A Corpus for English-Japanese Multimodal Neural Machine Translation with Comparable Sentences

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Abstract

Multimodal neural machine translation (NMT) has become an increasingly important area of research over the years because additional modalities, such as image data, can provide more context to textual data. Furthermore, the viability of training multimodal NMT models without a large parallel corpus continues to be investigated due to low availability of parallel sentences with images, particularly for English-Japanese data. However, this void can be filled with comparable sentences that contain bilingual terms and parallel phrases, which are naturally created through media such as social network posts and e-commerce product descriptions. In this paper, we propose a new multimodal English-Japanese corpus with comparable sentences that are compiled from existing image captioning datasets. In addition, we supplement our comparable sentences with a smaller parallel corpus for validation and test purposes. To test the performance of this comparable sentence translation scenario, we train several baseline NMT models with our comparable corpus and evaluate their English-Japanese translation performance. Due to low translation scores in our baseline experiments, we believe that current multimodal NMT models are not designed to effectively utilize comparable sentence data. Despite this, we hope for our corpus to be used to further research into multimodal NMT with comparable sentences.

1 Introduction

In recent years, the effectiveness of utilizing image data in tandem with a text corpus to improve the quality of machine translation has been a source of extensive investigation. Several proposals have been made to incorporate visual data, such as using a doubly-attentive decoder for image and text data (Calixto et al., 2017a), initializing the encoder or decoder hidden state with image features (Calixto et al., 2017b), and using a deliberation network approach to refine translations using image data (Ive et al., 2019). However, a common difficulty is the lack of publicly available multimodal corpora, particularly for English-Japanese translation tasks. Currently, two of the only available English-Japanese multimodal datasets are the Japanese extension of the Pascal sentences (Funaki and Nakayama, 2015) and Flickr30k Entities JP (Nakayama et al., 2020), which is a Japanese translation of the Flickr30k Entities dataset (Plummer et al., 2015).

In order to contribute to the current list of English-Japanese multimodal corpora, we propose a new multimodal English-Japanese corpus with comparable sentences. Comparable sentences are sentences that contain bilingual terms and parallel phrases that describe a similar topic, but are not direct translations (Chu et al., 2015). This data is of particular interest due to its natural prevalence across various areas of media. For example, e-commerce sites in different countries may have product descriptions for similar products in different languages, or social media users may comment about images in several different languages.

In this study, we created a large comparable training corpus by compiling the existing image captions from the MS-COCO (Lin et al., 2015) and STAIR (Yoshikawa et al., 2017) captioning datasets. Furthermore, for validation and testing purposes, we translated a small subset of MS-COCO captions that
contain ambiguous verbs. The advantage of comparable sentences in relation to their available quantity can be clearly seen in Table 1, with our proposed corpus containing almost twice as many sentence pairs as Flickr30k Entities JP, the current largest parallel multimodal English-Japanese corpus. As a benchmark of current multimodal NMT models on our corpus, we performed an English-Japanese translation experiment using several baseline models, which confirmed that current NMT models are not well suited to a comparable translation task. However, we believe that our corpus can be used to facilitate research into creating multimodal NMT models that can better utilize comparable sentences.

2 Dataset Construction

Our corpus is an extension of the MS-COCO image captioning dataset (Lin et al., 2015) and the STAIR Japanese captions for MS-COCO images (Yoshikawa et al., 2017). MS-COCO contains 164,062 images and 5 corresponding English captions per image. Conversely, STAIR provides 5 Japanese captions for each of the images from the 2014 MS-COCO dataset. Because the STAIR Japanese captions were generated independently from the MS-COCO English captions but describe the same images, they are considered comparable. The textual part of our proposed corpus is split into two main portions: the training data, which is comprised of only comparable sentence pairs, and the validation and test data, which is comprised of a relatively small number of parallel sentences. On the left in Figure 1, there is an example of an English-Japanese comparable sentence pair describing an image of a restaurant. On the right, we give an example of a parallel translation from our test set that describes an image of a woman brushing her teeth.

2.1 Training Data

We started by combining the MS-COCO and STAIR training and validation datasets into one large training set, excluding images and captions that belong to our validation and test data. This left 122,826 images with 5 English and Japanese captions per image. Because there are 5 captions in both languages, there are 25 possible combinations of sentence pairs that could be associated with a single image. However, for our experiments, we selected one English and Japanese caption in order to create a single comparable sentence pair for each of the images. Overall, the training data totals to 122,826 images and an equal number of English-Japanese comparable sentence pairs.

