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Simple Parser Combination

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Abstract
This paper presents an ensemble system for dependency parsing: three parsers are separately trained and combined by means of a majority vote. The three parsers are (1) the MATE parser [http://code.google.com/p/mate-tools/], (2) the DeSR parser [http://sites.google.com/site/desrparser/], and (3) the MALT parser [http://maltparser.org/]. The MATE, that was never used before on Italian language, drastically outperforms the other parsers in the SPLeT shared task. Nonetheless, a simple voting combination further improves its performances.

Keywords: ensemble parsing, MATE parser, DeSR parser, MALT parser

1. Introduction
In last few years parsing community devoted great attention to dependency formalisms, and today dependency parsing can be seen as the first step in many applicative NLP systems (Kühler et al., 2009). Larger dependency treebanks and more sophisticated parsing algorithms allowed improved performances of dependency parsers for many languages (Nivre et al., 2007; Hajič et al., 2009). Indeed, dependency parsing performances constantly increased for Italian. As reported in the Evalita evaluation campaigns specific for NLP systems for Italian (EVALITA 2011 Organization Comitee, 2012), the best scores for Italian dependency parsing (expressed in Labelled Attachment Score, LAS) were obtained by using the Turin University Treebank, a dependency treebank for Italian (Bosco and Lombardo, 2004) (see the Section 4.). However, statistical dependency parsing seems to be still improved. On the one hand, new promising specific algorithms for learning and classification are emerging; on the other hand researchers are applying universal machine learning techniques to this specific task. Some are trying to use larger sets of syntactic features (e.g. (McDonald and Pereira, 2006; Carreras, 2007)), while others are trying to apply general techniques to combine together the results of various parsers (Zeman and Žabokrtský, 2005; Sagae and Lavie, 2006; Hall et al., 2007; Attardi and dell’Orletta, 2009; Surdeanu and Manning, 2010; Lavelli, 2012).

Our system in the SPLeT competition follows both these mentioned directions. We employ three state of art statistical parsers, which use sophisticated parsing algorithms and advanced feature sets. The three parsers are (1) the MATE parser (Bohnet, 2010), (2) the DeSR parser (Attardi, 2006), (3) the MALT parser (Nivre et al., 2006). Moreover, in our system we combine these three parsers by using two very simple voting algorithms (Breiman, 1996; Zeman and Žabokrtský, 2005). We decided to apply an “out of box” approach, i.e. we apply each parser with its standard configurations for learning and classification. In the next Sections we first give a short description of the three parsers (Section 2.), then we describe our approach for ensemble parsing (Section 3.) and we report the results of our experiments (Section 4.), before to conclude the paper (Section 5.).

2. The three parsers
In this Section we give a brief description of the three parsers applied in our experiments, i.e. MATE, DeSR and MALT parser. The MATE parser (Bohnet, 2009; Bohn et, 2010) is a development of the algorithms described in (Carreras, 2007; Johansson and Nuges, 2008). It basically adopts the second order maximum spanning tree dependency parsing algorithm. In particular, Bohnet exploits hash kernel, a new parallel parsing and feature extraction algorithm that improves the accuracy as well as the parsing speed (Bohnet, 2010). The MATE performances on English and German, which are 90.14% and 87.64% respectively (LAS), posed this parser at the state of art for these languages (Hajič et al., 2009; Bohnet, 2010; Anders et al., 2010).

The DeSR parser (Attardi, 2006) is a transition (shift-reduce) dependency parser similar to (Yamada and Matsumoto, 2003). It builds dependency structures by scanning input sentences in left-to-right and/or right-to-left direction. For each step, the parser learns from the annotated dependencies if to perform a shift or to create a dependency between two adjacent tokens. DeSR can use different set of rules and includes additional rules to handle non-projective dependencies. The parser can choose among several learning algorithms (e.g Multi Layer Perceptron, Simple Vector Machine), providing user-defined feature models. In our experiments we adopted for DeSR the Multi Layer Perceptron algorithm, which is the same configuration that the parser exploited when it won the Evalita 2009 competition. The MALT parser (Nivre et al., 2006) implements the transition-based approach to dependency parsing too. In particular MALT has two components: (1) a (non-deterministic) transition system that maps sentences to dependency trees; (2) a classifier, that predicts the next transition for every possible system configuration. MALT performs a greedy deterministic search into the transition system guided by the classifier. In this way, it is possible to perform parsing in linear time for projective dependency
trees and quadratic time for arbitrary (non-projective) trees (Nivre, 2008). MALT has several built-in transition systems, but in our experiments we adopted just the standard “Nivre arc-eager” system, that builds structure incrementally from left to right. Moreover, we use the standard classifier provided by MALT, i.e. the SVM (Simple Vector Machine) basic classifier on the standard “NivreEager” feature model.

