Extension schemes for the Alignment Model of English-Malayalam Statistical Machine Translator

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Abstract—**In Statistical Machine Translation from English to Malayalam, an unseen English sentence is translated into its equivalent Malayalam sentence using statistical models. A parallel corpus of English-Malayalam is used in the training phase. Word to word alignments has to be set among the sentence pairs of the source and target language before subjecting them for training. This paper deals with certain techniques which can be adopted for improving the alignment model of SMT. Methods to incorporate the parts of speech information into the bilingual corpus has resulted in eliminating many of the insignificant alignments. Also identifying the name entities and cognates present in the sentence pairs has proved to be advantageous while setting up the alignments. Presence of Malayalam words with predictable translations has also contributed in reducing the insignificant alignments. Moreover, reduction of the unwanted alignments has brought in better training results. Experiments conducted on a sample corpus have generated reasonably good Malayalam translations and the results are verified with F measure, BLEU and WER evaluation metrics.**

***Keywords*—alignment, training, machine translation, English Malayalam translation**

I Introduction

Statistical Machine Translation (SMT) is one of the upcoming applications in the field of Natural Language Processing. As discussed in [1], during the training phase of SMT a learning algorithm is applied to huge volumes of previously translated text termed as parallel corpus. By examining these samples, an SMT system automatically translates previously unseen sentences. In [2] a methodology of statistical machine translator that translates a sentence in English to Malayalam is discussed.

Since English and Malayalam belong to two different language families, various issues are encountered when English is translated into Malayalam using SMT. As a part of resolving these issues, the basic underlying structure of the SMT is modified to an extent. The training results are improved when the Malayalam corpus is subjected to certain pre-processing techniques like suffix separation and stop word elimination. Various handcrafted rules based on 'sandhi' rules in Malayalam are designed for the suffix separation process and these rules are classified based on the Malayalam syllable preceding the suffix in the inflected form of the word. A technique to remove the insignificant alignments from the bilingual corpus using a Parts of Speech (PoS) Tagger is also employed. While decoding a new unseen English sentence, the structural disparity that exists between the English Malayalam pair is fixed by applying order conversion rules. The statistical output of the decoder is further furnished with the missing suffixes by applying mending rules.

In training the SMT, sentence pairs in the parallel corpus are examined and alignment vectors are set to identify the alignments that exist between the word pairs. It is observed that many of the alignments in a sentence pair are insignificant and carry little meaning. By removing these insignificant word alignments from the sentence pairs the quality of training can be enhanced. Moreover word alignments can be refined by aligning words based on the word categories like named entities and cognates. In this paper we discuss about an alignment model with morphological knowledge which enables to filter the irrelevant alignment pairs in the corpus. Furthermore a discussion on certain techniques that aids in improving the word to word alignments that exist between the English-Malayalam sentences is done.

The rest of this paper is organized as follows: The related work done in this area is presented in Section 2. In Section 3, an overview of SMT from English into Malayalam is discussed. The alignment model and the training technique adopted in SMT are explained in Section 4. Section 5 presents the details about the techniques adopted in improving the word alignments. Some observations and results obtained from the experiments conducted on a sample English/Malayalam corpus is discussed in Section 6. Finally, the work is concluded in Section 7.

II Related Work

Experiments on statistical machine translation were carried out among many foreign languages and English. For SMT, development of statistical models as well as resources for training is needed. Due to the scarcity of fully fledged bilingual corpus, works in this area remain almost stagnant. Therefore accomplishment of an inclusive SMT system for Indian languages still remains a goal to be achieved. A work on English to Hindi statistical machine translation [4] which uses a simple and computationally inexpensive idea for incorporating morphological information into the SMT framework has been reported. Another work on English to Tamil statistical machine translation is also reported in [5]. The morphological richness and complex nature of the Malayalam language account for the very few attempts made

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to translate texts from other languages into Malayalam. A pure statistical machine translation from/in the Malayalam language is yet to be published. The ideas integrated from the similar works in machine translation have been the source of motivation and the inputs gathered from the related methodologies has facilitated in outlining the framework of the proposed SMT from English to Malayalam.

