The LIGM-Alpage Architecture for the SPMRL 2013 Shared Task: Multiword Expression Analysis and Dependency Parsing

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Abstract

This paper describes the LIGM-Alpage system for the SPMRL 2013 Shared Task. We only participated to the French part of the dependency parsing track, focusing on the realistic setting where the system is informed neither with gold tagging and morphology nor (more importantly) with gold grouping of tokens into multi-word expressions (MWEs). While the realistic scenario of predicting both MWEs and syntax has already been investigated for constituency parsing, the SPMRL 2013 shared task datasets offer the possibility to investigate it in the dependency framework. We obtain the best results for French, both for overall parsing and for MWE recognition, using a reparsing architecture that combines several parsers, with both pipeline architecture (MWE recognition followed by parsing), and joint architecture (MWE recognition performed by the parser).

1 Introduction

As shown by the remarkable permanence over the years of specialized workshops, multiword expressions (MWEs) identification is still receiving considerable attention. For some languages, such as Arabic, French, English, or German, a large quantity of MWE resources have been generated (Baldwin and Nam, 2010). Yet, while special treatment of complex lexical units, such as MWEs, has been shown to boost performance in tasks such as machine translation (Pal et al., 2011), there has been relatively little work exploiting MWE recognition to improve parsing performance.

Indeed, a classical parsing scenario is to pre-group MWEs using gold MWE annotation (Arun and Keller, 2005). This non-realistic scenario has been shown to help parsing (Nivre and Nilsson, 2004; Eryigit et al., 2011), but the situation is quite different when switching to automatic MWE prediction. In that case, errors in MWE recognition alleviate their positive effect on parsing performance (Constant et al., 2012). While the realistic scenario of syntactic parsing with automatic MWE recognition (either done jointly or in a pipeline) has already been investigated in constituency parsing (Cafferkey et al., 2007; Green et al., 2011; Constant et al., 2012; Green et al., 2013), the French dataset of the SPMRL 2013 Shared Task (Seddah et al., 2013) offers one of the first opportunities to evaluate this scenario within the framework of dependency syntax.

In this paper, we discuss the systems we submitted to the SPMRL 2013 shared task. We focused our participation on the French dependency parsing track using the predicted morphology scenario, because it is the only data set that massively contains MWEs. Our best system ranked first on that track (for all training set sizes). It is a reparsing system that makes use of predicted parses obtained both with pipeline and joint architectures. We applied it to the French data set only, as we focused on MWE analysis for dependency parsing. Section 2 gives its general description, section 3 describes the handling of MWEs. We detail the underlying parsers in section 4 and their combination in section 5. Experiments are described and discussed in sections 6 and 7.

2 System Overview

Our whole system is made of several single statistical dependency parsing systems whose outputs are combined into a reparser. We use two types of sin-
gle parsing architecture: (a) pipeline systems; (b) "joint" systems.

The pipeline systems first perform MWE analysis before parsing. The MWE analyzer (section 3) merges recognized MWEs into single tokens and the parser is then applied on the sentences with this new tokenization. The parsing model is learned on a gold training set where all marked MWEs have been merged into single tokens. For evaluation, the merged MWEs appearing in the resulting parses are expanded, so that the tokens are exactly the same in gold and predicted parses.

The "joint" systems directly output dependency trees whose structure comply with the French dataset annotation scheme. As shown in Figure 1, such trees contain not only syntactic dependencies, but also the grouping of tokens into MWEs, since the first component of an MWE bears dependencies to the subsequent components of the MWE with a specific label $\text{dep}_{\text{cpd}}$. At that stage, the only missing information is the POS of the MWEs, which we predict by applying a MWE tagger in a post-processing step.

![Figure 1: French dependency tree for La caisse d'épargne avait fermé la veille](image)

**Figure 1:** French dependency tree for *La caisse d’épargne avait fermé la veille* (*The savings bank had closed the day before*), containing two MWEs (in red).

### 3 MWE Analyzer and MWE Tagger

The MWE analyzer we used in the pipeline systems is based on Conditional Random Fields (CRF) (Lafferty et al., 2001) and on external lexicons following (Constant and Tellier, 2012). Given a tokenized text, it jointly performs MWE segmentation and POS tagging (of simple tokens and of MWEs), both tasks mutually helping each other\(^1\). CRF is a prominent statistical model for sequence segmentation and labelling. External lexicons used as sources of features greatly improve POS tagging (Denis and Sagot, 2009) and MWE segmentation (Constant and Tellier, 2012). Our lexical resources are composed of two large-coverage general-language lexicons: the Lefff\(^2\) lexicon (Sagot, 2010), which contains approx. half a million inflected word forms, among which approx. 25,000 are MWEs; and the DELA\(^3\) (Courtois, 2009; Courtois et al., 1997) lexicon, which contains approx. one million inflected forms, among which about 110,000 are MWEs. These resources are completed with specific lexicons freely available in the platform Unitex\(^4\): the toponym dictionary Prolex (Piton et al., 1999) and a dictionary of first names.

