Towards Unsupervised Morphological Analysis of Polysynthetic Languages

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Abstract

Polysynthetic languages present a challenge for morphological analysis due to the complexity of their words and the lack of high-quality annotated datasets needed to build and/or evaluate computational models. The contribution of this work is twofold. First, using linguists’ help, we generate and contribute high-quality annotated data for two low-resource polysynthetic languages for two tasks: morphological segmentation and part-of-speech (POS) tagging. Second, we present the results of state-of-the-art unsupervised approaches for these two tasks on Adyghe and Inuktitut. Our findings show that for these polysynthetic languages, using linguistic priors helps the task of morphological segmentation and that using stems rather than words as the core unit of abstraction leads to superior performance on POS tagging.

1 Introduction

Polysynthetic languages are highly synthetic languages, where a single multi-morpheme verbal complex can express what would be a whole sentence in English. For example, in Inuktitut, "tusaat-siarrunangittualuujunga" corresponds to the English sentence "I cannot hear very well" (Klavans, 2018). These languages pose two main challenges for computational models. First, they are often characterized by a significant number of morphemes per word and a high degree of ambiguity of their roots with respect to the part-of-speech specification (Baker, 1996). Second, these languages are low-resource, lacking large scale annotated datasets needed to build computational models.

We focus on surface-level morphological segmentation and part-of-speech tagging for two polysynthetic languages: Adyghe and Inuktitut. Progress in morphological analysis of polysynthetic languages has been made possible by two efforts: morphological segmentation frameworks that move away from rule-based methods to unsupervised machine learning models, which crucially are able to include linguistic priors to guide the learning process (Sirts and Goldwater, 2013; Mager et al., 2018; Eskander et al., 2021; Le and Sadat, 2021), and the growth in corpora for some of these languages (Farley, 2009; Sorokin, 2020; Micher, 2019; Arkhangel’skii and Medvedeva, 2016; Arkhangel’skii and Lander, 2015). A particularly fruitful line of work has been the use of unsupervised models based on Adaptor Grammars (Johnson et al., 2007), such as MorphAGram (Eskander et al., 2020a) that enables the use of linguistic priors, either through grammar definition or linguist-provided affixes (Eskander et al., 2021; Le and Sadat, 2021). We investigate whether linguistic priors in MorphAGram help the task of morphological segmentation for Adyghe and Inuktitut. POS tagging for polysynthetic languages, on the other hand, is in its infancy. We investigate whether unsupervised approaches based on cross-lingual projection developed for low-data scenarios (Yarowsky et al., 2001; Agić et al., 2015; Das and Petrov, 2011; Buys and Botha, 2016; Täckström et al., 2013; Eskander et al., 2020b) could be useful for POS tagging of polysynthetic languages. These methods rely on the use of parallel data (e.g., the Bible) to project POS tags from a source language for which a POS tagger is accessible onto a target language across word-level alignments. The projected tags then become the basis to train a POS model for the target language. Eskander et al. (2022) have recently proposed an approach for cross-lingual projection in low-data scenarios, where the unit of abstraction could be either the word or the stem, thus exploring either word-level or stem-level alignments for projection\textsuperscript{1}. We show that for Adyghe and Inuktitut, using stems as the unit of abstraction improves the results for POS tagging. We contribute Adyghe and Inuktitut evalu-

\textsuperscript{1}See Eskander (2021) for broad experimentation in several monolingual and multilingual settings.
ation datasets both for morphological segmentation and POS tagging.

2 Languages and Data Annotation

Adyghe, also known as West Circassian, is a member of the Northwest Caucasian language family with about 118K speakers. Adyghe is characterized by a complex encoding of clausal arguments in the verb form: person markers appear in the preverbal position, and in addition to subject and object markers include markers of additional arguments introduced by applicative morphemes in the verbal paradigm. Many researchers have noted the difficulty of distinguishing between inflection and derivation in the verbal morphology (Kimmelman, 2010; Arkadiev and Maisak, 2018).

Eastern Canadian Inuktitut (Inuit-Yupik-Unangan) is spoken in the Canadian Arctic by about 40K speakers. The degree of polysynthesis in terms of the number of morphemes per word is high. The language possesses closed classes of verbs that obligatorily trigger either noun incorporation or verb incorporation. The language makes extensive use of category-changing morphology (Johns, 2014), including what Mattissen (2017) calls “ping-pong recategorization”, whereby the category of a word switches back and forth due to the presence of multiple verbalizers and nominalizers. Another challenge for morphological segmentation is that the morphemes are relatively short and the phoneme inventory is small, leading to a fair amount of homophony and a high number of potential parses.

