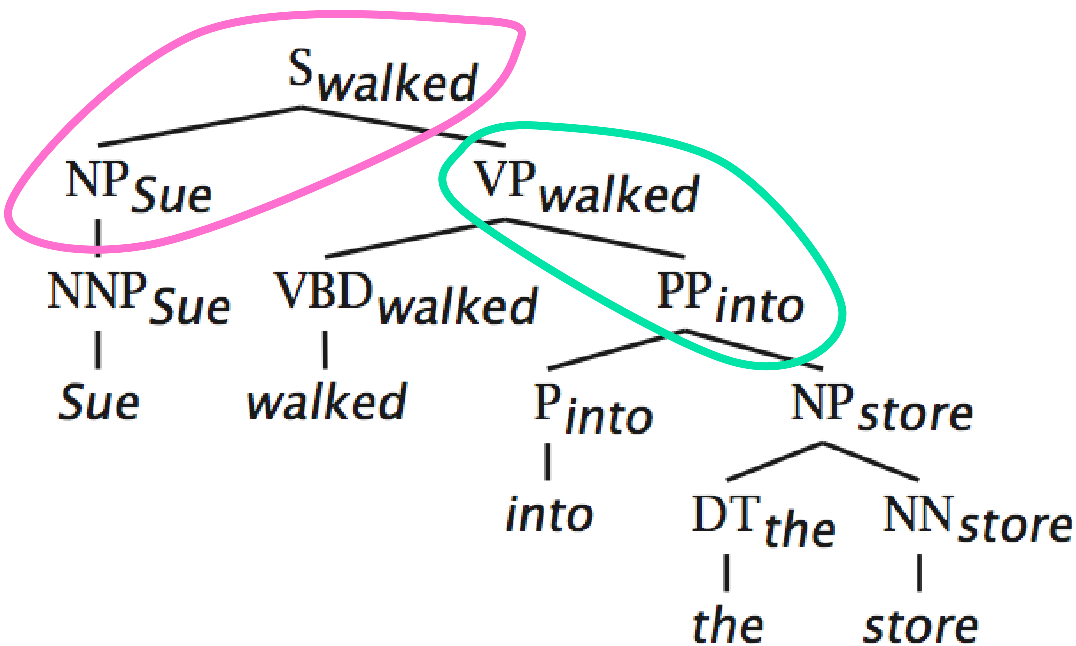
Statistical Parsing

Gerald Penn
CS224N
[based on slides by Chrisophter Manning]

(Head) Lexicalization of PCFGs

[Magerman 1995, Collins 1997; Charniak 1997]

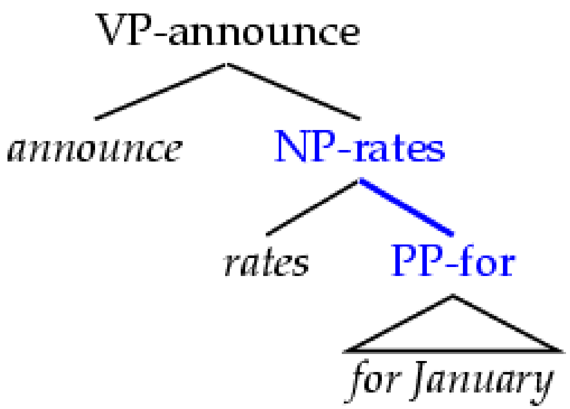
- The head word of a phrase gives a good representation of the phrase's structure and meaning
- Puts the properties of words back into a PCFG

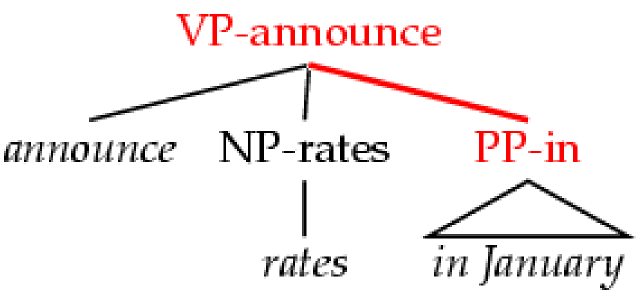


(Head) Lexicalization of PCFGs

[Magerman 1995, Collins 1997; Charniak 1997]

- Word-to-word affinities are useful for certain ambiguities
  - See how PP attachment is (partly) captured in a local PCFG rule. What isn't captured?



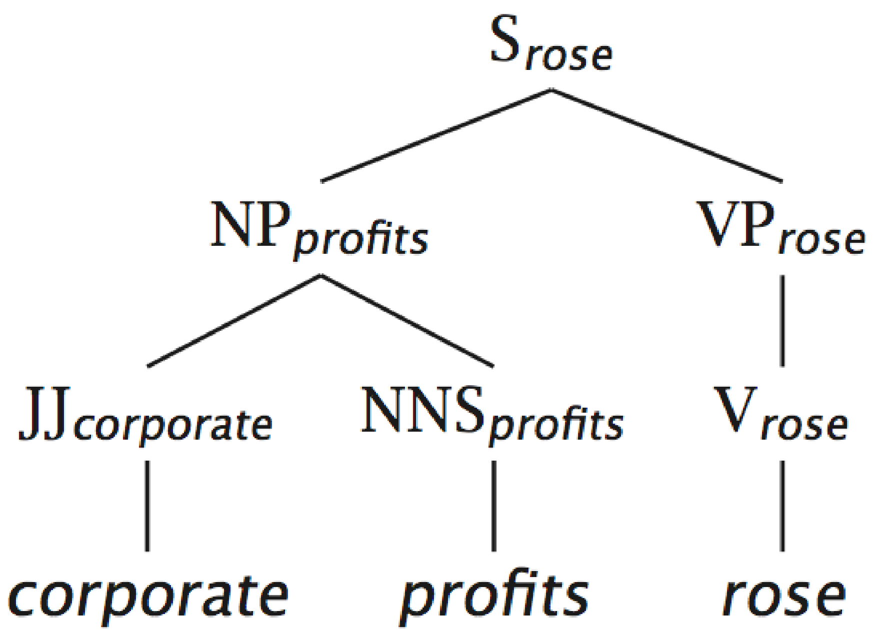


Lexicalized Parsing was seen as the breakthrough of the late 90s

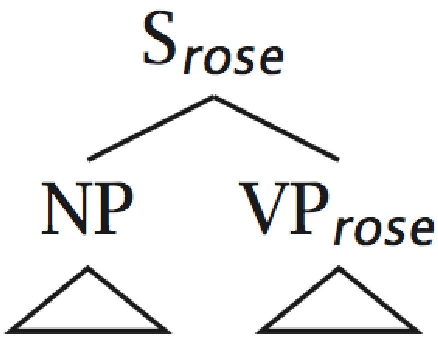
- Eugene Charniak, 2000 JHU workshop: "To do better, it is necessary to condition probabilities on the actual words of the sentence. This makes the probabilities much tighter:
  - $p(\text{VP} \rightarrow \text{V NP NP}) = 0.00151$
  - $p(\text{VP} \rightarrow \text{V NP NP} \mid \text{said}) = 0.00001$
  - $p(\text{VP} \rightarrow \text{V NP NP} \mid \text{gave}) = 0.01980$ "
- Michael Collins, 2003 COLT tutorial: "Lexicalized Probabilistic Context-Free Grammars … perform vastly better than PCFGs (88% vs. 73% accuracy)"

Parsing via classification decisions: Charniak (1997)

- A very simple, conservative model of lexicalized PCFG
- Probabilistic conditioning is "top-down" like a regular PCFG (but actual computation is bottom-up)



