Accurate Deep Syntactic Parsing of Graphs: The Case of French

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Abstract

Parsing predicate-argument structures in a deep syntax framework requires graphs to be predicted. Argument structures represent a higher level of abstraction than the syntactic ones and are thus more difficult to predict even for highly accurate parsing models on surfacic syntax. In this paper we investigate deep syntax parsing, using a French data set (Ribeyre et al., 2014a). We demonstrate that the use of topologically different types of syntactic features, such as dependencies, tree fragments, spines or syntactic paths, brings a much needed context to the parser. Our higher-order parsing model, gaining thus up to 4 points, establishes the state of the art for parsing French deep syntactic structures.

Keywords: deep syntax, graph parsing, syntactic features

1. Introduction

The availability of many manually annotated syntactic corpora allows data-driven syntactic parsing to perform efficiently on English (routinely reaching 92% of labeled attachment accuracy) as well as on languages with a richer level of morphology (85% to 88%) (e.g. French, German, Arabic). However, despite this impressive level of performance, it has now become clear that such surface syntactic parses are often insufficient for semantically-oriented tasks such as question-answering systems (Berant et al., 2013). This is because many predicate-argument dependencies, such as those arising for instance in control-verb constructions, it-cleft constructions, participle clauses and so on, are lacking from the annotation schemes underlying most data set used by surfacic parsers.

Representing such constructs in a dependency scheme often leads to graph representations, which are a real challenge to predict, as shown, for example, by the performance obtained in Abstract Meaning Representation parsing (Banarescu et al., 2013; Flanigan et al., 2014; Artzi et al., 2015) or in graph-based semantic dependency parsing (Oepen et al., 2014). Even though some recent works have made good progresses in parsing full-fledged semantic structures (Beschke et al., 2014; Berant and Liang, 2014), they mostly focus on English.1

We propose to dig into that direction by relying on the recent release of a deep syntactic graphbank for French, the DEEPFTB, (Ribeyre et al., 2014a), whose deep syntactic graphs were automatically annotated on top of the dependency version of the French Treebank (Abellé and Barrier, 2004; Candito et al., 2010). In order to draw meaningful comparisons with recent results for English, we use the same types of features as Ribeyre et al. (2015), which were extracted from the DM corpus (Oepen et al., 2014), an English predicate-argument structure corpus sharing similarities with the DEEPFTB.

Despite the differences of language and annotation scheme, we observe that the same combination of different topological syntactic information leads to the best models for both French and English.

2. Deep Syntactic French Annotation Scheme and Corpus

<table>
<thead>
<tr>
<th></th>
<th>DM CORPUS</th>
<th></th>
<th>DEEPFTB CORPUS</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TRAIN</td>
<td>DEV</td>
<td>TRAIN</td>
<td>DEV</td>
</tr>
<tr>
<td># SENTENCES</td>
<td>32,389</td>
<td>1,614</td>
<td>14,759</td>
<td>1,235</td>
</tr>
<tr>
<td># TOKENS</td>
<td>742,736</td>
<td>36,810</td>
<td>457,872</td>
<td>40,055</td>
</tr>
<tr>
<td>% VOID TOKENS</td>
<td>21.63</td>
<td>21.58</td>
<td>11.97</td>
<td>12.19</td>
</tr>
<tr>
<td>% VOID TOKENS (no punct)</td>
<td>NA</td>
<td>NA</td>
<td>35.34</td>
<td>35.57</td>
</tr>
<tr>
<td># PLANAR GRAPHS</td>
<td>18,855</td>
<td>972</td>
<td>8,292</td>
<td>664</td>
</tr>
<tr>
<td># NON PLANAR</td>
<td>13,534</td>
<td>642</td>
<td>6,467</td>
<td>571</td>
</tr>
<tr>
<td># DAGS</td>
<td>32,389</td>
<td>1,614</td>
<td>3,911</td>
<td>283</td>
</tr>
<tr>
<td>% CROSSING EDGES</td>
<td>4.24</td>
<td>4.05</td>
<td>3.70</td>
<td>3.87</td>
</tr>
<tr>
<td>LABEL SET</td>
<td>52</td>
<td>36</td>
<td>27</td>
<td>24</td>
</tr>
</tbody>
</table>

Table 1: DM and DEEPFTB Properties.

We exploit a French corpus annotated following the deep syntactic scheme presented in (Perrier et al., 2014) and already instantiated on the Deep Sequoia corpus (Candido et al., 2014). This scheme aims at abstracting away from some syntactic variations by expliciting which expressions fill the canonical subcategorization frames of verbs and adjectives. Canonical grammatical functions are roughly those that would be assigned to an argument, if its predicate were in the most unmarked construction. This results mainly in (i) normalized grammatical functions in the case of syntactic alternations (e.g. the subject of a passive verb is taken as the canonical object) (ii) added dependencies for the subject of non-finite verbs (in particular in control/raising constructions) (iii) added dependencies in the case of arguments shared by coordinated heads and (iv) inverted dependencies in the case of modifying verbs or adjectives (for instance, in (the French counterpart) of 'Children born after 2010 get free tickets', the participle born both modifies the noun Children, and has this noun as (deep) subject). Moreover, semantically empty functional words are marked as such, and “shunted off” (for instance in ‘Anna a parlé à Paul’ (Anna has talked to Paul), both the auxiliary and the prepo-

1An exception is the work of Ballesteros et al. (2014) on deep syntacting parsing for Spanish, but their work is restricted to tree structure parsing.
sition à are marked as empty, and Paul is directly linked to the verb.

