Natural Language Dependency Parsing

SPFLODD

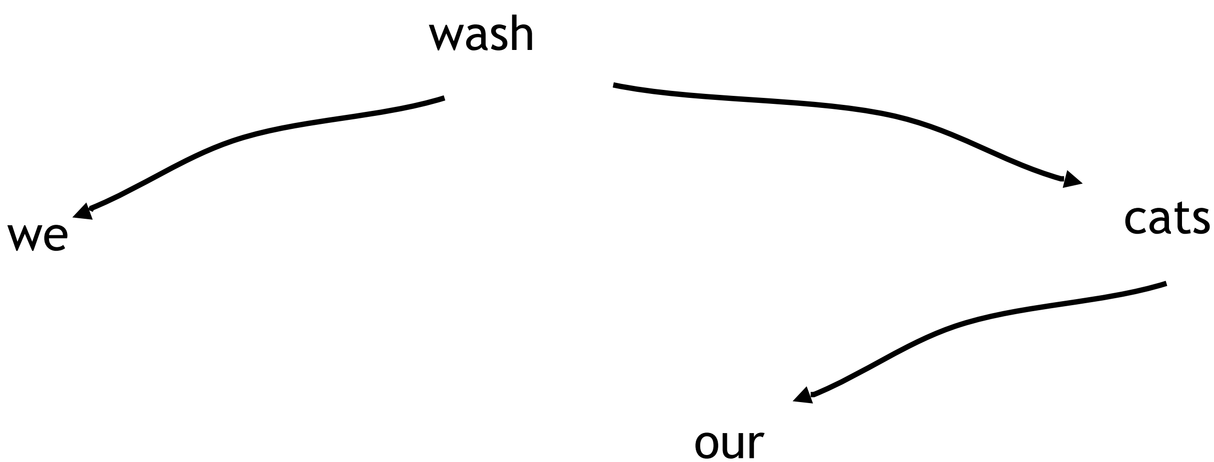
October 6, 2015

Dependency Grammar

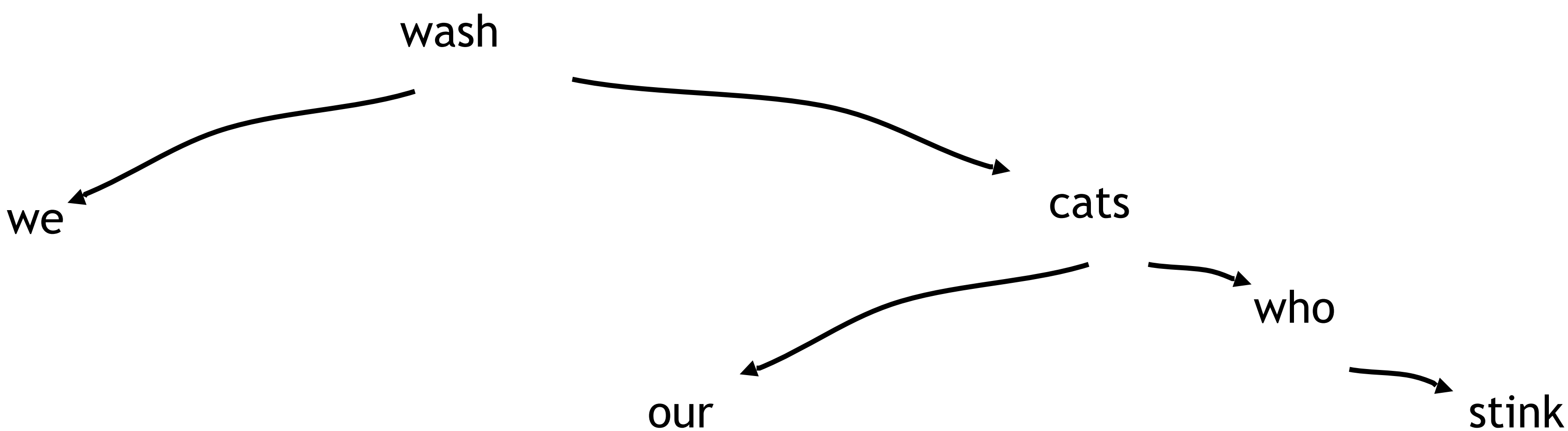
- A variety of theories and formalisms
- Focus on relationship between **words** and their syntactic relationships
- Correlates with study of languages that have free(r) word order (e.g., Czech)
- Lexicalization is central, phrases secondary

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

Bare Bones Dependency Parse



Bare Bones Dependency Parse



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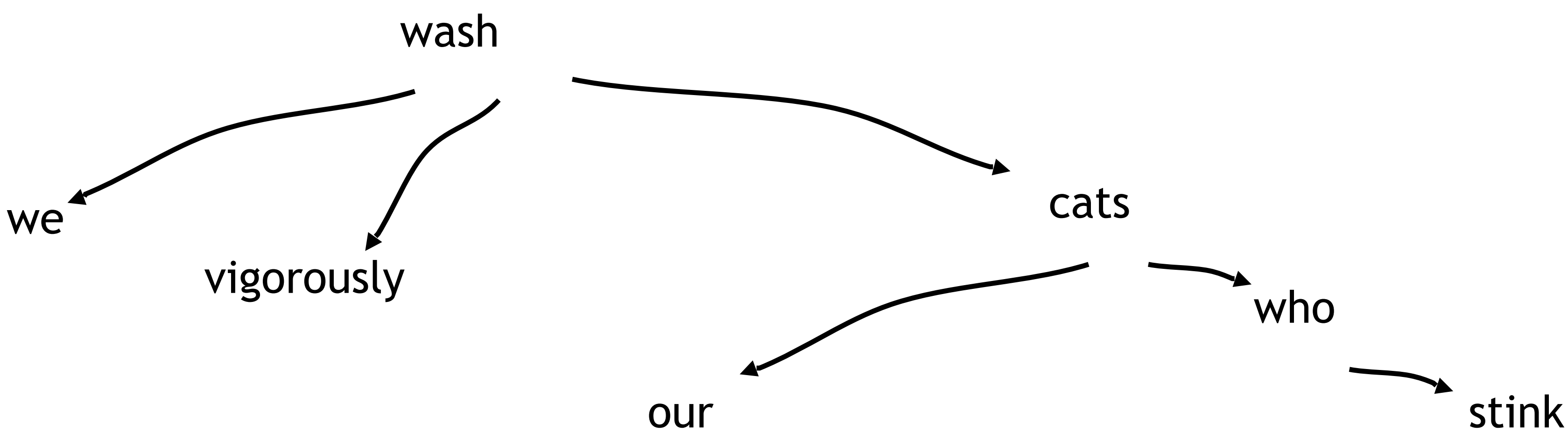

