Abstract

The utility of using morphological features in part-of-speech (POS) tagging is well established in the literature. However, the usefulness of exploiting information about POS tags for morphological segmentation is less clear. In this paper we study the POS-dependent morphological segmentation in the Adaptor Grammars framework. We experiment with three different scenarios: without POS tags, with gold-standard tags and with automatically induced tags, and show that the segmentation F1-score improves when the tags are used. We show that the gold-standard tags lead to the biggest improvement as expected. However, using automatically induced tags also brings some improvement over the tag-independent baseline.

1 Introduction

Linguistically, part-of-speech (POS) tagging and morphology are closely related and this relation has been heavily exploited in both supervised and unsupervised POS tagging. For instance, the supervised Stanford tagger (Toutanova et al., 2003) as well as some unsupervised POS taggers (Berg-Kirkpatrick et al., 2010; Lee et al., 2010) use character prefix and/or suffix features, while the model by Christodoulopoulos et al. (2011) makes use of suffixes learned with an unsupervised morphological segmentation model.

There have been some attempts to exploit the relation in the opposite direction to learn the segmentations dependent on POS tags. For instance, the segmentation procedures described by Freitag (2005) and Can and Manandhar (2009) find the syntactic clusters of words and then perform morphology learning using those clusters. Few works have included a small number of syntactic classes directly into the segmentation model (Goldwater et al., 2006; Lee et al., 2011). However, Goldwater et al. (2006) only trains the model on verbs, which means that the classes model different verb paradigms rather than POS tags. Secondly, the model is never evaluated in a single class configuration and thus it is not known whether incorporating those classes gives any actual improvement. The results of Lee et al. (2011) show small improvements when the POS-word component (a bigram HMM) is incorporated into the model. However, the number of syntactic categories they learn is only 5, which is smaller than the number of main POS categories in most annotated corpora. Moreover, the main gain in the segmentation F-score is obtained by modeling the agreements between adjacent words, rather than exploiting the relation to syntactic classes.

Another line of previous work has attempted to model the POS tags and morphological segmentations jointly in an unsupervised model (Can, 2011; Sirts and Alumäe, 2012; Frank et al., 2013). However, the results presented in those papers fail to demonstrate clearly the utility of using the tag information in segmentation learning over the scenario where the tags are missing.

The goal of this paper is to explore the relation between POS tags and morphological segmentations and in particular, to study if and how much the POS tags help to learn better segmentations. We start with experiments learning segmentations without POS tags as has been standard in previous literature (Goldsmith, 2001; Creutz and Lagus, 2007; Sirts and Goldwater, 2013) and then add the POS information. We first add the information about gold-standard tags, which provides a kind of upper bound of how much the segmentation accuracy can gain from POS information. Secondly, we also experiment with automatically induced tags. We expect to see that gold-standard POS tags improve the segmentation accuracy and that induced tags...
are also helpful. The results of these experiments can be informative to whether directing effort into developing joint unsupervised models for POS tagging and segmentation is justified, or whether the efforts of exploiting synergies in morphology learning should be focused elsewhere.

We define the segmentation model in the Adaptor Grammars framework (Johnson et al., 2007) that has been previously successfully applied to learning morphological segmentations (Johnson, 2008; Sirts and Goldwater, 2013). In fact, we will use some of the grammars defined by Sirts and Goldwater (2013) but enrich the grammar rules with information about POS tags. Our POS-dependent grammars are inspired by the grammars used to learn topic models (Johnson, 2010), which have separate rules for each topic. In a similar fashion we will have a separate set of rules for each POS tag.

We conduct experiments both in English and Estonian—a morphologically rich inflective and agglutinative language—and show that the grammars exploiting information about the gold-standard POS tags indeed learn better morphological segmentations in terms of F1-score. The gain in scores when compared to the tag-independent segmentations is up to 14%, depending on the language and the grammar. When the model uses automatically induced tags, the learned segmentations in English are still better than the tag-independent baseline, but the differences in scores are smaller, reaching up to 11% absolute improvement. Although the scores show improvements in Estonian as well, the closer inspection of segmentations of different POS category words reveals that in most cases there are no major differences between segmentations learned with and without tags.

