Dzongkha to English translation using the neural machine translation approach

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ABSTRACT

In this era of technology, a communication barrier is a thing of the past. With each passing day, different types of language-based applications are being launched. There are 109 official languages Google has translated to date. However, the Dzongkha translation has not been studied. The purpose of this paper was to study Dzongkha to English translation. The parallel corpus was collected from the Dzongkha development commission of Bhutan. The dataset consisted of 53018 sentence pairs. Unique words in Dzongkha and English were 13,393 and 12,506 respectively. Different neural machine translation models were implemented. The experimental results show that the bleu score of Seq2Seq models followed a fluctuating trend. However, the bleu score of the transformer model increases gradually. It was observed that the transformer outperformed the Seq2Seq models. The highest accuracy and the lowest training loss obtained were 84.46% and 0.014858 respectively with a bleu score of 64.89.

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1. INTRODUCTION

In the past, communication and interaction between different tribes were difficult and limited. As a result, the ideas and information could not be shared. Moreover, the cultural exchange and discussion were confined to the neighborhood. Furthermore, regional and international collaboration and cooperation, such as business and tourism were difficult and limited. In addition, becoming a solo traveler around the world then was impossible. However, with the advancement of computational representation of natural languages and machine translation systems, the communication barrier has been resolved. Machine translation (MT) saves time, and unit people more locally and globally, socially, culturally, and technologically [1]. Natural language processing applications have been benefitting business entities, tourism sectors, and travelers immensely with globalization. There are 109 official languages that Google translates. However, Dzongkha is not on the list. To date, there has been no attempt to study English to Dzongkha translation or vice-versa. Nonetheless, next syllables prediction for Dzongkha [2], Dzongkha word segmentation [3], text to speech [4], part-of-speech (POS) tagging, and annotation of the corpus have been studied. To keep on par with the advancement of technologies and to resolve the digital divide in the country, the study on Dzongkha translation is timely.

MT is one of the sub-fields of computational linguistics. MT translates one language into another language [5]. The first-ever translation tasks using computers and subsequently different translation methods have been used for human language translation [6]. There are two traditional MT methods: rule-based machine translation (RBMT) and statistical machine translation (SMT). Furthermore, RBMT has three different categories: direct system, transfer RBMT system, and interlingual RBMT system. Similarly, SMT has three categories: language models, word-based SMT, and phrase based SMT [5]. RBMT is complex and requires a detailed understanding of the language. The RBMT-based systems are comprised of rules and a lexicon [7]. Rules have the syntactic knowledge of the language, whereas lexicon describes the semantic information, morphological, and syntactic rules of the language [7]. However, both rules and lexicon are based on linguistics knowledge. Therefore, these systems are difficult to maintain and expensive [7], [8]. Hurskainen and Tiedemann [9] discussed the translation of English to Finnish using RBMT. They used lexicon and syntactic information of both source and target languages. They found better results with more grammatically structured sentences. Similarly, Rajan *et al.* [10] translated English to Malayalam using RBMT. They used bilingual dictionaries and POS tags for translation.

SMT is based on a statistical analysis of bilingual text corpora [7]. The SMT, contrary to RBMT, derives rules automatically [11]. According to [12], the source language can be statistically formulated and translated into the target language. They assumed that sentence $\boldsymbol{S}$ of the source language has the possible translation $\boldsymbol{T}$ in the target language and assigned a pair $\boldsymbol{(S, T)}$ to every sentence. The probability of $\boldsymbol{S}$ given $\boldsymbol{T}$ which is represented as $\boldsymbol{P(S|T)}$ is a language model [12]. One of the SMT methods, phrase-based SMT was used [13] to translate English into Sanskrit. They proposed an SMT framework with several features such as phrase translation probability, inverse phrase translation probability, lexical weighing probability, inverse lexical weighing probability, phrase penalty, language model probability, simple distance-based distortion model, and word penalty. Over the years, different SMT paradigms have been used with multiple approaches. hybrid machine translation (HMT) approaches have been used to obtain better performance and functionality than traditional methods [14]. However, HMT is computationally expensive [11]. Furthermore, traditional approaches have performance issues. According to [5], statistical approaches do not account for phrase similarity which leads to sparsity problems. They found that models are not able to translate unseen phrases and are difficult to adapt to similar languages.

