# Statistical Parsing

Christopher Manning

CS224N

# 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

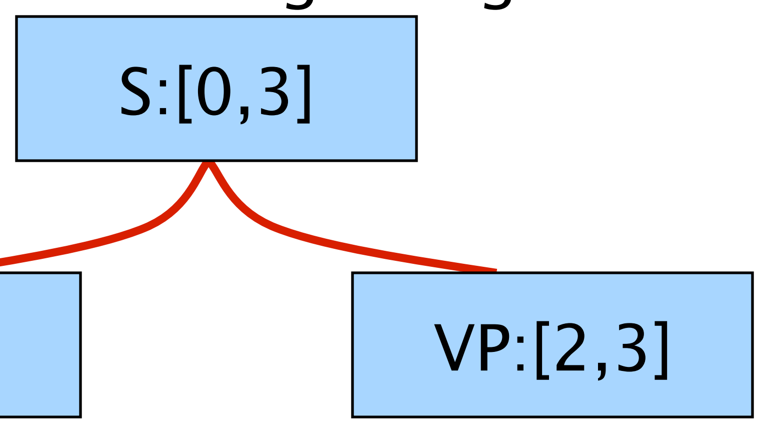
} Mainly useful if just want the best parse

# Parse as search definitions

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

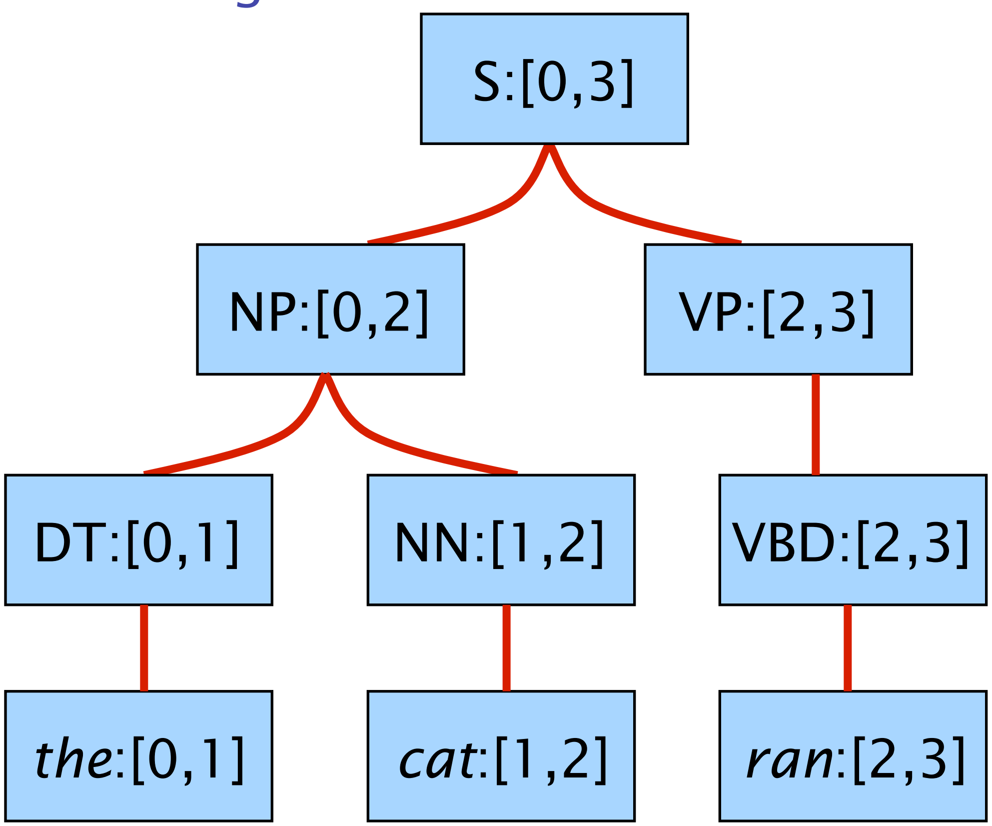
*the*:[0,1]  NP:[0,2]

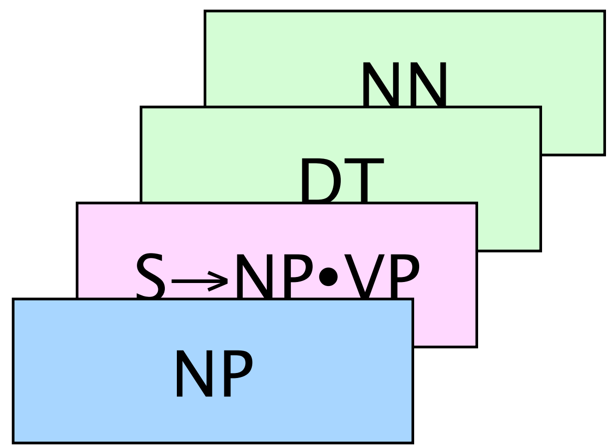
- Backtraces/traversals represent the combination of adjacent edges into a larger edges:



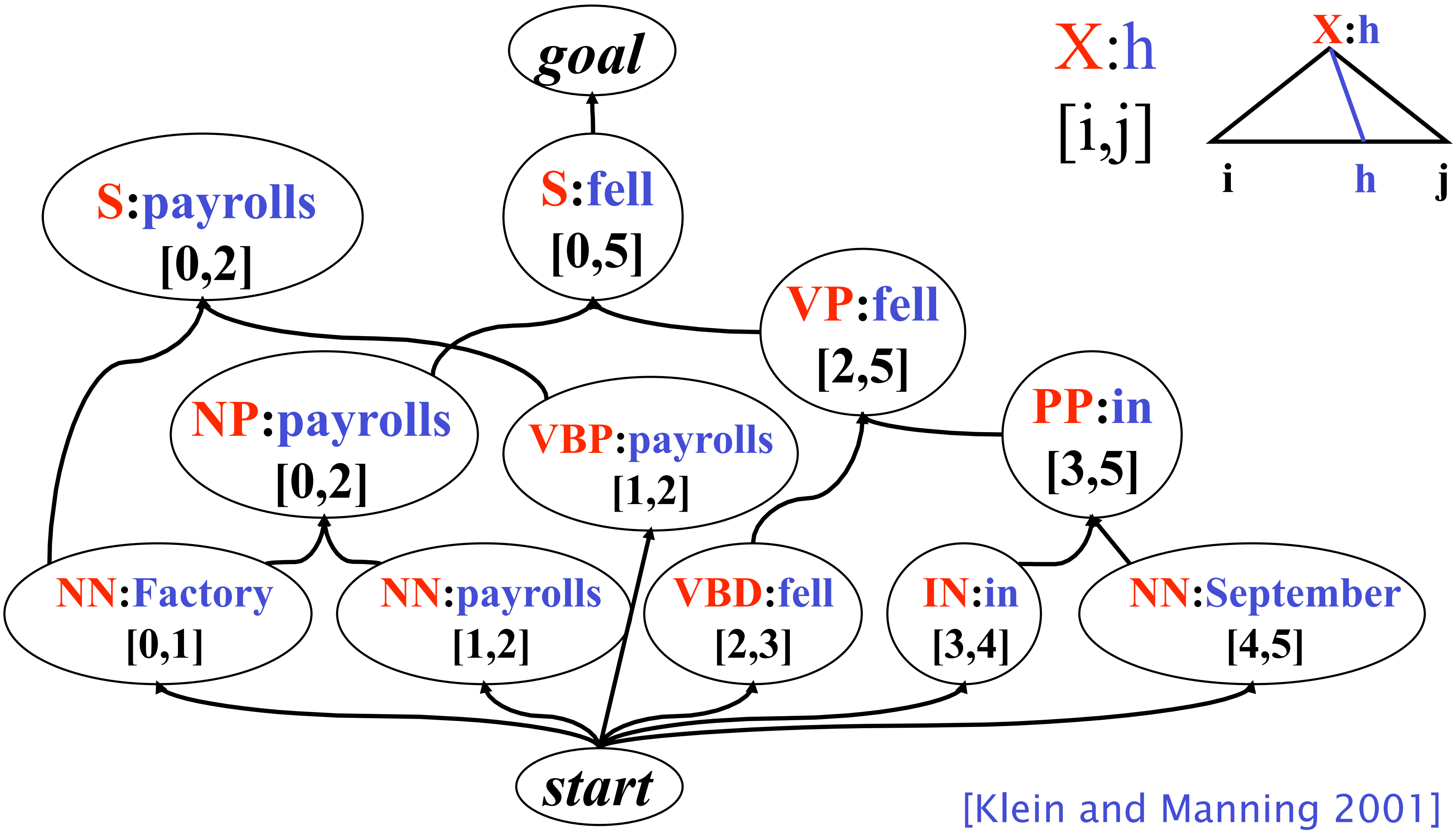
# Parse trees and parse triangles

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



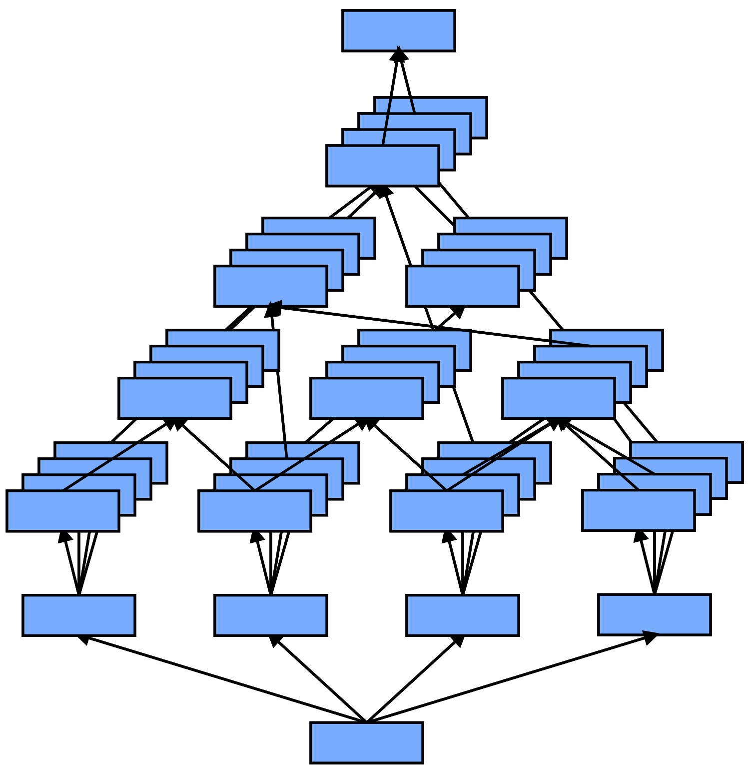
# Parsing as search: The parsing directed B-hypergraph




[Klein and Manning 2001]

# 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 $\delta(X,i,j)$
  - Records the best score of a parse of X over [i,j]
    - If the scores are negative log probabilities, then entries start at $\infty$ 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 $\delta(X,i,i)$ = lex.score(w,t)

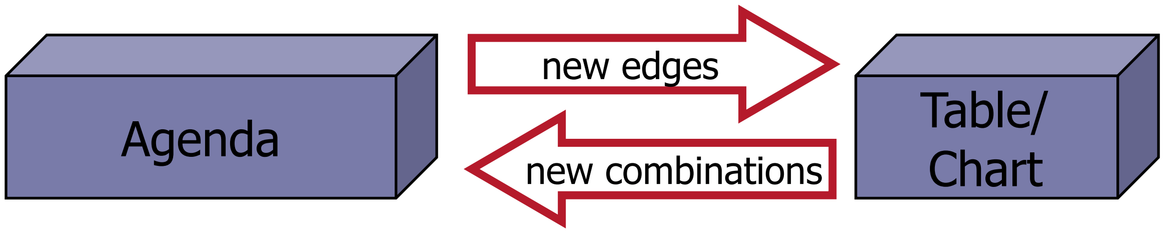
# Agenda-based parsing

- Keep a list of edges called an agenda
  - Edges are triples [X,i,j]
  - The agenda is a priority queue

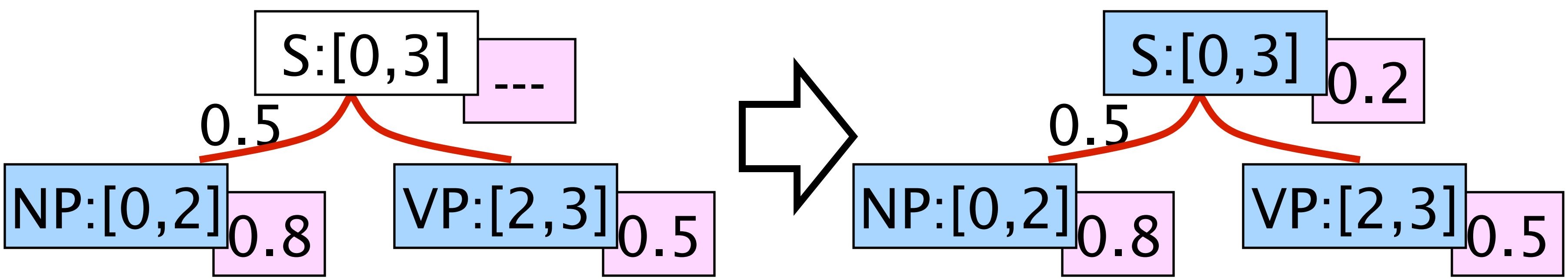
- Every time the score of some $\delta(X,i,j)$ improves (i.e. gets lower):
  - Stick the edge [X,i,j]-score into the agenda
  - (Update the backtrace for $\delta(X,i,j)$ if your storing them)

# 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?

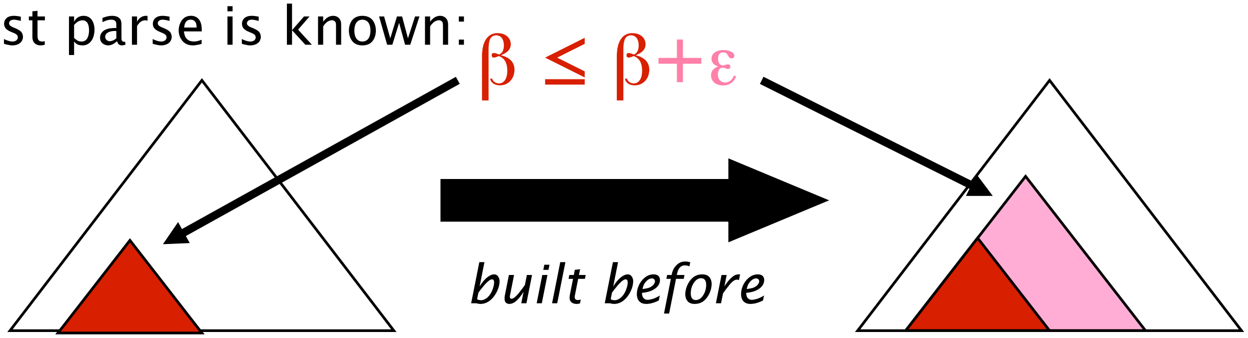
# Agenda-based parsing

- 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 $\delta(X,i,j)$ 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]

# Uniform-Cost Parsing

- We want to work on good parses inside-out.
  - CKY does this synchronously, by tiers.
  - Uniform-cost does it asynchronously, ordering edges by their best known parse score.
- Why best parse is known:




  - Adding structure incurs probability cost.
  - Trees have lower probability than their sub-parts.
  - The best-scored edge in the agenda cannot be waiting on any of its sub-edges.
  - We never have to propagate. We don’t explore truly useless edges.

