Lemmatization and morphological tagging in German and Latin: A comparison and a survey of the state-of-the-art

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Abstract

This paper relates to the challenge of morphological tagging and lemmatization in morphologically rich languages by example of German and Latin. We focus on the question what a practitioner can expect when using state-of-the-art solutions out of the box. Moreover, we contrast these with older methods and implementations for POS tagging. We examine to what degree recent efforts in tagger development pay out in improved accuracies — and at what cost, in terms of training and processing time. We also conduct in-domain vs. out-domain evaluation. Out-domain evaluations are particularly insightful because the distribution of the data which is being tagged by a user will typically differ from the distribution on which the tagger has been trained. Furthermore, two lemmatization techniques are evaluated. Finally, we compare pipeline tagging vs. a tagging approach that acknowledges dependencies between inflectional categories.

Keywords: morphological tagging, lemmatization, morphologically rich languages

1. Introduction

Lemmatization and part-of-speech (POS) tagging are critical preprocessing steps for many natural language processing (NLP) tasks such as information retrieval, knowledge extraction, or semantic analysis. In morphologically rich languages such as German and Latin, both problems are non-trivial due to the variability of lexical forms. This results both in large tagsets for POS tagging — which list such inflectional categories as case, gender, degree, etc., besides coarse-grained POS labels — and a large number of (potentially unseen) forms associated with each lemma. In this work, we survey tagging and lemmatization techniques for the two languages mentioned. Our survey includes both older, such as the TreeTagger (Schmid, 1994) and TnT (Brants, 2000), and more modern approaches to tagging and lemmatization. Although our expectation is clearly that technology steadily improves with time, it is apropro not obvious how large the gap between older and more modern approaches is, and also what the ordering of the most recent generation of systems is. We test our systems under the following requirements:

1. Ideally, we would want a learned system to perform well on the distribution (a specific text genre, historical language variant, etc.) on which it has been trained (in-domain (ID)) but also to perform decently on corpora of similar but different genres, registers, language varieties, etc. (out-domain (OD)).
2. Since coarse-grained POS tagging may be insufficient for linguistic applications and unsatisfactory for practitioners, we expect a system to perform well on fine-grained morphological tagging, not only on coarse-grained POS labels.
3. Finally, run times of systems may be of considerable interest for practitioners. Therefore, we include both training and testing time estimations of the different techniques.

2. Lemmatization

We view lemmatization as the problem of transforming a word form into its canonical form, or lemma. In a machine learning context, lemmatization has e.g. been considered as a character-level string transduction process (Dreyer et al., 2008; Nicolai et al., 2015; Eger, 2015), a prefix and suffix transformation problem (Jursic et al., 2010; Gesmundo and Samardzic, 2012) or as a pattern matching task (Durrett and DeNero, 2013; Ahlberg et al., 2014). While character-level string transducers may yield excellent results (Nicolai et al., 2015), particularly when trained and tested on lists of words randomly extracted from a lexicon (Eger, 2015), they tend to be slower to learn and typically consider the lemmatization problem in isolation, ignoring contextual word form cues.

In this work, we experiment with two approaches to lemmatization, both based on prefix and suffix transformations. LemmaGen (Jursic et al., 2010) learns ‘ripple down rules’ (Compton and Jansen, 1988), that is, tree-like decision

1 An ideal system can also make use of the fact that there are strong dependencies between POS tagging and lemmatization, which should substantially improve its performance relative to approaches where the tasks are treated independently (Müller et al., 2015).
structures, from pairs of strings. Rule conditions are suffixes of word forms, and rule consequents are transformations which replace the suffix in question by a new suffix. The second approach we experiment with is the casting of lemmatization as a classification task (Gesmundo and Samardzic, 2012), which we call LAT: lemmatization is viewed here as a 4-tuple indicating the prefix and suffix transformations involved in the lemmatization process. For example, the transformation of German verb form gespielt into its lemma spielen is encoded by the tuple (2, 0, 1, en), indicating that, to derive spielen, the first two characters of gespielt are replaced by the empty string, and the last character is replaced by en. This compact encoding allows to view lemmatization as a classification problem where the size of the output space is relatively small, on the orders of at most hundreds or thousands of labels. Moreover, lemmatization can then also be treated as a sequence labeling problem, where dependence between subsequent labels may be taken into account.

