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Graph-based dependency parsing

Syntactic analysis (5LN455)

2024

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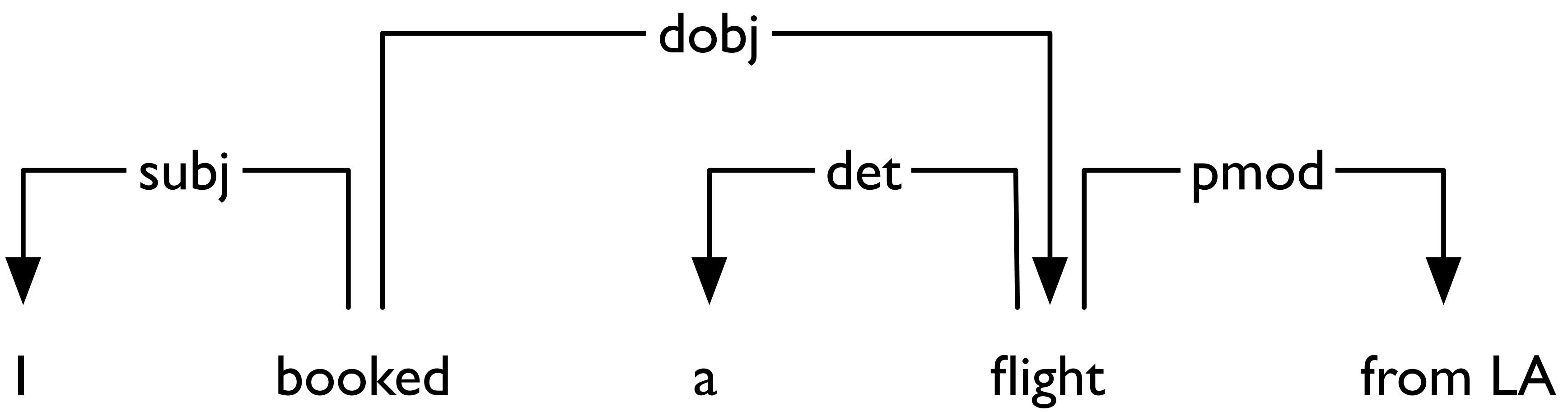
Partially based on slides from Marco Kuhlmann

Arc-factored dependency parsing

Ambiguity

Just like phrase structure parsing, dependency parsing has to deal with ambiguity.



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Ambiguity

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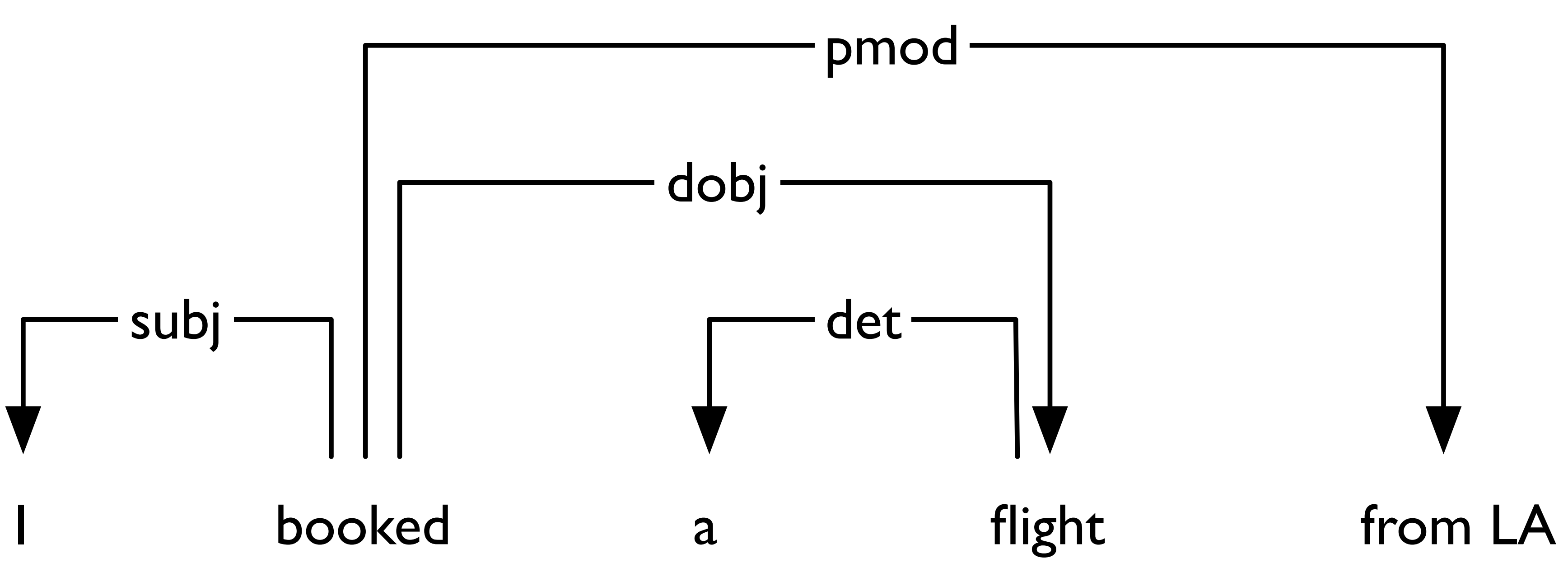

Disambiguation

- We need to disambiguate between alternative analyses.
- We develop mechanisms for scoring dependency trees, and disambiguate by choosing a dependency tree with the highest score.

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Scoring models and parsing algorithms

Distinguish two aspects:

- Scoring model:
  How do we want to score dependency trees?
- Parsing algorithm:
  How do we compute a highest-scoring dependency tree under the given scoring model?

The arc-factored model

- Split the dependency tree t into parts $p_1, \ldots, p_n$, score each of the parts individually, and combine the score into a simple sum.

  $$\text{score}(t) = \text{score}(p_1) + \ldots + \text{score}(p_n)$$

- The simplest scoring model is the arc-factored model, where the scored parts are the arcs of the tree.

Examples of classic features

- ‘The head is a verb.’
- ‘The dependent is a noun.’
- ‘The head is a verb
  and the dependent is a noun.’
- ‘The head is a verb
  and the predecessor of the head is a pronoun.’
- ‘The arc goes from left to right.’
- ‘The arc has length 2.’

Training using structured prediction

- Take a sentence *w* and a gold-standard dependency tree *g* for *w*.
- Compute the highest-scoring dependency tree under the current weights; call it *p*.
- Increase the weights of all features that are in *g* but not in *p*.
- Decrease the weights of all features that are in *p* but not in *g*.

Training using structured prediction

- Training involves repeatedly parsing (treebank) sentences and refining the weights.
- Hence, training presupposes an efficient parsing algorithm.

Higher order models

- The arc-factored model is a first-order model, because scored subgraphs consist of a single arc.
- An nth-order model scores subgraphs consisting of (at most) n arcs.
- Second-order: siblings, grand-parents
- Third-order: tri-siblings, grand-siblings
- Higher-order models capture more linguistic structure and give higher parsing accuracy, but are less efficient

Parsing algorithms

- Projective parsing
  - Inspired by the CKY algorithm
    - Collins' algorithm
    - Eisner's algorithm
- Non-projective parsing:
  - Minimum spanning tree (MST) algorithms
    - e.g. Chu-Liu-Edmunds algorithm (CLE)

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Collins’ algorithm

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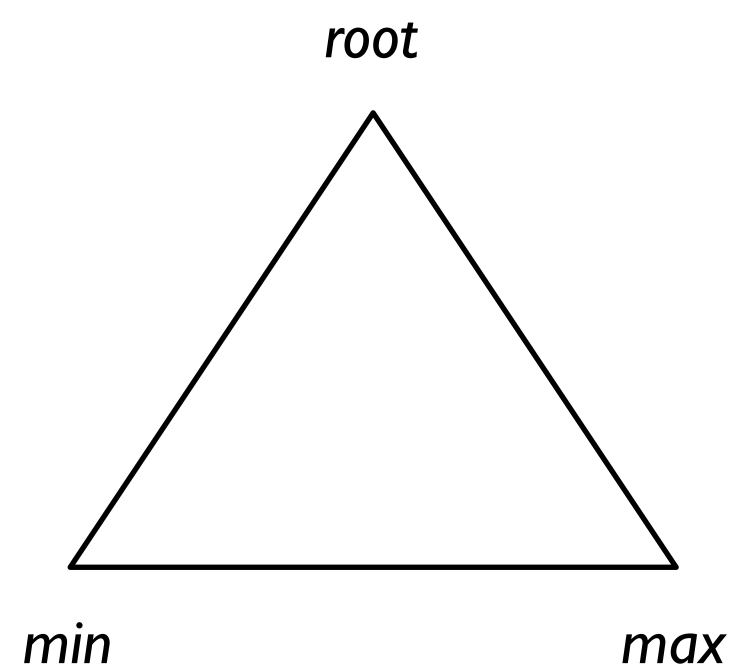
Collins' algorithm

