An empirical study on English-Mizo Statistical Machine Translation with Bible Corpus

Original Scientific Paper

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Abstract – *Machine Translation (MT) is the process of automatically converting the text or speech in one natural language to another language with the help of a machine. This work presents a Bidirectional Statistical Machine Translation (SMT) system of an extremely low resource language pair Mizo-English, built in a low resource setting. A total of 30800 sentences are collected from the English Bible dataset and manually translated to Mizo by a native linguistic expert to generate the English-Mizo parallel dataset. After subjecting to various pre-processing steps, the parallel dataset is used to build our MT system using MOSES tools. Our framework uses different tools, such as GIZA++ for creating the Translation Model (TM) and IRSTLM to determine the probability of the target model. The quality of our MT system is evaluated using two automatic evaluation metrics: BLEU and METEOR. Our MT systems are also manually evaluated using two parameters: adequacy and fluency.*

Keywords: *Low resource, Statistical Machine Translation, Language Model, Translation Model, English, Mizo, Moses*

1. INTRODUCTION

Machine translation (MT) is becoming a driving factor for every sector, such as academia and industry, as the demand for global communication increases. MT is an application of Natural Language Processing (NLP), and its development is correlated to data availability. Corpus-Based MT systems utilize a self-educated way of source-to-target study mapping. Corpus-Based MT systems include Example-Based Machine Translation (EBMT) [1,2], Statistical Machine Translation (SMT) [3,4] and Neural Machine Translation (NMT) [5,6]. SMT system's performance is correlated to the amount of parallel text (a text and its translation into another language) used to train the system. The basic principle of SMT is to employ huge parallel text in the training model to produce a better translation. The inability to correctly utilize information, computational complexity, and the need for many separate independently trained parts are only a few of the primary limitations of SMT systems. Although employing language-independent intermediate representation for translation is intriguing (as in the instance of Interlingua-based Machine Translation), linguistic diversity poses a challenge and rules out its viability. Most people now use the Internet for personal and professional activities, and the distinction between the real and digital worlds is becoming increasingly blurred. This digital world is becoming a reality for most of the world's population, and information security is becoming as important as physical security.

Mizo is the lingua franca of Mizoram, a northeastern state of India, and is spoken by around one million people. Mizo is the dominant language spoken by the resident people of Mizoram. Mizo is a Kuki-chin language, a branch of the Sino-Tibetan language, and belongs to the Tibeto-Burman family. The word order in English and Mizo is different; English follows SVO (Subject-Verb-

Object), and Mizo follows OSV (Object-Subject-Verb); however, Mizo sometimes follows SVO like English [7]. Furthermore, the second person pronoun "*you*" is used in English to represent both the singular and plural, whereas the Mizo language has unique phrases for this (for singular "*I*" and plural "*in*"). Although English rigorously maintains the order in which words must appear to construct a meaningful sentence, Mizo does not. English and Mizo are hardly related; however, both languages use the same Roman script. Prefixes and suffixes are affixes related to language morphology. Some of the Mizo language prefixes include "*in*," "*ti*," and "*inti*", and depending on the sentence, "ti" is occasionally adjusted and used as "*tih*" [7]. When suffixes are added after the stem word in Mizo, they can affect the part of speech, similar to how suffixes in English can change a verb into a noun. Furthermore, Mizo is a tonal language, which means that a word with various tones might have distinct meanings. There are eight tones in the language, four of which are reduced and four of which are long.

In this work, a manually translated parallel dataset of English to Mizo is built with the help of a native linguistic expert. The dataset is then used to train Statistical Machine Translation (SMT) systems with various settings. The MT systems are evaluated using automatic evaluation metrics: BLEU (Bilingual Evaluation Understudy) [8], METEOR (Metric for Evaluation of Translation with Explicit ORdering) [9], and F-measure. System-generated translations were subjected to both human and automated examinations to assess the efficacy of statistical techniques in the context of the Mizo language. The significant findings of this work are:

- Building an English-Mizo Bible corpus,
- Evaluate the system performance with the n-gram phrase-base language model
- Automatic evaluation of SMT in terms of BLEU and METEOR.
- Manual evaluation in terms of adequacy and fluency with the help of a native linguistic expert

We organized the paper in the following way: Section 2 discusses the previous works on the MT Problem. Section 3 describes the overview of SMT architecture. Then, Section 4 illustrates the details of our corpus and preprocessing step. The experimental findings and evaluation of our system are discussed in Section 5, followed by the conclusion and future works in Section 6.

