Upper Bounds for Unsupervised Parsing with Unambiguous Non-Terminally Separated Grammars

Franco M. Luque Gabriel Infante-Lopez

Grupo de Procesamiento de Lenguaje Natural
Fa.M.A.F., Universidad Nacional de Córdoba

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Outline of the Talk

1. Introduction
2. UNTS Grammars
3. Finding the Best Grammar
   - The W Measure
4. Bounding the F1
5. Bounds for the WSJ10
6. Conclusions

Introduction

Design of Unsupervised Parsers

- A main issue is choosing a model.
- Models have learnability (L) and expresiveness (E) properties.
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- L: Good properties (PAC-learnable in polynomial time).
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Measuring Closeness

- Use natural language *gold treebanks* as reference.
- Use standard measure for unsupervised parsing: Unlabeled F1. Results comparable with state-of-the art parsers.
- Consider all the ways UNTS grammars can parse the sentences.
- Find F1 upper bounds for the entire class of UNTS grammars. No hill-climbing. Hard upper bound independent of the learning algorithm.

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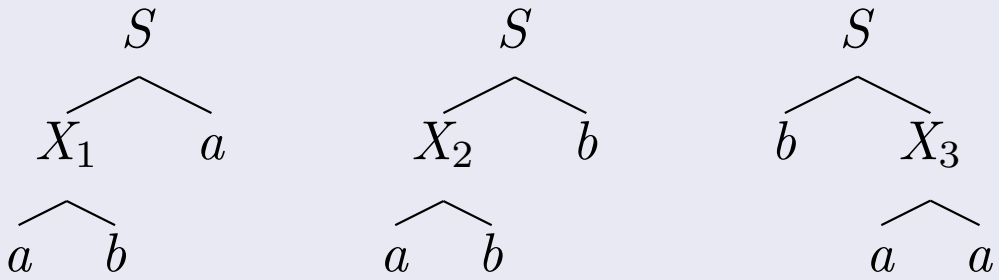

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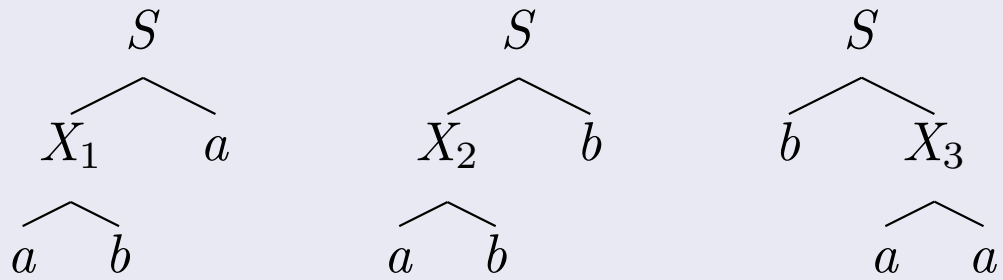

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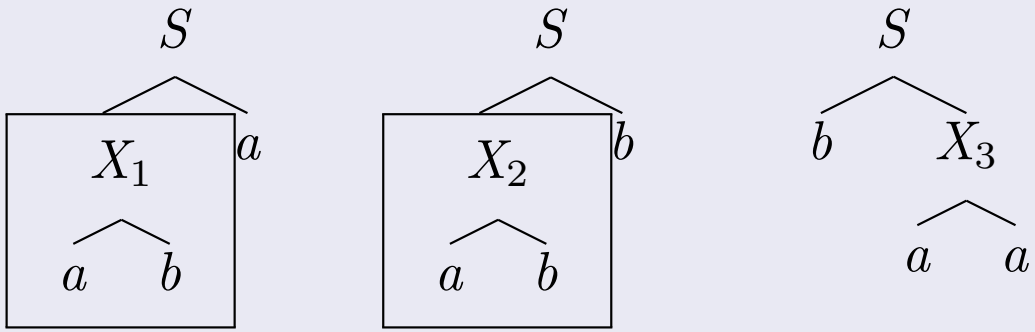

