NLPHut’s Participation at WAT2021

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Abstract

This paper provides the description of shared tasks to the WAT 2021 by our team “NLPHut”. We have participated in the English→Hindi Multimodal translation task, English→Malayalam Multimodal translation task, and Indic Multilingual translation task. We have used the state-of-the-art Transformer model with language tags in different settings for the translation task and proposed a novel “region-specific” caption generation approach using a combination of image CNN and LSTM for the Hindi and Malayalam image captioning. Our submission tops in English→Malayalam Multimodal translation task (text-only translation, and Malayalam caption), and ranks second-best in English→Hindi Multimodal translation task (text-only translation, and Hindi caption). Our submissions have also performed well in the Indic Multilingual translation tasks.

1 Introduction

Machine translation (MT) is considered to be one of the most successful applications of natural language processing (NLP)1. It has significantly evolved especially in terms of the accuracy of its output. Though MT performance reached near to human level for several language pairs (see e.g. Popel et al., 2020), it remains challenging for low resource languages or translation effectively utilizing other modalities (e.g. image, Parida et al., 2020).

1https://morioh.com/p/d596d2d4444d

The Workshop on Asian Translation (WAT) is an open evaluation campaign focusing on Asian languages since 2013 (Nakazawa et al., 2020). In WAT2021 (Nakazawa et al., 2021) Multimodal track, a new Indian language Malayalam was introduced for English→Malayalam text, multimodal translation, and Malayalam image captioning task.2 This year, the MultiIndic3 task covers 10 Indic languages and English.

In this system description paper, we explain our approach for the tasks (including the subtasks) we participated in:

Task 1: English→Hindi (EN-HI) Multimodal Translation
- EN-HI text-only translation
- Hindi-only image captioning

Task 2: English→Malayalam (EN-ML) Multimodal Translation
- EN-ML text-only translation
- Malayalam-only image captioning

Task 3: Indic Multilingual translation task.

Section 2 describes the datasets used in our experiment. Section 3 presents the model and experimental setups used in our approach. Section 4 provides the official evaluation results of WAT20214 followed by the conclusion in Section 5.

2https://ufal.mff.cuni.cz/malayalam-visual-genome/wat2021-english-malayalam-multi
3http://lotus.kuee.kyoto-u.ac.jp/WAT/indic-multilingual/
4http://lotus.kuee.kyoto-u.ac.jp/WAT/WAT2021/index.html
2 Dataset

We have used the official datasets provided by the WAT2021 organizers for the tasks.

Task 1: English→Hindi Multimodal Translation For this task, the organizers provided HindiVisualGenome 1.1 (Parida et al., 2019)\(^5\) dataset (HVG for short). The training part consists of 29k English and Hindi short captions of rectangular areas in photos of various scenes and it is complemented by three test sets: development (D-Test), evaluation (E-Test) and challenge test set (C-Test). Our WAT submissions were for E-Test (denoted “EV” in WAT official tables) and C-Test (denoted “CH” in WAT tables). Additionally, we used the IITB Corpus\(^6\) which is supposedly the largest publicly available English-Hindi parallel corpus (Kunchukuttan et al., 2017). This corpus contains 1.59 million parallel segments and it was found very effective for English-Hindi translation (Parida and Bojar, 2018). The statistics of the datasets are shown in Table 1.

| Set      | Sentences | Tokens |
|----------|-----------|--------|
|          | Train     | D-Test | E-Test | C-Test |
|          | 28930     | 998    | 1595   | 1400   |
|          | 143164    | 4922   | 7853   | 8186   |
|          | 145448    | 4978   | 7852   | 8639   |
|          | 107126    | 3619   | 5689   | 6044   |
| IITB Train | 1.5M      | 20.6M  | 22.1M  | –      |

Table 1: Statistics of our data used in the English→Hindi and English→Malayalam Multimodal task: the number of sentences and tokens.