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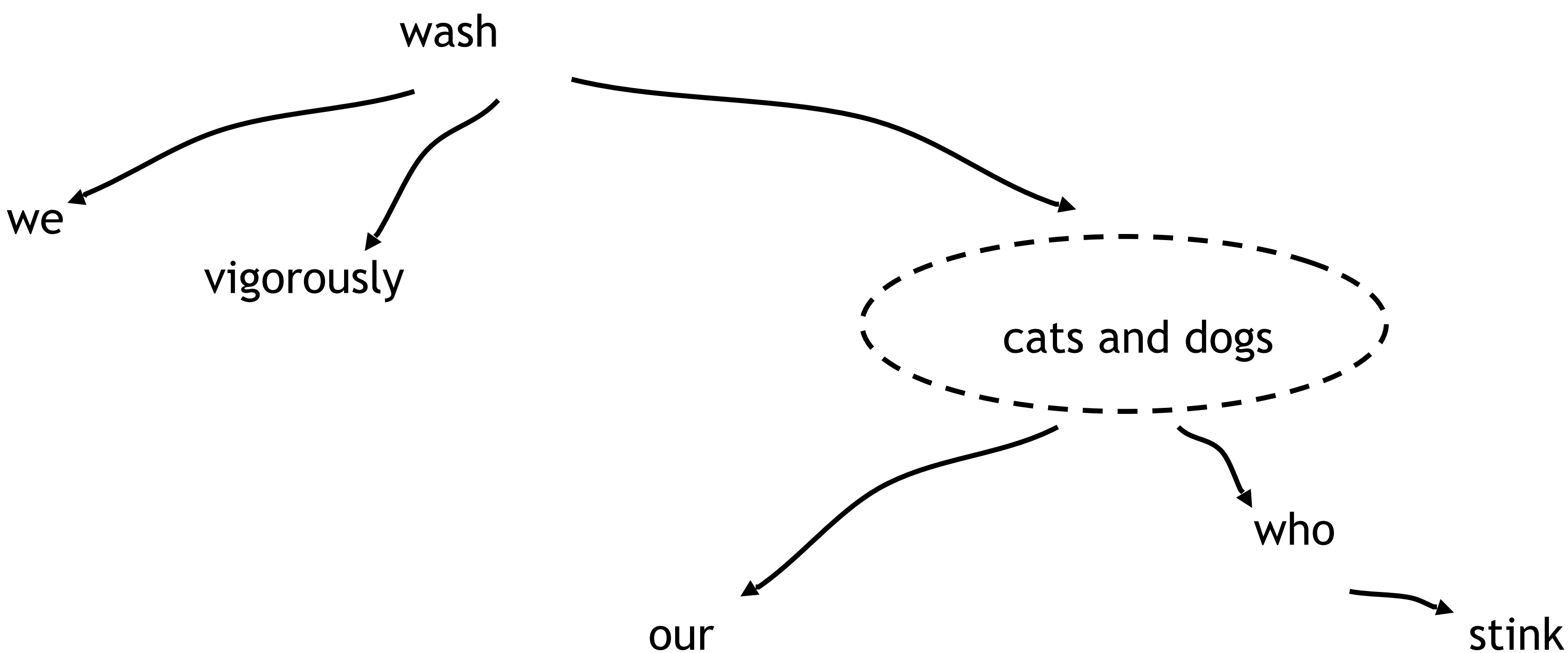
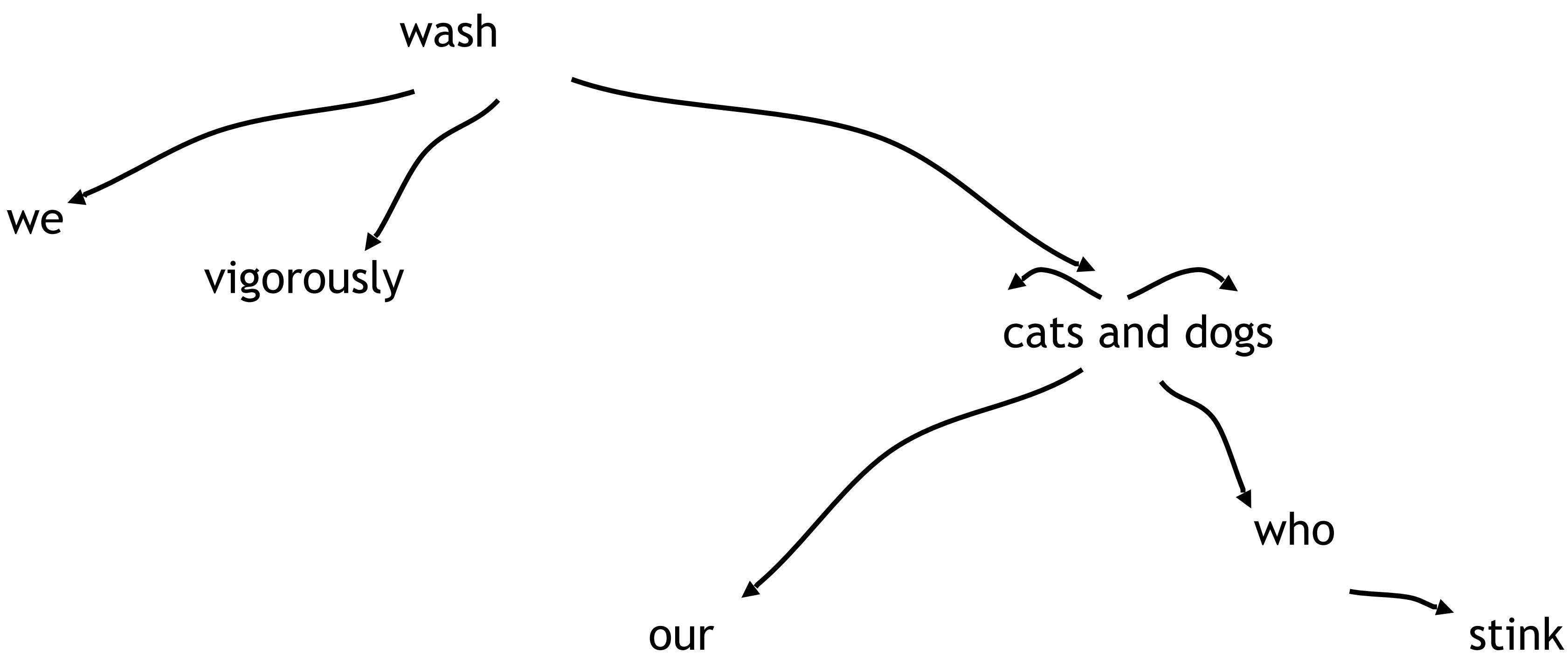


Bare Bones Dependency Parse



Bare Bones Dependencies and Labels

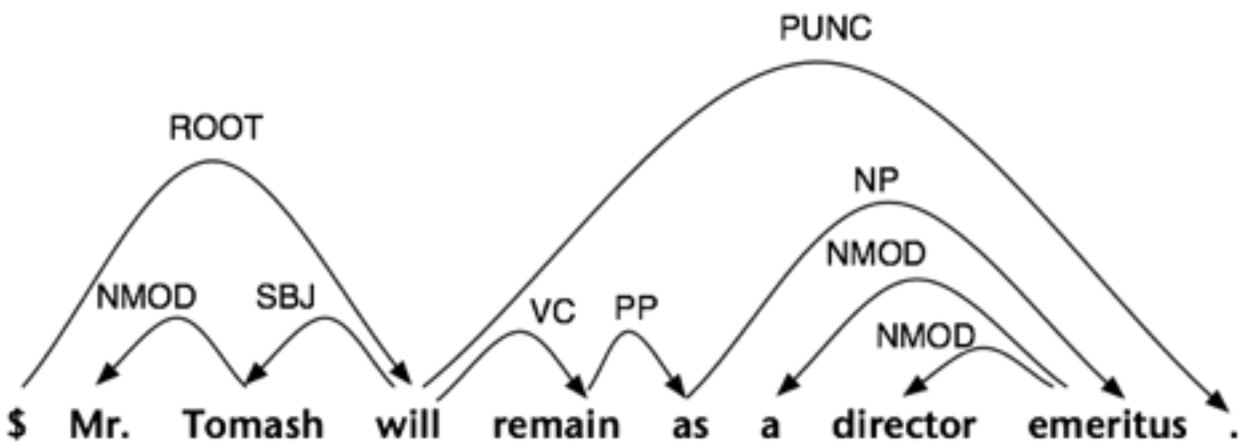
- The way to represent a lot of phenomena is clear (predicate-argument and modifier relationships)
- Conjunctions pose a problem
- Sometimes words that “should” be connected are not, because of the single-parent rule
- From bare bones to **labels**:
  - consider labeled edges
  - most algorithms can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

