UCSYNLP-Lab Machine Translation Systems for WAT 2019

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Abstract

This paper describes the UCSYNLP-Lab submission to WAT 2019 for Myanmar-English translation tasks in both direction. We have used the neural machine translation systems with attention model and utilized the UCSY-corpus and ALT corpus. In NMT with attention model, we use the word segmentation level as well as syllable segmentation level. Especially, we made the UCSY-corpus to be cleaned in WAT 2019. Therefore, the UCSY corpus for WAT 2019 is not identical to those used in WAT 2018. Experiments show that the translation systems can produce the substantial improvements.

1 Introduction

In recent years, Neural Machine Translation (NMT) (Bahdanau et al., 2015) as achieved state-of-the-art performance on various language pairs (Sennrich et al., 2016) and often outperforming traditional Statistical Machine Translation (SMT) techniques. Therefore, a lot of researchers have been attracted to investigate the machine translation based on neural methods. This paper describes the NMT systems of UCSYNLP-Lab for the WAT 2019 evaluation. We participated in Myanmar-English and English-Myanmar translations in both directions.

Although Myanmar sentences are clearly delimited by a sentence boundary maker but words or phrases are not always delimited by spaces. In Myanmar language, words are composed of one or more syllables and syllables are composed of characters. And syllables are not usually separated by white space. Therefore, word segmentation and syllable segmentation are essential steps for machine translation systems. Figure 1 describes the formation of Myanmar word and Myanmar syllable in one sentence.

Moreover, Myanmar language is one of the low resource languages and there are a few parallel corpus. It is necessary to be cleaned these corpus. So, we made the UCSY-corpus to be cleaned, therefore, the UCSY corpus for WAT 2019 is not identical to those used in WAT 2018. To enhance the performance of the model, we tried NMT with attention model with word level as well as syllable level. We employed NMT with attention model as our baseline model and built our translation system based on OpenNMT open source toolkit.

The remainder of this paper is organized as follows: section 2 describes about the dataset. Section 3 describes the experimental set up and results are presented in section 4. Finally, we conclude in section 5.

2 Dataset

This section describes the dataset provided by WAT 2019 for the translation task. The datasets for Myanmar-English translation tasks at WAT2019 consists of parallel corpora from two different domains, namely, the ALT corpus and UCSY corpus. The ALT corpus is one part from

Figure 1: Formation of Myanmar sentence.

1 http://github.com/OpenNMT/OpenNMT-py
the Asian Language Treebank (ALT) project (Riza et al., 2016), consisting of twenty thousand Myanmar-English parallel sentences from the Wikinews. The UCSY corpus (Yi Mon Shwe Sin and Khin Mar Soe, 2018) is constructed by the NLP Lab, University of Computer Studies, Yangon (UCSY), Myanmar. The corpus consists of 200 thousand Myanmar-English parallel sentences collected from different domains, including news articles and textbooks.

ALT corpus size is extremely small, so a larger out-of-domain corpus for the same language pair also known as the UCSY corpus is provided. The UCSY corpus and a portion of the ALT corpus are used as training data, which are around 220,000 lines of sentences and phrases. The development and test data are from the ALT corpus. Therefore, the training data for Myanmar-English and English-Myanmar translation tasks is a mix domain data collected from different sources. Table 1 shows data statistics used for the experiments.

### 3.1 Training Data

The UCSY corpus and a portion of the ALT corpus are used as training data, which are around 220,000 lines of sentences and phrases. The development and test data are from the ALT corpus. Therefore, the training data for Myanmar-English and English-Myanmar translation tasks is a mix domain data collected from different sources. Table 2 shows the data about the training detail.

| Domain | Number of Word | Myanmar Syllable tokens |
|--------|---------------|-------------------------|
| ALT    | 698,347       | 436,923                 |
| UCSY   | 2,966,666     | 2,255,630               |
| Total  | 36,650,13     | 2,692,553               |

Table 2: Training Details Information.

### 3.2 Tokenization

The collected raw sentences are not segmented correctly and some do not have almost no segmentation. The UCSYNLP word segmenter (Win Pa Pa and Ni Lar Thein, 2008) for Myanmar word segmentation and Myanmar syllable segmenter for syllable segmentation.

UCSYNLP word segmenter is implemented a combined model, bigram and word juncture. This segmenter works by longest matching and bigram method with a pre-segmented corpus of 50,000 words collected manually from Myanmar Text Books, Newspapers, and Journals. The corpus is in Unicode encoding. After segmenting the Myanmar sentence by UCSYNLP word segmenter the “_” from the result is removed and replaced with space. Figure 2 shows the process of UCSYNLP word segmenter. It is not able to segment when “?” and “%” contains in Myanmar sentences. Examples are shown in Figure 3 and Figure 4. These sentences are segmented manually.

