Parse Me if You Can: Artificial Treebanks for Parsing Experiments on Elliptical Constructions

Kira Droganova, Daniel Zeman
Charles University, Faculty of Mathematics and Physics
Malostranské náměstí 25, Praha, Czechia
{droganova, zeman}@ufal.mff.cuni.cz

Abstract
In this work we focus on a particular linguistic phenomenon, ellipsis, and explore the latest parsers in order to learn about parsing accuracy and typical errors from the perspective of elliptical constructions. For this purpose we collected and processed outputs of several state-of-the-art parsers that took part in the CoNLL 2017 Shared Task. We extended the official shared task evaluation software to obtain focused evaluation of elliptical constructions. Since the studied structures are comparatively rare, and consequently there is not enough data for experimentation, we further describe the creation of a new resource, a semi-artificially constructed treebank of ellipsis.

Keywords: Ellipsis, Syntactic parsing, Evaluation, Universal Dependencies

1. Introduction
Ellipsis, i.e. omission of linguistic content that is silently understood by both the speaker and the addressee, is a phenomenon present—in various forms—in many natural languages. Ellipsis obviously makes natural language understanding harder; but sometimes it also complicates syntactic parsing of the content that is not omitted. In dependency syntax (which is the framework within which we operate), a parent node may be missing while its dependents are present. One might either create an “empty” node for the missing word, or choose a substitute parent among the words that are not missing. Both options make parsing difficult: in the former case, the parser must learn where to generate empty nodes; in the latter, relations are drawn between nodes that would not be connected otherwise, hence they are not easily learned from data.

In any case, modern dependency parsers are data-driven and they can hardly account for those types of ellipsis that are not represented in training data. If the data contains empty nodes, the parser can try to learn generating them. If the data does not contain any specific annotation of ellipsis, we have to hope that the parser learns to occasionally attach dependents to strange parents, even without knowing that it is ellipsis what caused the lack of better options.

In this study we focus on elliptical constructions in the so-called basic representation of Universal Dependencies (UD) (Nivre et al., 2016). The annotation style of UD does not mark ellipsis explicitly when it does not have to: most types are solved by simply promoting one orphaned dependent to the position of its missing parent. Admittedly, there are treebanks that overtly annotate a wider range of elliptical structures. Our main reason for working with UD is the idea of such adaptation is to save evaluation techniques that were proposed and implemented by the 2017 task organizers. Since the data was selected relying on these techniques, we hope that following the same line, especially regarding word alignments and sentence segmentation, helps us to be more precise. The script is available at the Shared Task page. The adapted script can be found on github. The adapted script provides information of two types:

- Statistics on correctly predicted orphan relations;
- Statistics on erroneously predicted or missed orphan relations and typical errors.

1http://universaldependencies.org/conll17/evaluation.html
2https://github.com/Kira-D/conll2017/tree/deprelCalc
4. Evaluation

Table 1 shows the statistics on correctly predicted orphan relations. In these calculations we use the relative number of all orphan nodes for every team, which is based on alignment between system output words and gold standard words. In other words, only successfully aligned orphan nodes from gold standard are included in this number. It is clearly seen that both Recall and F-measure are rather low. At the same time, percentage of correctly predicted dependency labels for head nodes is quite high. Table 2 shows the statistics on erroneously predicted or missed orphan labels. For every parser that we selected for the experiment, we calculate error pairs “relation1-relation2”, where the first relation was taken from the aligned gold word and the second relation was assigned by the system. Table 2 provides top 5 error pairs. Every cell contains the following information:

- the error pair;
- the contribution of the pair to the number of all errors concerning orphan label (percentage);
- the number of instances of the error type (frequency);
- h.error shows erroneously predicted head nodes (percentage and absolute number).

It seems that parsers make mistakes in similar conditions: the error types and their frequencies are almost the same from parser to parser. What is important, the number of orphan labels is just a tiny fraction of all labels and the contribution of their low values of Recall and F-measure to the final figures calculated on the whole amount of data goes virtually unseen. Hence, the question is if the parsers perform really poorly or it is simply the lack of data. We would answer with the proposal of creating artificial treebanks for parsing experiments and find out.

5. Creating artificial treebanks

Figure 2: An example of a gapping pattern.