Task 2: English→Malayalam Multimodal Translation For this task, the organizers provided MalayalamVisualGenome 1.0 dataset\(^7\) (MVG for short). MVG is an extension of the HVG dataset for supporting Malayalam, which belongs to the Dravidian language family (Kumar et al., 2017). The dataset size and images are the same as HVG. While HVG contains bilingual (English and Hindi) segments, MVG contains bilingual (English and Malayalam) segments, with the English shared across HVG and MVG, see Table 1.

Task 3: Indic Multilingual Translation For this task, the organizers provided a training corpus that comprises in total 11 million sentence pairs collected from several corpora. The evaluation (dev and test set) contain filtered data of the PMIndia dataset (Haddow and Kirefu, 2020).\(^8\) We have not used any additional resources in this task. The statistics of the dataset are shown in Table 2.

3 Experimental Details

This section describes the experimental details of the tasks we participated in.

3.1 EN-HI and EN-ML text-only translation For the HVG text-only translation track, we train a Transformer model (Vaswani et al., 2017) using the concatenation of IIT-B training data and HVG training data (see Table 1).

For both EN-HI and EN-ML translation, we trained SentencePiece subword units (Kudo and Richardson, 2018) setting maximum vocabulary size to 8k. The vocabulary was learned jointly on the source and target sentences of HVG and IIT-B for EN-HI and of MVG for EN-ML. The number of encoder and decoder layers was set to 3 each; while the number of heads was set to 8. We have set the hidden size to 128, along with the dropout value of 0.1. We initialized the model parameters using Xavier initialization (Glorot and Bengio, 2010) and used the Adam optimizer (Kingma and Ba, 2014) with a learning rate of \(5e^{-4}\) for optimizing model parameters. Gradient clipping was used to clip gradients greater than 1. The training was stopped when the development loss did not improve for 5 consecutive epochs. While EN-HI training using concatenated IIT-B + HVG data and the subsequent training using only HVG data, we used the same HVG dev set for determining early stopping. For generating translations, we used greedy decoding and generated tokens autore-

\(^5\)https://lindat.mff.cuni.cz/repository/xmlui/handle/11234/1-3267
\(^6\)http://www.cfilt.iitb.ac.in/iitb_parallel/
\(^7\)https://lindat.mff.cuni.cz/repository/xmlui/handle/11234/1-3533
\(^8\)http://data.statmt.org/pmindia/
Table 2: Statistics of the data used for Indic multilingual translation.

| Language pair | en-bn | en-hi | en-gu | en-ml | en-mr | en-ta | en-te | en-pa | en-or | en-kn |
|---------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Train (ALL)   | 1756197 | 3534387 | 518015 | 1204503 | 781872 | 1499441 | 686626 | 518508 | 252160 | 396865 |
| Train (PMI)   | 23306 | 50349 | 41578 | 26916 | 28974 | 32638 | 33380 | 28294 | 31966 | 28901 |
| Dev           | 1000  |       |       |       |       |       |       |       |       |       |
| Test          | 2390  |       |       |       |       |       |       |       |       |       |

English Text: The snow is white. Hindi Text: बफर्सफे द है
Malayalam Text: മഞ്ഞ് ആവളുത്തതാണ്
Gloss: Snow is white

Figure 1: Sample image with specific region and its description for caption generation. Image taken from Hindi Visual Genome (HVG) and Malayalam Visual Genome (MVG) (Parida et al., 2019)

(i.e., overall understanding) around the region that can essentially be captured from the entire image as shown in Figure 1. It is challenging to generate the caption “snow” only considering the specific region (red bounding box).

We propose a region-specific image captioning method through the fusion of encoded features of the region as well as that of the complete image. Our proposed model for this task consists of three modules – an encoder, fusion, and decoder – as shown in Figure 2.