The MWE tagger we used in the joint systems takes as input a MWE within a dependency tree, and outputs its POS. It is a pointwise classifier, based on a MaxEnt model that integrates different features capturing the MWE local syntactic context, and in particular the POS at the token level (and not at the MWE level). The features comprise: the MWE form, its lemma, the sequence of POS of its components, the POS of its first component, its governor's POS in the syntactic parse, the POS following the MWE, the POS preceding the MWE, the bigram of the POS following and preceding the MWE.

### 4 Dependency Parsers

For our development, we trained 3 types of parsers, both for the pipeline and the joint architecture:

- **MALT**, a pure linear-complexity transition-based parser (Nivre et al., 2006)
- **Mate-tools 1**, the graph-based parser available in *Mate-tools*\(^5\) (Bohnet, 2010)
- **Mate-tools 2**, the joint POS tagger and transition-based parser with graph-based completion available in *Mate-tools* (Bohnet and Nivre, 2012).

\(^1\)Note though that we keep only the MWE segmentation, and use rather the Morfette tagger-lemmatizer, cf. section 4.

\(^2\)We use the version available in the POS tagger MElt (Denis and Sagot, 2009).

\(^3\)We use the version in the platform Unitex (http://igm.univ-mlv.fr/~unitex). We had to convert the DELA POS tagset to the FTB one.

\(^4\)http://igm.univ-mlv.fr/~unitex

\(^5\)Available at http://code.google.com/p/mate-tools/. We used the Anna3.3 version.
Such parsers require some preprocessing of the input text: lemmatization, POS tagging, morphology analyzer (except the joint POS tagger and transition-based parser that does not require preprocessed POS tagging). We competed for the scenario in which this information is not gold but predicted. Instead of using the predicted POS, lemma and morphological features provided by the shared task organizers, we decided to retrain the tagger-lemmatizer Morfette (Chrupała et al., 2008; Seddah et al., 2010), in order to apply a jackknifing on the training set, so that parsers are made less sensitive to tagging errors. Note that no feature pertaining to MWEs are used at this stage.

5 Reparser

The reparser is an adaptation to labeled dependency parsing of the simplest system proposed in (Sagae and Lavie, 2006). The principle is to build an arc-factored merge of the parses produced by \( n \) input parsers, and then to find the maximum spanning tree among the resulting merged graph. We implemented the maximum spanning tree algorithm of (Eisner, 1996) devoted to projective dependency parsing. During the parse merging, each arc is unlabeled, and is given a weight, which is the frequency it appears in the \( n \) input parses. Once the maximum spanning tree is found, each arc is labeled by its most voted label among the \( m \) input parses containing such an arc (with arbitrary choice in case of ties).

6 Experiments

6.1 Settings

MWE Analysis and Tagging

For the MWE analyzer, we used the tool lgtagger (version 1.1) with its default set of feature templates. The MWE tagger model was trained using the Wapiti software (Lavergne et al., 2010). We used the default parameters and we forced the MaxEnt mode.

Parsers

For MALT (version 1.7.2), we used the arceager algorithm, and the liblinear library for training. As far as the features are concerned, we started with the feature templates given in Bonsai10 (Candito et al., 2010), and we added some templates (essentially lemma bigrams) during the development tests, that slightly improved performance. For the two Mate-tools parsers, we used the default feature sets and parameters proposed in the documentation.

Morphological prediction

Predicted lemmas, POS and morphology features are computed with Morfette version 0.3.5 (Chrupała et al., 2008; Seddah et al., 2010)11, using 10 iterations for the tagging perceptron, 3 iterations for the lemmatization perceptron, default beam size for the decoding of the joint prediction, and the Lefff (Sagot, 2010) as external lexicon used for out-of-vocabulary words. We performed a jackknifing on the training corpus, with 10 folds for the full corpus, and 20 folds for the 5k track12.

6.2 Results

We first provide the results on the development corpus. Table 1 shows the general parsing accuracy of our different systems. Results are displayed in three different groups corresponding to each kind of systems: the two single parser architectures ones (joint and pipeline) and the reparsing one. Each system was tested both when learned on the full training data set and on the 5k one. The joint and pipeline systems were evaluated with the three parsers described in section 4. For the reparser, we tested different combinations of parsers in the full training data set mode. We found that the best combination includes all parsers but MALT in joint mode. We did not tune our reparsing system in the 5k training data set mode. We assumed that the best combination in this mode was the same as with full training.