Recent research (Schuster et al., 2017; Droganova and Ze- man, 2017) provides a detailed overview of elliptical constructions within the UD framework and presents typical patterns that can be used for detection of elliptic constructions. This information allows us to develop a script that transforms non-elliptic UD style trees to elliptic trees. Figure 3 provides the tree structure of this sentence. The sentence has a verb as a “root” node, which is linked with an auxiliary verb with “aux” relation and with an adjective with “conj” relation and this adjective linked with its dependent auxiliary with “cop” relation, therefore it would be a match.

The methodology requires manual efforts. After application of the script, the data have to be checked and corrected:

- After artificial omission sentences must remain grammatically correct;
- The patterns are designed to match as many instances as possible, so the erroneous instances have to be filtered out.

Potentially, the methodology can be applied to all UD treebanks. We are currently working on Russian, Czech, and

Table 1: Correctly predicted orphan relations. Parser: names of the teams in alphabetic order; All: number of orphan labels; Correct: number of correctly predicted orphan labels; Recall: number of correct orphan labels divided by the number of gold-standard orphan nodes; F1: f-measure: 2PR / (P+R); Parent: number of correctly predicted parent nodes; Parent %: percent of correctly predicted parent nodes;
English. We are planning to release these artificial elliptic UD treebanks after our manual checks and corrections. Artificial treebanks can facilitate testing and improving parsers performance regarding ellipsis. Hence, they would allow us to pay decent attention to this rare linguistic phenomenon.

6. Acknowledgements
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| System                | orphan-conj | orphan-nmod | conj-orphan | orphan-obl | orphan-advmod | h.error | orphans | Corrected | orphans | Corrected | orphans | Corrected |
|-----------------------|-------------|-------------|-------------|------------|---------------|---------|---------|------------|---------|------------|---------|------------|
| C2L2                  | 23.0%       | 15.05%      | 8.8%        | 14.5%      | 14.5%         | 327     | 85.63%  | 15.05%     | 14.5%   | 14.5%      | 85.63%  | 15.05%     |
| darc                  | 14.3%       | 12.6%       | 7.98%       | 5.91%      | 5.91%         | 232     | 78.23%  | 12.6%      | 7.98%   | 5.91%      | 78.23%  | 12.6%      |
| HIT-SCIR              | 16.05%      | 10.38%      | 8.99%       | 6.12%      | 6.05%         | 266     | 79.32%  | 10.38%     | 8.99%   | 6.12%      | 79.32%  | 10.38%     |
| IMS                   | 24.92%      | 12.49%      | 6.16%       | 5.9%       | 6.05%         | 227     | 81.4%   | 12.49%     | 6.16%   | 5.9%       | 81.4%   | 12.49%     |
| Koc-University        | 20.5%       | 12.67%      | 6.16%       | 5.5%       | 5.9%          | 343     | 79.01%  | 12.67%     | 6.16%   | 5.5%       | 79.01%  | 12.67%     |
| LATTICE               | 17.24%      | 13.33%      | 9.73%       | 6.03%      | 4.83%         | 300     | 82.09%  | 13.33%     | 9.73%   | 6.03%      | 82.09%  | 13.33%     |
| NAIST-SATO            | 17.23%      | 11.73%      | 9.73%       | 6.7%       | 4.83%         | 257     | 82.11%  | 11.73%     | 9.73%   | 6.7%       | 82.11%  | 11.73%     |
| Orange-Deskin         | 15.14%      | 9.76%       | 10.34%      | 5.6%       | 5.6%          | 262     | 71.37%  | 9.76%      | 10.34%  | 5.6%       | 71.37%  | 9.76%      |
| Stanford              | 17.71%      | 6.7%        | 10.9%       | 5.3%       | 5.23%         | 247     | 85.43%  | 6.7%       | 10.9%   | 5.3%       | 85.43%  | 6.7%       |
| TurkuNLP              | 19.96%      | 8.8%        | 12.19%      | 5.3%       | 5.23%         | 329     | 74.77%  | 8.8%       | 12.19%  | 5.3%       | 74.77%  | 8.8%       |
| UFAL-UDPipe-1-2       | 17.12%      | 8.8%        | 12.38%      | 5.95%      | 5.95%         | 288     | 81.94%  | 8.8%       | 12.38%  | 5.95%      | 81.94%  | 8.8%       |
| UParse                | 14.96%      | 6.57%       | 12.5%       | 9.11%      | 9.11%         | 243     | 81.48%  | 6.57%      | 12.5%   | 9.11%      | 81.48%  | 6.57%      |

Table 2: Erroneously predicted or missed orphan labels and their frequencies.