A probabilistic generative model for an intermediate constituency-dependency representation
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A probabilistic generative model for an intermediate constituency-dependency representation

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Abstract

We present a probabilistic model extension to the Tesnière Dependency Structure (TDS) framework formulated in (Sangati and Mazza, 2009). This representation incorporates aspects from both constituency and dependency theory. In addition, it makes use of junction structures to handle coordination constructions. We test our model on parsing the English Penn WSJ treebank using a re-ranking framework. This technique allows us to efficiently test our model without needing a specialized parser, and to use the standard evaluation metric on the original Phrase Structure version of the treebank. We obtain encouraging results: we achieve a small improvement over state-of-the-art results when re-ranking a small number of candidate structures, on all the evaluation metrics except for chunking.

1 Introduction

Since its origin, computational linguistics has been dominated by Constituency/Phrase Structure (PS) representation of sentence structure. However, recently, we observe a steady increase in popularity of Dependency Structure (DS) formalisms. Several researchers have compared the two alternatives, in terms of linguistic adequacy (Nivre, 2005; Schneider, 2008), practical applications (Ding and Pulver, 2005), and evaluations (Lin, 1995).

Dependency theory is historically accredited to Lucien Tesnière (1959), although the relation of dependency between words was only one of the various key elements proposed to represent sentence structures. In fact, the original formulation incorporates the notion of chunk, as well as a special type of structure to represent coordination.

The Tesnière Dependency Structure (TDS) representation we propose in (Sangati and Mazza, 2009), is an attempt to formalize the original work of Tesnière, with the intention to develop a simple but consistent representation which combines constituencies and dependencies. As part of this work, we have implemented an automatic conversion of the English Penn Wall Street Journal (WSJ) treebank into the new annotation scheme.

In the current work, after introducing the key elements of TDS (section 2), we describe a first probabilistic extension to this framework, which aims at modeling the different levels of the representation (section 3). We test our model on parsing the WSJ treebank using a re-ranking framework. This technique allows us to efficiently test our system without needing a specialized parser, and to use the standard evaluation metric on the original PS version of the treebank. In section 3.4 we also introduce new evaluation schemes on specific aspects of the new TDS representation which we will include in the results presented in section 3.4.

2 TDS representation

It is beyond the scope of this paper to provide an exhaustive description of the TDS representation of the WSJ. It is nevertheless important to give the reader a brief summary of its key elements, and compare it with some of the other representations of the WSJ which have been proposed. Figure 1 shows the original PS of a WSJ tree (a), together with 3 other representations: (b) TDS, (c) DS, and (d) CCG (Hockenmaier and Steedman, 2007).
Words and Blocks  In TDS, words are divided in functional words (determiners, prepositions, etc.) and content words (verbs, nouns, etc.). Blocks are the basic elements (chunks) of a structure, which can be combined either via the dependency relation or the junction operation. Blocks can be of two types: standard and junction blocks. Both types may contain any sequence of functional words. Standard blocks (depicted as black boxes) represent the elementary chunks of the original PS, and include exactly one content word.

Coordination  Junction blocks (depicted as yellow boxes) are used to represent coordinated structures. They contain two or more blocks (conjunctions) possibly coordinated by means of functional words (conjunctions). In Figure 1(d) the yellow junction block contains three separate standard blocks. This representation allows to capture the fact that these conjunctions occupy the same role: they all share the relativizer ‘that’, they all depend on the noun ‘activities’, and they all govern the noun ‘abortion’. In Figure 1(a,c), we can notice that both PS and DS do not adequately represent coordination structures: the PS annotation is rather flat, avoiding to group the three verbs in a unique unit, while in the DS the last noun ‘abortion’ is at the same level of the verbs it should be a dependent of. On the other hand, the CCG structure of Figure 1(d), properly represents the coordination. It does so by grouping the first three verbs in a unique constituent which is in turn binarized in a right-branching structure. One of the strongest advantages of the CCG formalism, is that every structure can be automatically mapped to a logical-form representation. This is one reason why it needs to handle coordinations properly. Nevertheless, we conjecture that this representation of coordination might introduce some difficulties for parsing: it is very hard to capture the relation between ‘advocate’ and ‘abortion’ since they are several levels away in the structure.