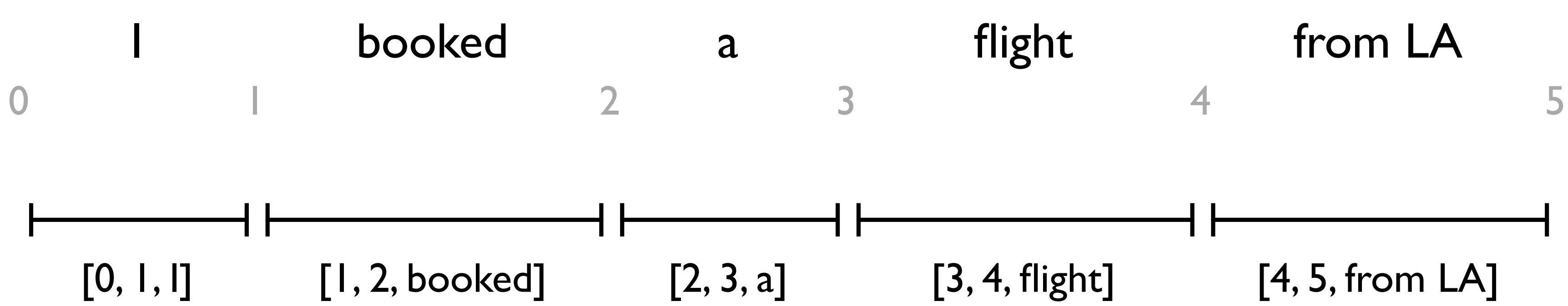
- Collin's algorithm is a simple algorithm for computing the highest-scoring dependency tree under an arc-factored scoring model.
- It can be understood as an extension of the CKY algorithm to dependency parsing.
- Like the CKY algorithm, it can be characterized as a bottom-up algorithm based on dynamic programming.

Signatures, Collins’

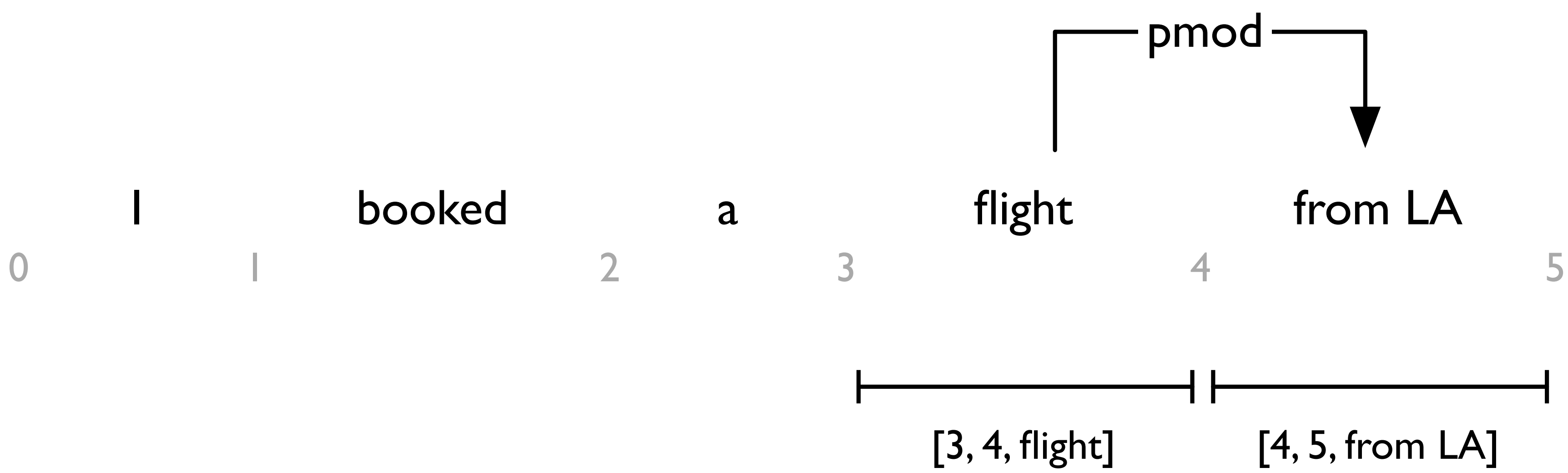


[*min*, *max*, *root*]

Initialization



Adding a left-to-right arc



Collins' algorithm

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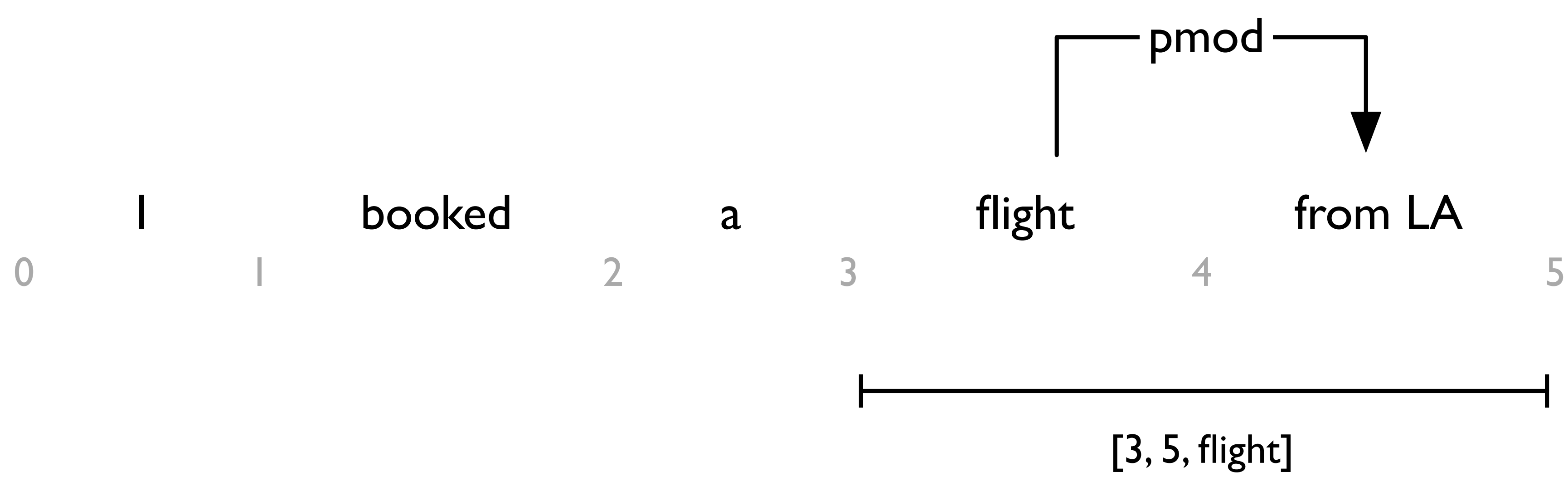

