Natural Language Dependency Parsing

SPFLODD

October 13, 2011

Quick Review from Tuesday

- What are CFGs? PCFGs? Weighted CFGs?
- Statistical parsing using the Penn Treebank
  - What it looks like
  - How to build a simple treebank (P)CFG
  - How to evaluate your treebank parser
- Weighted CFG parsing algorithms
  - CKY
  - Earley's algorithm
- Decorating the treebank: parent annotation, heads, lexicalization
- The Collins parser

Some Famous Parsers

(Review from Tuesday)

Collins Model 1 (1997)

- Trees are headed and lexicalized
  - What's the difference?

- Huge number of rules!

$VP_{saw} \rightarrow \underline{V}_{saw}\ NP_{man}\ PP_{through}$

$VP_{saw} \rightarrow \underline{V}_{saw}\ NP_{man}\ PP_{with}$

$VP_{saw} \rightarrow \underline{V}_{saw}\ NP_{woman}\ PP_{through}$

$VP_{saw} \rightarrow \underline{V}_{saw}\ NP_{man}$

- Key: factor probabilities within rule.

(REVIEW FROM TUESDAY)

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- Everything factors down to rules, then further. We're given the parent nonterminal and head word.

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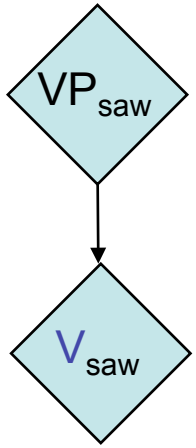
- Randomly generate the head child's nonterminal.



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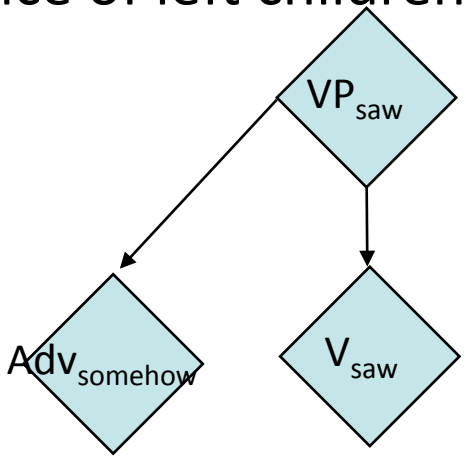

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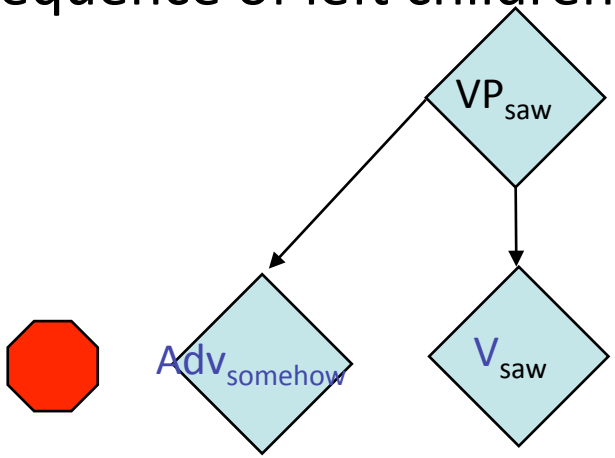

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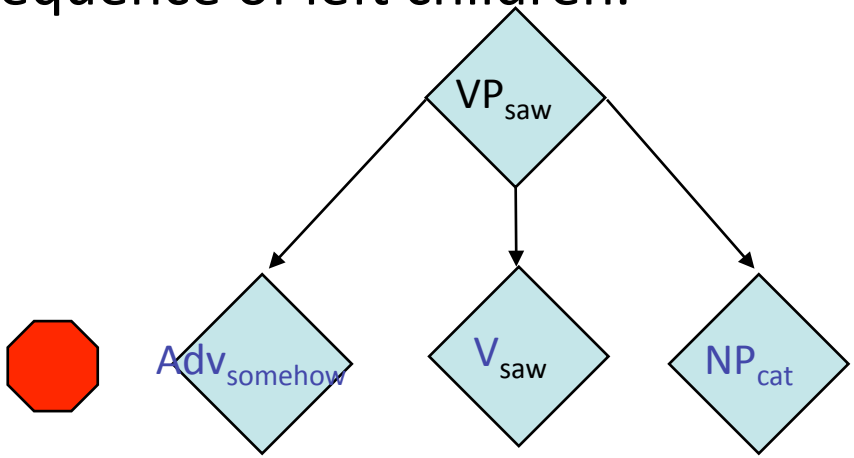

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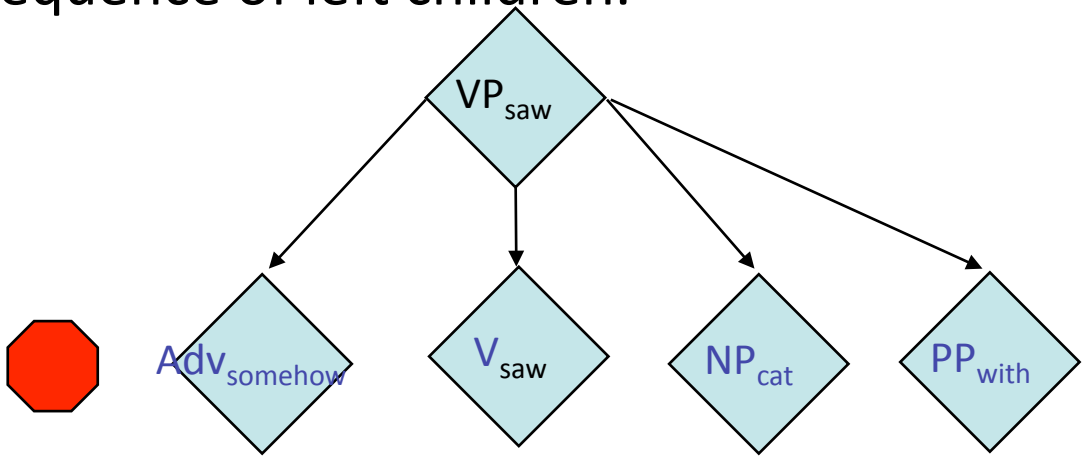

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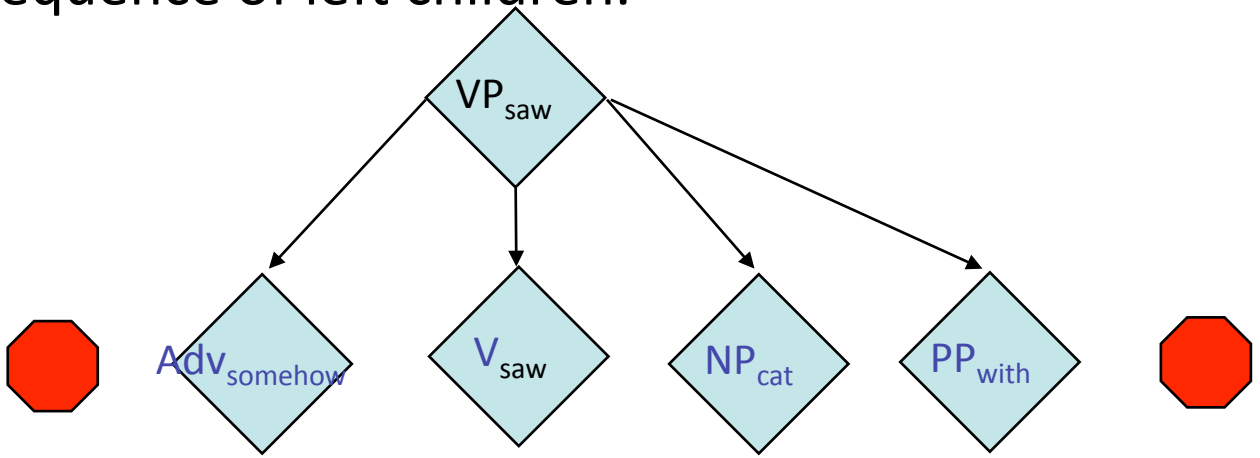

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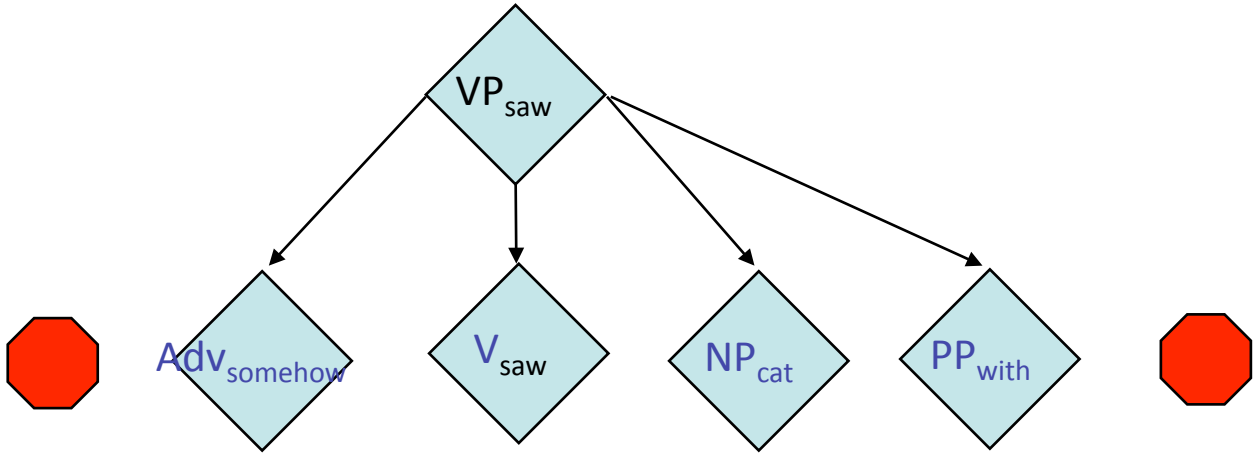
Collins Model 1 (1997)

- Interesting twist: want to model the **distance** between head constituent and child constituent. How?



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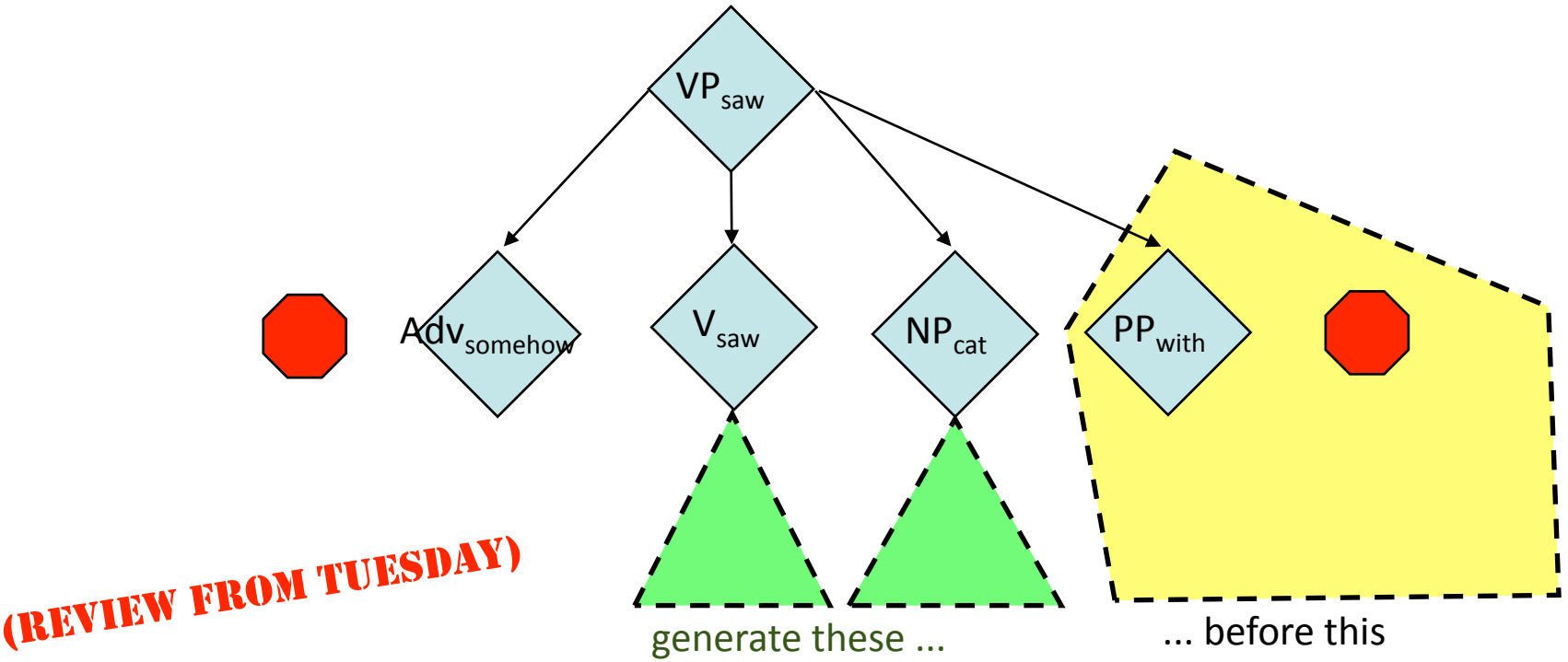