2.1 Morphological Segmentation

To create the evaluation datasets we had to decide the relevant level of granularity for morphological analysis and to include all plausible segmentations.

Adyghe. To build our training and evaluation datasets, we rely on an electronically annotated corpus, which allows searching based on specific morphological information (Arkhangelskiy and Medvedeva, 2016; Arkhangelskiy and Lander, 2015). To build the training dataset for MorphAGram, we select 50K unsegmented words by randomly sampling according to the logarithmic distribution of words’ POS tags, with weighting for word frequency in the corpus. The gold-standard dataset contains 1000 words together with their morphological segmentation from the original corpus, which was automatically obtained. The segmentations are manually verified and corrected by a trained linguist with knowledge of Adyghe to ensure accuracy. Among the 1000 words, there are 208 verbs, 177 nouns, 167 adjectives, and 146 adverbs.

Inuktitut. For training the segmentation models, we collect the 50K most frequent words (unsegmented) from the Inuktitut Wikipedia, the Nunavut Hansard (NH) corpus, and the Bible. The primary data for the gold standard is collected from the UQAILAUT Project (Farley, 2009) and consists of 1094 words and their associated segmentations. Most words contain only one possible segmentation in this original dataset. Two trained linguists working on Inuktitut reviewed and corrected the dataset, including: regularizing inconsistencies in how inflectional morphology is segmented, regularizing lexicalized stem inconsistencies and segmenting spurious dual and plural morphemes, excluding sequences of words that were accidentally fused due to a missing space in the source data, and providing alternative segmentations, when appropriate. This corpus contains mostly nouns (85.4%). As verbs generally exhibit a higher degree of polysynthesis in Inuktitut, we collect an additional set of 100 words from the Nunavut Hansard corpus that consists of nouns (22), verbs (66), and participles (12), and that is manually segmented by two trained linguists. Our gold Inuktitut dataset contains words that have alternative segmentations (Table 1).

2.2 POS tagging

Adyghe. For training the POS tagger, we extract the available parallel Bible data (Russian-Adyghe) from the corpus introduced by Arkhangelskiy and Medvedeva (2016); Arkhangelskiy and Lander (2015). For the gold-standard dataset, a simple random sample of 200 sentences with well-formed data is extracted from the entire corpus and verified by a linguist, all after mapping the POS tags to the UD POS schema. The final distribution of POS is: VERB (31.9%), NOUN (27.8%), PUNCT (23.8%), ADJ (6.4%), PRON (5.1%), ADV (3.6%), NUM (0.7%), CCONJ (0.5%) and ADP (0.1%).

Inuktitut. For training the POS tagger, we collect the English-Inuktitut Bible data. For evaluation, we annotate a small dataset containing 124 sentences: 50 are extracted from the Nunavut Hansard and 74 are taken from three articles in Inuktitut Magazine. Word forms are manually tagged by a master student specializing in Inuktitut morphosyntax following the UD POS tagging conventions. The distribution of the tags in the
gold dataset is: NOUN (46.0%), VERB (27.3%), PUNCT (18.6%), CCONJ (4.6%), PROPN (3.1%), PRON (0.4%) and ADV (0.1%).

3 Approach

3.1 Morphological Segmentation

To conduct the experiments for morphological segmentation, we use MorphAGram \(^2\) (Eskander et al., 2020a), a state-of-the-art, publicly available framework for unsupervised morphological segmentation that is based on Adaptor Grammars (AGs) (Johnson et al., 2007). AGs are nonparametric Bayesian models that utilize probabilistic context-free grammars (PCFGs). An AG is composed of two main components: a PCFG and an adaptor that adapts the probabilities of individual subtrees and acts as a caching mechanism. In the case of morphological segmentation, a PCFG represents a morphological grammar that specifies word formation, where the purpose is to learn latent tree structures of morphological segments given a list of unsegmented words.

While MorphAGram was originally developed for learning in a fully unsupervised manner, it also allows the use of linguistic priors to enhance morphological segmentation in a minimally supervised fashion. Eskander et al. (2021) introduce two methods for including linguistic priors: grammar definition and linguist-provided affixes. In the former, a linguist tailors the language independent grammars used by MorphAGram to more accurately model the word structure of the target language. In the latter, an expert in the target language compiles a list of affixes and seeds it into the grammars using the Scholar-Seeded learning setting (Eskander et al., 2016). For all of our experiments and languages in this paper, we apply the second approach where linguist-provided affixes are used.