2.2 Validation and Test Data

In order to create a test scenario to accompany our training data, we examined a subset of the MS-COCO captions known as Ambiguous COCO (Elliott et al., 2017), which consists of 461 captions that were chosen due to the ambiguous nature of their verbs. Ambiguous COCO originally only contained English, German, and French captions, so we had the English captions translated into Japanese by a translation company. This company was provided with the English captions as well as the corresponding images, and they were instructed to refer to those images during translation. The translated data was split in half, allocating 230 images and sentence pairs to the validation data and 231 to the test data.

Table 1: Summary of currently available multimodal English-Japanese corpora compared to ours.
3 Benchmarks

3.1 Baseline Models

To get preliminary performance numbers for our corpus, we tested the translation quality of several baseline NMT models that we will refer to as TEXT, DAD, and IMG. The TEXT model is an attention-based text-only NMT model (Calixto et al., 2017b) based on Bahdanau et al. (2014). The DAD model is an extension of the TEXT model that incorporates visual features through a doubly-attentive decoder RNN with two separate attention mechanisms for visual features and source sentences (Calixto et al., 2017a). Finally, the IMG model is another expansion of the TEXT model that incorporates visual features by using them as an input to initialize the hidden state of the decoder RNN (Calixto et al., 2017b). We consider these models to be good baselines for our corpus because the TEXT model is a de facto standard sequence-to-sequence model for text-based NMT, and the DAD and IMG models are representative models for multimodal NMT.

3.2 Sentence Weighting

We also investigated the effects of a method to better utilize the comparable sentences in our corpus. Inspired by the work of Chen et al. (2019), we implemented a mechanism for weighting sentences during training. The primary goal of this mechanism is to encourage the models to favor sentences that are more closely related to each other during training.

To create weights for the training sentence pairs, we started by producing a GIZA++ word alignment (Brown et al., 1993) for the concatenation of our training dataset and a large web-crawled English-Japanese parallel corpus called jParaCrawl (Morishita et al., 2020). The inclusion of a large parallel corpus helps produce better word alignments. Once the alignments were generated, we averaged the translation probabilities of every word alignment in each sentence by using the bilingual lexicon produced by GIZA++. We then normalized the resulting weights between 0 and 1 with min-max normalization. During training, we multiplied the weight for each sentence pair by the corresponding sentence-level loss.
The loss function for our sentence weighting is described in the following equation, with $N$ representing the minibatch size, $u^{(n)}$ representing the sentence weight, $T_y$ representing the last token in the target sentence, $x$ representing the source sentence, $y$ representing the target sentence tokens, and $\theta$ representing the parameters of the neural network:

$$L_{\text{weighted}} = \frac{1}{N} \sum_{n=1}^{N} u^{(n)} \sum_{i}^{T_y} \log \left( p \left( y^{(n)}_i \mid p \left( y^{(n)}_{<i}, x^{(n)}, \theta \right) \right) \right)$$  \hspace{1cm} (1)

### 3.3 Experiment Settings

First, the visual features were extracted by feeding the images into a pre-trained VGG19 network\(^3\) (Simonyan and Zisserman, 2014). Following Calixto et al. (2017b), all of the baseline models were then trained using stochastic gradient descent with Adadelta (Zeiler, 2012) and minibatches of size 40. Each model’s BLEU (Papineni et al., 2001) performance was evaluated after every epoch with our validation data, and training was stopped if performance did not improve for 20 epochs. Once the models finished training, the 230 test sentences were translated from English to Japanese. We then evaluated the translation quality of the baseline models with and without sentence weighting using the BLEU-4 (Papineni et al., 2001) and RIBES (Isozaki et al., 2010) evaluation metrics.

### 3.4 Results

Table 2 summarizes the BLEU-4 and RIBES performance of the baseline models with and without sentence weighting. Because our training data consists of comparable sentences instead of parallel sentences, it is unsurprising to see the low performance on our corpus. In the test scenario without sentence weighting, the IMG\(_D\) model performs the best out of the three models, achieving a BLEU-4 score of 7.32 and a RIBES score of 0.503. Sentence weighting did show slight BLEU-4 score improvements for both the TEXT and DAD models, but performance was still very low for all models. Conversely, the RIBES scores decreased slightly for all three models after sentence weighting. Overall, the experimental results showed that more complex changes will need to be made to existing models in order to effectively use comparable sentences for training multimodal NMT models.

### 4 Conclusion

In this paper, we have proposed a new multimodal English-Japanese corpus with comparable sentences. Based on the baseline performance of this data, we believe that current multimodal NMT models are not well suited to this type of task, and further research is required in order to better leverage the comparable sentences and images together in order to improve translation performance. In the future, we hope to see our corpus used to encourage research into multimodal machine translation tasks with comparable sentences instead of parallel sentences.

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\(^3\)Following Calixto et al. (2017b), we use the activations of the FC7 layer of the VGG19 network in Simonyan and Zisserman (2014)’s paper, which encodes information about the whole image.
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