Word Alignment System for Myanmar-English Machine Translation

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Abstract

Word alignment in bilingual corpora has been an active research topic in the Machine Translation research groups. In this paper, the system describes an alignment system that aligns English-Myanmar texts at word level in parallel sentences. Since word alignment research on Myanmar and English languages is still in its infancy, it is not a trivial task for Myanmar - English text. Thus, the main purpose of this system is to construct word-aligned parallel corpus to be able in Myanmar-English machine translation. The proposed approach is combination of corpus based approach and dictionary lookup approach. The corpus based approach is based on the first three IBM models and Expectation Maximization (EM) algorithm. For the dictionary lookup approach, the proposed system uses the bilingual Myanmar-English dictionary.

1. Introduction

Myanmar language is like Chinese, Japanese, India, and Thailand and so on in Asian Languages. The words are not separated by the space. Therefore, it is considerable more difficult than for Western Languages. Bilingual word alignment is the first step of most current approaches to Statistical Machine Translation or SMT [2]. One simple and very old but still quite useful approach for language modeling is n-gram modeling. Separate language models are built for the source language (SL) and the target language (TL). For this stage, monolingual corpora of the SL and the TL are required. The second stage is called translation modeling and it includes the step of finding the word alignments induced over a sentence aligned bilingual (parallel) corpus. This paper deals with the step of word alignment.

Corpora and other lexical resources are not yet widely available in Myanmar. Research in language technologies has therefore not progressed much. In this paper we describe our efforts in building an English-Myanmar aligned parallel corpus. A parallel corpus is a collection of texts in two languages, one of which is the translation equivalent of the other. Although parallel corpora are very useful resources for many natural languages processing applications such as building machine translation systems, multilingual dictionaries and word sense disambiguation, they are not yet available for many languages of the world. Myanmar language is no exception.

Building a parallel corpus manually is a very tedious and time-consuming task. A good way to develop such a corpus is to start from available resources containing the translations from the source language to the target language. A parallel corpus becomes very useful when the texts in the two languages are aligned. This system used the IBM models to align the texts at word level.

Many words in natural languages have multiple meanings. It is important to identify the correct sense of a word before we take up translation, query-based information retrieval, information extraction, question answering, etc. Recently, parallel corpora are being employed for detecting the correct sense of a word. Ng [7] proposed that if two languages are not closely related, different senses in the source language are likely to be translated differently

in the target language. Parallel corpus based techniques for word sense disambiguation therefore work better when the two languages are dissimilar. It may be noted that English-Myanmar scores well here.

The remainder of the paper is formed as follows. Section 2 describes some related work. Overview of statistical machine translation for Myanmar to English is presented in section 3. Section 4, discuss about IBM alignment models. In section 5, we describe proposed alignment model. The proposed System is discussed in section 6. In section 7, we present experimental results. Finally, section 8 presents conclusion and future work.

2. Related Work

G. Chinnappa and Anil Kumar Singh [6] proposed a java implementation of an extended word alignment algorithm based on the IBM models. They have been able to improve the performance by introducing a similarity measure (Dice coefficient), using a list of cognates and morph analyzer. Li and Chengqing Zong [11] addressed the word alignment between sentences with different valid word orders, which changes the order of the word sequences (called word reordering) of the output hypotheses to make the word order more exactly match the alignment reference.

K-vec algorithm [13] makes use of the word position and frequency feature to find word correspondences using Euclidean distance. Ittycheriah and Roukos [8] proposed a maximum entropy word aligner for Arabic-English machine translation. Martin et al. [9] have discussed word alignment for languages with scarce resources. Bing Xiang, Yonggang Deng and Bowen Zhou [1] proposed Diversify and Combine: Improving Word Alignment for Machine Translation on Low-Resource Languages. This approach on an English-to-Pashto translation task by combining the alignments obtained from syntactic reordering, stemming, and partial words. Jamie Brunning, Adria de Gispert and William Byrne proposed Context-Dependent Alignment Models for Statistical Machine Translation [10]. This models lead to an improvement in alignment quality, and an increase in translation quality when the alignments are used in Arabic-English and Chinese-English translation.

