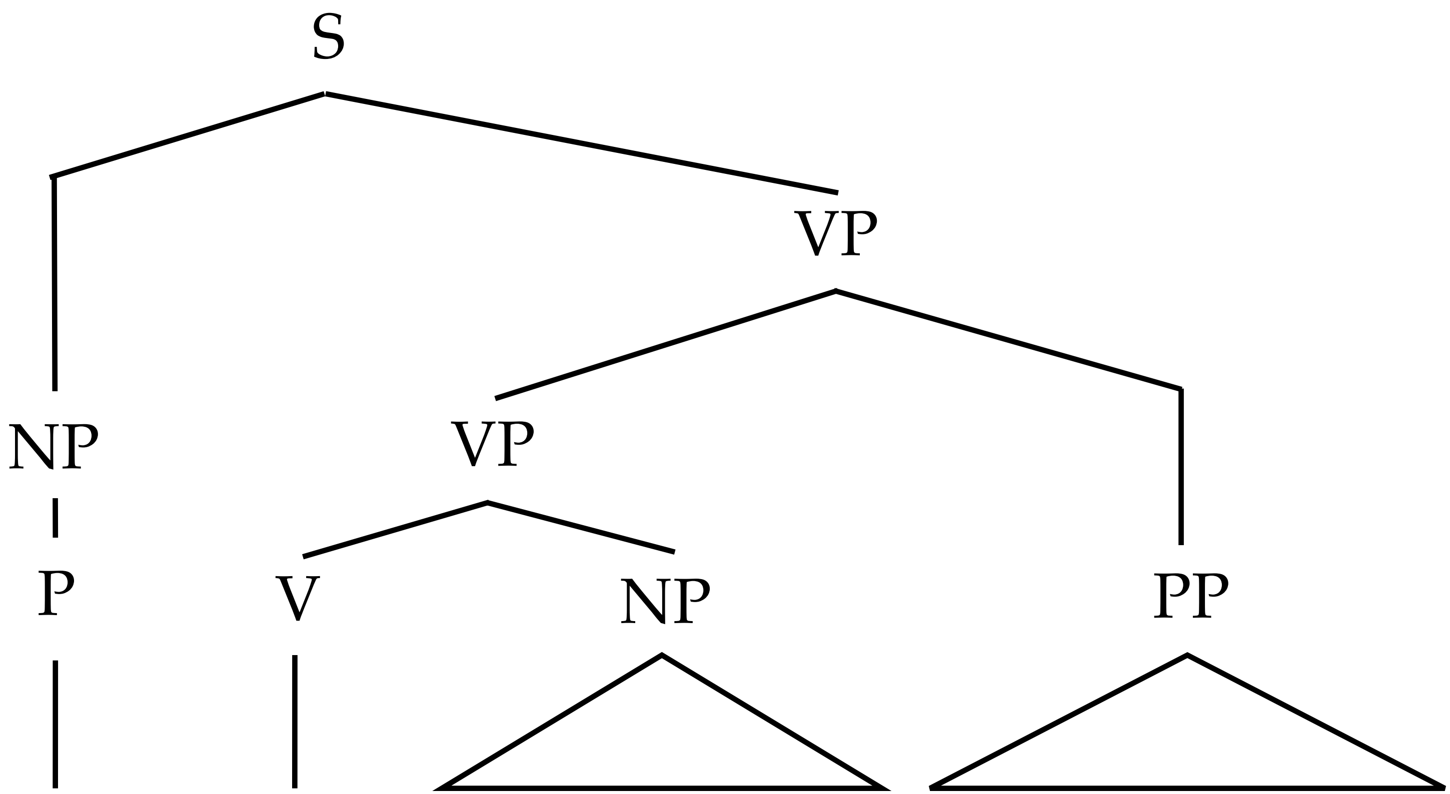
Syntax and Parsing

Slav Petrov – Google Research

Thanks to: Dan Klein, Ryan McDonald

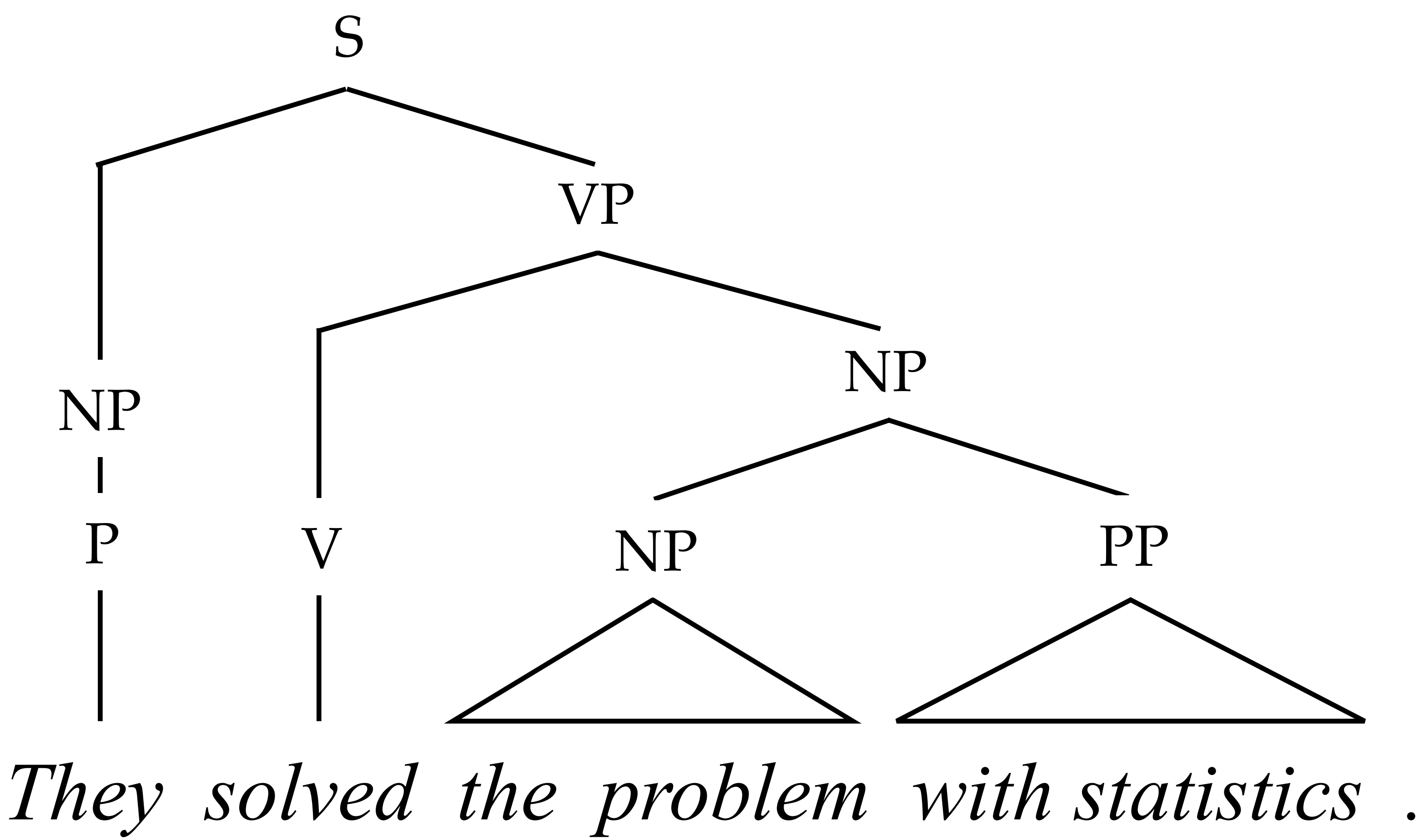
Lisbon Machine Learning School

Analyzing Natural Language

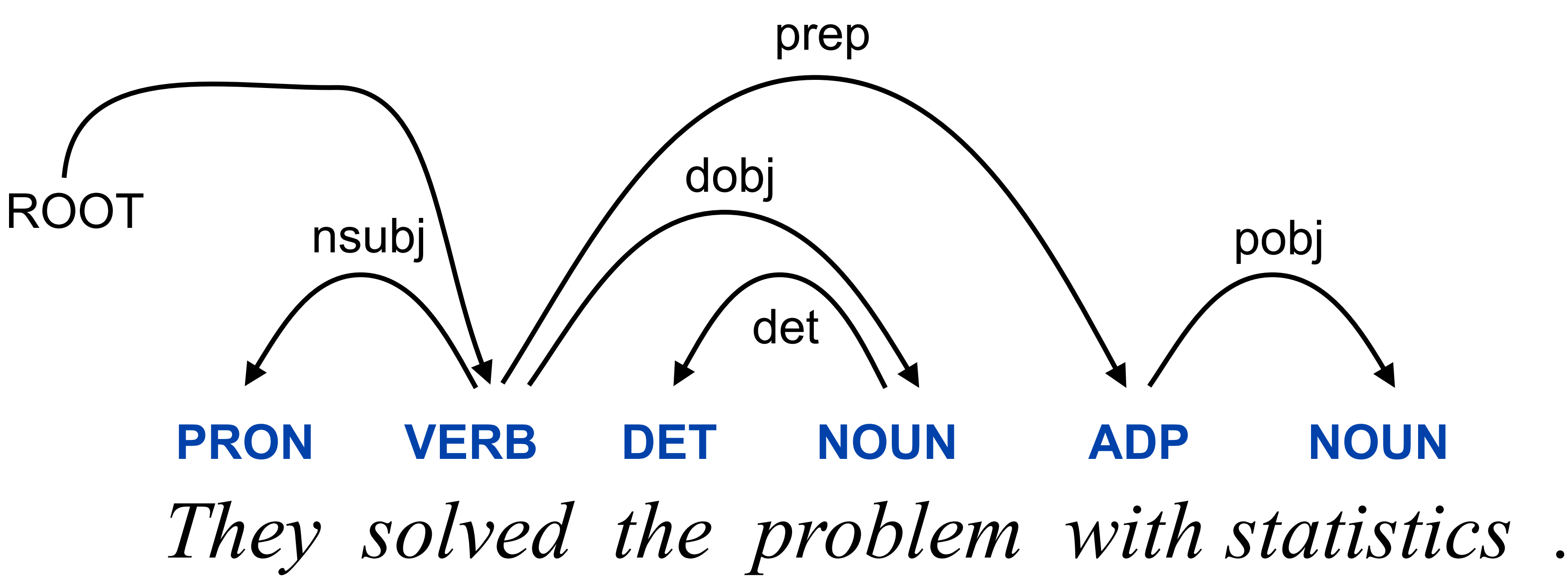


They [*solved* [*the problem*] *with statistics*].

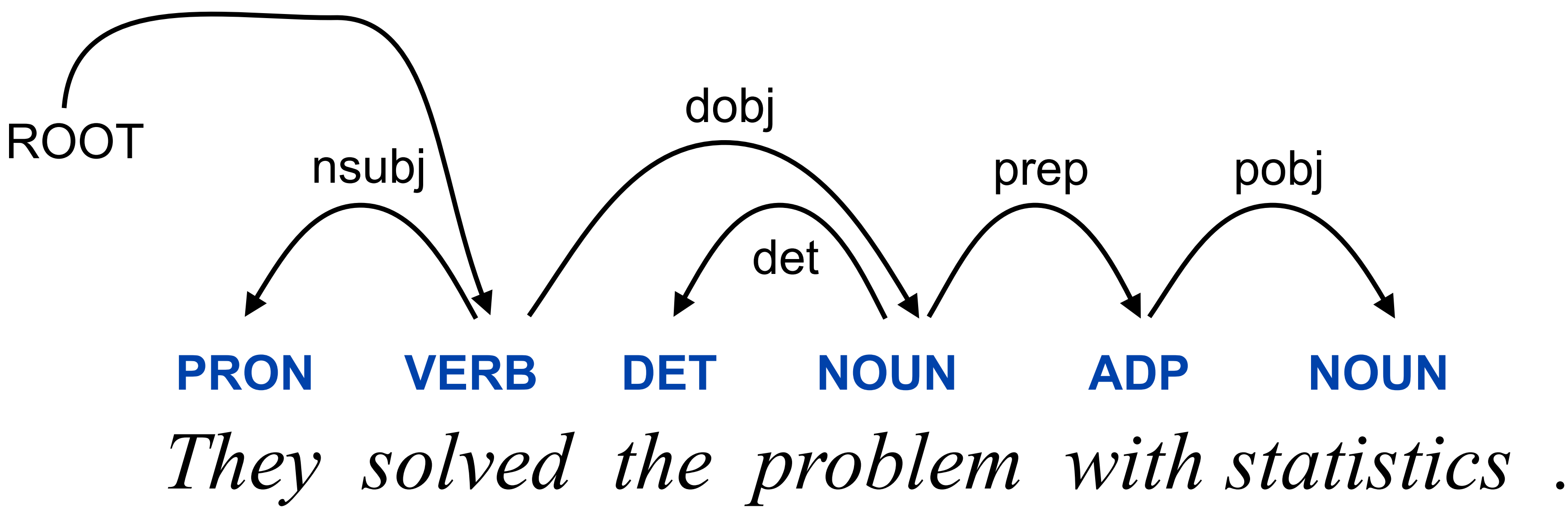
Syntax and Semantics



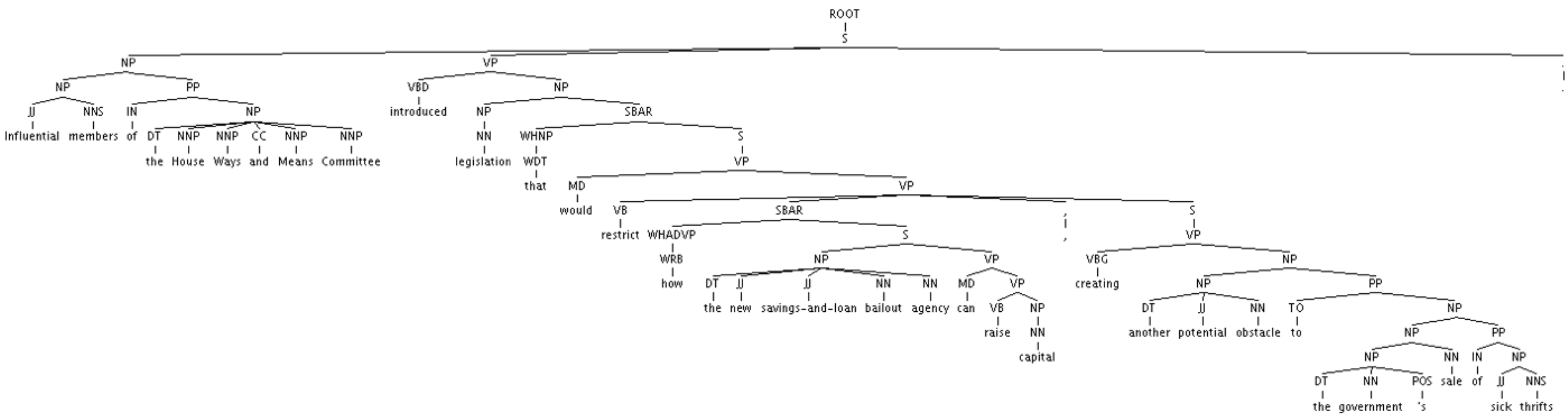
Constituency and Dependency



Constituency and Dependency



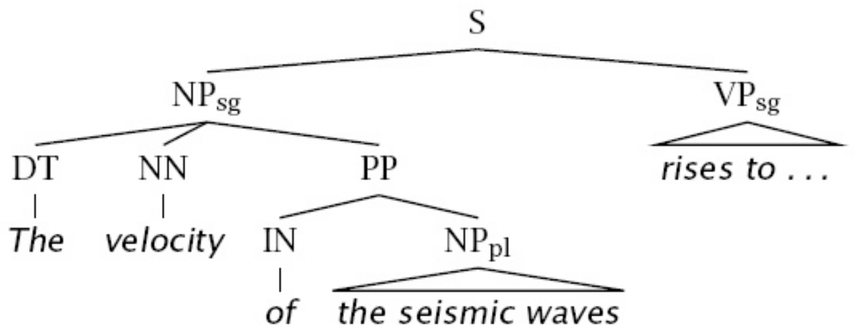
A “real” Sentence



Influential members of the House Ways and Means Committee introduced legislation that would restrict how the new savings-and-loan bailout agency can raise capital, creating another potential obstacle to the government's sale of sick thrifts.