2. RELATED WORKS

Machine Translation is the early application of NLP, which started its journey in 1959 but was performed in 1980 in India. Some of the MT systems in the Indian Language include Sampark[10], Mantra[11], and AnuBharti[11]. Mantra is an MT system designed for the Rajya Sabha Secretariat at C-DAC, Bangalore. An MT system called "AnglaBharti" was built using the rule method and the generalized form of the lexicon. It was created in the year 1991 at IIT Kanpur. Following "AnglaBharti," another MT system called "AnuBharti" was built by the same organization in 2004 [11]. This system has been used to translate Hindi to English. IndicTrans is recent work on the MT system for Indian languages trained on the Samanantar dataset [12]. Furthermore, there has been reports of MT for other Indian languages focusing on low resource scenario such as Khasi [13], Hindi [14-15] and Manipuri [16-18].

Previous Natural Language Processing (NLP) study on the Mizo language includes an analysis on post-editing effort required to build English-Mizo parallel dataset [19], a Multi-Word Expression (MWE) for Mizo language [20], identifying criteria for recognition of Name Entity Classes in Mizo language [21], resource building and POS tagging for the Mizo language [22]. The preliminary study of POS tagging in the Mizo language [23] addressed the distinctive characteristics of the Mizo language and the limitations of the Mizo tagging system. The framework of MT systems for English to Mizo needs more work. [24] discussed the development of various applications of NLP for Mizo Language and the pre-processing steps for English to Mizo SMT system. [25] trained an NMT system for English to Mizo on a parallel corpus of 10,675 sentences and evaluated it on a test dataset of 100 sentences. The author reported that the MT system prediction is reasonable based on fluency but worse on accuracy. [7] conducted a study to evaluate the English to Mizo NMT system on several test datasets from different domains. [26] conducted a study on English to Mizo MT systems (SMT and NMT) on a training dataset collected from various online sources. [27] extended the work of [26] with additional training dataset of 31,764 parallel sentences and evaluated their systems on three tests dataset of sizes 100, 100, and 798 sentences. The author trained their systems with PB-SMT and NMT (LSTM, BiLSTM, and Transformer). The NMT-Transformer model was reported to outperform their baseline system.

3. STATISTICAL MACHINE TRANSLATION MODEL

This section discusses our approach for English to Mizo translation. Statistical Machine Translation is a machine translation system that uses a corpus based on the Noisy Channel concept. We use MOSES [28] to implement our English to Mizo MT system on a Bible parallel corpus. The statistical technique may be categorized as Empirical or Corpus-based machine translation, which necessitates a sizeable parallel text corpus to produce a high-quality translation. The SMT technique gives a solution to ambiguity concerns in natural languages. Some advantages of the Statistical model are that it is simple to create and run, requires little language skills to extract knowledge from a corpus, lowers human effort, and saves time [28]. SMT aims to produce the target sentence from the source sentence using the parallel corpus. Fig. 1 shows the outline of the Statistical Machine Translation system.

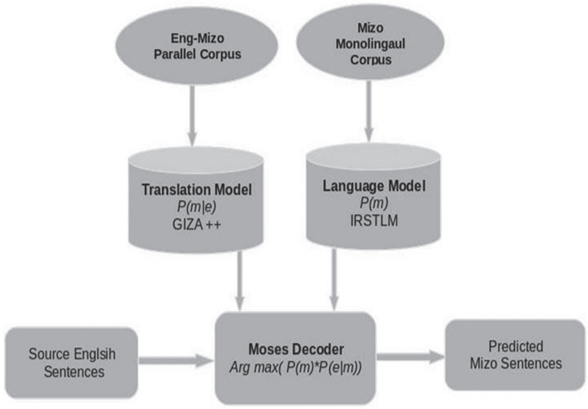

Fig. 1. Architecture of Statistical Machine Translation

The SMT architecture consists of three parts, namely, Language Model, Translation Model and Decoder.

