Lecture 13

Parsing

Part 1: Definition and Representation

Machine Learning for Structured Data

Vlad Niculae · LTL, UvA · `https://vene.ro/mlsd`

1. **Definition and Representation**

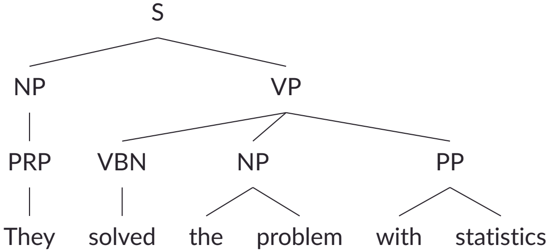
2. Bracketing: Algorithm

3. Extensions and Evaluation

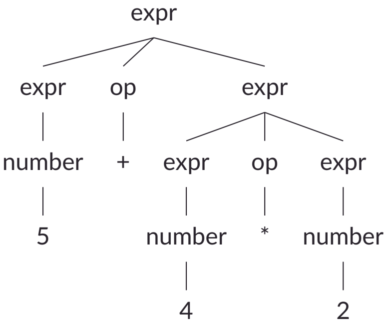
Syntactic analysis

Syntax is an underlying structure of languages, often analyzed using parse trees.

human language (English):

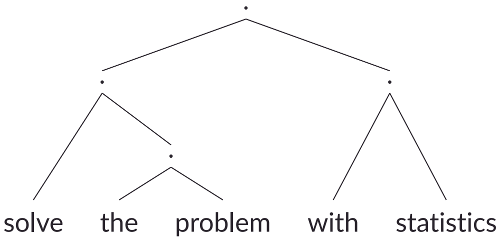


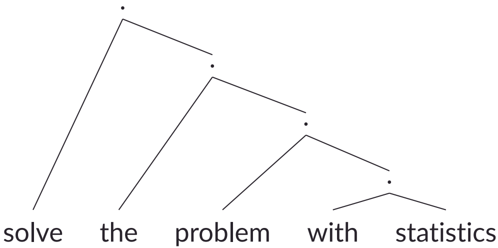
programming language (Python):



Binary Parsing

There are many kinds of complicated syntactic analysis formalisms. For simplicity, we focus on: binary trees. Let's start without labels too.





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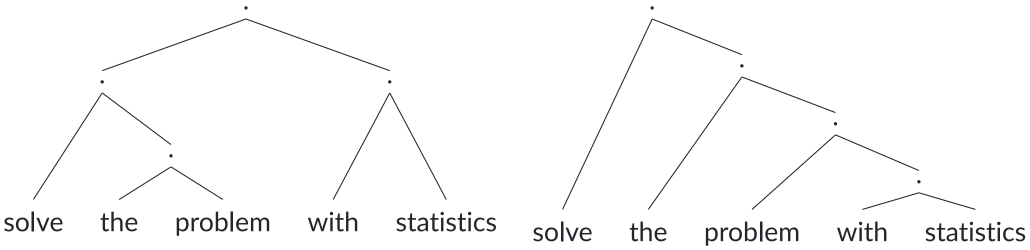
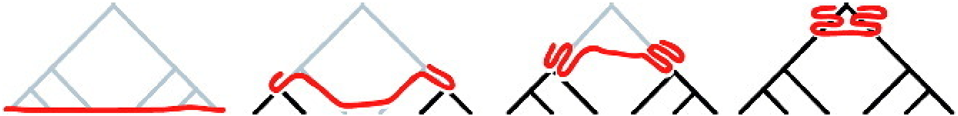


A binary parse tree with no labelling is the same thing as a bracketing:

((solve (the problem)) (with statistics)) ((solve (the (problem (with statistics)))))

