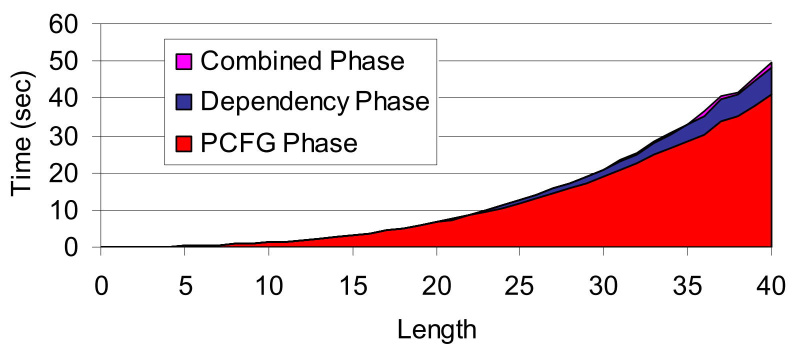
- You can also speed up the search without sacrificing optimality
- For agenda-based parsers:
  - Can select which items to process first
  - Can do with any "figure of merit" [Charniak 98]
  - If your figure-of-merit is a valid A* heuristic, no loss of optimiality [Klein and Manning 03]



Projection-Based A*



A* Speedup

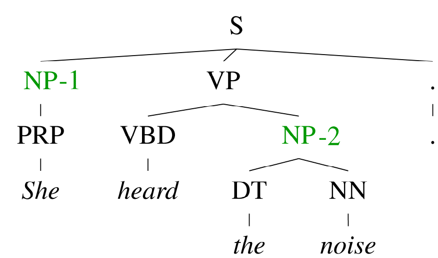


- Total time dominated by calculation of A* tables in each projection… $O(n^3)$

Results

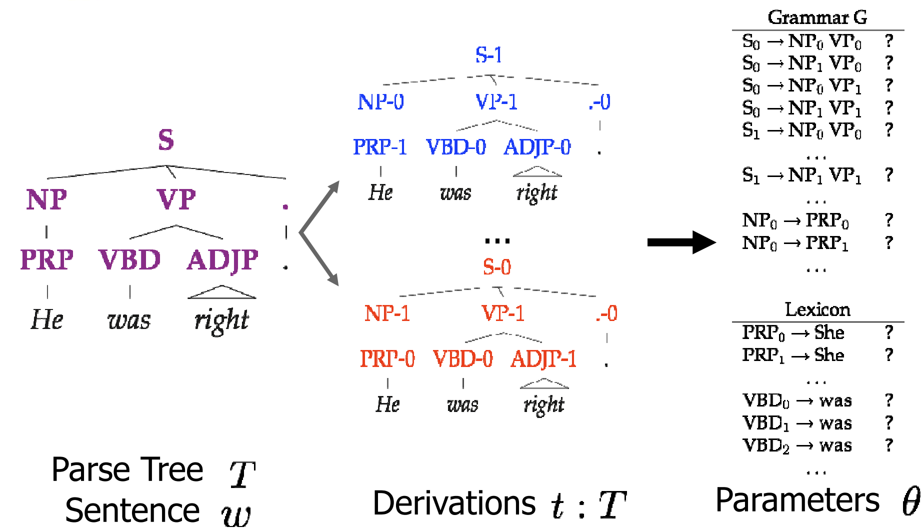
- Some results
  - Collins 99 – 88.6 F1 (generative lexical)
  - Charniak and Johnson 05 – 89.7 / 91.3 F1 (generative lexical / reranked)
  - Petrov et al 06 – 90.7 F1 (generative unlexical)
  - McClosky et al 06 – 92.1 F1 (gen + rerank + self-train)
- However
  - Bilexical counts rarely make a difference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

The Game of Designing a Grammar



- Annotation refines base treebank symbols to improve statistical fit of the grammar
  - Structural annotation
  - Head lexicalization
  - Automatic clustering?

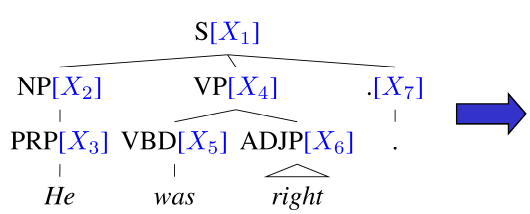
Latent Variable Grammars

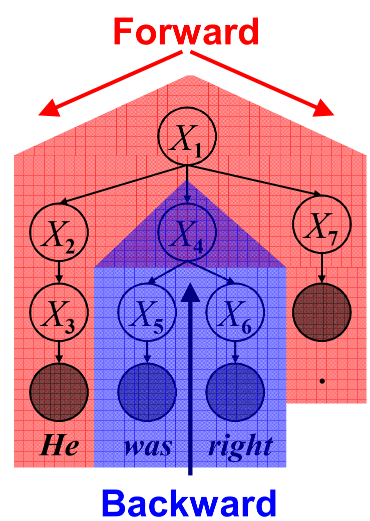


Learning Latent Annotations

EM algorithm:

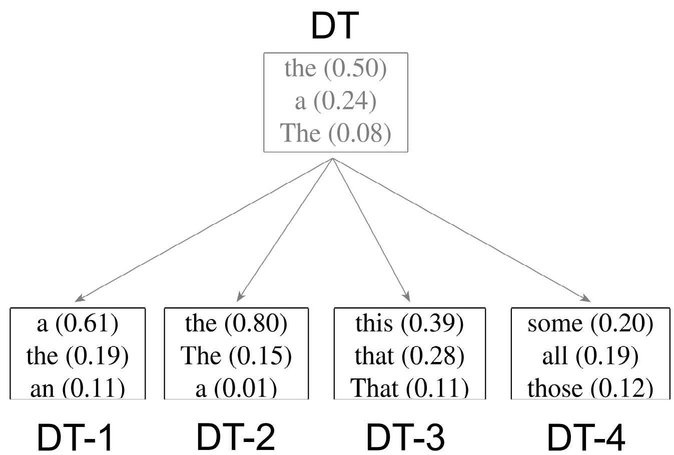
- Brackets are known
- Base categories are known
- Only induce subcategories



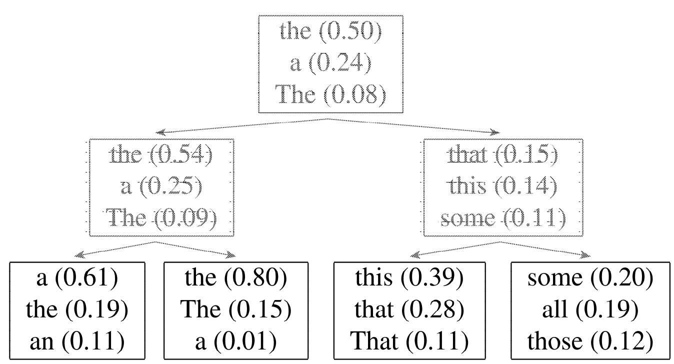


Just like Forward-Backward for HMMs.

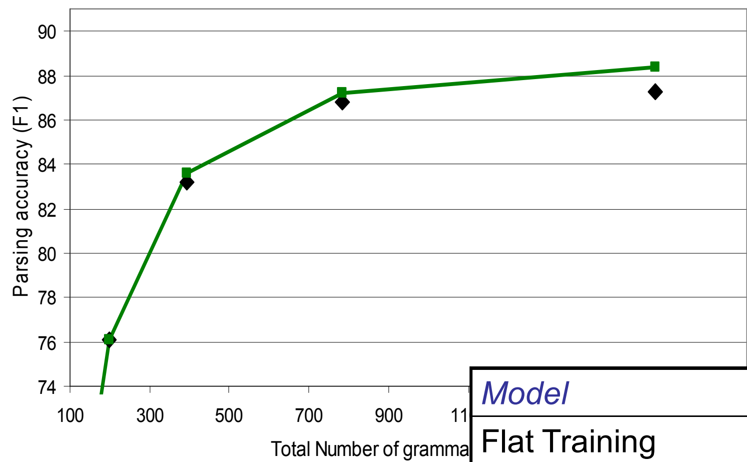
Refinement of the DT tag



Hierarchical refinement



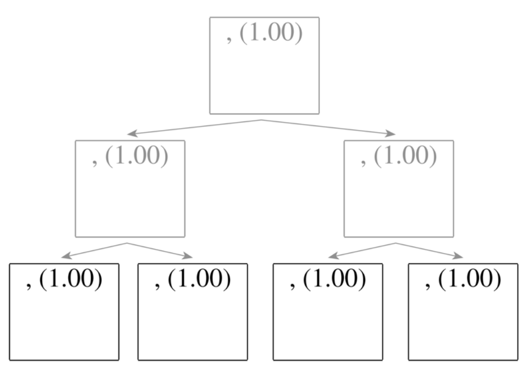
Hierarchical Estimation Results



Model	*F1*
Flat Training	87.3
Hierarchical Training	88.4

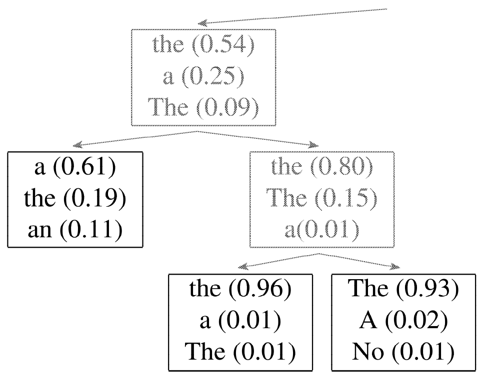
Refinement of the , tag

- Splitting all categories equally is wasteful:

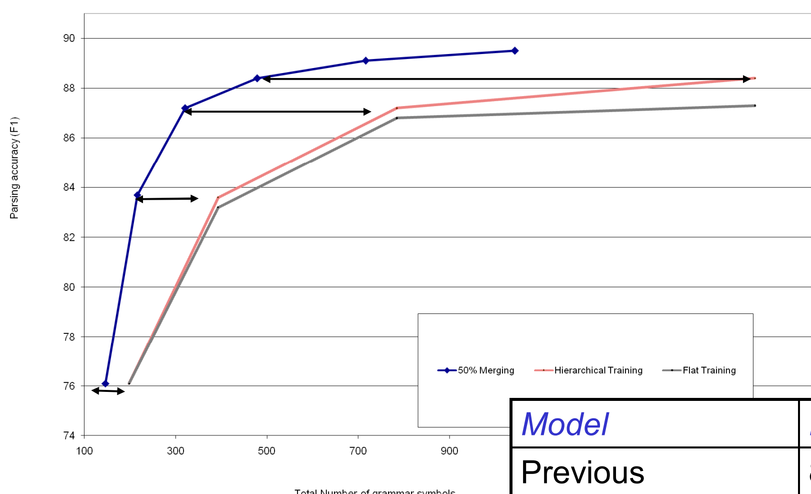


Adaptive Splitting

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

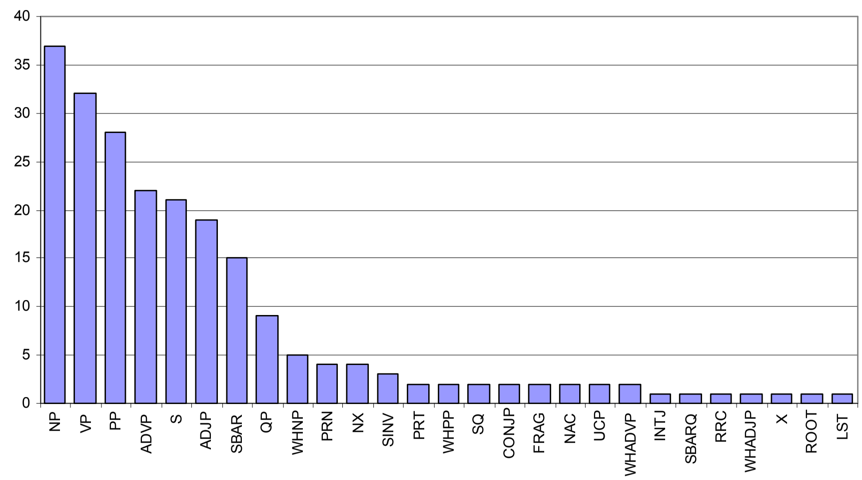


Adaptive Splitting Results

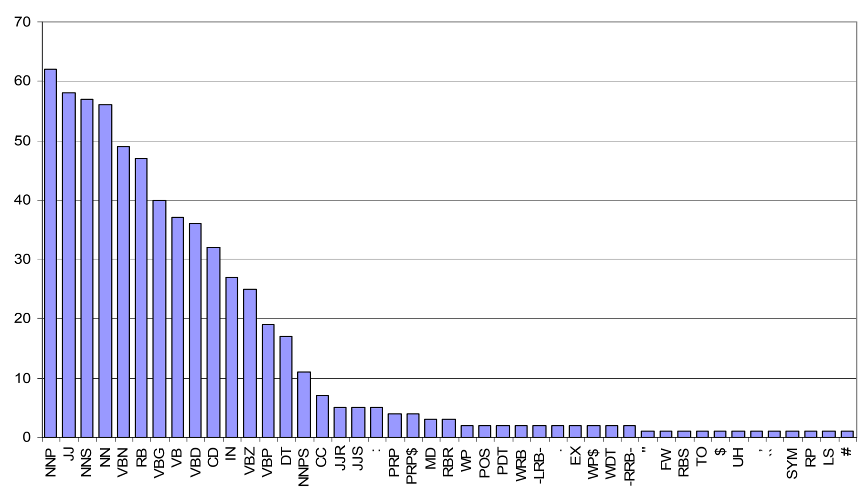


Model	*F1*
Previous	88.4
With 50% Merging	89.5

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):