**Image Encoder**: To textually describe an image or a region within, it first needs to be encoded into high-level complex features that capture its visual attributes. Several image captioning works (Yang and Okazaki, 2020; Yang et al., 2017; Lindl et al., 2018; Staniūtė and Šešok, 2019; Miyazaki and Shimizu, 2016; Wu et al., 2017) have demonstrated that the outputs of final or pre-final convolutional (conv) layers of deep CNNs are excellent features for the aforementioned objective. Along with features of the entire image, we propose to extract the features of the subregion as well using the same set of outputs of the conv layer. Let $\mathbf{F} \in \mathbb{R}^{MNC}$ be the features of the final conv
Figure 2: Architecture of the proposed model for region-specific image caption generator. The Encoder module consists of a pre-trained image CNN as feature extractor, while an LSTM-based decoder generates captions. Both modules are connected by a Fusion module.

layer of a pre-trained image CNN where $C$ represents the number of channels or maps, and $M, N$ are the spatial dimensions of each feature map. From the dimensions of the input image and the values of $M, N$, we compute the spatial scaling factor. Through this factor and nominal interpolation, we obtain a corresponding location of the subregion in the conv layer, say with dimensionality $(m, n)$. This subset, $F_s \in \mathbb{R}^{mnC}$, predominantly consists of features from the subregion. The subset $F_s$ is obtained through the region of interest (RoI) pooling ([Girshick, 2015]). We do not modify the channel dimensions of $F_s$. The final features, thus obtained, are linearized to form a single column vector. We denote the region-subset features as $S_{feat}$. The features of the complete image are nothing but $F$. We apply spatial pooling on this feature set to reduce their dimensionality, and obtain the linearized vector of full-image features denoted as $I_{feat}$.

**Fusion Module:** The region-level features capture details of the region (objects) to be described; whereas image-level features provide an overall context. To generate meaningful captions for a region of the image, we consider the features of the region $S_{feat}$ along with the features of the entire image $I_{feat}$. This combining of feature vectors is crucial in generating descriptions for the region. In this work, we propose to conduct fusion through the concatenation of weighted features from the region and those from the entire image for region-specific caption generation. The fused feature, $f$, can be represented as $f = [\alpha S_{feat}; (1 - \alpha) I_{feat}]$, where $\alpha$ is the weightage parameter in $[0.50, 1]$ indicating relative importance provided to region-features $S_{feat}$ over the features of the whole image. For $\alpha = 0.66$, the region-level features are weighted twice as high as the entire image-level features. The weighing of a feature vector scales the magnitude of the corresponding vector without altering its orientation. Unlike the fusion mechanisms based on weighted addition, we do not modify the complex information captured by the features (except for scale); however, its relative importance with respect to the other set of features is adjusted for better caption generation. The fused feature $f$ with the dimensionality of the sum of both feature vectors are then fed to the LSTM-based decoder.

**LSTM Decoder:** In the proposed approach, the encoder module is not trainable, it only extracts the image features however the LSTM decoder is trainable. We used LSTM decoder using the image features for caption generation using greedy search approach ([Soh]). We used the cross-entropy loss during decoding ([Yu et al., 2019]).

3.3 **Indic Multilingual Translation**

Sharing parameters across multiple languages, particularly low-resource Indic languages, results in gains in translation performance ([Dabre et al., 2020]). Motivated by this finding, we train neural MT models with shared parameters across multiple languages for the Indic multilingual translation task. We additionally apply transfer learning where we train a neural MT model in two phases ([Kocmi and Bojar, 2018]). The first phase consists of
training a multilingual translation model on training pairs drawn from one of the following options: (a) any Indic language from the dataset as the source and corresponding English target; (b) English as the source and any corresponding Indic language as the target; and (c) combination of (a) and (b), that is, the model is trained to enable translation from any Indic language to English and also English to any Indic language. The second phase involves fine-tuning of the model at the end of phase 1 using pairs from a single language pair. For phase 1, we used the PMI dataset for all the languages combined; whereas, for phase 2, we used either only the PMI portion or all the bilingual data available for the desired language pair. In Table 2, the training data sizes are denoted as Train (PMI) for phase 1 of training.