Protein folding as binary parse trees

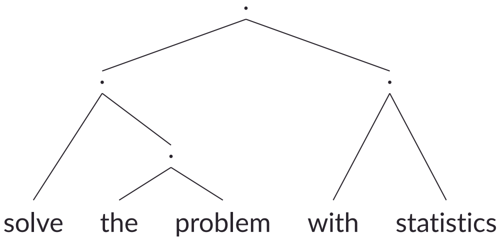


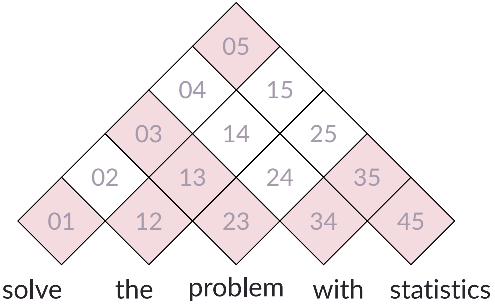
Julia Hockenmaier, Aravind K. Joshi, Ken A. Dill,
Routes are trees: The parsing perspective on protein folding. Proteins, 66–1, 2007.

Bracketing: Representation

Assign a score a_{ij} to the span from i to j (fencepost).

The score of a parse tree is the sum of all scores of its (nested!) spans.





$$\text{score}(y) = a_{01} + a_{12} + a_{23} + a_{34} + a_{45} + a_{13} + a_{35} + a_{03} + a_{05}$$

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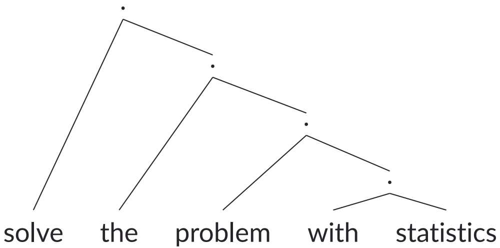

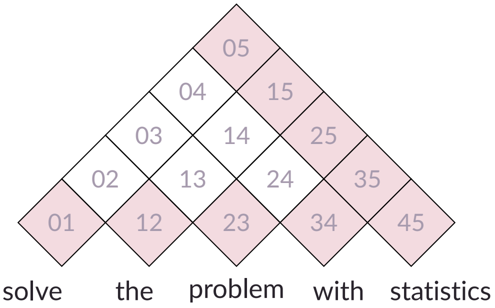

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Part 2: Bracketing: Algorithm

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1 Definition and Representation

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Algorithm

Possible parses of the subsequence (0, 3):

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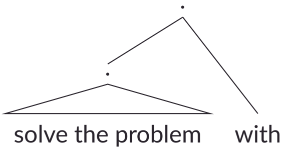
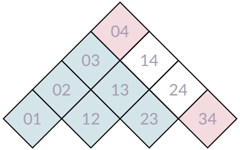
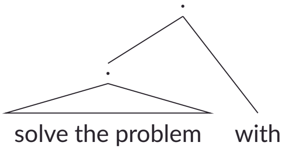
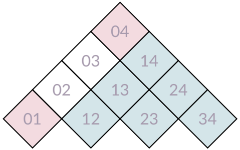
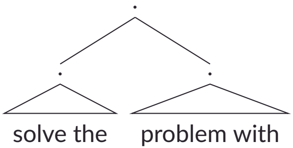
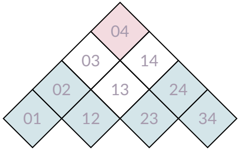




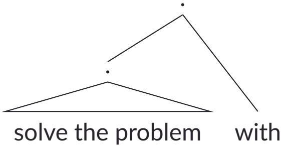


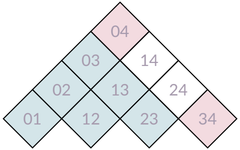


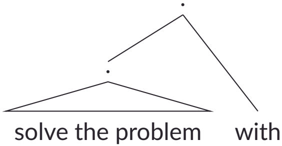


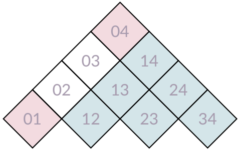


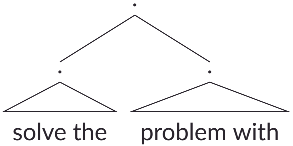
Possible parses of the subsequence (0, 4): see the pattern?