We follow Eskander et al. (2021) by applying their on-average best performing grammar, namely PrStSu+SM \(^3\), in which a word is modelled as a sequence of prefixes, a stem and a sequence of suffixes. Additionally, both prefixes and suffixes are recursively defined to allow for affix compounding, and the morphemes are further split into non-linguistically driven sub-morphemes that allow for better utilization of the generated latent subtrees (See Eskander et al. (2021) for more details). For Inuktitut, we use the affixes from Inuktitut Tusaalanga Grammar\(^4\).

3.2 Part-of-Speech Tagging

To conduct the experiments for POS tagging, we use a publicly available fully unsupervised cross-lingual POS tagger that projects the annotations across some parallel text between a source language and the target one \(^5\) (Eskander et al., 2020b, 2022). First, we utilize the Bible as the source of parallel data to train bidirectional alignment models between the source and target languages using GIZA++ (Och and Ney, 2003). We then tag the source side for POS using an off-the-shelf tagger. In our study, we use English as the source language and utilize Stanza (Qi et al., 2020) to tag the English text for the Universal-Dependencies

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\(^2\) [https://github.com/rnd2110/MorphAGram](https://github.com/rnd2110/MorphAGram)

\(^3\) [https://github.com/rnd2110/MorphAGram/blob/master/data/georgian/grammar/standard/grammar1.txt](https://github.com/rnd2110/MorphAGram/blob/master/data/georgian/grammar/standard/grammar1.txt)

\(^4\) [https://tusaalanga.ca/grammar](https://tusaalanga.ca/grammar)

\(^5\) [https://github.com/rnd2110/unsupervised-cross-lingual-POS-tagging](https://github.com/rnd2110/unsupervised-cross-lingual-POS-tagging)
Table 2: Morphological segmentation results (BPR F1) on the entire test sets (All), Nouns and Verbs. AG-LI is the MorphAGram Standard language-independent model, while AG-SS is the model using linguistic priors.

| Language   | AG-LI | AG-SS |
|------------|-------|-------|
|            | All   | Noun  | Verb | All   | Noun  | Verb |
| Adyghe     | 66.1  | 69.3  | 56.5 | 78.9  | 70.8  | 69.4 |
| Inuktitut  | 58.1  | 64.4  | 50.3 | 60.4  | 67.6  | 49.2 |

Table 3: POS tagging results for word-based and stem-based alignment and projection.

| Alignment Type | Adyghe | Inuktitut |
|----------------|--------|-----------|
|                | All    | Noun     | Verb | All   | Noun  | Verb |
|                 | 62.4   | 49.2     | 67.1 | 57.3  | 62.3  | 39.6 |
| Word-Based      | 70.4   | 66.4     | 73.2 | 64.6  | 68.8  | 44.5 |
| Stem-Based      |        |          |      |       |       |      |

(UD) POS tagset\(^6\). The English tags are then projected onto the target side across the intersecting bidirectional alignments, while a target word that is not part of an alignment or part of an alignment in one direction but not the other receives a NULL POS assignment. This is followed by a refinement phase in which we couple both token and type constraints and only consider highly scoring sentences, where sentence score is defined as the harmonic mean of its projection density and alignment confidence. Finally, we learn a neural Bi-LSTM model (Hochreiter and Schmidhuber, 1997) given the induced annotations. We conduct the experiments using two different approaches for alignment and projection as introduced recently by Eskander et al. (2022): (1) word-based; and (2) stem-based. In the word-based approach, we utilize the parallel text to train models that align the source and target sides at the word level. After generating the POS annotations for the source language, these annotations are then projected onto the target across the word-level alignments. In the stem-based approach, we perform both alignment and projection in the stem space. In this setup, we first conduct stemming for the source and target texts using MorphAGram and learn stem-based alignment models between the two sides. We then apply the source annotations to the underlying stems and project them onto the stemmed target across the stem-level alignments. Finally, we replace each tagged target stem by its corresponding word so that we can train the neural POS tagger at the word level. We experiment with both approaches for Adyghe and Inuktitut.

It is worth noting that MorphAGram performs surface-level morphological segmentation in which the stem is automatically specified without supervision, where starting and ending frequent morphemes are highly likely to receive an affix assignment.