Evaluation

- Attachment accuracy
  - Labeled
  - Unlabeled

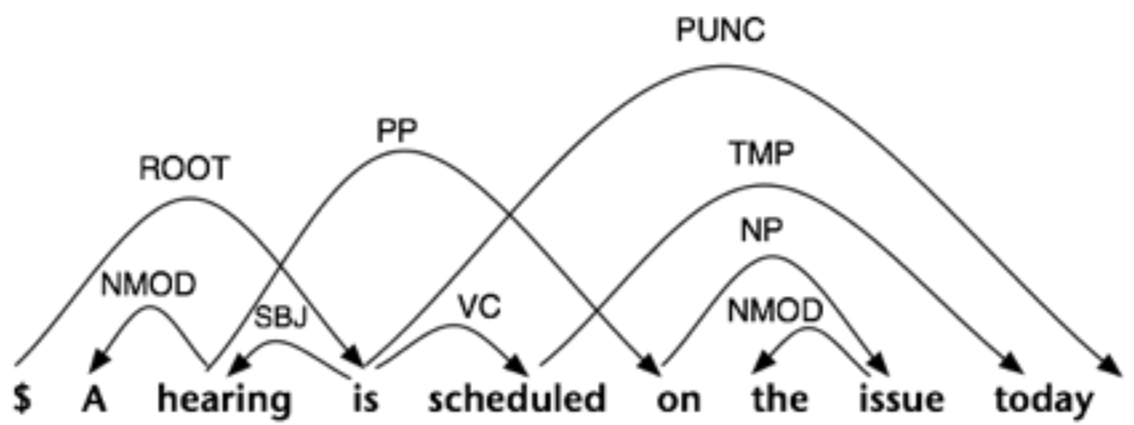
Dependencies and Context-Freeness

- **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.

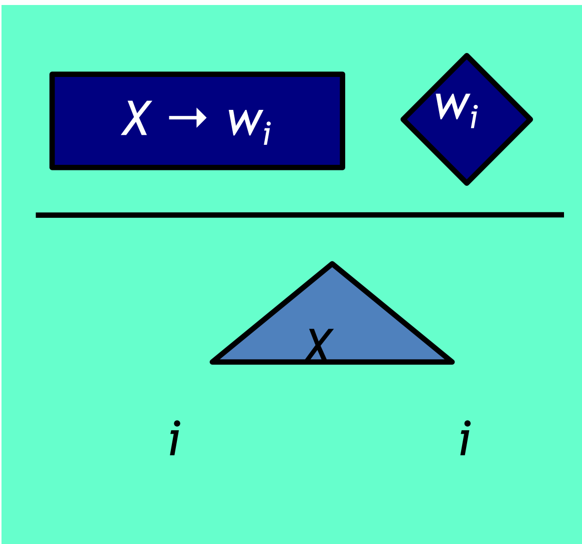
Algorithms != Models

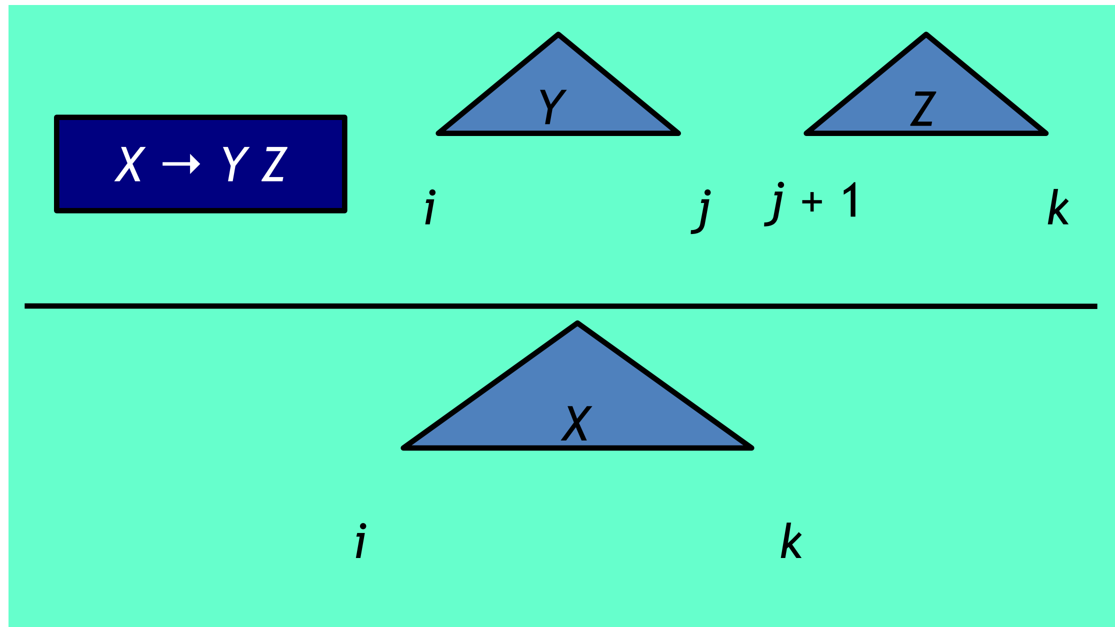
- As in HMMs, PCFGs, etc., the algorithms we need depend on the independence assumptions, **not** on the specific formulation of the statistical scores.
- We assume, from here on, that the scores are factored by dependency tree edges.

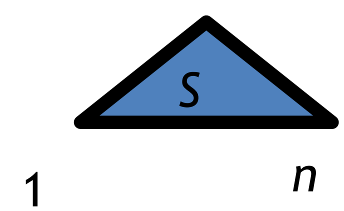
$$s(\tau) = \sum_{i=1}^{n} s(w_1^n, \tau(w_i))$$