Most current SMT systems [14] use a generative model for word alignment such as the one implemented in the freely available tool GIZA++ [16]. GIZA++ is an implementation of the IBM alignment models [15]. These models treat word alignment as a hidden process, and maximize the probability of the observed (e, f) sentence pairs using the Expectation Maximization (EM) algorithm, where e and f are the source and the target sentences. In [4] all the conducted experiments prove that the augmented approach, on multiple corpuses, performs better when compared to the use of GIZA++ and NATools individually for the task of English-Hindi word alignment. D.Wu, (1994) [3] has developed Chinese and English parallel corpora in the Department of Computer Science and University of Science and Technology in Clear Water Bay, Hong Kong. Here two methods are applied which are important once. Firstly, the gale's methods is used to Chinese and English which shows that length-based methods give satisfactory result even between unrelated languages which is a surprising result. Next, it shows the effect of adding lexical cues to a length –based methods. According to these results, using lexical information increases accuracy of alignment from 86% to 92%.

A hybrid approach to align sentences and words in English-Hindi parallel corpora[12] presented an alignment system that aligns English-Hindi texts at the sentence and word level in parallel corpora. They described a simple sentence length approach to sentence alignment and a hybrid, multi-feature approach to perform word alignment. They use regression techniques in order to learn parameters, which characterize the relationship between the lengths of two sentences in parallel text. They used a multi-feature approach with dictionary lookup as a primary technique and other methods such as local word grouping, transliteration similarity (edit-distance) and a nearest aligned neighbors

approach to deal with many-to-many word alignment. Their experiments based on the EMILLE (Enabling Minority Language Engineering) corpus. They obtained 99.09% accuracy for many-to-many sentence alignment and 77% precision and 67.79% recall for many-to-many word alignment.

3. Overview of the Statistical Machine Translation of Myanmar to English

Figure 1 shows overview architecture of the statistical machine translation of Myanmar to English. The source language model includes Part-of-Speech (POS) tagging and finding grammatical relations. The translation model includes phrase extraction, translation by using bilingual Myanmar to English corpus. The translation model also interacts with WSD (Word Sense Disambiguation) to solve ambiguities when a phrase has with more than one sense. The target language model includes reordering the translated English sentence and smoothing it by reducing grammar errors. In this Myanmar to English machine translation system, we focus on Alignment model. The main goal is to construct Myanmar-English word-aligned parallel corpus. Alignment model is central components of any statistical machine translation system. The result corpus will be used in most parts of the Myanmar-English machine translation.

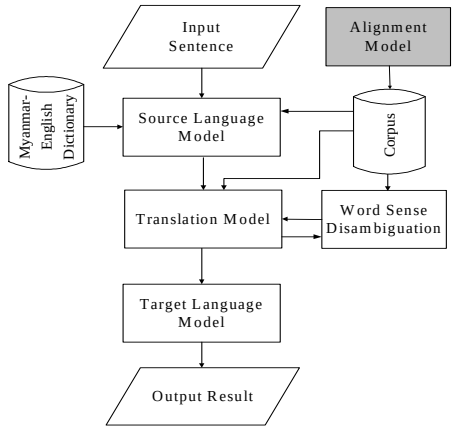


Figure 1. Machine Translation System of Myanmar- English

4. Alignment Model

Alignment is a central issue in the construction and exploitation of parallel corpora. One of the central modeling problems in statistical machine translation (SMT) is alignment between parallel texts. The duty of alignment methodology is to identify translation equivalence between sentences, words and phrases within sentences. In most literature, alignment methods are categorized as either association approaches or estimation approaches (also called heuristic models and statistical models). Association approaches use string similarity measures, word order heuristics, or co-occurrence measures (e.g. mutual information scores).

The central distinction between statistical and heuristic approaches is that statistical approaches are based on well-founded probabilistic models while heuristic ones are not. Estimation approaches use probabilities estimated from parallel corpora, inspired from statistical machine translation, where the computation of word alignments is part of the computation of the translation model.