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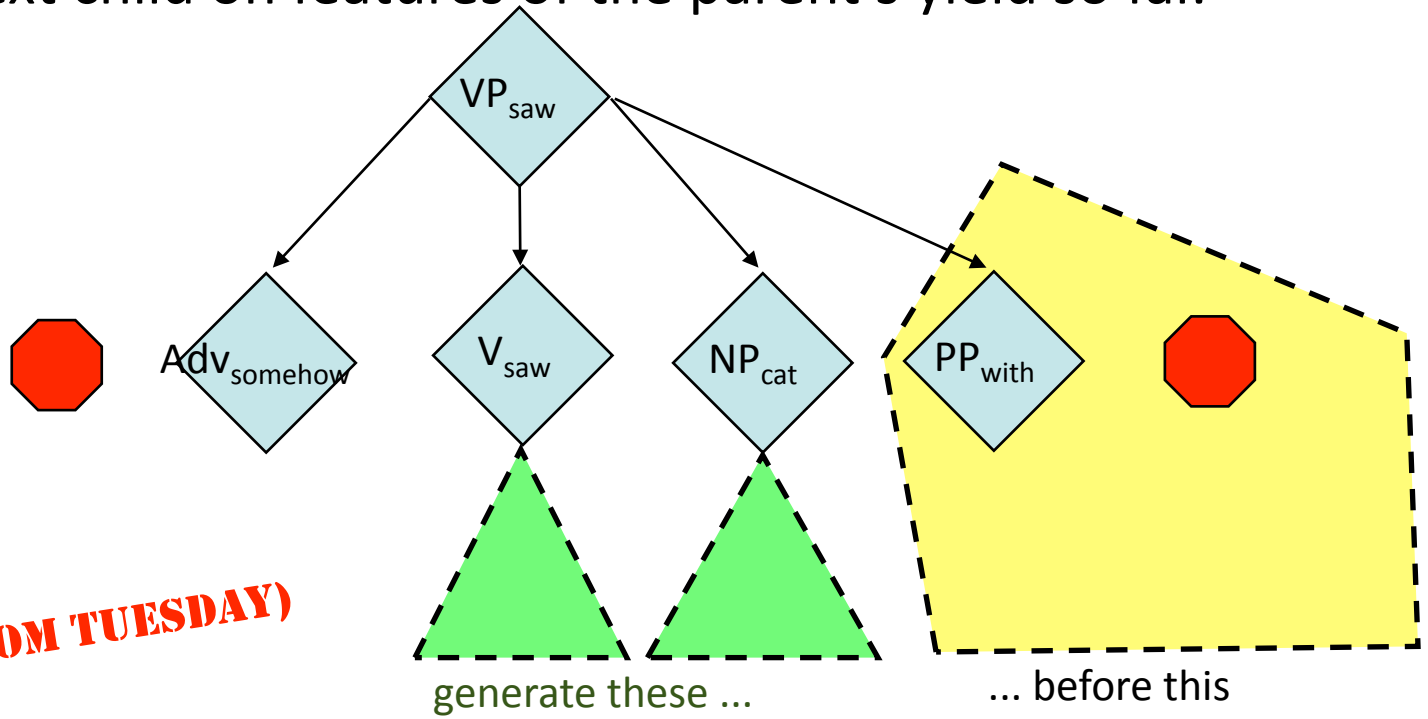
- Condition next child on features of the parent's yield so far.



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- Depth-first recursion.
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$$p(\text{PP}_{\text{with}} \mid \text{VP}_{\text{saw}}, \text{right}, \text{“the cat who liked milk”}) \approx p(\text{PP}_{\text{with}} \mid \text{VP}_{\text{saw}}, \text{right}, \text{length} > 0, +\text{verb})$$

$$\begin{aligned} & p(L_n, u_n, L_{n-1}, u_{n-1}, ..., L_1, u_1, H, w, R_1, v_1, R_2, v_2, ..., R_m, v_m \mid P, w) \\ = \; & p(H \mid P, w) \\ & \cdot \prod_{i=1}^{n} p(L_i, u_i \mid P, w, H, \text{left}, \Delta_i) \\ & \cdot p(\text{stop} \mid P, w, H, \text{left}, \Delta_{n+1}) \\ & \cdot \prod_{i=1}^{m} p(R_i, v_i \mid P, w, H, \text{right}, \Delta'_i) \\ & \cdot p(\text{stop} \mid P, w, H, \text{right}, \Delta'_{n+1}) \end{aligned}$$

(REVIEW FROM TUESDAY)

Charniak (1997) - in brief

- Generally similar to Collins
- Key differences:
  - Used an additional 30 million words of unparsed text in training
  - Rules not fully markovized: pick full nonterminal sequence, then lexicalize each child independently

Charniak (1997) - in brief

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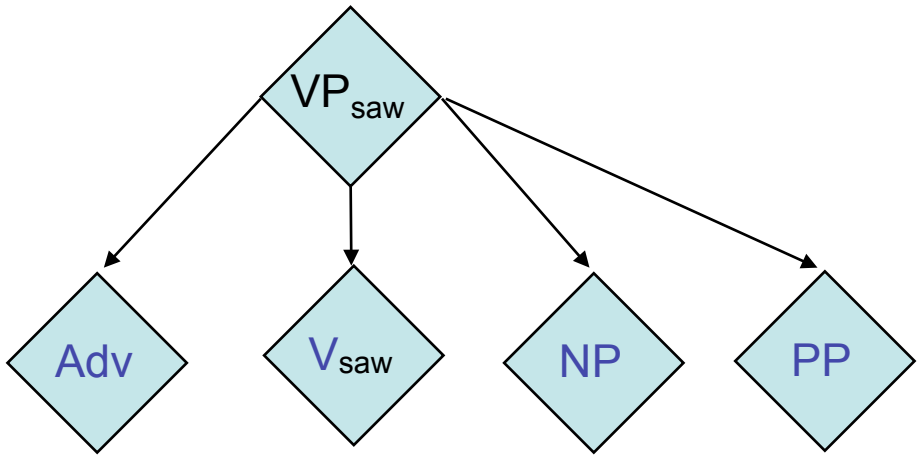
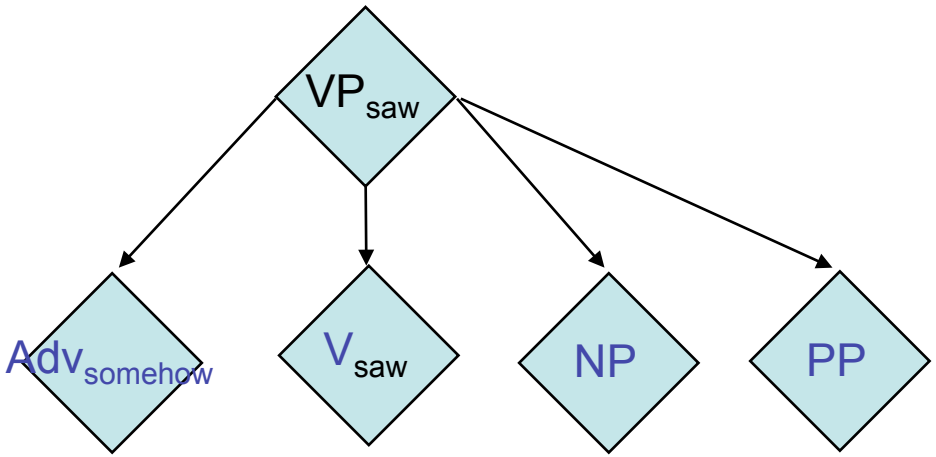
$VP_{saw} \rightarrow Adv \underline{V} NP PP$



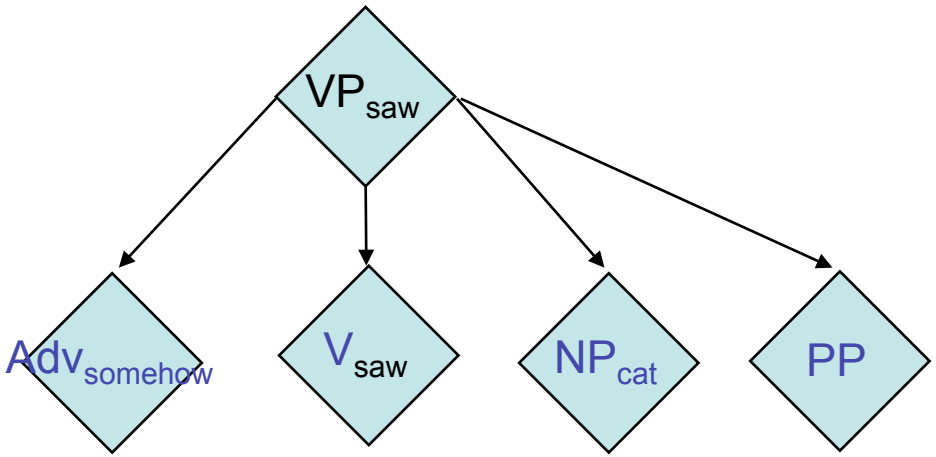
Charniak (1997) - in brief

p(somehow | VP_{saw}, Adv)



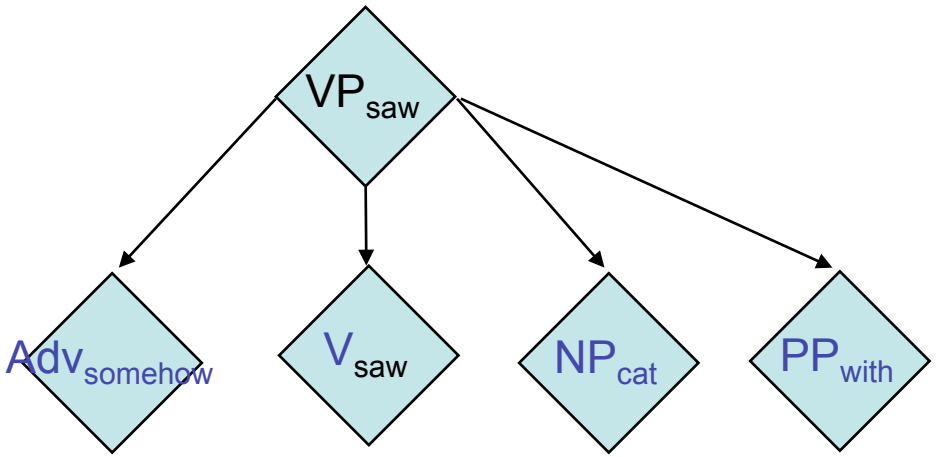
Charniak (1997) - in brief

$p(\text{cat} \mid VP_{saw}, NP)$



Charniak (1997) - in brief

p(with | VP_{saw}, PP)



Charniak (2000)

- Uses grandparents (Johnson ’98 transformation)
- Markovized children (like Collins)
- Bizarre probability model:
  - Smoothed estimates at many backoff levels
  - Multiply them together
  - “Maximum entropy inspired”
  - Kind of a product of experts (untrained)