III OVERVIEW OF ENGLISH MALAYALAM SMT

In SMT from English to Malayalam, a bigram estimator [6] is employed as the language model to check the fluency of Malayalam. For the translation model, which assigns probabilities to English-Malayalam sentence pairs, IBM Hidden Markov Model (Model 1) training technique [7] is chosen. A variation of Beam Search method [8] is used by the decoder to work with the statistical models. In the training process the translations of a Malayalam word is determined by finding the translation probability of an English word for a given Malayalam word. The method used for finding the translation probability estimate in SMT is the EM algorithm discussed in [3].

As discussed in [9], Malayalam language is enriched with enormous suffixes and the words appear mostly with multiple suffixes. A Suffix separator is employed to extract roots from its suffixes. The Malayalam corpus after suffix separation contains many suffixes extracted from root words that have no meaningful word translation in English. Most of them are the suffixes of nouns and verbs in Malayalam. Since these words are useless in the translation process, they are not included in the corpus. The deletion of these stop words will bring down the complexity of the training process as well as improve the quality of the results expected from it. Similarly stops words in English language are also identified and are eliminated from the corpus before subjecting it to training.

On obtaining the estimates for the translation parameter from the training phase, an unseen English sentence can be translated by the decoder by applying Bayes rule [6]. In the decoder different syntactic tags are used to denote the syntactic category of English words. Order conversion rules are framed to reorder English according to the sentence structure and the word group order of Malayalam. Various hypotheses for the sentence to be translated are created by choosing translation options and the best translation is determined by extending the hypotheses and picking the one with maximum score. Since SMT is trained with root words in Malayalam, the outcome of the decoder lacks the required suffixes in the words generated. This undesirable result has been set right by applying various mending rules which helps in appending suffixes to the Malayalam output.

IV TRAINING THE PARRALLEL CORPUS

In the training phase the corpus used is a sentence aligned one where a sentence in Malayalam is synchronized with its equivalent English translation. The aligned sentence pairs are subjected to training mechanism which in turn leads to the calculation of translation probability of all English words. This results in generating a collection of translation options in English with different probability values for each Malayalam word. Of these translation options the one with the highest translation probability is selected as the word to word translation of the Malayalam word.

For a sentence pair all the possible alignments have to be considered in the training process. The nature of the alignment truly depends on the characteristics of the language chosen. Since Malayalam with suffix separation holds a one to one mapping with words in the English sentence, only one to one alignment vectors are taken into consideration during training.

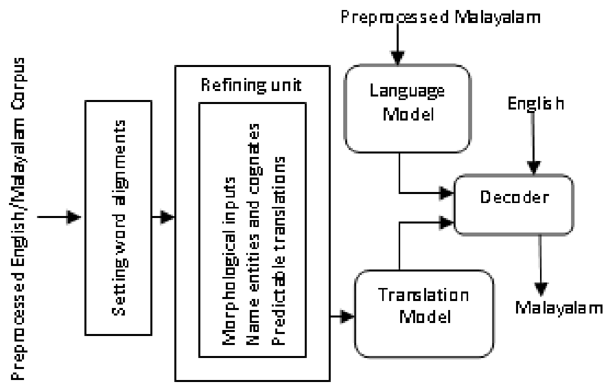

Figure1. Training in SMT from English to Malayalam

The EM algorithm defines a method of estimating the parameter values of translation for IBM model 1. By this algorithm there is equal chance for a Malayalam word to get aligned with any English word in the corpus. Therefore initially the translation probability of all English words is set to a uniform value. Suppose there is N number of English words in the corpus, the probability of all Malayalam words to get mapped to an English word is $1/N$. To start with the training process this value is set as the Initial Fractional Count (IFC) of the translation probability. Alignment weight for a sentence pair is calculated by observing the IFC of all the word pairs present in the alignment vector. The Alignment Probability (AP) of all the sentences is calculated by multiplying the individual alignment weight of each word pair in the sentence pair. The calculated alignment probability of the sentence pairs is then normalized to get Normalized Alignment Probability (NAP).