4.1. The IBM Alignment Models 1 through 3

In their systematic review of statistical alignment models (Och and Ney ,2003 [5]), Och and Ney describe the essence of statistical alignment as trying to model the probabilistic relationship between the source language string m, and target language string e, and the alignment a between positions in m and e. The mathematical notations commonly used for statistical alignment models follow.

$$m^J_1=m_1,\ldots m_j,\ldots,m_J \qquad e^I_1=e1,\ldots,e_i,\ldots,e_I \tag{1}$$

Myanmar and English sentences m and e, contain a number or tokens, J and I (Equation 1). Tokens in sentences m and e can be aligned, correspond to one another. The set of possible alignments is denoted A, and each alignment

from j to i (Myanmar to English) is denoted by a_j which holds the index of the corresponding token i in the English sentence (see equation 2).

$$A \subseteq \{(j,i) : j = 1,...,J; i = 1,...,I\}$$
$$j \rightarrow i = a_j \quad (2)$$
$$i = a_j$$

The basic alignment model using the above described notation can be seen in Equation 3.

$$\Pr(m_1^J | e_1^J)$$
$$\Pr(m_1^J, a_1^J | e_1^J) \quad (3)$$
$$\Pr(m_1^J | e_1^J) = \sum_{a_i^J} \Pr(m_1^J, a_1^J | e_1^J)$$

From the basic translation model $\Pr(m_1^J|e_1^J)$, the alignment is included into equation to express the likelihood of a certain alignment mapping one token in sentence m to a token in sentence e, $\Pr(m_1^J,a_1^J|e_1^J)$. If all alignments are considered, the total likelihood should be equal to the basic translation model probability.

The above described model is the **IBM Model 1**. In model-1 word positions are not considered.

Model 2

One problem of Model 1 is that it does not have any way of differentiating between alignments that align words on the opposite ends of the sentences, from alignments which are closer. Model 2 add this distinction.

Model 3

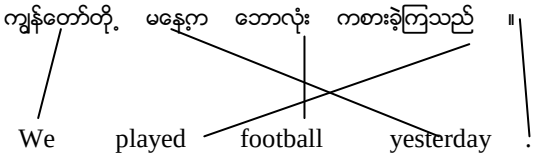
Languages such as Swedish and German make use of compound words. Myanmar language also makes use of compound words. Languages such as English do not. This difference makes translating between such languages impossible for certain words, the previous models 1 and 2 would not be capable of mapping one Myanmar, Swedish or German word into two English words. Model 3 however introduces fertility based alignment, which considers such one to many translations probable.

4.2. Problem Statements and Solutions

In approaches based on IBM models, the problem of word alignment is divided into several different problems.

The first problem: is to find the most likely translations of an SL word, irrespective of positions.

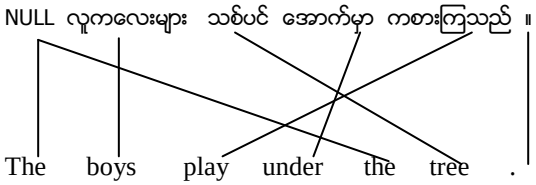
Solution: This part is taken care of by the translation model. This model describes the mathematical relationship between two or more languages. The main thing is to predict whether expressions in different languages have equivalent meanings. For example:



Translation (one to one alignment)

The second problem: is to align positions in the source language (SL) sentence with positions in the target language (TL) sentence.

Solution: This problem is addressed by the distortion model. It takes care of the differences in word orders of the two languages. A novel metric to measure word order similarity (or difference) between any pair of languages based on word alignments. For example:

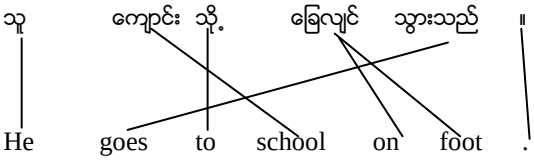


Distortion (word order) and NULL Insertion (spurious words)

The third problem: is to find out how many TL words are generated by one SL word. Note

that an SL word may sometimes generate no TL word, or a TL word may be generated by no SL word (NULL insertion).

Solution: The fertility model is supposed to account for this. For example:



Fertility (one to many alignment)

5. Proposed Alignment Model

The proposed system is combination of corpus based approach and dictionary lookup approach. The following sections explain each approach.