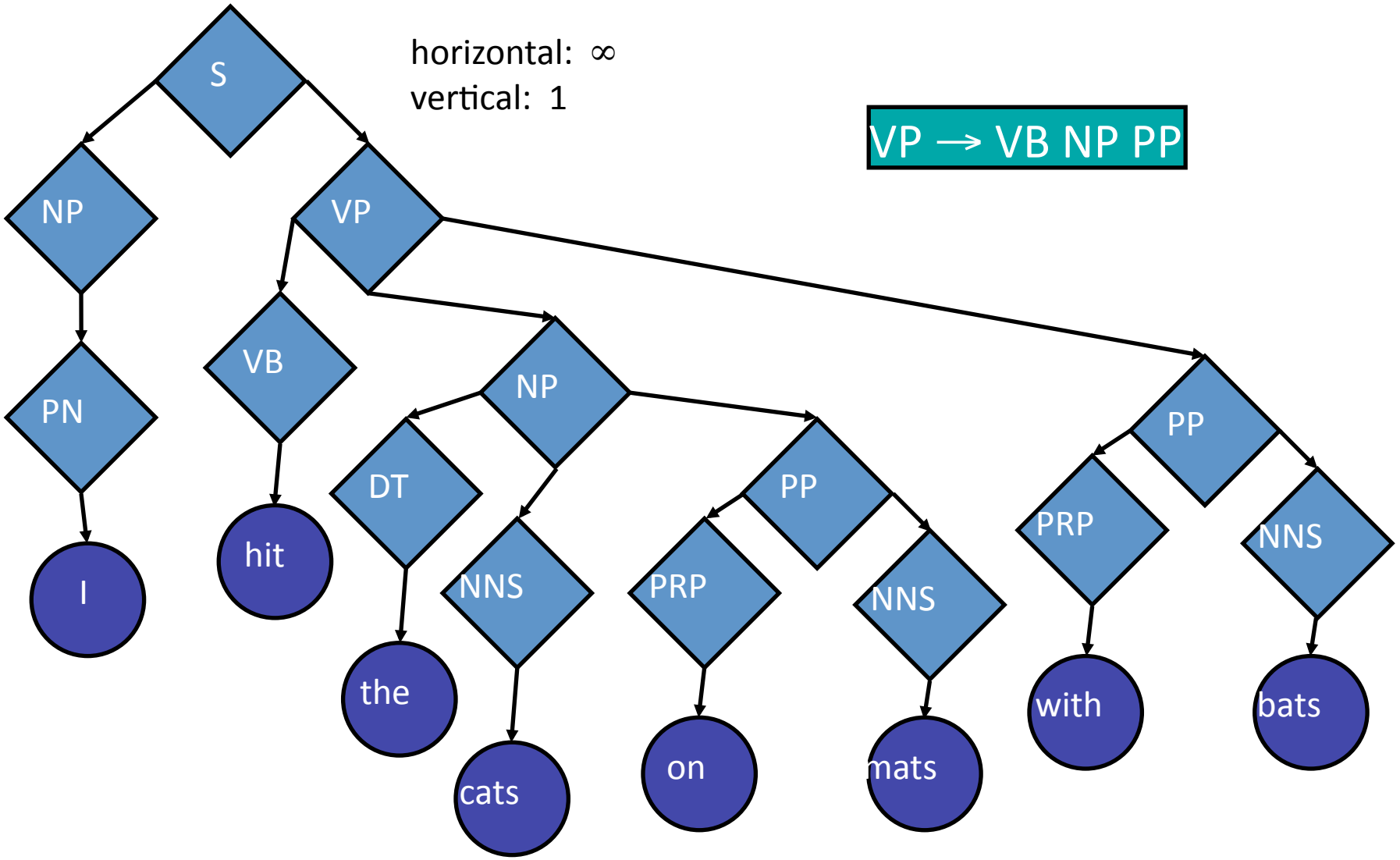
Comparison

		labeled recall	labeled precision	average crossing brackets
Collins	Model 1	87.5	87.7	1.09
	Model 2	88.1	88.3	1.06
	Model 3	88.0	88.3	1.05
Charniak	1997	86.7	86.6	1.20
	2000	89.6	89.5	0.88

Klein and Manning (2003)

- By now, lexicalization was kind of controversial
  - So many probabilities, such expensive parsing: is it necessary?
- Goal: reasonable unlexicalized baseline
  - What tree transformations make sense?
  - Markovization (what order?)
  - Add all kinds of information to each node in the treebank
- Performance close to Collins model, much better than earlier unlexicalized models

Markovization



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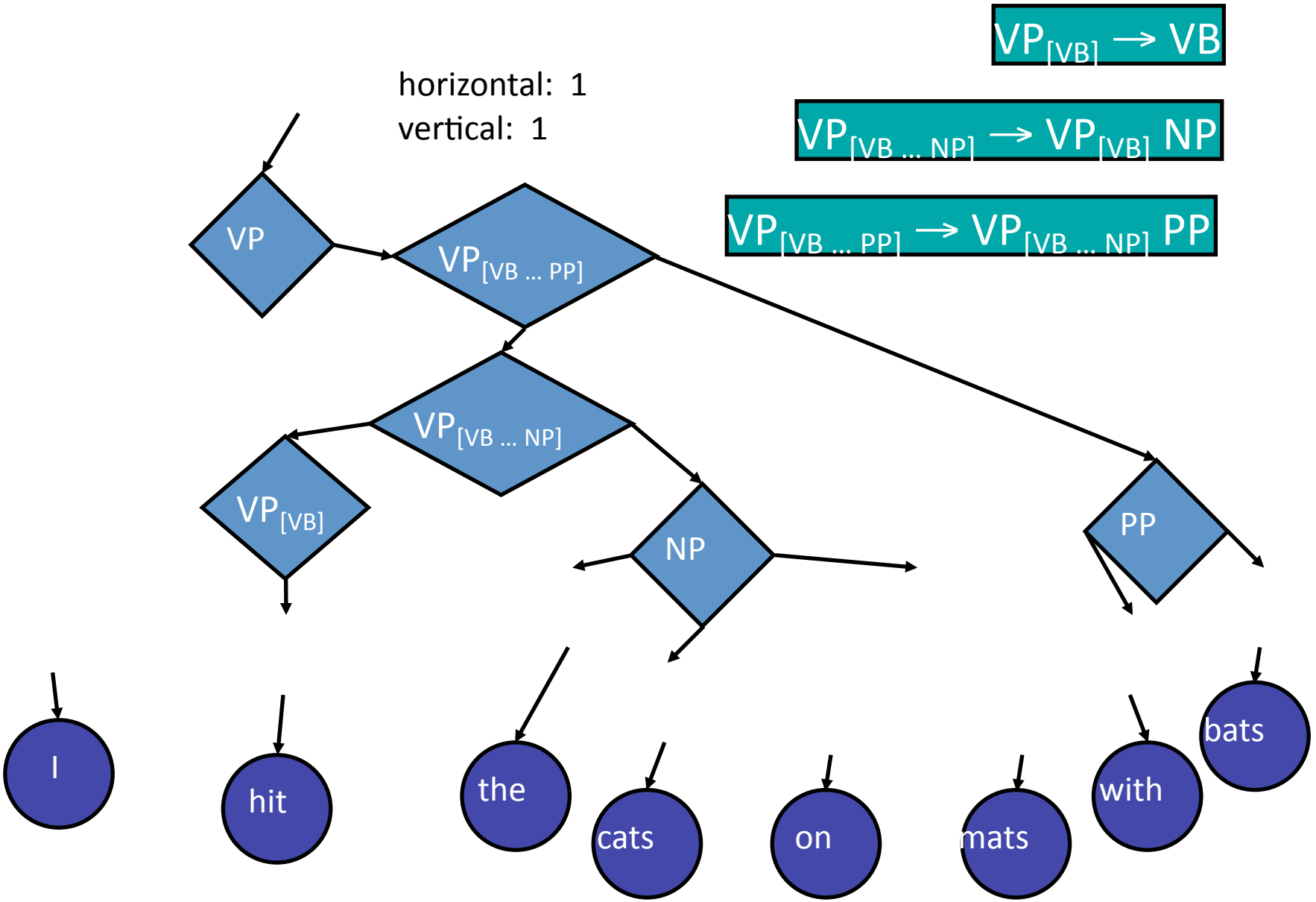

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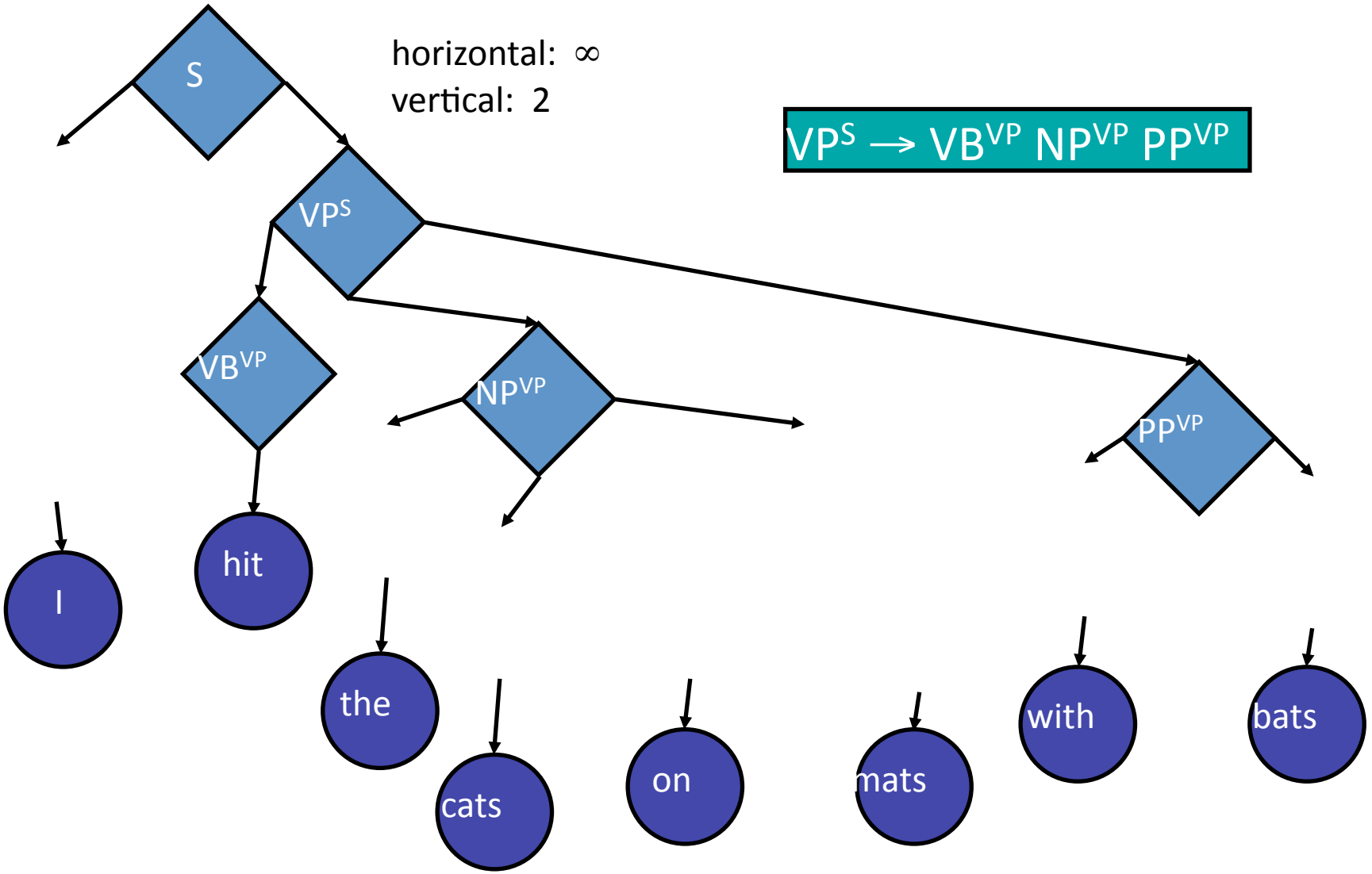

Markovization

- More vertical Markovization is better
  - Consistent with Johnson (1998)
- Horizontal 1 or 2 beats 0 or ∞
- Used (2, 2), but if sparse "back off" to 1

Other Tree Decorations

- Mark nodes with only 1 child as UNARY
- Mark DTs (determiners), RBs (adverbs) when they are only children
- Annotate POS tags with their parents
- Split IN (prepositions; 6 ways), AUX, CC, %
- NPs: temporal, possessive, base
- VPs annotated with head tag (finite vs. others)
- DOMINATES-V
- RIGHT-RECURSIVE NP