A language model computes the probability of a sentence using an n-gram model. A language model may be thought of as a computation of the probability of a single word given all of the words that come before it in a sentence. It is divided into the conditional probability product. Using the chain rule, the probability of a phrase t, P(t) is divided into the probability of individual words {w1,w2,w3, … ,wn}, P(w) as follows:

P(t) = P(w1,w2,w3, ... ,wn)

=P(w1)P(w2|w1)P(w3|w1w2)
P(w4|w1w2w3)....P(wn|w1w2 … wn-1)

The Translation Model aids in calculating the conditional probability P(m|e). It is the probability assigned to any pair of target sentence e and source sentence m. The parallel corpus of target-source pairings is used to train it. The process of computing the translation model is divided into smaller units, such as words or phrases, and their probabilities are learned. The translation of the source sentence is assumed to be generated word by word from the source. The translation of a target statement is as follows:

*(Ram is Riding his Bicycle /
Ram chuan a thirsakawr a khalh)*

The sentence pair having the possible alignment is given as,

*(Ram is Riding his Bicycle /
ram (1) chuan a (2) thirsakawr (5) a khalh (3,4).*

A variety of alignments are conceivable. To keep things simple, the translation model is aligned word by word. Consider the set of alignment by *B(e,m)*. If the length of the target m is l and the length of the source e is *n*, then there are *l X n* different connection of all possible alignment for each target position are equally likely, so the order of words in *m* and *e* has no effect on *P(m|e)* and the likelihood of *(m|e)* can be expressed as conditional probability *P(m,a|e)* as *P(e|m) = sum (e,a|m)*. The total is more than the element of the alignment set *B(e, m)*.

Decoder: To find the best translation from the given source sentence in target language by statistical model that compute the probability of language model and the probability of translation model. The *P(e,m)* is the total possible outcome of the probability of alignment e and m. Now, we need to search for a pair (m,a) which P(m,a|e) is maximize. By Bayes theorem, finding (m,a) which maximize *P(m,a|e) = P(e,a|m)*P(m)*. The early phrase-based statistical decoder model use the greedy hill-climbing algorithm [36], whereas the Moses decoder of phrase-base statistical model uses a beam search algorithm [37].

4. BUILDING CORPUS AND PRE-PROCESSING

This section discusses our corpus collection and data preparation.

For the experiment, 30,800 sentences in English are collected from the Bible monolingual corpus [29]. The collected sentences are manually translated to Mizo by the native speakers. Following is a sample example of the translation of an English sentence to Mizo:

English: *for god shall cast upon him, and not spare: he would fain flee out of his hand.*

Mizo: *zahngai lovin a nuai ang a, a thiltihtheihna hmaah chuan a kat rawk rawk ang.*

In the pre-processing step, non-ASCII special characters are removed from the parallel corpus to remove noise. The cleaned corpus is then tokenized with Moses Tokenizer [30]. Table 1 show the statistics of our experimental dataset.

Table 1. Statistics of English-Mizo parallel dataset

Language	Number of types	Number of unique types
English	920948	21235
Mizo	904484	13360

5. EXPERIMENTAL SETUP AND RESULTS

This section describes our experimental design and the evaluation of our English to Mizo MT systems. Table 2 contains essential information regarding the data utilized for the MT system.

Table 2. Data split up of the experimental dataset

Types	Number of sentences
Training	28300
Tuning	1500
Testing	1000

The MT systems are trained using the Moses toolkit. GIZA++ Toolkit [31] is used to generate the word alignment of the parallel corpora in both directions. IRSTLM [32] toolkit was used to train the language models (word and phrase-based). Tuning is performed by decoding and minimum error rate training (MERT) [33]. The alignments are then integrated using the growdiag-final and heuristic to produce a symmetric word alignment model [35].