Charniak (1997) example

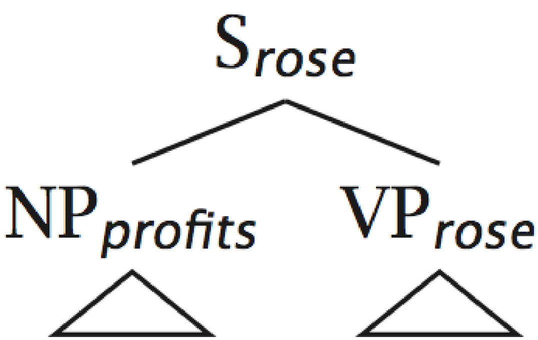


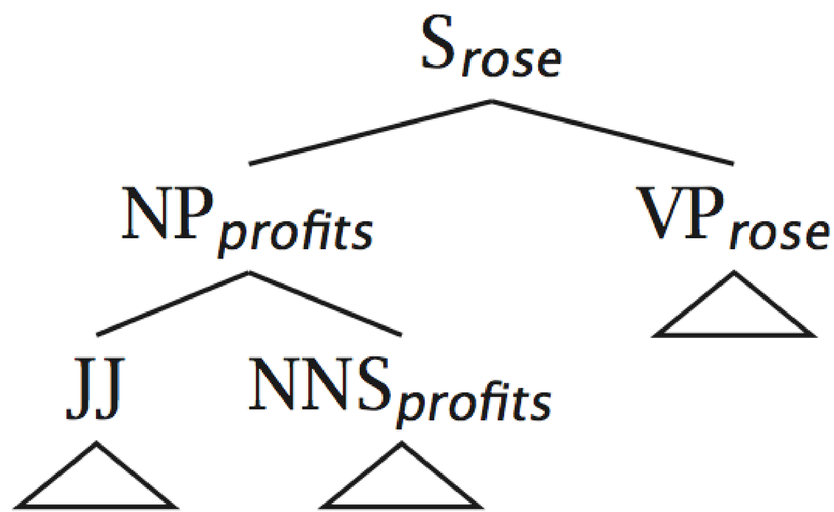
a. $h = profits;\ c = \mathrm{NP}$

b. $ph = rose;\ pc = \mathrm{S}$

c. $P(h \mid ph, c, pc)$

d. $P(r \mid h, c, pc)$





Lexicalization sharpens probabilities: rule expansion

- E.g., probability of different verbal complement frames (often called “subcategorizations”)

Local Tree	*come*	*take*	*think*	*want*
VP $\rightarrow$ V	9.5%	2.6%	4.6%	5.7%
VP $\rightarrow$ V NP	1.1%	32.1%	0.2%	13.9%
VP $\rightarrow$ V PP	34.5%	3.1%	7.1%	0.3%
VP $\rightarrow$ V SBAR	6.6%	0.3%	73.0%	0.2%
VP $\rightarrow$ V S	2.2%	1.3%	4.8%	70.8%
VP $\rightarrow$ V NP S	0.1%	5.7%	0.0%	0.3%
VP $\rightarrow$ V PRT NP	0.3%	5.8%	0.0%	0.0%
VP $\rightarrow$ V PRT PP	6.1%	1.5%	0.2%	0.0%

Lexicalization sharpens probabilities: Predicting heads

"Bilexical probabilities"

- p(prices | n-plural) = .013
- p(prices | n-plural, NP) = .013
- p(prices | n-plural, NP, S) = .025
- p(prices | n-plural, NP, S, v-past) = .052
- p(prices | n-plural, NP, S, v-past, fell) = .146

Charniak (1997) linear interpolation/shrinkage

$$\begin{aligned}\hat{P}(h|ph,c,pc) &= \lambda_1(e)P_{\mathsf{MLE}}(h|ph,c,pc)\\ &+\lambda_2(e)P_{\mathsf{MLE}}(h|C(ph),c,pc)\\ &+\lambda_3(e)P_{\mathsf{MLE}}(h|c,pc)+\lambda_4(e)P_{\mathsf{MLE}}(h|c)\end{aligned}$$

- $\lambda_i(e)$ is here a function of how much one would expect to see a certain occurrence, given the amount of training data, word counts, etc.
- $C(ph)$ is semantic class of parent headword
- Techniques like these for dealing with data sparseness are vital to successful model construction

Charniak (1997) shrinkage example

	$P(\text{prft}\mid\text{rose, NP, S})$	$P(\text{corp}\mid\text{prft, JJ, NP})$
$P(h\mid ph, c, pc)$	0	0.245
$P(h\mid C(ph), c, pc)$	0.00352	0.0150
$P(h\mid c, pc)$	0.000627	0.00533
$P(h\mid c)$	0.000557	0.00418

- Allows utilization of rich highly conditioned estimates, but smoothes when sufficient data is unavailable
- One can't just use MLEs: one commonly sees previously unseen events, which would have probability 0.

Sparseness & the Penn Treebank

- The Penn Treebank – 1 million words of parsed English WSJ – has been a key resource (because of the widespread reliance on supervised learning)
- But 1 million words is like nothing:
  - 965,000 constituents, but only 66 WHADJP, of which only 6 aren't *how much* or *how many*, but there is an infinite space of these
    - *How clever/original/incompetent (at risk assessment and evaluation) …*
- Most of the probabilities that you would like to compute, you can't compute

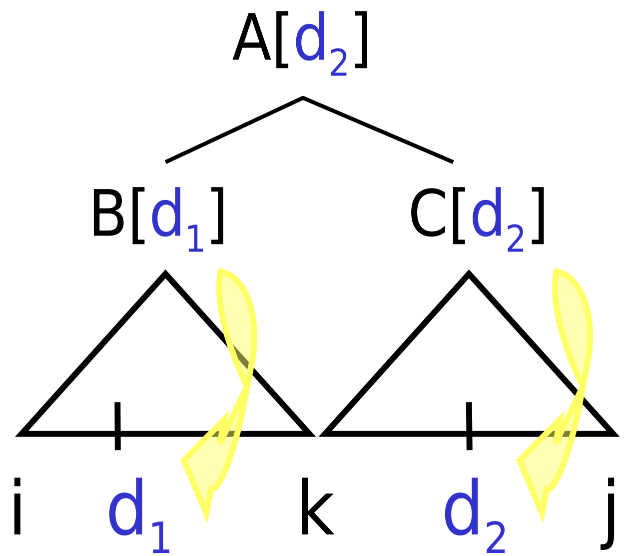
Quiz question!