In our knowledge this is the first work that experimented the MATE parser on Italian, while DeSR and MALT parsers have been used in many occasions on Italian (e.g. (Lavelli, 2012; Attardi et al., 2012)), reaching the best results in several contests.

3. The combination algorithms

In order to combine the three parsers we used two very simple algorithms, COM1 and COM2, both implemented in PERL programming language. These algorithms have been previously experimented in (Zeman and Zabokrtský, 2005) and in (Surdeanu and Manning, 2010).

The main idea of the COM1 algorithm is to do a democratic voting among the parsers. For each word of the sentence, the dependency (parent and edge label) assigned to the word by each parser is compared: if at least two parsers assign the same dependency, the COM1 algorithm selects that dependency. In the case that each parser assigns a different dependency to the word, the algorithm selects the dependency assigned by the “best parser”, that in our experiments on development set was the MATE parser (see below). As noted by (Zeman and Zabokrtský, 2005), that uses the name voting for COM1, this is the most logical decision if it is possible to identify a priori the “best parser”, in contrast with the more democratic random choice.

The COM2 algorithm is a variation of the COM1. COM1 is a single word combination algorithm that does not consider the whole dependency structure. This means that incorrect dependency trees can be produced by the COM1 algorithm: cycles and several roots can corrupts the “tree-ness” of the structure. The solution that we adopt in the COM2 algorithm is very simple: if the tree produced by the COM1 algorithm for a sentence is corrupted, then it is selected as dependency structure for that sentence the tree produced by the “best parser”.

Again, in accord (Zeman and Zabokrtský, 2005), that uses the name switching for COM2, this is the most logical decision since MATE is without doubts the best parser on development score.

4. Experimental Results

We used two machines for experiments. A powerful Linux workstation, equipped with 16 cores, processors 2GHz, and 128 GB ram has been used for the MATE parser, so that the average time for learning is 8 hours. Another Linux workstation equipped with a a single processor 1GHz, and 2 GB ram has been used for learning of the DeSR and MALT parsers, that usually required a couple of hours, and for testing that required several minutes for MATE parser and few minutes for MALT and DeSR parsers. MALT and

\[\text{FOREACH sentence} \]
\[\text{FOREACH word} \text{IN sentence} \]
\[\text{IF } [L-\text{DeSR(word)}==L-\text{MALT(word)}] \]
\[L-\text{COM1(word)} := L-\text{DeSR(word)} \]
\[\text{ELSE} \]
\[L-\text{COM1(word)} := L-\text{MATE(word)} \]

Table 1: The combination algorithm COM1, that correspond to the voting algorithm reported in (Zeman and Žabokrtský, 2005)

DeSR parsers accept as input the CONLL-07 format, that is the format provided by the SPLEt organizers. In contrast MATE accept the CONLL-09 format: simple conversions scripts have been implemented to manage this difference.

In the first experiment, in order to evaluate the “best parser” in the COM1 and COM2 algorithms, we used the ISST training (file: \textit{isst\_train.splet}, 71,568 words, 3,275 sentences) as learning set and the ISST development (file: \textit{isst\_test.splet}, 5,165 words, 231 sentences) as development set.

The second row in Table 3 shows the results of the three parsers in this first experiment. MATE parser outperforms the DeSR and MALT parsers: in particular, MATE does ~ 3% better than DeSR and ~ 5% better than MALT.

In the second experiment, we use the whole ISST as learning set (files: \textit{isst\_train.splet} and \textit{isst\_test.splet}, total 76,733 words, 3,506 sentences) and we use the blind file provided by the organizers as test set (file: \textit{EU\_Law\_test.blind.splet}, 5,662 words, 240 sentences, European Directives Laws). The first row in Table 3 shows the results of the three parsers in this second experiment: the value 83.08%, produced by the COM2 algorithm, is the final result of our participation to the SPLEt shared task. Note that there is a ~ 0.1% difference between the COM1 and COM2 results: similar to (Zeman and Žabokrtský, 2005).

\[\text{FOREACH sentence} \]
\[\text{FOREACH word} \text{IN sentence} \]
\[\text{IF } [L-\text{DeSR(word)}==L-\text{MALT(word)}] \]
\[L-\text{COM2(word)} := L-\text{DeSR(word)} \]
\[\text{ELSE} \]
\[L-\text{COM2(word)} := L-\text{MATE(word)} \]

Table 2: The combination algorithm COM2, that correspond to the switching algorithm reported in (Zeman and Žabokrtský, 2005)

\[\text{FOREACH sentence} \]
\[\text{FOREACH word} \text{IN sentence} \]
\[\text{IF } [L-\text{DeSR(word)}==L-\text{MALT(word)}] \]
\[L-\text{COM2(word)} := L-\text{DeSR(word)} \]
\[\text{ELSE} \]
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In the second experiment, we use the whole ISST as learning set (files: \textit{isst\_train.splet} and \textit{isst\_test.splet}, total 76,733 words, 3,506 sentences) and we use the blind file provided by the organizers as test set (file: \textit{EU\_Law\_test.blind.splet}, 5,662 words, 240 sentences, European Directives Laws). The first row in Table 3 shows the results of the three parsers in this second experiment: the value 83.08%, produced by the COM2 algorithm, is the final result of our participation to the SPLEt shared task. Note that there is a ~ 0.1% difference between the COM1 and COM2 results: similar to (Zeman and Žabokrtský, 2005).