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2 [https://github.com/ye-kyaw-thu/sylbreak](https://github.com/ye-kyaw-thu/sylbreak)
For Myanmar syllable-based neural machine translation model, "sylbreak" is used to segment the Myanmar sentence into syllable level. Syllable segmentation is an important preprocess for many natural language processing (NLP) such as romanization, transliteration and grapheme-to-phoneme (g2p) conversion. "sylbreak" is a syllable segmentation tool for Myanmar language (Burmese) text encoded with Unicode (e.g. Myanmar3, Padauk). After segmenting the Myanmar sentence into syllable segmentation, the "|" from the result is removed and replaced with space and leading the trim process. Figure 5 shows the process of syllable segmentation for Myanmar syllable-based NMT model.

### 3.3 NMT with attention

Our NMT system is built upon NMT with attention model that links blocks of Long Short-Term Memory (LSTM) in an RNN. We used open source OpenNMT. The experiments were run on Tesla K80 GPU. We trained the word-based NMT and Myanmar Syllable-based NMT. Based on different parameter settings, the training time is different. Table 3 shows the settings of network hyper-parameters for NMT models.

The basic architecture of the Encoder-Decoder model includes two recurrent neural networks (RNNs). A source recurrent neural network (RNN) encoder reads the source sentence \( x = (x_1, \ldots, x_i) \) and encodes it into a sequence of hidden states \( h = (h_1, \ldots, h_i) \). The target decoder is a recurrent neural network that generates a corresponding translation \( y = (y_1, \ldots, y_j) \) based on the encoded sequence of hidden states \( h \). The encoder and decoder are join to train to produce the maximum log-probability of the correct translation.

In attention based encoder-decoder architecture, encoder uses a bi-directional recurrent unit that gets a better performance for long sentences. Encoder encodes the annotation of each source word to summarize getting the preceding word and the following word. Likewise, the decoder also becomes a GRU and each word \( y_j \) is predicted based on a recurrent hidden state, the previously predicted word \( y_{j-1} \), and a context vector. Unlike the previously encoder-decoder approach, the probability is conditioned on a distinct vector for each target word. This context vector is obtained from the weighted sum of the annotations \( h_k \), which is computed through an alignment model \( jk \). Training is performed using stochastic gradient descent on a parallel corpus.

![Figure 2: The process of word level segmentation.](image)

![Figure 3: Sentences that are manually segmented.](image)

![Figure 4: Sentences that are manually segmented.](image)

![Figure 5: The process of syllable level segmentation.](image)

| Hyper-parameter            | NMT models       |
|----------------------------|------------------|
| src vocab size             | 25,087 (Word Level) |
| tgt vocab size             | 50,004 (Word Level) |
| src vocab size             | 25,087 (Syllable Level) |
| tgt vocab size             | 50,004 (Syllable Level) |
| Number of hidden units     | 500              |
| Encoder layer              | 2                |
| Decoder layer              | 2                |
| Learning rate              | 1.0              |
| Dropout rate               | 0.3              |
| Mini-batch size            | 64               |

**Table 3: Hyper-parameter of NMT models.**

### 4 Experimental Results

Our systems are evaluated on the ALT test set using the evaluation metrics such as Bilingual Evaluation Understudy (BLEU) and Rank-based...
Intuitive Bilingual Evaluation Score (RIBES). Table 4 and Table 5 show the different evaluation metrics for Myanmar-English and English-Myanmar translation pairs. We also investigated how segmentation level affects the MT performance in all experiments. The experimental results reveal that word level segmentation can give better performance for Myanmar to English NMT with attention model while syllable level segmentation can give better performance for English to Myanmar NMT.

|          | BLEU | RIBES     |
|----------|------|-----------|
| Word     | 19.64| 0.707789  |
| Syllable | 15.96| 0.657564  |

Table 4: Myanmar to English Translation.

|          | BLEU | RIBES     |
|----------|------|-----------|
| Word     | 14.84| 0.697153  |
| Syllable | 20.86| 0.698507  |

Table 5: : English to Myanmar Translation.

In Myanmar to English translation, word-based NMT model outperforms Myanmar syllable-based NMT model in terms of BLEU score and the RIBES score. For Myanmar to English NMT system, word level segmentation NMT system performed much better than syllable level segmentation NMT system. That is, nearly 4 BLEU scores. However, Myanmar syllable-based NMT model gets higher score than word-based NMT in English to Myanmar translation. Interestingly, there is little difference in scores of RIBES in Myanmar syllable-based NMT model for English to Myanmar translation. For English to Myanmar NMT system, syllable level segmentation NMT system got the high BLEU scores that is nearly 6 BLEU scores. Best scores among those of the experimental results are submitted in this description.

5 Conclusions

In this system description for WAT2019, we submitted our NMT systems, which are NMT with attention. We evaluated our systems on Myanmar-English and English-Myanmar translations at WAT 2019. In the future, we will collect the more parallel sentences to get a large-sized MT corpus. And we also intend to do more and more experiments with more recent evolutions of the translation models.

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