10http://alpage.inria.fr/statgram/frdep/frstatdep_parsing.html
11Available at https://sites.google.com/site/morfetteweb/
12Note that for the 5k track, we retrained Morfette using the 5k training corpus only, whereas the official 5k training set contains predicted morphology trained on the full training set.
Table 1: Parsing results on development corpus (38820 tokens)

| type    | parser | full | 5k |
|---------|--------|------|----|
| Joint   | MALT   | 80.91| 78.61|
|         | Mate-tools 1 | 84.60 | 82.02 |
|         | Mate-tools 2 | 84.40 | 81.66 |
| Pipeline| MALT   | 82.56| 80.79|
|         | Mate-tools 1 | 85.28 | 83.23 |
|         | Mate-tools 2 | 84.82 | 82.79 |
| Reparser| joint only | 85.28 | - |
|         | pipeline only | 85.79 | - |
|         | all | 86.12 | - |
|         | best ensemble | 86.23 | 84.25 |

Table 2: MWE Results on the development corpus (2119 MWEs) with full training.

|      | COMP | MWE | MWE+POS |
|------|------|-----|---------|
|      | R    | P   | F      | R    | P   | F  | R    | P   | F  |
| joint Mate-tools 1 | 76.3 | 82.4 | 79.2 | 74.3 | 80.6 | 77.3 | 70.7 | 76.7 | 73.6 |
| pipeline Mate-tools 1 | 80.8 | 82.7 | 81.7 | 79.0 | 83.6 | 81.2 | 75.6 | 80.1 | 77.8 |
| best reparser | 81.1 | 82.5 | 81.8 | 79.2 | 83.0 | 81.0 | 76.1 | 79.8 | 77.9 |

Table 2 contains the MWE results on the development data set with full training, for three systems: the best single-parser joint and pipeline systems (i.e. with Mate-tools 1) and the best reparser. We do not provide results for the 5k training because they show similar trends. We provide the 9 MWE-related measures defined in the shared task. The symbols R, P and F respectively correspond to recall, precision and F-measure. COMP corresponds to evaluation of the non-head MWE components (i.e. the non-first MWE components, cf. Figure 1). MWE corresponds to the recognition of a complete MWE. MWE+POS stands for the recognition of a complete MWE associated with its correct POS.

We submitted to the shared task our best (reparser) system according to the tuning described above. We also sent the two best pipeline systems (Mate-tools 1 and Mate-tools 2) and the best joint system (Mate-tools 1), in order to compare our single systems to the other competitors. The official results of our systems are provided in table 3 for general parsing and in table 4 for MWE recognition. We also show the ranking of each of these systems in the competition.

7 Discussion

In table 3, we can note that for the 5k training set scenario, there is a general drop of parsing performance (approximately 2 points), but the trends are exactly the same as for the full training set scenario. Concerning the performance on MWE analysis (table 4), the pipeline Mate-tools-1 system very slightly outperforms the best reparser system in the 5k scenario, contrary to the full training set scenario, but the difference is not significant. In the following, we focus on the full training set scenario.

Let us first discuss the overall parsing performance, by looking at the results on the development corpus (table 1). As far as the single-parser systems are concerned, we can note that for both the joint and pipeline systems, MALT achieves lower performance than the graph-based (Mate-tools-1) and the joint tagger-parser (Mate-tools-2), which have comparable performance. Moreover, the pipeline systems achieve overall better than their joint counterpart, though the increase between joint and pipeline architecture is much bigger for MALT than for the Mate parsers (for MALT, compare
Table 3: Official parsing results on the evaluation corpus (75216 tokens)

| training type | parser        | LAS   | UAS   | LaS   | Rank |
|---------------|---------------|-------|-------|-------|------|
| Full          | Reparser      | 85.86 | 89.19 | 92.20 | 1    |
|               | Pipeline Mate-tools 1 | 84.91 | 88.35 | 91.73 | 3    |
|               | Pipeline Mate-tools 2 | 84.87 | 88.40 | 91.51 | 4    |
|               | Joint         | 84.14 | 87.67 | 91.24 | 7    |
| 5k            | Reparser      | 83.60 | 87.40 | 90.76 | 1    |
|               | Pipeline Mate-tools 1 | 82.53 | 86.51 | 90.14 | 4    |
|               | Pipeline Mate-tools 2 | 82.15 | 86.18 | 89.79 | 6    |
|               | Joint         | 81.63 | 85.76 | 89.56 | 7    |

Table 4: Official MWE results on the evaluation corpus (4043 MWEs). The scores correspond to the F-measure.