As with the DM corpus (Oepen et al., 2014), DEEPFTB is comparable in the sense that the semantic arguments of verbs and adjectives are made explicit, but it leans a little less towards a semantic representation (hence the “deep syntactic” name). In particular it sticks to (canonical) syntactic labels subj, obj,... instead of using numbered semantic labels arg1, arg2,... Also, in the case of a predicate modifying one of its semantic argument (e.g. an attributive adjective), both the modifier dependency and the predicative dependency are kept in the deep graph: for instance for an attributive adjective like in a perfect day, day is taken as the subject of perfect, and perfect as a modifier of day. This choice was made in order to keep both the predicate-argument structures and the general information structure of a sentence. So for instance in Figure 1, while the copula is ignored in DM, it is kept in the French scheme. It can be noted though that it causes a high number of cycles in the resulting graphs as seen in Table 1.

3. Graph Parsing
An increasing number of works have been proposed over the last few years to cope with graphs (Sagae and Tsujii, 2008; Flanigan et al., 2014; Martins and Almeida, 2014), whether acyclic or not. Because it has been shown to be one of the top performers on the SemEval 2014 shared task (Oepen et al., 2014), we reuse the higher-order arc-factorized parser of (Martins and Almeida, 2014) (TSPARSER), which takes advantage of dual decomposition methods based on AD (Martins et al., 2011). Another motivation for using this parser is that we want to assess whether using predicted syntactic features, which do provide additional context, is beneficial even when using a globally optimized parser.

4. Syntactic Features
Using syntactic features is widely known to help predicate-argument structure parsing by providing more context (Chen and Rambow, 2003; Moschitti et al., 2008). Following Farkas et al. (2011) and Ribeyre et al. (2015), we explore the impact of topologically different syntactic features extracted from the surfacic syntax and their respective combinations. Both our surfacic parsers use the French treebank (Abellé et al., 2003) in its (Seddah et al., 2013) instance, with predicted POS and morphological features. The constituency features come from the Berkeley Parser (Petrov et al., 2006) trained in a 10-fold jackknifing setting. Respective parsers’ performance scores are shown in Table 2.

Table 2: Scores on surfacic for the BKY (F1) and FRMG (LAS) parsers.

<table>
<thead>
<tr>
<th></th>
<th>BKY</th>
<th>FrMG</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dev</td>
<td>80.19</td>
<td>83.41</td>
</tr>
<tr>
<td>Test</td>
<td>80.14</td>
<td>83.22</td>
</tr>
</tbody>
</table>

This parser generates dependency trees after disambiguation and conversion from a shared derivation forest (Villemonte De La Clergerie, 2013b).

3. Tree Fragments (BKY)
These consist of fragments of syntactic constituency trees. They have been extracted using the same method as in (Carreras and Márquez, 2005).

5. Experiments & Discussion

<table>
<thead>
<tr>
<th></th>
<th>LP</th>
<th>LR</th>
<th>LF</th>
</tr>
</thead>
<tbody>
<tr>
<td>BASLINE</td>
<td>83.04</td>
<td>78.80</td>
<td>80.86</td>
</tr>
<tr>
<td>BKY</td>
<td>83.63</td>
<td>79.67</td>
<td>81.60</td>
</tr>
<tr>
<td>SPINES</td>
<td>83.72</td>
<td>80.05</td>
<td>81.84</td>
</tr>
<tr>
<td>PATHS</td>
<td>84.75</td>
<td>81.17</td>
<td>82.92</td>
</tr>
<tr>
<td>FRMG</td>
<td>86.50</td>
<td>82.74</td>
<td>84.58</td>
</tr>
<tr>
<td>FRMG+PATHS+BKY</td>
<td>86.11</td>
<td>83.68</td>
<td>84.88</td>
</tr>
<tr>
<td>FRMG+PATHS+SPINES</td>
<td>86.15</td>
<td>83.71</td>
<td>84.91</td>
</tr>
</tbody>
</table>

Table 3: Best results and gains (TSPARSER).