5.1. AUTOMATIC EVALUATION

We examine the performance of our MT systems in terms of BLEU [8] and METEOR [9]. BLEU is an n-gram precision parameter, with higher values indicating better performance. METEOR rewards recollection by altering the BLEU brevity penalty, considers higher order n-grams to reward word order matches, and use arithmetic rather than geometric averaging.

We separately trained the MT system with three language models for the basic system (5, 4, and 3-grams standard phrase-based language models).

Table 3. SMT-LM System (English-Mizo)

n-gram	BLEU	METEOR	F-measure
3-gram	16.99	0.20	0.45
4-gram	17.36	0.21	0.46
5-gram	18.71	0.21	0.46

Table 4. SMT-LM System (Mizo-English)

n-gram	BLEU	METEOR	F-measure
3-gram	18.04	0.23	0.50
4-gram	19.25	0.23	0.51
5-gram	19.44	0.24	0.51

Table 3 and Table 4 shows the performance of English to Mizo and Mizo to English SMT systems in terms of BLEU, METEOR and F-measure. The result shows that the MT system with a 5-gram order of LM outperforms the 3-gram and 4-gram for both the English to Mizo and Mizo to English directions. The highest BLEU score for the English to Mizo SMT system is 18.71, and for the Mizo to English SMT system is 19.44.

Our results show similar performance of the MT system in terms of METEOR. For English to Mizo, the SMT system trained with the 4-gram and 5-gram order of LM achieve the same score of 0.21 and for Mizo to English, the SMT system trained with the 5-gram order of LM achieve the highest score of 0.24.

5.2. ANALYSIS OF THE MT SYSTEM BASED ON SENTENCE LENGTH

We also conducted an analysis of SMT systems based on the length of the sentences. Fig. 2 and Fig. 3 show the results from our English to Mizo and Mizo to English SMT systems, respectively. 3o-LM, 4o-LM, and 5o-LM are the SMT systems trained with 3-gram, 4-gram, and 5-gram orders of the Language Model, respectively.

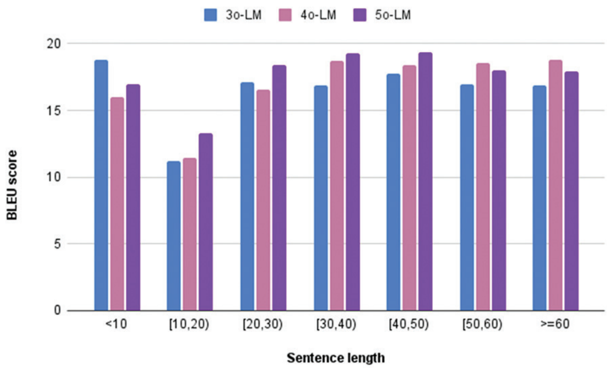

Fig. 2. Evaluation of our English to Mizo SMT systems

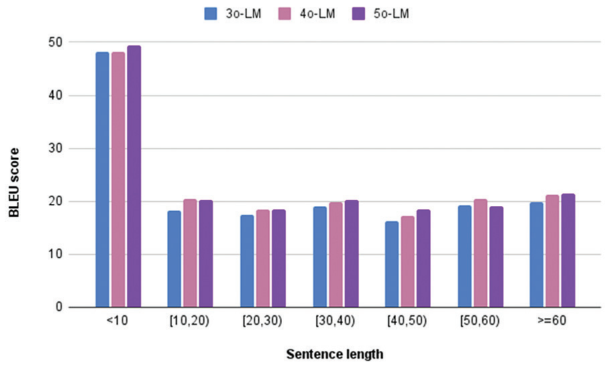

Fig. 3. Evaluation of our Mizo to English SMT systems

English to Mizo: The results from Fig.2 show that for short sentences with a length of less than 10, the 3o-LM MT system significantly outperforms the other MT systems. In the case of sentences of length greater than and equal to 50, the 4o-LM MT system performs best. However, overall the 5o-LM MT system is observed to perform better than the 3o-LM and 4o-LM SMT systems.