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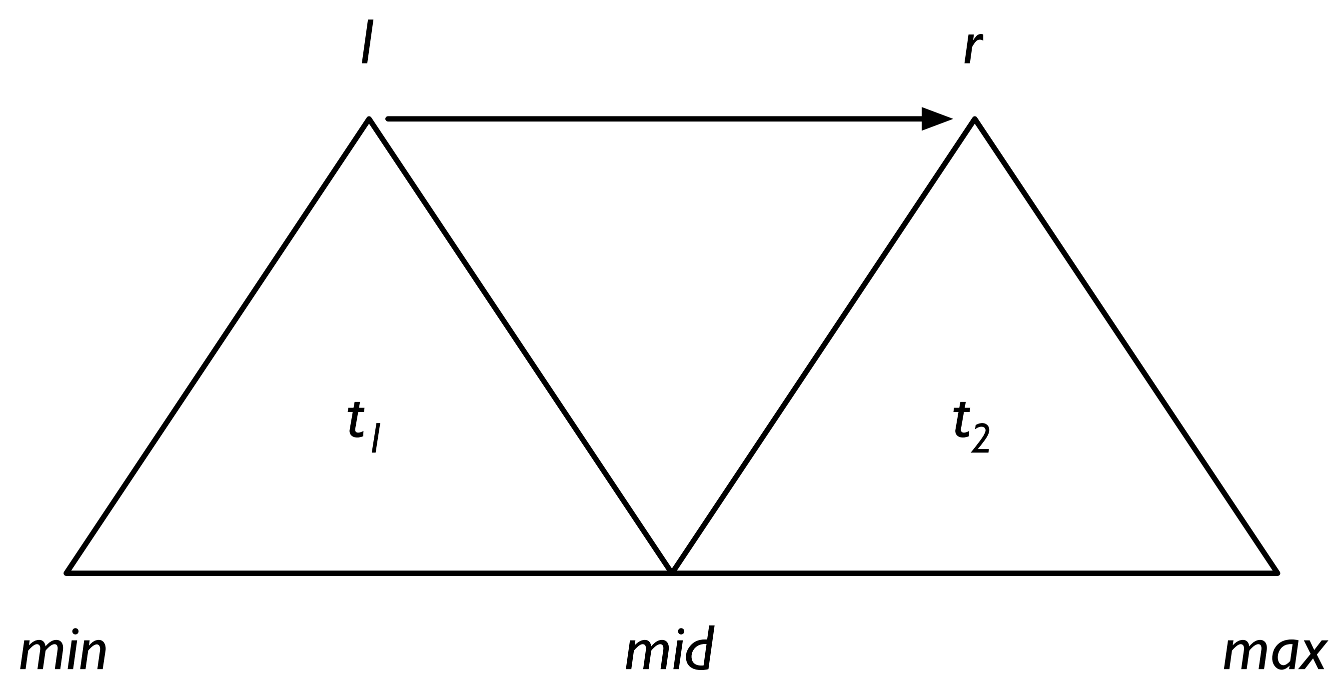

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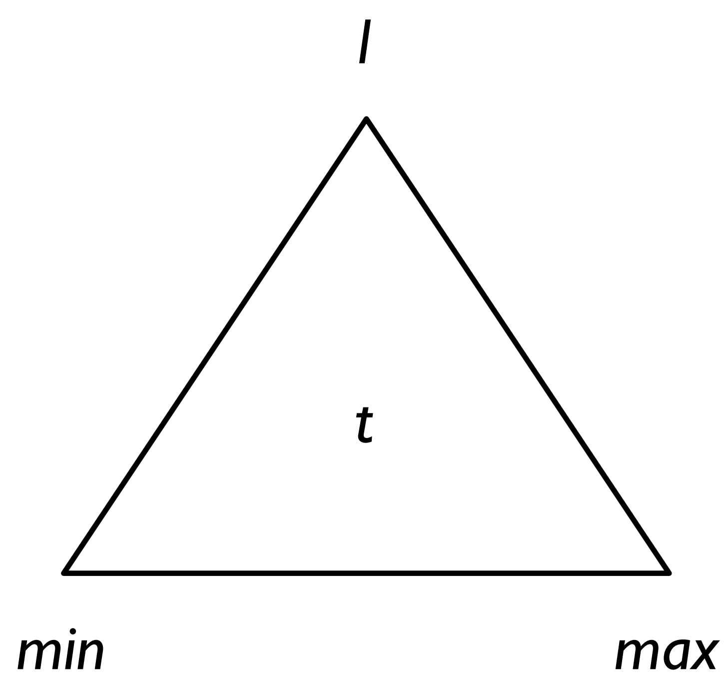


$$\text{score}(t) = \text{score}(t_1) + \text{score}(t_2) + \text{score}(l \rightarrow r)$$

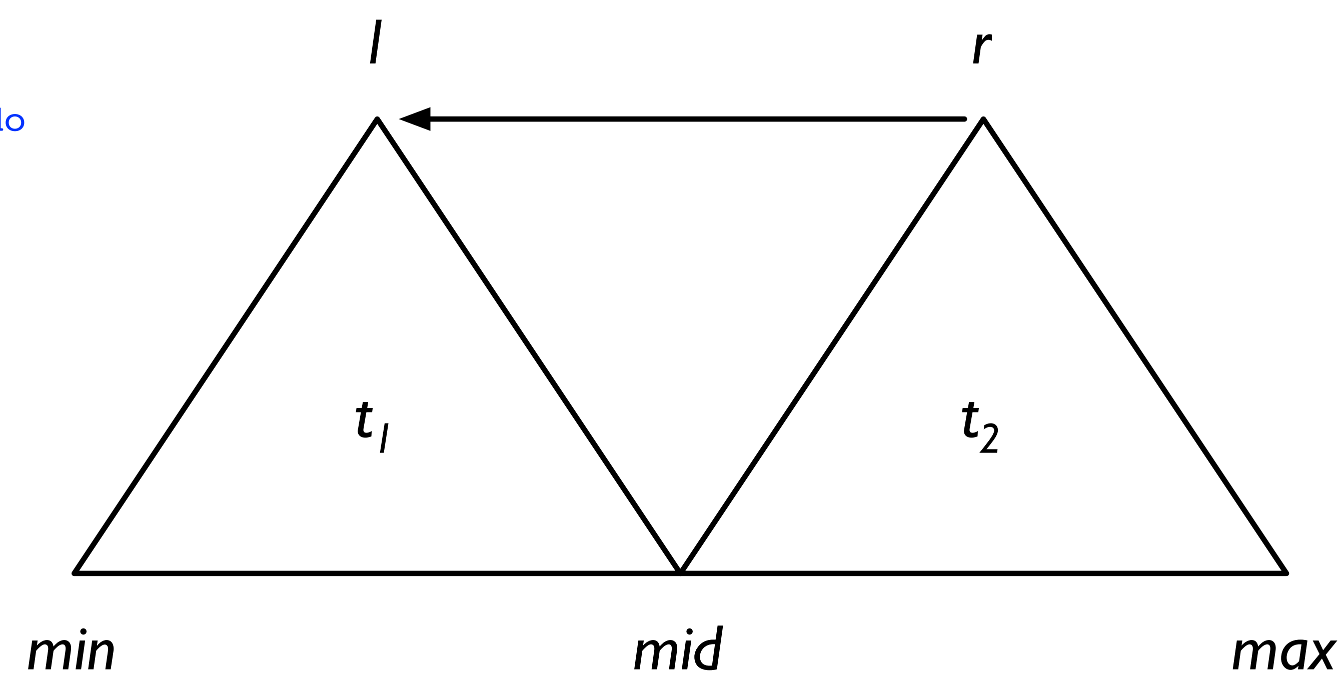
Adding a left-to-right arc

```
for each [min, max] with max - min > 1 do
  for each l from min to max - 2 do
    double best = score[min][max][l]
    for each r from l + 1 to max - 1 do
      for each mid from l + 1 to r do
        t1 = score[min][mid][l]
        t2 = score[mid][max][r]
        double current = t1 + t2 + score(l → r)
        if current > best then
          best = current
    score[min][max][l] = best
```

Complexity analysis

- Runtime?
- Space?

```
for each [min, max] with max - min > 1 do
  for each r from min + 1 to max - 1 do
    double best = score[min][max][r]
    for each l from min to r - 1 do
      for each mid from l + 1 to r do
        t₁ = score[min][mid][l]
        t₂ = score[mid][max][r]
        double current = t₁ + t₂ + score(r → l)
        if current > best then
          best = current
    score[min][max][r] = best
```



Complexity analysis

- Space requirement:
  $O(|w|^3)$
- Runtime requirement:
  $O(|w|^5)$

Extension to the labeled case

- It is important to distinguish dependencies of different types between the same two words.

  Example: subj, dobj

- For this reason, practical systems typically deal with labeled arcs.
- The question then arises how to extend Collins' algorithm to the labeled case.