3. POS tagging

POS tagging (or sequence labeling) has witnessed several milestones such as including dependencies between output labels (as in Markov models such as HMMs or CRFs), the broad use of lexical features (Ratnaparkhi, 1996; Toutanova et al., 2003), or the concept of the margin introduced in SVMs. The most recent class of taggers is characterized by the availability to include word representations learned from unlabeled data, the possibility to apply feature-rich models to problems with large output spaces, and/or by making use of deep (rather than shallow) models such as neural networks that can in addition function without handcrafting features.

In this work, we consider the following part-of-speech tagging systems, listed by the order of their year of publication: TreeTagger (Schmid, 1994), TnT (Brants, 2000), Stanford tagger (Toutanova et al., 2003), Lapos (Tsuruoka et al., 2011), Mate (Bohnet and Nivre, 2012). We also include the OpenNLP Tagger, an official Apache project. For these systems, we refer to the original works for descriptions. Among the most recent generation of taggers, we consider the MarMoT (Müller et al., 2013) tagger, which implements a higher order CRF with approximations such that it can deal with large output spaces. In addition, MarMoT can be trained to fire on the predictions of lexical resources as well as on word embeddings, real vector-valued representations of words. FLORS (Schnabel and Schütze, 2014) tags a given word by constructing a feature vector representation of its local context and then classifying this vector by an SVM. The feature vector representation of each word in a context includes distributional, shape, and suffix information and the feature vector for the entire context is the concatenation of the word vector representations. In principle, the vector representations of words are the same for known and unknown words, whence FLORS is potentially very well-suited for OD tasks. In our work, we use online FLORS (Yin et al., 2015), which incrementally updates word representations for each new test sentence encountered.

In Table 1, we list some of the properties of our surveyed taggers. While most models make use of features (except for HMMs as TnT is based on, for which the inclusion of arbitrary features is non-trivial), not all of them allow users to specify user-defined features.

4. Datasets

| corpus      | language | sentences | tokens |
|-------------|----------|-----------|--------|
| Tiger       | German   | 50,472    | 888,238|
| TGermaCorp  | German   | 7,274     | 123,742|
| Capitularies| Latin    | 15,572    | 481,578|
| Proiel      | Latin    | 1,147     | 22,280 |

Table 2: Statistics of corpora used in the experiments.

For German, we train and test on the Tiger corpus (Brants et al., 2004) and TGermaCorp (Lücking et al., 2016). For Latin, we similarly use the capitularies (Mehler et al., 2015; Eger et al., 2015) and the Proiel corpus (Haug and Johndal, 2008). See Table 2 for details. In general, for ID experiments, we perform 3-fold random subset validation with a 90%/10% split on one of the corpora for each language. For the OD experiments, we use the entire corpora, per language, as training and test sets, respectively. As additional resources, we include the following:

- We train CBOW word embeddings using word2vec (Mikolov et al., 2013) on the German Wikipedia and, for Latin, on the Patrologia Latina.
- As lexicons, for German, we extract a lexicon from the German Wiktionary. Extracting lemmas and syntactic words (including all grammatical categories available) from a Wiktionary instance in a thorough and robust way is not a trivial task. Even though guidelines and templates exist they differ significantly between Wiktionary instances and also vary in the way they are used within the same language. Our approach parses the HTML code of a Wiktionary instance that has been setup on a local server using the XML-dump from 2015-09-01. This is, according to our experience, more accurate than trying to parse the MedialWiki sources directly and it saves bandwidth on the official Wiktionary servers. For the current experiments we used a random subset of Proiel for which tag labels had been manually synchronized with those of the capitularies.