To support multilinguality (i.e., going beyond a bilingual translation setup), we have to either fix the target language (many-to-one setup) or provide a language tag for controlling the generation process. We highlight below the four setups to achieve this:

**Many-to-one setup with source language tag** We use a transformer model where the source language tag explicitly informs the model about the language of the source sentence as in Lample and Conneau (2019). We provide the language information at every position by representing each source token as the sum of token embedding, positional embedding, and language embedding; which is then fed to the encoder (see Figure 3 for the inputs to the encoder). The training data for phase 1 of the training process is the same as in the previous setup.

**One-to-many setup with target language tag** This setup is based on a transformer model where the target language embedding is injected to the decoder at every step and it explicitly informs the model about the desired language of the target sentence (Lample and Conneau, 2019). In this setup, the source is always in English. Similar to the previous setup, we represent each target token as the sum of token embeddings, positional embedding, and language embedding. Figure 3 shows the inputs to the decoder. In phase 1 of the training process, we concatenate across all Indic languages the pairs drawn from English as the source and the corresponding Indic language target and use the resulting data for training.

**Many-to-many setup with both the source and target language tags** In this setup, we use a transformer model where both the encoder and decoder are informed about the source and target languages explicitly through language embedding at every token (Lample and Conneau, 2019). For instance, the same model can be used for hi-en translation and also for en-hi translation. As shown in the architecture in Figure 3, the source token representation is computed as the sum of the token embedding, positional embedding, and source language embedding. Similarly, the target token representation is computed as the sum of the token embedding, positional embedding, and target language embedding. The source and the target token representations are provided to the encoder and decoder, respectively. The rest of the modules in the transformer model architecture are same as in Vaswani et al. (2017). The training

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**Figure 3:** Architecture for Indic Multilingual translation. We show here the setup in which both the source and the target language tags are used.
data for phase 1 of the training process is the combination of the training datasets for the previous two setups.

In all the four setups described above, the training data for phase 2 is the bilingual data corresponding to the desired language pair. The bilingual data is either the PMI training data or all the available bilingual training data sizes for which are provided in Table 2.

We now outline the training details for all the setups. We first trained sentence-piece BPE tokenization (Kudo and Richardson, 2018) setting maximum vocabulary size to 32k.\footnote{BPE based tokenization performed better in comparison to word-level tokenization using Indic tokenizers (Kunchukuttan, 2020).} The vocabulary was learnt jointly on all the source and target sentence pairs. The number of encoder and decoder layers was set to 3 each, and the number of heads was set to 8. We have considered the hidden size of 128; while the dropout rate was set to 0.1. We initialized the model parameters using Xavier initialization (Glorot and Bengio, 2010). Adam optimizer (Kingma and Ba, 2014) with a learning rate of $5 \times 10^{-4}$ was used for optimizing model parameters. Gradient clipping was used to clip gradients greater than 1. The training was stopped when the development loss did not improve for 5 consecutive epochs. The same early stopping criterion was followed for both phase 1 and phase 2 of the training process. For phase 1, we used the combination of the development data for all the language pairs in the training data; whereas, for phase 2, we only used the desired language pair’s development data. For generating translations, we used greedy decoding where we picked the most likely token at each generation time step. The generation was done token-by-token till the end-of-sentence token is generated or the maximum translation length is reached. The maximum translation length was set to 100.

To compare the training under various setups related to the usage of language tags, we show the perplexity of the training and the development data in Figure 4a. The best (lowest) perplexity is obtained by using the target language tag. However, using the target language tag requires more epochs to converge, where convergence is determined by the early stopping criterion described above.

We show the development BLEU scores, computed using sacreBLEU (Post, 2018) in Table 3 for each language pair. Results indicate that the usage of language tags produces better translation overall. It may also be noted that using both languages’ (source and target) tags resulted in the highest development BLEU scores for 8 out of 10 Indic languages while translating to English. For translation from English to Indic languages, the target language tag setup performed the best overall obtaining the highest development BLEU scores in 9 out of 10 languages. We selected the best systems (20 in total) based on the dev BLEU scores for each language pair and used them to generate translations of the test inputs.