| training type | parser        | COMP  | MWE   | MWE+POS | Rank |
|---------------|---------------|-------|-------|---------|------|
| Full          | Reparser      | 81.3  | 80.7  | 77.5    | 1    |
|               | Pipeline Mate-tools 1 | 81.2  | 80.8  | 77.4    | 2    |
|               | Pipeline Mate-tools 2 | 81.2  | 80.8  | 76.6    | 3    |
|               | Joint         | 79.6  | 77.4  | 74.1    | 6    |
| 5k            | Pipeline Mate-tools 1 | 78.7  | 77.7  | 74.0    | 1    |
|               | Reparser      | 78.9  | 77.2  | 73.8    | 2    |
|               | Pipeline Mate-tools 2 | 78.7  | 77.7  | 73.3    | 5    |
|               | Joint         | 75.9  | 72.2  | 75.9    | 10   |

LAS=80.91 for the joint system, and LAS=82.56 for the pipeline architecture, while for Mate-tools-1, compare LAS=84.60 with LAS=85.28. The best reparser system provides a performance increase of approximately one point over the best single-parser system (Mate-tools-1), both for LAS and UAS, which suggests that the parsers have complementary strengths.

When looking at performance on MWE recognition and tagging (2), we can note greater variation between the F-measures obtained by the single-parser systems, but this is due to the much lower number of MWEs with respect to the number of tokens (there are 38820 tokens and 2119 MWEs in the dev set). The MWE analyzer used in the pipeline systems leads to better MWE recognition ($F$-measure = 81.2 on dev set) than when the analysis is left to the bare “joint” parsers (Joint Mate-tools 1 achieves $F$-measure= 77.3).

Contrary to the situation for overall parsing performance, the reparser system does not lead to better MWE recognition with respect to the MWE analyzer of the pipeline systems. Indeed the performance on MWEs are quite similar between the reparser system and the MWE analyzer (for the MWE metric, on the dev set we get $F=81.0$ versus 81.2 for best reparser and pipeline systems respectively, whereas we get 80.7 and 80.8 on the test set. These differences are not significant). This is because the MWEs predicted by the MWE analyzer are present in three of the single-parser systems taken into account in the reparsing process, and are thus much favored in the voting.

In order to understand better our parsing systems’ performance on MWE recognition, we provide in table 5 the MWE+POS results broken down by MWE part-of-speech, for the dev set. Not surprisingly, we can note that performance varies greatly depending on the POS, with better performance on closed classes (conjunctions, determiners, prepositions, pronouns) than on open classes. The lowest performance is on adjectives and verbs, but given the raw numbers of gold MWEs, the major impact on overall performance is given by the results on nominal MWEs (either common or proper nouns). A little less than one third of the nominal gold MWEs
| POS    | R    | P    | F    | Nb gold | Nb predicted | Nb correct |
|--------|------|------|------|---------|--------------|------------|
| adjectives | 46.9 | 75.0 | 57.7 | 32      | 20           | 15         |
| adverbs   | 74.7 | 83.0 | 78.7 | 360     | 324          | 269        |
| conjunctions | 90.1 | 83.7 | 86.8 | 91      | 98           | 82         |
| clitics    | 96.0 | 96.8 | 96.4 | 252     | 250          | 242        |
| determiners | 72.7 | 76.2 | 74.4 | 973     | 928          | 707        |
| nouns      | 84.6 | 84.9 | 84.8 | 345     | 344          | 292        |
| pronouns   | 75.0 | 87.5 | 80.8 | 28      | 24           | 21         |
| verbs      | 66.7 | 66.7 | 66.7 | 33      | 33           | 22         |
| unknown    | 0    | 0    | 0    | 5       | 0            | 0          |
| ALL        | 77.9 | 81.6 | 79.7 | 2119    | 2022         | 1650       |

Table 5: MWE+POS results on the development corpus, broken down by POS (recall, precision, F-measure, number of gold MWEs, predicted MWEs, correct MWEs with such POS.

is not recognized (R = 72.7), and about one quarter of the predicted nominal MWEs are wrong (P = 76.2). Though these results can be partly explained by some inconsistencies in MWE annotation in the French Treebank (Constant et al., 2012), there remains room for improvement for open class MWE recognition.

8 Conclusion

We have described the LIGM-Alpage system for the SPMRL 2013 shared task, restricted to the French track. We provide the best results for the realistic scenario of predicting both MWEs and dependency syntax, using a reparsing architecture that combines several parsers, both pipeline (MWE recognition followed by parsing) and joint (MWE recognition performed by the parser). In the future, we plan to integrate features specific to MWEs into the joint system, so that the reparser outperforms both the joint and pipeline systems, not only on parsing (as it is currently the case) but also on MWE recognition.

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