- Which of the following is also (the beginning of) a WHADJP?
  a) how are
  b) how cruel
  c) how about
  d) however long

Sparseness & the Penn Treebank (2)

- Many parse preferences depend on bilexical statistics: likelihoods of relationships between pairs of words (compound nouns, PP attachments, …)
- Extremely sparse, even on topics central to the WSJ:
  - *stocks plummeted* 2 occurrences
  - *stocks stabilized* 1 occurrence
  - *stocks skyrocketed* 0 occurrences
  - #*stocks discussed* 0 occurrences
- So far there has been very modest success in augmenting the Penn Treebank with extra unannotated materials or using semantic classes – once there is more than a little annotated training data.
  - Cf. Charniak 1997, Charniak 2000; but see McClosky et al. 2006

Complexity of lexicalized PCFG parsing



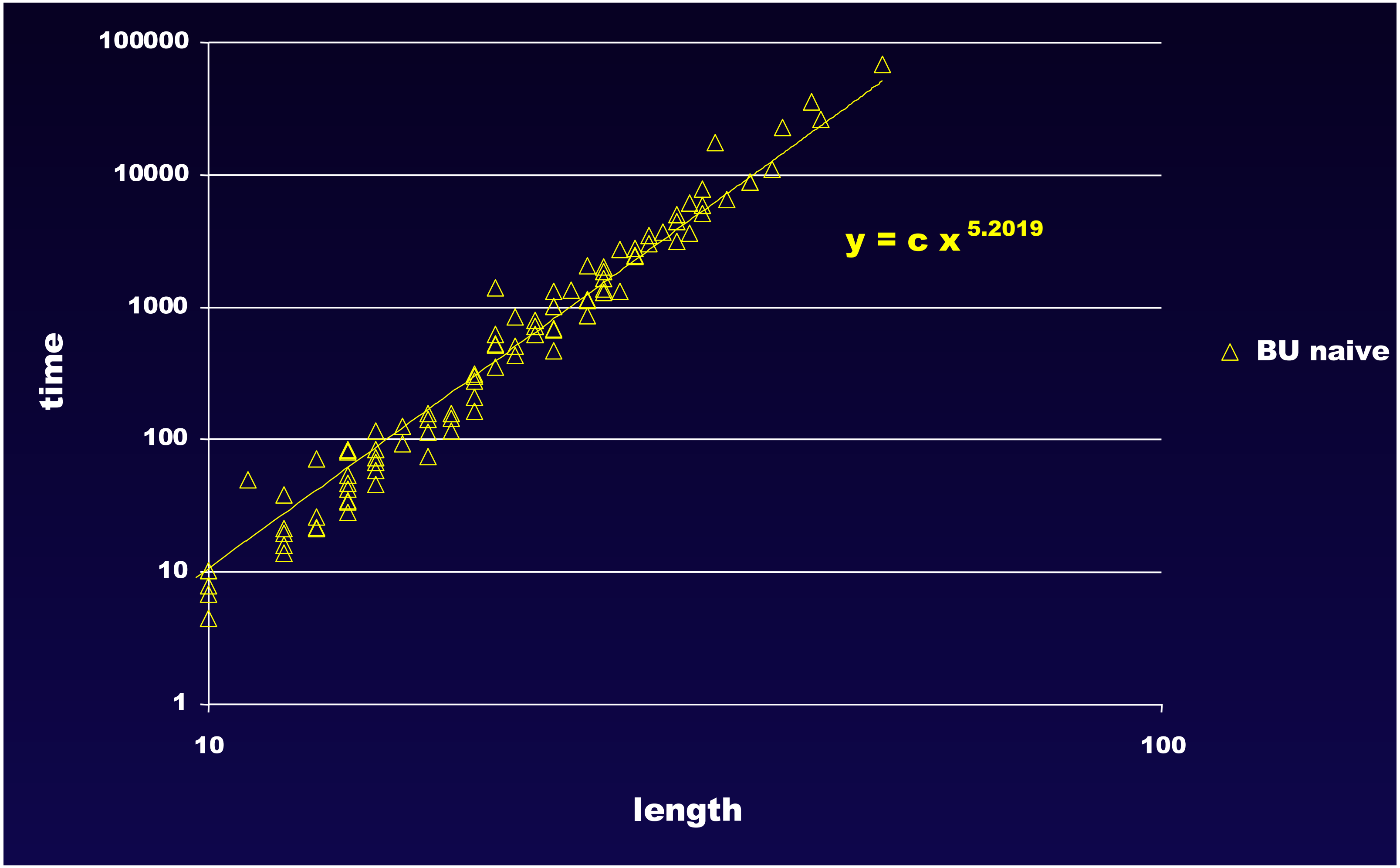
Time charged :

- i, k, j $\Rightarrow$ n^3
- A[d_2], B[d_1], C[d_2] $\Rightarrow$ G^3
- Done naively, G^3 is huge ($G^3 = g^3 V^3$; unworkable)
- A, B, C $\Rightarrow$ g^3
- d_1, d_2 $\Rightarrow$ n^2

Running time is $O(g^3 \times n^5)$!!

n = sentence length
g = # of nonterminals
G = # of lexicalized nonterms
V = vocabulary size (# of words)

Complexity of exhaustive lexicalized PCFG parsing



Complexity of lexicalized PCFG parsing

- Work such as Collins (1997) and Charniak (1997) *is* $O(n^5)$ – but uses heuristic search to be fast in practice
- Eisner and Satta (2000, etc.) have explored various ways to parse more restricted classes of bilexical grammars in $O(n^4)$ or $O(n^3)$ time
  - Neat algorithmic stuff!!!
  - See example later from dependency parsing

Refining the node expansion probabilities

- Charniak (1997) expands each phrase structure tree in a single step.
- This is good for capturing dependencies between child nodes
- But it is bad because of data sparseness.
- A pure dependency, one child at a time, model is worse.
- But one can do better by in between models, such as generating the children as a Markov process on both sides of the head (Collins 1997; Charniak 2000)
  - Cf. the accurate unlexicalized parsing discussion

Collins (1997, 1999); Bikel (2004)

- Collins (1999): also a generative model
- Underlying lexicalized PCFG has rules of form

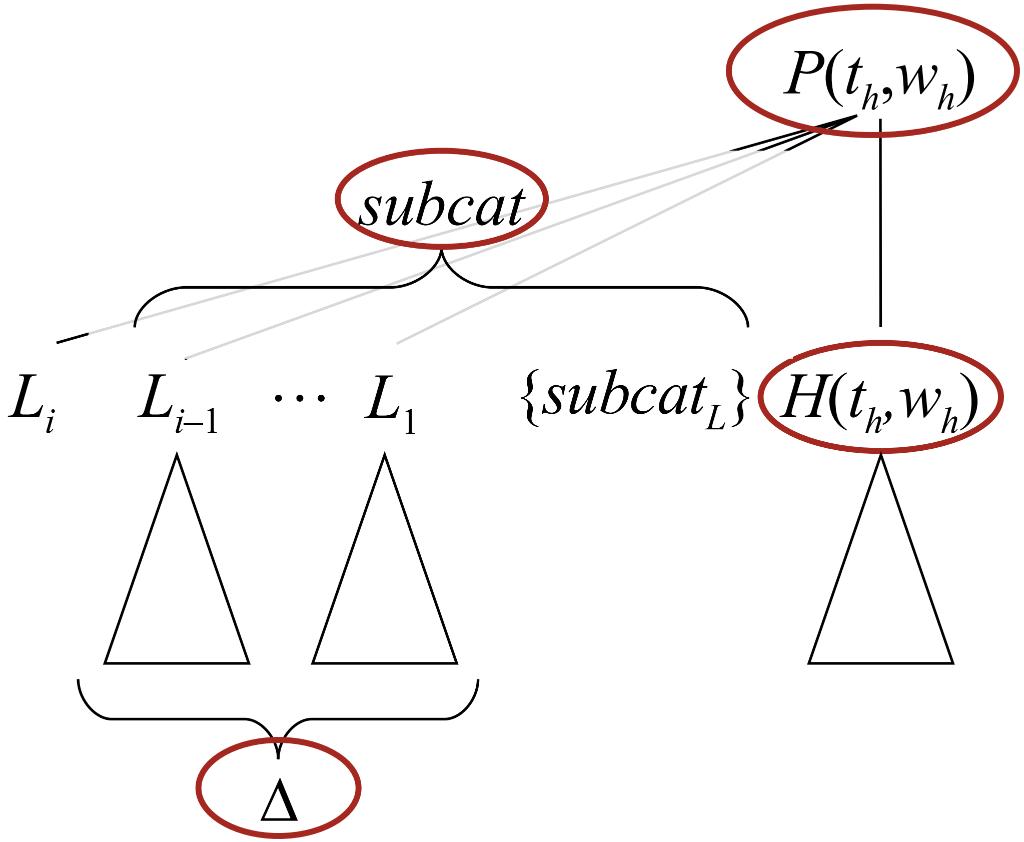
$$P \rightarrow L_j L_{j-1} \ldots L_1 H R_1 \ldots R_{k-1} R_k$$