Fractional count for a word pair can be revised from the normalized alignment probabilities. A word in Malayalam may be aligned to a same English word in many sentences. Therefore when the fractional count of a word pair is recomputed, all sentence pairs are analyzed to check whether it holds that particular word pair. If it is present in any pair of sentence, the alignment probabilities of the alignment vectors holding that word pair are added up to obtain the Revised Fractional Count (RFC). By normalizing the revised fractional counts (NFC) new values of translation probability is obtained. The new values thus achieved are better since they take into account the correlation data in the parallel corpus. Equipped with these better parameter values, new alignment probabilities for the sentence pairs are again computed. From these values a set of even-more-revised fractional counts for word pairs is obtained. By repeating this process over and over, fractional count converges to extremely better values.

V TECHNIQUES FOR IMPTOVING WORD ALIGNMENTS

On introducing the training method described earlier into the parallel corpus, a large number of alignment vectors are obtained [10]. Out of it a major share belongs to the group of insignificant alignments. To get rid of the alignments which have no significance and to reduce the burden of calculating the fractional count and alignment probabilities for every alignment of sentence pairs, the morphological information is incorporated into the corpora. The bilingual corpus is tagged and then subjected to training. Tagging is done by considering the parts of speech entities of a sentence.

By tagging the corpus extra meaning is embedded into each word which definitely helps in the formation of reasonably good alignments. The structure of the Malayalam sentence is analyzed and the different Parts of Speech (PoS) categories are identified. In a sentence there may be many words belonging to the same PoS category. After the tagging process, words that don't have an exact translation in Malayalam may be deleted to improve the efficiency of the training phase. The English sentence is tagged in the same manner and paired with its tagged Malayalam translation. The word to word alignments are found only for the words that belong to the same PoS category of both languages.

Without tagging, when all the words in a sentence is considered, the number of alignments (NA) generated is equal to the factorial of its word count and is shown as

$$NA = \text{factorial}(Ws) . \qquad (1)$$

where Ws is the number of words in the sentence. The same corpus when tagged produces number of alignments less than factorial (Ws). The number of alignments for words belonging to same PoS category is factorial (Wc) where Wc is the number of words in a category. The total number of alignments of a sentence formed by tagging (NAT) is given by

$$NAT = \prod_{i=1}^{m} \text{factorial}(Wci) . \qquad (2)$$

alignment vectors, where m is the number of PoS categories in a sentence pair. The Insignificant Alignments (IA) eliminated can be represented as the difference between Equation 1 and 2 and is given below:

$$IA = \text{factorial}(Ws) - \prod_{i=1}^{m} \text{factorial}(Wci) . \qquad (3)$$

The insignificant alignments are further reduced by identifying the name entities and cognates present in the English Malayalam sentence pair. Name Entity identification [11] is a process in which the atomic elements in a text is located and classified into different predefined categories. The categories may include name of persons, organizations, places, time units, monetary units, quantities etc. Since entity identification is a subtask of information extraction, it is implemented using local pattern-matching techniques. A Name Entity Database (NED) that contains a large set of name entities is employed for the dictionary look up. In linguistics, cognates are defined as two words having a common etymological origin. Cognates in two different languages are words that are pronounced in a similar way or with a minor change**.** For example the word car in English and the word കാർ in Malayalam are similarly pronounced. Transliteration similarity between the word pairs can be considered for identifying such words.

$$IA = \text{factorial}(Ws) - \prod_{i=1}^{m} \text{factorial}(Wci) - (N_{NE} + N_C) \qquad (4)$$

where N_{NE} is the number of word pairs aligned with name entity and N_C is the number of word pairs aligned with cognates.