5.1. Corpus Based Approach

The corpus based approach is based on the first three IBM models and Expectation Maximization (EM) algorithm. The Expectation-Maximization (EM) algorithm is used to iteratively estimate alignment model probabilities according to the likelihood of the model on a parallel corpus. In the Expectation step, alignment probabilities are computed from the model parameters and in the Maximization step, parameter values are re-estimated based on the alignment probabilities and the corpus. The iterative process is started by initializing parameter values with uniform probabilities for IBM Model 1. The EM algorithm is only guaranteed to find a local maximum which makes the result depend on the starting point of the estimation process. This system is implemented EM algorithm and deals with problem statements. The iterative EM algorithm corresponding to the translation problem can be described as:

Step-1: Collect all word types from the source and target corpora. For each source word m collect all target words e that co-occurs at least once with m.

Step-2: Initialize the translation parameter uniformly (uniform probability distribution), i.e., any target word probably can be the translation of a source word e. In this step, there are two main tasks for aligning the source and target sentences. The detail algorithm of each task is shown Figure 2 and Figure 3.The first task is pre-processing and the second task is the usage of the first three IBM models.

Pre-processing Phase
Accept Source Sentence;
Accept Target Sentence;
Remove Stop Word in Source Words (S) eg: သည်,ပြီး
For each Source Sentence S do
Separate into words;
Store Source Words Indexes;
End For
For each Target Sentence T do
Separate into words;
Store Target Words Indexes;
End For

Figure 2. Algorithm for Pre-processing

Step-1: Collect all word types from the source and target corpora.
For each source word *m* collect all target words *e* that co occurs at least once with *m*.
Step-2: Any target word (e) probably can be the translation of a source word (m) and the lengths of the source and target sentences are s and t, respectively.
Initialize the expected translation count Tc and Total to 0
Step-3: Iteratively refine the translation probabilities.
For i=1 to *s* do
Create Source Words with N-grams Method
Select Target Words FROM Bilingual corpus WHERE Source Similar m_i
total+=$T(m_i)$ in corpus
For j=1 to t do
If e_j Found in Corpus
$Tc(e_j|m_i)$+= $T(e_j|m_i)$

Store Source Word Index and Target Word Index
Align Source Word and Target Word and Store in Corpus
Else if
Use the English Pattern (combine English words with N-grams method)
If T (m_i) with Target Word found in Corpus
$Tc(e_j|m_i)$+= $T(e_j|m_i)$
Store Source Word Index and Target Word Index
Align Source Word and Target Word and Store in Corpus
Else English Word with Null insertion
End If
End For
Calculate Probability T
End For

Figure 3. The First Three IBM Models Based Algorithm

Myanmar Word	English Word
အိမ်	house
	home
	building
ရှိသည်	is
	exist
	are
	has
	have
ကျွန်း	island
	teak

Figure 4. Example of Ambiguity Words

[0]ကျွန်တော်တို့/[0]We<PP>
[1]ဘုရား/[3]pagoda<NN> [2]သို့/[2]to<TO>
[3]သွားသည်/[1]go<VBP>

Figure 5. Bilingual Corpus Format

N-Gram	Phrases
Unigram	ခွေး၊ များ၊ သည်၊ အသား၊ စား၊ သည်
Bigram	ခွေးများ၊များသည်၊သည်အသား၊အသားစား၊စားသည်
Trigram	ခွေးများသည်၊များသည်အသား၊သည်အသားစား၊အသားစားသည်

Figure 6. N-gram based Phrases

5.2. Dictionary Lookup Approach

We have used dictionary (bilingual Myanmar-English dictionary) which consists of 10,000 word to word translations. The dictionary lookup approach algorithm for alignment is as below:

Let M_E be the set of English Meanings based on Myanmar word and its POS.
For each Myanmar word
Begin
Find M_E in Myanmar-English Dictionary
If $|M_E|>1$ then
Match each meaning in M_E with the input English word
If the matching is found then
Align these two words And
Store these two words in corpus
End if
End if
End

Figure 7. Dictionary Lookup Algorithm

6. The Proposed System

The proposed system consists of two main steps. They are preprocessing and alignment. The inputs are Myanmar and English sentences. In preprocessing step, the two input sentences are segmented, stemmed and removed the stop words. Alignment step uses corpus based approach as first and dictionary lookup approach.