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6 We also wanted to include NonLexNN (Labreau et al., 2015), a non-lexicalized neural network architecture for POS tagging. By operating on the subword/character-level it promises to yield higher performance on OD tasks, similarly as the FLORS tagger. However, we could not make this tagger perform on-par with the other taggers surveyed. One reason for this was its immense runtime — on the orders of several days on a single training fold — so that we could not sufficiently experiment with its parameters.

7 We used a random subset of Proiel for which tag labels had been manually synchronized with those of the capitularies.

8 See https://opennlp.apache.org/.

9 The implementation of FLORS includes language (= English) specific features. This is expected to decrease its performance on the Latin and German datasets we consider.

10 http://de.wiktionary.org

11 http://de.wiktionary.org
dewiki.dumps.wikimedia.org/dewiktionary/20150901/
detailed below, we used a lexicon containing 67,034 lemmas and 1,817,735 syntactic words. This lexicon consists of nouns, proper nouns, verbs and adjectives. For Latin, we make use of Collex-LA (Mehler et al., 2015).

Among our taggers, only the MarMoT tagger can make use of these additional resources. Finally, we feed the first 500,000 sentences from German Wikipedia to the FLORS tagger as additional resource from which to induce word representations.

5. Experiments

In this section, we detail our experiments. For POS tagging, we pursue two sets of experiments. First, we train and test on each subcategory (pos, case, gender, etc.) independently (pipeline learning). Subsequently, we train on complex tag labels, which encode the different subcategories (‘joint learning’). Of course, joint learning is more accurate in principle — though not always computationally feasible, depending on the tagger — since it better captures the dependencies between the different categories (a noun does not admit a comparison degree, for example). We note that we generally perform no hyperparameter optimization, which may be considered an art in itself. Rather, we treat the taggers as black boxes and use default parametrizations.

5.1. POS Tagging

5.1.1. Pipeline learning

We start by focussing on the results for pos (see Table 3) and case (Table 6), as tagging pos is the classical instance of (coarse-grained) POS tagging, and case is the most difficult category for both German and Latin. Here we run all taggers without additional resources.

For pos, MarMoT and FLORS perform best and for case, MarMoT and Lapos achieve best accuracies, although the performances of FLORS and Mate are not substantially worse. It is interesting to observe that the accuracies of the feature-poor models TnT and TreeTagger are substantially worse on case (up to 11 percentage points), relative to the best taggers, than they are on pos (less than 2 percentage points). Concerning run times, TnT and TreeTagger are extremely fast, while feature-richer models take substantially longer to both train and test. This hints at an interesting time-accuracy tradeoff.

The results also demonstrate the significant loss of accuracy when the training and test datasets stem from different domains (OD): the accuracies typically drop about 8-10%, across all taggers, and even beyond 30% points in particular cases. Table 4 shows, however, how the results for MarMoT improve for the OD tasks when we supply the system with additional resources in the form of embeddings and lexicon predictions. Improvements are particularly striking when training data is scarce, as is the case for the Proiel dataset. For example, accuracy in the scenario Proiel→Capit improves from 63,13% to 71.17%, when both embeddings and the lexicon is included.

Table 7 depicts the accuracies of all systems when fine-grained morphological tagging is the goal (under the current pipeline approach). Here, all subcategories have to match with the gold-standard. The top three systems in this setting are MarMoT, Lapos, and FLORS, while the worst two systems are TnT and the TreeTagger. Overall, differ-

| System          | Training | Testing |
|-----------------|----------|---------|
| FLORS           | 5:11:55  | 3:55    |
| Lapos           | 6:44     | 0:13    |
| MarMoT (Em.&L.) | 5:00 (16:42) | 0:10 (1:12) |
| Mate            | 30:12    | 0:36    |
| OpenNLP         | 11:02    | 0:06    |
| Stanford        | 27:08:17 | 0:08    |
| TnT             | 0:02     | 0:01    |
| TreeTagger      | 0:01     | 0:01    |