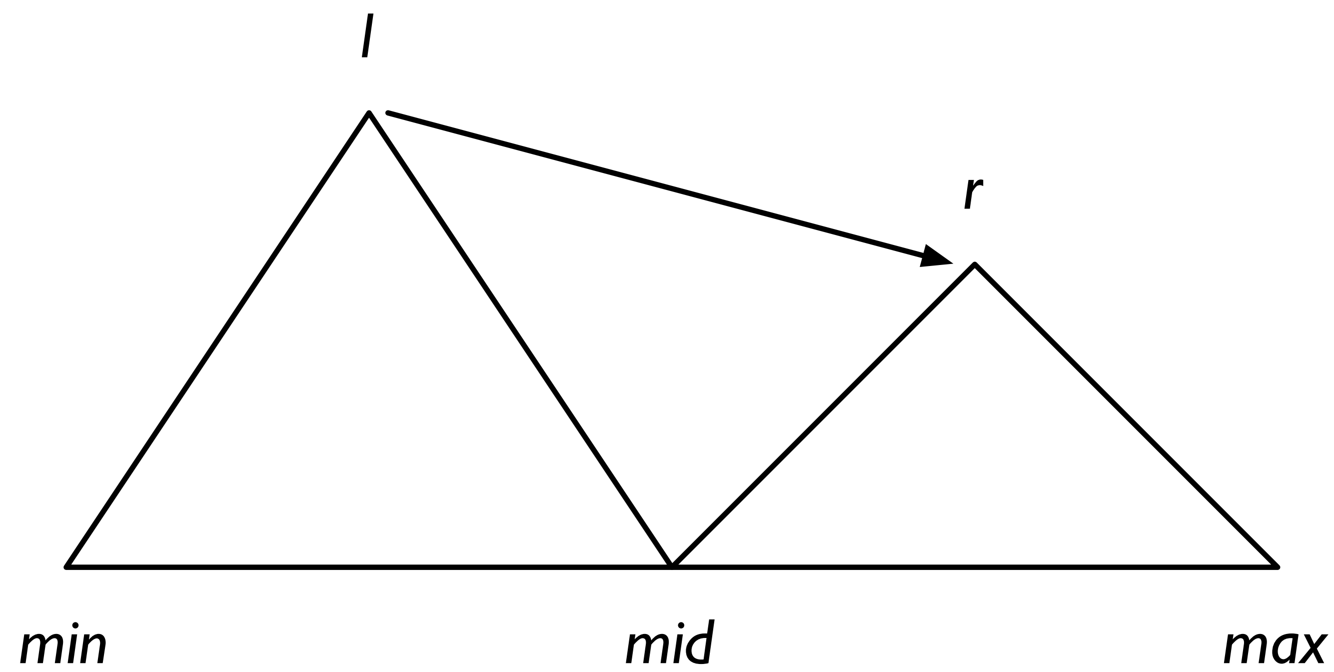
Smart approach

- Before parsing, compute a table that lists, for each head-dependent pair (h, d), the label that maximizes the score of arcs $h \rightarrow d$.
  - This is guaranteed to be the arcs that could be used in a highest-scoring tree
- During parsing, simply look up the best label in the pre-computed table.
- This adds (not multiplies!) a factor of $|L||w|^2$ to the overall runtime of the algorithm.

Eisner's algorithm

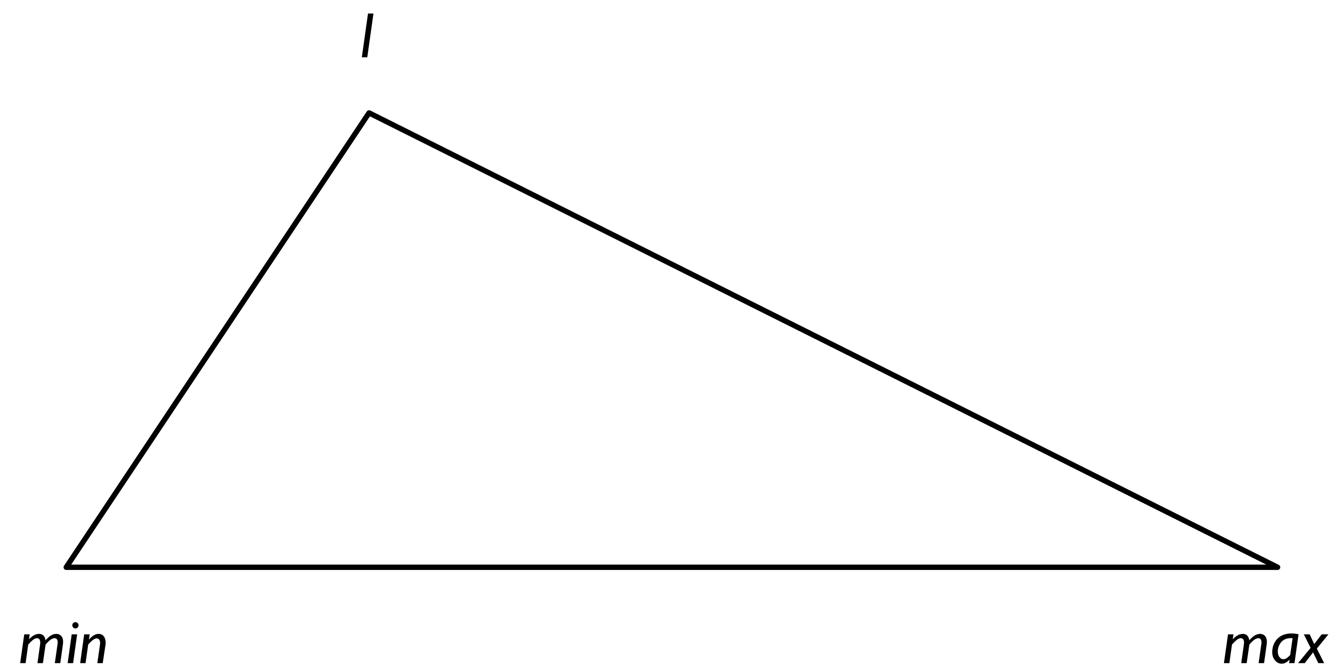
- With its runtime of $O(|w|^5)$, Collins' algorithm may not be of much use in practice.
- With Eisner's algorithm we will be able to solve the same problem in $O(|w|^3)$.
  - Intuition: collect left and right dependents independently

Basic idea



In Collins' algorithm, adding a left-to-right arc is done in one single step, specified by 5 positions.