- A more elaborate set of grammar transforms and factorizations to deal with data sparseness and interesting linguistic properties
- Each child is generated in turn: given *P* has been generated, generate *H*, then generate modifying nonterminals from head-adjacent outward with some limited conditioning

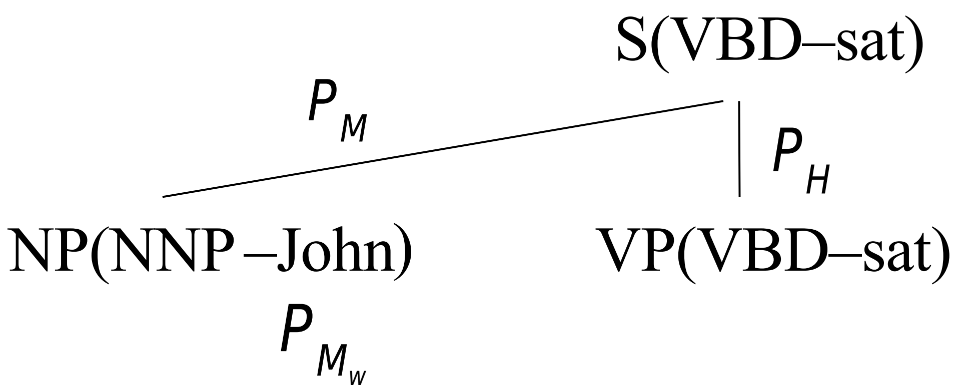
Overview of Collins' Model

L_i generated

conditioning on



Modifying nonterminals generated in two steps



Smoothing for head words of modifying nonterminals

Back-off level	$P_{M_w}(w_{M_i} \mid ¼)$
0	$M_i, t_{M_i}, \text{coord}, \text{punc}, P, H, w_h, t_h, D_M, subcat_{side}$
1	$M_i, t_{M_i}, \text{coord}, \text{punc}, P, H, t_h, D_M, subcat_{side}$
2	t_{M_i}

- Other parameter classes have similar or more elaborate backoff schemes

Collins model … and linguistics

- Collins had 3 generative models: Models 1 to 3
- Especially as you work up from Model 1 to 3, significant linguistic modeling is present:
  - Distance measure: favors close attachments
    - Model is sensitive to punctuation
  - Distinguish base NP from full NP with post-modifiers
  - Coordination feature
  - Mark gapped subjects
  - Model of subcategorization; arguments vs. adjuncts
  - Slash feature/gap threading treatment of displaced constituents
    - Didn't really get clear gains from this last one.

Bilexical statistics: Is use of maximal context of P_{M_w} useful?

- Collins (1999): "Most importantly, the model has parameters corresponding to dependencies between pairs of headwords."
- Gildea (2001) reproduced Collins' Model 1 (like regular model, but no subcats)
  - Removing maximal back-off level from P_{M_w} resulted in only 0.5% reduction in F-measure
  - Gildea's experiment somewhat unconvincing to the extent that his model's performance was lower than Collins' reported results

Choice of heads

- If not bilexical statistics, then surely choice of heads is important to parser performance…
- Chiang and Bikel (2002): parsers performed decently even when all head rules were of form "if parent is X, choose left/rightmost child"
- Parsing engine in Collins Model 2–emulation mode: LR 88.55% and LP 88.80% on §00 (sent. len. ≤40 words)
  - compared to LR 89.9%, LP 90.1%

Use of maximal context of P_{M_W}

[Bikel 2004]

	LR	LP	CBs	0 CBs	≤2 CBs
Full model	89.9	90.1	0.78	68.8	89.2
No bigrams	89.5	90.0	0.80	68.0	88.8

Performance on §00 of Penn Treebank
on sentences of length ≤40 words

Use of maximal context of P_{M_W}

Back-off level	Number of accesses	Percentage
0	3,257,309	1.49
1	24,294,084	11.0
2	191,527,387	87.4
Total	219,078,780	100.0

Number of times parsing engine was able to deliver a probability for the various back-off levels of the mod-word generation model, P_{M_w}, when testing on §00 having trained on §§02–21

Bilexical statistics *are* used often

[Bikel 2004]

- The 1.49% use of bilexical dependencies suggests they don’t play much of a role in parsing
- But the parser pursues many (very) incorrect theories
- So, instead of asking how often the decoder can use bigram probability *on average*, ask how often *while pursuing its top-scoring theory*
- Answering question by having parser *constrain-parse* its own output
  - train as normal on §§02–21
  - parse §00
  - feed parse trees as *constraints*
- Percentage of time parser made use of bigram statistics shot up to **28.8%**
- So, used often, but use barely affect overall parsing accuracy
- Exploratory Data Analysis suggests explanation
  - distributions that include head words are usually sufficiently similar to those that do not, so as to make almost no difference in terms of accuracy

Charniak (2000) NAACL: A Maximum-Entropy-Inspired Parser

- There was nothing maximum entropy about it. It was a cleverly smoothed generative model
- Smoothes estimates by smoothing ratio of conditional terms (which are a bit like maxent features):

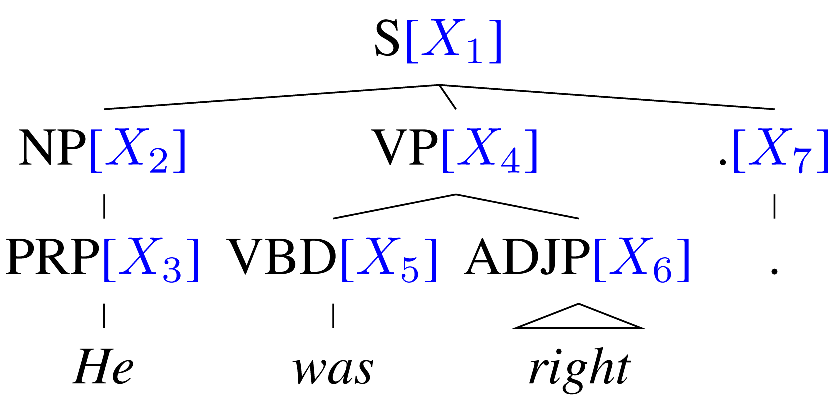
$$\frac{P(t \mid l, l_p, t_p, l_g)}{P(t \mid l, l_p, t_p)}$$