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K&M	2003	86.3	85.1	1.31

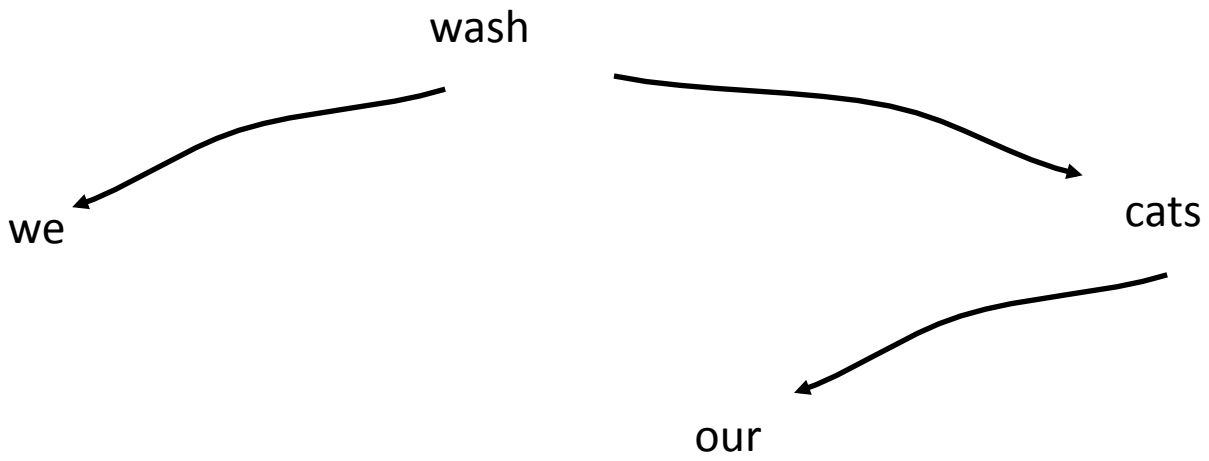
Dependency Parsing

Dependency Grammar

- A variety of theories and formalisms
- Focus on relationship between **words** and their syntactic relationships
- Correlates with study of languages that have free(r) word order (e.g., Czech)
- Lexicalization is central, phrases secondary

- We will talk about **bare bones** dependency trees (Eisner, 1996), then consider adding dependency labels

Bare Bones Dependency Parse



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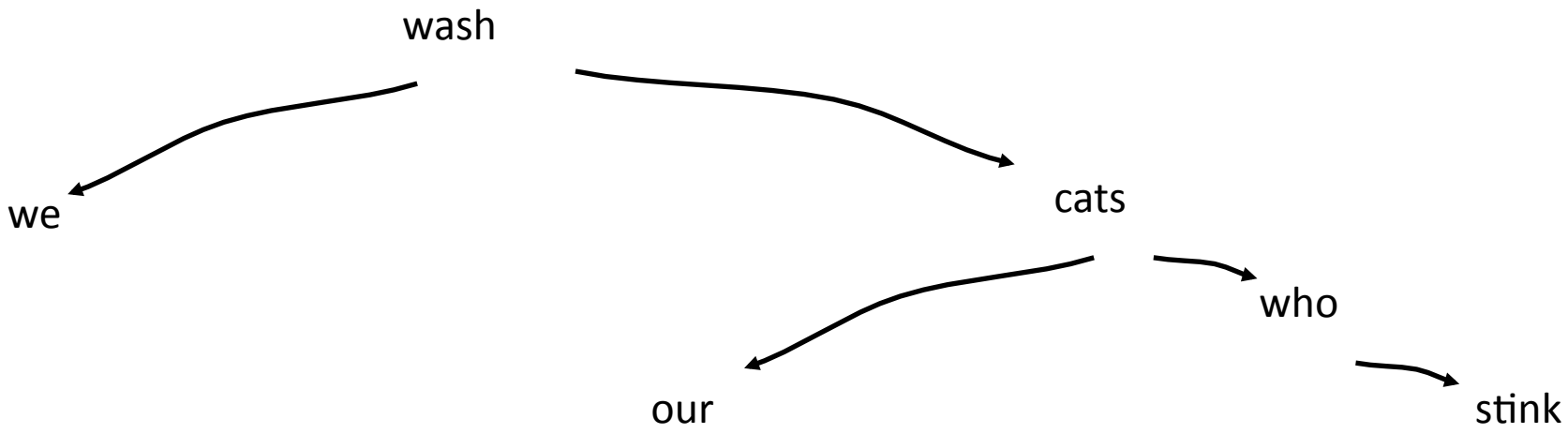

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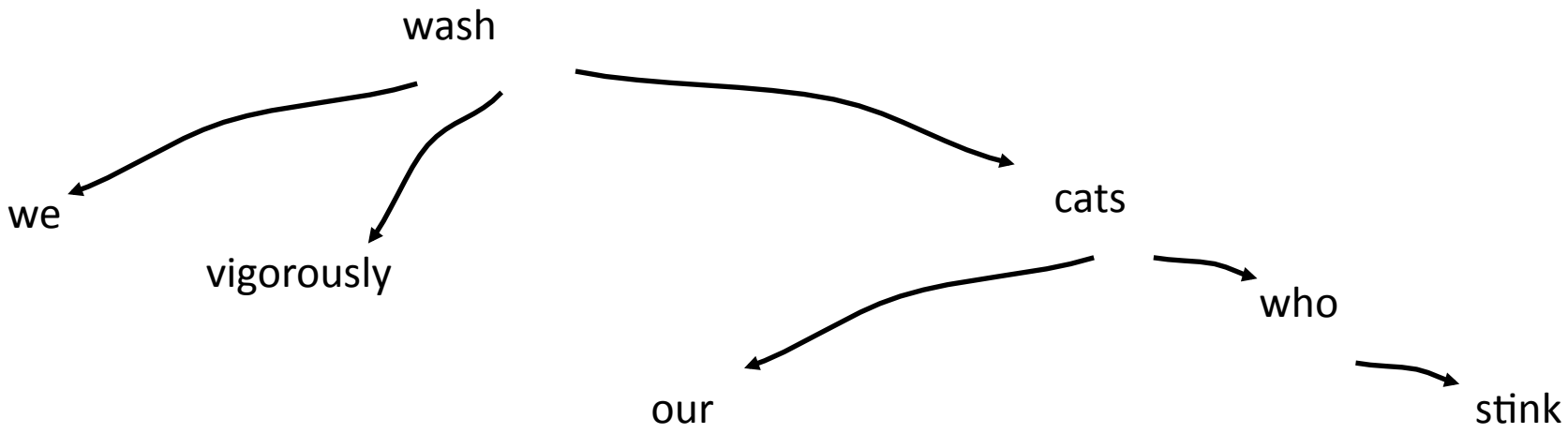

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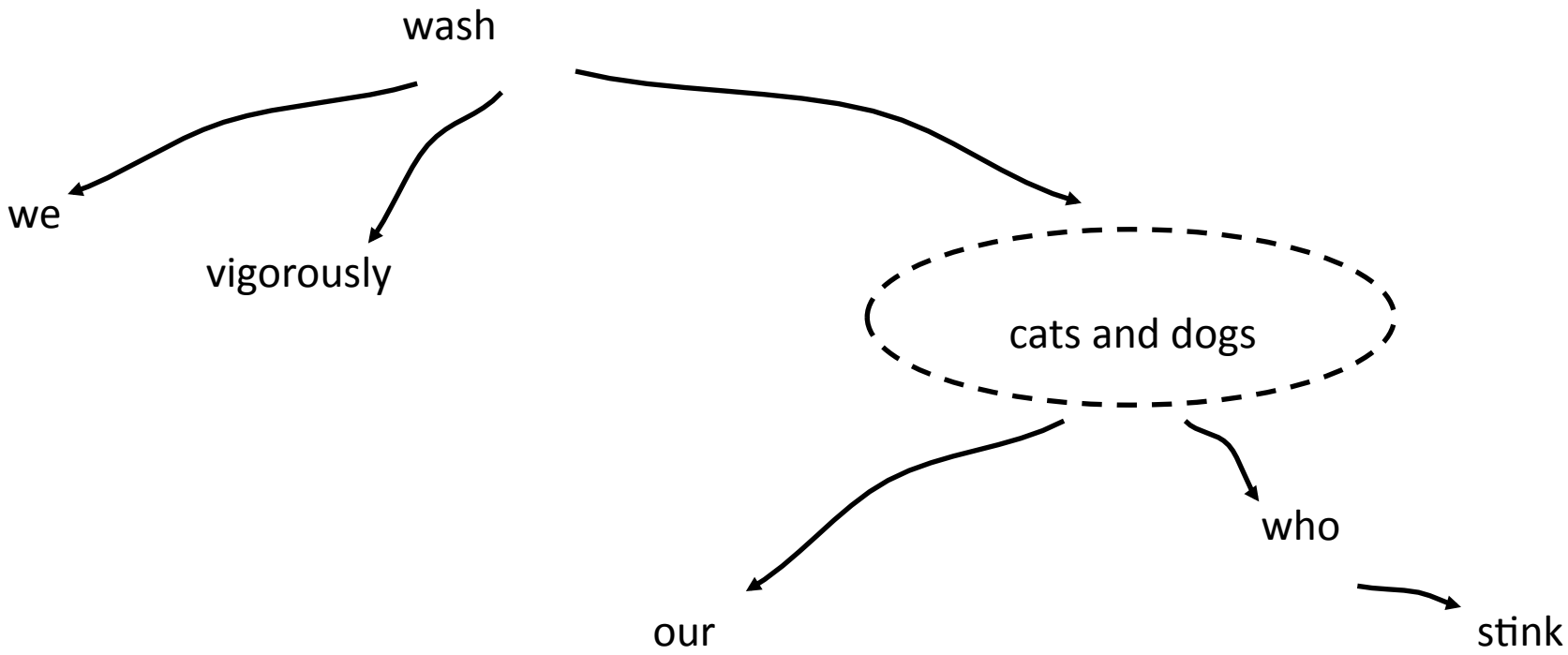

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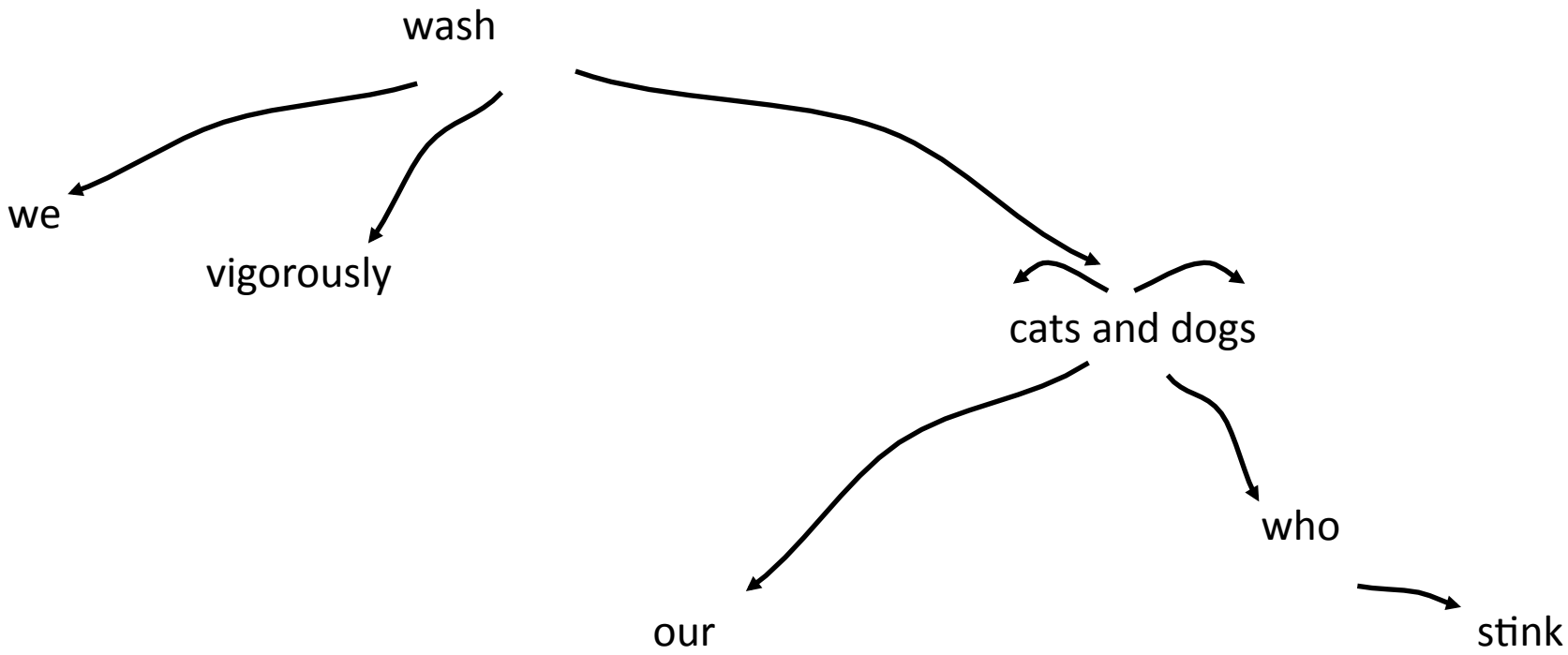