Basic idea



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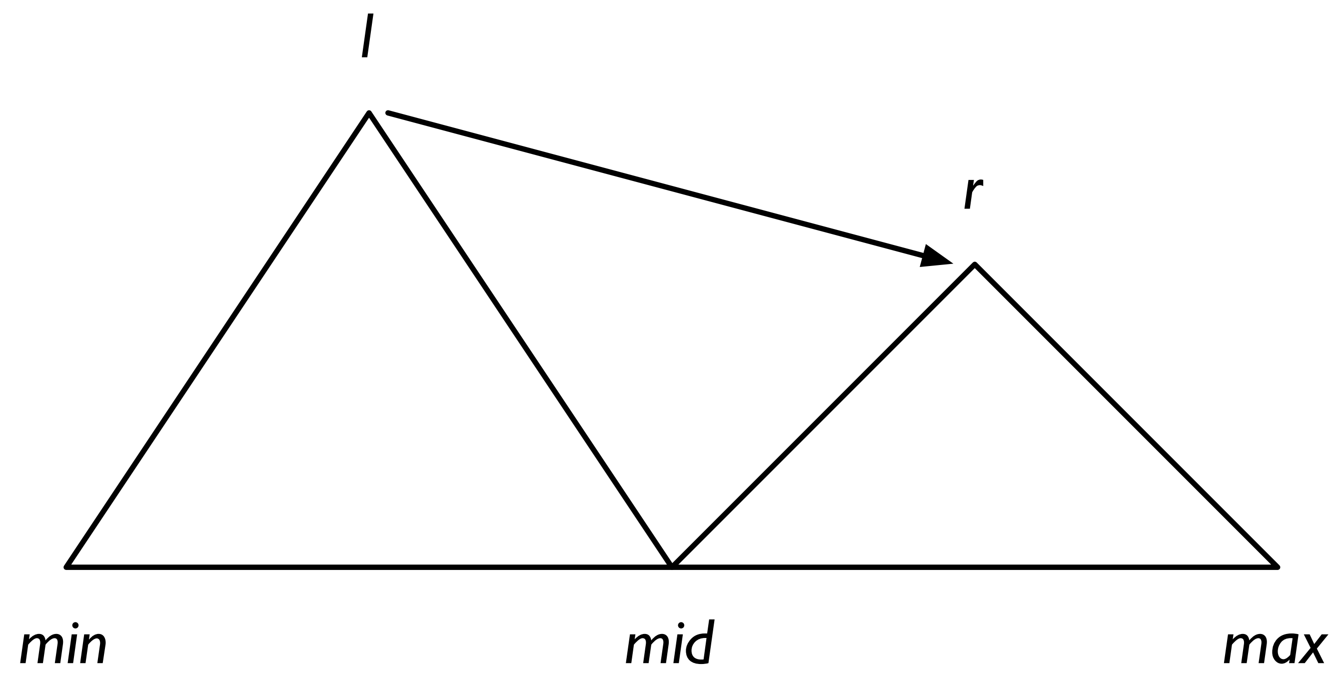
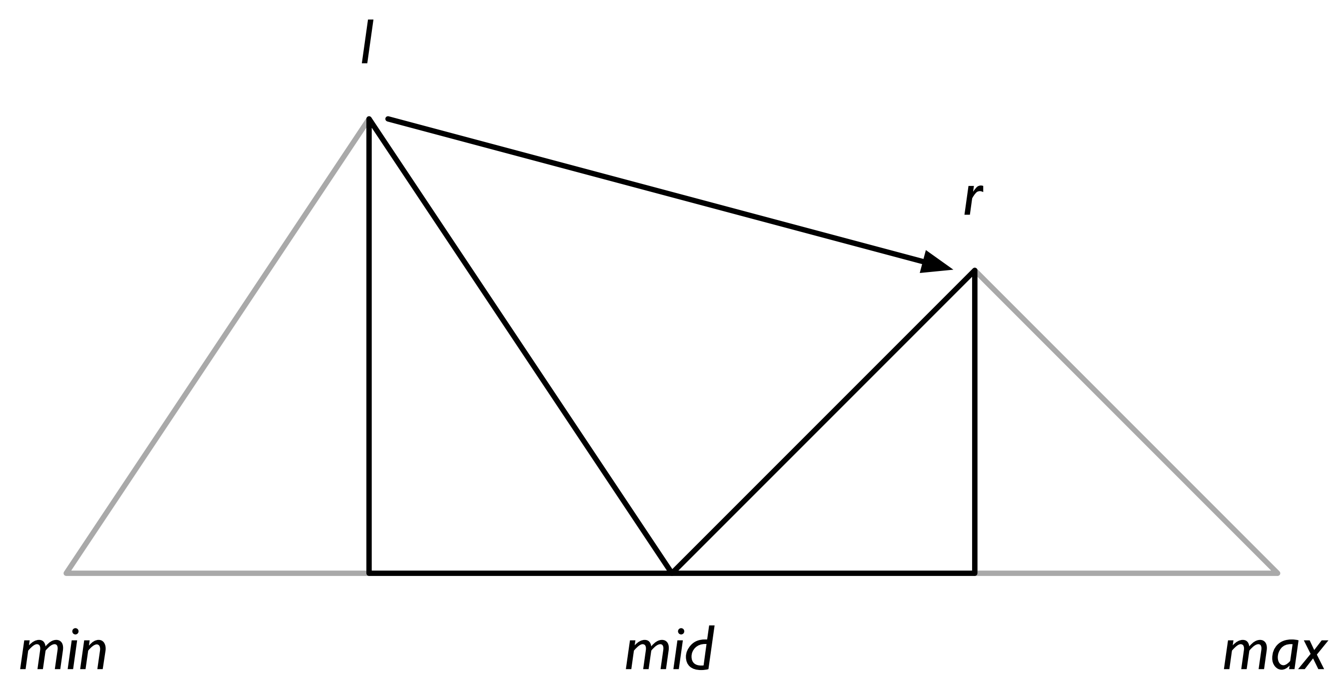


In Eisner’s algorithm, the same thing is done in three steps, each one specified by 3 positions.

Basic idea



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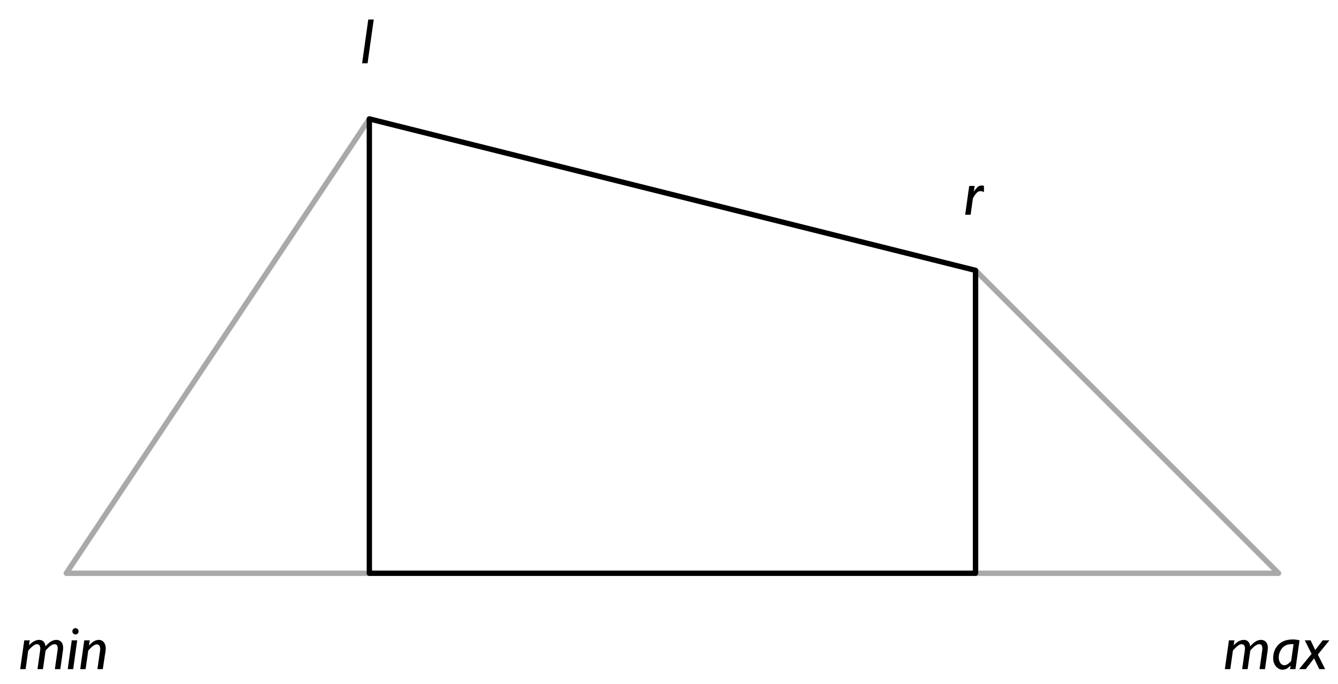

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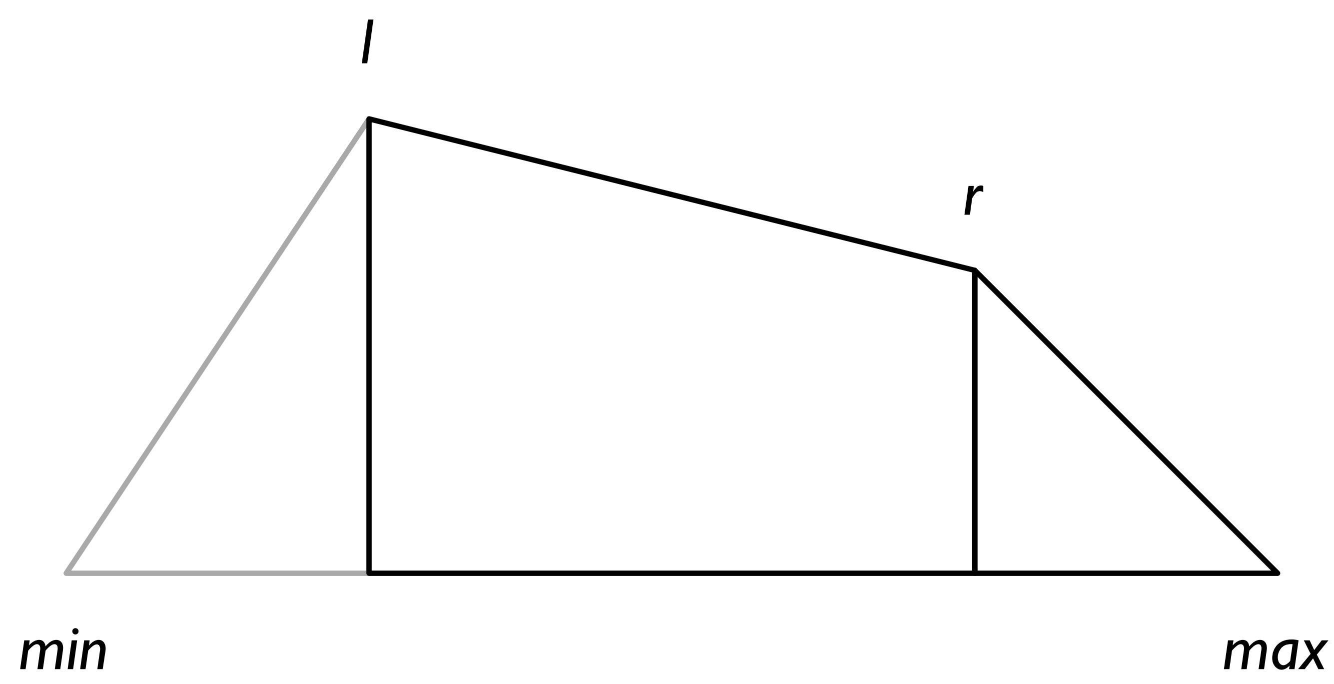