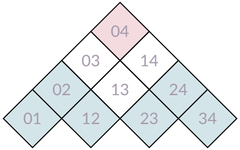






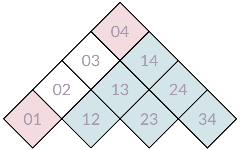


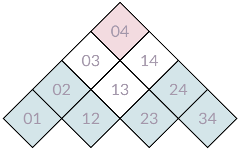


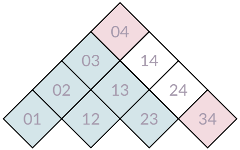


The CYK Algorithm

In general: a partial parse that covers subsequence (i, j) must consist of two partial parses: one covering (i, k) and one covering (k, j) for some $i < k < j$.







Fill in the table bottom-up: **dynamic programming**.

Cocke, Kasami, and Younger independently discovered it in the 1960s.

The CYK Algorithm

In general: a partial parse that covers subsequence (i, j) must consist of two partial parses: one covering (i, k) and one covering (k, j) for some $i < k < j$.

Define M_{ij} as the maximum-scoring parse of subtree from i to j. Then:

$$\begin{aligned} M_{j-1,j} &= a_{j-1,j} \\ M_{i,j} &= \max_{i<k<j} a_{i,j} + M_{i,k} + M_{k,j} \end{aligned}$$

Fill in the table bottom-up: **dynamic programming**.

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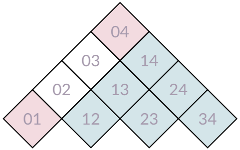
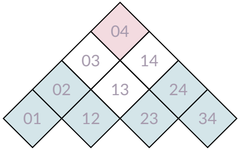
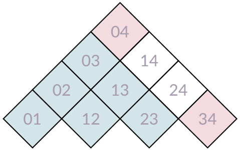
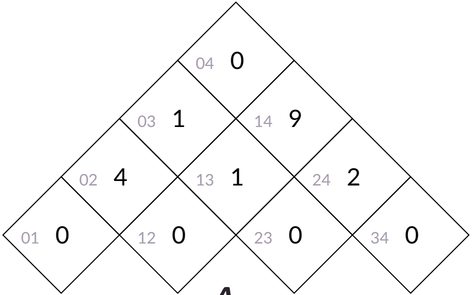


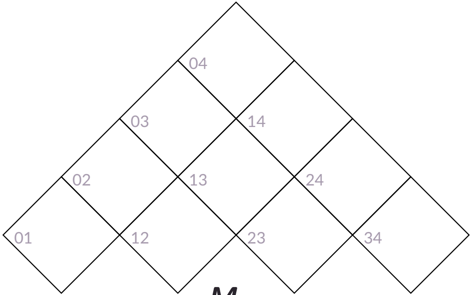




The CYK Algorithm: Example



$\boldsymbol{A} =$



$\boldsymbol{M} =$

CYK vs Segmentation

- The two algorithms have the same inputs: a table of scores for every possible segment.
- The segmentation problem seeks the best low-level chunking.
- CYK seeks an entire tree of chunk “splits”.
- Segmentation is the simplest possible DAG. CYK cannot be represented as a DAG at all!

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Part 3: Extensions and Evaluation

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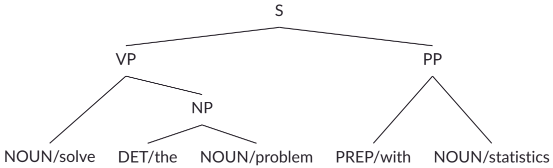
3. **Extensions and Evaluation**

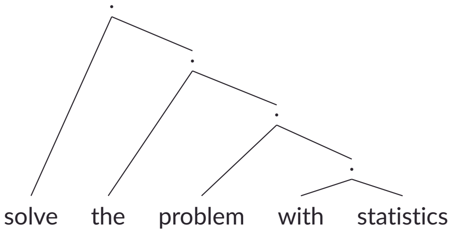
Labelled Parsing



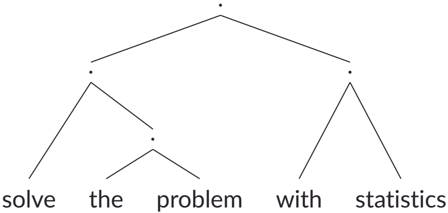
- Simple case: replace all segments with labeled segments (i, j, c).
- In this case, like for segmentation, we can pick the best label for each segment before starting Viterbi, and ignore the rest.
- However, we might want a form of "transition scores": prefer forming a S out of NP VP than out of VP NP.
  - related to *probabilistic context-free grammars*
  - can be handled by the same DP algorithm.