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

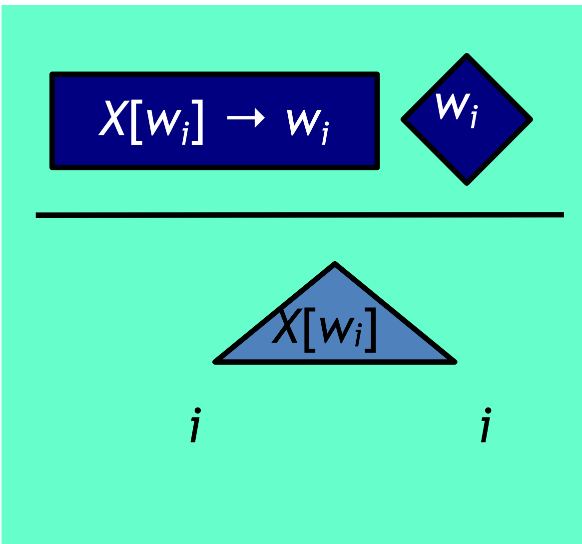
CKY

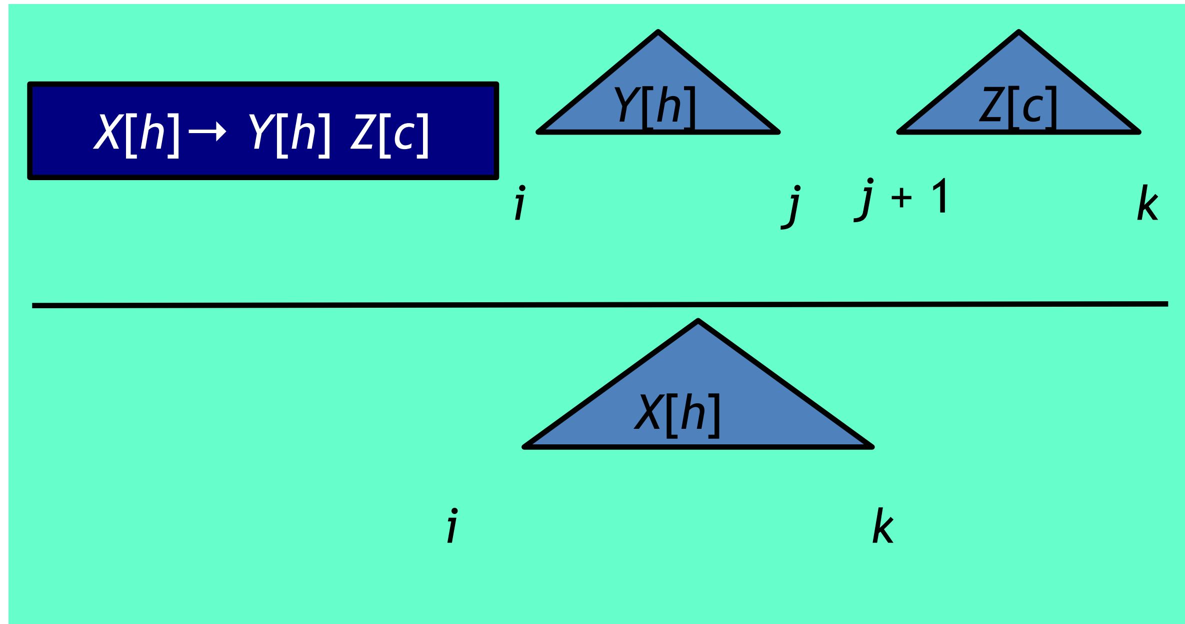


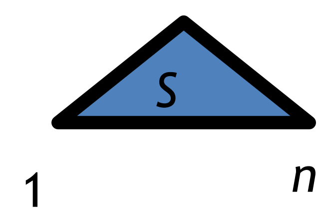




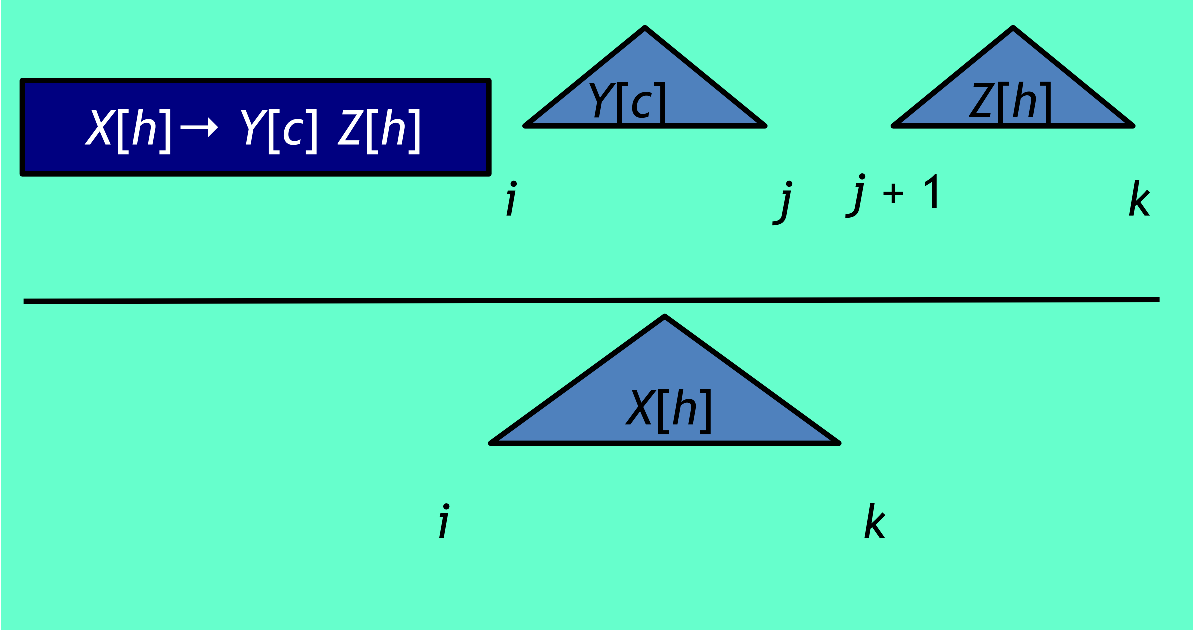
CKY with Heads



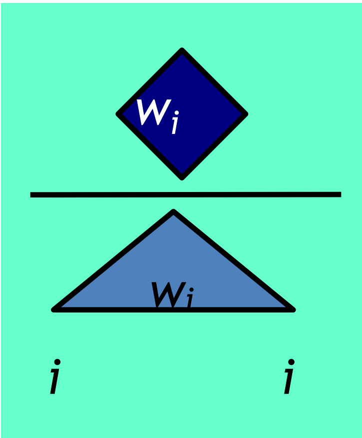


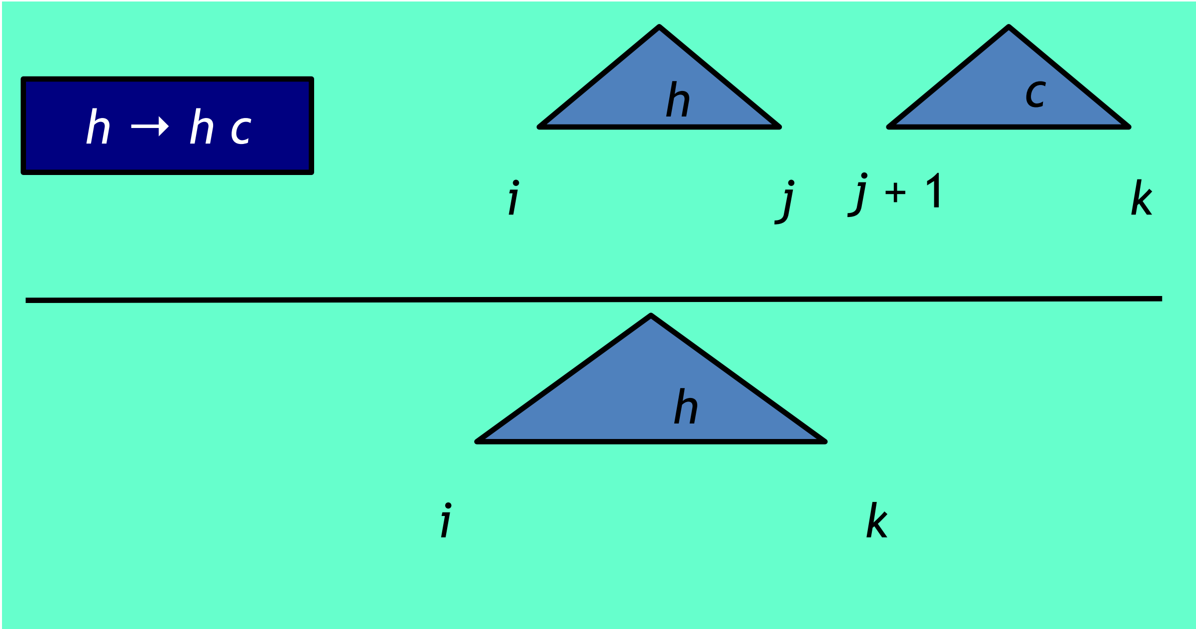


CKY with Heads (one more rule)



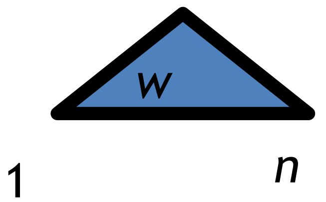
CKY with Heads, without Nonterminals





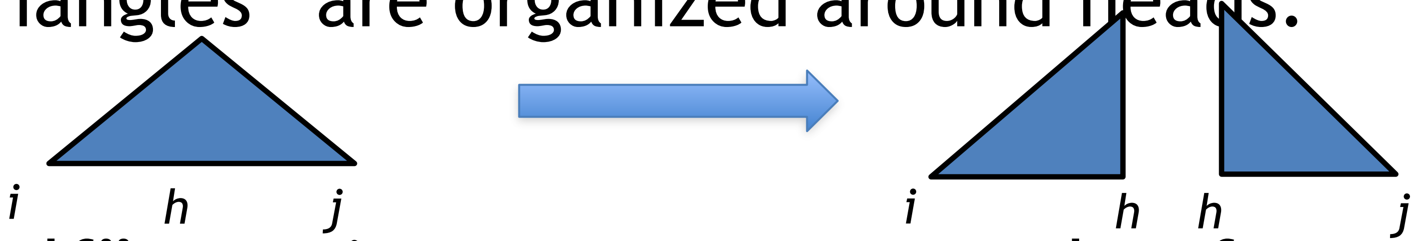
*Plus the rule for $h \rightarrow c\ h$.

