Abstract

We present a method for learning bilingual translation dictionaries between English and Bantu languages. We show that exploiting the grammatical structure common to Bantu languages enables bilingual dictionary induction for languages where training data is unavailable.

1 Introduction

Bilingual dictionaries mostly exist for resource-rich language pairs, for example, English-German and English-Chinese (Koehn and Knight, 2002; Haghighi et al., 2008; Ammar et al., 2016; Faruqui and Dyer, 2014). Such dictionaries are useful for many natural language processing (NLP) tasks including statistical machine translation, cross-lingual information retrieval, and cross-lingual transfer of NLP models such as those for part-of-speech tagging and dependency parsing (Täckström et al., 2012; Guo et al., 2015; Gouws and Søgaard, 2015). In this paper, we consider the task of bilingual dictionary induction for English and Bantu languages. Bantu languages are a family of over 300[1] mutually intelligible languages spoken over much of central and southern Africa, see the map[2] in Figure 1 (Guthrie, 1948; Nurse and Philippson, 2003).

As with other low resource languages, labeled data for Bantu languages is scarce. We seek to exploit the Bantu grammar structure to mitigate lack of labeled data. More specifically, we ask the following question: given a small bilingual dictionary between English and one Bantu language, $L_{bantu1}$, can we 1) infer missing entries in the English $- L_{bantu1}$ dictionary 2) generate a new bilingual dictionary English $- L_{bantu2}$ for another Bantu language for which labeled data is unavailable. To answer this question we propose an approach based on distributed representations of words (Turney and Pantel, 2010; Mikolov et al., 2013a). The first step is to create a vector space for each language, derived from a text corpus for the language. Notice that these text corpora need not be aligned. The second step is to perform dictionary induction by learning a linear projection, in the form of a matrix, between language vector spaces (Mikolov et al., 2013b; Dinu and Baroni, 2014; Lazaridou et al., 2015). Our key insight for Bantu languages is that one can create a single vector space for them, obviating the need for learning a projection matrix for each Bantu language. This means we only need to learn a single projection matrix, for inducing multiple English to Bantu bilingual dictionaries, using the

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[1] Between 300 and 600, depending on where the line is drawn between language and dialect.
[2] Image from http://getyours-it.nl/a-cultura/afrikaanse-stammen/bantu-stammen
[3] https://www.ethnologue.com

Figure 1: Bantu languages are spoken over much of central and southern Africa.
small bilingual dictionary $\textit{English} - L_{\text{bantu1}}$. Additionally, we modify the corpus corresponding to $L_{\text{bantu2}}$ to have a greater vocabulary intersection with $L_{\text{bantu1}}$. This step is inspired by the extensive use of bases and affixes, common to Bantu languages. Words with the same meaning often differ only in the affixes with the base being similar or the same. We therefore use edit distance to replace some fraction of the words of $L_{\text{bantu2}}$ with similar words in $L_{\text{bantu1}}$.

**Contribution.** 1). *Unsupervised Bantu language dictionary induction*: To the best of our knowledge, our work is the first effort to create bilingual dictionaries for Bantu languages using unsupervised machine learning methods. 2) *Data*: We collect corpora for seven Bantu languages. Having had access to a first language speaker of two Bantu languages, we obtained labeled which we make available along with the corpora, for further research into NLP for Bantu languages. 3) *Dictionary induction almost from scratch*: We propose a method for dictionary induction that only requires training data in one of the Bantu languages. Our experiments show the potential of our approach.

2 Approach

2.1 Distributed Representation

Distributed representations of words, in the form of real-valued vectors, encode word semantics based on collocation of words in text (Turney and Pantel, 2010; Mikolov et al., 2013a; Ammar et al., 2016). Such vector representations have been shown to improve performance of various NLP tasks including semantic role labeling, part-of-speech tagging, and named entity recognition (Collobert et al., 2011). In this work we use the skip-gram model with negative sampling to generate word vectors (Mikolov et al., 2013a). It is one of the most competitive methods for generating word vector representations, as demonstrated by results on a various semantic tasks (Baroni et al., 2014; Mikolov et al., 2013b).