Mizo to English: The results from Fig.3 show that the 5o-LM MT system significantly outperforms the other MT systems in most cases.

From the above experimental results, we observe that unlike the results of English to Mizo SMT systems, the performance of the Mizo to English SMT system differs significantly for the sentences with lengths less than ten and the sentences with lengths greater than and equal to 10. The Mizo to English SMT is observed to be more robust for short sentences compared to English to Mizo SMT systems.

5.3. MANUAL EVALUATION

Manual evaluation is the best way of judging the quality of MT systems. Linguistic experts judge the output of MT quality based on the two-parameter: Adequacy and Fluency. Adequacy measures the amount of translation meaning of reference translation, which is included in a candidate translation.

Fluency is considered as well-formed grammatical sentences of the target language [35]. The scale used to measure the Adequacy and Fluency of our MT systems is shown in Table 5.

Table 5. Scale for Adequacy and Fluency

Scale	Adequacy	Fluency
5	All meaning	Flawless language
4	Most meaning	Good language
3	Much meaning	Non-native language
2	Little meaning	Disfluent language
1	None	Incomprehensible

Table 6. SMT-LM System (Mizo-English).

Order of N-gram LM	Adequacy	Fluency
3-gram	2.4	2.1
4-gram	3.3	3.1
5-gram	**3.6**	**3.3**

Table 7. SMT-LM System (English-Mizo)

Order of N-gram LM	Adequacy	Fluency
3-gram	3.1	2.0
4-gram	3.6	3.3
5-gram	**3.9**	**3.6**

Table 6 and Table 7 shows the Adequacy and Fluency score of our MT systems evaluated by the native linguistic experts. The results obtained from the manual evaluation complemented our findings from the automatic evaluation.

Following are the sample outputs from our SMT systems:

English to Mizo sample input-output:

English: all the cities of the children of aaron , the priests , were thirteen cities with their suburbs .

Reference: arona thlah , puithiamho khawpui zawng zawng chu khawpui sâwm leh pathum a ni , a daivêlte nên .

3o-LM: khawpui zawng zawng chu arona thlah , puithiam chu khaw sâwm leh a daivêlte nên .

4o-LM: khawpui zawng zawng chu arona thlah puithiamte chu an ni , " a ti a , khawpui sâwm leh pathum a ni , a daivêlte nên .

5o-LM: khawpui zawng zawng chu arona thlah , puithiam chu khawpui sâwm leh pathum a ni , a daivêlte nên .

Mizo to English sample input-output:

Mizo: an vaiin an ei a , an tlai ta hlawm a , an sem bâng chu bâwm sarihah an dah khat a .

Reference: and they did all eat , and were filled : and they took up of the broken meat that was left seven baskets full .

3o-LM: and they were they did eat , and were filled , and they took up the ark was left seven baskets .

4o-LM: and they were they did eat , and were filled : and they took up of the broken meat that was left seven baskets .

5o-LM: and they were they did eat , and were filled : and they took up of the broken meat that was left seven baskets .

6. CONCLUSION

This paper discusses corpus standardization and a strategy for developing standardized datasets. The parameter for generating the best performance for bidirectional English-Mizo SMT is also determined. An analysis of the n-gram order of the language model for the SMT system is carried out in this work. The advantage of this method is that it employs the exact phrases found in the translation table and those included in the target part of each entry. The extensive experiments on English-to-Mizo and Mizo-to-English translation indicate that the phrase-based language model can increase the quality of the SMT system. The systems are assessed using the automated scoring methodologies BLEU and METEOR score and manual evaluation by linguistic experts. The SMT systems trained with 5-gram order of Language Model outperform the other MT systems by achieving a BLEU score of 18.71 for English to Mizo and 19.44 for Mizo to English. The automatic evaluation results show that the performance of the MT system increases with the n-gram order of LM. In the future, we will analyze the result of the English-Mizo MT systems by increasing the corpus size from different domains.

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