# Example of uniform cost search vs. CKY parsing: The grammar, lexicon, and sentence

- S → NP VP %% 0.9
- S → VP %% 0.1
- VP → V NP %% 0.6
- VP → V %% 0.4
- NP → NP NP %% 0.3
- NP → N %% 0.7

- N → people %% 0.8
- N → fish %% 0.1
- N → tanks %% 0.1
- V → people %% 0.1
- V → fish %% 0.6
- V → tanks %% 0.3

- *people fish tanks*

# Example of uniform cost search vs. CKY parsing: CKY vs. order of agenda pops in chart

N[0,1] -> people  %% 0.8  %% [0,1]
V[0,1] -> people  %% 0.1
NP[0,1] -> N[0,1]  %% 0.56
VP[0,1] -> V[0,1]  %% 0.04
S[0,1] -> VP[0,1]  %% 0.004
N[1,2] -> fish  %% 0.1  %% [1,2]
V[1,2] -> fish  %% 0.6
NP[1,2] -> N[1,2]  %% 0.07
VP[1,2] -> V[1,2]  %% 0.24
S[1,2] -> VP[1,2]  %% 0.024
N[2,3] -> tanks  %% 0.1  %% [2,3]
V[2,3] -> fish  %% 0.3
NP[2,3] -> N[2,3]  %% 0.07
VP[2,3] -> V[2,3]  %% 0.12
S[2,3] -> VP[2,3]  %% 0.012
NP[0,2] -> NP[0,1] NP[1,2]  %% 0.01176  %% [0,2]
VP[0,2] -> V[0,1] NP[1,2]  %% 0.0042
S[0,2] -> NP[0,1] VP[1,2]  %% 0.12096
S[0,2] -> VP[0,2]  %% 0.00042
NP[1,3] -> NP[1,2] NP[2,3]  %% 0.00147  %% [1,3]
VP[1,3] -> V[1,2] NP[2,3]  %% 0.0252
S[1,3] -> NP[1,2] VP[2,3]  %% 0.00756
S[1,3] -> VP[1,3]  %% 0.00252
S[0,3] -> NP[0,1] VP[1,3]  %% 0.0127008 %% [0,3] Best
S[0,3] -> NP[0,2] VP[2,3]  %% 0.0021168
VP[0,3] -> V[0,1] NP[1,3]  %% 0.0000882
NP[0,3] -> NP[0,1] NP[1,3]  %% 0.00024696
NP[0,3] -> NP[0,2] NP[2,3]  %% 0.00024696
S[0,3] -> VP[0,3]  %% 0.00000882

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NP[1,3] -> NP[1,2] NP[2,3]  %% 0.00147
NP[0,3] -> NP[0,2] NP[2,3]  %% 0.00024696

# What can go wrong?

- We can build too many edges.
  - Most edges that can be built, shouldn't.
  - CKY builds them all!

Speed: build promising edges first.

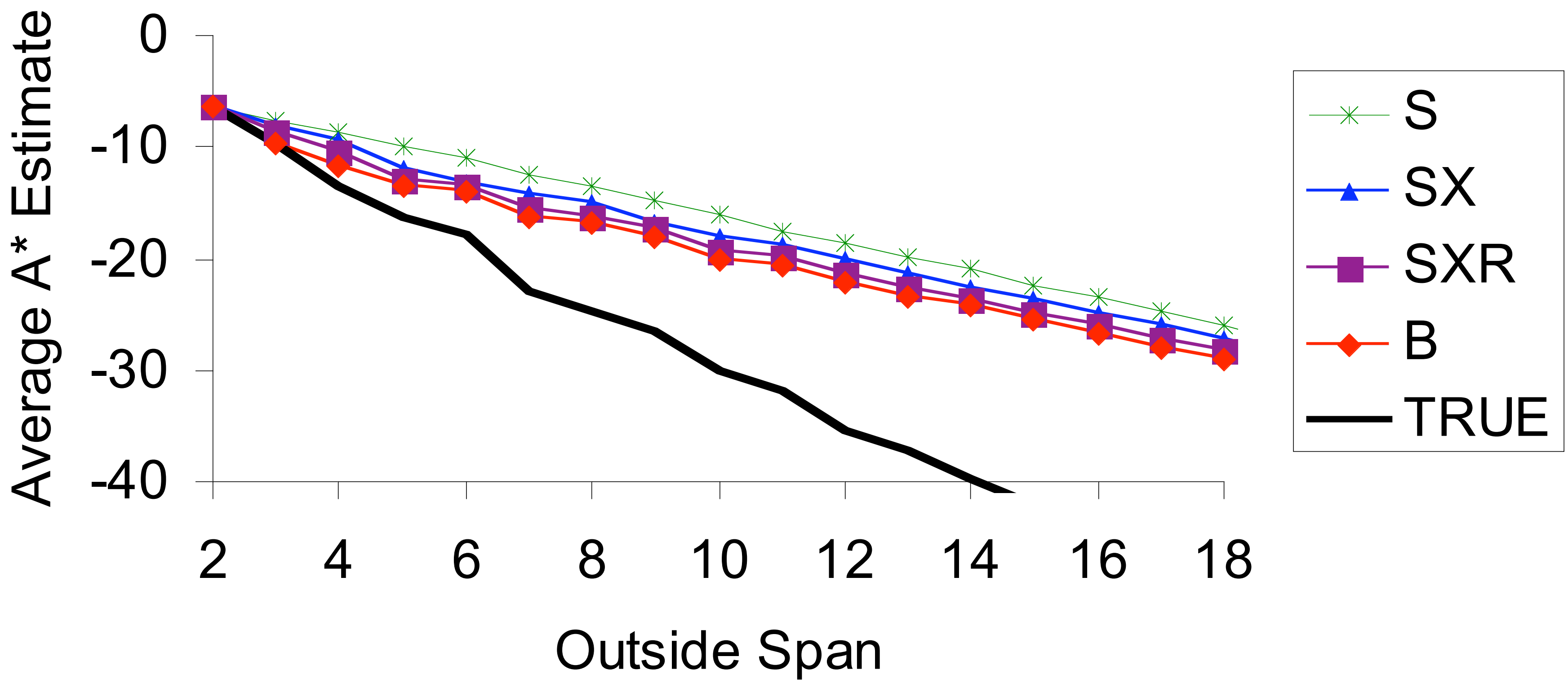
- We can build in an bad order.
  - Might find bad parses for parse item before good parses.
  - Will trigger best-first propagation.

Correctness: keep edges on the agenda until you're sure you've seen their best parse.

# Speeding up agenda-based parsers

- Two options for doing less work
  - The optimal way: A* parsing
    - Klein and Manning (2003)
  - The ugly but much more practical way: "best-first" parsing
    - Caraballo and Charniak (1998)
    - Charniak, Johnson, and Goldwater (1998)

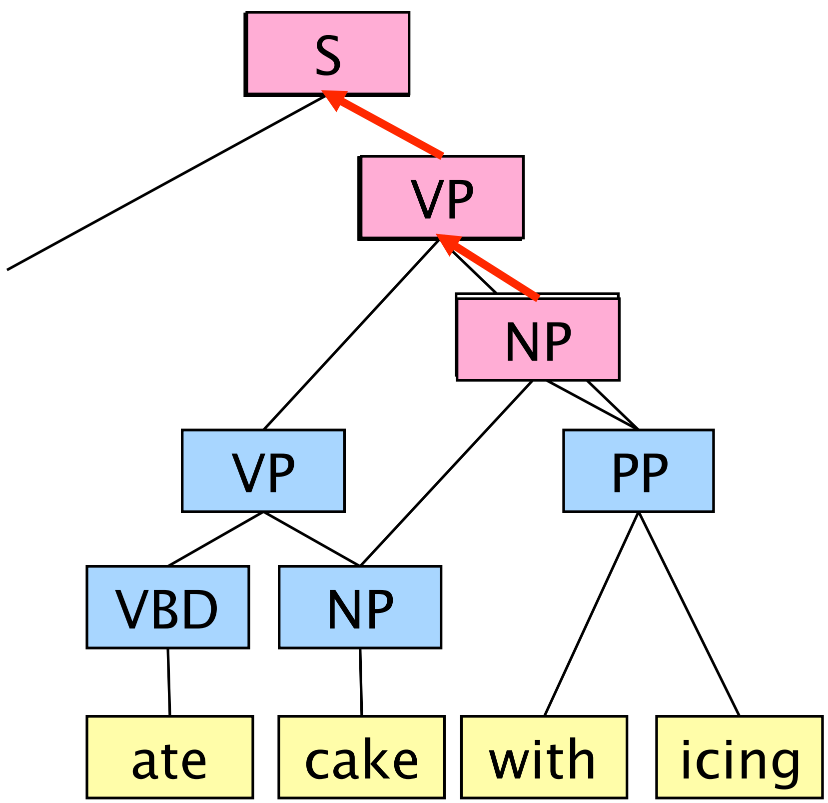
# A* Context Summary Sharpness




Adding local information changes the intercept, but not the slope!