Table 3 displays the baseline scores, the scores for each type of features separately and our best models. As we can see, our baseline is weak especially in term of recall, leading us to believe that it is indeed difficult to recover the deep structure. Whereas the parser explores a large part of the search space, it seems to need more context to cope with complex linguistic structures. As expected, the use of each single feature increases the scores over the baseline, the improvement ranging from 0.74 using tree fragments (BKY) up to 3.72 points using the dependency features provided by the TAG parser. It is worth noticing that providing a wider context, namely using the PATHS features give an improvement that is closer to the best performing features (around 2 points), whereas the vertical context brought by the spines features does not give an improvement that is comparable in the sense that the semantic arguments of verbs and adjectives are made explicit...
8.3. Prédiction de la syntaxe profonde au moyen de traits syntaxiques :
approche à l’état de ... Le cercle autour de PP marque son appartenance à deux types de traits: BKY (fragment d’arbres) et Head Path.

A similar technique is almost impossible to apply to other crops, such as cotton, soybeans and rice. As regards FrMG features, because of the extended domain of locality of its elementary unit (tree-based), attachment decisions are taken with a more global view than classical transition-based parsers. In facts, these decisions ought to be more accurate in the case of complex linguistic phenomena such as coordinations, etc. This was suggested by the state-of-the-art results on French using a transition-based parser and such TAG-based features (Ville-monte de la Clergerie, 2014). As a matter of fact, the parser is able to cope, for example, with a few cases of elliptic coordinations and so we expect that the resulting surface trees would provide more accurate guiding information for building a deep representation.

Expected results are observed using syntactic features that improve over a baseline as it was already demonstrated for DM (Ribeyre et al., 2015). However, it is important to understand what is indeed improved with those features. Figure 3 gives a detailed analysis when increasing the length of the sentence and the length of edges. We observe that the increase is two times higher with longest dependencies than with short dependencies (Fig. 3(b)). This is expected when considering our low recall: when we include wider contexts into the parsing model, we enable it to recover longest dependencies that are common in complex constructions such as elliptic coordinations. This is corroborated by the increase in performances with respect to the sentence length. For short sentences (between 1 and 10 words), the improvements is small (around 1.5 points), whereas it increased by a factor of 4 (around 6 points) for longer sentences.

Discussion To assess the validity of our approach, we used a beam-based transition parser with early aggressive updates (DYALOG-SR, (Villemonte De La Clergerie, 2013a)), capable of handling general graphs through
an extended set of transitions\(^5\) described in (Ribeyre et al., 2014b).

<table>
<thead>
<tr>
<th>Test set</th>
<th>DEEPFTB</th>
<th>DM</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>BEST (TSPARSER)</strong></td>
<td>85.18</td>
<td>89.70</td>
</tr>
<tr>
<td><strong>BEST (DYALOG-SR)</strong></td>
<td>82.92</td>
<td>85.66</td>
</tr>
<tr>
<td>BASELINE (TSPARSER)</td>
<td>80.79</td>
<td>88.08</td>
</tr>
<tr>
<td>BASELINE (DYALOG-SR)</td>
<td>75.42</td>
<td>83.91</td>
</tr>
<tr>
<td>TSPARSER (SURF.)+RULES</td>
<td>80.45</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 4: Comparison of baselines and best LF results for DEEPFTB and DM. (DEEPFTB’s best: FRMG+PATHS+SPINES & DM’s best: BN+SPINES+PATHS).

Table 4 reports a comparison between the best results for DEEPFTB and DM and the baseline for both parsers. The last row includes results from the TSPARSER, trained on the FTB surface dependencies,\(^5\) whose outputs were fed to a tree-to-graph rewriting system (Ribeyre et al., 2012), following Ribeyre (2016).\(^1\) This setup provides slightly inferior performance than the TSPARSER baseline parser and is vastly over-performed by our best setup (by almost 5pt). Despite validating our approach, this leads us to wonder if a graph-to-graph rewriting system could not be developed to push the envelope even further. This is left for future work. Interestingly enough, except for the fact that our feature set generalizes well with another parser, we see that the best model for both corpora are of the same kind: mixing dependencies information with spinal trees and head paths. Even tough these corpora differ in terms of constituent and dependency annotations at the surfacic and deep levels, both parsers need vertical (spines) and horizontal (paths) contexts combined with the functional label provided by the dependencies to be able to accurately predict argument structures. This seems to corroborate the hypothesis that when going further into abstracting away from syntactic divergences, argument-structure retrieval on French and English benefits from the same topological extra information, regardless of the language. Extensive cross-language experiments would be of course required to explore this potentially interesting point.

6. Conclusion

In this paper, we investigated deep syntactic parsing for French. We showed that mixing topologically different sort of syntactic features provides contextual information that improves the prediction of deep syntactic graphs. We also observed that the best models in French are the same for DM in English, regardless of the difference of language and annotation scheme (both at the surfacic and deep levels). This is coherent with the intuitive belief that language differences diminish when abstracting away from morphological and (surface) syntax variation.

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\(^5\)The parser also uses noop transitions, allowed on final items, in order to compensate for paths of various lengths (avoiding to favor either longest or shortest paths).

\(^6\)With performance (LAS/UAS) on the FTB test set of 80.45/84.42 and 83.60/84.43 on the dev set.

\(^7\)Using DYALOG-SR as a basis, this architecture was used to annotate the DEEPFTB, see (Ribeyre et al., 2014a) for details.

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