2.2 Bilingual Dictionary Induction

To induce a bilingual dictionary for a pair of languages, we use the projection matrix approach (Mikolov et al., 2013b; Dinu and Baroni, 2014; Lazaridou et al., 2015). It takes as input a small bilingual dictionary containing pairs of transla-

tions from the source language to the target language. Training data is comprised of vector representations of word pairs $D^{tr} = \{x_i, y_i\}_{i=1}^m$, where $x_i \in \mathbb{R}^s$ is the vector for word $i$ in the source language, and $y_i \in \mathbb{R}^t$ is the vector for its translation in the target language. At test time, we predict the target word translations for new source language words, $D^{te} = \{x_j\}_{j=1}^n$, where $x_j \in \mathbb{R}^s$. In our case, the source language is a Bantu language and the target language is English.

This approach assumes that there is linear relationship between the two vector spaces. Thus, the learning problem is to find a matrix $W$ that maps a source language word vector $x_j$ to the vector of its translation $y_i$ in the target language. As in (Dinu and Baroni, 2014), we use an l2-regularized least squares error to learn the projection matrix $W$.

$$W = \arg \min_{W \in \mathbb{R}^{s \times t}} ||XW - Y||_F + \lambda ||W||_1$$

where $X$ and $Y$ are matrices representing the source and target vectors in the training data, respectively. For a new Bantu word whose vector representation is $x_j \in \mathbb{R}^s$, we map it to English by computing $\hat{y}_j = WX_j$, where $\hat{y}_j \in \mathbb{R}^t$, and then finding the English word whose vector representation is closest to $\hat{y}_j$, as measured by the cosine similarity distance metric.

2.3 Bantu Language Structure

The word “Bantu” is derived from the word for “people”, which has striking similarities in many Bantu languages (Guthrie, 1948; Nurse and Philippson, 2003). In Zulu (South Africa) “abantu” means *people*; in Swahili (Kenya, Uganda) “watu”; in Ndonga (Namibia) “aantu”; in Sesotho (Lesotho) “batho”; in Herero (Namibia) “ovandu”; and in Kwanyama (Namibia, Angola) “ovanhu”. It is often used in the philosophical sense “”. While Bantu languages may differ in vocabulary, in some cases quite substantially, they share the same

*Ubuntu is Zulu for humanity or the essence of being human.

*South African Nobel Laureate Archbishop Desmond Tutu describes Ubuntu as: “It is the essence of being human. It speaks of the fact that my humanity is caught up and is inextricably bound up in yours. “A person with Ubuntu is open and available to others, affirming of others, does not feel threatened that others are able and good, based from a proper self-assurance that comes from knowing that he or she belongs in a greater whole and is diminished when others are humiliated or diminished, when others are tortured or oppressed.”
grammatical structure. A prominent aspect of the grammar of Bantu languages is the extensive use of bases and affixes. For example, in the country of Botswana, from the base Tswana, the people of Botswana are the Batswana, one person is a Motswana, and the language is Setswana. We seek to exploit this property by performing edit distance corpus modifications before learning the projection matrix.

### 2.4 Single Projection Matrix

We hypothesize that we only need to learn one projection matrix, $W$ in Equation 1. Our labeled data is a small bilingual dictionary $\text{English} - L_{\text{bantu}}$, between English and a Bantu language $L_{\text{bantu}}$. We would like to be able to infer missing entries in the $\text{English} - L_{\text{bantu}}$ dictionary, and to generate a new dictionary, $\text{English} - L_{\text{bantu}2}$, a language pair for which labeled data is unavailable. The core idea is to create only one vector space for the two Bantu languages. First we generate a lexicon, $\text{lex}_{b2}$, containing words that appear in the corpus of $L_{\text{bantu}2}$. Next, for each $w \in \text{lex}_{b2}$ we find all words in $\text{lex}_{b1}$, the lexicon of language $L_{\text{bantu}1}$, whose edit distance to $w$ is a small value $\Phi$. Thus, each word $w \in \text{lex}_{b2}$ has a list of words from $\text{lex}_{b1}$, $S_w = \{w1 \in L_{\text{bantu}1} : \text{editdistance}(w, w1) \leq \Phi\}$. We then go through corpus $L_{\text{bantu}2}$ and with probability $\Pi$ we replace word $w \in \text{lex}_{b2}$ with one of its cross-lingually similar words in $S_w$. Random selection is used to pick the replacement word.