# Best-First Parsing

- In best-first, parsing, we visit edges according a figure-of-merit (FOM).




- A good FOM focuses work on “quality” edges.
  - The good: leads to full parses quickly.
  - The (potential) bad: leads to non-MAP parses.
  - The ugly: propagation
    - If we find a better way to build a parse item, we need to rebuild everything above it
  - In practice, works well!

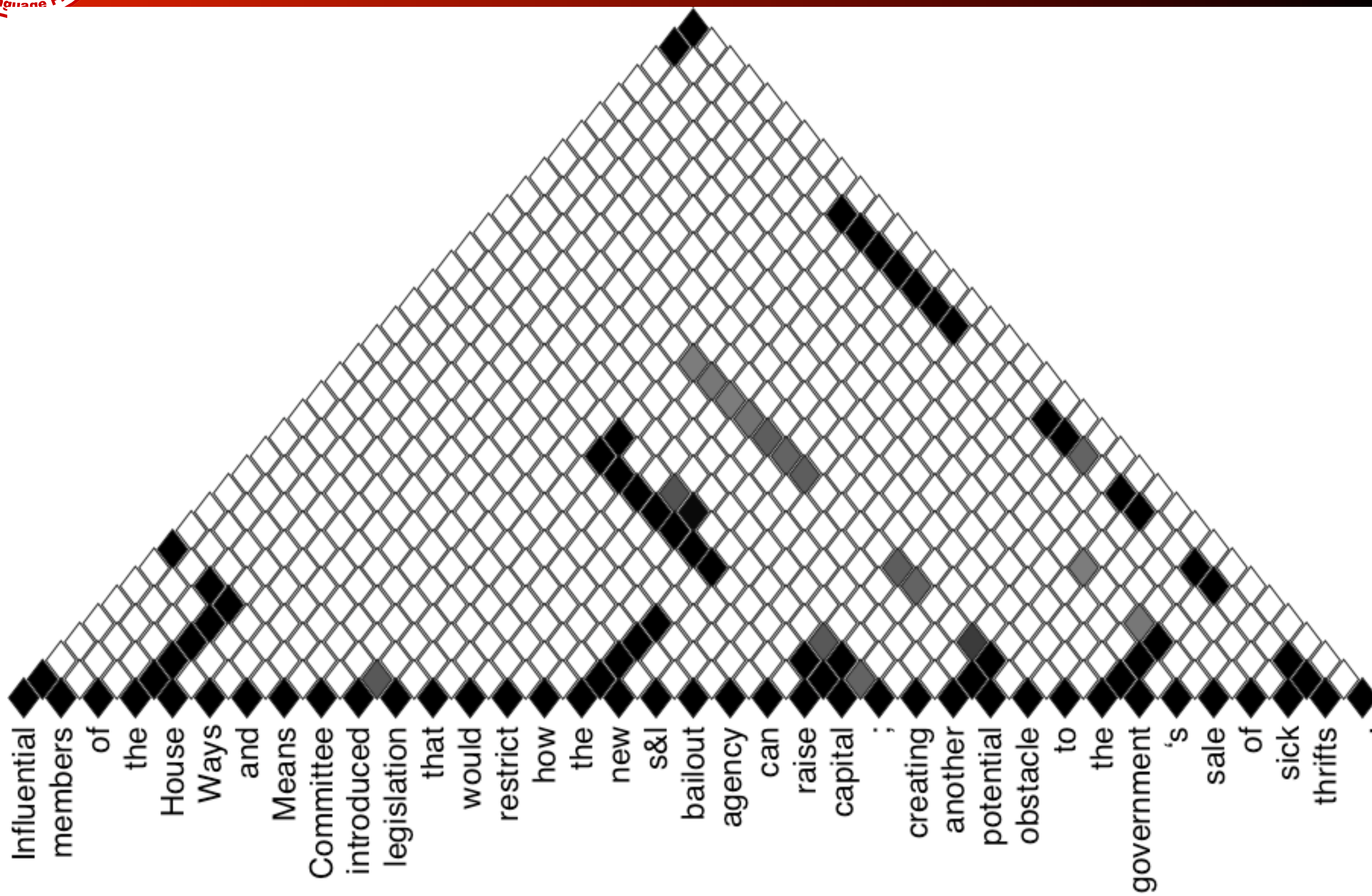
# Search in modern lexicalized statistical parsers

- Klein and Manning (2003b) do optimal A* search
  - Done in a restricted space of lexicalized PCFGs that "factors", allowing very efficient A* search
- Collins (1999) exploits both the ideas of beams and agenda based parsing
  - He places a separate beam over each span, and then, roughly, does uniform cost search
- Charniak (2000) uses inadmissible heuristics to guide search
  - He uses very good (but inadmissible) heuristics – "best first search" – to find good parses quickly
  - Perhaps unsurprisingly this is the fastest of the 3.

# Coarse-to-fine parsing

- Uses grammar projections to guide search
    - VP-VBF, VP-VBG, VP-U-VBN, … → VP
    - VP[*buys*/VBZ], VP[*drive*/VB], VP[*drive*/VBP], … → VP
  - You can parse much more quickly with a simple grammar because the grammar constant is way smaller
  - You restrict the search of the expensive refined model to explore only spans and/or spans with compatible labels that the simple grammar liked
- Very successfully used in several recent parsers
  - Charniak and Johnson (2005)
  - Petrov and Klein (2007)

# Coarse-to-fine parsing: A visualization of the span posterior probabilities from Petrov and Klein 2007

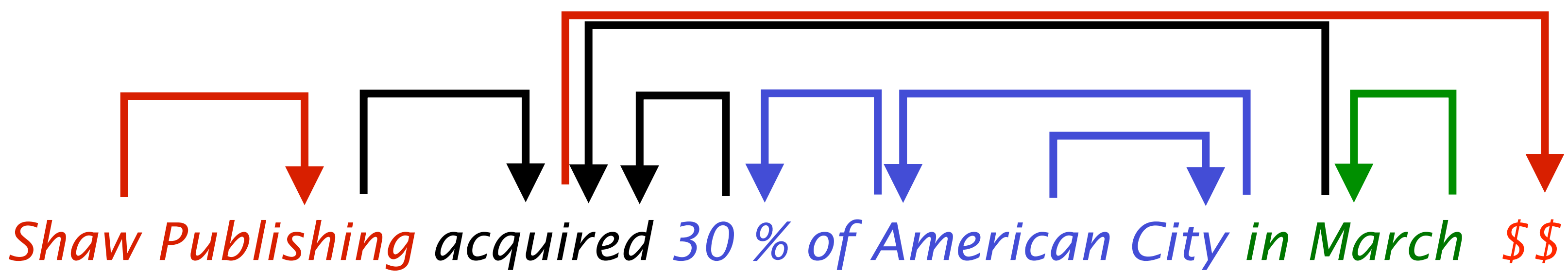


# Dependency parsing

# Dependency Grammar/Parsing

- A sentence is parsed by relating each word to other words in the sentence which depend on it.
- The idea of dependency structure goes back a long way
  - To Pāṇini's grammar (c. 5th century BCE)
- Constituency is a new-fangled invention
  - 20th century invention
- Modern work often linked to work of L. Tesniere (1959)
  - Dominant approach in "East" (Russia, China, …)
  - Basic approach of 1$^{st}$ millenium Arabic grammarians
- Among the earliest kinds of parsers in NLP, even in US:
  - David Hays, one of the founders of computational linguistics, built early (first?) dependency parser (Hays 1962)