What's the runtime?

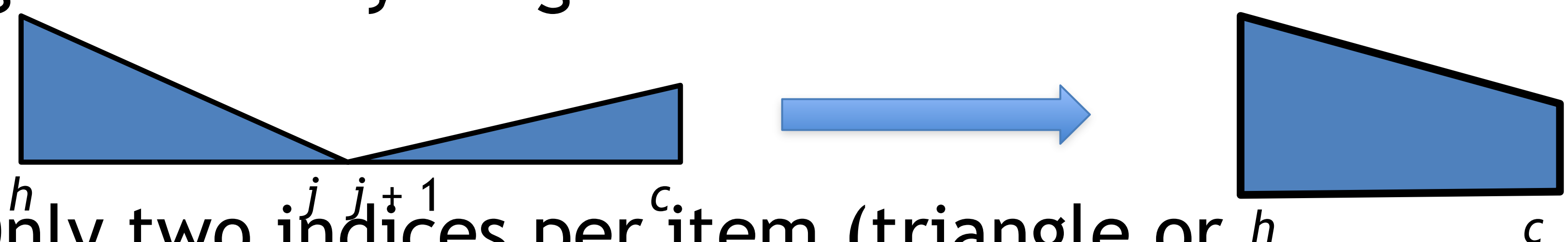


Eisner's (1996) Algorithm

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

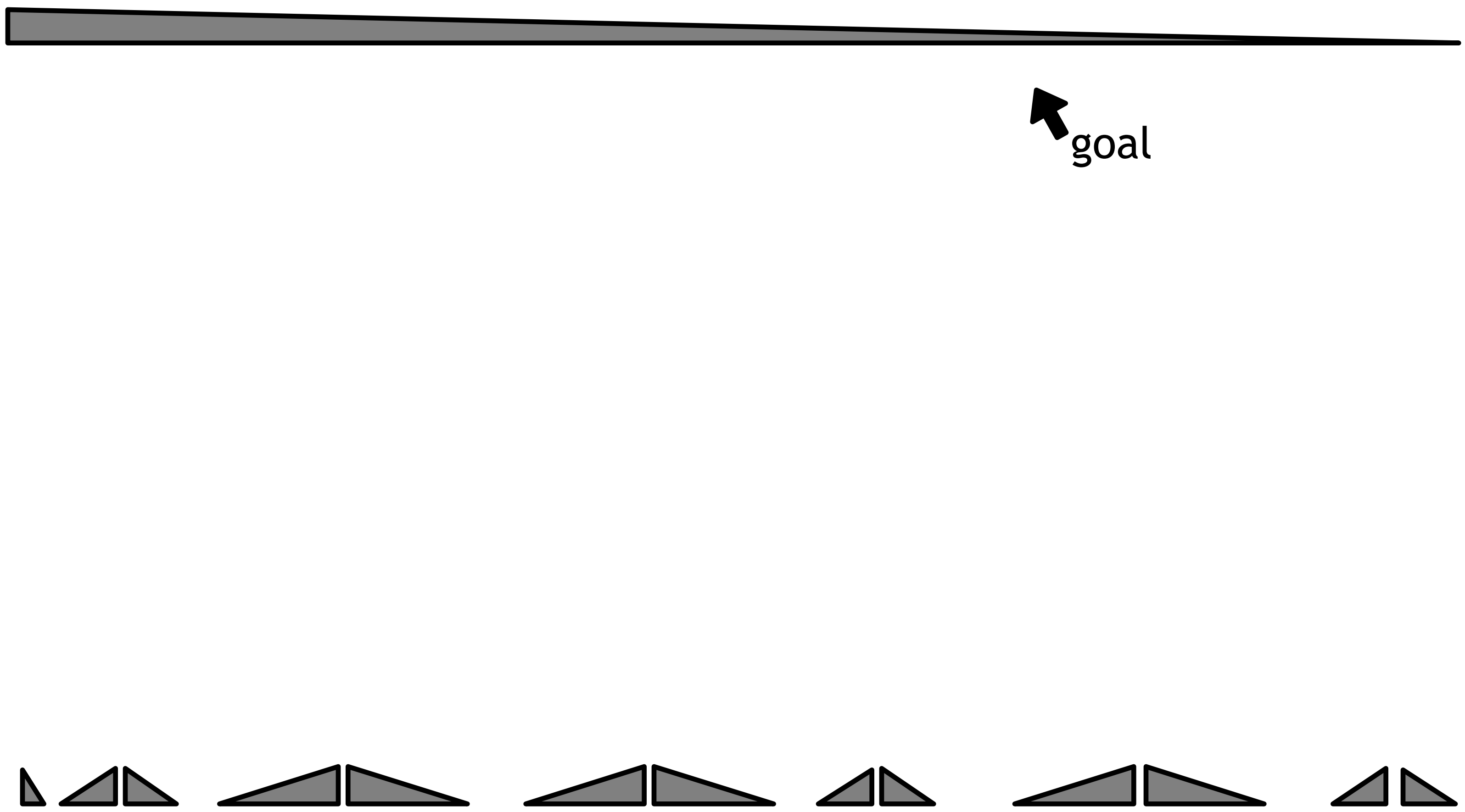


- "Half" constituents get put together from head outward; attaching a child to a parent ignores everything not between the two.



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

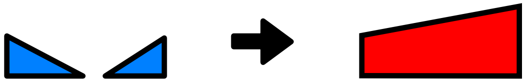
Example of the Eisner Algorithm

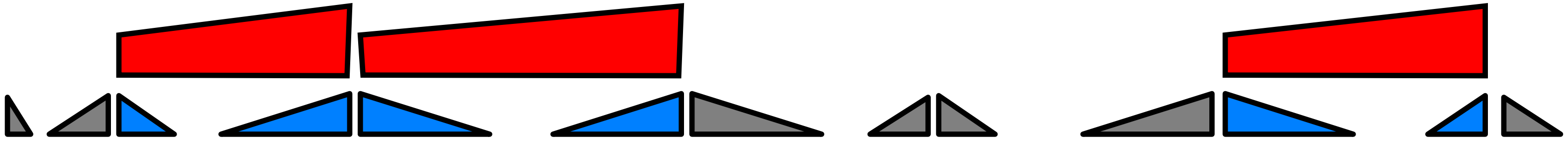


$ The professor chuckled with unabashed glee

Example of the Eisner Algorithm

Attach:





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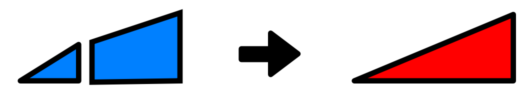
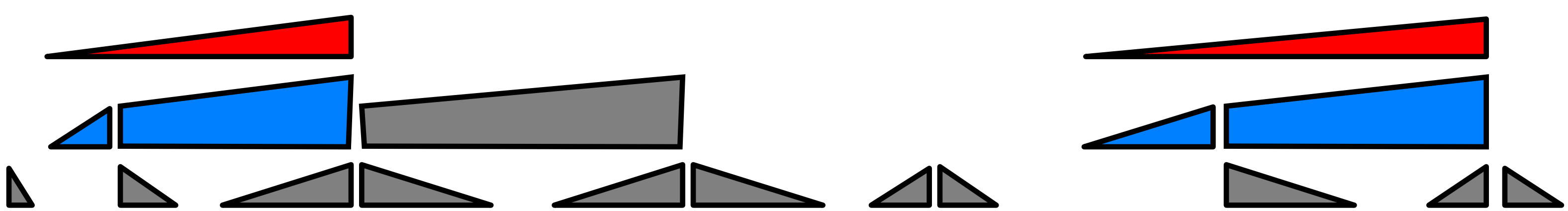
Complete: 