4 Results and Error Analysis

4.1 Morphological Segmentation.

The performance of MorphAGram segmentation models is shown in Table 2. Adding scholarly seeded affixes improves the BPR F1-score (Virpioja et al., 2011) by 19.4% for Adyghe and 4.0% for Inuktitut. Table 2 also shows the segmentation performance for noun and verbs. While for Adyghe the linguistic priors help substantially for verbs, for Inuktitut we do not see this effect, indicating that more care needs to be given to the linguist-provided affixes related to verbal constructions and/or exploring linguistic priors as grammar definition (Le and Sadat, 2021).
| Language | Model       | Example Sentence                                      |
|----------|-------------|-------------------------------------------------------|
| Adyghe   | Gold        | Ау_CCONJ джырэ_ADV нэс_ADP къулыкъум_NOUN йоф_NOUN эмчтп-|
|          | Word-Based  | Ау_CCONJ джырэ_NOUN нэс_PROPN а_VERB къулыкъум_VERB йоф_NOUN эмчтп-|
|          | Stem-Based  | Ау_CCONJ джырэ_ADV нэс_ADP а_СCONJ къулыкъум_NOUN йоф_NOUN эмчтп-|
| Inuktitut| Gold        | тайма_NOUN _-PUNCT qaujigumavunga_VERB qanuq_NOUN pilirivingit_NOUN piliriaqattarmangaata_VERB taimait-tunik_NOUN qimaavit_NOUN matutuinnariaqaliraimmata_VERB nunalinni_NOUN кинайнуяутутайту-aramik_VERB _-PUNCT |
|          | Word-Based  | тайма_ADV _-PUNCT qaujigumavunga_NOUN itsivautaaq_VERB _-PUNCT minista_NOUN uqarunnarmangaqaq_VERB qanuq_NOUN pilirivingit_NOUN piliriaqattarmangaata_NOUN taimaittunik_NOUN qimaavit_NOUN matutuinnariaqaliraimmata_NOUN nunalinni_NOUN кинайнуяутутайтуруарарик_NOUN _-PUNCT |
|          | Stem-Based  | тайма_ADV _-PUNCT qaujigumavunga_VERB qanuq_PRON pilirivingit_NOUN piliriaqattarmangaata_NOUN taimait-tunik_NOUN qimaavit_NOUN matutuinnariaqaliraimmata_NOUN nunalinni_NOUN кинайнуяутутайтуруарарик_NOUN _-PUNCT |

Table 4: POS tagging comparison between ground truth, word-based, and stem-based models for Adyghe and Inuktitut. Green indicate correctly identified POS tags, while red indicates incorrect POS tags.

4.2 Part-of-Speech Tagging.

Table 3 shows our results for POS tagging using the word-level and stem-level alignment and projection for Adyghe and Inuktitut on all POS tags (All) as well as the performance on Nouns and Verbs. The stem-based approach outperforms the word-based one, which lends support that using the stem as the unit of abstraction for the POS tagging of polysynthetic languages is a fruitful avenue of research. In terms of accuracy, stem-based POS tagging outperforms word-based POS tagging by 8.0% for Adyghe, and 7.3% for Inuktitut across all POS tags. Moreover, we see substantial improvements on both nouns and verbs when using stem-based over word-based POS tagging (F1 metric). As an example for Adyghe, the stem-based model correctly tags the word къулыкъум as a noun, while the word-based model misclassifies it as a verb (Table 4). This shows that even though in Adyghe both verbs and nouns can end in –ъум, the stem-based model is able to determine that the word is a noun. For Inuktitut, the stem-based model correctly classifies the word qaujigumavunga as a verb, while the word-based model incorrectly labels it as a noun.

5 Conclusion

We contribute high-quality datasets for Inuktitut and Adyghe, both for morphological segmentation and POS tagging. We show that unsupervised approaches that consider linguistic priors are a promising avenue for tackling morphological segmenters for polysynthetic languages. We also show that unsupervised cross-lingual projection approaches for POS tagging that use the stem as a unit of abstraction are a fruitful avenue of research on POS tagging for polysynthetic languages.

Acknowledgements

This research is based upon work supported by the National Science Foundation (awards #1941742 and #1941733). The views and conclusions herein are those of the authors and should not be interpreted as necessarily representing official policies, expressed or implied, of NSF or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for governmental purposes notwithstanding any copyright annotation therein.

Ethical Considerations

The annotations were done by linguists with appropriate compensation after educating them about the research purpose and the annotation process. The quality of the annotations was examined manually and empirically. The source code and the data will be released open-source. Finally, the limitations of the work lay within the reported performance. There should be no potential risks given these stated limitations.
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