Table 5: Elapsed time (in hh:mm:ss) for pos tagging and testing of a Tiger subset. Training and test data consists of 45,424 and 5,048 sentences, respectively.
Table 3: pos accuracy in %

|        | FLORS | Lapos | MarMoT | Mate | OpenNLP | Stanford | TnT | TreeTagger |
|--------|-------|-------|--------|------|---------|----------|-----|------------|
| TG     | 92.36 | 93.02 | 93.63  | 93.06| 91.75   | 91.05    | 92.39| 92.40      |
| Tiger  | 97.75 | 97.89 | 98.04  | 97.93| 96.85   | 97.31    | 97.32| 97.25      |
| TG→Tiger | 89.09 | 89.62 | 89.86  | 88.22| 86.65   | 84.02    | 88.28| 87.74      |
| Tiger→TG | 90.59 | 90.18 | 89.83  | 90.13| 88.66   | 88.37    | 89.49| 89.29      |
| Capit  | 95.33 | 95.97 | 95.93  | 95.71| 94.73   | 94.86    | 95.31| 95.04      |
| Proiel | 92.80 | 95.23 | 95.42  | 94.93| 93.12   | 90.97    | 93.63| 93.21      |
| Capit→Proiel | 84.50 | 87.34 | 87.36  | 86.54| 82.46   | 81.41    | 85.62| 85.34      |
| Proiel→Capit | 62.39 | 63.60 | 63.13  | 64.05| 62.38   | 54.43    | 62.92| 61.23      |

Table 6: case accuracy in %

|        | FLORS | Lapos | MarMoT | Mate | OpenNLP | Stanford | TnT | TreeTagger |
|--------|-------|-------|--------|------|---------|----------|-----|------------|
| Tiger  | 92.36 | 94.28 |        |      |         |          |     |            |
| Capit  | 92.68 | 94.71 |        |      |         |          |     |            |
| FLORS  |       |       | 92.58  | 94.76| 95.42   | 94.93    |     |            |
| Lapos  |       |       | 92.46  | 94.62| 95.38   | 94.93    |     |            |
| MarMoT |       |       | 92.29  | 94.62| 93.53   | 93.12    |     |            |
| Mate   |       |       | 91.92  | 93.53| 91.43   | 90.97    |     |            |
| OpenNLP| 84.38 | 92.97 | 90.56  | 90.66| 90.56   | 90.97    |     |            |
| Stanford| 81.74 | 88.46 | 85.50  | 85.34| 85.81   | 88.81    |     |            |

Table 7: all categories (pipeline) - accuracy in %

Table 8: all categories (joint) - accuracy in %

German and Latin ID datasets.

|        | Baseline | +Emb | +Emb+Lex |
|--------|----------|------|----------|
| pos    | 98.01    | 98.16| 98.20    |
| case   | 94.45    | 94.52| 94.53    |
| degree | 99.60    | 99.65| 99.65    |
| gender | 96.83    | 97.13| 97.27    |
| mood   | 99.39    | 99.41| 99.42    |
| number | 97.90    | 98.06| 98.07    |
| person | 99.42    | 99.44| 99.45    |
| tense  | 99.45    | 99.48| 99.49    |
| ALL    | 90.56    | 90.91| 91.04    |

Table 9: MarMoT-'Joint learning' — Tiger, ID

Table 10: FLORS-'Joint learning' — Tiger, ID

Table 11: best possible performances of all systems for the fine-grained morphological tagging task. Here, MarMoT is clearly the best system and the only system surpassing the 90% accuracy threshold, for both the

ences across tagging tasks accumulate to an up to 14% difference on the fine-grained morphological tagging task between systems.