Evaluation

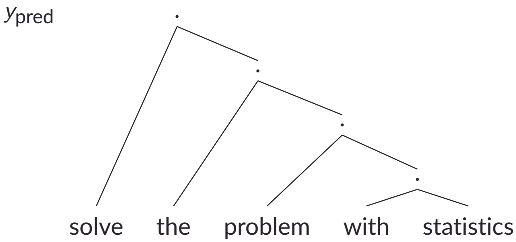
y_{pred}

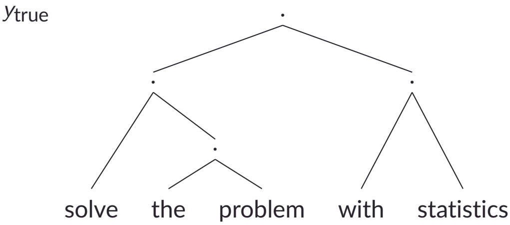


y_{true}



Evaluation





Predicted spans:
(0, 1), (0, 5) (1, 2), (1, 5), (2, 3), (2, 5), (3, 4) (3, 5), (4, 5)

True spans:
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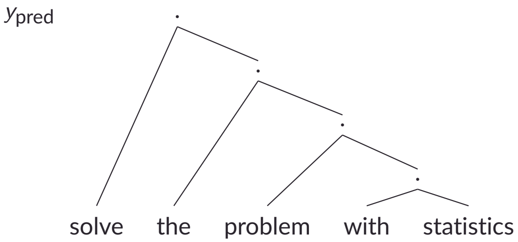

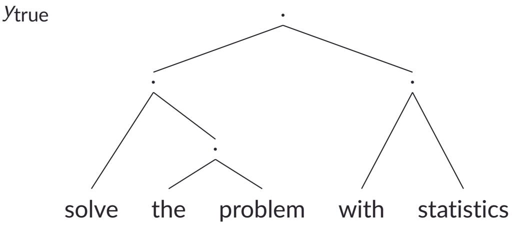

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$P = \frac{\text{n. correct}}{\text{n. predicted}}$ $\qquad R = \frac{\text{n. correct}}{\text{n. true}}$ $\qquad F_1 = \frac{2PR}{P+R}$

Note: in the unlabelled case, P=R, since the number of segments in a bracketing is always the same.

In the labelled case: usually common to compute per-label P/R/F, averaged over the entire dataset.

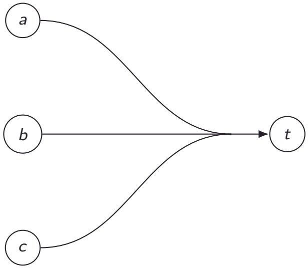
In linguistic applications, “real” parsing evaluation is more complicated, since trees are not binary.

Hyperedges and Hypergraphs

There is a formalism that generalizes DAGs and can express the CYK parsing problem, but its details are too complicated for our scope. Nevertheless, here is a glimpse.

Given nodes $V = \{1, 2, \ldots, n\}$

- **edge**: $(s, t) : s \in V, t \in V$.
- **hyperedge**: $((s_1, \ldots, s_k), t) : s_i \in V, t \in V$.



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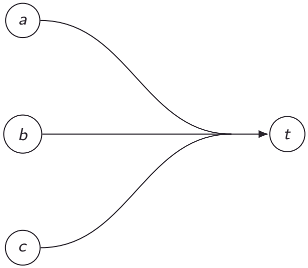
Any directed graph can be represented as a directed hypergraph: if (s, t) is an edge in G, then make $((s), t)$ a hyperedge in HG.

Generalizations of DAG and topological sort exist; and Viterbi & Forward algorithms work.

Read more: Liang Huang, Advanced Dynamic Programming in Semiring and Hypergraph Frameworks, COLING 2008 tutorial.



Summary

- Binary parsing / bracketing can be solved with dynamic programming (even if it can't be represented as a DAG)
- Many applications in computational linguistics: relationship to *grammars*.
- Can generalize the algorithms seen to compute logsumexp and sampling with DP, using a *hypergraphs* formalism.