The rest of the paper is organized as follows. In section 2 we briefly introduce the Adaptor Grammars framework, section 3 describes the tag-dependent grammars used in experiments. Section 4 lists the experimental scenarios. In section 5 we describe the experimental setup. Section 6 presents the results, followed by the discussion in section 7, section 8 concludes the paper.

2 Adaptor Grammars

Adaptor Grammars (AG) (Johnson et al., 2007) is a non-parametric Bayesian framework for learning latent structures over sequences of strings. In the current context, the sequence of strings is a sequence of characters making up a word, and the latent structures of interest are the morphemes.

An AG consists of two components: a probabilistic context-free grammar (PCFG) that can generate all possible latent structures for the given inputs, and a Pitman-Yor process (PYP) adaptor function that transforms the probabilities of the parse trees in such a way that the probabilities of the frequently occurring subtrees are much higher than they would be under the PCFG model.

A simple morphological grammar for the AG model could be (Sirts and Goldwater, 2013):

\[
\text{Word} \rightarrow \text{Morph}^+ \\
\text{Morph} \rightarrow \text{Char}^+,
\]

where each word consists of one or more morphemes and each morpheme is a sequence of characters. The grammar here uses an abbreviated notation for denoting the recursive rules and thus the first rule is a short-hand writing for:

\[
\text{Word} \rightarrow \text{Morphs} \\
\text{Morphs} \rightarrow \text{Morph} \\
\text{Morphs} \rightarrow \text{Morph Morphs}
\]

The underline denotes the adapted non-terminals, i.e. the sub-trees rooted in those non-terminals are cached by the model and their probabilities are computed according to the PYP. In the given example the Morph non-terminal is adapted, which means that the model prefers to re-generate the same subtrees denoting the morphemes repeatedly.

We use in our experiments an existing AG implementation¹, the technical details of this implementation are described in (Johnson and Goldwater, 2009).

3 POS-dependent Grammars

The POS-dependent grammars are inspired by the grammars that have been used to learn topic models (Johnson, 2010). Whereas the topic modeling grammars have one rule for every latent topic, the POS-dependent grammars have one rule for each possible tag, which enables the model to cache the subtrees corresponding to morphemes in words with specific syntactic category.

¹available from http://web.science.mq.edu.au/~mjohnson/Software.htm
Consider for instance a tagset that contains three tags: verb, noun and adjective. Then, in order to make the simple morpheme sequences generating grammar shown in the previous section to be POS-dependent, the rules for each POS tag have to be replicated:

\[
\begin{align*}
\text{Word} & \rightarrow \text{Noun Morph}_{\text{N}}^+ \\
\text{Word} & \rightarrow \text{Verb Morph}_{\text{V}}^+ \\
\text{Word} & \rightarrow \text{Adj Morph}_{\text{A}}^+ \\
\text{Morph}_{\text{N}} & \rightarrow \text{Char}^+ \\
\text{Morph}_{\text{V}} & \rightarrow \text{Char}^+ \\
\text{Morph}_{\text{A}} & \rightarrow \text{Char}^+, \\
\end{align*}
\]

Each rule rooted in Word now first generates a non-terminal that corresponds to a particular POS tag and a sequence of POS-specific morphemes. In order to make the grammar complete, we also add rules that generate the terminal symbols corresponding to specific POS tags. We add an underscore to the terminal symbols corresponding to tags to distinguish them from other terminal symbols that are used to generate the words themselves.

\[
\begin{align*}
\text{Noun} & \rightarrow \text{N}_- \\
\text{Verb} & \rightarrow \text{V}_- \\
\text{Adj} & \rightarrow \text{A}_-, \\
\end{align*}
\]

We experiment with three different grammars that generate POS-dependent morphological segmentations. The first two of them, \textbf{MorphSeq} and \textbf{SubMorph} are essentially the same as the ones used for morphological segmentation in (Sirts and Goldwater, 2013). The third one, \textbf{CollocMorph}, adds another layer of latent structure on top of morphemes. All three grammars are made tag-dependent by replicating the relevant rules by using tag-specific non-terminals as explained above.