The recently proposed MT method is neural machine translation (NMT) [15]. NMT uses neural networks to represent linguistic units such as characters, words, phrases, sentences, and documents [5]. The neural network’s parameters are fine-tuned to achieve better performance and higher accuracy with minimum error. NMT uses variants of neural network architecture: encoders-decoders, encoder-decoders with attention, transformer, and BART for language translations. The recurrent neural network (RNN) encoder-decoder was proposed in [16] and is the base model for NLP sequence-to-sequence models in machine translation. The source language is given as the input to the encoder and the decoder generates translated target language. According to [17], encoder-decoder is one of the popular RNN architectures. Furthermore, deep neural networks have shown state-of-the-art in computer vision [18], [19] and natural language processing [20], [21].

The main purpose of the paper was to translate Dzongkha to English using NMT algorithms. Furthermore, the study was conducted to create a base model and parallel corpus for Dzongkha translation. The remaining section of the paper is organized as follows. Section 2 explains the parallel corpus and NMT models implemented for the translation followed by results illustration and discussion in section 3. Section 4 concludes the paper with future directions.

2. METHOD

The overview of the paper is shown in Figure 1. Substantial literature studies were conducted followed by model selection and data collection. Next, the parallel corpus was curated and NMT models were trained using Facebook’s ***fastText*** pre-trained word embedding. The details of the different phases are discussed in the following sections.

2.1. Parallel corpus

The parallel corpus was compiled from the Dzongkha development commission (DDC) of Bhutan. In addition, the dataset was accumulated from the online published article [22] that has both word and sentence-level translations. Linguists from DDC have verified translated sentences. The corpus encompasses different genres such as short stories, books, newspaper articles, songs, poetry, and daily basic conversation. The maximum sequence length of Dzongkha and English in the dataset was 29 and 13 respectively as shown in Figure 2. It was observed that Dzongkha sentences were longer than English sentences.

In the pre-processing phase, special characters and extra spaces were removed. Furthermore, sentences with digits were discarded to reduce complexity and computation. The parallel corpus consisted of 53,018 sentence pairs with 13,393 and 12,506 unique words in Dzongkha and English respectively.