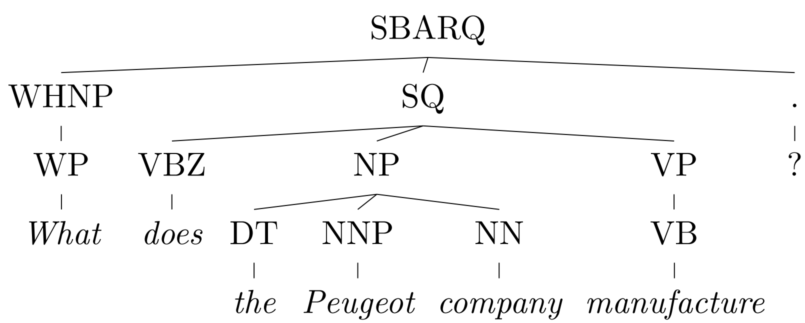
Phrase Structure Parsing

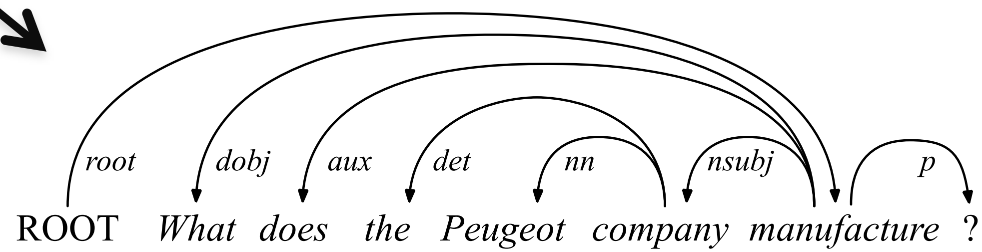
- Phrase structure parsing organizes syntax into *constituents* or *brackets*
- In general, this involves nested trees
- Linguists can, and do, argue about details
- Lots of ambiguity
- Not the only kind of syntax…
- First part of today's lecture



new art critics write reviews with computers

Dependency Parsing





- Directed edges between pairs of word (head, dependent)
- Can handle free word-order languages
- Very efficient decoding algorithms exist
- Second part of today's lecture

Classical NLP: Parsing

- Write symbolic or logical rules:

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

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
  - Real-size grammar: many millions of parses
- This scaled very badly, didn’t yield broad-coverage tools

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

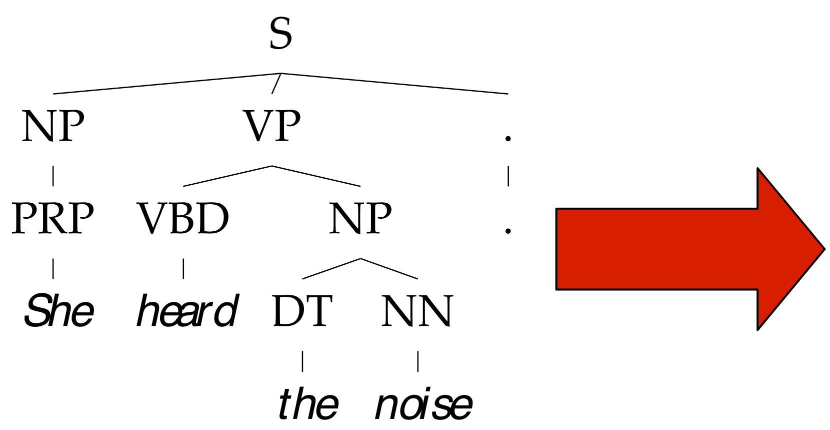
Probabilistic Context-Free Grammars

- 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 Grammars

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

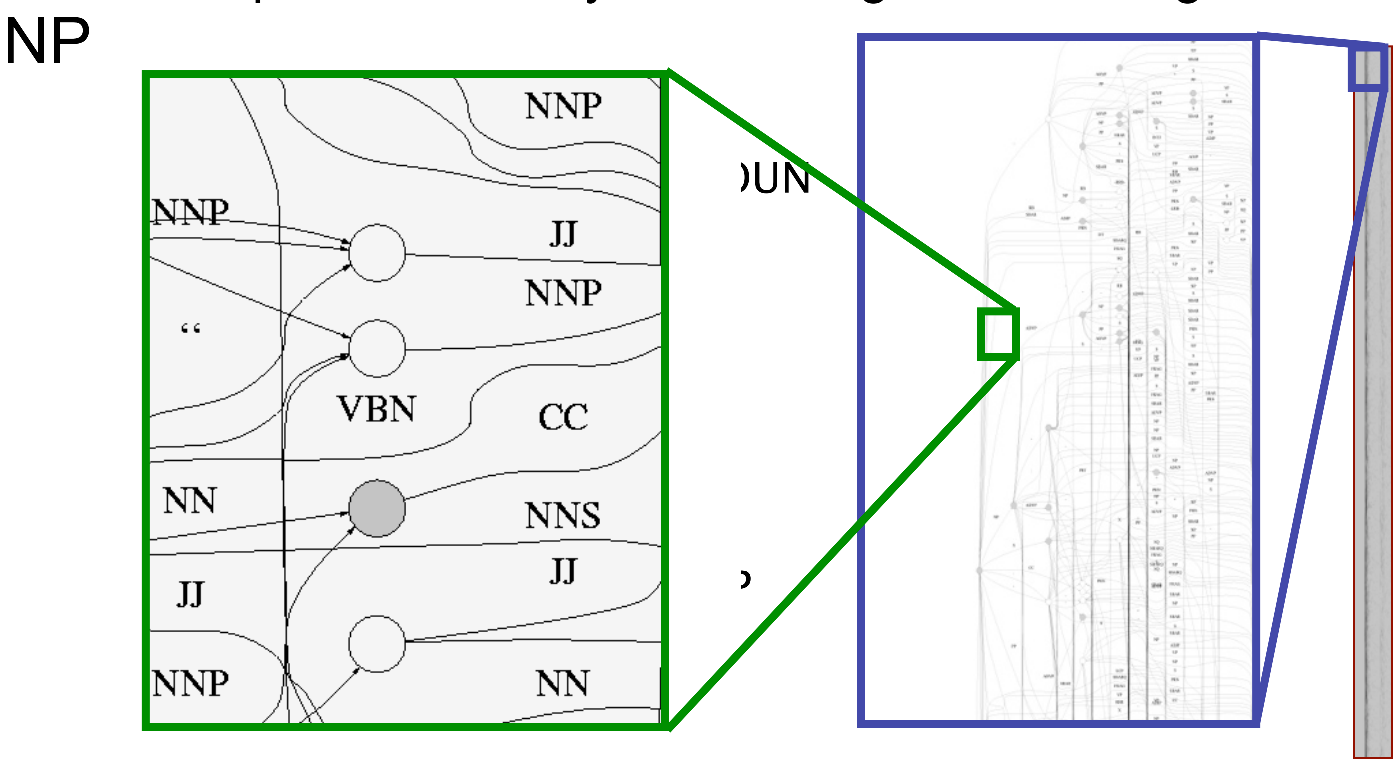


S → NP VP .	1
NP → PRP	0.5
NP → DT NN	0.5
VP → VBD NP	1
PRP → She	1
…	

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

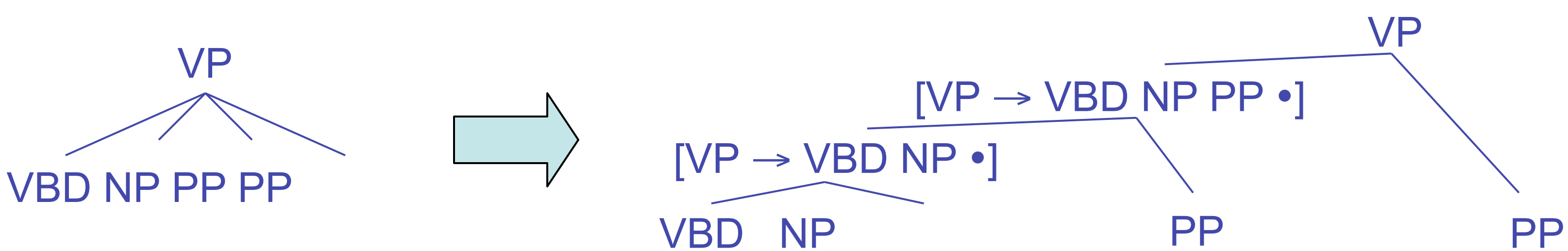
Treebank Grammar Scale

- 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



Chomsky Normal Form

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



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

A Recursive Parser

```
bestScore(X,i,j,s)
      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

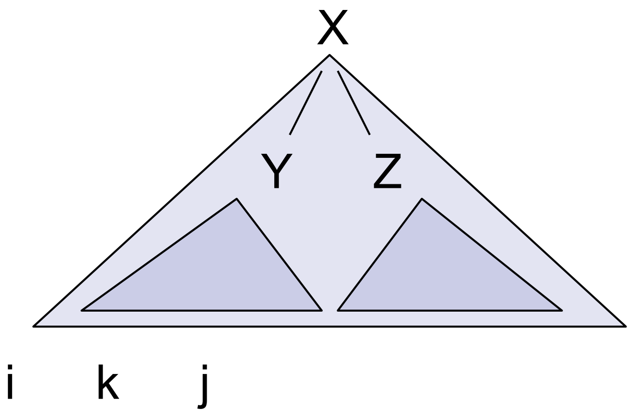
- One small change:

```
bestScore(X,i,j,s)
    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]
```



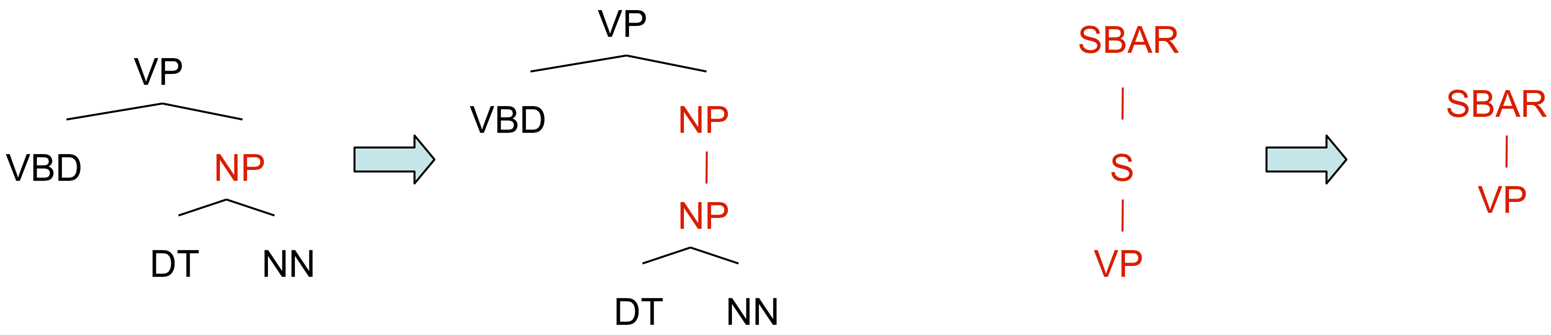
Unary Rules

- 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

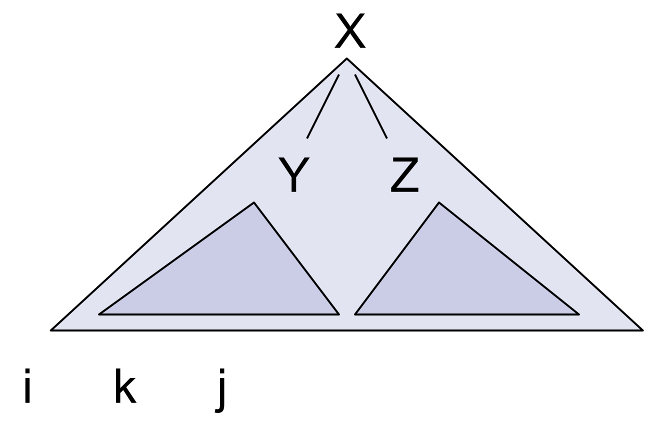


  - Alternate unary and binary layers
  - Reconstruct unary chains afterwards

Time: Theory

- How much time will it take to parse?

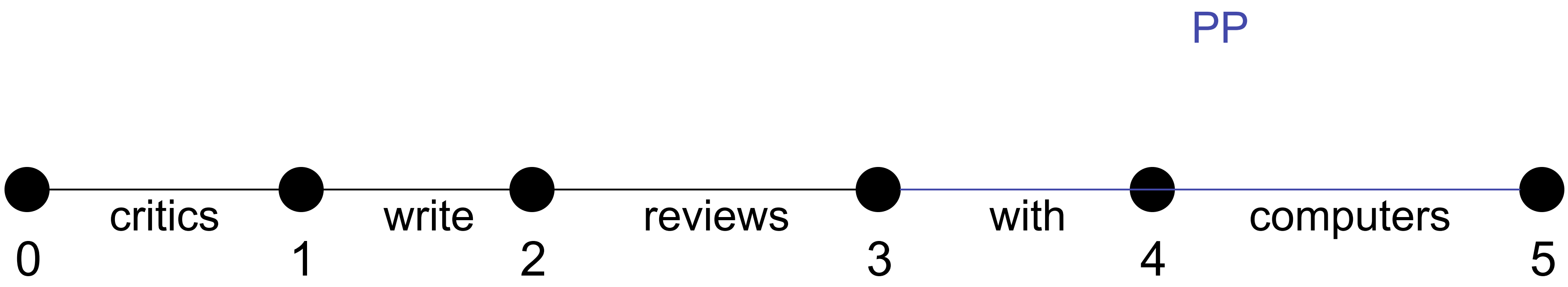
  - For each diff (<= n)
    - For each i (<= n)
      - For each rule X → Y Z
        - For each split point k
          Do constant work



  - Total time: |rules|*n^3
  - Something like 5 sec for an unoptimized parse of a 20-word sentences, or 0.2sec for an optimized parser

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

Item Successors

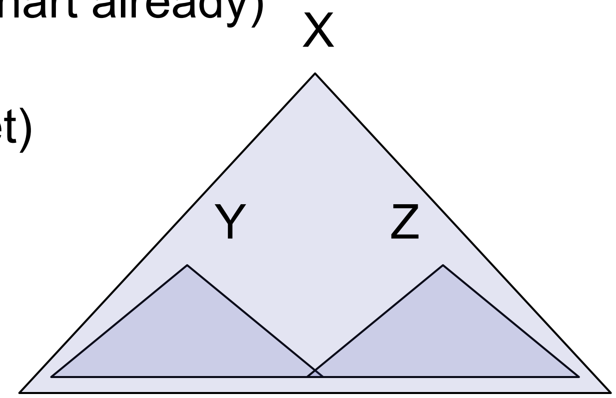
- When we pop items off of the agenda:
  - Graph successors: unary projections (NNS → critics, NP → NNS)

    Y[i,j] with X → Y forms X[i,j]

  - Hypergraph successors: combine with items already in our chart

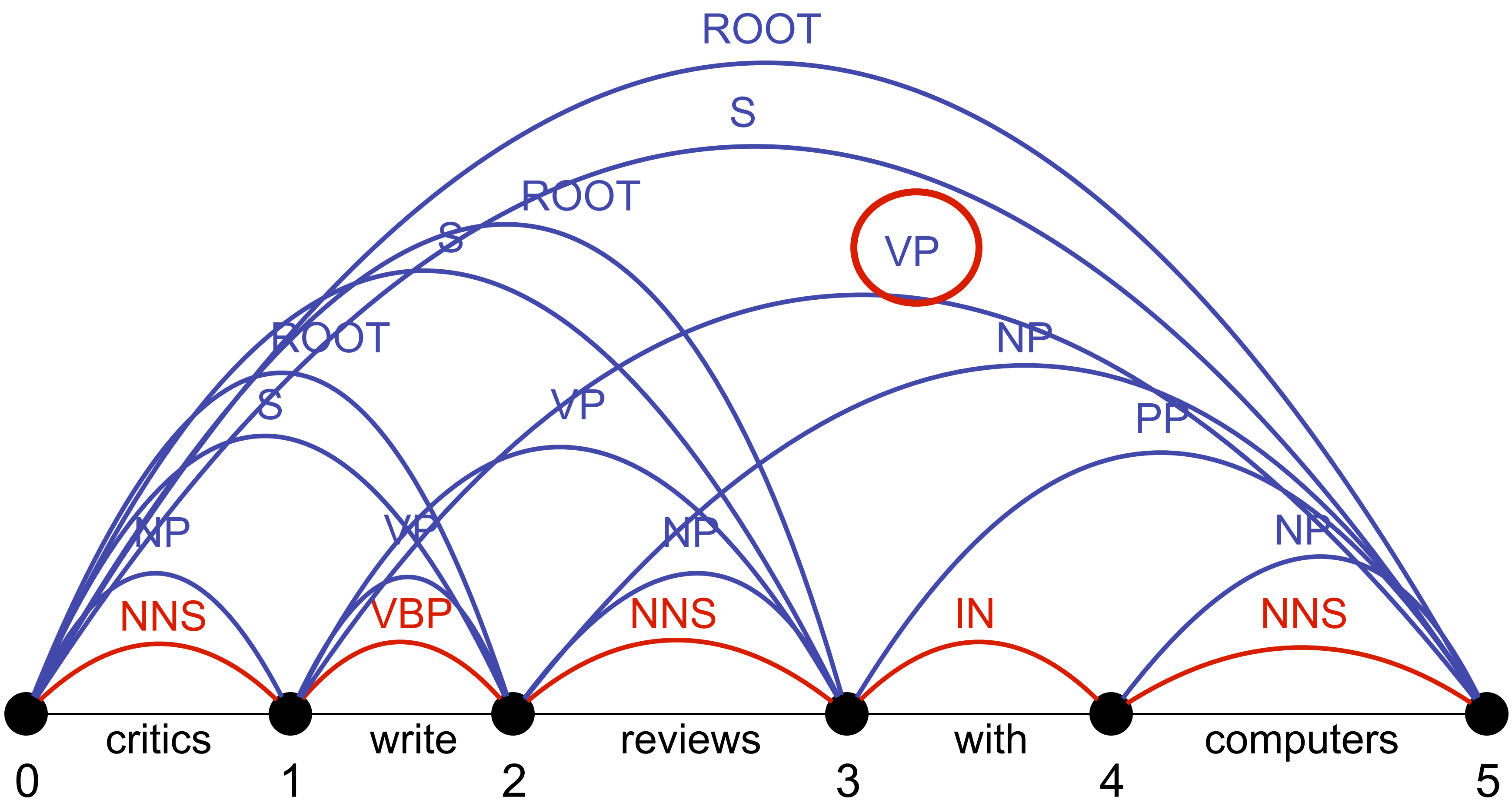
    Y[i,j] and Z[j,k] with X → Y Z form X[i,k]

  - 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

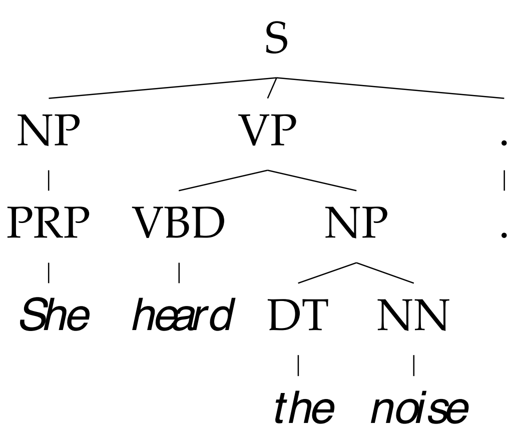
NNS[0,1] VBP[1,2] NNS[2,3] IN[3,4] NNS[3,4] NP[0,1] VP[1,2] NP[2,3] NP[4,5] S[0,2]
VP[1,3] PP[3,5] ROOT[0,2] S[0,3] VP[1,5] NP[2,5] ROOT[0,3] S[0,5] ROOT[0,5]



Treebank Grammars

[Charniak '96]

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



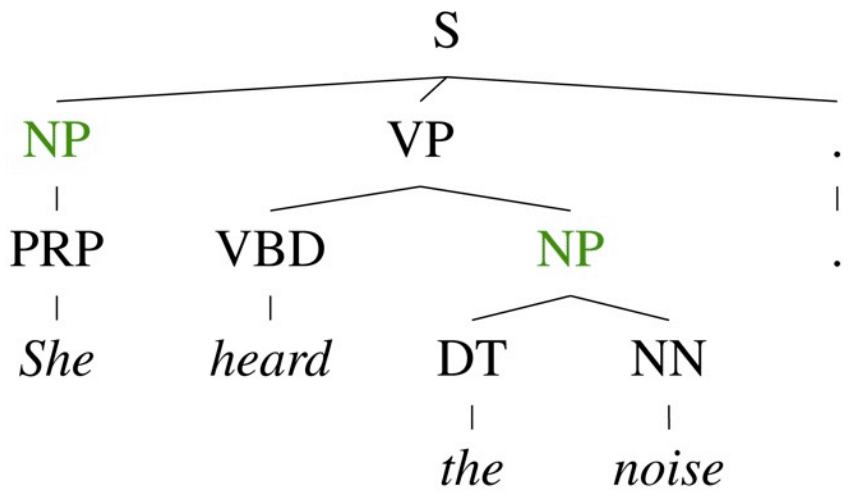
S → NP VP .	1
NP → PRP	0.5
NP → DT NN	0.5
VP → VBD NP	1
PRP → She	1
…	

- Better results by enriching the gramma
- Can also get reasonable parsers witho

Model	*F1*
Charniak '96	72.0

Conditional Independence?

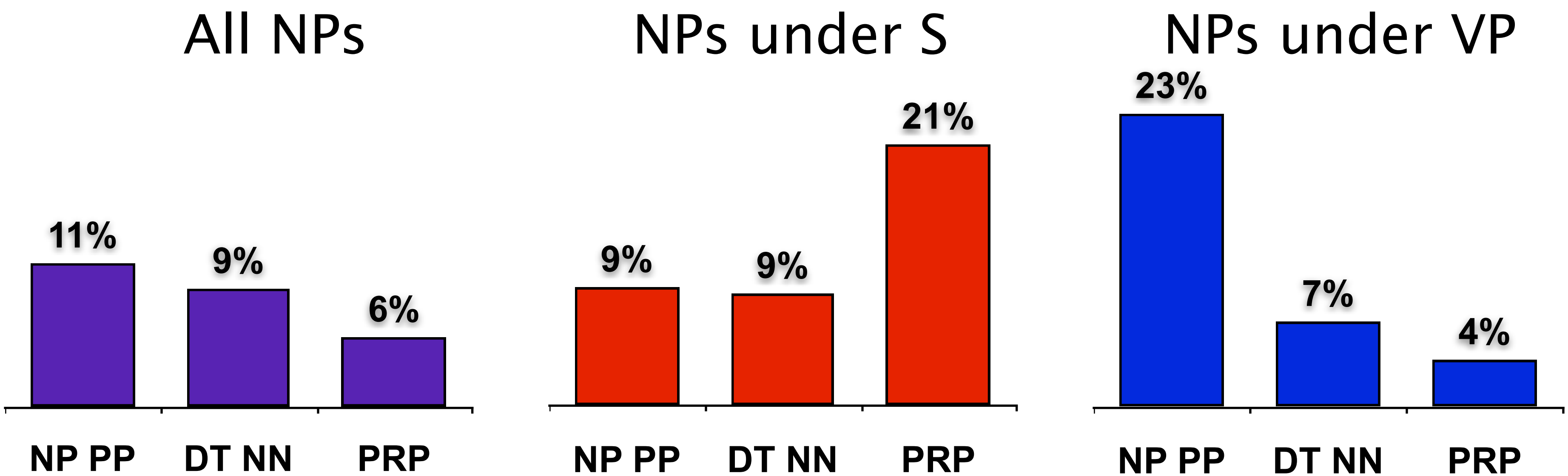
- Not every NP expansion can fill every NP slot



- A grammar with symbols like “NP” won’t be context-free
- Statistically, conditional independence too strong

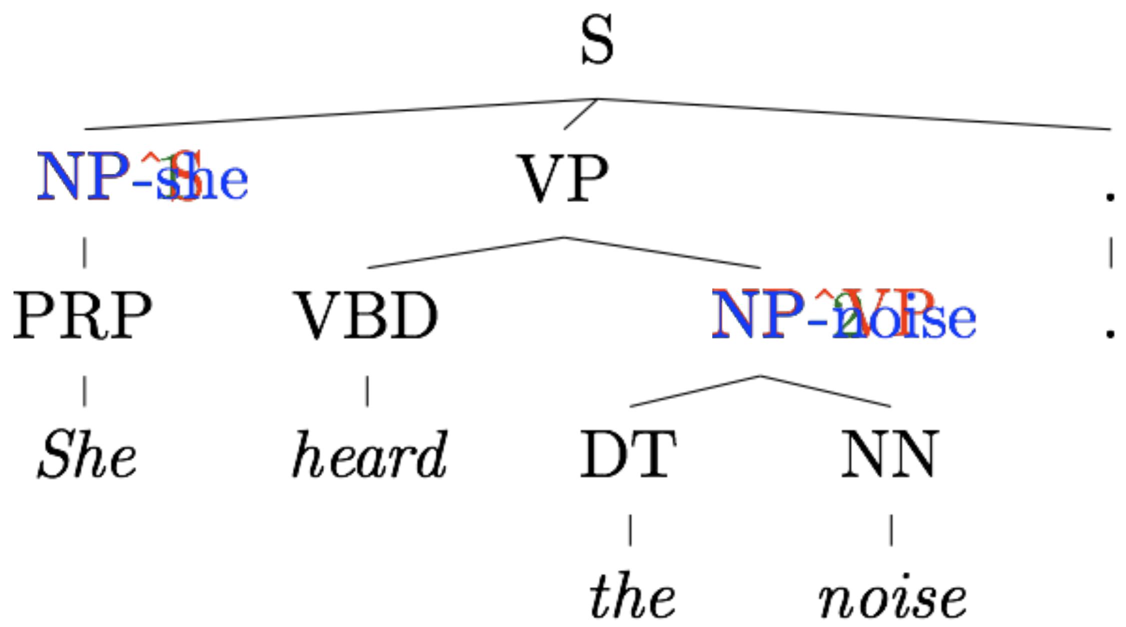
Non-Independence

- 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!

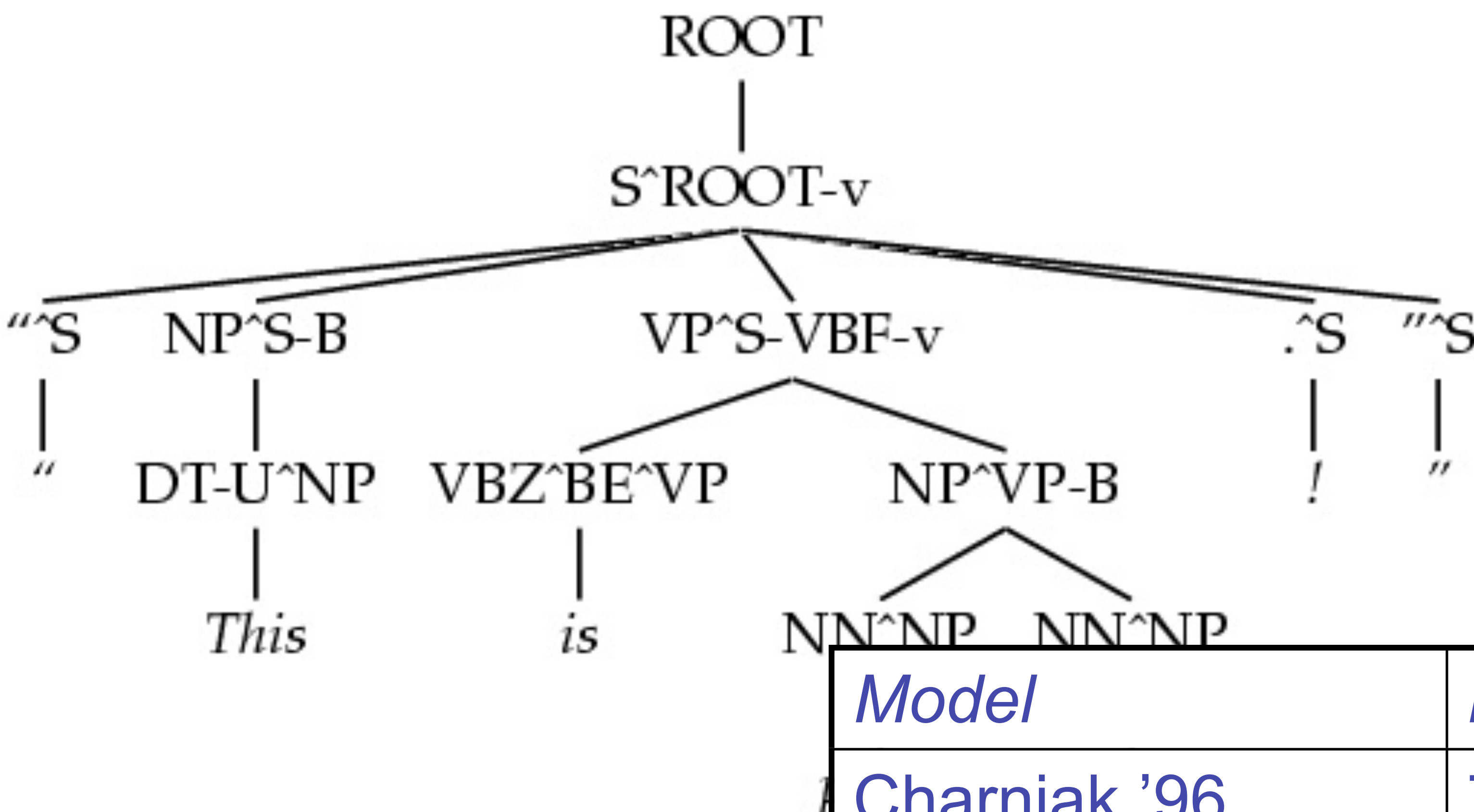
The Game of Designing a Grammar



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