# Dependency structure

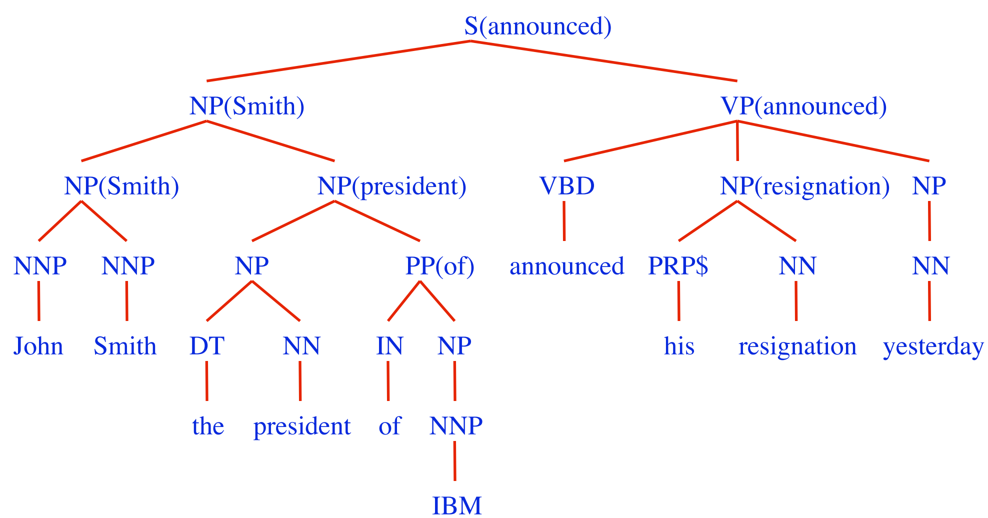



- Words are linked from head (regent) to dependent
- Warning! Some people do the arrows one way; some the other way (Tesniere has them point from head to dependent…).
- Usually add a fake ROOT so every word is a dependent

# Relation between CFG to dependency parse

- A dependency grammar has a notion of a head
- Officially, CFGs don't
- But modern linguistic theory and all modern statistical parsers (Charniak, Collins, Stanford, …) do, via hand-written phrasal "head rules":
  - The head of a Noun Phrase is a noun/number/adj/…
  - The head of a Verb Phrase is a verb/modal/….
- The head rules can be used to extract a dependency parse from a CFG parse (follow the heads).
- A phrase structure tree can be got from a dependency tree, but dependents are flat (no VP!)

# Propagating head words

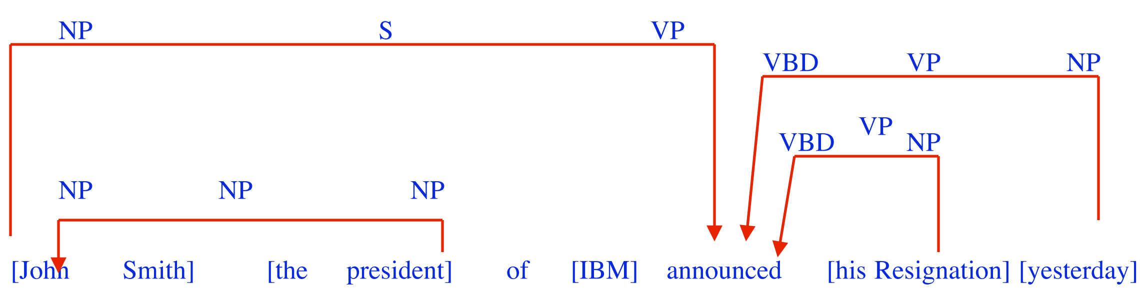



- Small set of rules propagate heads

# Extracted structure

**NB.** Not all dependencies shown here

- Dependencies are inherently untyped, though some work like Collins (1996) types them using the phrasal categories



# Dependency Conditioning Preferences

Sources of information:

- bilexical dependencies
- distance of dependencies
- valency of heads (number of dependents)

A word's **dependents** (adjuncts, arguments)

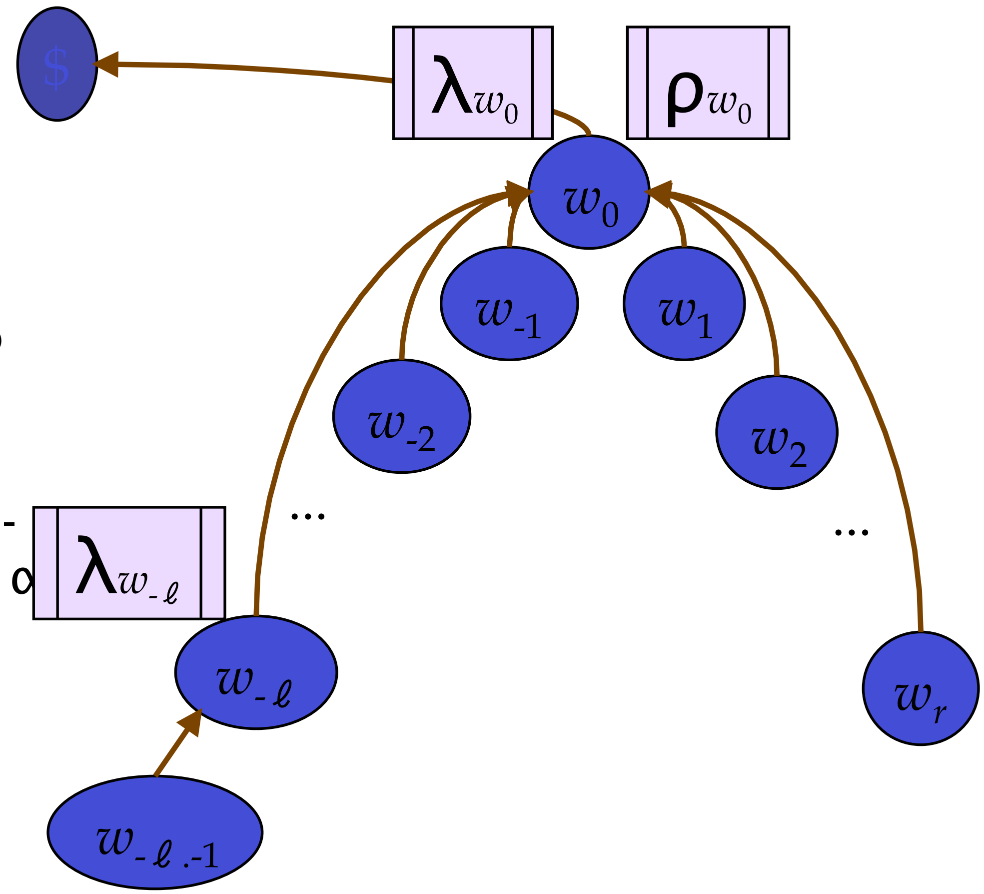
tend to fall **near** it

in the string.