Bare Bones Dependencies and Labels

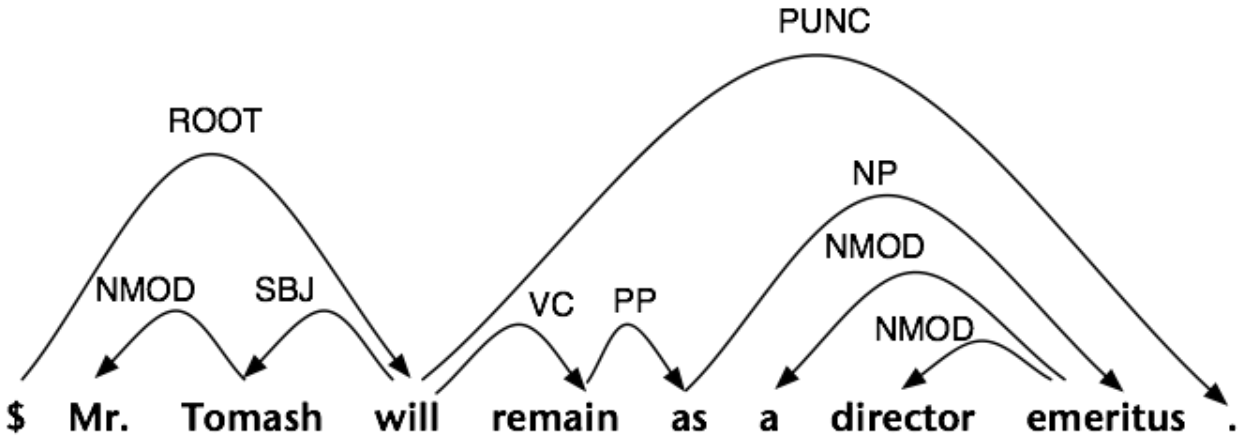
- The way to represent a lot of phenomena is clear (predicate-argument and modifier relationships)
- Conjunctions pose a problem
- Sometimes words that "should" be connected are not, because of the single-parent rule
- From bare bones to **labels**:
  - consider labeled edges
  - most algorithms can be easily extended for labeled dependency parsing
- Linguistically imperfect, but computationally attractive

Evaluation

- Attachment accuracy
  - Labeled
  - Unlabeled

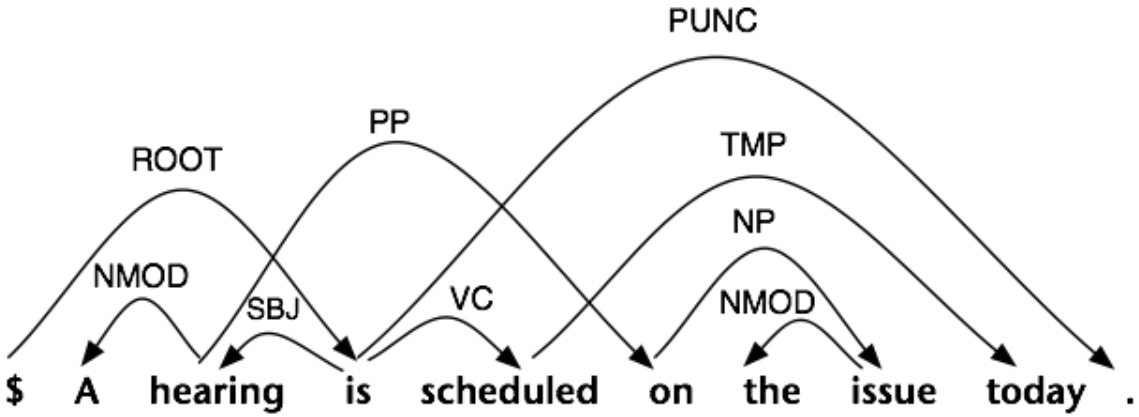
Dependencies and Context-Freeness

- **Projective** dependency trees are ones where edges don't cross
- Projective dependency parsing means searching only for projective trees
- English is mostly projective...



Dependencies and Context-Freeness

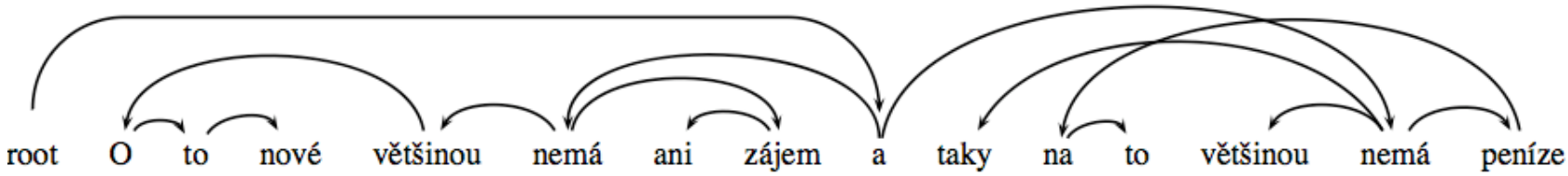
- But not entirely!



- Dependencies constructed through simple means from the Penn treebank will be projective. Why?

Dependencies and Context-Freeness

- Other languages are arguably less projective



- **Projective** dependency grammars generate **context-free** languages
- **Non-projective** dependency grammars can generate **context-sensitive** languages

Projective Dependency Parsing

- Major assumption: edge-factored model

$$p(\tau, w_1^n) \propto \prod_{i=1}^{n} \phi(w_1^n, \tau(w_i))$$

- Carroll and Charniak (1992) described a PCFG that has this property
- Eisner (1996) described several stochastic models for generating projective trees like this
- You should see that this is a linear model with a certain kind of feature locality
- We're not going to go into the details of the features that have been proposed!

Graph-based vs. Transition-based

- All models above optimize a global score and resort to local features
  - These are sometimes known as **graph-based models.**
- Just like in the phrase-structure/constituent world, there are also approaches that use shift-reduce algorithms.
- With good statistical learning methods, you can get very high performance using **greedy** search without back-tracking!
- "Local decisions, global features"
  - These are known as **transition-based models**; they reduce a structured problem to a lot of classification decisions, kind of like MEMMs.
  - See work by J. Nivre.

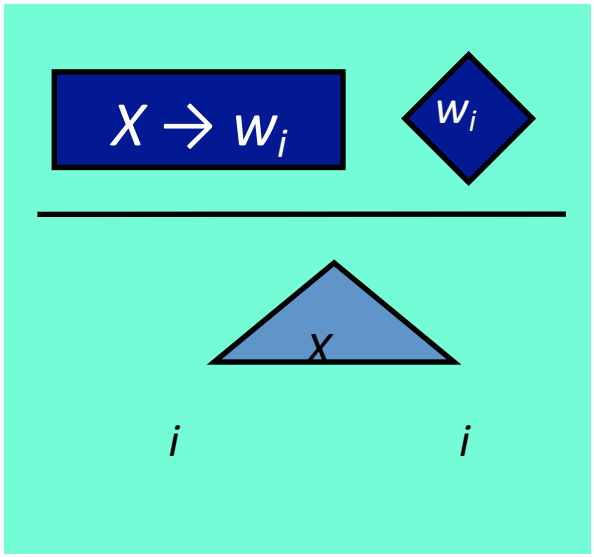
Algorithms != Models

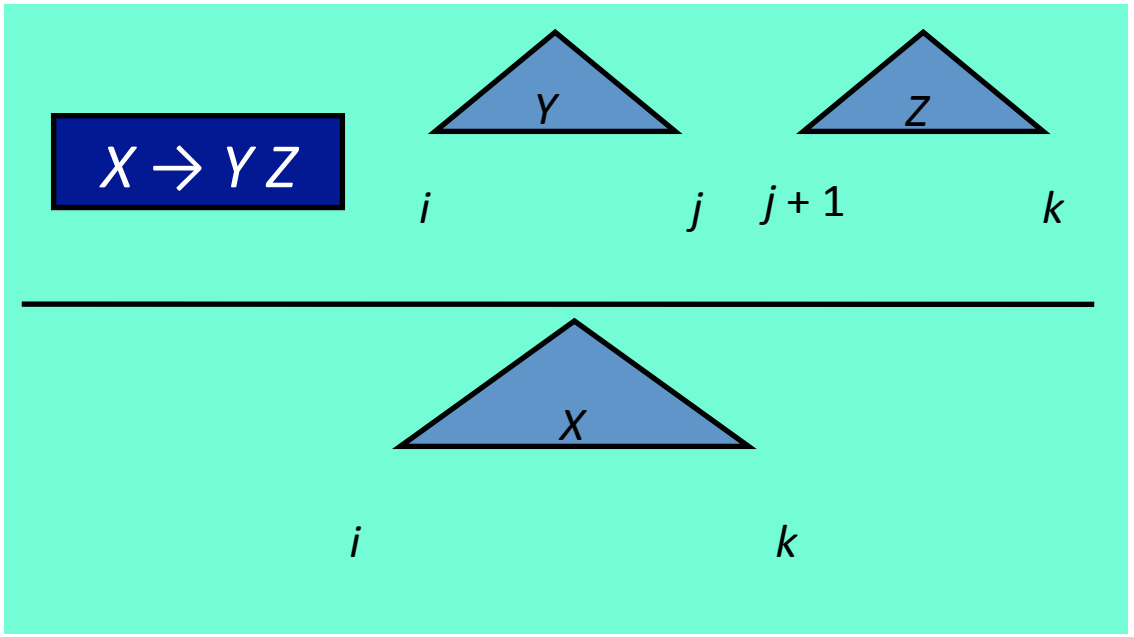
- As in HMMs, PCFGs, etc., the algorithms we need depend on the independence assumptions, **not** on the specific formulation of the statistical scores.
- We assume, from here on, that the scores are factored by dependency tree edges.

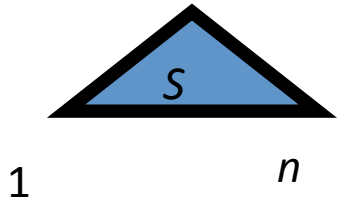
$$s(\tau) = \sum_{i=1}^{n} s(w_1^n, \tau(w_i))$$

- Projective algorithm (Eisner, 1996)
- Non-projective algorithm (McDonald et al., 2005)