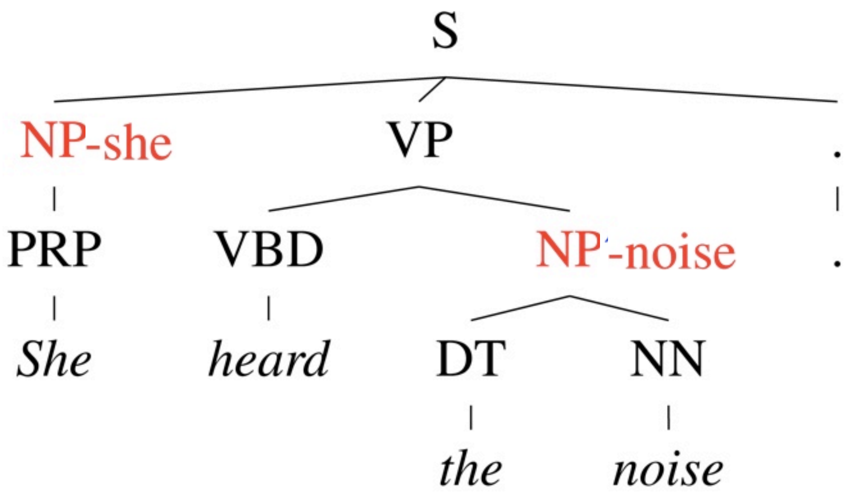
A Fully Annotated (Unlexicalized) Tree

[Klein & Manning ‘03]



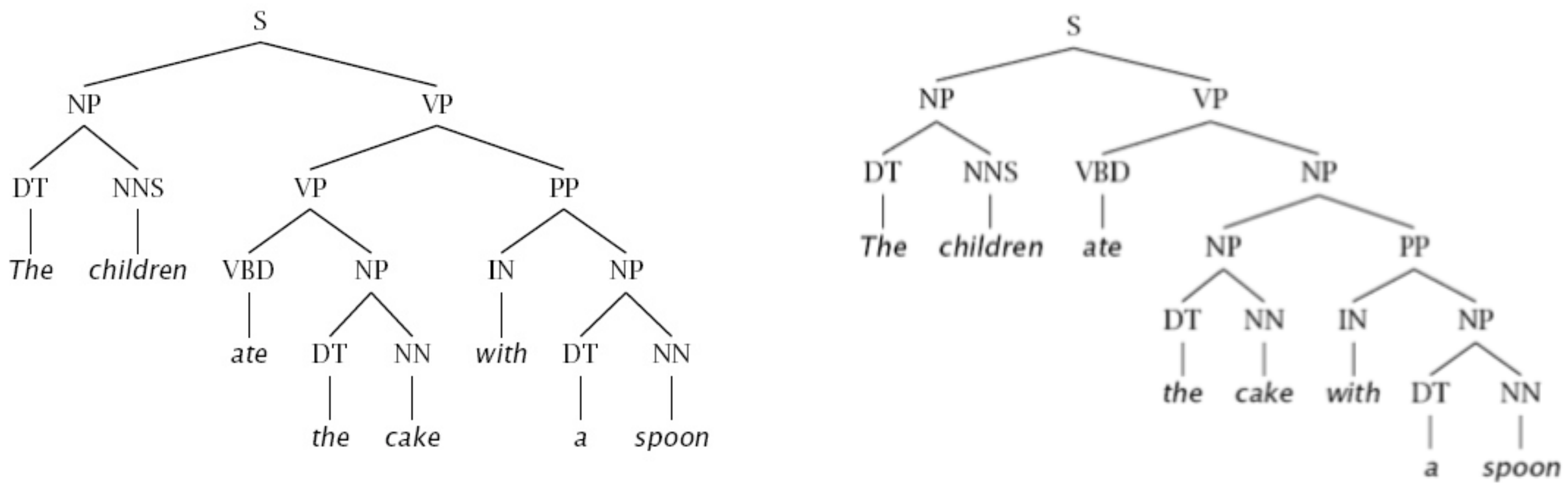
Model	*F1*
Charniak ’96	72.0
Klein&Manning ’03	86.3

The Game of Designing a Grammar



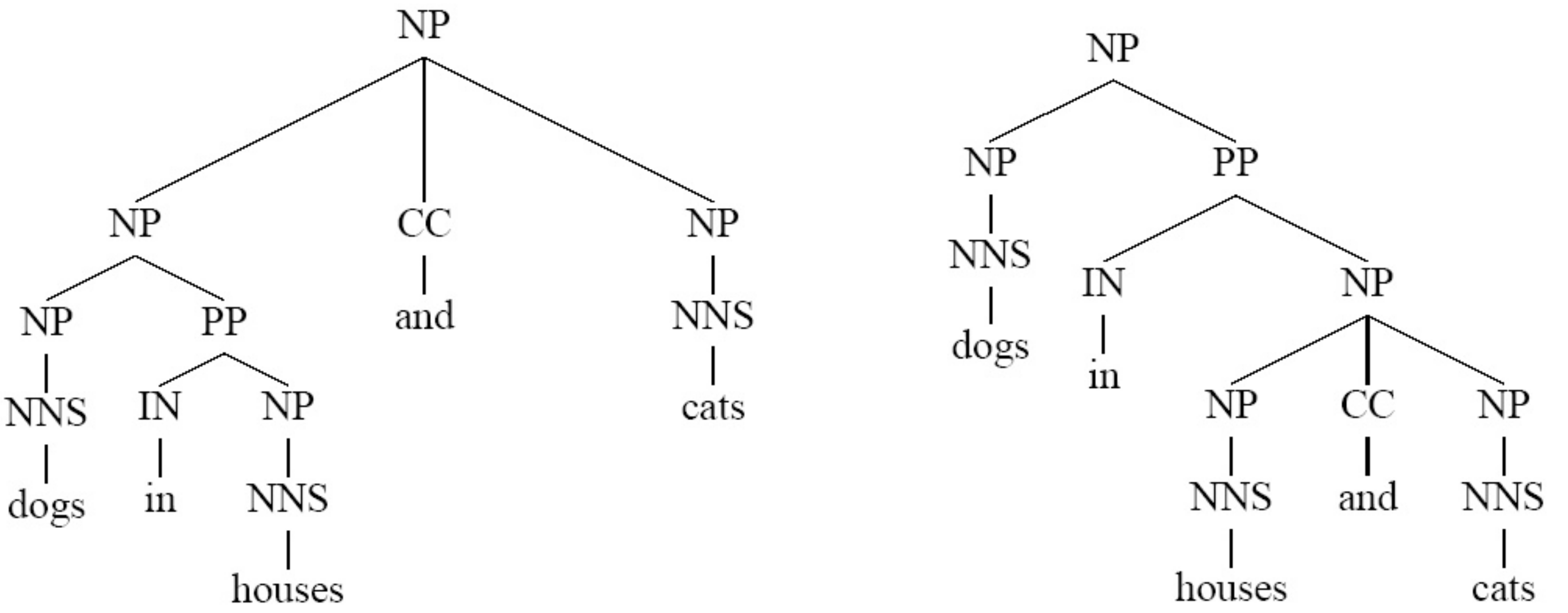
- Annotation refines base treebank symbols to improve statistical fit of the grammar
  - Head lexicalization [Collins ’99, Charniak ’00]

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

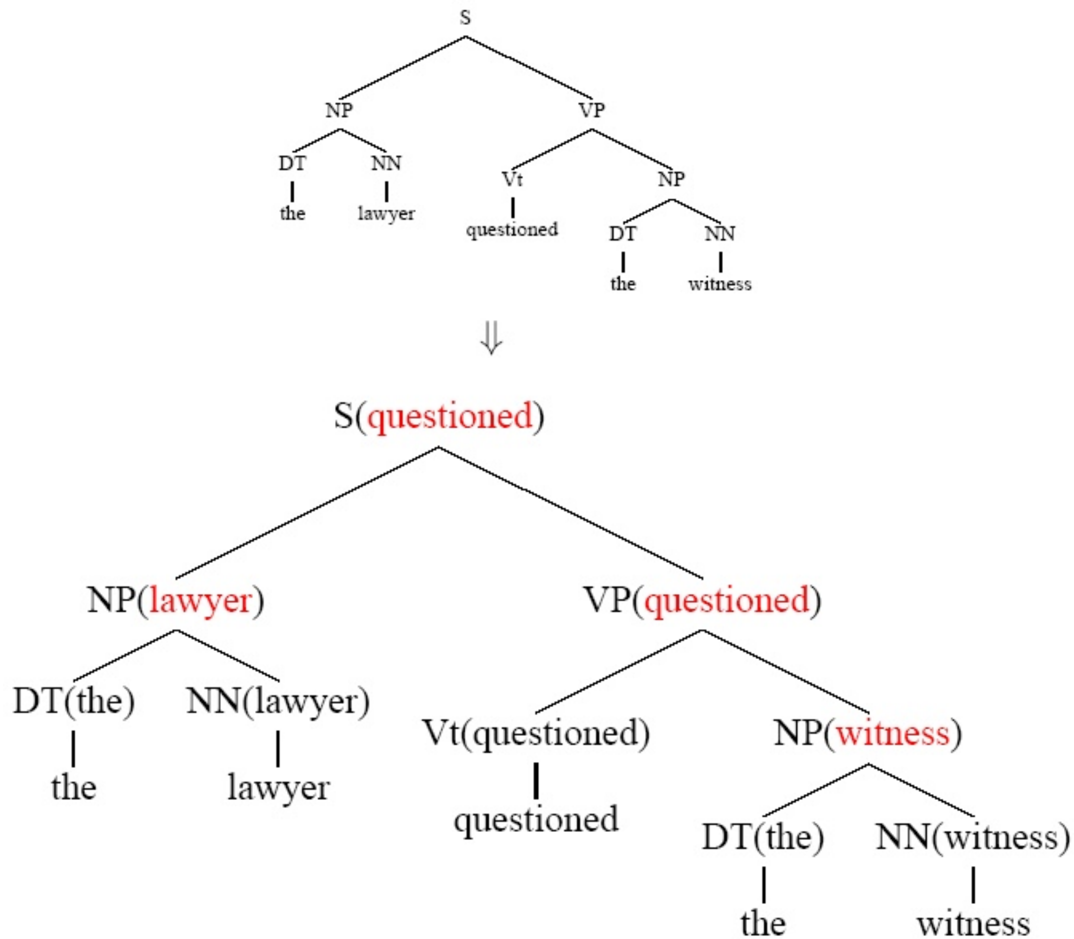


- What's different between basic PCFG scores here?
- What (lexical) correlations need to be scored?

Lexicalized Trees

[Charniak '97, Collins '97]

- 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

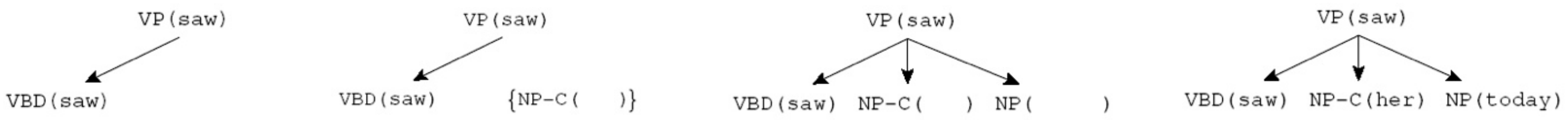


Lexicalized PCFGs?

- Problem: we now have to estimate probabilities like

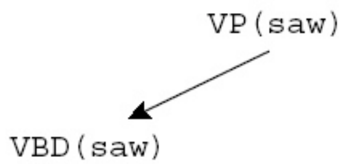
```
VP(saw) -> VBD(saw) NP-C(her) NP(today)
```

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

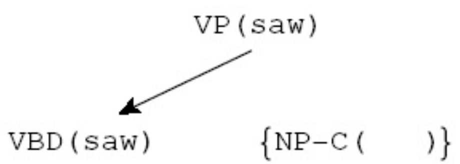


Lexical Derivation Steps

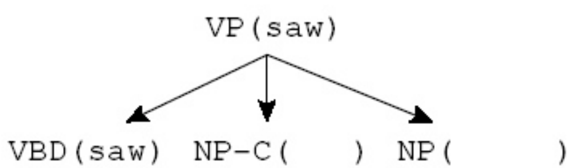
- A derivation of a local tree [Collins '99]



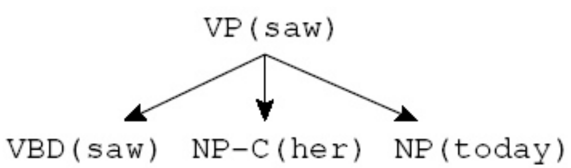
Choose a head tag and word



Choose a complement bag



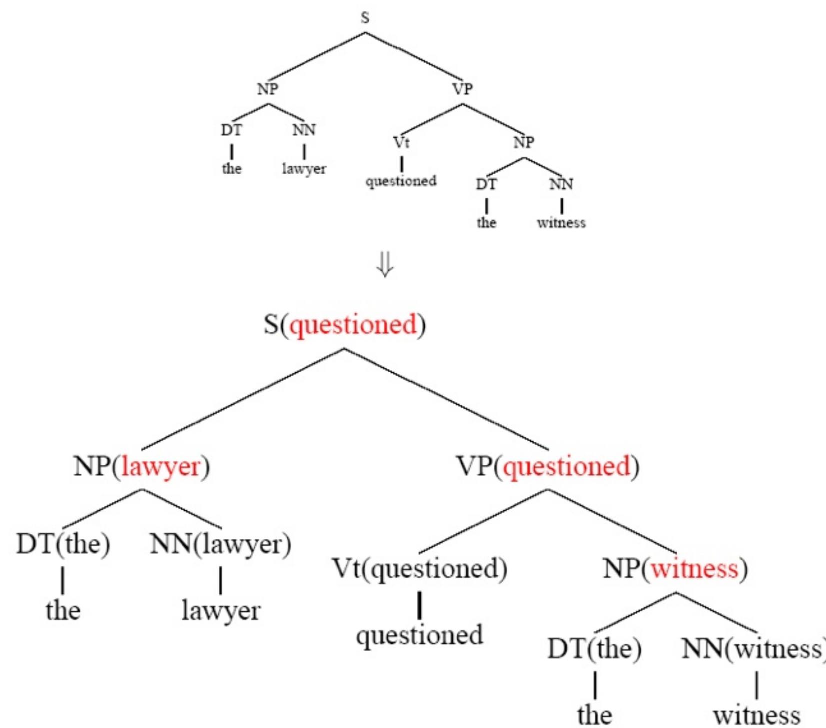
Generate children (incl. adjuncts)



Recursively derive children

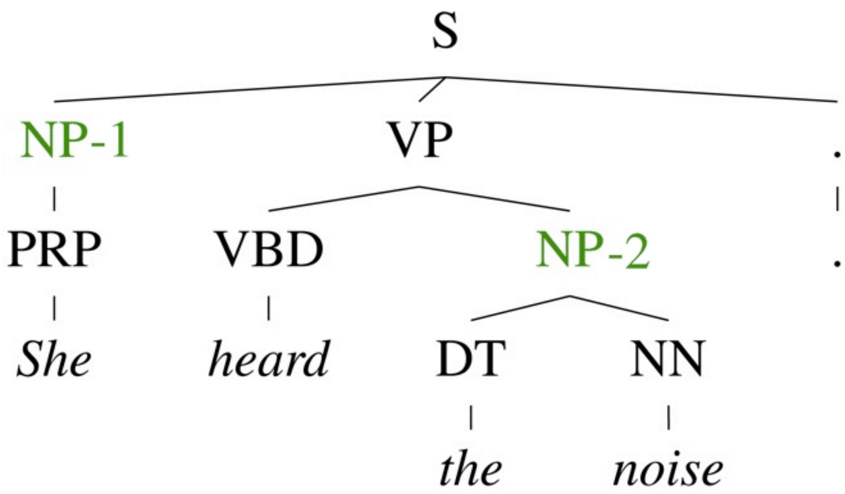
Lexicalized Grammars

- Challenges:
  - Many parameters to estimate: requires sophisticated smoothing techniques
  - Exact inference is too slow: requires pruning heuristics
  - Difficult to adapt to new languages: At least head rules need to be specified, typically more changes needed



Model	*F1*
Klein&Manning '03	86.3
Charniak '00	90.1

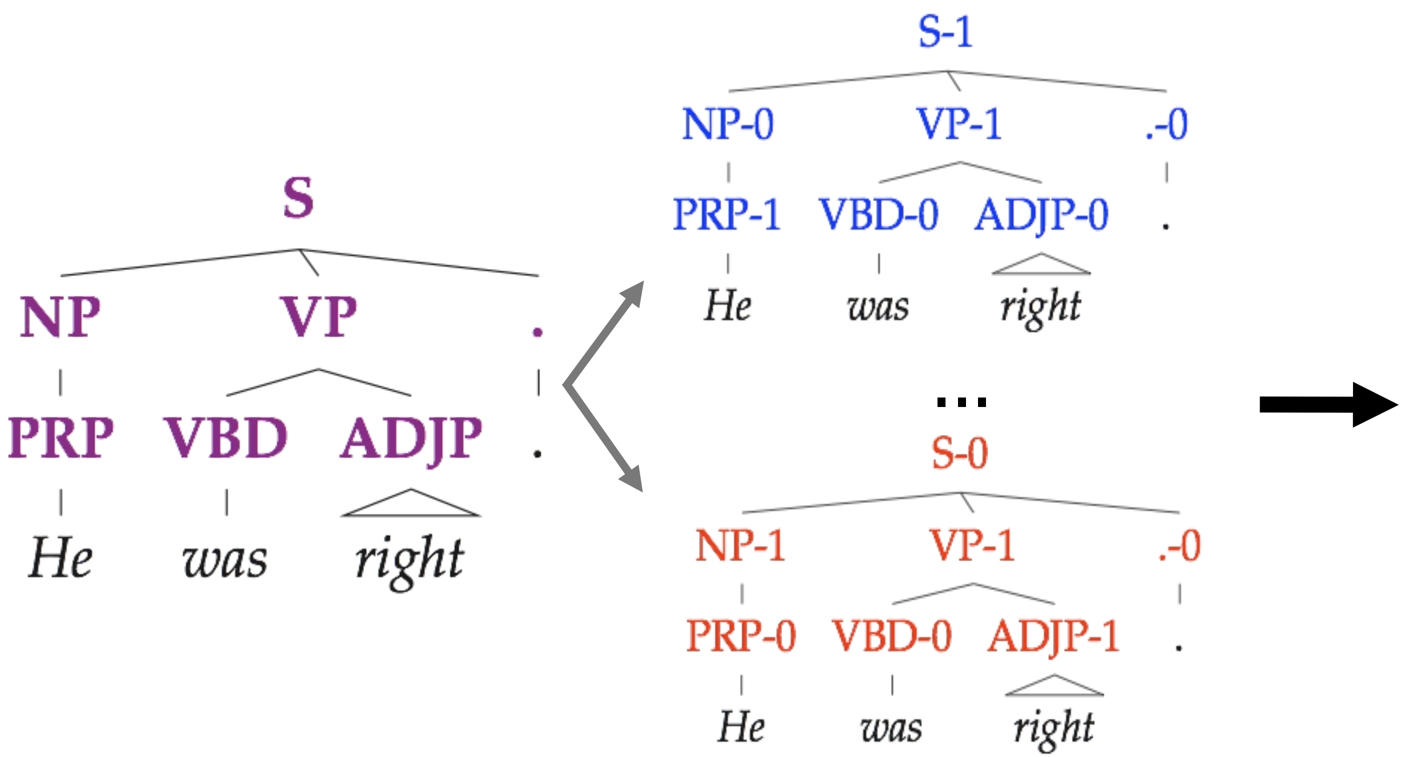
The Game of Designing a Grammar



- Annotation refines base treebank symbols to improve statistical fit of the grammar
  - Automatic clustering

[Matsuzaki et al. ’05, Petrov et al. ‘06]

Latent Variable Grammars



Parse Tree T
Sentence w

Derivations $t : T$

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

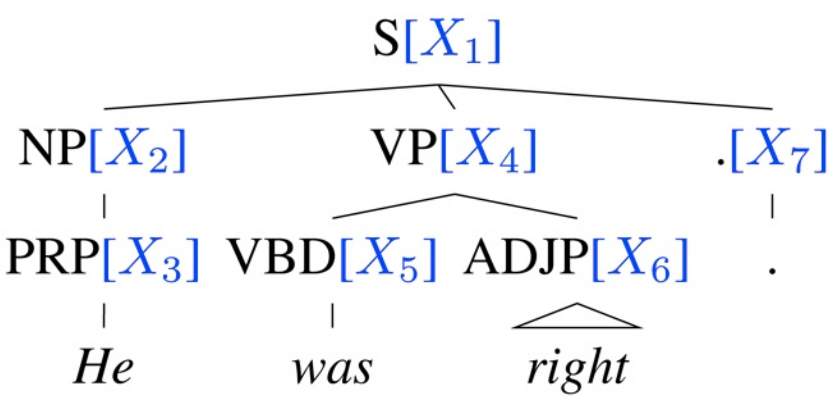
$PRP_0 \rightarrow$ She	?
$PRP_1 \rightarrow$ She	?
...	
$VBD_0 \rightarrow$ was	?