## Table 1: Corpora crawled from Bible.com: seven Bantu and two Indo-European languages.

| Language   | Tokens | Vocabulary | KW vocab ∩ |
|------------|--------|------------|------------|
| KW-Kwanyama | 732,939 | 33,522     | 33,522     |
| ND-Ndonga  | 732,939 | 33,522     | 3,769      |
| SW-Swahili | 694,511 | 49,356     | 173        |
| KK-Kikuyu  | 718,320 | 53623      | 126        |
| SH-Shona   | 570,778 | 64,073     | 222        |
| CW-Chewa   | 669,352 | 53148      | 206        |
| TS-Tswana  | 101,175 | 23,384     | 126        |

## Table 2: Examples of English, Kwanyama, and Ndongo translations

|              | **English -EN** | **Kwanyama-KW** | **Ndongo-ND** |
|--------------|-----------------|-----------------|---------------|
| people       | ovanhu          | galuka          | aantu         |
| return       | aluka           | omonuna         | galuka        |
| child        | okaana          | inima           | omakutsi      |
| things       | inima           | omakutsi        | aakiintu      |
| ears         | omakutwi        | omakutsi        | omakutsi      |
| women        | ovakainhu       | elaka           | elaka         |
| tongue       | elaka           | omulaulu        | oomilema      |
| darkness     | omulaulu        | oomilema        | oomilema      |
| feet         | eemhadi         | omunona         | oompadi       |
| sins         | omunona         | omakutsi        | oondjo        |

## Table 3: Training and test data for dictionary induction.

|              | **Target Vocabulary** | **Training Dictionary** | **Test** |
|--------------|-----------------------|-------------------------|----------|
| EN-KW        | 33,522                | 2,142                   | 107      |
| EN-IT        | 200,000               | 5,000                   | 1,500    |
| EN-ND        | 32,026                | 0                       | 104      |

$C_{\text{bantu}} = C_{\text{bantu}1} \cup \hat{C}_{\text{bantu}2}$. Applying the skip-gram model to $C_{\text{bantu}}$, generates word vectors, every $w_i \in C_{\text{bantu}}$ has a vector $x_i \in \mathbb{R}^d$. For English, we use the 300-dimensional pre-trained vectors trained the Google News dataset$^5$ so that every English word has a vector $y_i \in \mathbb{R}^d$. Finally, we $W$ using the training data, $D_{tr} = \{x_i, y_i\}_{i=1}^m$. At test time, we predict the target word translations for unseen Bantu words, $D_{te} = \{x_i\}_{i=1}^n$, which can either be in language $L_{\text{bantu}1}$ or $L_{\text{bantu}2}$.

## 3 Experimental Evaluation

### Data

We crawled Bible.com for bibles of 9 languages, 7 Bantu and 2 Indo-European, Italian and English. The latter were used for comparison. Corpora statistics are shown in Table 1. In our experiments, we focused on Kwanyama, spoken Namibia and Angola, as we had access to a first language speaker who could annotate data. The last column of Table 1 shows the vocabulary intersection between Kwanyama and other languages. The language with the most words in common with Kwanyama is Ndonga, spoken in Namibia, with an 11% vocabulary overlap.

$^5$https://code.google.com/archive/p/word2vec
in common have different meanings. For example: The word “male” in English refers to gender, in Kwanyama “male” means “tall” or “deep”. Our Kwanyama first language speaker also has five years of formal training in Ndonga, which is a dialect of the same language as Kwanyama. We therefore focus on these two Bantu languages in our experiments. Table 2 shows some examples of English, Kwanyama and Ndonga translations. Details of the training and test data are shown in Table 3. For all languages, we used 300-dimensional word vectors.