The \textbf{MorphSeq} grammar is the simplest grammar that just generates each word as a sequence of morphemes. It is essentially a unigram morphology model. The tag-dependent version we used is the following:

\[
\begin{align*}
\text{Word} & \rightarrow \text{Tag Morph}_{\text{tag}}^+ \quad \text{for } \forall \text{ tag} \in \mathcal{T} \\
\text{Morph}_{\text{tag}} & \rightarrow \text{Morph} \quad \text{for } \forall \text{ tag} \in \mathcal{T} \\
\text{Tag} & \rightarrow \tau \quad \text{for } \forall \tau \in \mathcal{T} \\
\text{Morph} & \rightarrow \text{Char}^+ \\
\end{align*}
\]

Here, \(\mathcal{T}\) is the set of non-terminal symbols denoting different tags. For instance, this set could be \{N, V, A\} denoting nouns, verbs and adjectives. \(\mathcal{T}\) is the corresponding set of tag terminal symbols. Each tag-specific Morph non-terminal also generates a general back-off Morph non-terminal which is shared between all tags. This is desirable because words with different syntactic categories may share the same set of stems. Also, some suffixes are reused across different syntactic categories, either due to agreement or polysemy.

The \textbf{SubMorph} grammar adds an additional level of latent structure below the morphemes by generating each morpheme as a sequence of sub-morphemes. In (Sirts and Goldwater, 2013), this was shown to improve the segmentation results considerably. We define the morphemes as tag-specific and specify that sub-morphemes are shared across all tags. In preliminary experiments we also tried to make sub-morphemes tag-specific but this grammar did not produce good results.

\[
\begin{align*}
\text{Word} & \rightarrow \text{Tag Morph}_{\text{tag}}^+ \quad \text{for } \forall \text{ tag} \in \mathcal{T} \\
\text{Morph}_{\text{tag}} & \rightarrow \text{Morph} \quad \text{for } \forall \text{ tag} \in \mathcal{T} \\
\text{Tag} & \rightarrow \tau \quad \text{for } \forall \tau \in \mathcal{T} \\
\text{Morph} & \rightarrow \text{Char}^+ \\
\end{align*}
\]

The third grammar, \textbf{CollocMorph}, extends the SubMorph grammar and adds another layer of morpheme collocations on top of Morphs. In this grammar both morpheme collocations and morphemes are tag-specific while sub-morphemes are again general:

\[
\begin{align*}
\text{Word} & \rightarrow \text{Tag Colloc}_{\text{tag}}^+ \quad \text{for } \forall \text{ tag} \in \mathcal{T} \\
\text{Colloc}_{\text{tag}} & \rightarrow \text{Morph}^+ \quad \text{for } \forall \text{ tag} \in \mathcal{T} \\
\text{Morph}_{\text{tag}} & \rightarrow \text{Morph} \quad \text{for } \forall \text{ tag} \in \mathcal{T} \\
\text{Tag} & \rightarrow \tau \quad \text{for } \forall \tau \in \mathcal{T} \\
\text{Morph} & \rightarrow \text{SubMorph}^+ \\
\text{SubMorph} & \rightarrow \text{Char}^+ \\
\end{align*}
\]
4 Experimental Scenarios

In order to assess how much the syntactic tags affect the accuracy of the morphological segmentations, we conducted experiments using four different scenarios:

1. POS-independent morphological segmentation;
2. POS-dependent morphological segmentation using gold-standard tags;
3. POS-dependent segmentation using syntactic clustering learned with an unsupervised model;
4. POS-dependent segmentation using randomly generated tags.

The first scenario does not use any tags at all and is thus the standard setting used in previous work for conducting unsupervised morphological segmentation. This is the baseline we expect the other, tag-dependent scenarios to exceed.

The second scenario, which uses gold-standard POS tags, is an oracle setting that gives an upper bound of how much the tags can help to improve the segmentation accuracy when using a particular segmentation model. Hypothetically, there could exist tagging configurations, which improve the segmentations more than the oracle tags but in our experiments this was not the case.

The third scenario uses the tags learned with an unsupervised POS induction model. Our expectation here is that the segmentations learned with this scenario are better than the baseline without any tags and worse than using gold-standard tags. The experimental results presented later confirm that this is indeed the case.

The final scenario is the second baseline using tags generated uniformly at random. By evaluating this scenario we hope to show that not just any tagging configuration improves the segmentation results but the tags must really correspond at least to some extent to real syntactic tags.