$VBD_1 \rightarrow$ was	?
$VBD_2 \rightarrow$ was	?
...	

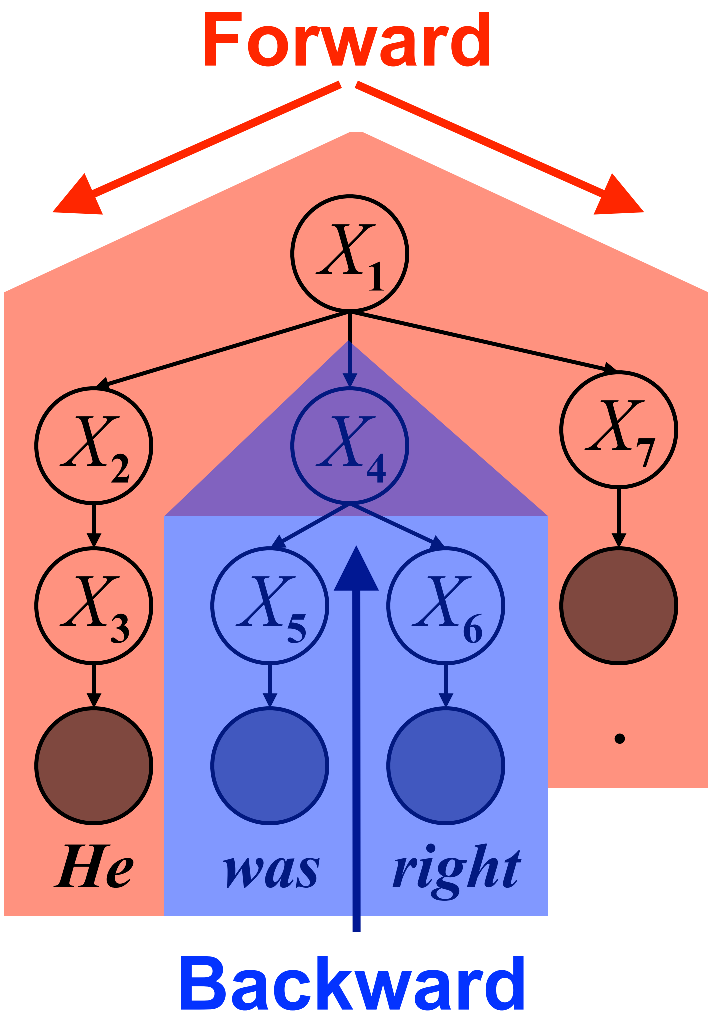
Parameters θ

Learning Latent Annotations

EM algorithm:

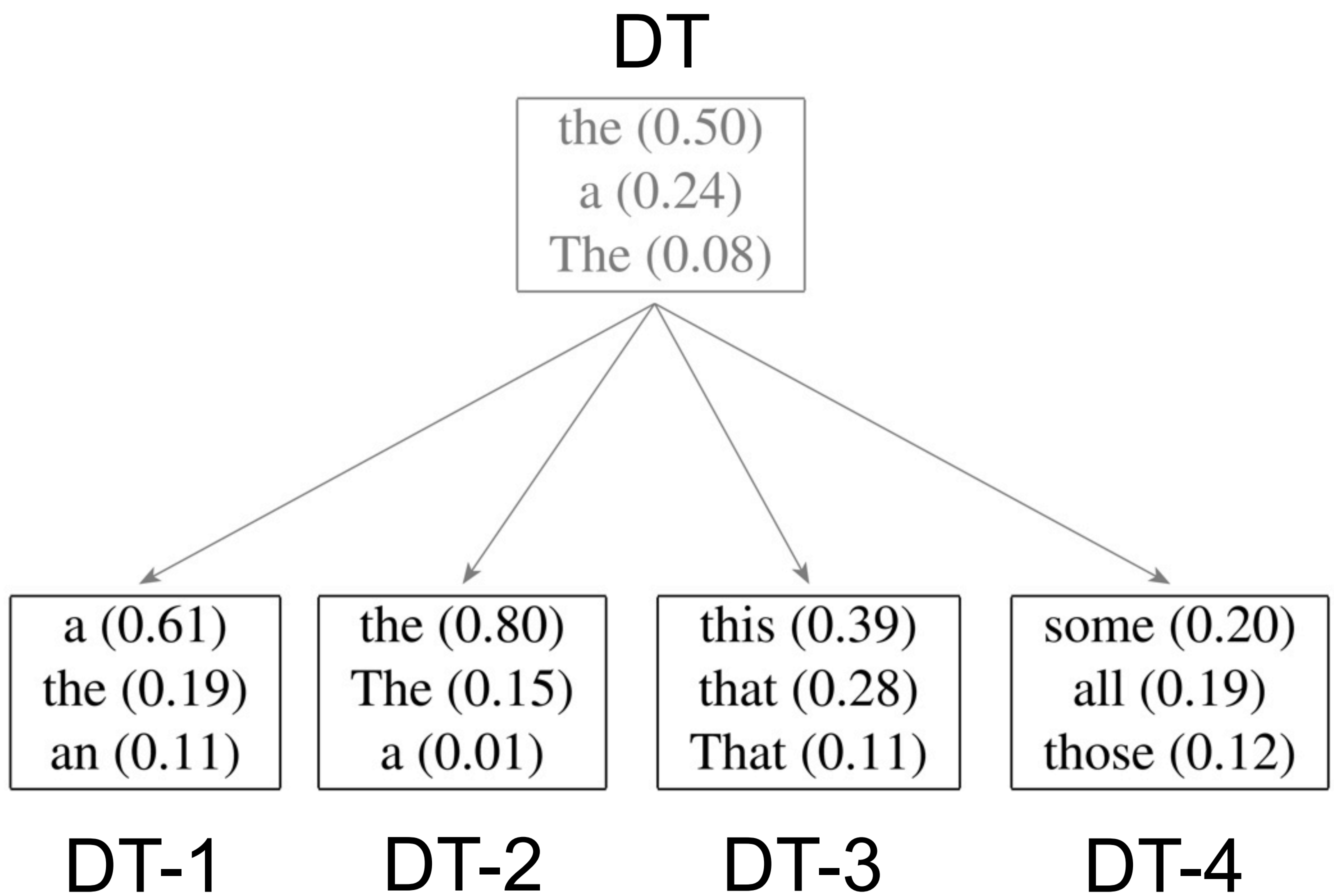
- Brackets are known
- Base categories are known
- Only induce subcategories





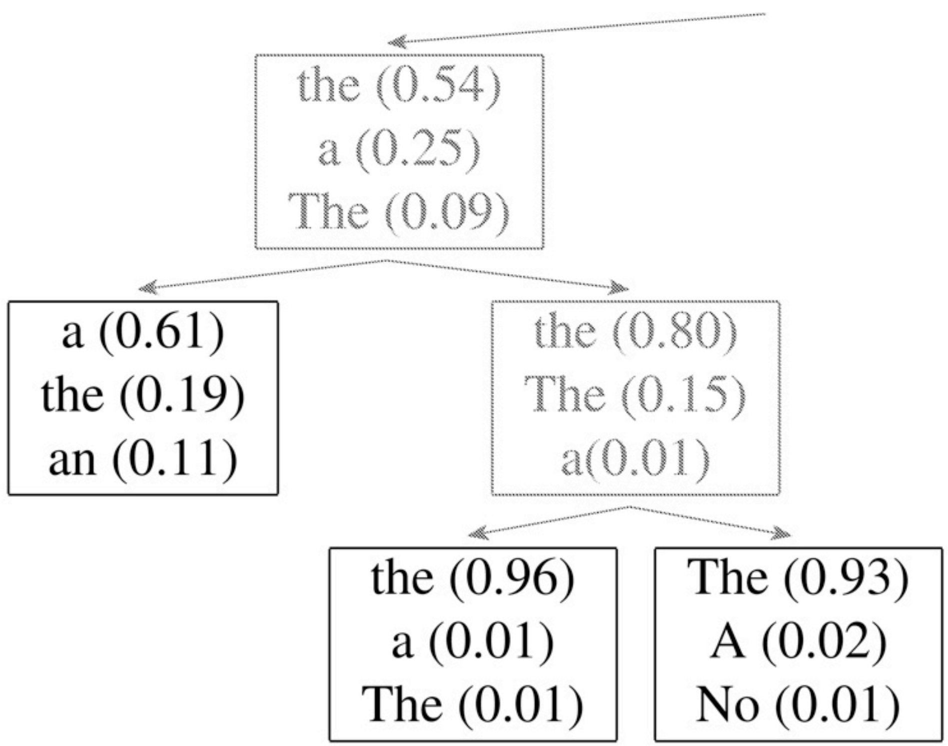
Just like Forward-Backward for HMMs.

Refinement of the DT tag



Adaptive Splitting

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



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

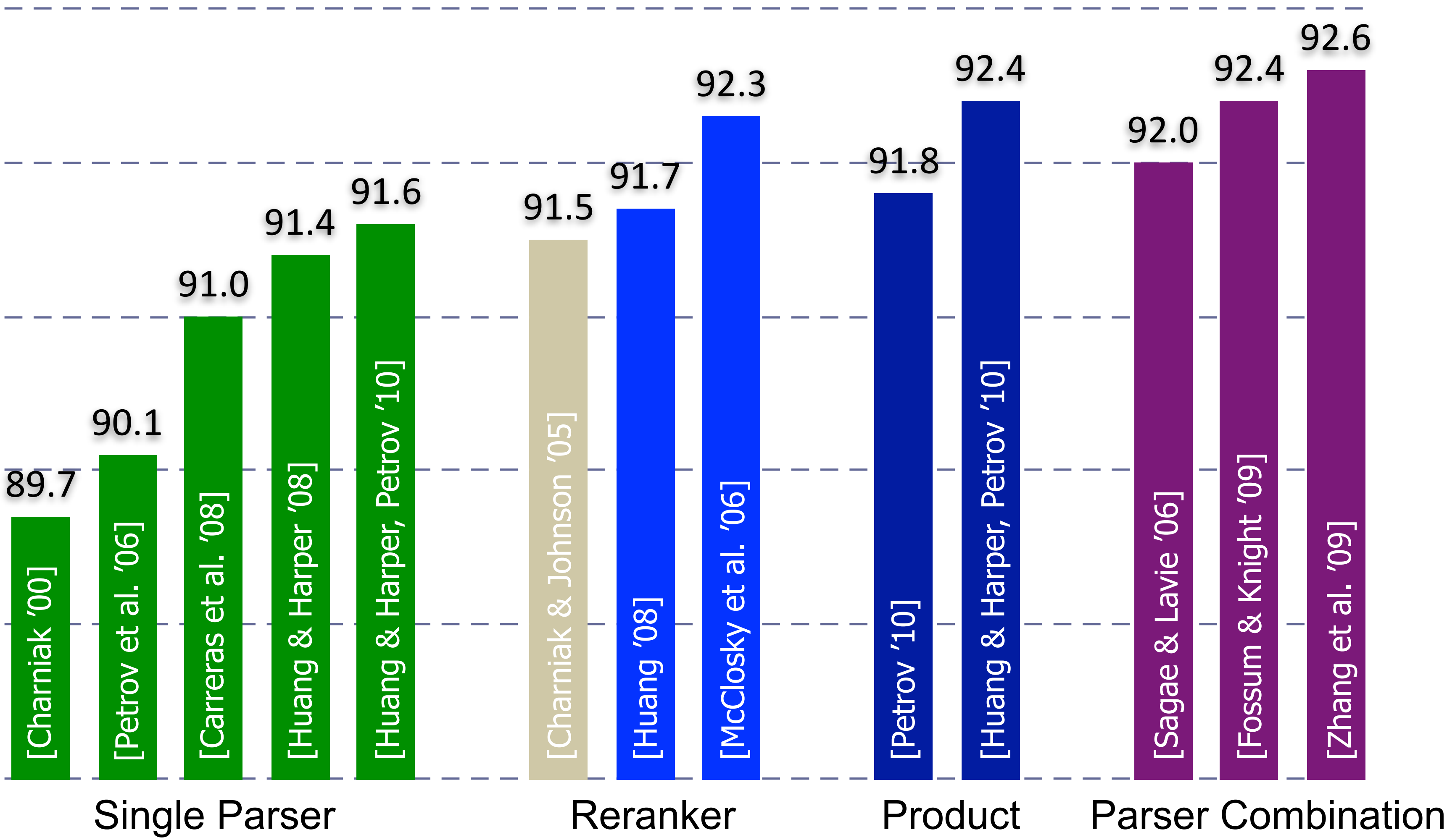
- Relative adverbs (RBR):

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

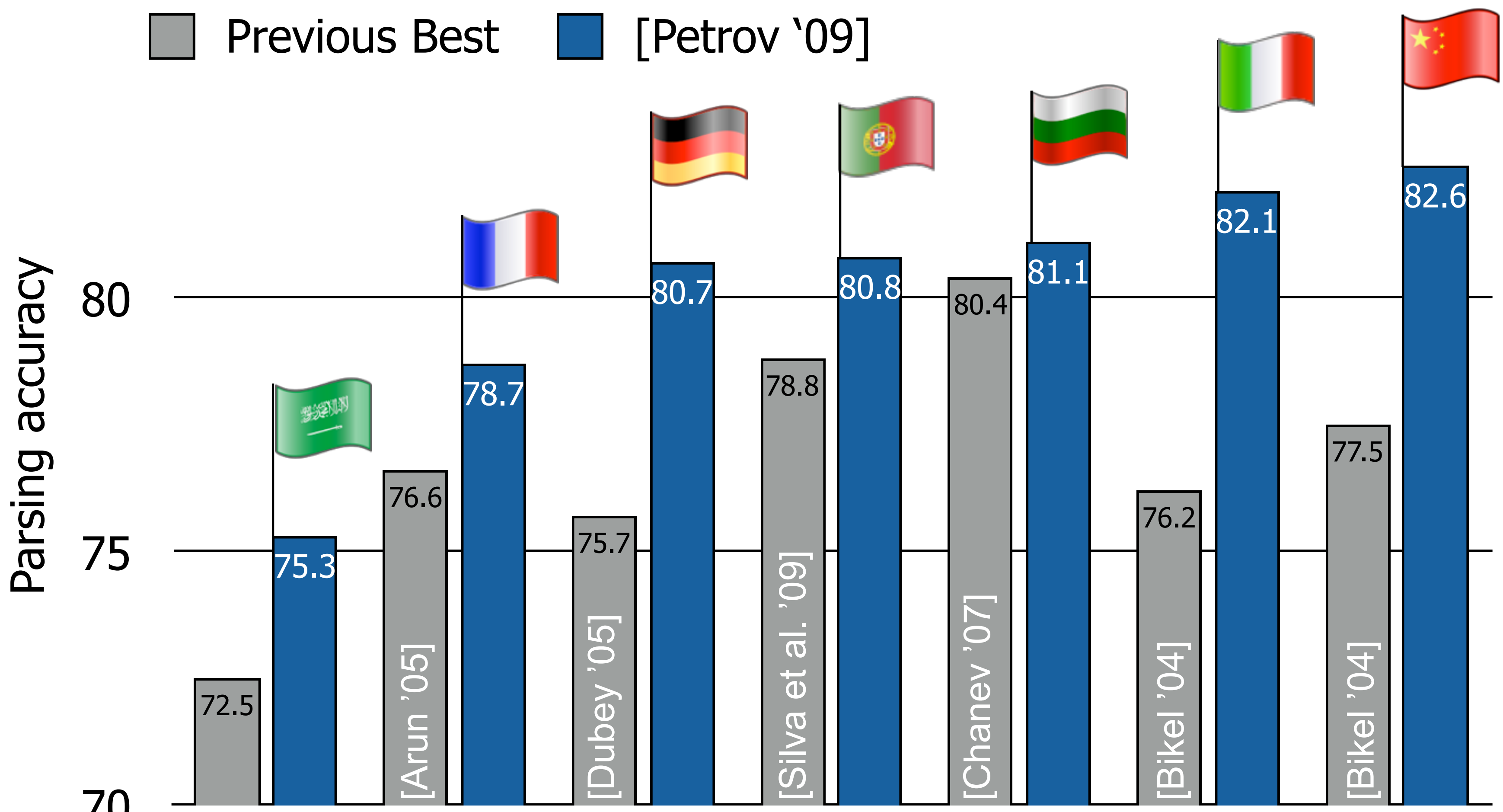
- Cardinal Numbers (CD):

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

Detailed English Results



Multi-Lingual Results

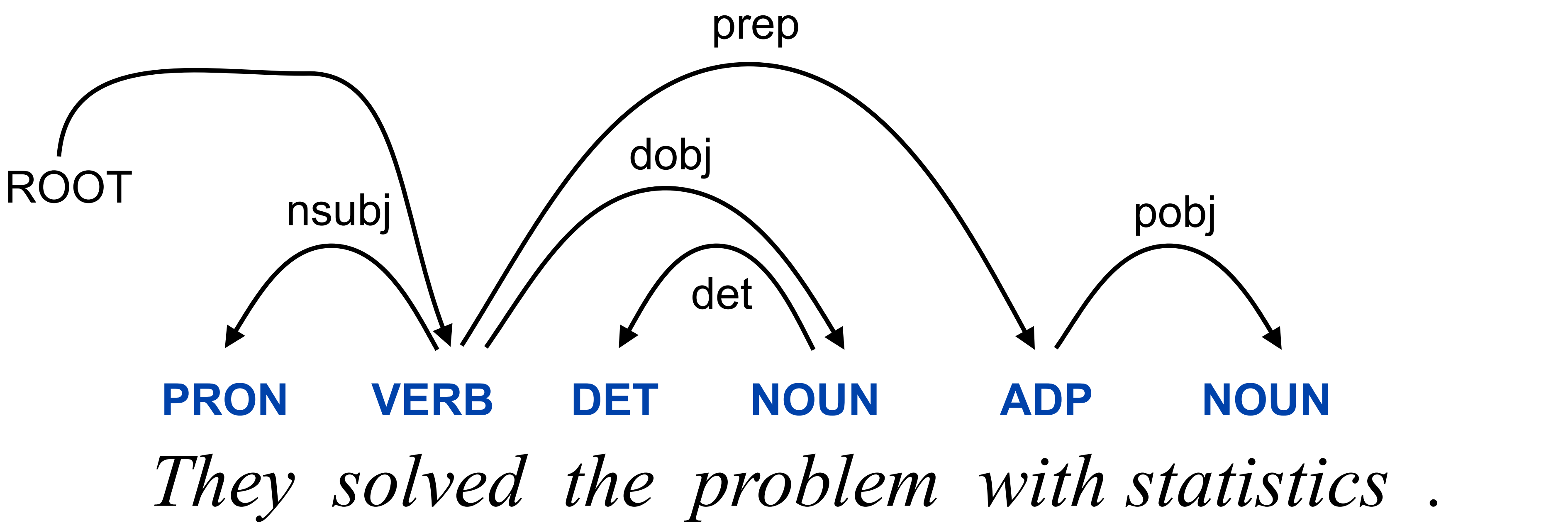


Syntax and Parsing

Slav Petrov – Google Research

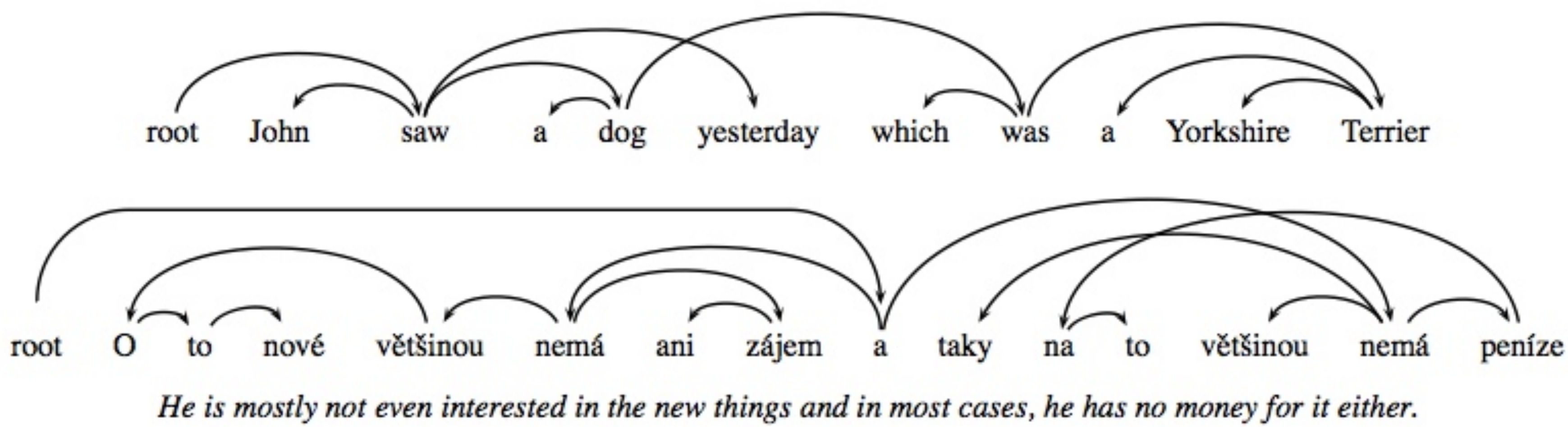
Lisbon Machine Learning School

Dependency Parsing



(Non-)Projectivity

- Crossing Arcs needed to account for non-projective constructions
- Fairly rare in English but can be common in other languages (e.g. Czech):



Formal Conditions

- For a dependency graph $G = (V, A)$
- With label set $L = \{l_1, \ldots, l_{|L|}\}$
- G is (weakly) connected:
  - If $i, j \in V$, $i \leftrightarrow^* j$.
- G is acyclic:
  - If $i \to j$, then not $j \to^* i$.
- G obeys the single-head constraint:
  - If $i \to j$, then not $i' \to j$, for any $i' \neq i$.
- G is projective:
  - If $i \to j$, then $i \to^* i'$, for any i' such that $i < i' < j$ or $j < i' < i$.

Arc-Factored Models

- Assumes that the score / probability / **weight** of a dependency graph factors by its arcs

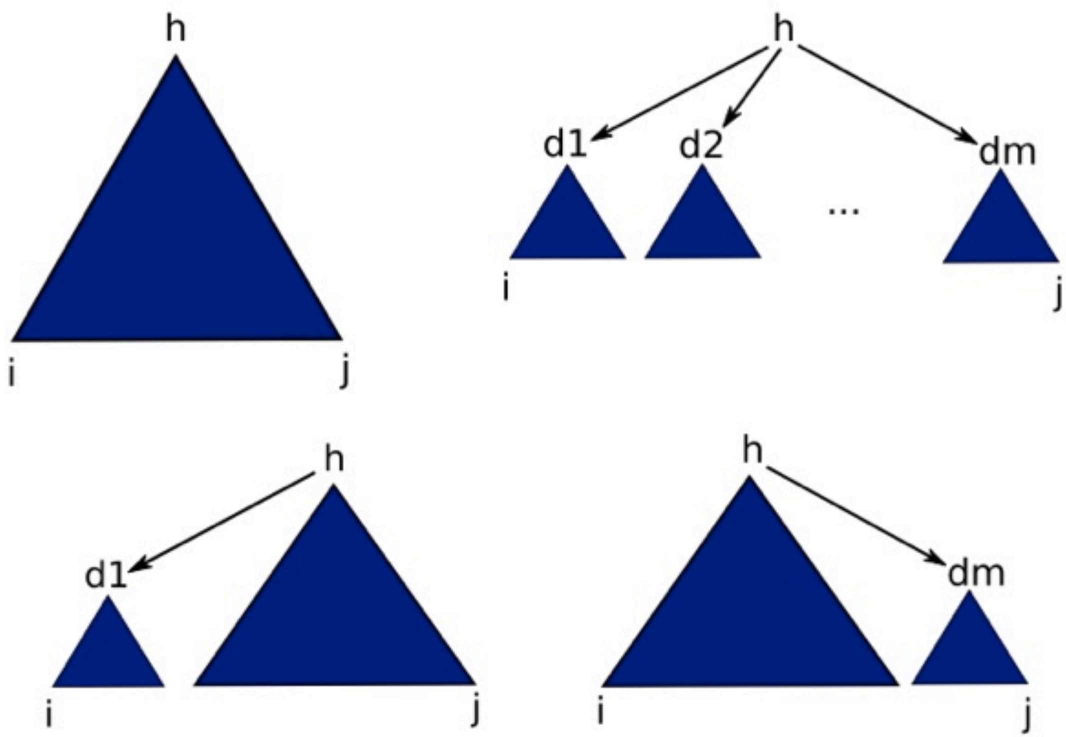
$$w(G) = \prod_{(i,j,k) \in G} w_{ij}^{k}$$

look familiar?

- w_{ij}^{k} is the weight of creating a dependency from word w_i to w_j with label l_k
- Thus there is an assumption that each dependency decision is independent
  - Strong assumption! Will address this later.

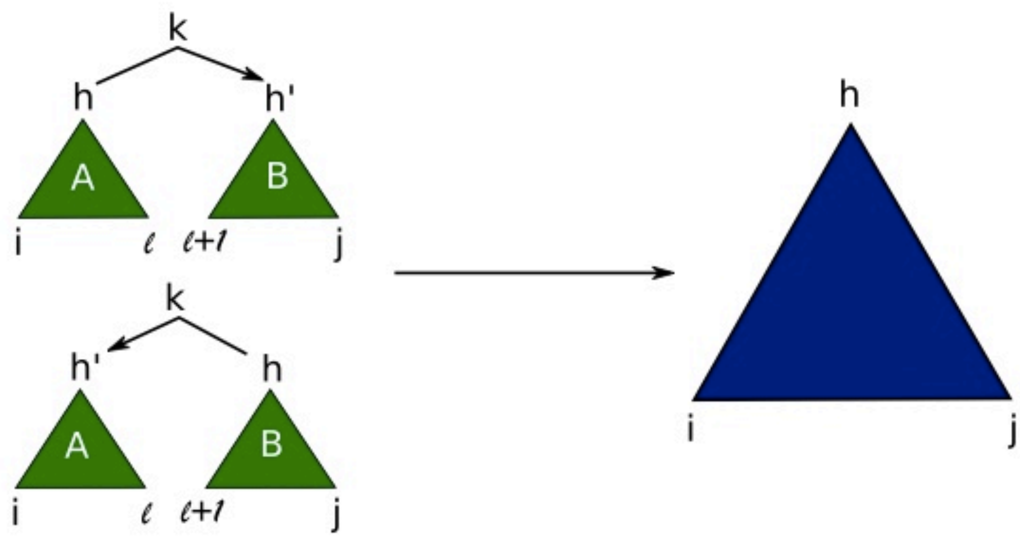
Arc-factored Projective Parsing

- All projective graphs can be written as the combination of two smaller adjacent graphs