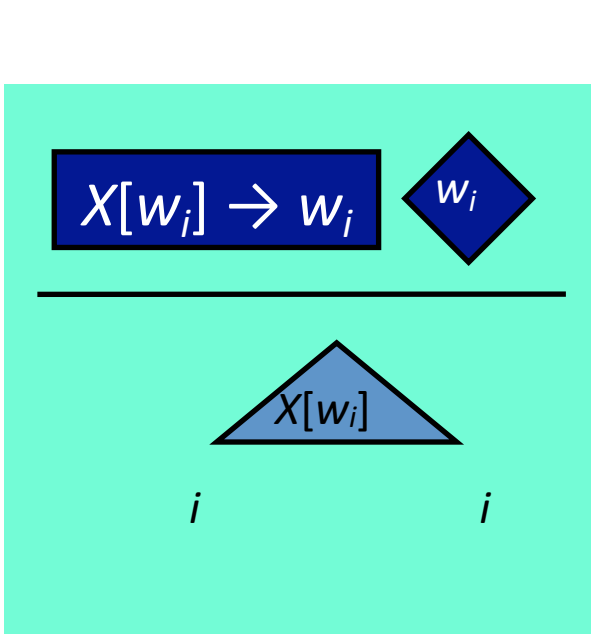
CKY

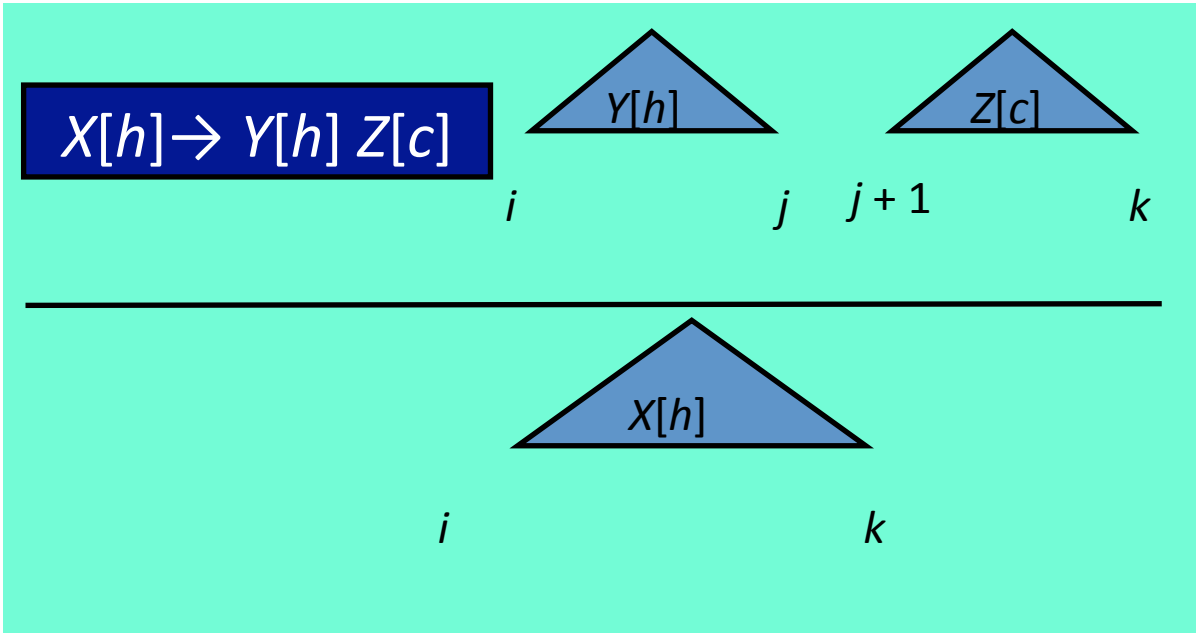


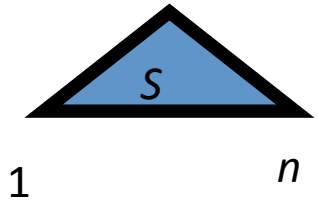




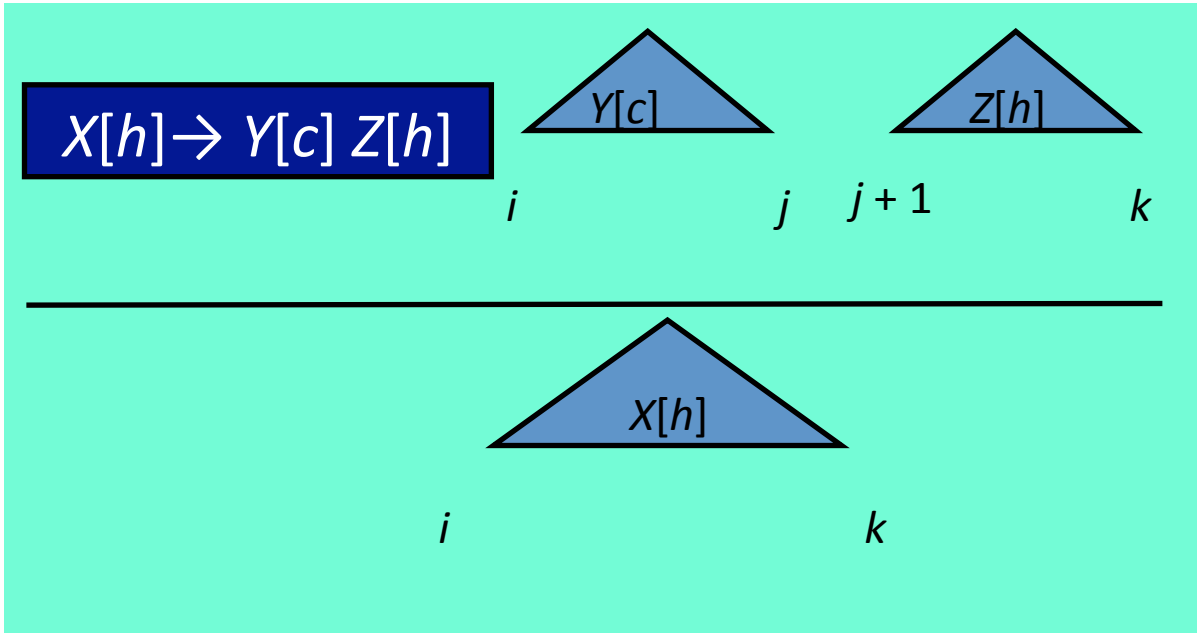
CKY with Heads



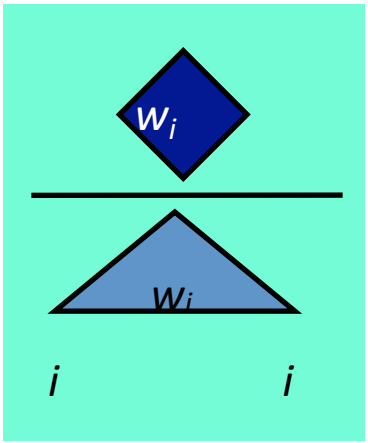


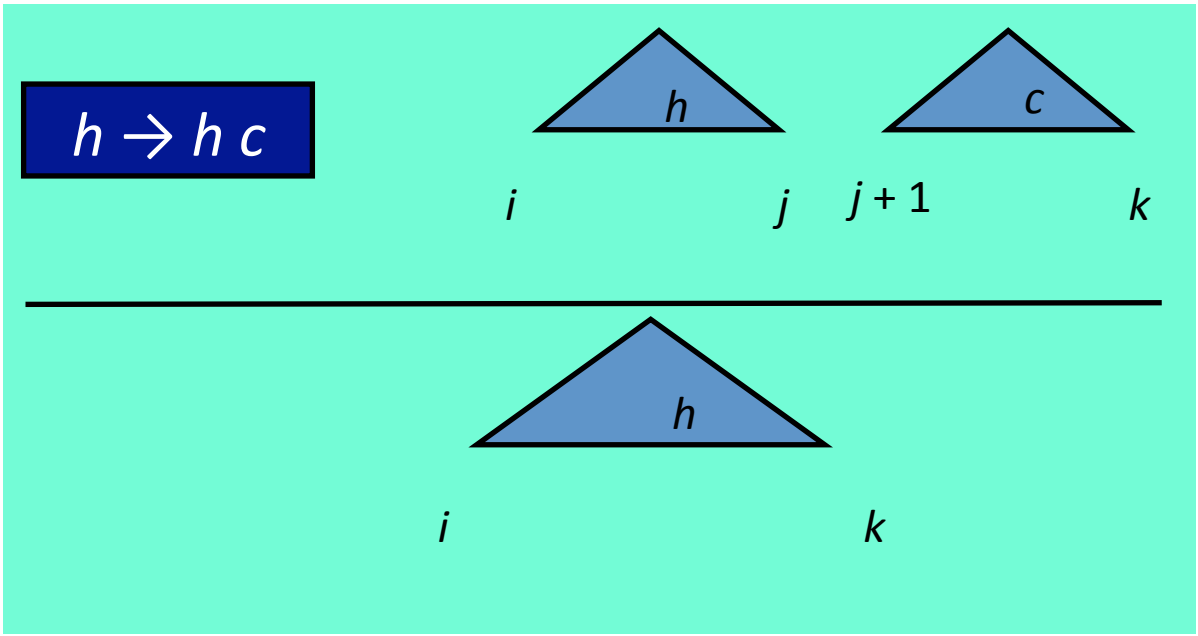


CKY with Heads (one more rule)



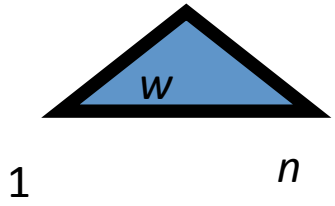
CKY with Heads, without Nonterminals





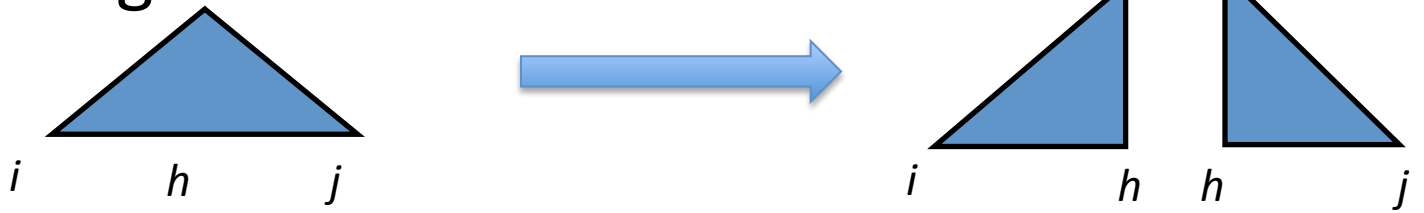
*Plus the rule for $h \rightarrow c\ h$.

What's the runtime?

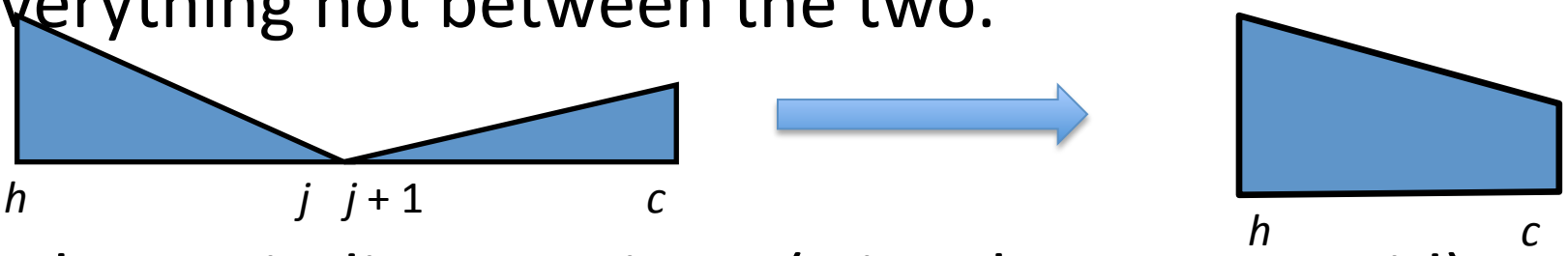


Eisner's (1996) Algorithm

- Restructure the computation so that "triangles" are organized around heads.

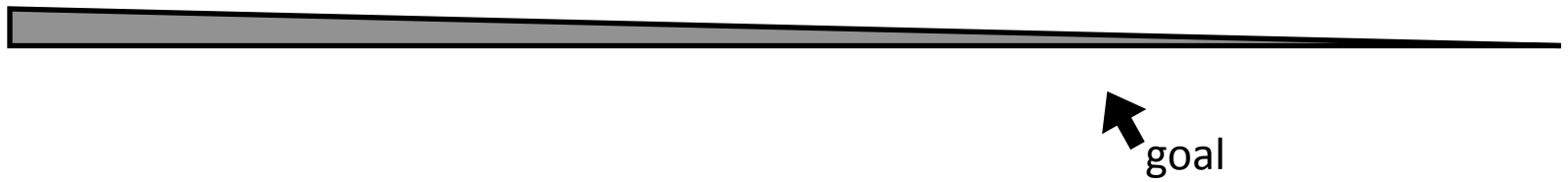


- "Half" constituents get put together from head outward; attaching a child to a parent ignores everything not between the two.



- Only two indices per item (triangle or trapezoid).