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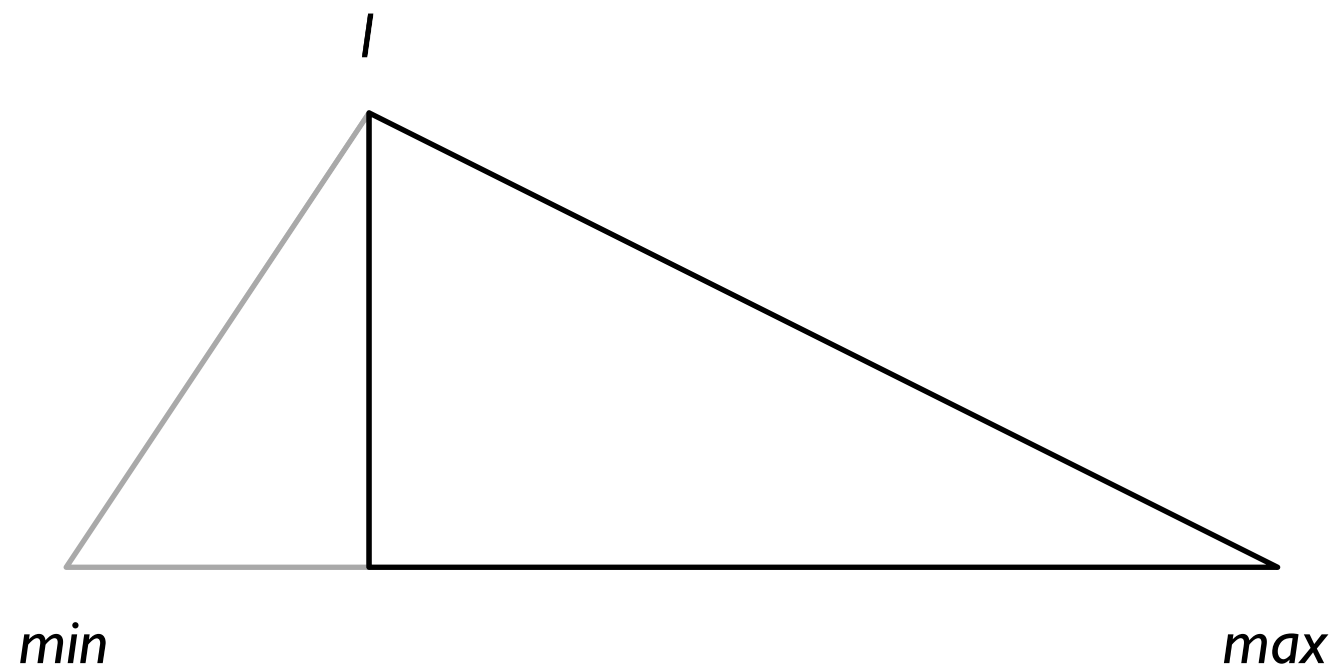

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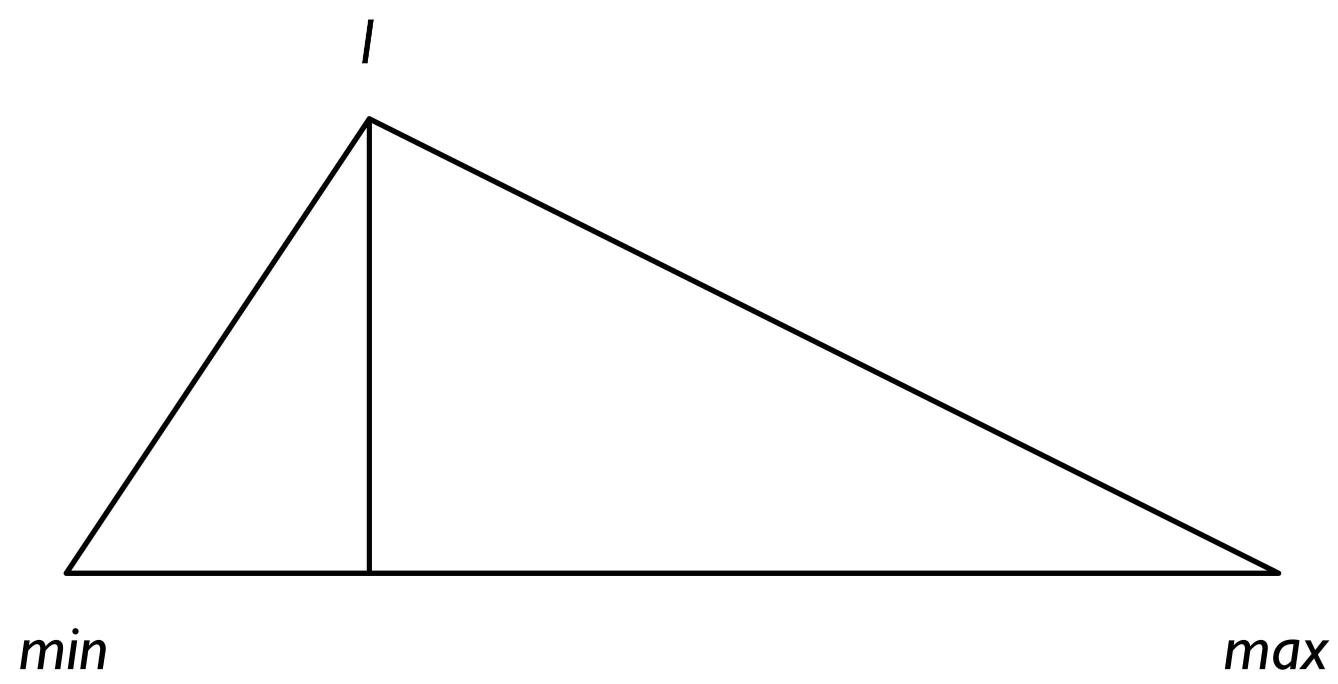

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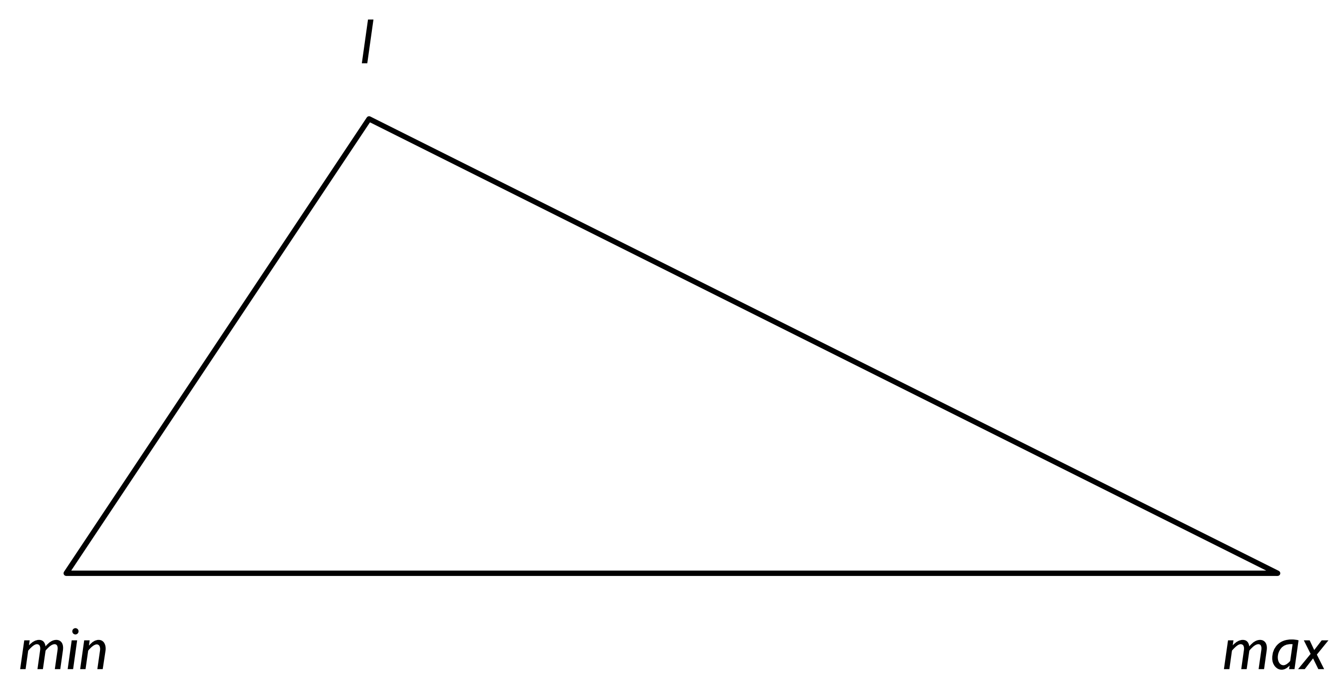