Categories and Transference  There are 4 different block categories, which are indicated with little colored bricks (as well as one-letter abbreviation) on top and at the bottom of the corresponding blocks: verbs (red, V), nouns (blue, N), adverbs (yellow, A), and adjectives (green, J). Every block displays at the bottom the original category determined by the content word (or the original category of the conjunctions if it is a junction structure), and at the top, the derived category which relates to the grammatical role of the whole block in relation to the governing block. In several cases we can observe a shift in the categories of a block, from the original to the derived category. This phenomenon is called transference and often occurs by means of functional words in the block. In Figure 1(b) we can observe the transference of the junction block, which has the original category of a verb, but takes the role of an adjective (through the relativizer ‘that’) in modifying the noun ‘activities’.

Figure 1: Four different structure representations, derived from a sentence of the WSJ treebank (section 00, #977). (a) PS (original), (b) CCG, (c) DS, (d) TDS.
Table 1: Equation (1) gives the likelihood of a structure $S$ as the product of the likelihoods of generating three aspects of the structure, according to the three models (BGM, BEM, WFM) specified in equations (2-4) and explained in the main text.

3 A probabilistic Model for TDS

This section describes the probabilistic generative model which was implemented in order to disambiguate TDS structures. We have chosen the same strategy we have described in (Sangati et al., 2009). The idea consists of utilizing a state of the art parser to compute a list of $k$-best candidates of a test sentence, and evaluate the new model by using it as a reranker. How well does it select the most probable structure among the given candidates? Since no parser currently exists for the TDS representation, we utilize a state of the art parser for PS trees (Charniak, 1999), and transform each candidate to TDS. This strategy can be considered a first step to efficiently test and compare different models before implementing a full-fledged parser.

3.1 Model description

In order to compute the probability of a given TDS structure, we make use of three separate probabilistic generative models, each responsible for a specific aspect of the structure being generated. The probability of a TDS structure is obtained by multiplying its probabilities in the three models, as reported in the first equation of Table 2.

The first model (equation 2) is the Block Generation Model (BGM). It describes the event of generating a block $B$ as a dependent of its parent block (governor). The dependent block $B$ is identified with its categories (both original and derived), and its functional words, while the parent block is characterized by the original category only. Moreover, in the conditioning context we specify the direction of the dependent with respect to the parent, and its adjacent left sister (null if not present) specified with the same level of details of $B$. The model applies only to dependent blocks.

The second model (equation 3) is the Block Expansion Model (BEM). It computes the probability of a generic block $B$ of known derived category, to expand to the list of elements it is composed of. The list includes the category of the content word, in case the expansion leads to a standard block. In case of a junction structure, it contains the conjunctions and the conjunct blocks (each identified with its categories and its functional words) in the order they appear. Moreover, all functional words in the block are added to the list. The model applies to all blocks.

The third model (equation 4) is the Word Filling Model (WFM), which applies to each standard block $B$ of the structure. It models the event of filling $B$ with a content word ($cw$), given the content word of the governing block, the categories ($cats$) and functional words ($fw$) of $B$, and further information about the context in which $B$ occurs. This model becomes particularly interesting.

\[
P(S) = P_{BGM}(S) \cdot P_{BEM}(S) \cdot P_{WFM}(S) \tag{1}
\]

\[
P_{BGM}(S) = \prod_{B \in \text{dependentBlocks}(S)} P(B|\text{parent}(B), \text{direction}(B), \text{leftSibling}(B)) \tag{2}
\]

\[
P_{BEM}(S) = \prod_{B \in \text{blocks}(S)} P(\text{elements}(B)|\text{derivedCat}(B)) \tag{3}
\]

\[
P_{WFM}(S) = \prod_{B \in \text{standardBlocks}(S)} P(\text{cw}(B)|\text{cw}(\text{parent}(B)), \text{cats}(B), \text{fw}(B), \text{context}(B)) \tag{4}
\]
ing when a standard block is a dependent of a junction block (such as ‘abortion’ in Figure 1(d)). In this case, the model needs to capture the dependency relation between the content word of the dependent block and each of the content words belonging to the junction block.

3.2 Smoothing

In all the three models we have adopted a smoothing technique based on back-off level estimation as proposed by Collins (1999). The different back-off estimates, which are listed in decreasing levels of details, are interpolated with confidence weights derived from the training corpus.

The first two models are implemented with two levels of back-off, in which the last is a constant value \(10^{-6}\) to make the overall probability small but not zero, for unknown events.

The third model is implemented with three levels of back-off: the last is set to the same constant value \(10^{-6}\), the first encodes the dependency event using both pos-tags and lexical information of the governor and the dependent word, while the second specifies only pos-tags.