5 Experimental Setup

We conduct experiments in both English and Estonian—a morphologically complex language belonging to Fenno-Ugric language group, using all four scenarios explained above and all three described grammars. AG is a stochastic model and thus it may produce slightly different results on different runs. Therefore, we run the AG in each setting consisting of the language-scenario-grammar triple for 10 times with different random initialisations. We run the sampler for 1000 iterations, after which we collect a single sample and aggregate the samples from all runs by using maximum marginal decoding (Johnson and Goldwater, 2009; Stallard et al., 2012). We use batch initialisation, table label resampling is turned on and all hyperparameters are inferred.

5.1 Data

All experiments were conducted on English and Estonian parts of the Multext-East (MTE) corpus (Erjavec, 2004) that contains G. Orwell’s novel "1984". The MTE corpora are morpho-syntactically annotated and the label of each word also contains the POS tag, which we can use in the oracle experiments that make use of gold-standard tags. However, the annotations do not include morphological segmentations. For Estonian, this text is also part of the morphologically disambiguated corpus, which has been manually annotated and also contains segmentations. We use Celex (Baayen et al., 1995) as the source for English gold-standard segmentations, which have been extracted with the Hutmegs package (Creutz and Lindén, 2004). Although not all the words from the MTE English part are annotated in Celex, most of them do, which provides a reasonable basis for our evaluations.

We conduct experiments only on a subset of word types from the MTE corpora, in particular on nouns, verbs and adjectives only. These POS categories constitute open class words and thus are expected to contain the most morphological richness. The statistics about the number of word types in the training and evaluation sets as well as the number of words belonging to different POS categories for both English and Estonian are given in Table 1. The counts of nouns, verbs and adjectives

|             | English | Estonian |
|-------------|---------|----------|
| MTE types   | 8438    | 15132    |
| Eval types  | 7659    | 15132    |
| Eval nouns  | 3831    | 8162     |
| Eval verbs  | 2691    | 4004     |
| Eval adjectives | 1629 | 3111 |

Table 1: The number of open class words (nouns, verbs and adjectives) used for training and evaluation.

http://www.cl.ut.ee/korpused/morfkorpus/index.php?lang=en
Table 2: F1-scores of all experiments in English and Estonian using different grammars and settings.

|                     | English | Estonian |
|---------------------|---------|---------|
|                     | No POS | Gold    | Learned | Rand | No POS | Gold | Learned | Rand |
| MorphSeq            | 51.4   | 54.3    | 55.7    | 52.5 | 48.1   | 53.2 | 52.5    | 49.1 |
| SubMorph            | 63.3   | 69.6    | 68.1    | 64.3 | 66.5   | 66.5 | 64.3    | 65.5 |
| CollocMorph         | 56.8   | 71.0    | 68.0    | 66.6 | 65.4   | 68.5 | 66.5    | 68.4 |

The number of different tags in automatically learned tagset is larger than three, although the training still contains only nouns, verbs and adjectives. This is because even the best unsupervised POS taggers usually learn quite noisy clusters, where one POS category may be split into several different clusters and each cluster may contain a set of words belonging to a mix of different POS categories.

For the random tag baseline we just generate for each word a tag uniformly at random from the set of three tags: \{0, 1, 2\}, and reformat the input in a similar way as explained above about the automatically induced tags.

5.3 Evaluation

We evaluate the segmentations using the F1-score of the learned boundaries. The evaluation is type-based (as is also our training), meaning that the segmentation of each word type is calculated into the score only once. This is the simplest evaluation method for morphological segmentation and has been widely used in previous work (Virpioja et al., 2011).

6 Results

We present two sets of results. First we give the F-scores of all evaluated words in each language and then we split the evaluation set into three and evaluate the results for all three POS classes separately.

6.1 General results

The segmentation results are given in Table 2. The first thing to notice is that the models trained with gold-standard POS tags always perform the best. Intuitively this was expected, however, the differences between segmentation F1-scores are in most
Table 3: F1-scores of segmentations for different POS classes in English and Estonian using different grammars and settings. MorphSeq generates sequences of morphemes, SubMorph adds the sub-morphemes, and CollocMorph adds the morpheme collocations. N denotes nouns, V stands for verbs and A are adjectives. No POS are the models trained without tags, Gold uses goldstandard POS tags, Learned uses tags learned by an unsupervised POS induction model, and Rand uses randomly generated tags.