These next 6 slides are based on slides by Jason Eisner and Noah Smith

# Probabilistic dependency grammar: generative model

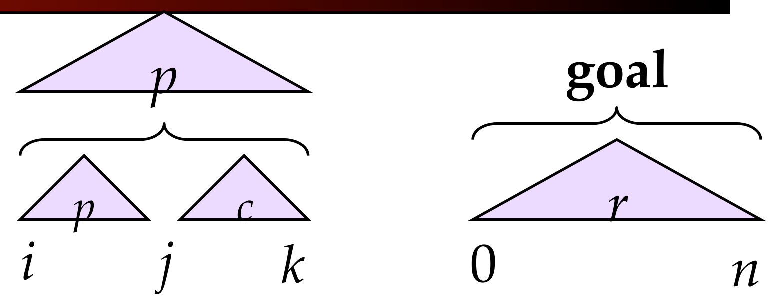
1. Start with left wall \$
2. Generate root $w_0$
3. Generate left children $w_{-1}$, $w_{-2}$, ..., $w_{-\ell}$ from the FSA $\lambda_{w_0}$
4. Generate right children $w_1$, $w_2$, ..., $w_r$ from the FSA $\rho_{w_0}$
5. Recurse on each $w_i$ for $i$ in $\{-\ell, ..., -1, 1, ..., r\}$, sampling $\alpha_i$ (steps 2-4)
6. Return $\alpha_{\ell} \ldots \alpha_{-1} w_0 \alpha_1 \ldots \alpha_r$

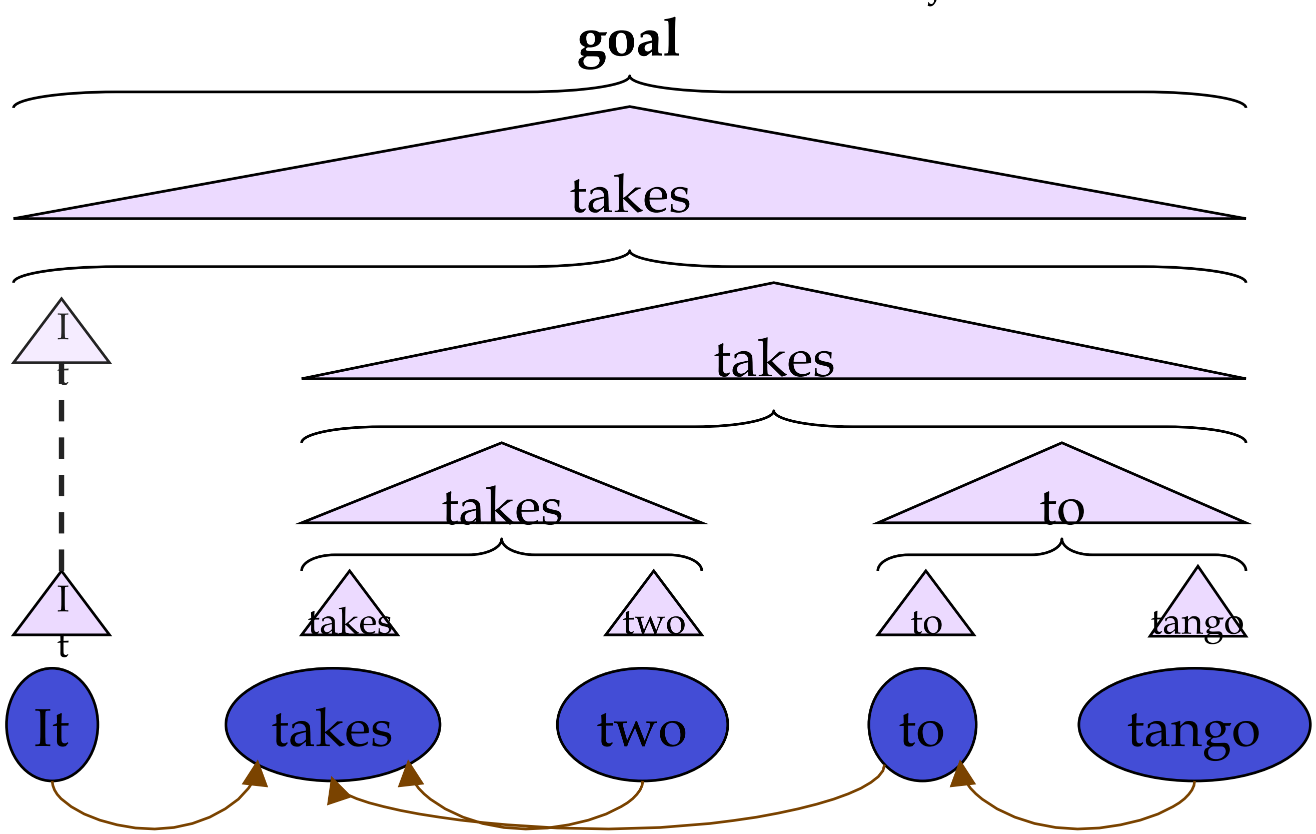


# Naïve Recognition/Parsing

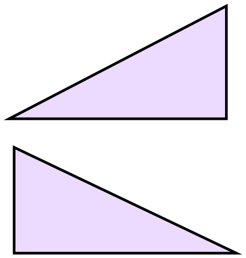
$O(n^5N^3)$ if $N$ nonterminals

$O(n^5)$ combinations

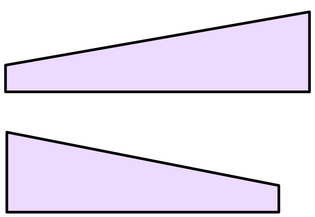


# Dependency Grammar Cubic Recognition/ Parsing (Eisner & Satta, 1999)

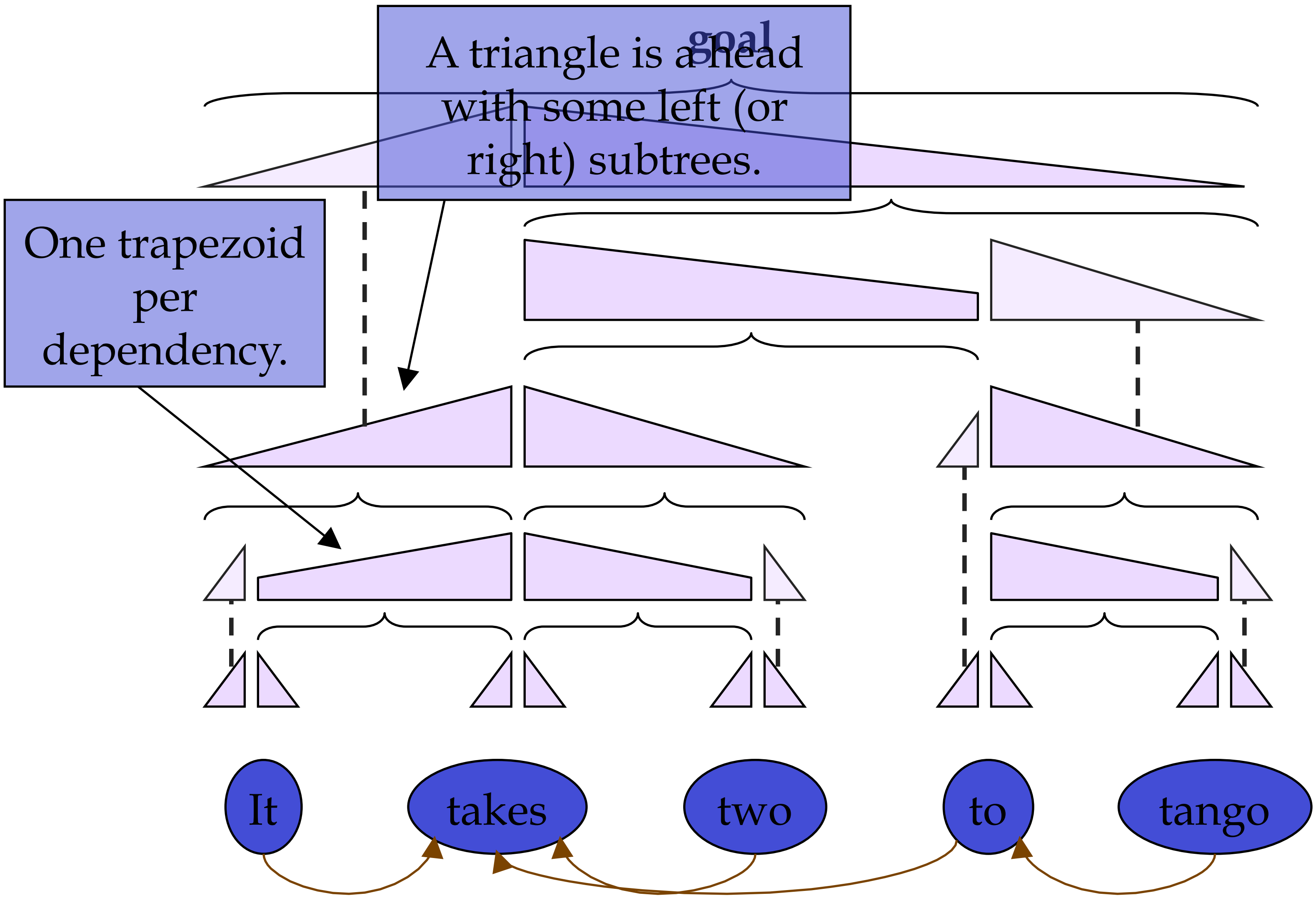


- ***Triangles***: span over words, where tall side of triangle is the head, other side is dependent, and no non-head words expecting more dependents