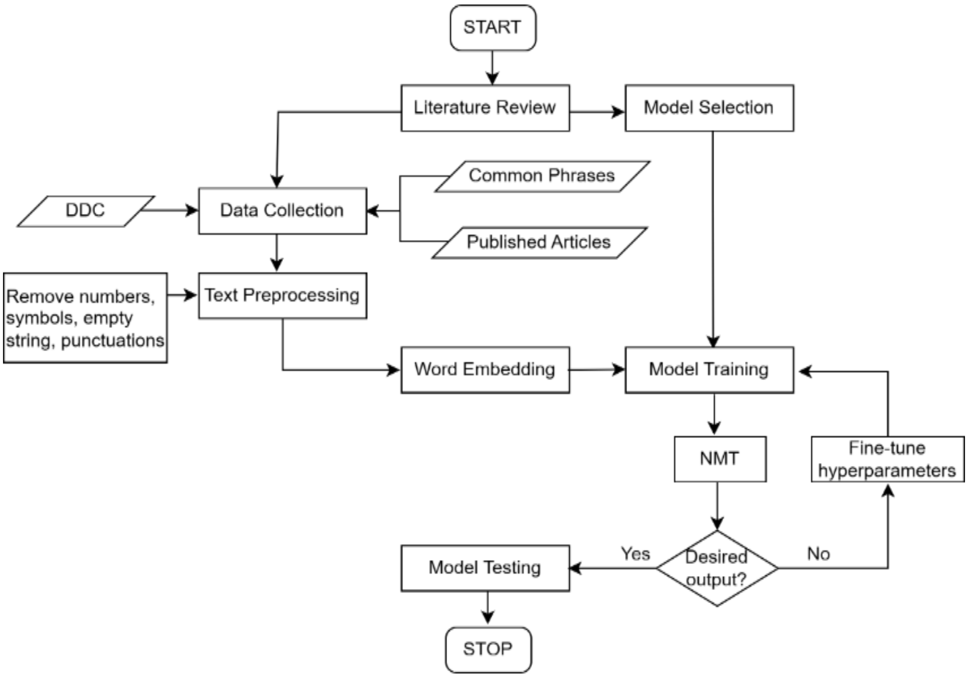

Figure 1. Overview of the study

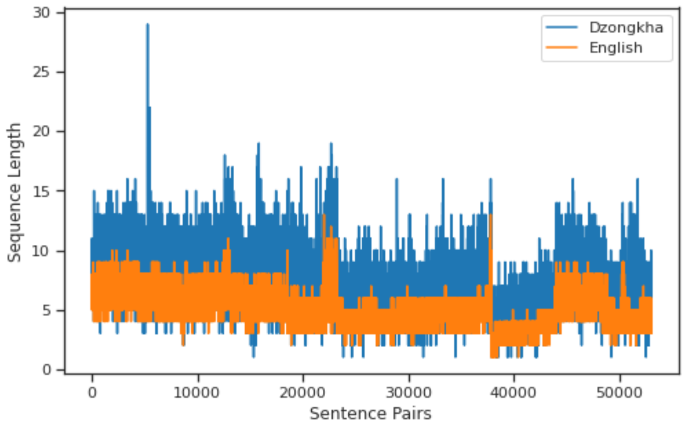

Figure 2. Varying sentence lengths of curated parallel corpus

2.2. Word embedding

Word embedding is the numeric representation of words. It captures the semantic and syntactic information of words. Similar words have similar representations. We have used pre-trained word embedding from ***fastText***. The ***fastText*** is the word embedding library released by the Facebook AI research lab in 2015. The word embeddings were trained using the continuous bag of words (CBOW) model on common crawl and Wikipedia. Word vectors were trained using CBOW with position-weights, embedding dimension of 300, n-gram characters of length five, and a window of size five and 10 negatives.

Facebook AI researchers have pre-trained 157 languages [23] to date. However, Dzongkha word embedding has not been trained. Nevertheless, Tibetan word embedding was trained. Tibetan and Dzongkha have the same alphabets, digits, and similar special symbols. As a result, Tibetan and English pre-trained word embedding were used for this paper. The size of the pre-trained word embedding available for Tibetan and English to date is 2.16 GB and 4.19 GB respectively.

2.3. Model selection and training

The NMT models such as Seq2Seq gated recurrent unit (GRU), Seq2Seq with teacher forcing, Seq2Seq with attention, and transformer were implemented. NMT addresses the shortcomings of traditional machine translation systems [24]. The architecture of NMT has two RNNs. The first RNN takes the source language as the input to the NMT and the second RNN generates translated target language as the output of the NMT. Researchers apply either LSTM or GRU to overcome the weakness of RNN. The encoder-decoder GRU was used for Dzongkha to English translation. GRU was proposed in [25] to capture dependencies of the sequences by each recurrent unit. GRU merges short and long-term memory into a single memory state. GRU is the lighter version of the LSTM and has two gates: the update gate that retains past memory and the reset gate that forgets past memory. The update $\boldsymbol{z_t}$ gate and reset $\boldsymbol{r_t}$ gate are defined in (1) and (2) respectively [25]. Both the gates depend on the current state $\boldsymbol{x_t}$ and past state $\boldsymbol{h_{t-1}}$. $\boldsymbol{\hat{h}_t}$ and $\boldsymbol{h_t}$ are GRU output and the hidden state output respectively as defined by (3) and (4) where $\boldsymbol{W}$, $\boldsymbol{U}$, and $\boldsymbol{b}$ are parameters. GRU uses two activation functions: sigmoid $\boldsymbol{\sigma_g}$ and hyperbolic tangent $\boldsymbol{\sigma_h}$. The notation $\odot$ is used to denote the element-wise product.