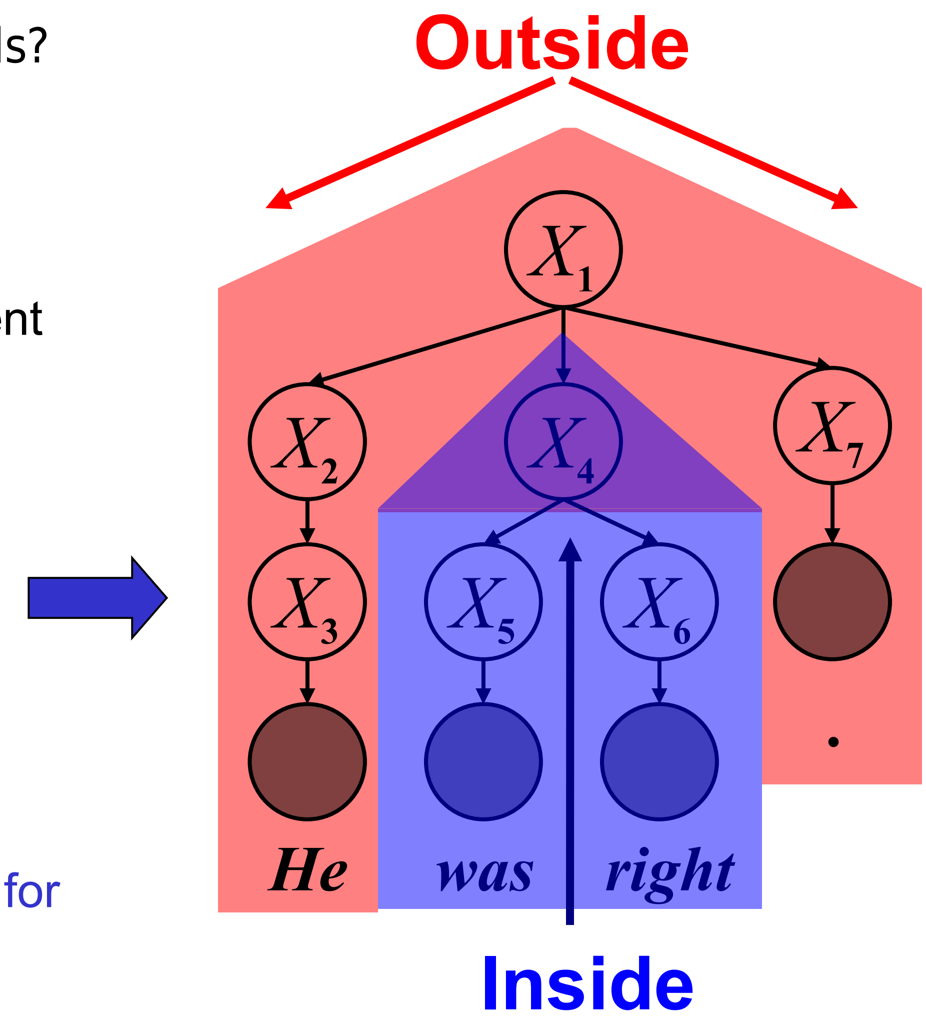
- Biggest improvement is actually that generative model predicts head tag first and then does P(*w*|*t*,…)
  - Like Collins (1999)
- Markovizes rules similarly to Collins (1999)
- Gets 90.1% LP/LR F score on sentences ≤ 40 wds

Petrov and Klein (2006): Learning Latent Annotations

Can you automatically find good symbols?

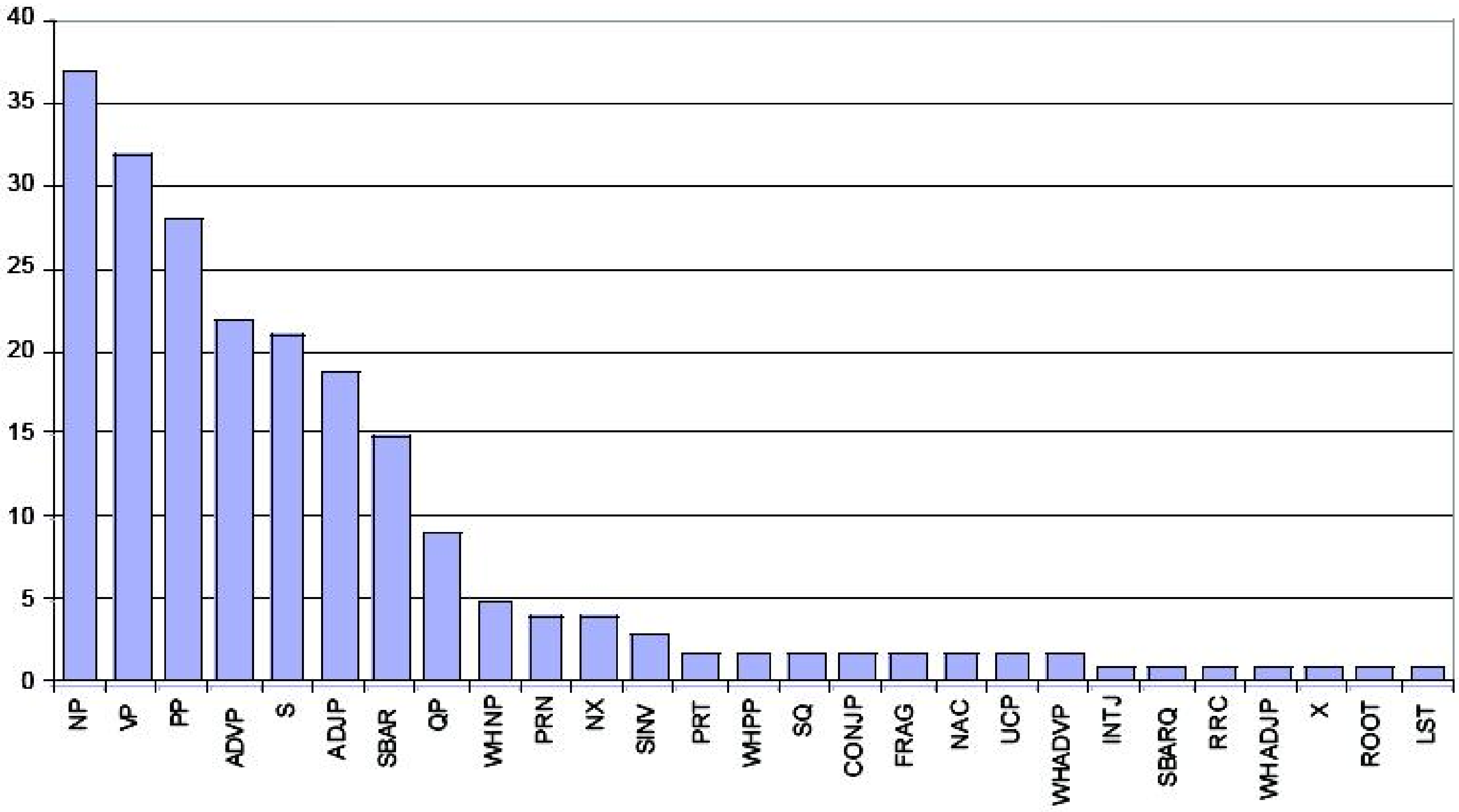
- Brackets are known
- Base categories are known
- Induce subcategories
- Clever split/merge category refinement





EM algorithm, like Forward-Backward for HMMs, but constrained by tree.