Arc-factored Projective Parsing

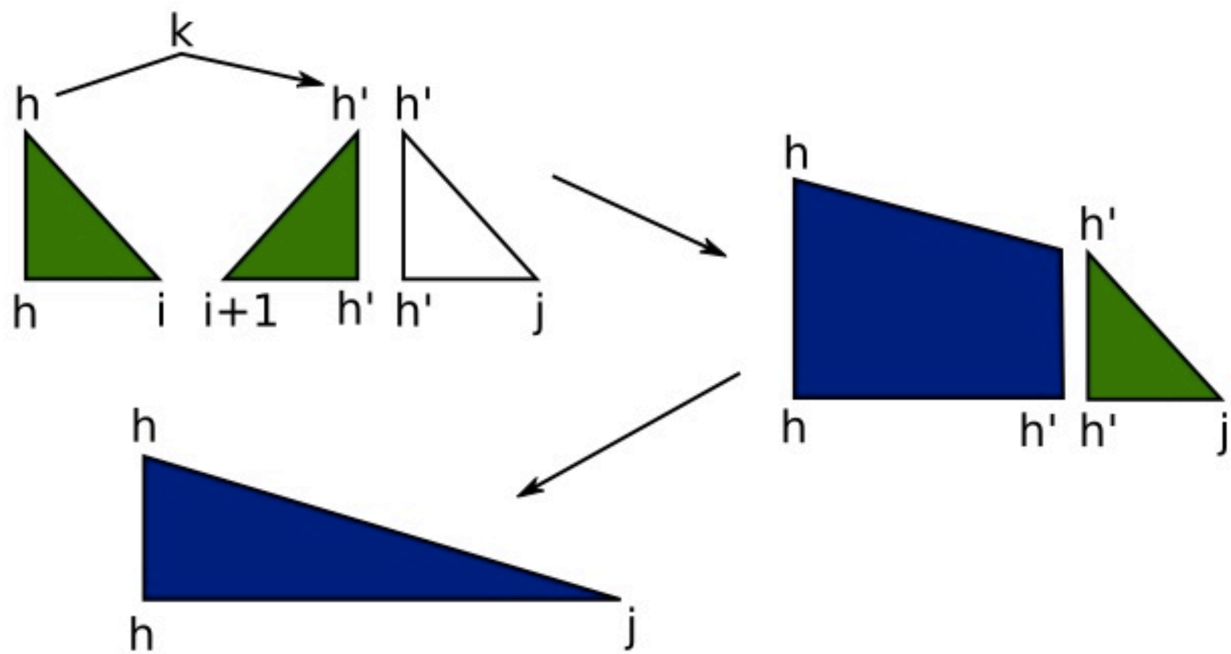
- Chart item filled in a bottom-up manner
  - First do all strings of length 1, then 2, etc. just like CKY



- Weight of new item: $\max_{l,j,k} \; w(A) \times w(B) \times w_{hh'}^{k}$
- Algorithm runs in $O(|L|n^5)$
- Use back-pointers to extract best parse (like CKY)

Eisner Algorithm

- $O(|L|n^5)$ is not that good
- [Eisner 1996] showed how this can be reduced to $O(|L|n^3)$
  - Key: split items so that sub-roots are always on periphery



Eisner Algorithm PseudoCode

Initialization: $C[s][s][d][c] = 0.0 \quad \forall s, d, c$

for $k : 1..n$

  for $s : 1..n$

    $t = s + k$

    if $t > n$ then break

    % First: create incomplete items

    $C[s][t][\leftarrow][0] = \max_{s \leq r < t} \ (C[s][r][\rightarrow][1] + C[r+1][t][\leftarrow][1] + s(t, s))$

    $C[s][t][\rightarrow][0] = \max_{s \leq r < t} \ (C[s][r][\rightarrow][1] + C[r+1][t][\leftarrow][1] + s(s, t))$

    % Second: create complete items

    $C[s][t][\leftarrow][1] = \max_{s \leq r < t} \ (C[s][r][\leftarrow][1] + C[r][t][\leftarrow][0])$

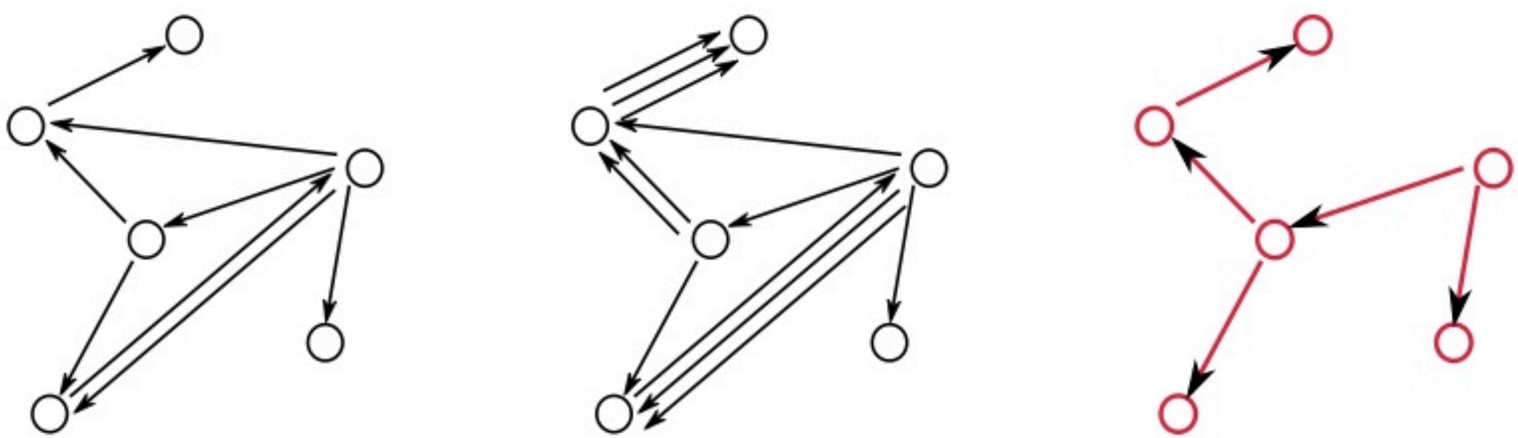
    $C[s][t][\rightarrow][1] = \max_{s < r \leq t} \ (C[s][r][\rightarrow][0] + C[r][t][\rightarrow][1])$

  end for

end for

Maximum Spanning Trees (MSTs)

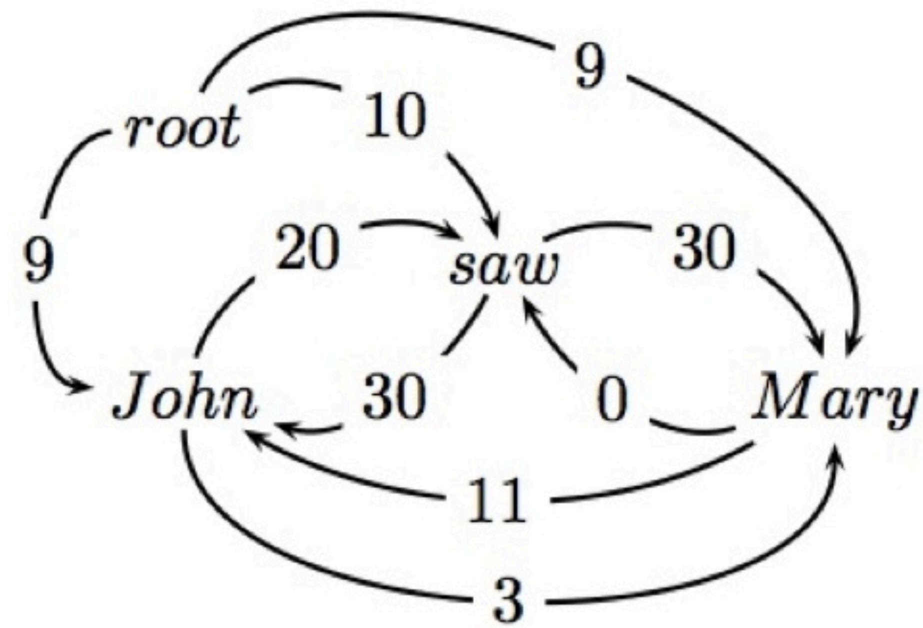
- A directed spanning tree of a (multi-)digraph $G = (V, A)$, is a subgraph $G' = (V', A')$ such that:
  - $V' = V$
  - $A' \subseteq A$, and $|A'| = |V'| - 1$
  - G' is a tree (acyclic)
- A spanning tree of the following (multi-)digraphs



Can use MST algorithms for nonprojective parsing!

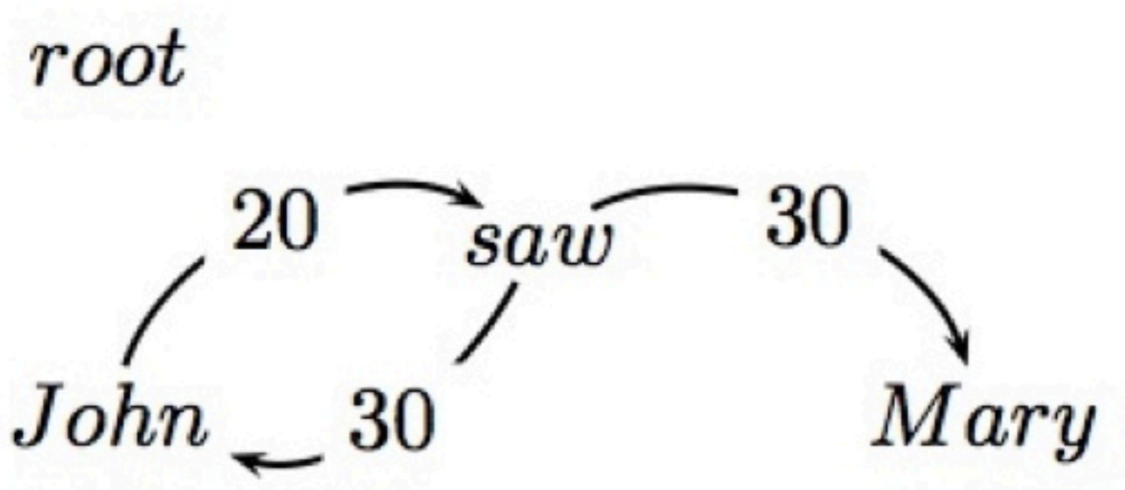
Chu-Liu-Edmonds

- x = root John saw Mary



Chu-Liu-Edmonds

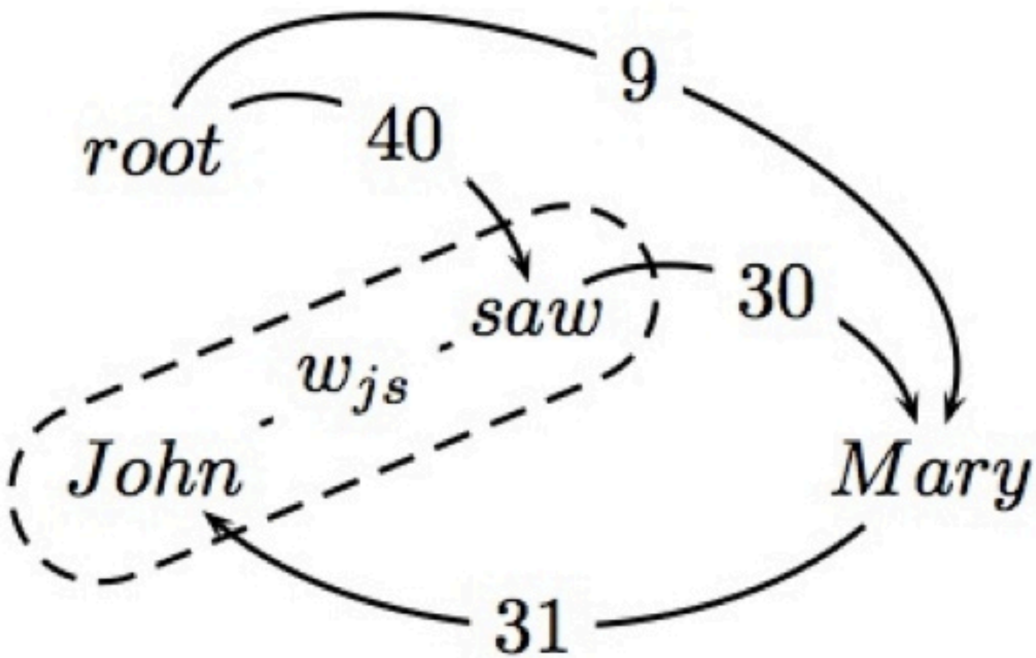
- Find highest scoring incoming arc for each vertex



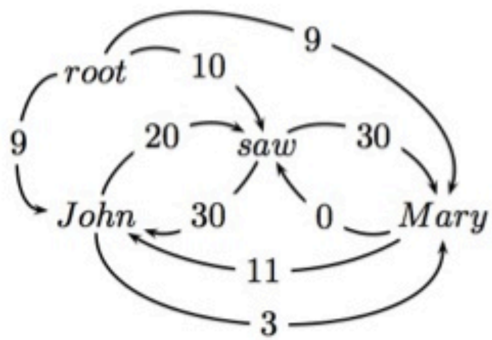
- If this is a tree, then we have found MST!!

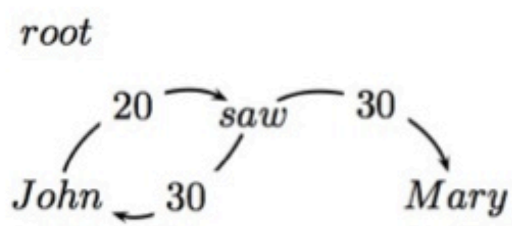
Find Cycle and Contract

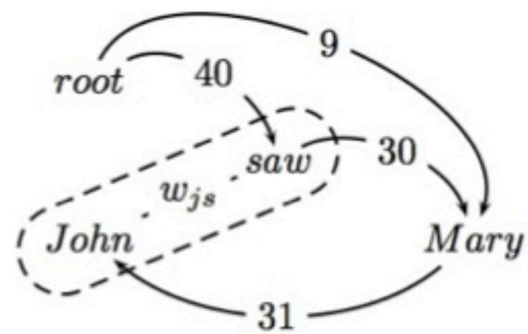
- If not a tree, identify cycle and contract
- Recalculate arc weights into and out-of cycle



Recalculate Edge Weights