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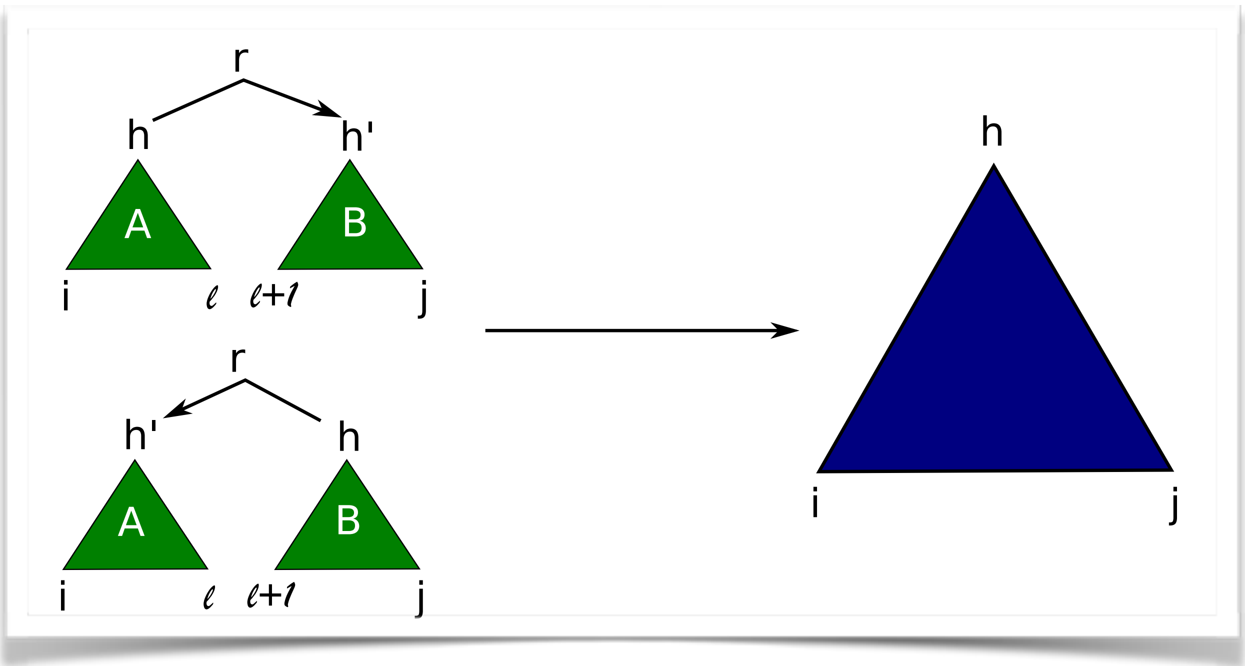
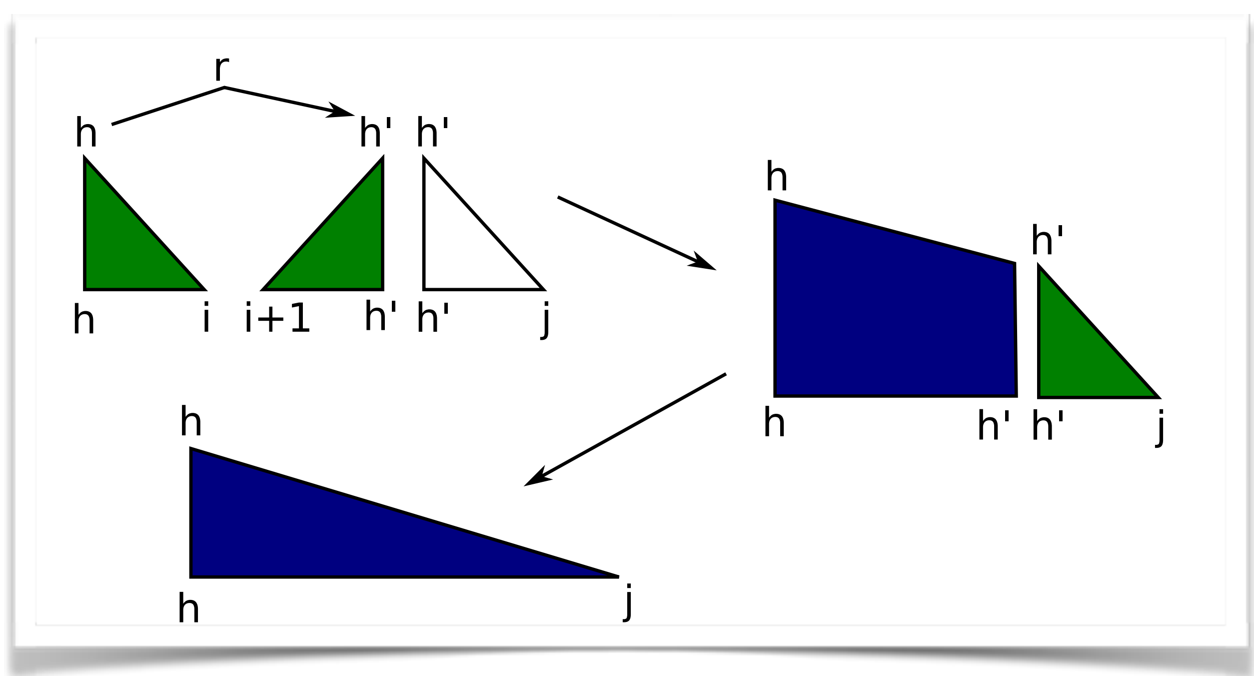
Comparison



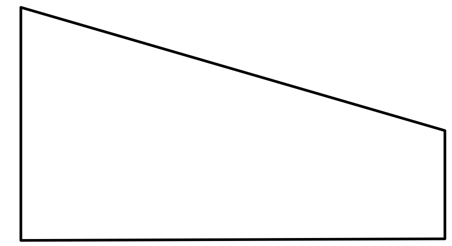


Dynamic programming tables

- Collins':
  - [min,max,head]
- Eisner's
  - [min,max,head-side,complete]
    - head-side (binary): is head to the left or right?
    - complete (binary:) is the non-head side still looking for dependents?