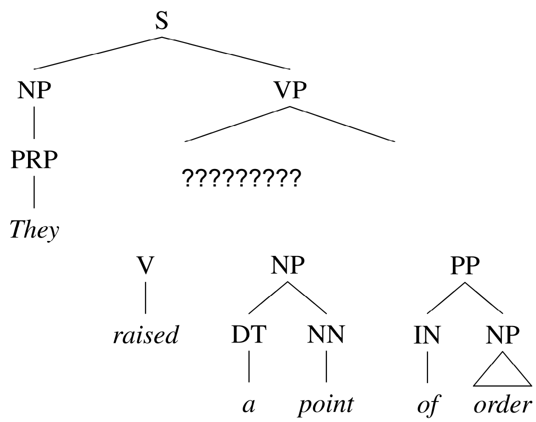
RBR-0	further	lower	higher
RBR-1	more	less	More
RBR-2	earlier	Earlier	later

- 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

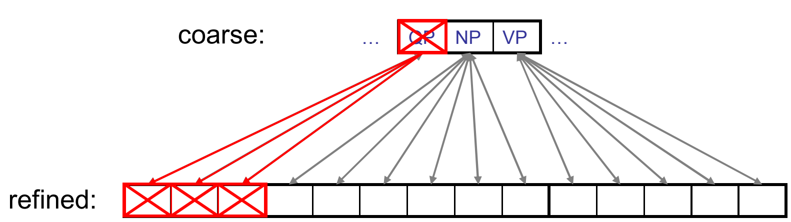


Prune?

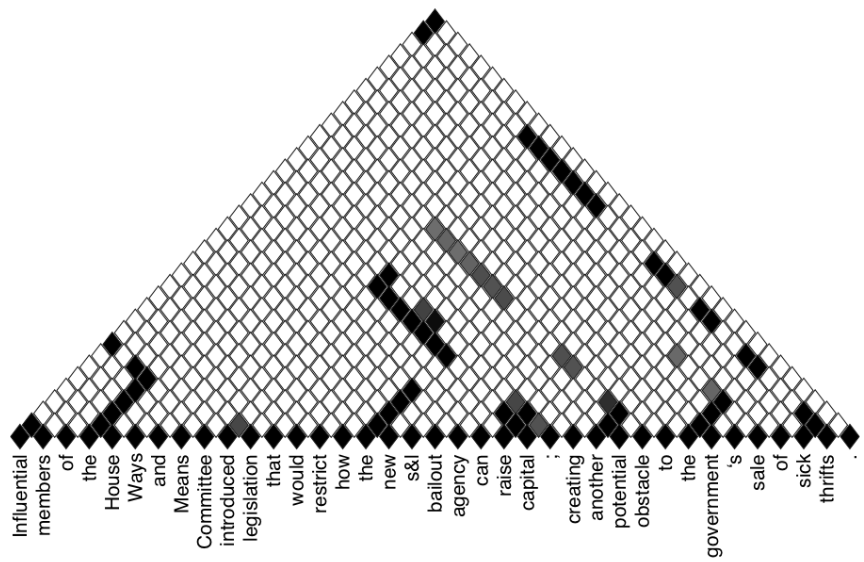
For each chart item $X[i,j]$, compute posterior probability:

$$\frac{\mathrm{P}_{\mathrm{IN}}(X,i,j)\cdot \mathrm{P}_{\mathrm{OUT}}(X,i,j)}{\mathrm{P}_{\mathrm{IN}}(root,0,n)} < \textbf{\textit{threshold}}$$

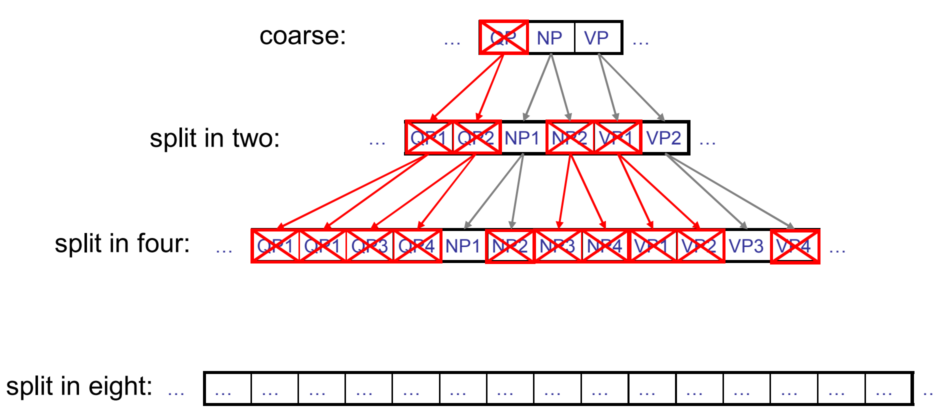
E.g. consider the span 5 to 12:



Bracket Posteriors



Hierarchical Pruning



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