$$z_t = \sigma_g(W_z x_t + U_z h_{t-1} + b_z) \tag{1}$$

$$r_t = \sigma_h(W_r x_t + U_r h_{t-1} + b_r) \tag{2}$$

$$\hat{h}_t = \phi_h(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h) \tag{3}$$

$$h_t = z_t \odot h_t + (1 - z_t) + \hat{h}_t \tag{4}$$

Figure 3 shows the GRU architecture for Dzongkha to English translation adapted from [26]. There are two components: encoder and decoder. The source language (Dzongkha) was given as the input to the encoder. Similarly, the decoder was given the target language (English) for translation. During the training, both syntactic and semantic information about the language was learned. Under the hood, the encoder accepts the sequence of words from a sentence and generates a hidden state $\boldsymbol{S}$. The hidden state contains the squashed information about the entire sentence. Similarly, a hidden state for all the sentences will be generated. The encoder-generated $\boldsymbol{S}$ is passed to the decoder. The decoder considers $\boldsymbol{S}$ as input from the previous state $\boldsymbol{h_{t-1}}$ and the target sentence as the input of the current state x_t to predict the next translated word or sentence.

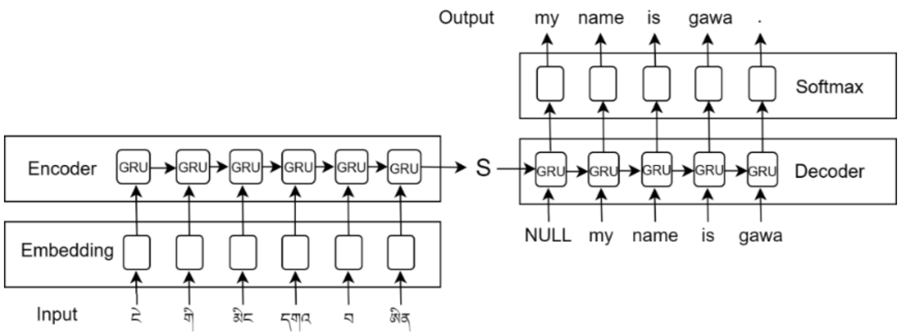

Figure 3. Seq2Seq GRU architecture [26]

The GRU has been a popular variant of RNN for maintaining long-term dependency. However, it has low learning efficiency and slow convergence. We have implemented Seq2Seq with teacher forcing, Seq2Seq with attention, and a transformer to train the translation model.

The teacher forcing solves slow convergence and efficiently trains GRU. GRU consumes output from prior time steps as input. However, teacher forcing applies ground truth from a prior time step as input that addresses the issue of GRU [27]. Furthermore, deeper GRU takes a longer duration to train and results in vanishing gradients. Consequently, gradient signals learned in the forward propagation are forgotten as it backpropagates. The attention mechanism addresses this issue. Attention considers the output of the encoder with the hidden state to pay attention to relevant words to predict the output sentence. Using ***SoftMax*** activation, the weighted sum of the outputs of the encoder is computed. The attention weights are computed and added to the input of the decoder with the linear combination of the output of the encoder as shown in Figure 4. The computation of the longer input sentences is the drawback of the attention mechanism. For each decoder output, calculation over all the encoded source sentences have to be performed [26].

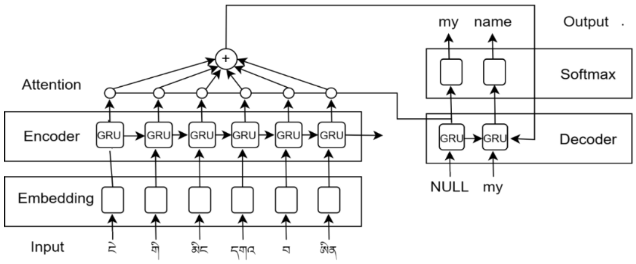

Figure 4. Seq2Seq GRU with attention mechanism [26]

In recent years, the transformer has become the biggest breakthrough in the history of natural language processing (NLP). Transformer architecture was studied by Google Brain. It consists of a stack of encoders and decoders with self-attention and pointwise, fully connected layers. Table 1 illustrates the hyperparameter settings for Dzongkha to English translation.