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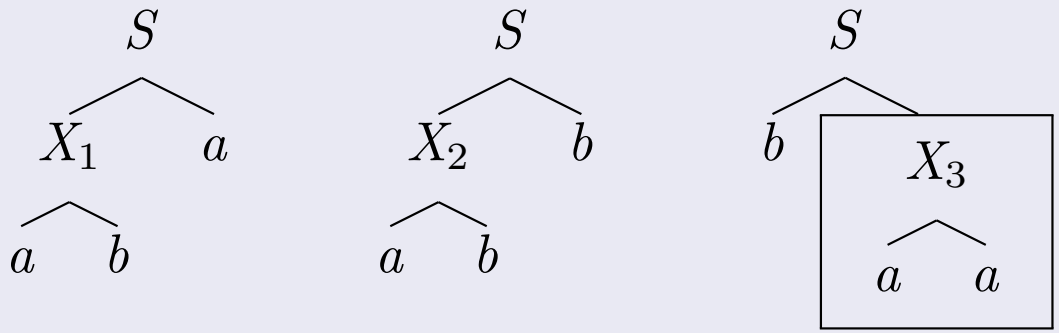

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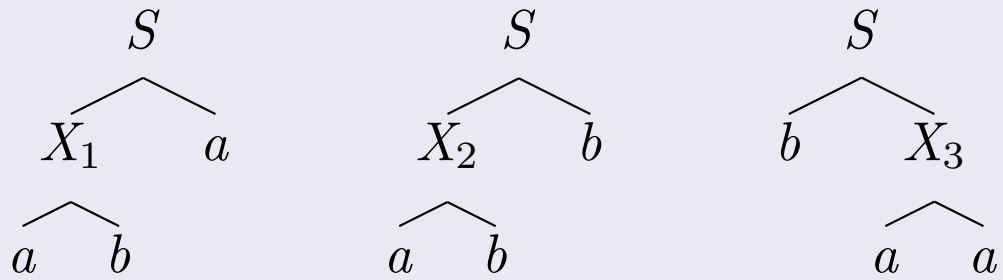

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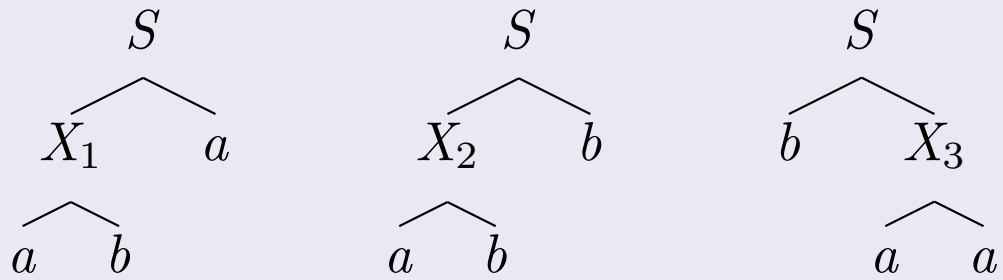

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  - The distituents are $D = \{ba, bb\}$. (find them!)

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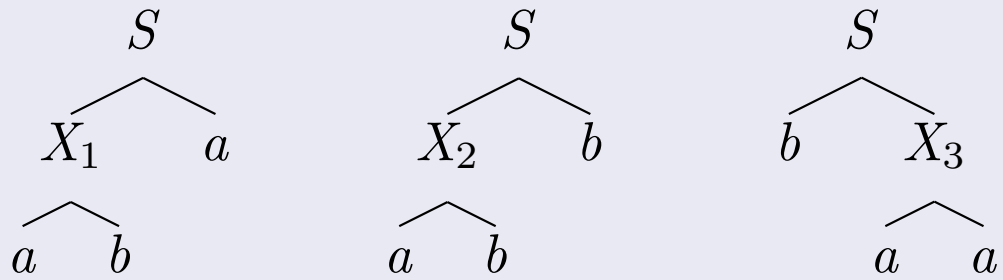

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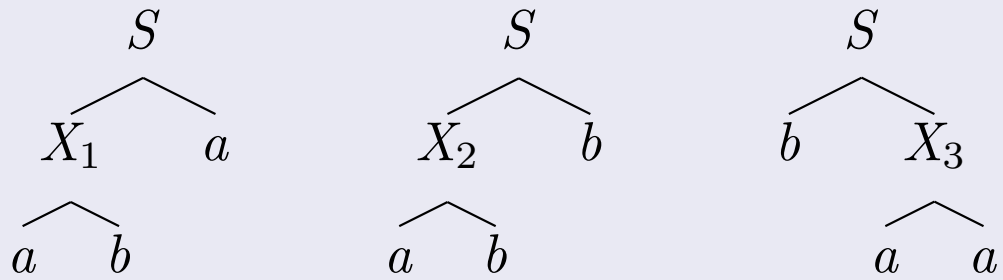

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- If two strings *overlap* and *occur overlapped* in L, both can not belong to C. We call them *incompatible*.
  - For instance: ab and ba occur overlapped in aba, so they are incompatible.