The proposed system finds English word in the bilingual Myanmar-English corpus by using Myanmar N-grams words. If we found the search word in corpus, we align input Myanmar word and English word.

Otherwise we use dictionary lookup approach. When we search in Myanmar-English dictionary, we use Myanmar root word and POS. If we found, we get the English word. If the resulting English word is the same with the root word of input English word, we align input Myanmar word and English word and then store this alignment in parallel corpus. Parallel corpus is used as training data set and also the output of the system.

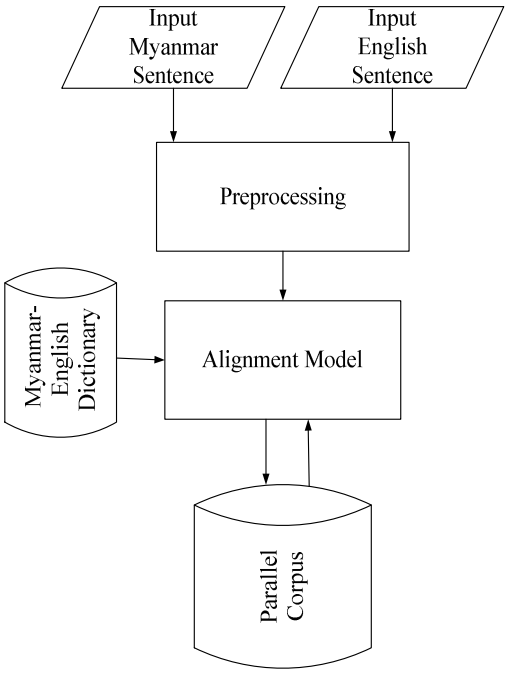


Figure 8. Proposed Alignment System

7. Experimental Results

We used the Myanmar-English corpus (1000 sentence pairs) and 100 sentence pairs for testing. The sentences were at least 4 words long. We report the performance of our alignment Models in terms of precision and recall defined as:

$$\text{Re}\,call = \frac{W_{correct}}{W_{Dtotal}} \times 100\%$$

$$\text{Pr}\,ecision = \frac{W_{correct}}{W_{Stotal}} \times 100\%$$

$$F - measure = \frac{2 \times \text{Pr}\,ecision \times \text{Re}\,call}{\text{Pr}\,ecision + \text{Re}\,call} \times 100\%$$

Where, $W_{correct}$ is the number of correctly aligned words, W_{DTotal} is the number of words and W_{STotal} is the number of aligned words by the system. According to the experimental results, it shows in Figure 9. By using combination of Corpus based approach and dictionary lookup approach, the precision increased.

Experiment

A is Corpus Based Approach
B is Dictionary Lookup Approach
C is Corpus Based Approach + Dictionary Lookup Approach

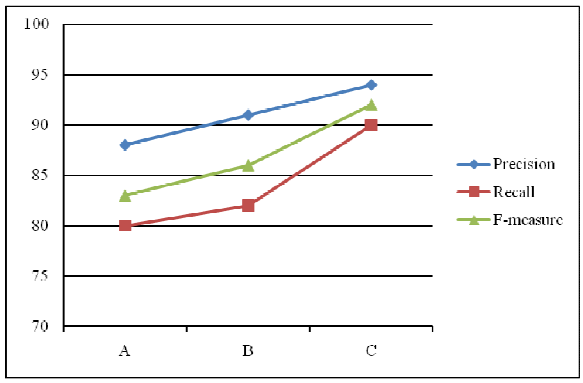


Figure 9. Precision, Recall and F-measure Graph

8. Conclusion and Future Work

The main goal of word alignment is to improve statistical Myanmar-English machine translation. The second objective is to build the standard system for Myanmar-English parallel Corpus. Word alignments can have better performance on sentence-based SMT system.

Since the proposed approach is based on corpus based and dictionary based approaches, this system can generate correct alignment words. Most of the Myanmar languages are morphologically rich. Thus, in future, the proposed model will be better result by using a list of cognates and morphological analysis. This system can be extended as phrase alignment model, name (proper noun) and compound word.

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