Graphic representation

- [min,max,left,yes]



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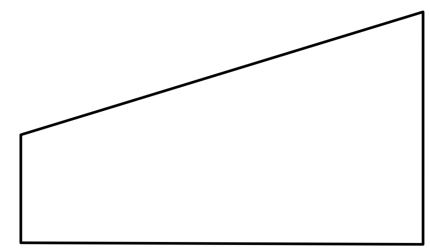
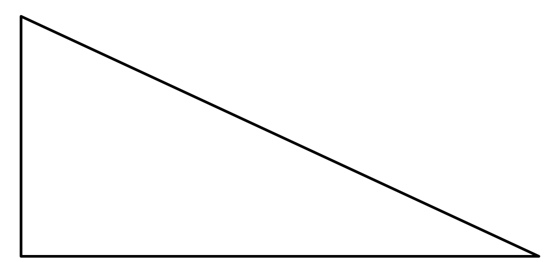


- [min,max,left,no]



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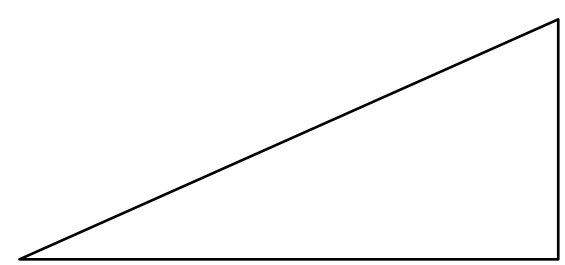

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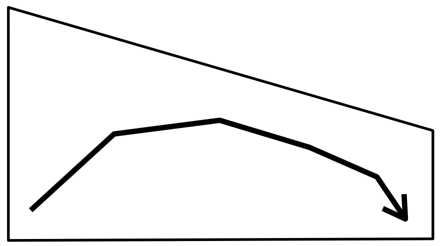

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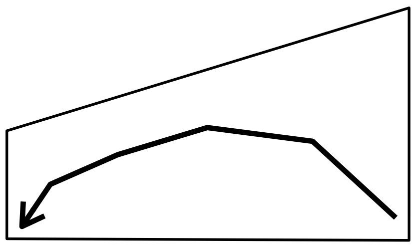

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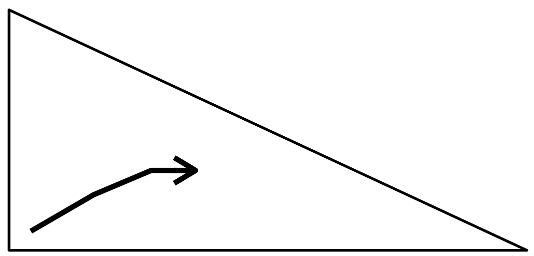

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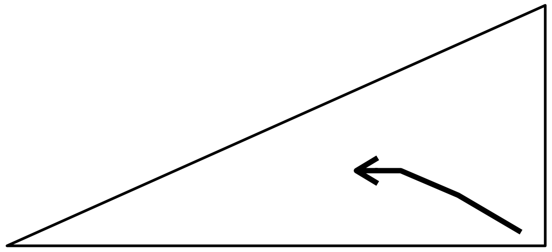
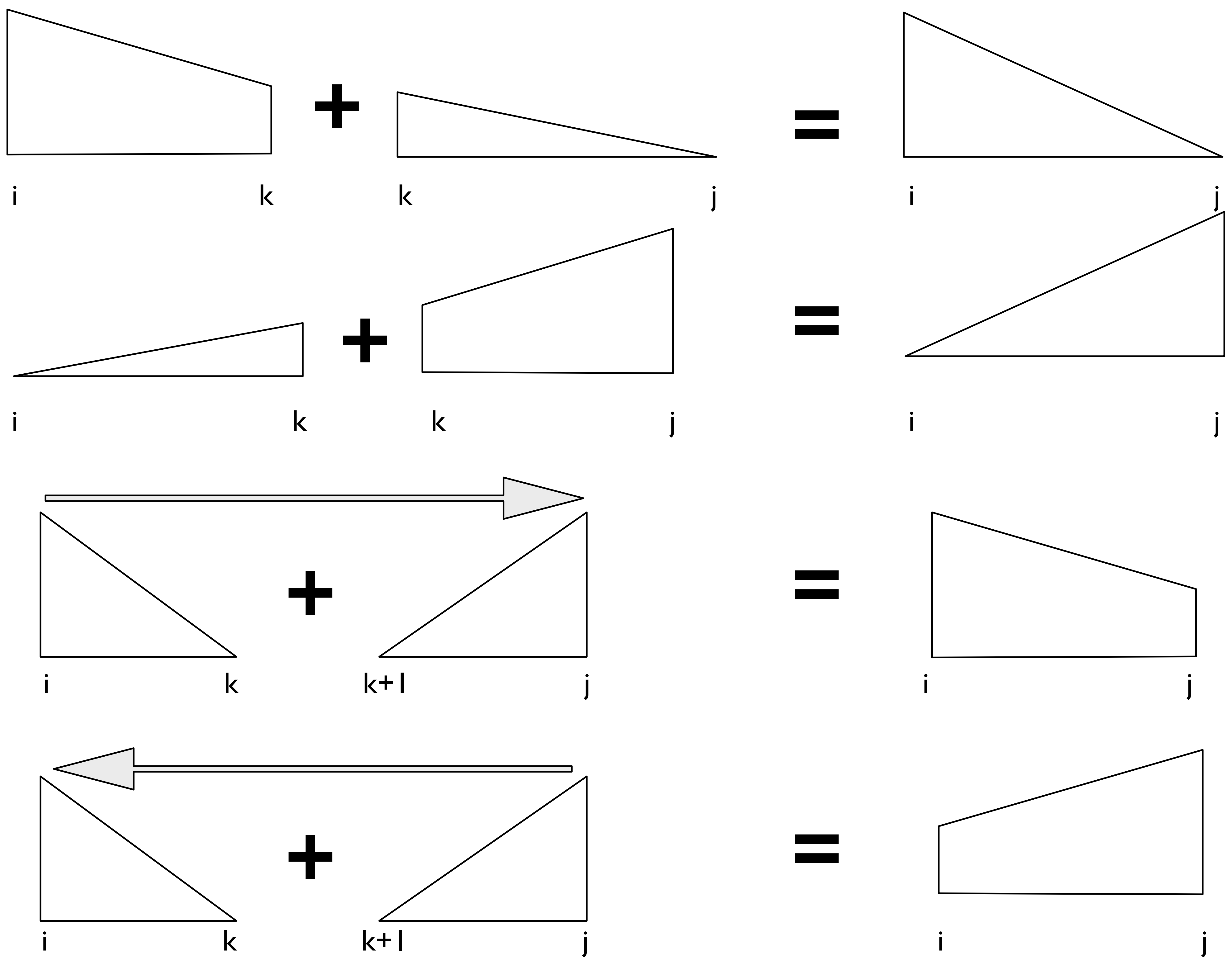


Possible operations



Pseudo code

```
for each i from 0 to n and all d,c do
   C[i][i][d][c] = 0.0
for each m from 1 to n do
  for each i from 0 to n-m do
     j = i+m
     C[i][j][←][1] = max_{i≤q<j}(C[i][q][→][0] + C[q+1][j][←][0]+score(w_j,w_i)
     C[i][j][→][1] = max_{i≤q<j}(C[i][q][→][0] + C[q+1][j][←][0]+score(w_i,w_j)
     C[i][j][←][0] = max_{i≤q<j}(C[i][q][←][0] + C[q][j][←][1])
     C[i][j][→][0] = max_{i≤q<j}(C[i][q][→][1] + C[q][j][→][0])
return [0][n][→][0]
```

Summary

- Eisner’s algorithm is an improvement over Collin’s algorithm that runs in time $O(|w|^3)$.
- The same scoring model can be used.
- The same technique for extending the parser to labeled parsing can be used, adding $O(|L||w|^2)$ to the run time.
- Eisner’s algorithm is the basis of current arc-factored dependency parsers.

Projectivity

- Eisner's algorithm, as well as Collin's algorithm, builds the tree bottom-up
- They only produce projective trees
- What about non-projective graph-based parsing?
  - Based on minimum-spanning tree algorithms

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Minimum-spanning tree parsing

- Based on graph algorithms to find the minimum spanning tree
  - Often: Chu-Liu-Edmonds algorithm (CLU)
- Directly produces non-projective trees
- First suggested in the MSTparser
- One of the most popular algorithms today

Minimum-spanning tree parsing

- **Intuition:**
- Score all word pairs in both directions
- Create a fully connected graph with these scores
- Remove all edges going into ROOT
- For each node, greedily keep only the highest-scoring incoming arc
    - If this produces a tree: done!
    - Otherwise: handle each cycle in the graph:
    - Recursively contract cycles, and recalculate incoming weights

Minimum-spanning tree parsing

- **Complexity:**
- Naive implementation:
  - O(n^3):
  - At most n recursive calls to contract graph, in each call find highest incoming edge: n^2
- Efficient implementation:
  - O(n^2)
  - Tarjan (1977)
- Naturally can produce non-projective trees

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Coming up

- March 4: literature seminar 2
  - Groups on the web page (note: new groups)
- Supervision in Chomsky+Turing :
  - March 6 and March 13
- Final seminar:
  - March 25 (NOTE: moved)
- Assignment 3, deadline March 11
- Project report, deadline March 22