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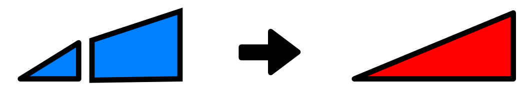

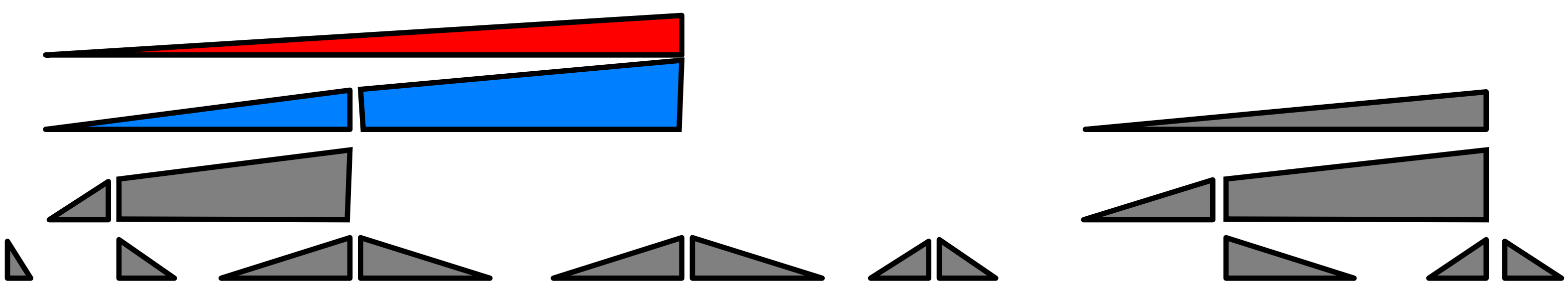

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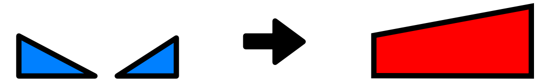
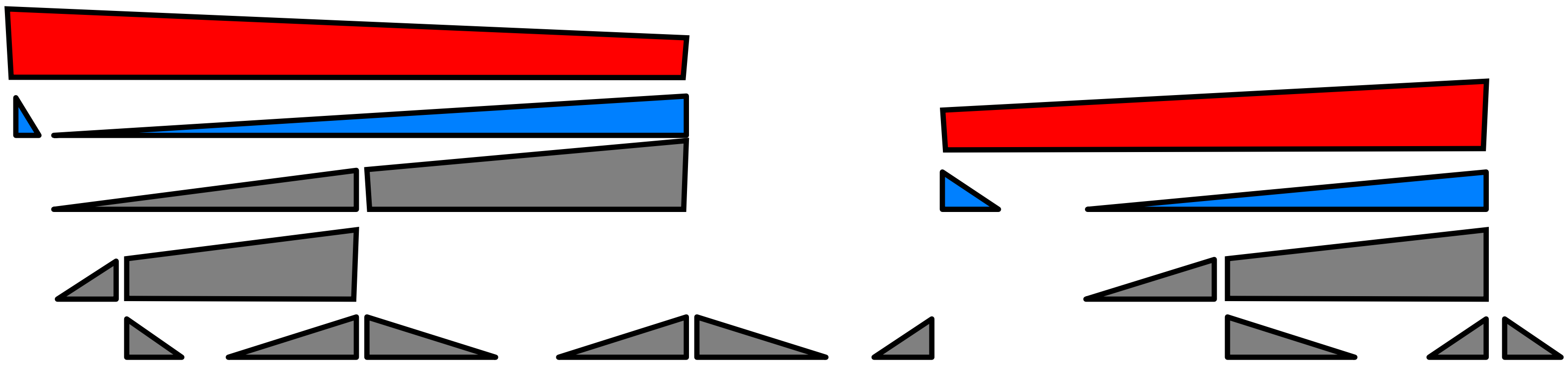
Attach: 



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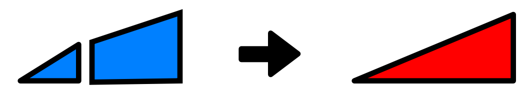

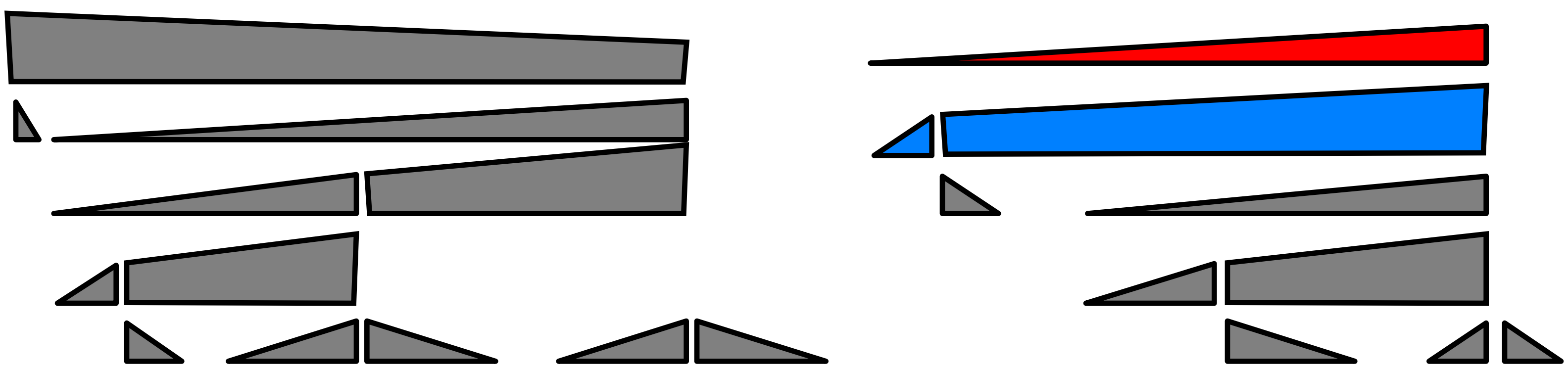

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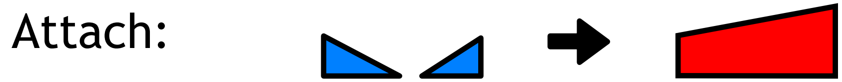