Number of phrasal subcategories



POS tag splits' commonest words: effectively a class-based model

- 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

Recent Parsing Results…

Parser	*F1* *≤ 40 words*	*F1* *all words*
Klein & Manning unlexicalized 2003	86.3	85.7
Matsuzaki et al. simple EM latent states 2005	86.7	86.1
Charniak generative, lexicalized (“maxent inspired”) 2000	90.1	89.5
Petrov and Klein NAACL 2007	90.6	90.1
Charniak & Johnson discriminative reranker 2005	92.0	91.4

Statistical parsing inference: The General Problem

- Someone gives you a PCFG *G*
- For any given sentence, you might want to:
  - Find the best parse according to *G*
  - Find a bunch of reasonably good parses
  - Find the total probability of all parses licensed by *G*
- Techniques:
  - CKY, for best parse; can extend it:
    - To *k*-best: naively done, at high space and time cost – k^2 time/*k* space cost, but there are cleverer algorithms! (Huang and Chiang 2005: http://www.cis.upenn.edu/~lhuang3/huang-iwpt.pdf)
    - To all parses, summed probability: the inside algorithm
  - Beam search (like in MT)
  - Agenda/chart-based search

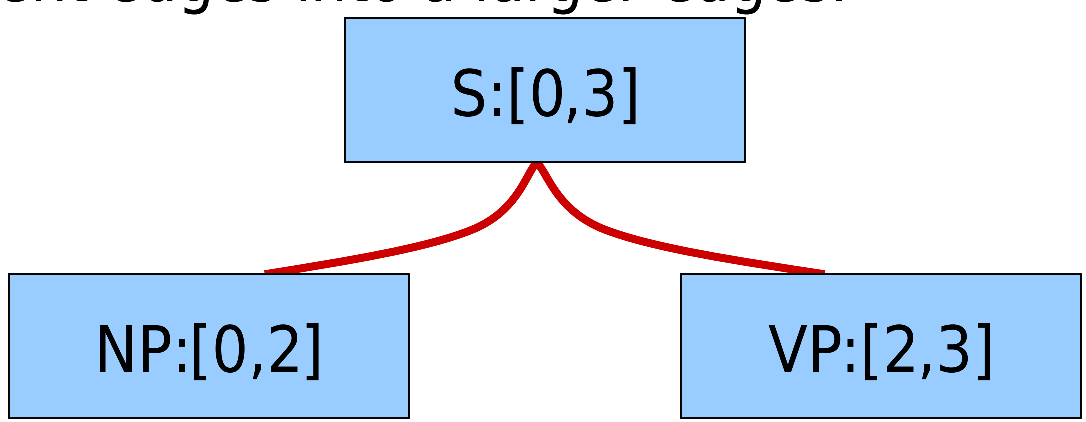
} Mainly useful if just want the best parse

Parsing as search definitions

- Grammar symbols: S, NP, @S->NP_
- Parse items/edges represent a grammar symbol over a span:

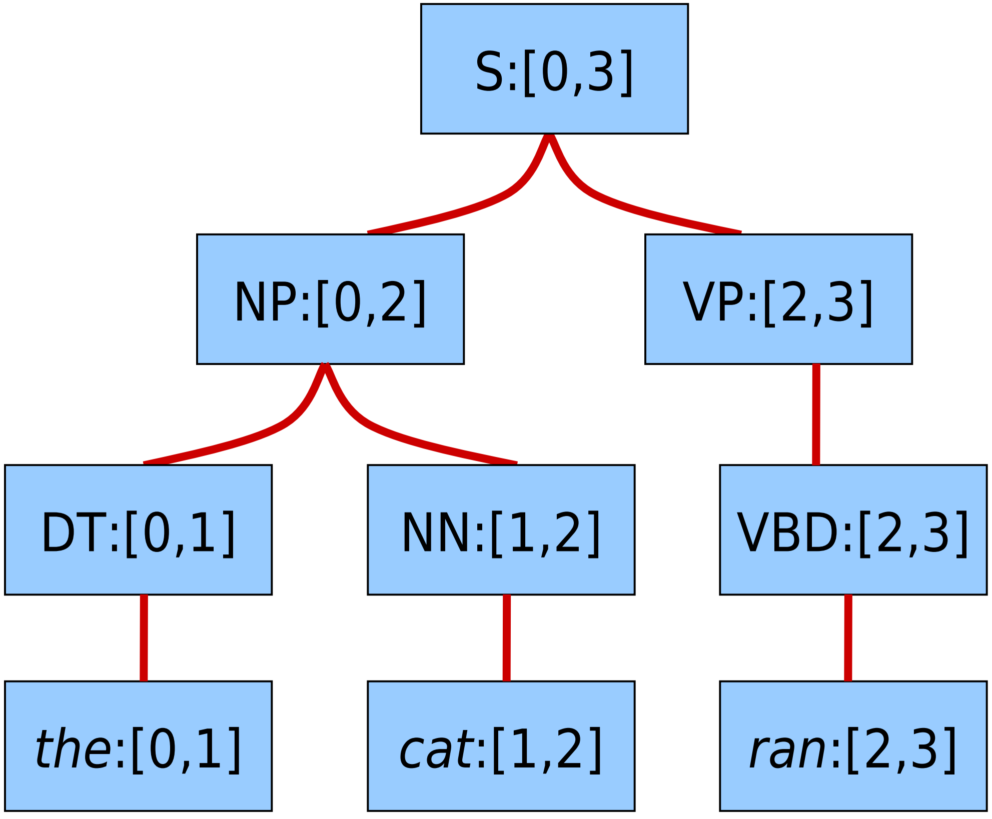
the:[0,1] NP:[0,2]

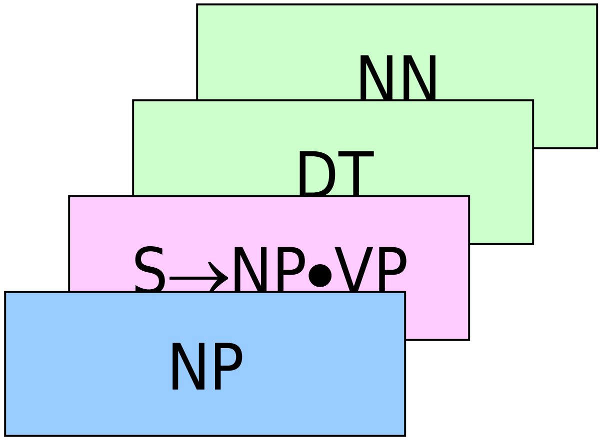
- Backtraces/traversals represent the combination of adjacent edges into a larger edges:



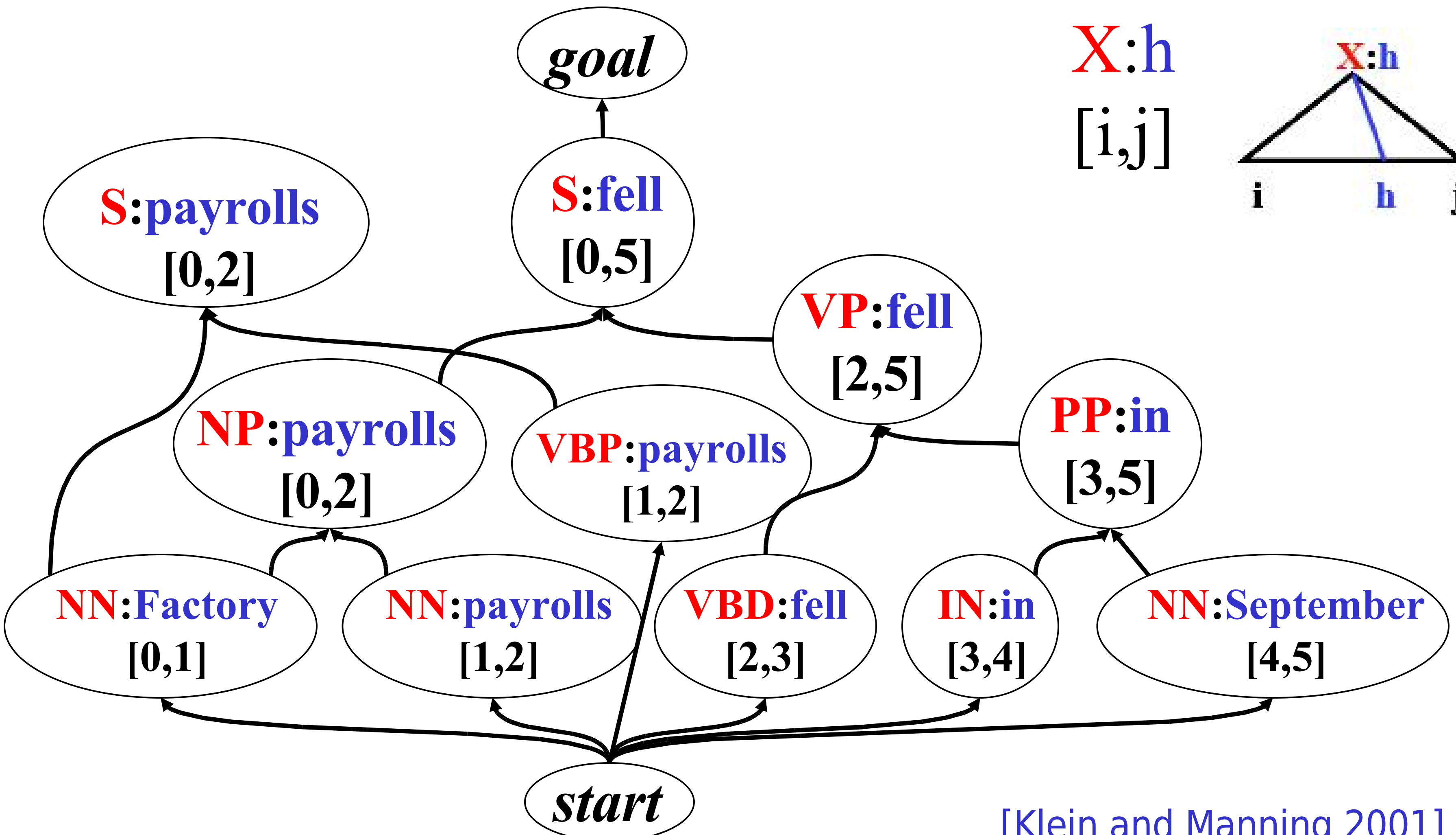
Parse trees and parse triangles

- A parse tree can be viewed as a collection of edges and traversals.
- A parse triangle groups edges over the same span



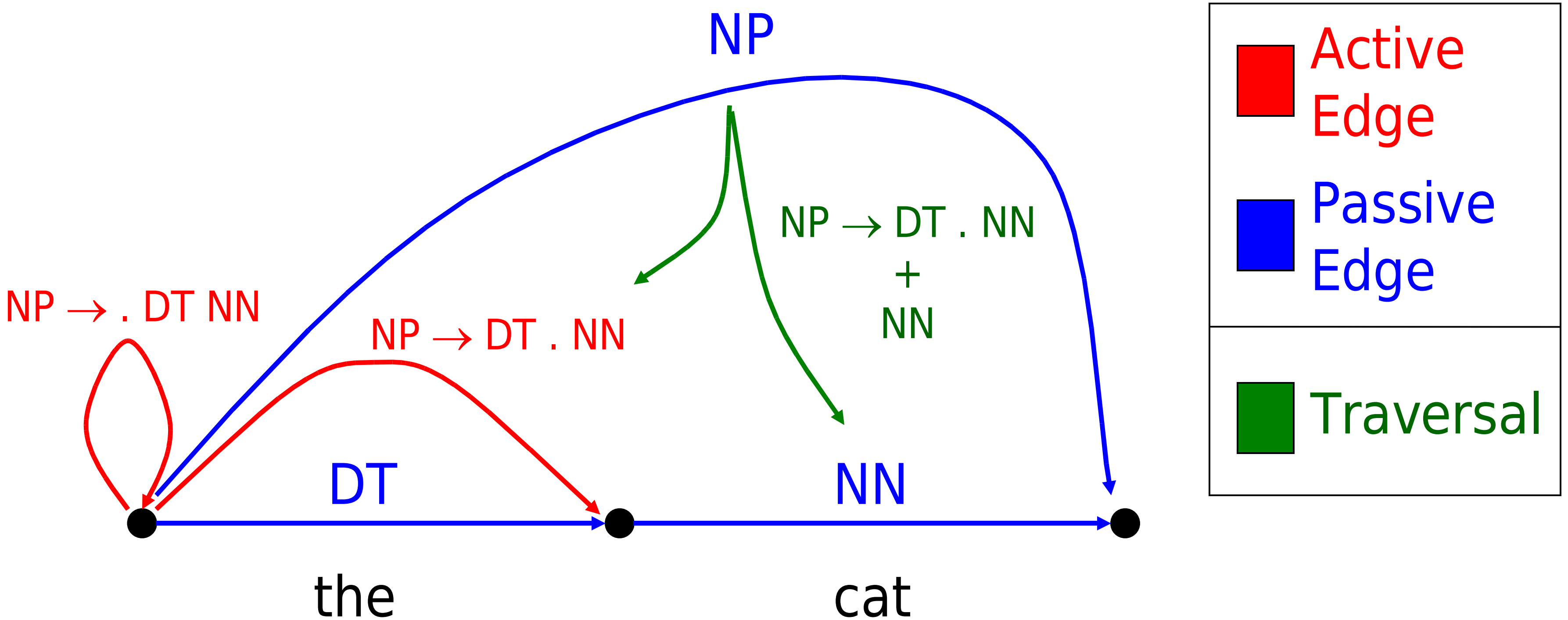


Parsing as search: The parsing directed B-hypergraph



[Klein and Manning 2001]

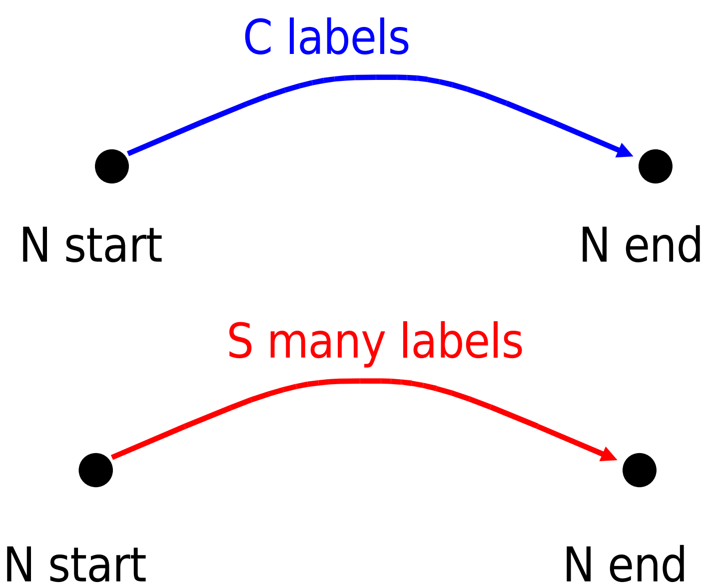
Chart example: classic picture



Earley dotted rules

Space and Time Bounds

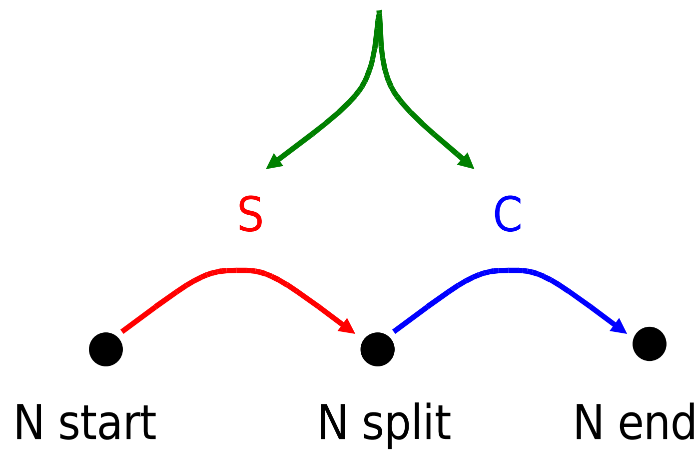
Space = O(Edges)