- ***Trapezoids***: span over words, where larger side is head, smaller side is dependent, and smaller side is still looking for dependents on its side of the trapezoid

# Dependency Grammar Cubic Recognition/ Parsing (Eisner & Satta, 1999)

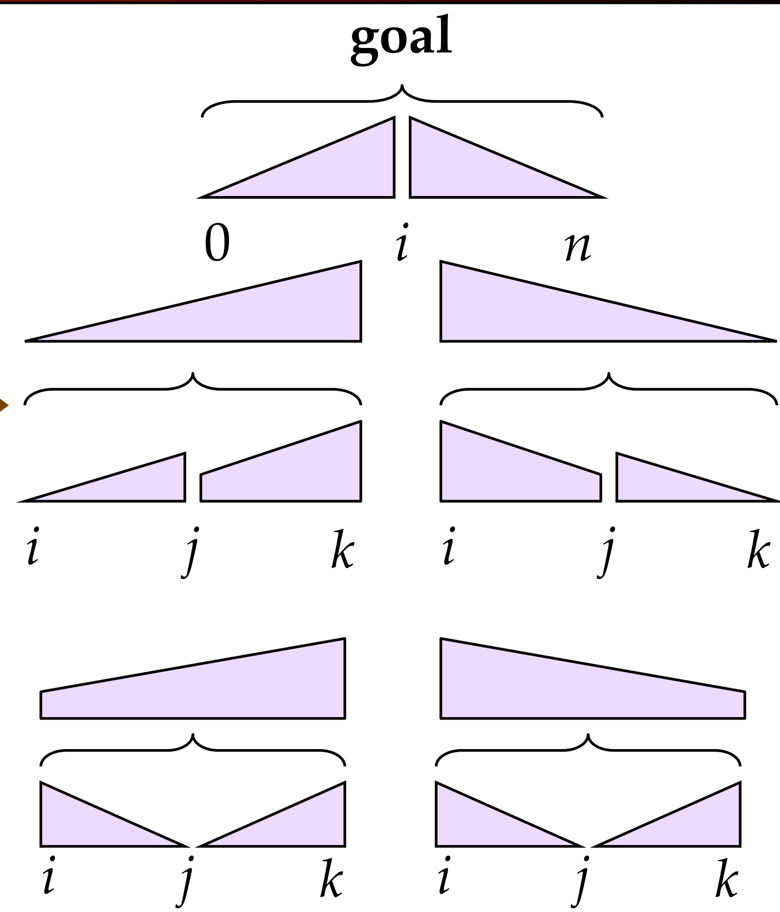


# Cubic Recognition/Parsing (Eisner & Satta, 1999)

$O(n)$ combinations

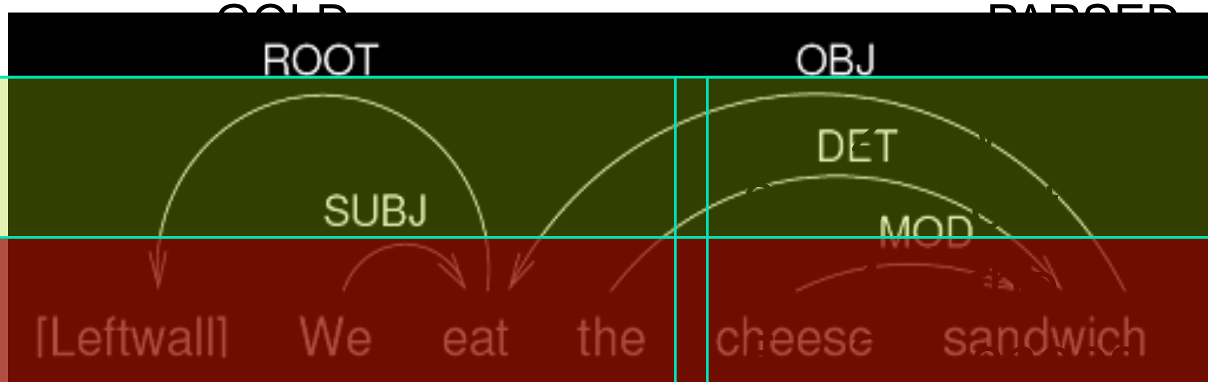
$O(n^3)$ combinations

$O(n^3)$ combinations




Gives $O(n^3)$ dependency grammar parsing

# Evaluation of Dependency Parsing: Simply use (labeled) dependency accuracy




1 2 3 4 5

| | | | |
|---|---|---|---|
| | | | SUBJ |
| | | | ROOT |
| | | | DET |
| | | | OBJ |
| 6 | 2 | sandwich | PRED |

| | | | |
|---|---|---|---|
| 1 | 2 | We | SUBJ |
| 3 | 0 | eat | ROOT |
| 4 | 5 | the | DET |
| 5 | 5 | cheese | MOD |
| 6 | 2 | sandwich | SUBJ |

$$\text{Accuracy} = \frac{\text{number of correct dependencies}}{\text{total number of dependencies}}$$

$= 2 / 5 = 0.40$

40%

# McDonald et al. (2005 ACL):

## Online Large-Margin Training of Dependency Parsers

- Builds a discriminative dependency parser
- Can condition on rich features in that context
  - Best-known recent dependency parser
  - Lots of recent dependency parsing activity connected with CoNLL 2006/2007 shared task
- Doesn’t/can’t report constituent LP/LR, but evaluating dependencies correct:
  - Accuracy is similar to but a fraction below dependencies extracted from Collins:
    - 90.9% vs. 91.4% … combining them gives 92.2% [all lengths]
    - Stanford parser on length up to 40:
      - Pure generative dependency model: 85.0%
      - Lexicalized factored parser: 91.0%

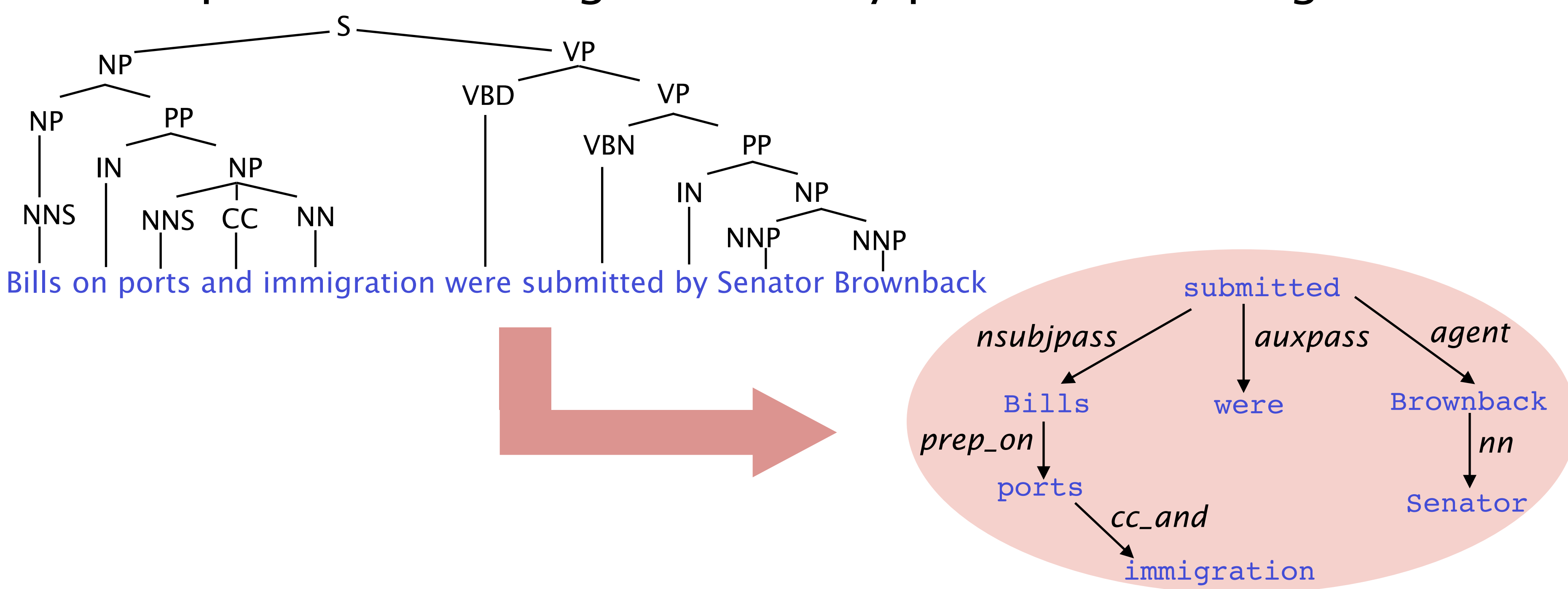
# McDonald et al. (2005 ACL):
## Online Large-Margin Training of Dependency Parsers

