English to Bengali Multimodal Neural Machine Translation using Transliteration-based Phrase Pairs Augmentation

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Abstract

Automatic translation of one natural language to another is a popular task of natural language processing. Although the deep learning-based technique known as neural machine translation (NMT) is a widely accepted machine translation approach, it needs an adequate amount of training data, which is a challenging issue for low-resource pair translation. Moreover, the multimodal concept utilizes text and visual features to improve low-resource pair translation. WAT2022 (Workshop on Asian Translation 2022) organizes (hosted by the COLING 2022) English to Bengali multimodal translation task where we have participated as a team named CNLP-NITS-PP in two tracks: 1) text-only and 2) multimodal translation. Herein, we have proposed a transliteration-based phrase pairs augmentation approach which shows improvement in the multimodal translation task and achieved benchmark results on Bengali Visual Genome 1.0 dataset. We have attained the best results on the challenge and evaluation test set for English to Bengali multimodal translation with BLEU scores of 28.70, 43.90 and RIBES scores of 0.688931, 0.780669, respectively.

1 Introduction

In recent years, multimodal approaches have shown remarkable contributions in various NLP applications such as machine translation, caption generation, etc. Especially in machine translation, multiple input modalities, like text, image, or audio/speech, integrate with NMT, known as multimodal NMT (MNMT), attempts to improve low-resource pair translation by merging visual features in addition to textual features (Shah et al., 2016). The attention-based encoder-decoder architecture of NMT handles various issues of long-term dependency and variable-length phrases via sequence-to-sequence learning and attains a state-of-the-art technique of machine translation (MT) (Bahdanau et al., 2015; Luong et al., 2015). Also, NMT shows remarkable performance for low-resource Indian languages (Pathak and Pakray, 2018; Pathak et al., 2018; Laskar et al., 2019a,b, 2020a, 2021b, 2022b). Further, to handle the data scarcity problem, the authors (Sen et al., 2020) augmenting phrase pairs and the source language transliteration-based (Laskar et al., 2022a) approach to enhance text-only based for low-resource pair translation. This paper aims to investigate English to Bengali multimodal translation task in WAT2022 with a proposed transliteration-based phrase pairs augmentation approach.

The rest of the paper is organized as follows: Section 2 presents the review of related works. The system description is briefly discussed in Section 3. Section 4 reports the results and Section 5 concludes the paper with future scope.

2 Related Work

In the literature survey, there is minimal existing work, particularly on the English to Bengali multimodal translation task (Parida et al., 2021). In (Parida et al., 2021), they used Bengali Visual Genome 1.0 (Sen et al., 2022b) adopted ViTA (Gupta et al., 2021) approach where they extracted object tags from the image and utilized mBART model (Liu et al., 2020) for encoding English sentences with the object tags and decoding to generate the Bengali translation. The obtained BLEU scores were 43.5 and 26.8 on the evaluation and challenge test sets, respectively. Moreover, the related existing works are available on English to Hindi multimodal translation task (Dutta Chowdhury et al., 2018; Sanayai Meetei et al., 2019; Laskar et al., 2019c, 2020b, 2021a). The authors (Laskar et al., 2020b, 2021a) used Hindi Visual Genome 1.1 and adopts RNN-based MNMT model (Calixto and Liu, 2017; Calixto et al., 2017) with advantages pre-trained word embeddings on monolingual corpus, achieved BLEU scores of 39.28, 39.46 on
challenge and evaluation test set respectively. This work investigates transliteration-based phrase pairs augmentation to improve the multimodal translation task of English to Bengali.

3 System Description

We have carried out four operations: transliteration-based phrase pairs augmentation, data preprocessing, model training, and testing. The OpenNMT-py (Klein et al., 2017) tool is utilized to build multimodal and text-only models separately.

3.1 Dataset Description

The dataset namely, Bengali Visual Genome 1.0\(^1\) (Sen et al., 2022b,a) is used in this task, which is provided by WAT2022 organizer (Nakazawa et al., 2022). In this dataset, the duplicates (text and image) are present in the train set, which have image ID numbers 2328549, 2391240, and 2385507. Therefore, we have removed those duplicates, and thus train set contains 28,927 images and the same number of corresponding English-Bengali parallel sentences. The validation and test (evaluation and challenge) set contains 998, 1,595, and 1,400 images and parallel text data.

3.2 Transliteration-based Phrase Pairs Augmentation

In this phase, firstly, we have expanded the training amount of data via augmentation of phrase pairs to the train set. To improve low-resource pair translation, (Sen et al., 2020) utilized SMT-based phrase pairs to increase training data via augmentation strategy. We have also followed same (Sen et al., 2020) and utilized Giza++ (Och and Ney, 2003) to extract phrase pairs(Laskar et al., 2021a) from the English-Bengali parallel train set. Before augmentation to the parallel train set, duplicates and blank lines are removed. The statistics of extracted phrase pairs are shown in Table 1.

Secondly, English source sentences are transliterated using indic-trans\(^2\) (Bhat et al., 2014)in to Bengali script following (Laskar et al., 2022a). The goal of the transliteration approach is to allow subword-level lexical sharing between source and target sentences that will be shared during the training process.