UNTS Grammars: Properties

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- We parse a finite set of sentences (the gold treebank's).
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Properties

- The possible unlabeled finite UNTS treebanks are fully characterized by its' sets of constituents C.
- The sets C are subsets of substrings of the sentences of the treebank. This is the search space.
- All the strings that belong to a set of constituents must be compatible with each other. This is, C must be *compatible*.
- We call T_C the UNTS treebank generated by a set C.

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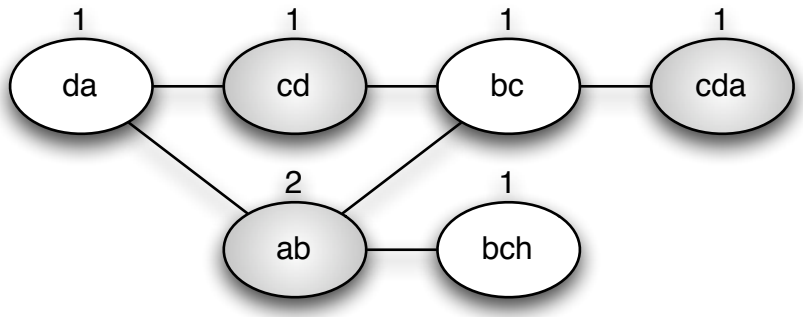

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$$W(C) = \sum_{s \in C} c(s) - d(s)$$

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Finding the Best UNTS Grammar: The W Measure

$$W(C) = H(C) - M(C)$$

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- We simultaneously maximize the hits and minimize the misses.
- So, we define the W measure with $w(s) = c(s) - d(s)$.
- We also define $H(C) = \sum_{s \in C} c(s)$ and $M(C) = \sum_{s \in C} d(s)$.

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Relating W and $F1$

- Write P and R in terms of H (hits) and M (misses):

$$P(C) = \frac{H(C)}{H(C)+M(C)}$$
$$R(C) = \frac{H(C)}{K}$$

- Write W in terms of precision and recall:

$$W(p, r) = (2 - \frac{1}{p})rK$$

Bounding the F1: The Bounds

A First Upper Bound

- Write $F1$ in terms of W and recall:

$$F1(r, w) = \frac{2r}{1 + 2r - \frac{w}{K}}$$

- $F1$ is monotonically increasing in r and w.
- If w is a bound of W, $F1(1.0, w)$ is a bound of $F1$.

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An Improved Upper Bound (not in the paper)

- If r is a bound of R, $F1(r, w)$ is a bound of $F1$.
- With $w(s) = c(s)$ the MWIS problem optimizes recall.

Bounds for the WSJ10: Introduction

A UNTS variant

- Not any set of sentences can be generated by strict UNTS. For instance: $\{ab, bc, abc\}$ and the WSJ10 sentences.
- We use a variant of UNTS that can generate any set.
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ILP Reduction

- The MWIS problem is translated to an Integer Linear Programming problem.
- The optimals W and recall are found using ILP software (SCIP, http://scip.zib.de).

Bounds for the WSJ10: Experiments and Results

The WSJ10 Treebank

- The sentences of length ≤ 10 of the WSJ Penn Treebank.
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Model	UP	UR	F1
RBranch	55.1	70.0	61.7
DMV+CCM	69.3	88.0	77.6
U-DOP	70.8	88.2	78.5
UML-DOP			82.9
Incremental	75.6	76.2	75.9
BestW	91.2	62.8	**74.4**
UBoundF1	69.8	100.0	**82.2**
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- a measure W that is related to F1 and is more tractable.
- that UNTS grammars over POS tags can not parse the WSJ10 with an F1 over 76.1%.

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- a measure W that is related to F1 and is more tractable.
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But...

- the method is too computationally complex to be applied to big treebanks.
- the method applies only to UNTS and small variants.

Further Work

Already done:

- Find bounds for the UNTS-SC class (subclass of UNTS).
- Prove that W optimization in UNTS is NP-hard.

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- Prove that W optimization in UNTS is NP-hard.

To do:

- Study expresiveness of ILP to encode other classes of grammars.
- Define a logic language to express classes of grammars.
- Compute upper bounds for several known classes.

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