$\leq CN^2 + SN^2$

$= O(SN^2)$

Time = O(Traversals)

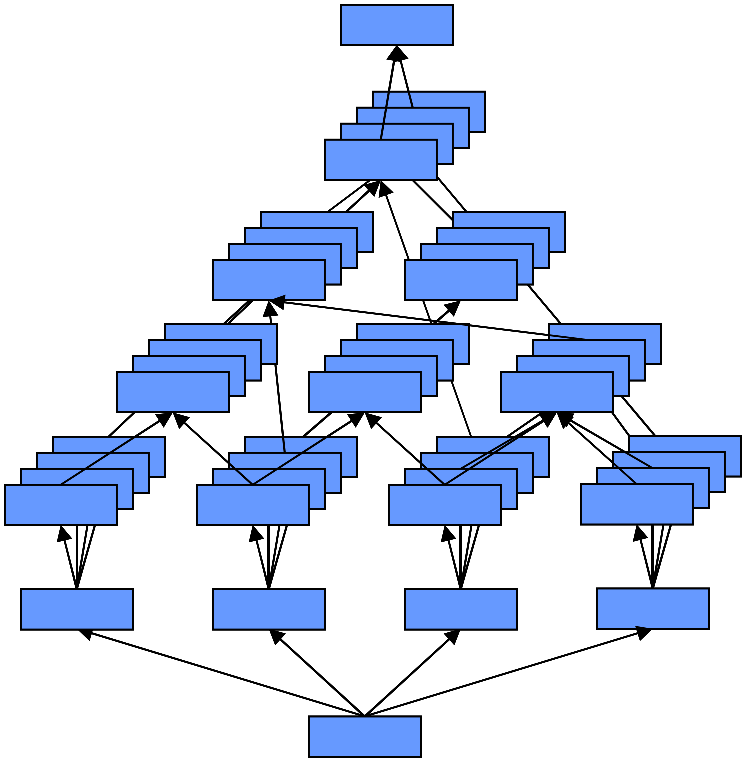


$\leq SCN^3$

$= O(SCN^3)$

CKY Parsing

- In CKY parsing, we visit edges tier by tier:



- Guarantees correctness by working inside-out.
- Build all small bits before any larger bits that could possibly require them.
- Exhaustive: the goal is in the last tier!

Agenda-based parsing

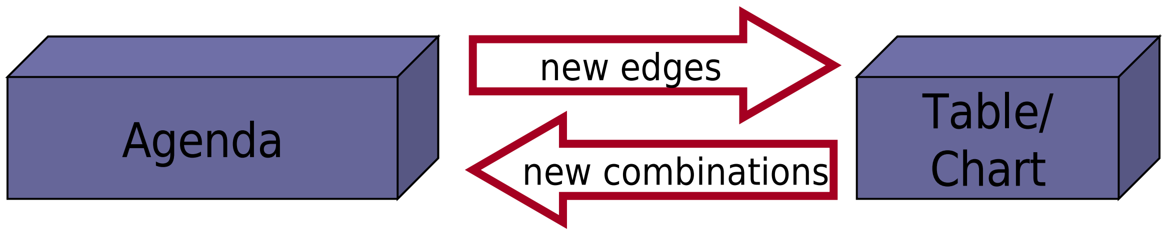
- For general grammars
- Start with a table for recording δ(X,i,j)
  - Records the best score of a parse of X over [i,j]
    - If the scores are negative log probabilities, then entries start at ∞ and small is good
    - This can be a sparse or a dense map
    - Again, you may want to record backtraces (traversals) as well, like CKY
- Step 1: Initialize with the sentence and lexicon:
  - For each word w and each tag t
    - Set δ(X,i,i) = lex.score(w,t)

Agenda-based parsing

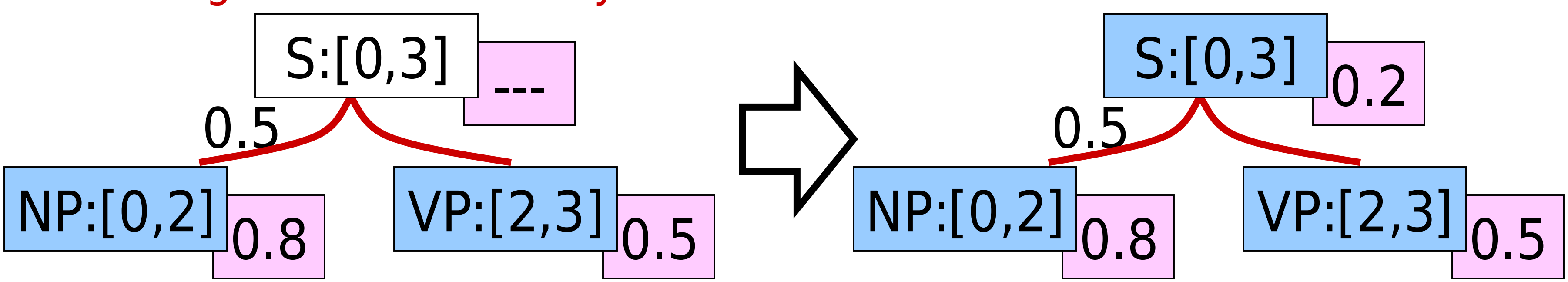
- Keep a list of edges called an agenda
  - Edges are triples [X,i,j]
  - The agenda is a priority queue
- Every time the score of some $\delta(X,i,j)$ improves (i.e. gets lower):
  - Stick the edge [X,i,j]-score into the agenda
  - (Update the backtrace for $\delta(X,i,j)$ if you're storing them)

Agenda-Based Parsing

- The agenda is a holding zone for edges.
- Visit edges by some ordering policy.
  - Combine edge with already-visited edges.
  - Resulting new edges go wait in the agenda.



- We might revisit parse items: A new way to form an edge might be a better way.



Agenda-based parsing

- Step II: While agenda not empty
  - Get the “next” edge [X,i,j] from the agenda
  - Fetch all compatible neighbors [Y,j,k] or [Z,k,i]
    - Compatible means that there are rules $A \rightarrow X\ Y$ or $B \rightarrow Z\ X$
  - Build all parent edges [A,i,k] or [B,k,j] found
    - $\delta(A,i,k) \leq \delta(X,i,j) + \delta(Y,j,k) + P(A \rightarrow X\ Y)$
    - If we’ve improved $\delta(A,i,k)$, then stick it on the agenda
  - Also project unary rules:
    - Fetch all unary rules $A \rightarrow X$, score [A,i,j] built from this rule on [X,i,j] and put on agenda if you’ve improved $\delta(A,i,k)$

- When do we know we have a parse for the root?

Agenda-based parsing

- Open questions:
  - Agenda priority: What did “next” mean?
  - Efficiency: how do we do as little work as possible?
  - Optimality: how do we know when we find the best parse of a sentence?

- If we use δ(X,i,j) as the priority:
  - Each edge goes on the agenda at most once
  - When an edge pops off the agenda, its best parse is known (why?)
  - This is basically uniform cost search (i.e., Dijkstra’s algorithm). [Cormen, Leiserson, and Rivest 1990; Knuth 1970]