Example of the Eisner Algorithm



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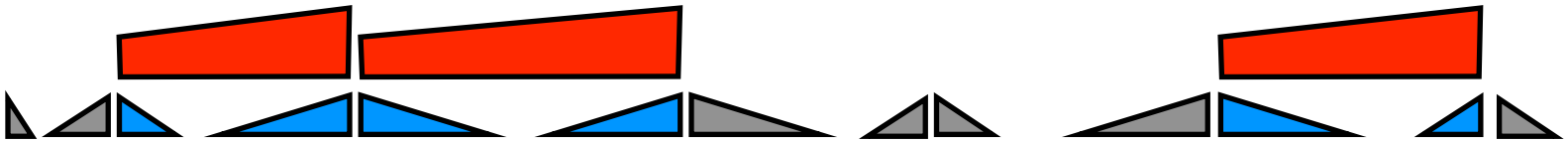
Example of the Eisner Algorithm

Attach:



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Example of the Eisner Algorithm

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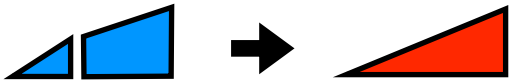
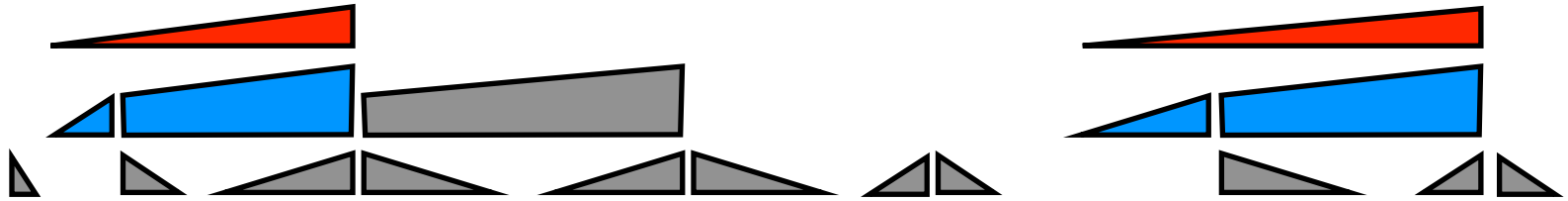
Complete:

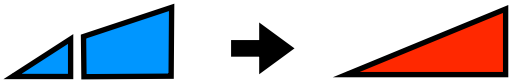


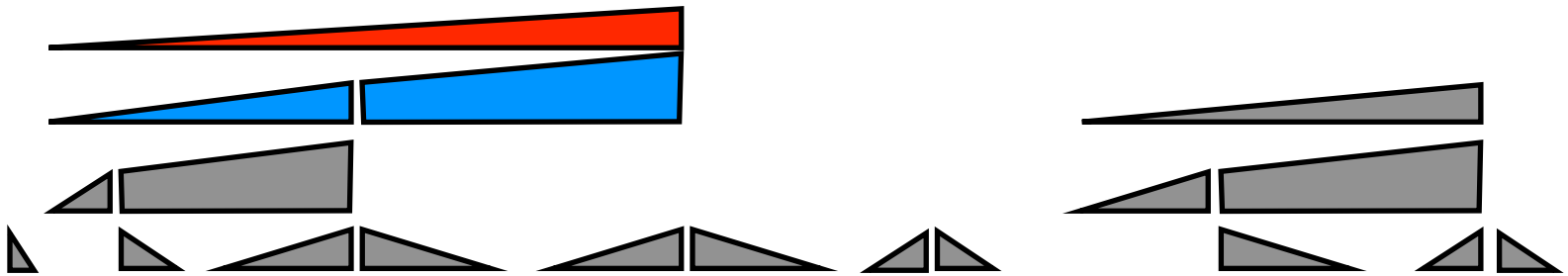


$ The professor chuckled with unabashed glee

Example of the Eisner Algorithm

Complete:





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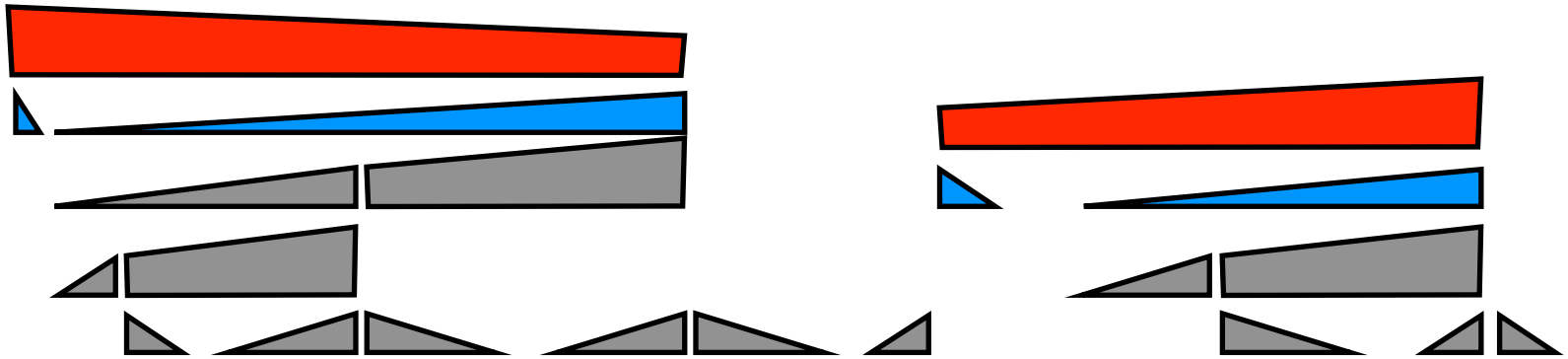
Example of the Eisner Algorithm

Attach:



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Example of the Eisner Algorithm

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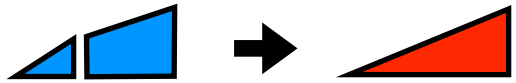

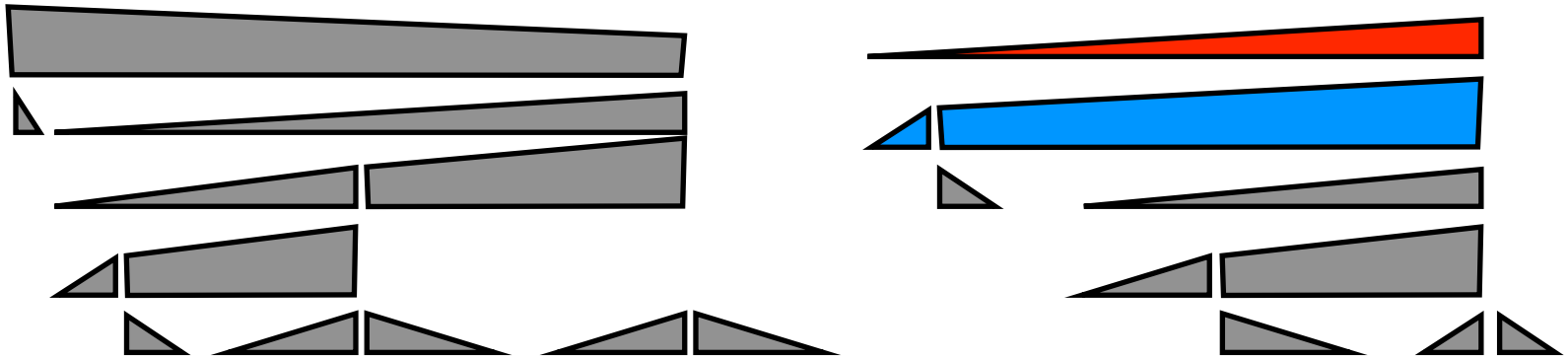

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Example of the Eisner Algorithm

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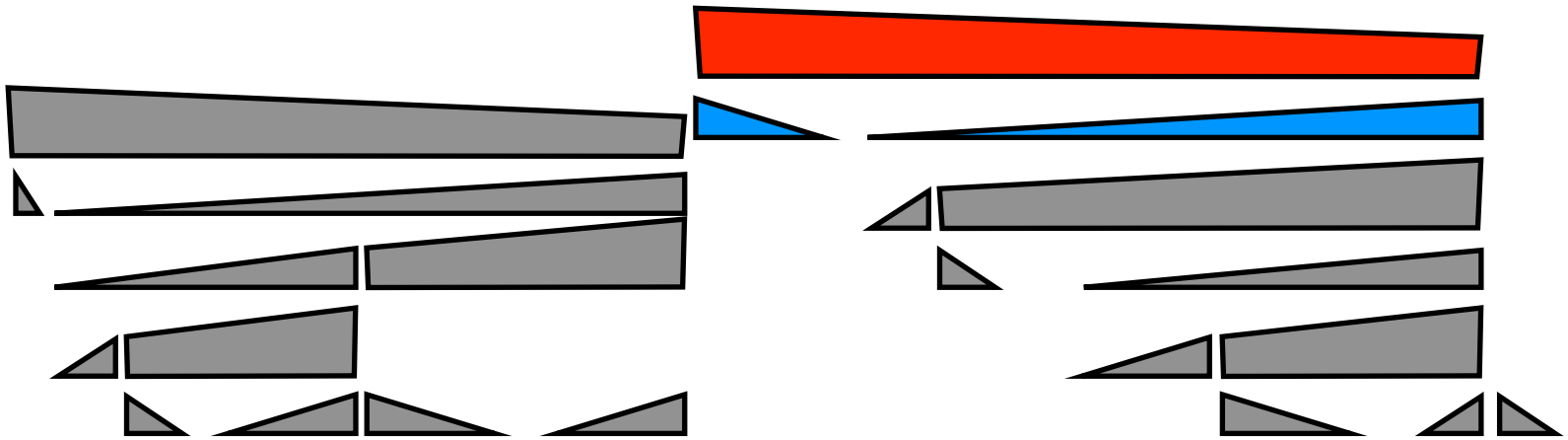

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Example of the Eisner Algorithm

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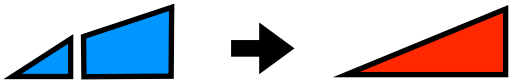