3.3 Experiment Setup

We have tested our model on the WSJ section of Penn Treebank (Marcus et al., 1993), using sections 02-21 as training and section 22 for testing. We employ the Max-Ent parser, implemented by Charniak (1999), to generate a list of \(k\)-best PS candidates for the test sentences, which are then converted into TDS representation.

Instead of using Charniak’s parser in its original settings, we train it on a version of the corpus in which we add a special suffix to constituents which have circumstantial role. This decision is based on the observation that the TDS formalism well captures the argument structure of verbs, and

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1In order to derive the probability of this multi-event we compute the average between the probabilities of the single events which compose it.

2Each back-off level obtains a confidence weight which decreases with the increase of the diversity of the context \(\theta(C_i)\), which is the number of separate events occurring with the same context \(C_i\). More formally if \(f(C_i)\) is the frequency of the conditioning context of the current event, the weight is obtained as \(f(C_i)/(f(C_i) \cdot \mu \cdot \theta(C_i))\); see also (Bikel, 2004). In our model we have chosen \(\mu\) to be 5 for the first model, and 50 for the second and the third.

3Those which have certain function tags (e.g. ADV, LOC, TMP). The full list is reported in (Sangati and Mazza, 2009). It was surprising to notice that the performance of this slightly modified parser (in terms of F-score) is only slightly lower than how it performs out-of-the-box (0.13%).

we believe that this additional information might benefit our model.

We then applied our probabilistic model to re-rank the list of available \(k\)-best TDS, and evaluate the selected candidates using several metrics which will be introduced next.

3.4 Evaluation Metrics for TDS

The re-ranking framework described above, allows us to keep track of the original PS of each TDS candidate. This provides an implicit advantage for evaluating our system, viz. it allows us to evaluate the re-ranked structures both in terms of the standard evaluation benchmark on the original PS (F-score) as well as on more refined metrics derived from the converted TDS representation. In addition, the specific head assignment that the TDS conversion procedure performs on the original PS, allows us to convert every PS candidate to a standard projective DS, and from this representation we can in turn compute the standard benchmark evaluation for DS, i.e. unlabeled attachment score\(^{(10)}\) (UAS) (Lin, 1995; Nivre et al., 2007).

Concerning the TDS representation, we have formulated 3 evaluation metrics which reflect the accuracy of the chosen structure with respect to the gold structure (the one derived from the manually annotated PS), regarding the different components of the representation:

**Block Detection Score (BDS):** the accuracy of detecting the correct boundaries of the blocks in the structure\(^{(11)}\).

**Block Attachment Score (BAS):** the accuracy of detecting the correct governing block of each block in the structure\(^{(12)}\).

**Junction Detection Score (JDS):** the accuracy of detecting the correct list of content-words composing each junction block in the structure\(^{(13)}\).

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\(^{(10)}\)UAS measures the percentage of words (excluding punctuation) having the correct governing word.

\(^{(11)}\)It is calculated as the harmonic mean between recall and precision between the test and gold set of blocks, where each block is identified with two numerical values representing the start and the end position (punctuation words are discarded).

\(^{(12)}\)It is computed as the percentage of words (both functional and content words, excluding punctuation) having the correct governing block. The governing block of a word, is defined as the governor of the block it belongs to. If the block is a conjunct, its governing block is computed recursively as the governing block of the junction block it belongs to.

\(^{(13)}\)It is calculated as the harmonic mean between recall and precision between the test and gold set of junction blocks expansions, where each expansion is identified with the list of content words belonging to the junction block. A recursive junction structure expands to a list of lists of content-words.
Table 2: Results of Charniak’s parser, the TDS-reranker, and the PCFG-reranker according to several evaluation metrics, when the number \( k \) of best-candidates increases.

