Bootstrapping Language Description: The case of Mpiemo (Bantu A, Central African Republic)

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Abstract

Linguists have long been producing grammatical descriptions of yet undescribed languages. This is a time-consuming process, which has already adapted to improved technology for recording and storage. We present here a novel application of NLP techniques to bootstrap analysis of collected data and speed-up manual selection work. To be more precise, we argue that unsupervised induction of morphology and part-of-speech analysis from raw text data is mature enough to produce useful results. Experiments with Latent Semantic Analysis were less fruitful. We exemplify this on Mpiemo, a so-far essentially undescribed Bantu language of the Central African Republic, for which raw text data was available.

1. Introduction

Descriptive linguistics, i.e., producing a grammatical description of a language (often previously unstudied or little-studied), is essential for the understanding of the language diversity in the world, for linguistic theory, for the historical study of populations and, last but not least, for the speakers themselves (van der Vooort, 2007). It is even more a priority given the current state of language endangerment (Brenzinger, 2007).

Describing a language typically consists of producing a grammar, a dictionary and a collection of texts. In this paper, we suggest that this process can benefit from technology in the sense that it can speed up the human tasks of analysis and organisation. In particular, we show that techniques from computational linguistics are now mature enough that morphological analysis, part-of-speech analysis and potentially lexical semantic analysis can be bootstrapped from raw text. As an example language, we use Mpiemo (Bantu A, Central African Republic), for which some raw text data was available.

We focus here on motivation and proof-of-concept, leaving the linguistic details to a specialist northwest Bantu audience, and the technical details to a computational linguistics audience.

2. Motivation and Related Work

In language documentation and language description, one is bang-up-to-date with technology for recording, storage, annotation, modularization and presentation (Gippert et al., 2006). But technology can be further used to bootstrap analysis and speed-up manual work. In particular, we suggest that some analysis and organizing can be automatically extracted from raw text data. Typically, a researcher works on grammar, texts and dictionary incrementally. A text is gathered first, which is then analysed and vacuumed for dictionary entries. Usually, texts can be gathered by a wider range of people, including people not schooled in linguistic theory, and there are many cases, old and new, where large text collections exist but there is no written down grammar/dictionary for the same language. In other words, large text collections already exist for various undescribed languages, and for many others, text collections can be gathered relatively cheaply. This motivates our approach of bootstrapping from text.

There are also other, perfectly legitimate, ways to adapt grammar writing to enable technological exploitation. Nordhoff (2007a), Nordhoff (2007b) describes the grammar authoring system GALOES where the researcher writes the data in a format which allows harvesting, i.e., a computational tool can automatically select and collect data from grammars written in this way. Considerable flexibility in presentation, i.e., away from the strictly linear format of book grammars, also come with this grammar authoring system. Similarly, Beermann Hellan (2007) describes TypeCraft which is a support tool for glossing and annotation which helps researchers with consistency and sharing.

1Cf. the issues of Language Archives News http://www.mpi.nl/LAN/

2Three examples from three continents are Alsea (isolate; North America) has a text collection from 1920 (Frachtenberg, 1920), Uduk (Koman; Africa) has a New Testament translation from 1963 (Sudan Interior Mission, 1963) and Tabo (isolate; Oceania) has a New Testament translation from 2006 (Schlatter and Schlatter, 2006).
This enables more systematic searching and harvesting as well. These approaches are complimentary to the one suggested in this paper because the analysis itself is still fully the researchers burden, and use of the tools require linguistic training as well as computer familiarity.

Similar, unsupervised, techniques as we describe in this paper exist for further applications such as Information Retrieval, Spell-Checking etc. which are on the want list for low-density languages (Saxena and Borin, 2006), but this is not the focus of the present paper. Unfortunately, we are not aware of any Speech Technology tools equally suitable for facilitating work on language description.

3. Mpiemo Profile and Data

Mpiemo is spoken predominantly in the southwest of the Central African Republic (CAR) and in neighbouring Cameroon and Congo (= République du Congo, or Congo-Brazzaville). There are approximately 24,000 speakers in the Central African Republic, about 5,000 in Cameroon and an unknown, but presumably small, number of people in Congo (Gordon, 2005).

In the Central African Republic, almost all speakers are bilingual in Sango (the lingua franca of CAR), and knowledge of (varieties of) Gbaya, French, Lingala is also common. Mpiemo is losing ground but is still being transmitted to children. At present it is not an endangered language. Traditionally Mpiemo is not written but an orthography has been developed recently by missionaries (Thornell, 2004a). Mpiemo is placed in the Bantu A.80 (or ‘Maka-Njem’) group, but there is no detailed understanding of its proper classification (Maho, 2003).

There is actually at least one known suffix in Mpiemo, a plural imperative plural imperative suffix, but it does not occur consistently with human analysis. (There is no point in a formal evaluation since the human analysis is not definitive, rather, the idea is to suggest segmentations that the researcher checks.)

| Segmentation | Comment               |
|--------------|-----------------------|
| a-           | class prefix for 5    |
| b-           | class prefix for 8    |
| bo-          | class prefix for 2    |
| bi-          | class prefix for 2    |
| b`ı-         | tonal allomorph for bı-? |
| b`e-         | allomorph for b’e-    |
| m-           | concord for 6         |
| m’e-         | class prefix for 6    |
| m`ı-         | tonal allomorph for m`ı- |
| y-           | concord for 9 and others |
| yi-          | concord for 9         |

Table 2: Outcome of affix extraction for Mpiemo.