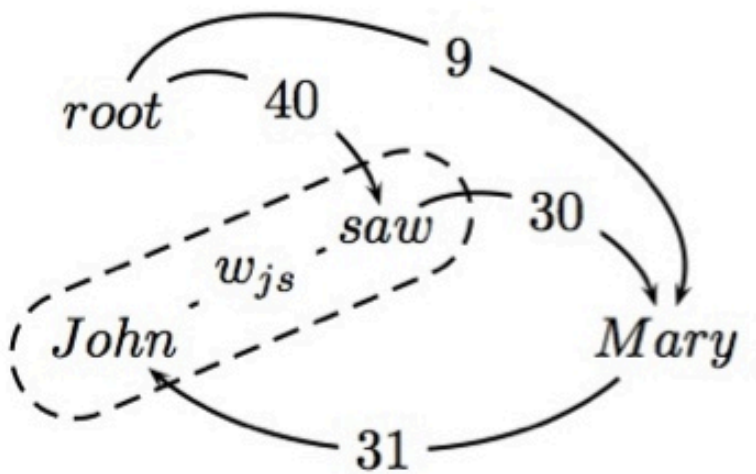




- Incoming arc weights
  - Equal to the weight of best spanning tree that includes head of incoming arc, and all nodes in cycle
  - root → saw → John is 40 (**)
  - root → John → saw is 29

Theorem

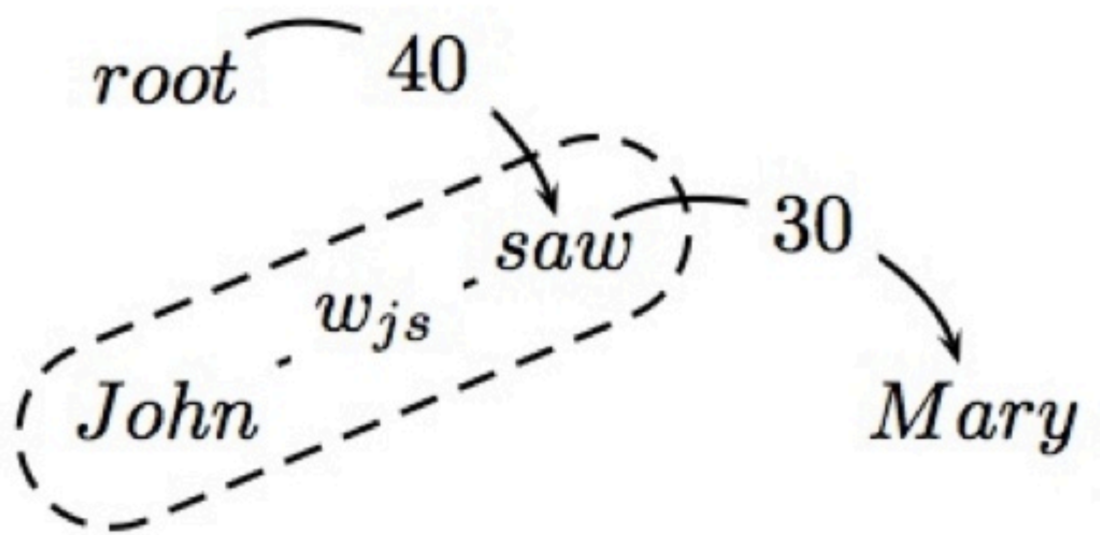
The weight of the MST of this contracted graph is equal to the weight of the MST for the original graph



- Therefore, recursively call algorithm on new graph

Final MST

- This is a tree and the MST for the contracted graph!!



- Go back up recursive call and reconstruct final graph

Chu-Liu-Edmonds PseudoCode

Chu-Liu-Edmonds(G_x, w)

1. Let $M = \{(i^*, j) : j \in V_x, i^* = \arg\max_{i'} w_{ij}\}$
2. Let $G_M = (V_x, M)$
3. If G_M has no cycles, then it is an MST: return G_M
4. Otherwise, find a cycle C in G_M
5. Let $< G_C, c, ma >= \text{contract}(G, C, w)$
6. Let $G = \text{Chu-Liu-Edmonds}(G_C, w)$
7. Find vertex $i \in C$ such that $(i', c) \in G$ and $ma(i', c) = i$
8. Find arc $(i'', i) \in C$
9. Find all arc $(c, i''') \in G$
10. $G = G \cup \{(ma(c, i'''), i''')\}_{\forall (c, i''') \in G} \cup C \cup \{(i', i)\} - \{(i'', i)\}$
11. Remove all vertices and arcs in G containing c
12. return G

- Reminder: $w_{ij} = \arg\max_k w_{ij}^k$

Chu-Liu-Edmonds PseudoCode

contract$(G = (V, A), C, w)$

1. Let G_C be the subgraph of G excluding nodes in C
2. Add a node c to G_C representing cycle C
3. For $i \in V - C : \exists_{i' \in C}(i', i) \in A$

   Add arc (c, i) to G_C with

   $ma(c, i) = \arg\max_{i' \in C} score(i', i)$

   $i' = ma(c, i)$

   $score(c, i) = score(i', i)$
4. For $i \in V - C : \exists_{i' \in C}(i, i') \in A$

   Add edge (i, c) to G_C with

   $ma(i, c) = \arg\max_{i' \in C} [score(i, i') - score(a(i'), i')]$

   $i' = ma(i, c)$

   $score(i, c) = [score(i, i') - score(a(i'), i') + score(C)]$

   where $a(v)$ is the predecessor of v in C

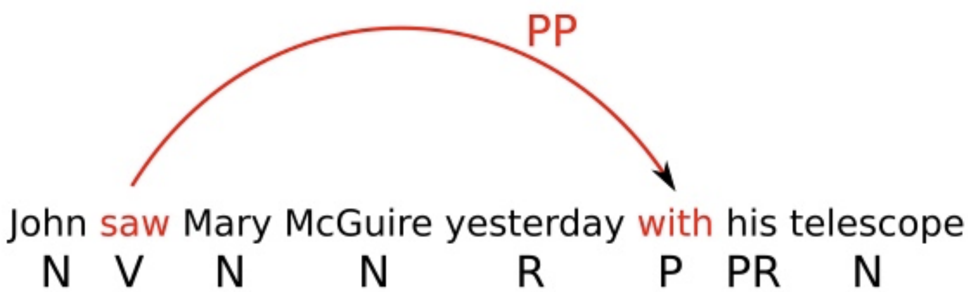
   and $score(C) = \sum_{v \in C} score(a(v), v)$
5. return $< G_C, c, ma >$

Arc Weights

$$w_{ij}^{k} = e^{\mathbf{w} \cdot \mathbf{f}(i,j,k)}$$

- Arc weights are a linear combination of features of the arc, **f**, and a corresponding weight vector **w**