|                        | English |          |          |          |          |       |       |          |          |          |          |          |          |
|------------------------|---------|----------|----------|----------|----------|-------|-------|----------|----------|----------|----------|----------|----------|
|                        | No POS  | Gold     | Learned  | Rand     | No POS   | Gold  | Learned | Rand     | No POS   | Gold     | Learned  | Rand     | No POS   | Gold     |
| MorphSeq N             | 49.5    | 50.7     | 52.5     | 50.0     | 51.6     | 56.3  | 55.0   | 52.5     | 56.3     | 55.0     | 52.5     | 56.3     | 55.0     | 52.5     |
| MorphSeq V             | 54.4    | 59.9     | 60.7     | 56.4     | 46.3     | 55.9  | 53.7   | 47.0     | 55.9     | 53.7     | 47.0     | 55.9     | 53.7     | 47.0     |
| MorphSeq A             | 50.2    | 54.6     | 55.1     | 51.7     | 41.1     | 42.5  | 44.6   | 42.7     | 42.5     | 44.6     | 42.7     | 42.5     | 44.6     | 42.7     |
| SubMorph N             | 61.1    | 66.9     | 65.7     | 61.3     | 64.6     | 65.8  | 64.1   | 63.8     | 65.8     | 64.1     | 63.8     | 65.8     | 64.1     | 63.8     |
| SubMorph V             | 67.8    | 75.4     | 73.7     | 70.9     | 78.9     | 80.8  | 75.3   | 77.8     | 80.8     | 75.3     | 77.8     | 80.8     | 75.3     | 77.8     |
| SubMorph A             | 61.2    | 67.0     | 64.7     | 60.8     | 56.6     | 51.3  | 51.6   | 55.5     | 51.3     | 51.6     | 55.5     | 51.3     | 51.6     | 55.5     |
| CollocMorph N          | 55.0    | 68.5     | 65.9     | 64.3     | 66.2     | 67.9  | 66.8   | 67.4     | 66.8     | 67.4     | 66.8     | 66.8     | 67.4     | 66.8     |
| CollocMorph V          | 60.5    | 75.9     | 73.4     | 72.1     | 68.7     | 76.0  | 75.2   | 79.6     | 75.2     | 79.6     | 75.2     | 79.6     | 75.2     | 79.6     |
| CollocMorph A          | 54.4    | 69.1     | 64.6     | 62.8     | 60.0     | 61.7  | 55.7   | 57.6     | 55.7     | 57.6     | 55.7     | 55.7     | 57.6     | 55.7     |

In order to gain more insight into the presented results we also computed F1-scores separately for different POS classes.
each of the three POS classes. Those results are given in Table 3. From this table we can see that the segmentation scores are quite different for words with different POS tags. For English, the scores for nouns and adjectives are similar, while the verbs are segmented much more accurately. This is reasonable because usually verbs are much simpler in structure, consisting usually of a stem and a single inflectional suffix, while nouns and adjectives can contain several stems and both derivational and inflectional suffixes. In all cases, segmentations with either gold or induced tags are better than segmentations learned with random or no tags at all. CollocMorph is the only grammar where the segmentations learned with random tags improve significantly over the tag-independent baseline. The gap is so large because, as explained above, the precision and recall of the CollocMorph grammar without tags evaluated on the middle grammar level are heavily biased towards recall and the results are oversegmented, while the grammar using randomly generated tags manages to learn segmentations with more balanced precision and recall.

In Estonian, the results are more mixed. For nouns, the only grammar where the POS tags seems to help is the simplest MorphSeq, while with other grammars even specifying gold standard POS tags only leads to minor improvements. Verbs, on the other hand gain quite heavily from tags when using MorphSeq or CollocMorph grammar, while with SubMorph grammar the tag-independent baseline is already very high. Closer inspection revealed that evaluating the CollocMorph grammar on the morpheme collocation level would have given more balanced precision and recall and a tag-independent F-score of 83.2%, which is even higher than the SubMorph 78.9%. Also, evaluating segmentations learned with gold standard tags on that level would have improved the F-score even more up to 89.4%. At the same time, the scores of segmentations learned with both random and induced tags would have dropped. Finally, the scores of the Estonian adjectives are in general the lowest and with both SubMorph and CollocMorph grammar adding the tags in most cases does not give any improvements.