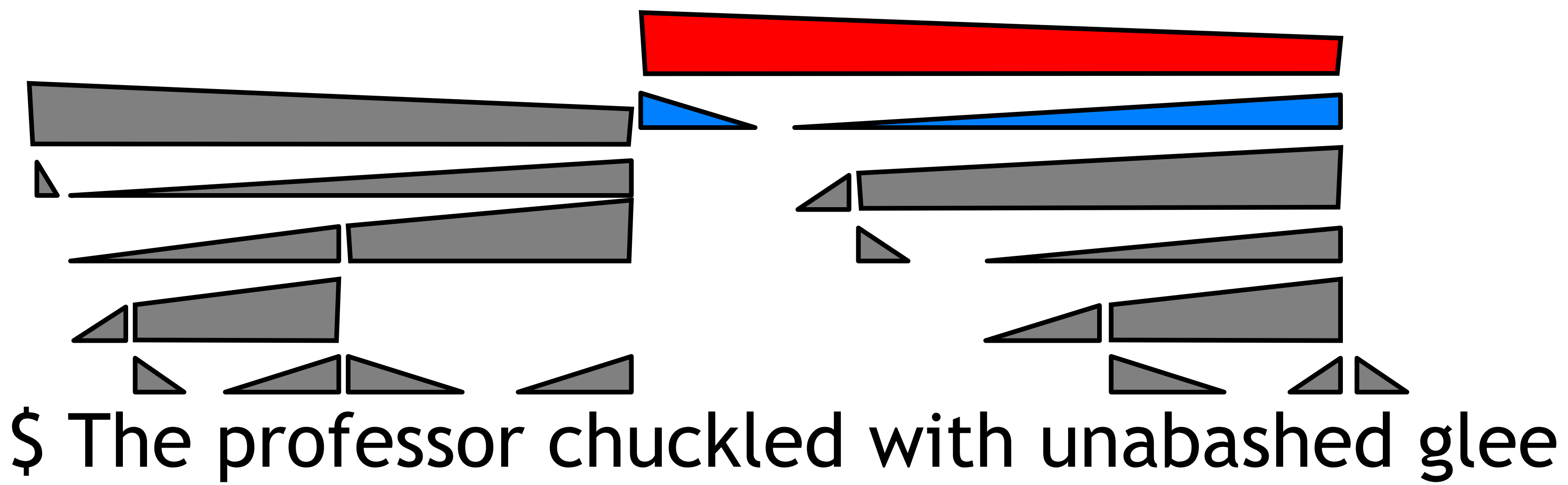

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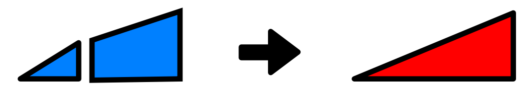

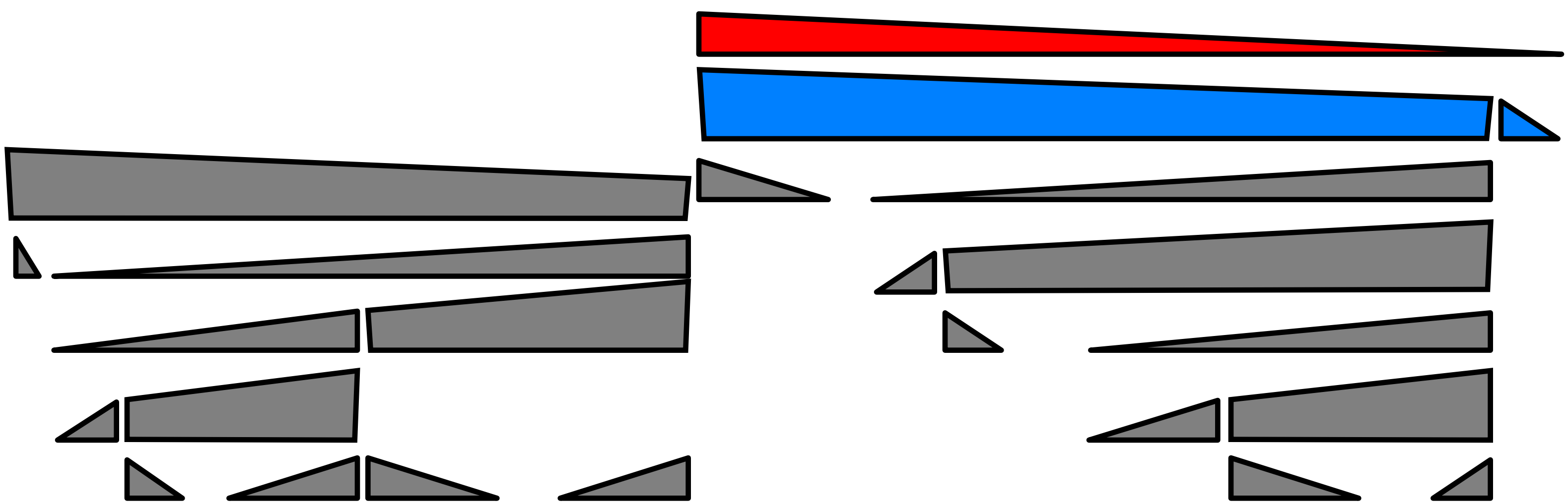

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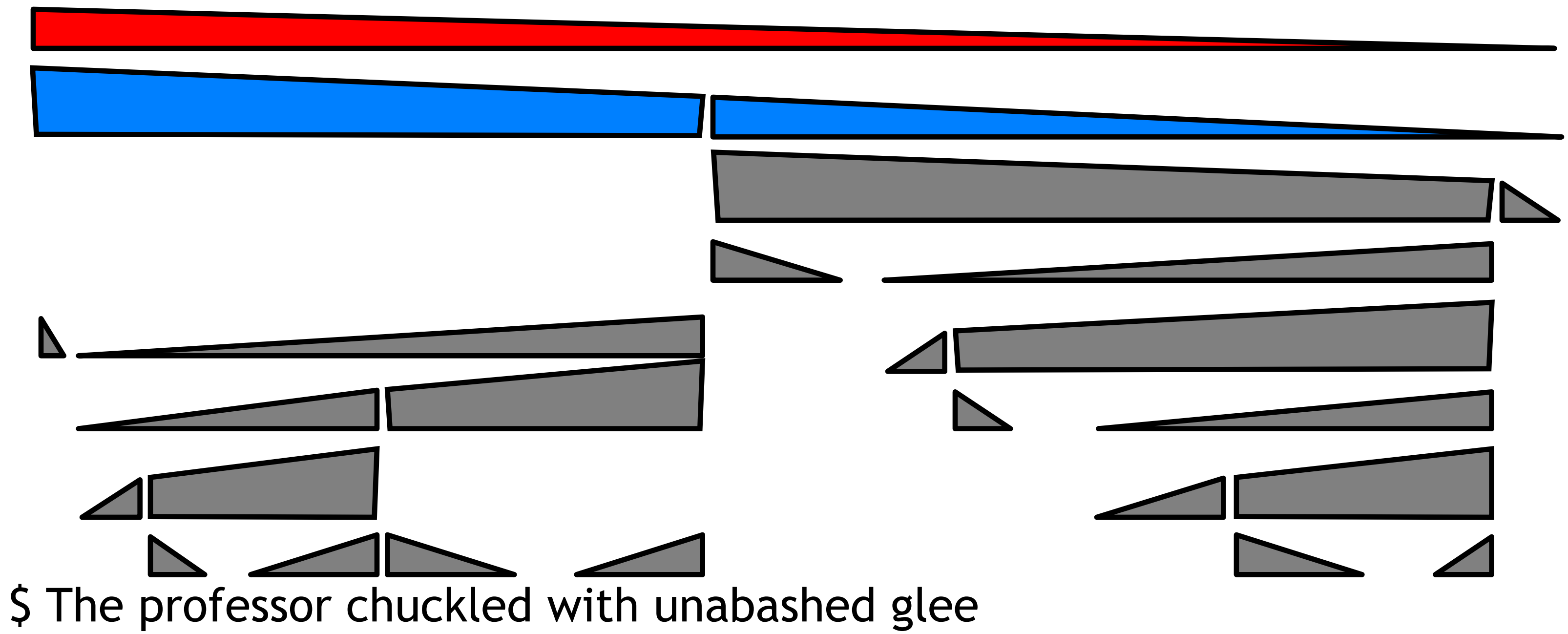