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\[\text{FOREACH word} \text{IN sentence} \]
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\[L-\text{COM2(word)} := L-\text{DeSR(word)} \]
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\[\text{FOREACH sentence} \]
\[\text{FOREACH word} \text{IN sentence} \]
\[\text{IF } [L-\text{DeSR(word)}==L-\text{MALT(word)}] \]
\[L-\text{COM2(word)} := L-\text{DeSR(word)} \]
\[\text{ELSE} \]
\[L-\text{COM2(word)} := L-\text{MATE(word)} \]
In the third experiment, we again use the whole
sentence combination that correspond to higher value of LAS
in the voting strategy. In other words, COM1 selects all the
derived dependencies that are produced by using the
three parsers (Blended, MALT, DeSR) on the SPLeT test set, development set, Regional laws set and on the Evalita
test.

Table 3: The performances (LAS score) of the three parsers, their simple combination (COM1 and COM2), their blended
combination (Blended$_{p2}$, Blended$_{p3}$, Blended$_{p4}$) on the SPLeT test set, development set, Regional laws set and on the Evalita
test.

<table>
<thead>
<tr>
<th>Set</th>
<th>MATE</th>
<th>DeSR</th>
<th>MALT</th>
<th>COM1</th>
<th>COM2</th>
<th>Blended$_{p2}$</th>
<th>Blended$_{p3}$</th>
<th>Blended$_{p4}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>TestSet</td>
<td>82.57</td>
<td>78.68</td>
<td>77.98</td>
<td>83.20</td>
<td>83.08</td>
<td>82.23</td>
<td>83.15</td>
<td>83.24</td>
</tr>
<tr>
<td>DevSet</td>
<td>81.92</td>
<td>78.99</td>
<td>77.04</td>
<td>82.54</td>
<td>82.36</td>
<td>81.45</td>
<td>82.54</td>
<td>82.63</td>
</tr>
<tr>
<td>NatReg</td>
<td>75.76</td>
<td>70.66</td>
<td>70.33</td>
<td>76.28</td>
<td>75.88</td>
<td>74.78</td>
<td>76.07</td>
<td>75.97</td>
</tr>
<tr>
<td>Evalita11</td>
<td>89.07</td>
<td>86.26</td>
<td>80.76</td>
<td>89.19</td>
<td>89.16</td>
<td>88.03</td>
<td>89.19</td>
<td>89.19</td>
</tr>
</tbody>
</table>

Table 4: The detailed performances (LAS score) of the three parsers and their simple combination on the SPLeT blind set, i.e. corresponding to the first row of the Table 3.

<table>
<thead>
<tr>
<th>Scores</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>MATE $==$ DeSR $==$ MALT</td>
<td>71.99</td>
</tr>
<tr>
<td>MATE $!=$ DeSR $==$ MALT</td>
<td>4.20</td>
</tr>
<tr>
<td>MATE $==$ DeSR $!=$ MALT</td>
<td>7.70</td>
</tr>
<tr>
<td>MATE $==$ MALT $!=$ DeSR</td>
<td>8.21</td>
</tr>
<tr>
<td>MATE $!=$ DeSR $!=$ MALT</td>
<td>7.89</td>
</tr>
</tbody>
</table>

In the third experiment, we again use the whole ISST as learning set (files: $i_{sst}$ _train.spl et and $i_{sst}$ _test.spl et, total 76,733 words, 3,506 sentences), but we use the NatReg file provided by the organizers as test set (file: $i_{NatRegLaw}$ _test_blind.spl et, 5,194 words, 119 sentences, Regional Laws of Piedmont Region). The third row in Table 3 shows the results of the three parsers in this third experiment: in this case we have 75.88% for COM2 algorithm. This lower result can be advocated to the different nature of the domain. It is interesting to note that in this experiment MALT and DeSR parsers give similar results (70%), while the MATE parser still outperforms them by $\approx 5\%$.