The choices related to the hyperparameters that determine the model size and the choice of the training data for phase 1 of the training process were made such that the per epoch
We note that there is room for improvement in our results: (a) the model size in any of the setups described earlier can be increased to match the size of the transformer big model (Vaswani et al., 2017), and (b) all the available training data can be used for phase 1 of the training process instead of just the PMI data.

## 4 Results

| Language pair | No tag | Src. tag | Tgy. tag | Src. & trg. tags |
|---------------|--------|----------|----------|-----------------|
|               | Phase 1 | Phase 2 | Phase 1 | Phase 2 | Phase 1 | Phase 2 | Phase 1 | Phase 2 |
| bn-en         | 11.8   | 12.1    | 11.5    | 12.9    | 13.2    | 11.7    | 14.1    | 14.7    | 11.7    |
| gu-en         | 17.7   | 17.8    | 24.4    | 19.4    | 19.3    | 24.9    | -       | -       | -       |
| hi-en         | 18.7   | 19.6    | 25.6    | 21.3    | 21.6    | 26.0    | -       | -       | -       |
| kn-en         | 14.5   | 15.1    | 16.5    | 16.6    | 16.8    | 15.5    | 18.7    | 19.5    | 17.0    |
| ml-en         | 12.2   | 12.6    | 12.2    | 13.6    | 13.4    | 12.3    | -       | -       | -       |
| mr-en         | 13.3   | 12.9    | 16.1    | 14.9    | 15.1    | 17.0    | -       | -       | -       |
| or-en         | 14.0   | 14.1    | 16.9    | 15.5    | 15.6    | 18.7    | -       | -       | -       |
| pa-en         | 17.4   | 17.8    | 27.0    | 18.9    | 19.0    | 26.3    | -       | -       | -       |
| ta-en         | 13.2   | 13.2    | 15.0    | 14.7    | 14.3    | 14.6    | -       | -       | -       |
| te-en         | 14.4   | 14.5    | 16.5    | 15.6    | 16.3    | 16.8    | -       | -       | -       |

Table 3: Development BLEU scores for Indic multilingual translations in various setups after phase 1 and phase 2 of the training process. Scores are shown for each language pair separately.

Training time is below an hour on a single GPU. We note that there is room for improvement in our results: (a) the model size in any of the setups described earlier can be increased to match the size of the transformer big model (Vaswani et al., 2017), and (b) all the available training data can be used for phase 1 of the training process instead of just the PMI data.

## 5 Conclusions

In this system description paper, we presented our systems for three tasks in WAT 2021 in which we participated: (a) English―Hindi Multimodal task, (b) English―Malayalam Multimodal task, and (c) Indic Multilingual translation task. As the next steps, we plan to explore further on the Indic Multilingual translation task by utilizing all given data and using additional resources for training. We are also working on improving the region-specific image captioning by fine-tuning the object detection model.
### Table 6: Sample captions generated for the evaluation test set using the proposed method: the top two rows present results of Hindi captions; and the bottom two rows are results of Malayalam caption.

| Gold | Gloss | Output | Gloss |
|------|-------|--------|-------|
| एक लड़की टेनिस खेल रही है | A girl is playing tennis | A man holding a tennis racket | A man in the water |
| आदमी समुद्र में सर्फिंग | man surfing in ocean | Wearing helmet | A black helmet on the head of a person |
| एक कुत्ता कूदता है | A dog is jumping | A clock on the wall | A bunch of bananas |
| एक आदमी के सिर पर एक काला हेलमेट | A man in the water | The traffic light glows red | A picture on the wall |
| तोड़ गया है | A dog is running | Bright green kite | A bunch of hanging bananas |

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The authors do not see any significant ethical or privacy concerns that would prevent the processing of the data used in the study. The datasets do contain personal data, and these are processed in compliance with the GDPR and national law.

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