Hammarström (2006b) is an unsupervised method to find stems which tend to appear with the same set of affixes, or, as one might call it, paradigm induction. Together with prefix extraction, we get a ranked list of <stem, prefix-set> pairs. The top pairs are shown in Table 3. The precision is excellent – fully conformant to human analysis – but recall is low. The paradigm of most stems cannot be inferred since they occur too sparsely, or, in other words, the corpus size is too small.

The value of these lists is that it speeds up the human analysis. Looking at the ranked lists, it is easy for a researcher to compare with other Bantu languages of the same region. The best described closely related language is Kol in

\[ \text{Segmentation} | \text{Comment}  \\
\hline
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\text{b`ı-} | \text{tonal allomorph for bı-?}  \\
\text{b`e-} | \text{allomorph for b’e-}  \\
\text{m-} | \text{concord for 6}  \\
\text{m’e-} | \text{class prefix for 6}  \\
\text{m`ı-} | \text{tonal allomorph for m`ı-}  \\
\text{y-} | \text{concord for 9 and others}  \\
\text{yi-} | \text{concord for 9} \\
\]
Bi- e.g., for prefixes, it is straightforward to compare and to see that, Cameroon (Henson, 2007). With stems neatly categorized.

pany. This is important, because most words of a running

and more than one verbal class. Impressionistically, also

classes emerge, but there is more than one nominal class

ing for a reasonable number of iterations, was of any help

imperfect knowledge of Mpiemo. The exact settings and

ations which are set ad hoc according to our existent but

The results are complicated by a number of parameter vari-

ables that need to be tweaked.

of-speech tags automatically, but there are a number of pa-

rameters that need to be tweaked.

The results are that nominal and verbal classes are infrequent, and a good first guess at their part-of-

speech can save a lot of time in dictionary making. ’go’ which may be a focal particle, is given a class of its own.

Pronouns and what appears to be a pre-verbal particle for

future marking always end up in the same class.

The results are good enough for some provisional assign-

ments, but the distributional nature of particles need further

study.

4.3. Semantic Grouping

Latent Semantic Indexing (Sahlgren, 2006) is a popular

technique that can be used to infer semantic distances be-

tween words from raw text data. The intuition is that words

that appear in the same “context” tend to be similar in

meaning, once frequency discrepancies are discounted for.

(Frequent words appear in all contexts, but they are not se-

mantically similar to “everything”). Sometimes a one-word

windows is used as the context, sometimes the sentence,

but most commonly the document is used as a context (the

raw text data used comes already divided into documents in

these cases). When latent semantic analysis is successfully

applied to major European languages, the raw data sources

are typically huge, with at least millions of word tokens.

The goal of experimenting with latent semantic analysis on

Mpiemo was to find semantically related words, such as

animates, and because many of the texts were about plants,

perhaps a category of plant names. In order for LSA tech-

niques to operate on the minuscule size of the corpus, we

had little choice but to use the sentence as context (any-

thing bigger would have made the data set tiny, and any-

thing smaller would reduce the semantic analysis towards

part-of-speech analysis, i.e., syntactically legal contexts).

We then tried simply to cluster on the LSA similarity mea-

sure. The result was that ‘question words’ was the clus-

ter deemed most semantically related, presumably because

of the question marks in sentences containing them. Little

more of value came out of the attempt, presumably because

the text corpus was simply too small.

4.4. Discussion

Bootstrapping from text data for grammar/dictionary writ-

ing is parallel to Machine Translation in that it will not re-

place humans in the foreseeable future. Its purpose is in-

stead to save time for the same humans. Even small time

saves are valuable. We have indicated that bootstrapping is

worthwhile if the text collection is of moderate size. There

are also some positive side-effects of the attempts that were

unforeseen:
• Transcription consistency checking (almost like spell-checking) came out naturally from the morphological listings.

• The automatically annotated texts, which would otherwise just have gathered dust after analysis, could easily be ported to other formats, for example TEI/XML to be used in a pedagogical tool which teaches grammar to linguistics students (Borin and Saxena, 2004).

NLP bootstrapping techniques can be seen as a generalization of a corpus concordancer. A concordancer highlights and selects raw data and presents it in a manner suitable for a human analysis. As we argue, the same can be done at least for morphological analysis and part-of-speech analysis.

The usefulness hinges on the existence of a large body of raw text data. For some languages, division of labour allows such data to be gathered relatively cheaply. For many other languages, text collections already exist and can be made use of.

5. Conclusion

We have shown that language technology can be used to save time in language description. For the particular language Mpiemo, the morphology is quite simple, and morphology induction works very well for it. The usefulness of part-of-speech induction is harder to assess, and we were not successful in exploiting techniques for latent semantic analysis. Some positive side effects that may arise from the applying NLP technology to languages which traditionally were not treated computationally, are consistency checking and usage of tagged corpora for teaching purposes.

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