Table 1. Hyperparameter settings of Dzongkha to English translation transformer model

Hyperparameter	Value
Encoders	6
Decoders	6
Attention head	8
Hidden layers	6
Embedding dimension	256
Dropout	0.0

3. RESULTS AND DISCUSSION

Google provides free cloud service for machine learning through web browsers called colab. However, it has memory limitations and the allocated time for training is 12 hours. The session frequently gets disconnected with the free colab. Consequently, models were trained using Google colab pro+. It provides higher memory machines and has the option to upgrade to more powerful premium GPUs. Furthermore, the model could be trained for 24 hours without getting the session disconnected. Google provides T4 GPU with 2,560 CUDA cores, 320 tensor cores, and 16 GB GDDR6 VRAM. The Dzongkha-English parallel corpus was collected from the Dzongkha development commission of Bhutan which encompasses different genres. We randomly sampled 53,018 pairs of sentences with maximum sentence lengths limited to 29 words. The parallel corpus consisted of different sequence lengths. As a result, paddings were added to make sentence length equal. We tokenized the corpus and the embedding was trained using Facebook's ***fastText*** library with Tibetan and English pre-trained word embeddings.

To date, no Dzongkha translation has been studied. As a result, there is no benchmark to compare our results. However, different NMT models were trained on our parallel corpus with ***PyTorch*** as the backend. The implementations were adopted from [27] and models were trained for 50 epochs. As shown in Table 2, the transformer outperforms all NMT models with the highest bleu score of 64.89 and the lowest training loss of 0.013424. However, vanilla Seq2Seq and Seq2Seq with teacher forcing models have the highest accuracy of 86.57 and lowest validation loss respectively.

Table 2. Training and validation loss, accuracy, and blue score obtained by each NMT model

Model	Training loss	Validation loss	Accuracy (%)	Bleu score
Seq2Seq	2.067448	0.730322	86.57	32.84
Seq2Seq+Teacher Forcing	2.043877	1.150841	80.73	35.47
Seq2Seq+Attention	1.277456	0.802907	84.70	38.69
Transformer	0.013424	0.861913	84.46	64.89

The experimental results show that the bleu score of Seq2Seq, Seq2Seq with teacher forcing, and Seq2Seq with attention models followed a fluctuating trend as shown in Figure 5. However, the bleu score of the transformer model increased steadily but remained stagnant from 41 epochs. The bleu score of Seq2Seq models increased in the first 5 epochs. However, the vanilla Seq2Seq blue score plummeted to 3.97 from 32.84 in the tenth epoch. It was observed that the transformer outperformed the Seq2Seq models.

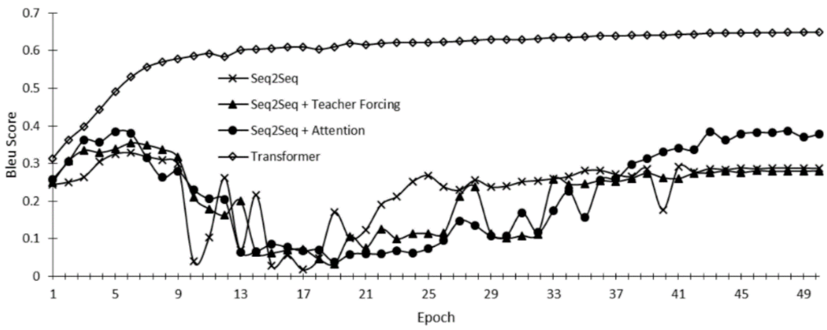

Figure 5. Comparison of bleu score of NMT models

Figure 6 illustrates NMT model accuracy and loss. Similar to the bleu score, the accuracy of Seq2Seq models followed the oscillating trend as shown in Figure 6(a). However, the accuracy of the transformer model rose gradually and remained steady from the tenth epoch. Furthermore, the training loss of Seq2Seq models decreased at the beginning and followed a similar fluctuating trend as shown in Figure 6(b). On the contrary, the loss of the transformer model gradually decreased. Our experiments performed better with the transformer compared to Seq2Seq models as illustrated in Table 3. We have observed that the Seq2Seq model with the teacher forcing and attention has repeated words in the translation sentences. However, translated sentences have the context of the input sentences and can be improved.