- Score of a parse is the sum of the scores of its dependencies
- Each dependency is a linear function of features times weights
- Feature weights are learned by MIRA, an online large-margin algorithm
  - But you could think of it as using a perceptron or maxent classifier
- Features cover:
  - Head and dependent word and POS separately
  - Head and dependent word and POS bigram features
  - Words between head and dependent
  - Length and direction of dependency

# Extracting grammatical relations from statistical constituency parsers

[de Marneffe et al. LREC 2006]

- Exploit the high-quality syntactic analysis done by statistical constituency parsers to get the grammatical relations [typed dependencies]
- Dependencies are generated by pattern-matching rules



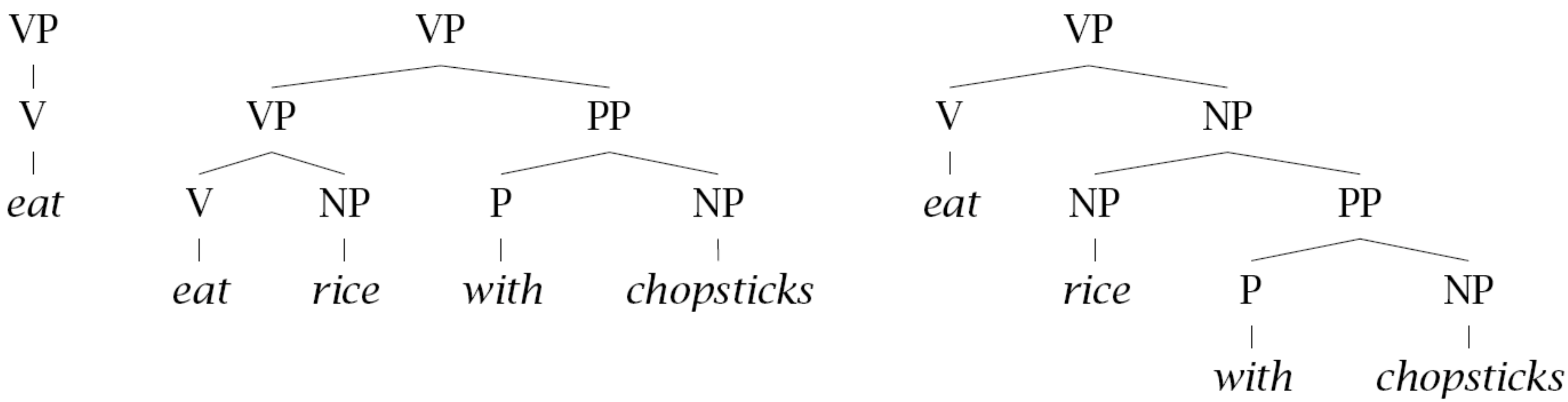
# Discriminative Parsing

# Discriminative Parsing as a classification problem

- Classification problem
  - Given a training set of iid samples $T=\{(X_1,Y_1) \ldots (X_n,Y_n)\}$ of input and class variables from an unknown distribution D(X,Y), estimate a function $\hat{h}(X)$ that predicts the class from the input variables
- The observed X's are the sentences.
- The class Y of a sentence is its parse tree
- The model has a large (infinite!) space of classes, but we can still assign them probabilities
  - The way we can do this is by breaking whole parse trees into component parts

1. Distribution-free methods
2. Probabilistic model methods

# Motivating discriminative estimation (1)




100 6 2

A training corpus of 108 (imperative) sentences.

Based on an example by Mark Johnson

# Motivating discriminative estimation (2)

- In discriminative models, it is easy to incorporate different kinds of features
  - Often just about anything that seems linguistically interesting
- In generative models, it's often difficult, and the model suffers because of false independence assumptions

- This ability to add informative features is the real power of discriminative models for NLP.
  - Can still do it for parsing, though it's trickier.

# Discriminative Parsers

- Discriminative Dependency Parsing
  - Not as computationally hard (tiny grammar constant)
  - Explored considerably recently. E.g. McDonald et al. 2005
- Make parser action decisions discriminatively
  - E.g. with a shift-reduce parser
- Dynamic-programmed Phrase Structure Parsing
  - Resource intensive! Most work on sentences of length <=15
  - The need to be able to dynamic program limits the feature types you can use
- Post-Processing: Parse reranking
  - Just work with output of k-best generative parser

# Discriminative models

Shift-reduce parser Ratnaparkhi (98)

- Learns a distribution P(T|S) of parse trees given sentences using the sequence of actions of a shift-reduce parser

$$P(T \mid S) = \prod_{i=1}^{n} P(a_i \mid a_1 \ldots a_{i-1} S)$$

- Uses a maximum entropy model to learn conditional distribution of parse action given history
- Suffers from independence assumptions that actions are independent of future observations as with CMM/MEMM
- Higher parameter estimation cost to learn local maximum entropy models
- **Lower** but still good accuracy: 86% - 87% labeled precision/recall

# Discriminative dynamic-programmed parsers

- Taskar et al. (2004 EMNLP) show how to do joint discriminative SVM-style ("max margin) parsing building a phrase structure tree also conditioned on words in O($n^3$) time
  - In practice, totally impractically slow. Results were never demonstrated on sentences longer than 15 words
- Turian et al. (2006 NIPS) do a decision-tree based discriminative parser
- Research continues….
  - Finkel, Kleeman, and Manning (2008 ACL) feature-based parser is just about practical.
    - We do parse long sentences

# Discriminative Models – Distribution Free Re-ranking (Collins 2000)

- Represent sentence-parse tree pairs by a feature vector F(X,Y)
- Learn a linear ranking model with parameters $\overline{\alpha}$ using the boosting loss

| Model | LP | LR |
|---|---|---|
| Collins 99 (Generative) | 88.3% | 88.1% |
| Collins 00 (BoostLoss) | 89.9% | 89.6% |

**13%** error reduction

Still very close in accuracy to generative model [Charniak 2000]

# Charniak and Johnson (2005 ACL):

## Coarse-to-fine *n*-best parsing and MaxEnt discriminative reranking

- Builds a maxent discriminative reranker over parses produced by (a slightly bugfixed and improved version of) Charniak (2000).
- Gets 50 best parses from Charniak (2000) parser
  - Doing this exploits the “coarse-to-fine” idea to heuristically find good candidates
- Maxent model for reranking uses heads, etc. as generative model, but also nice linguistic features:
  - Conjunct parallelism
  - Right branching preference
  - Heaviness (length) of constituents factored in
- Gets 91% LP/LR F1 (on *all* sentences! – up to 80 wd)