5.1.2. Joint learning

In this subsection, we train systems on complex POS label, which comprise the different subcategories. All systems gain now significantly (Table 8). The ordering of systems in terms of accuracy is virtually the same as for pipeline learning, however. In Table 9, we zoom in on the MarMoT tagger as we provide additional resources to the system: adding word embeddings increases accuracy on morphological tagging from 90.56% to 90.91%; including the Wiktionary lexicon further increases this number to 91.04%. Table 10 shows analogous improvements for the FLORS tagger as we supply the tagger with the unlabeled Wiktionary data.

Table 11 summarizes the best possible performances of all systems for the fine-grained morphological tagging task. Here, MarMoT is clearly the best system and the only system surpassing the 90% accuracy threshold, for both the
5.2. Lemmatization

Here, we train systems on (form,lemma) pairs as available in the respective training data. For LAT, we consider lemmatization as tagging task as in Gesmundo and Samardzic (2012). We use the MarMoT tagger for this, without any additional resources. In contrast, LemaGen cannot learn to lemmatize words in context. We find (Table 12) that LAT is consistently better than LemaGen, which corroborates results from (Gesmundo and Samardzic, 2012). We also note that ID accuracy on Tiger is higher than on TGERmaCorp. This is due to the fact that Tiger is a larger database than TGERmaCorp (around 50,000 sentences vs. around 7,500) and that Tiger is more homogeneous, while TGERmaCorp contains poems, various sorts of literature, etc. Finally, the OD results seem pretty low, compared to ID results, similarly as for tagging. We remark here that specific lemma conventions differ across the two datasets. In addition, TGERmaCorp contains spelling mistakes (Widersehen) and historical variants (Capital) that are conventionally lemmatized by their modern lemma forms (Kapital). Such cases are difficult for the trained systems to handle since they are absent in Tiger.

6. Discussion

In terms of accuracy, FLORS, Lapos, Mate, and particularly MarMoT are the methods of choice when (particularly) fine-grained morphological tagging is the goal. Moreover, the lexical resources as well as the word embeddings derived from unlabeled data that can be fed in to MarMoT (and FLORS) make the systems more robust to change of domain, which is an immensely important aspect of real-world POS tagging. But it is also interesting to have a closer look at the elapsed time for training and testing (see Table 5). TnT and TreeTagger, while typically performing worse — sometimes badly — in terms of accuracy, take only a fraction of training and testing time of the more recent tagger generation. For a practitioner, computing time can be a critical issue, however. For example, when it comes to tagging large corpora such as the entire Wikipedia even a few seconds per processed text can make a huge difference. So depending on the task at hand, even the older approaches may still be attractive.

7. Conclusion

We conducted a study of tagging German and (classical as well as medieval) Latin texts by examining a range of older taggers in comparison to younger ones. We experimented with coarse-grained as well as fine-grained POS tagging and with lemmatization. Our findings are in support of utilizing most recent achievements in the development of taggers. Especially, MarMoT performed best in most of the tasks considered here. We also show that out-domain (OD) tagging leads to a considerable loss in tagging accuracy. The same is true when we consider pipeline learning of inflectional categories. These findings hint at the need of further developing taggers possibly by extending the feature space (e.g., by morphological, syntactic or even semantic features). However, our experiments also show that such an extension may lead to a considerable increase of training and operating time and, thus, may be problematic in the case of time-critical scenarios. Last but not least, we evaluated two lemmatizers. Here, LAT performs best, that is, a model which regards lemmatization as a contextual classification task. Our experiments show once more that accuracy drops considerably below 90% if the lemmatizer is applied OD. As before, this is a good argument for further developments in this area of NLP, in particular, for addressing domain adaptation.

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14Please note that the computation times shown in Table 5 can only give a general impression. Firstly, elapsed times depend linearly on the hardware being used. Secondly, processing times depend on the configuration of the taggers — especially with regard to training a new model. Finally, the evaluated taggers are implemented in different programming languages. This particularly adversely affects the FLORS tagger, which, evidently suffers from an inefficient implementation, see http://cistern.cis.lmu.de/flors/. However, the results indicate what a black box user may expect when running each of the implementations.
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