3.3 Data Preprocessing, Model Training, and Testing

The image/visual features are independently extracted from the image data using pre-trained CNN-VGG19\(^3\) for train, validation, and test data. During feature extraction, the coordinate or bounded box region information (X, Y, width, height) of the images is considered, which is available in the Bengali Visual Genome 1.0 (Sen et al., 2022b). Moreover, we have augmented image features of extracted phrase pairs. To select relevant images of the corresponding phrase pairs, we have searched each phrase in the original parallel corpus (train set), if it is found, then the corresponding image and its coordinate information are considered. But there is a problem if multiple sentences contain the same phrase subset. To tackle this issue, a filtering step solution is considered.

- First, for every phrase pair extracted from the corpus, we found the matching English segments from the corpus which have the English phrase of the En-Bn phrase pair as a sub-string (filter-1).

- If the length of the resulting data frame, i.e., the number of matching English segments for the English part of the phrase is 0, then the phrase is skipped and considered invalid. If the length is 1, since only one English segment matches it, that segment is directly selected.

- On the other hand, if the length is more than 1, i.e., more than 1 English segments have the English phrase as a sub-string, the resulting English segments are again filtered (filter-2) to check if the corresponding Bengali phrase of the phrase pairs also has subset in the Bengali segments.

  - If after filter-2, the result is 0, i.e., there are no matching Bengali segments that have the Bengali phrase as a sub-string, then from the filter-1 data-frame, i.e., the final segment from matching English segments is randomly selected.

  - If the number of matches after Bengali segment matching is 1, then that single segment is selected.

\(^1\)https://lindat.mff.cuni.cz/repository/xmlui/handle/11234/1-3722

\(^2\)https://github.com/libindic/indic-trans

\(^3\)https://github.com/iaercalixto/MultimodalNMT
| Number of Phrase Pairs | Tokens |
|------------------------|--------|
|                        | En     | Bn    |
| 127,897                | 442,657| 364,644|

Table 1: Statistics of extracted phrase pairs.

- If the number of Bengali phrase matches is more than 1, then a matching segment is randomly selected with a seed value.

For tokenization and preprocessing of text data, the OpenNMT-py toolkit is utilized. We have trained separately for multimodal and text-only NMT using the OpenNMT-py toolkit. During multimodal NMT training, the bidirectional RNN (BRNN) at the encoder and doubly-attentive RNN at the decoder are used by following default settings of (Calixto and Liu, 2017; Calixto et al., 2017). We have trained on a single GPU with early stopping criteria i.e., the model training is halted if does not converge on the validation set for more than 10 epochs. We have used a batch size of 32 during the training process. The optimum trained models of multimodal and text-only NMT are applied to the evaluation and challenge test set. The primary difference in the testing phase is that multimodal NMT uses visual features of image test data. The source English sentences of test data are transliterated and then applied to the trained model to generate the predicted target Bengali sentences.

4 Result and Analysis

The WAT2022 shared task organizer (Nakazawa et al., 2022) published the evaluation result of the multimodal translation task for English to Bengali, where our team achieves the first position in multimodal submission for both challenge and evaluation test set. Herein, we have participated with a team named CNLP-NITS-PP in the multimodal and text-only submission tracks, where a total of three teams participated. The automatic evaluation metrics, BLEU (Papineni et al., 2002), RIBES (Isozaki et al., 2010) are used for evaluation of results. Table 2 presents the results of our system. The quantitative results show that the multimodal NMT outperforms text-only NMT due to the use of visual and textual features. Furthermore, we have attained benchmark results on the evaluation and challenge test set, which is higher compared to (Parida et al., 2021). It shows +0.40 and +1.9 increment in terms of BLEU score, which realized that our approach i.e., transliteration-based phrase pairs augmentation improves the translational performance of multimodal NMT. Moreover, Figure 1 and 2 present best and worst outputs along with transliteration of Bengali words and Google translation. In Figure 1, the predicted sentences for both multimodal and text-only represent the same contextual meaning. Here, the only difference is that prachir ("wall") word in the case of the multimodal predicted sentence whereas dewal word in the case of the text-only predicted sentence and Google translation. These two words represent the same meaning corresponding to the reference sentence. However, both multimodal and text-only predicted wrong translations.

5 Conclusion and Future Work

In this work, we have proposed a transliteration-based phrase pairs augmentation approach which has been introduced in the WAT2022 multimodal translation task of English to Bengali. The multimodal NMT attains a higher score than the text-only NMT model and other existing works. Furthermore, the designed multilingual-based approach will be investigated to improve the translational performance of low-resource multimodal NMT.

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| Our System          | Test Set | BLEU | RIBES  |
|---------------------|----------|------|--------|
| Text-only NMT       | Challenge| 26.70| 0.680655|
|                     | Evaluation| 40.90| 0.752543|
| Multi-modal NMT     | Challenge| 28.70| 0.688931|
|                     | Evaluation| 43.90| 0.780669|

Table 2: Our system’s results (official) on English to Bengali multimodal translation task.
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