Finally, we performed a fourth experiment on totally different learning and test sets, by using a different Italian Treebank with a different PoS tag set and a different dependency format. We used the Evalita 2011 Development Set as learning set (file: evalita2011_train.con ll, 93,987 words, 3,452 sentences; balanced corpus of newspapers, laws, wikipedia) and we use the Evalita 2011 test as test set (file: evalita2011_test.con ll, 7,836 words, 300 sentences; balanced corpus), that are produced by using the Turin University Treebank (Bosco and Mazzei, 2012). The fourth row in Table 3 shows the results of the three parsers in this third experiment: in this case we have 89.16% for COM2 algorithm$^3$. It is interesting to note that the improvement of the COM2 algorithm w.r.t. with respect to the MATE parser is only $\approx 0,1\%$. In Table 5 we detailed the results of the three parsers in this fourth experiment on

-- This score is the third w.r.t. to Evalita 2011 dependency parsing shared task, where the Parisii Parser achieved the best score (91.23%) the DeSR parser achieved the second best score (89.88%).

In re–parsing, a new (not corrupted) dependency tree is produced by taking into account the tree produced by each parser of the ensemble: (Attardi and dell’Orletta, 2009). In re–parsing strategy (Sagae and Lavie, 2006; Hall et al., 2007; Attardi and dell’Orletta, 2009). Since COM1 can produce corrupted dependency trees, as in (Zeman and Žabokrtský, 2005) we used the COM2 algorithm, that checks the correctness of the tree and, in case of tree-corruption, returns the dependency structure produced by the “best parser” of the ensemble. We hypothesize that this strategy can produce good results in our system since one of the parser of the ensemble drastically outperforms the others. However, a general solution to the tree-corruption problem has been proposed: the re–parsing

Footnotes:

$^3$This score is the third w.r.t. to Evalita 2011 dependency parsing shared task, where the Parisii Parser achieved the best score (91.23%) the DeSR parser achieved the second best score (89.88%).

$^4$In the fourth experiment there are 8 corrupted trees.
node, then the highest-scoring children and so on; (Sagae and Lavie, 2006; Hall et al., 2007) apply a two-steps algorithm: (1) create a graph funding all the structures produced by the parser on the ensemble, and (2) extract the most probable dependency spanning tree from this graph. (Surdeanu and Manning, 2010) provided experimental evidence that re-parsing algorithms are a better choice for practical ensemble parsing in out-domains: in order to test this hypothesis we performed a number of experiment by using the “MaltBlender” tool (Hall et al., 2007). In Table 3, the columns Blended$W_2$, Blended$W_3$, Blended$W_4$ report the application of the algorithm described in (Hall et al., 2007). There are three weighting strategies: the results of the three parsers are equally weighted ($W_2$); the three parsers are weighted according to the total labeled accuracy on a held-out development set ($W_3$); the parsers are weighted according to labeled accuracy per coarse grainned PoS tag on a held-out development set ($W_4$).

For the first, the second and the third experiments (Table 4, first second and third row), the held-out development set is the SPLeT development set; for the fourth experiment (Table 4, fourth row), the held-out development set is the Evalita 2011 test set. Three evidences seems to emerge from this last experiment: (1) the re-parsing strategies always performs slightly better than COM2 algorithms but not always better than COM1 algorithm; (2) there is no winning weighting strategy for re-parsing; (3) it does not seem that blending performs better out-domain than in-domain.

5. Conclusions

In this paper we described our parsing system for the participation to the SPLeT 2012 Shared Task, and two main issues arise by our contribution. The first issue is that the MATE parser has very good performance on Italian ISST treebank, both in domain and out domain, reaching very good scores; similar results have been obtained on the Turin University Treebank. The second issue is that very simple combination algorithms, as well as more complex blending algorithms, can furthermore improve performance also in situations where a parser outperforms the other ones.

In future research we plan to repeat our experiments on larger set of parsers. In particular, on the basis of the consideration that “diversity” is an important value in ensemble parsing, we want to experiment the possibility to combine together statistical parsers with rule based parsers, e.g. (Lesmo, 2012).

Acknowledgements

We want to thank Alessia Visconti and Francesca Cordero for their valuable (human and machine) time. Moreover we like to thank Felice Dell’Orletta for the suggestion to use MaltBlender in the analysis of the results.

6. References


<table>
<thead>
<tr>
<th>Scores</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>MATE == DeSR == MALT</td>
<td>78.39</td>
</tr>
<tr>
<td>MATE != DeSR == MALT</td>
<td>3.38</td>
</tr>
<tr>
<td>MATE == DeSR != MALT</td>
<td>9.17</td>
</tr>
<tr>
<td>MATE == MALT != DeSR</td>
<td>4.27</td>
</tr>
<tr>
<td>MATE != DeSR != MALT</td>
<td>4.78</td>
</tr>
</tbody>
</table>

Table 5: The detailed performances (LAS score) of the three parsers and their combination on the Evalita 2011 test set, i.e. corresponding to the fourth row of the Table 3.