### Results

Table 4 shows the main results in terms of precision at top-k, the last column, $RD = 0.10$ shows precision at the value of $k$ which yields random chance of 10% precision. The top two rows show the results of bilingual dictionary induction between English and Kwanyama. We compare the projection matrix approach, EN-KW, to random chance, EN-KW (RD). We can see that EN-KW far outperforms chance. This result is promising given that our annotator only generated about 2,142 labeled examples. In particular, English-Italian (EN-IT) with a larger dictionary of 5,000 word pairs, produced by (Dinu and Baroni, 2014), achieves similar numbers, however it is worth noting that the EN-IT test data set is also much larger. For the English-Ndonga, EN-ND, language pair, we have no labeled data. We consider three cases: 1) EN-ND (J-KW), for this case, we concatenate the Kwanyama and Ndonga corpora and use the EN-KW training data to induce the EN-ND dictionary. 2) EN-ND (J-IT), we concatenate the Italian and Ndonga corpora and use the EN-IT training data to induce EN-ND dictionary. 3) EN-ND (J-KW-R), this is our approach where we first modify the Ndonga corpus to look more like Kwanyama before combining the two corpora, and using the EN-KW training data. Among these three options, EN-ND (J-KW-R) performs best, especially at small values of $k$, ie, $k = 1, 5, 10$. Additionally, EN-ND (J-KW) outperforms EN-ND (J-IT), which is to be expected because ND, Ndonga, a Bantu language is much more similar to KW, Kwanyama than to the Indo-European language, IT, Italian.

Figure 2 shows the top-k precision trends for various values of $k$. For the EN-KW pair, left of Figure 2 there is a bigger gap between EN-KW and random chance EN-KW (RD). On the other hand, for the EN-ND pair, the right of Figure 2 the gap between our approach EN-ND (J-KW-R) and random choice, EN-ND (RD) is smaller. However, it is also clear that the precision at top-k trend is much better when we make use of training data from Kwanyama EN-ND (J-KW-R), instead of training data from Italian EN-ND (J-IT). This result is encouraging for future work towards inducing accurate bilingual dictionaries for Bantu languages without labeled data. Future directions include collecting more training data from popular Bantu languages such as Swahili and Zulu; proposing alternative methods to dictionary induction; and inducing dictionaries for more Bantu languages.

### 4 Conclusion

In prior work, bilingual dictionary induction has been studied mostly for resource rich languages. (Lazaridou et al., 2015; Upadhyay et al., 2016; Faruqui and Dyer, 2014; Mikolov et al., 2013b; Ammar et al., 2016; Haghighi et al., 2008). We have introduced an approach where we create one vector space for Bantu languages in order to ex-

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Table 4: Precision at Top-K for various language pairs.

|                | P@1 | P@5 | P@10 | RD |
|----------------|-----|-----|------|----|
| EN-KW          | 0.30| 0.56| 0.58 | 0.86|
| EN-KW (RD)     | 0.00| 0.00| 0.00 | 0.10|
| EN-IT          | 0.34| 0.48| 0.54 | 0.94|
| EN-IT (RD)     | 0.00| 0.00| 0.00 | 0.10|
| EN-ND (J-IT)   | 0.00| 0.00| 0.00 | 0.39|
| EN-ND (J-KW)   | 0.07| 0.16| 0.18 | 0.63|
| EN-ND (J-KW-R) | 0.10| 0.18| 0.20 | 0.60|
| EN-ND (RD)     | 0.00| 0.00| 0.00 | 0.10|

Figure 2: Trend for precision at top-k
ploit labeled data available for one language but not for another. Given that there are over 300 Bantu languages, and not all of them have training data, we believe approaches that rely on their shared grammar will be important for bringing NLP methods to this family of languages.
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