7 Discussion

The main goal of this study was to assess, whether and how much do POS tags help to learn better morphological segmentations. The basis for this question was the intuition that because POS tags and morphological segmentations are linguistically related they should be able to exploit synergies during joint learning. However, the previous work in joint POS induction and morphological segmentation has failed to show the clear gains. Therefore we designed an oracle experiment that uses gold-standard POS tags to measure the upper bound of the gains the POS tags can provide in learning morphological segmentations.

On English, using gold-standard POS tags helps to gain 3-14% of F1-score depending on the grammar, while in Estonian the gains remain between 0-5%. The accuracy gained from tags varies for different POS classes. Both in Estonian and English verbs seem to benefit the most, which can be explained by the fact that in both languages verbs have the simple structure consisting mostly of a stem and an optional inflectional suffix which informs the POS class. At the same time, nouns and adjectives can also contain different derivational morphemes which can be shared by both POS classes. Also, in Estonian the adjectives must agree with nouns in case and number but the sets of suffixes both word classes use are not completely overlapping, which makes the relations between POS tags and segmentations more complex. Another reason for the difference between gains in English and Estonian can be that Estonian as morphologically more complex language may be able to exploit the capacity of the generative AG model more effectively even without tags. At the same time the morphologically simpler English gains more from adding additional information in the form of POS tags.

In general, the effect of POS tags on the segmentation accuracy is not huge, even when the linguistically correct gold-standard tags are used. One reason here can be that we provided the system with very coarse-grained syntactic tags while morphological suffixes are more closely related to the more fine-grained morpho-syntactic functions. This is especially true in English where for instance different verbal suffixes are almost in one-to-one relation with different morpho-syntactic functions. The situation is probably more complex with morphologically rich languages such as Estonian where there are different inflectional classes, which all express the same morpho-syntactic function with different allomorphic suffixes.
Table 4: Examples of both English and Estonian mostly incorrectly segmented words learned with CollocMorph grammar.

Although using automatically induced tags almost always improves the segmentation results, the gains are in most cases quite small. We assume that the induced tags cannot improve the segmentations more than the gold-standard tags. However, it is not clear whether the accuracy of the induced POS tags themselves affects the segmentations accuracy much. The experiments with the random baseline showed that the POS tags should not be completely random but how large differences in tagging accuracies start affecting the segmentations’ quality remains to be studied in future works.

Some examples of segmented words for both English and Estonian are given in Table 4. For those examples, the POS-independent grammar has learned incorrect segmentations. The various POS-dependent grammars are in some cases able to learn correct segmentations, in some cases learn more correct segmentations, but in some cases also learn equally false segmentations. For instance for English, all POS-dependent grammars are able to improve the segmentation of the word condemned, but only the grammar informed by gold POS tags gets it exactly right. The word matches is segmented correctly by grammars using both gold and induced tags, while the grammar with random tags undersegments. In Estonian for instance, only the grammar using random tags gets the word kūkitasid right, while all the other grammars oversegment it. On the other hand, the adjective pikkused is correctly segmented only by the grammar using automatically learned tags and all the other grammars either oversegment or place the segment boundary in an incorrect location.

8 Conclusion

Morphology is a complex language phenomenon which is related to many different phonological, orthographic, morpho-syntactic and morphotactic aspects. This complexity has the potential to create synergies in a generative model where several aspects of the morphology are learned jointly. However, setting up a joint model that correctly captures the desired regularities is difficult and thus it may be useful to study the synergistic potentials of different components in a more isolated setting.

The experiments in this paper focused on the relations between syntactic tags and concatenative morphological segmentations. We showed that both gold-standard POS tags as well as automatically induced tags can help to improve the morphological segmentations. However, the gains are on average not large—5.3% with gold-standard tags and 3.9% with induced tags. Moreover, deeper analysis by evaluating the segmentations of words from different POS classes separately reveals that in Estonian even the goldstandard POS tags do not affect the segmentations much.

These results suggest that perhaps other relations should be studied of how to use various aspects of morphology to create synergies. For instance, POS tags are clearly related to paradigmatic relations. Also, clustering words according to morpho-syntactic function could benefit from using methods developed for learning distributional representations. Finally, it could be helpful to learn morphological structures jointly on both orthographic and phonological level.
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