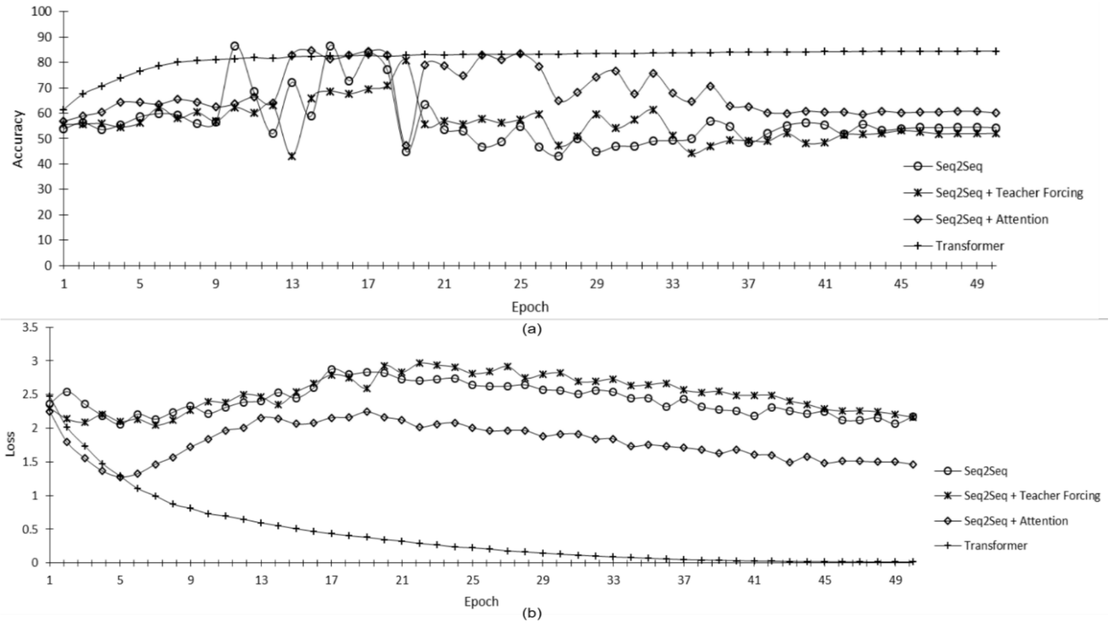

Figure 6. Comparison of NMT models (a) accuracy vs epoch and (b) loss vs epoch

Table 3. Testing the models

Model	Input sentence	Actual translation	Machine translation
Seq2Seq	ག་དེམ་ཅིག་ འབད་ ང་བཅས་ ཁྱོད་ ཀྱིས་ གྲངས་སུ་ འཛུལ་ བ་ ཅིན་ ཁྱོད་ ཀྱི་ སེམས་ ཁར་ ཐོག་ འོང་ ཡ	do you mind if we join you	how you we if do do do
+Teacher forcing			how do if if if do do
+Attention			do you if you do you
Transformer			do you mind if we join you
Seq2Seq	ག་ གིས་ ཡང་ ཁྱོད་ དང་ གཅིག་ཁར་ ལཱ་ འབད་ ནི་ གི་ རེ་ ཆེ་ མི་ བསྐྱེད	nobody wants to work with you	you do not to to to
+Teacher forcing			you one not to to with with
+Attention			no one to to work with you
Transformer			no wants to work with you
Seq2Seq	ང་ ལུ་ ཀཱར་ གསརཔ་ ཅིག་ ཉོ་ ནིའི་ སེམས་ ཅིག་ ཡོད	i have a mind to buy a new car	i am a new new car
+Teacher forcing			i am a a a car
+Attention			i am a a new car ca
Transformer			i have a new to buy a new car

4. CONCLUSION

In this paper, we have examined the appropriateness of neural machine translation models for Dzongkha to English translation. In our experiments, the transformer model outperformed sequence-to-sequence NMT models. As a result, the transformer model is suited for Dzongkha translation. The highest bleu score and the lowest training loss of the model were 64.89 and 0.013424 respectively. However, the model was trained on a subset corpus. We have analyzed and preprocessed parallel corpus. We have observed that the Dzongkha consisted of double translation, English characters, and uniform resource locators (URLs). Consequently, these sentences were discarded. In addition, sentences containing digits and long sentence lengths were removed to reduce the computational cost.

In the future, researchers can use our parallel corpus to improve the model. The accuracy and the performance of the translation model can be improved by using a bigger parallel corpus. Furthermore, zero-short learning using mT5, bidirectional and auto-regressive transformers (BART), and no language left behind (NLLB) pre-trained models can be tested with the Dzongkha-English parallel corpus.

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