On setting the alignment vectors to find English to Malayalam word translations, it is observed that certain words in the English sentence carry less sense when treated as single word units. Meaningful translations are generated only on considering group of words rather than individual ones. Representation of numbers in English is mainly expressed as a cluster which includes more than one word. For example, the number '22' is denoted as 'twenty two' in English. But in Malayalam the equivalent word translation of 'twenty two 'is given by a single word as ഇരുപത്തിരണ്ട് (irupathirandu). Sentences are analyzed and grouping rules are applied to frame word sets in English. A match of the Malayalam word to be aligned with the English word set is identified from the 'predictable words' database which consists of Malayalam words and its corresponding English translations. The number of insignificant alignments is further brought down by this approach where words of Malayalam are identified whose English translations can be predicted with ease. Equation 4 is modified by incorporating the knowledge of predictable Malayalam words and is given as

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$$IA = \text{factorial}(Ws) - \prod_{i=1}^{m} \text{factorial}(Wci) - \{N_{NE} + N_{C}\} - \{N_{MPT}\} \qquad (5)$$

where N_{MPT} is the number of alignments identified between Malayalam and its predicted English translation.

VI OBSERVATIONS AND RESULTS ACHIEVED

The sample corpus used for training includes 250 sentences with 1800 words(3)The experimental Malayalam corpus is built based on www.mathrubhumi.com, a news site providing local news on Kerala. For better training results, the corpus selected should be adequate enough to represent all the characteristics of the languages. Also, the strength and correctness of the corpus is a necessity to achieve the desired output. The process of extending the English/Malayalam corpus is still continuing. Evaluation metrics proposed in [12] were applied on sentences present in the training set and on totally unseen sentences. Three reference corpora were used for testing. The summary of the results are shown in Table 1.

Insignificant alignments take up time and space in training. Therefore the parallel corpus is strengthened with more information so that only the relevant alignment is included in calculating translation probabilities. It is observed that when the corpus is linked with a parts of speech tagger many irrelevant alignments are eliminated. It has been observed that the rate of generating alignment vectors have fallen down to a remarkably low value as shown by Equation 2. Here the alignment vectors are directly proportional to the number of words in the PoS category and not to the number of words in the sentence pair. Also, the training technique is further enhanced by aligning words based on the name entities and cognates identified. This method has brought down the insignificant alignments further as stated by Equation 4. Identifying Malayalam words in a sentence pair whose English translations are predicted with ease, also enhances the process of improving the alignment model.

By enhancing the training technique, it is observed that the translation probabilities calculated from the corpus shows better statistical values. The end product of the training phase is obtained much faster. In the iterative process of finding the best translation, it takes less number of rounds to complete the training process.

VII CONCLUSION

Alignment model used in SMT from English to Malayalam results in many insignificant alignments which brings down the quality of translations obtained from the training phase. Techniques to improve the word to word alignments between the English-Malayalam sentence pairs are discussed in this paper. Using the parts of speech tags as an additional knowledge source, the parallel corpus is enriched to contain more information for selecting the correct word translation for a Malayalam word. The alignment model with category tags is useful in diminishing the set of alignments for each sentence pair and thereby simplifying the complexity of the training phase. The name entities and cognates located in the sentence pairs also have an important role in reducing the insignificant alignments. Removing the alignments that exist between the predictable Malayalam words and its translation also contribute in improving the alignment model. These techniques helps to improve the quality of word translations obtained for Malayalam words from the parallel corpus. The performance of the SMT is evaluated using WER, F measure and BLEU metrics and the results prove that the translations are of fairly good quality.

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Type of sentence	Technique	Evaluation Metric		
		WER	F measure	BLEU
Sentences in training set	Baseline + with suffix	0.3313	0. 57	0.48
	Baseline + suffix separation	0.17732	0. 81	0.74
Unseen sentences	Baseline + with suffix	0.6083	0. 26	0.22
	Baseline + suffix separation	0.3461	0.52	0.43

Table 1. Summary of evaluation results