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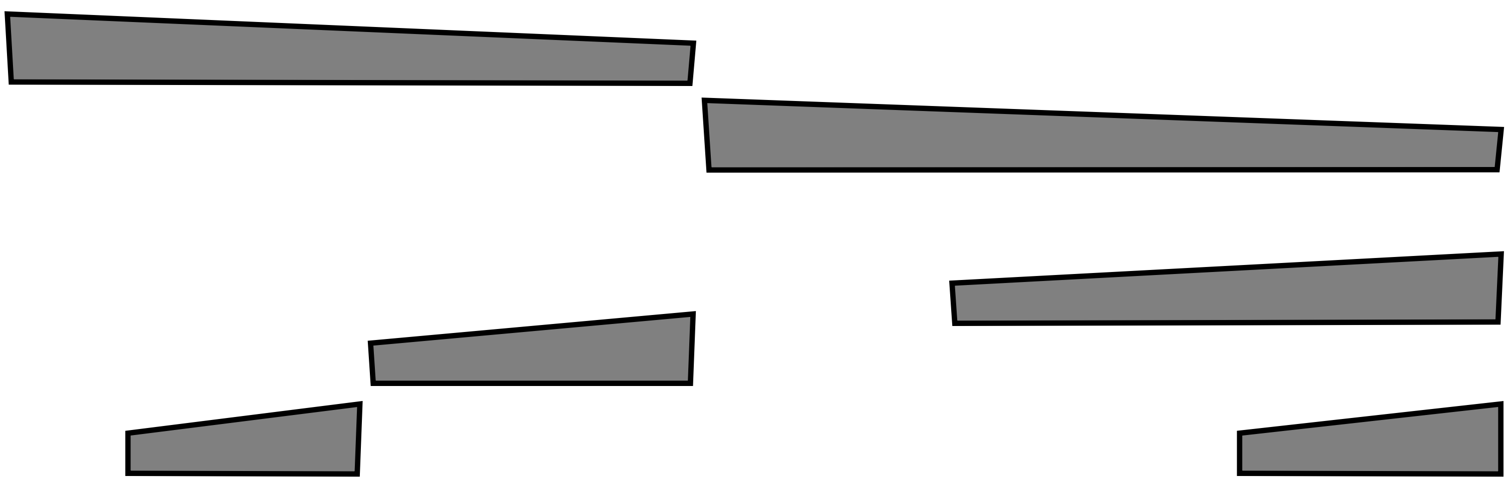

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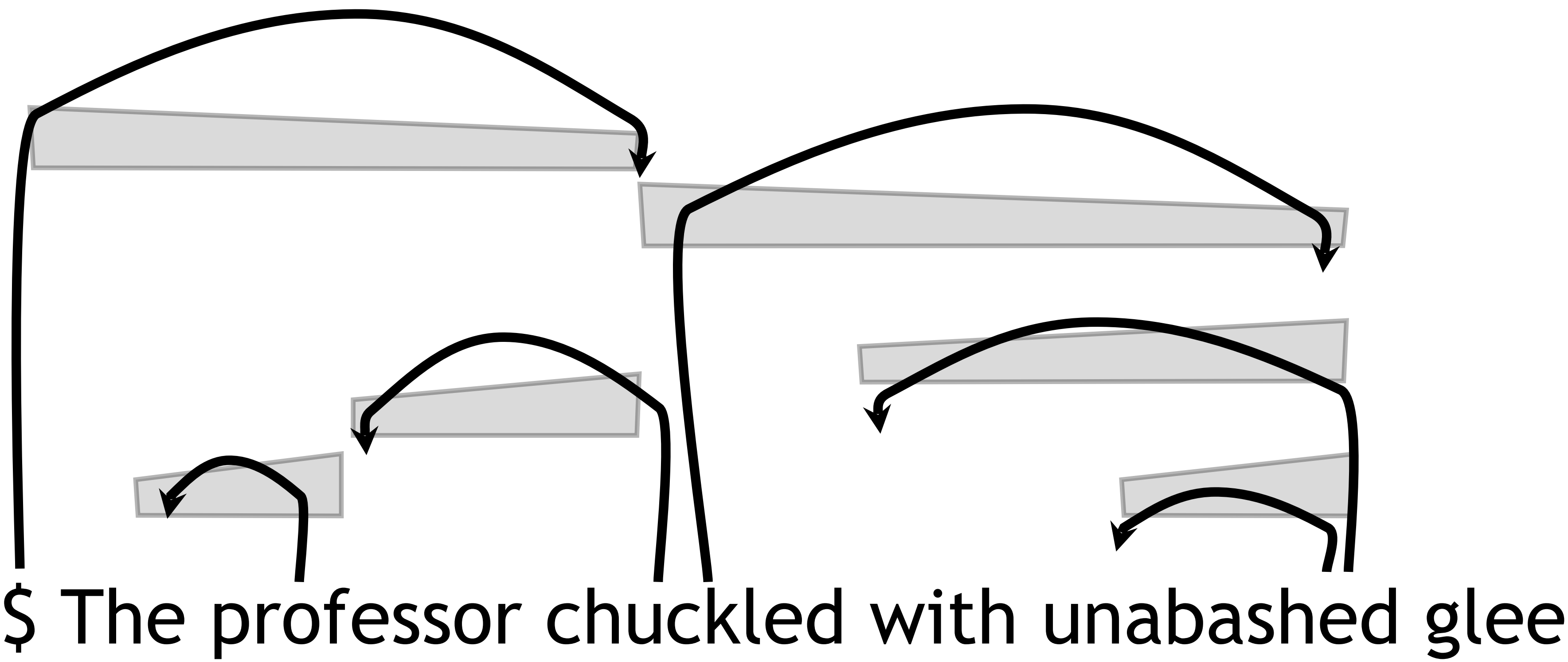
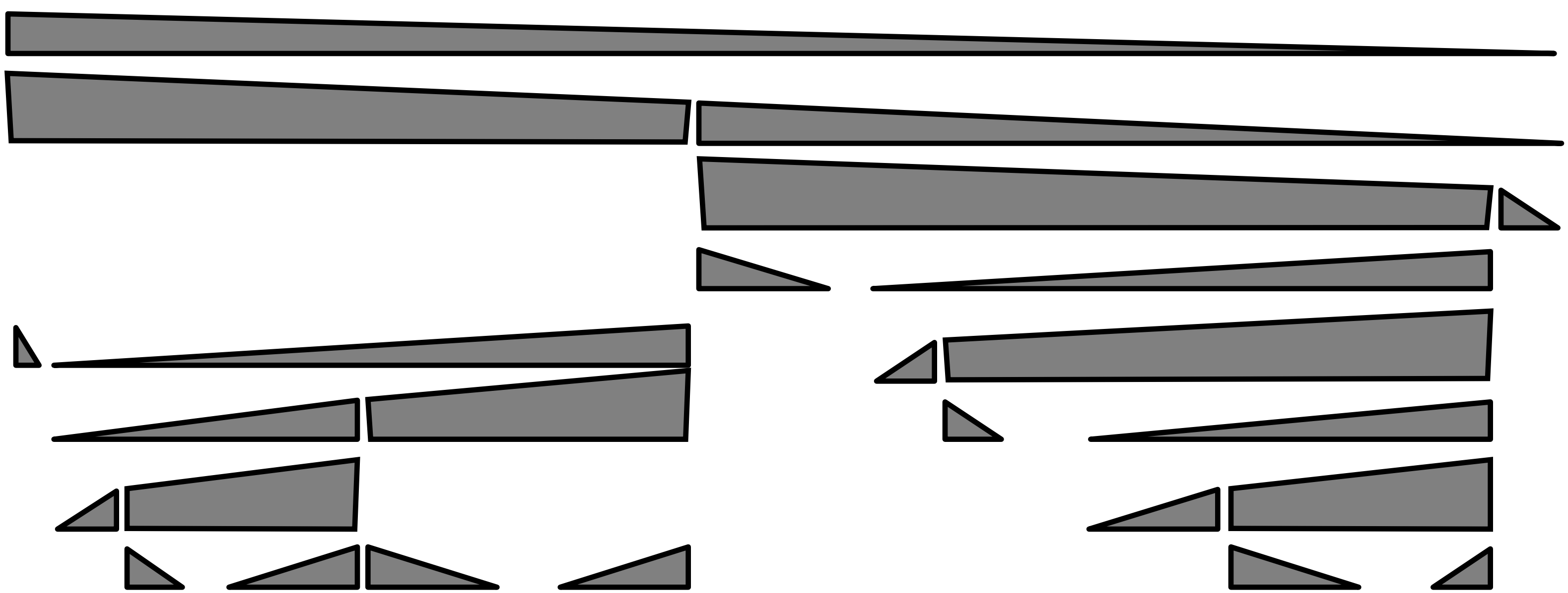


Example of the Eisner Algorithm

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.