- Raised to an exponent (simplifies some math ...)
- What arc features?
- [McDonald et al. 2005] discuss a number of binary features

Arc Feature Ideas for f(i,j,k)



- Identities of the words wi and wj and the label lk
- Part-of-speech tags of the words wi and wj and the label lk
- Part-of-speech of words surrounding and between wi and wj
- Number of words between wi and wj , and their orientation
- Combinations of the above

(Structured) Perceptron

Training data: $\mathcal{T} = \{(x_t, G_t)\}_{t=1}^{|\mathcal{T}|}$

1. $\mathbf{w}^{(0)} = 0;\ i = 0$
2. for $n : 1..N$
3. for $t : 1..T$
4. Let $G' = \arg\max_{G'} \mathbf{w}^{(i)} \cdot \mathbf{f}(G')$
5. if $G' \neq G_t$
6. $\mathbf{w}^{(i+1)} = \mathbf{w}^{(i)} + \mathbf{f}(G_t) - \mathbf{f}(G')$
7. $i = i + 1$
8. return $\mathbf{w}^i$

Partition Function

Partition Function: $Z_x = \sum_{G \in T(G_x)} w(G)$

- Lapacian Matrix Q for graph $G_x = (V_x, A_x)$

$$Q_{jj} = \sum_{i \neq j, (i,j,k) \in A_x} w_{ij}^k \quad \text{and} \quad Q_{ij} = \sum_{i \neq j, (i,j,k) \in A_x} -w_{ij}^k$$

- Cofactor Q^i is the matrix Q with the i^{th} row and column removed

The Matrix Tree Theorem [Tutte 1984]
The determinant of the cofactor Q^0 is equal to Z_x

- Thus $Z_x = |Q^0|$ – determinants can be calculated in $O(n^3)$
- Constructing Q takes $O(|L|n^2)$
- Therefore the whole process takes $O(n^3 + |L|n^2)$

Arc Expectations

$$\langle i, j, k \rangle_x = \sum_{G \in T(G_x)} w(G) \times \mathbb{1}[(i, j, k) \in A]$$

- Can easily be calculated, first reset some weights

$$w_{i'j}^{k'} = 0 \; \forall i' \neq i \text{ and } k' \neq k$$

- Now, $\langle i, j, k \rangle_x = Z_x$
- Why? All competing arc weights to zero, therefore every non-zero weighted graph must contain (i, j, k)
- Naively takes $O(n^5 + |L|n^2)$ to compute all expectations
- But can be calculated in $O(n^3 + |L|n^2)$ (see [McDonald and Satta 2007, Smith and Smith 2007, Koo et al. 2007])

Summary

- Constituency Parsing
  - CKY Algorithm
  - Lexicalized Grammars
  - Latent Variable Grammars

- Dependency Parsing
  - Eisner Algorithm
  - Maximum Spanning Tree Algorithm

There is lots more and these models are being actively used in practice!