<table>
<thead>
<tr>
<th></th>
<th>F-Score</th>
<th>UAS</th>
<th>BDS</th>
<th>BAS</th>
<th>JDS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Charniak ((k = 1))</td>
<td>89.41</td>
<td>92.24</td>
<td>94.82</td>
<td>89.29</td>
<td>75.82</td>
</tr>
<tr>
<td>Oracle Best F-Score ((k = 1000))</td>
<td>97.47</td>
<td>96.98</td>
<td>97.03</td>
<td>95.79</td>
<td>82.26</td>
</tr>
<tr>
<td>Oracle Worst F-Score ((k = 1000))</td>
<td>57.04</td>
<td>77.04</td>
<td>84.71</td>
<td>70.10</td>
<td>43.01</td>
</tr>
<tr>
<td>Oracle Best JDS ((k = 1000))</td>
<td>90.54</td>
<td>93.77</td>
<td>96.20</td>
<td>90.57</td>
<td>93.55</td>
</tr>
<tr>
<td>PCFG-reranker ((k = 5))</td>
<td>89.03</td>
<td>92.12</td>
<td><strong>94.86</strong></td>
<td>88.94</td>
<td><strong>75.88</strong></td>
</tr>
<tr>
<td>PCFG-reranker ((k = 1000))</td>
<td>83.52</td>
<td>87.04</td>
<td>92.07</td>
<td>82.32</td>
<td>69.17</td>
</tr>
<tr>
<td>TDS-reranker ((k = 5))</td>
<td><strong>89.65</strong></td>
<td><strong>92.33</strong></td>
<td>97.47</td>
<td><strong>89.35</strong></td>
<td><strong>76.23</strong></td>
</tr>
<tr>
<td>TDS-reranker ((k = 10))</td>
<td>89.10</td>
<td>92.11</td>
<td>94.58</td>
<td>88.94</td>
<td>75.47</td>
</tr>
<tr>
<td>TDS-reranker ((k = 100))</td>
<td>86.64</td>
<td>90.24</td>
<td>93.11</td>
<td>86.34</td>
<td>69.60</td>
</tr>
<tr>
<td>TDS-reranker ((k = 500))</td>
<td>84.94</td>
<td>88.62</td>
<td>91.97</td>
<td>84.43</td>
<td>65.30</td>
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<tr>
<td>TDS-reranker ((k = 1000))</td>
<td>84.31</td>
<td>87.89</td>
<td>91.42</td>
<td>83.69</td>
<td>63.65</td>
</tr>
</tbody>
</table>

Figure 2: **Left:** results of the TDS-reranking model according to several evaluation metrics as in Table 2. **Right:** comparison between the F-scores of the TDS-reranker and a vanilla PCFG-reranker (together with the lower and the upper bound), with the increase of the number of best candidates.

### 3.5 Results

Table 2 reports the results we obtain when re-ranking with our model an increasing number of \( k \)-best candidates provided by Charniak’s parser (the same results are shown in the left graph of Figure 2). We also report the results relative to a PCFG-reranker obtained by computing the probability of the \( k \)-best candidates using a standard vanilla-PCFG model derived from the same training corpus. Moreover, we evaluate, by means of an oracle, the upper and lower bound of the F-Score and JDS metric, by selecting the structures which maximizes/minimizes the results.

Our re-ranking model performs rather well for a limited number of candidate structures, and outperforms Charniak’s model when \( k = 5 \). In this case we observe a small boost in performance for the detection of junction structures, as well as for all other evaluation metrics, except for the BDS.

The right graph in Figure 2 compares the F-score performance of the TDS-reranker against the PCFG-reranker. Our system consistently outperforms the PCFG model on this metric, as for UAS, and BAS. Concerning the other metrics, as the number of \( k \)-best candidates increases, the PCFG model outperforms the TDS-reranker both according to the BDS and the JDS.

Unfortunately, the performance of the re-ranking model worsens progressively with the increase of \( k \). We find that this is primarily due to the lack of robustness of the model in detecting the block boundaries. This suggests that the system might benefit from a separate preprocessing step which could chunk the input sentence with higher accuracy (Sang et al., 2000). In addition the same module could detect local (intra-clausal) coordinations, as illustrated by (Marinčič et al., 2009).
4 Conclusions

In this paper, we have presented a probabilistic generative model for parsing TDS syntactic representation of English sentences. We have given evidence for the usefulness of this formalism: we consider it a valid alternative to commonly used PS and DS representations, since it incorporates the most relevant features of both notations; in addition, it makes use of junction structures to represent coordination, a linguistic phenomena highly abundant in natural language production, but often neglected when it comes to evaluating parsing resources. We have therefore proposed a special evaluation metrics for junction detection, with the hope that other researchers might benefit from it in the future. Remarkably, Charniak’s parser performs extremely well in all the evaluation metrics besides the one related to coordination.

Our parsing results are encouraging: the overall system, although only when the candidates are highly reliable, can improve on Charniak’s parser on all the evaluation metrics with the exception of chunking score (BDS). The weakness on performing chunking is the major factor responsible for the lack of robustness of our system. We are considering to use a dedicated pre-processing module to perform this step with higher accuracy.

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