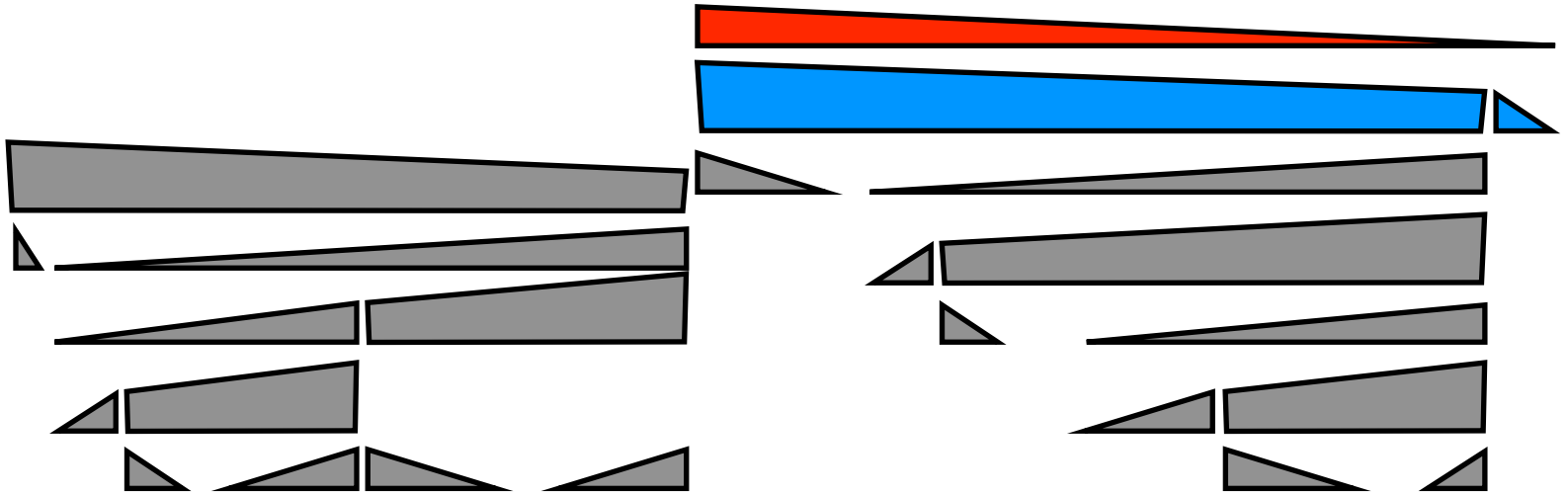

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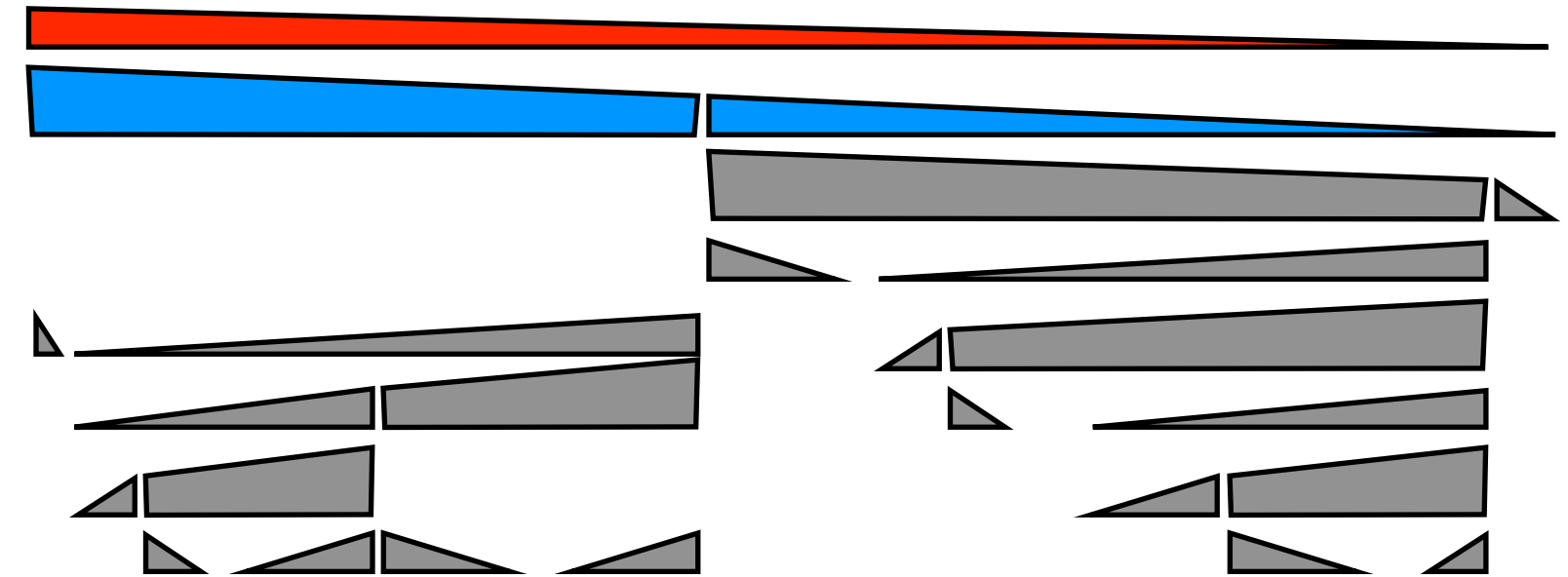
Example of the Eisner Algorithm



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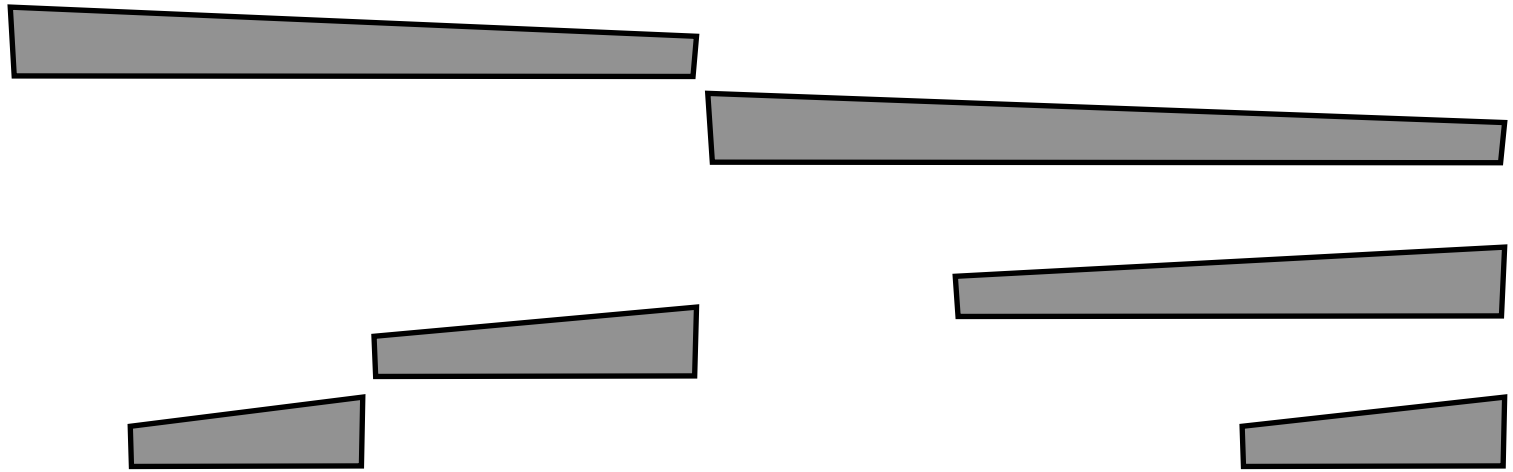
Example of the Eisner Algorithm



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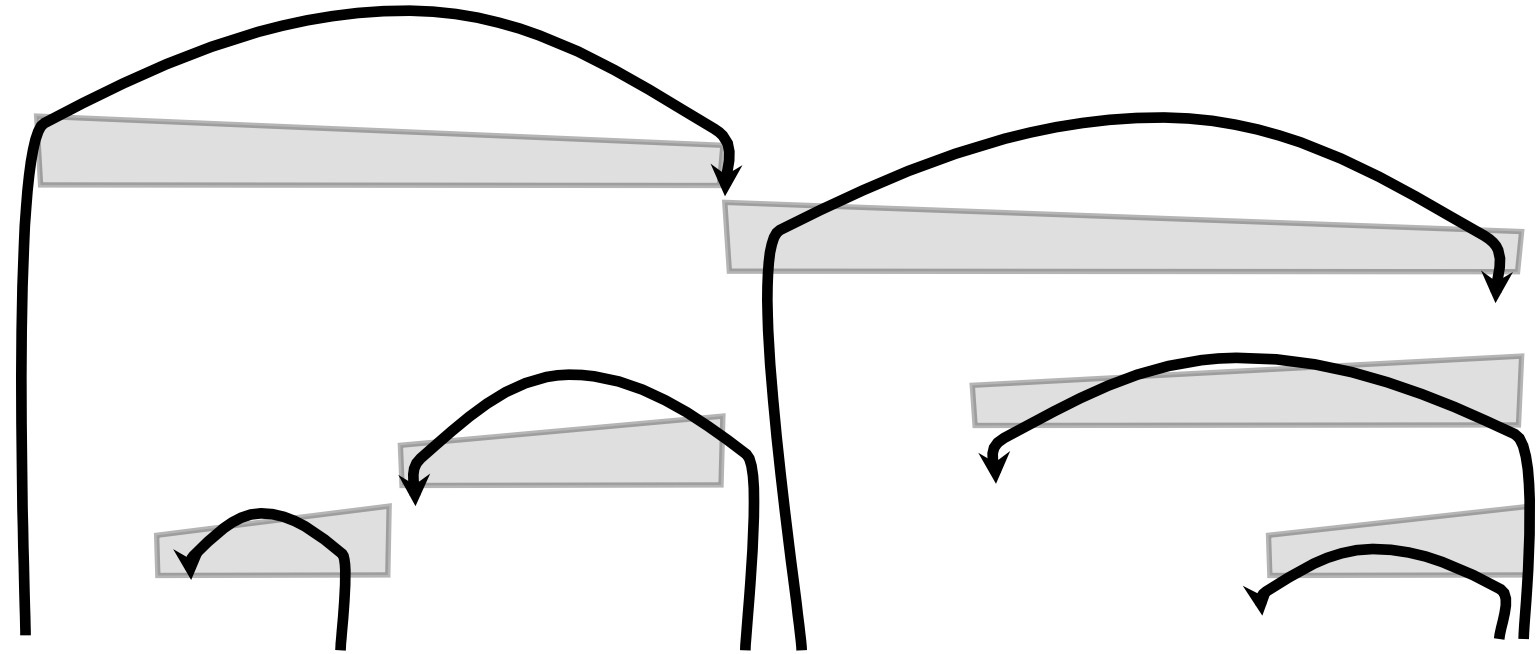
Example of the Eisner Algorithm



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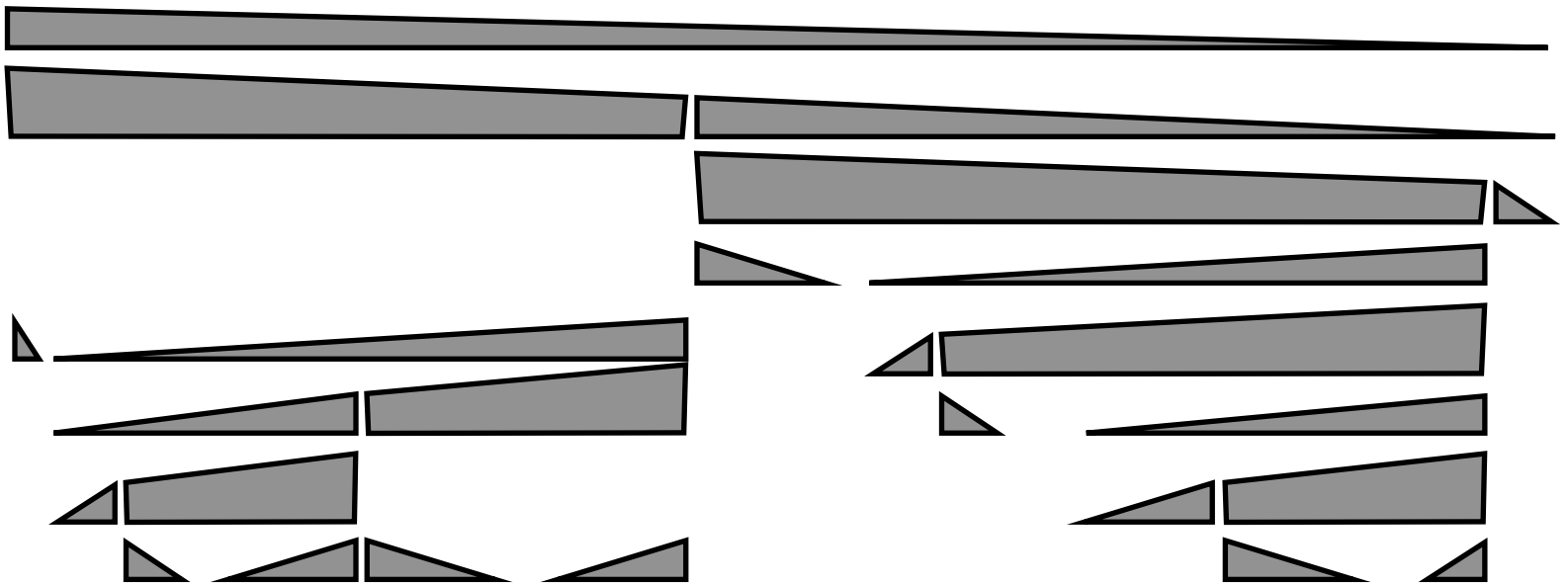
Example of the Eisner Algorithm

Of course, we have to build a lot of other triangles and trapezoids if we want to be sure we have the *best* parse.



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Punchline

- Rethinking the algorithm in terms of attachments rather than constituents gives us an asymptotic savings!
- Bare bones, projective dependency parsing is $O(n^3)$

- What about non-projectivity?

Non-projective Dependency Parsing (McDonald et al., 2005)

- Key idea: a non-projective dependency parse is a **directed spanning tree** where
  - vertices = words
  - directed edges = parent-to-child relations
- Well-known problem: minimum-cost spanning tree
- Solution: Chu-Liu-Edmonds algorithm (cubic)
  - Tarjan: quadratic for dense graphs (like ours)
- Good news: fast! can now recover non-projective trees!
- Bad news: much larger search space, potential for error

Breaking Independence Assumptions

- Adding labels doesn't fundamentally change Eisner or MST
- What about edge-factoring?
- Projective case: local statistical dependence among same-side children of a given head - still cubic (Eisner and Satta, 1999).
- Non-projective parsing with any kind of second-order features (e.g., on adjacent edges) is NP-hard.
  - McDonald explored approximations in his thesis
  - Find the best projective parse and then rearrange the edges as long as the score improves - $O(n^3)$
  - ILP (Martins et al., 2009)

CoNLL 2006 & 2007

- 2006 and 2007: dependency parsing on a variety of languages was the shared task at CoNLL - a few dozen systems.
- Many of the datasets are freely available.
- Parsing papers now typically evaluate on most or all of these datasets.

Parsing in 2011

Current Research Directions

- Better learning for parsing (e.g., max margin as in Taskar et al., 2004; CRFs as in Finkel et al., 2008; many other "parsing" papers that are really about learning for structured prediction)
- Integrating learning and search (Petrov, 2009)
- Synchronous grammars in machine translation; bilingual parsing
- Richer formalisms (CCG, TAG, unification-based grammars)
- Integrating parsing with morphological or semantic analysis