Transformer-based Neural Machine Translation System for Hindi –
Marathi: WMT20 Shared Task

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Abstract
This paper reports the results for the Machine Translation (MT) system submitted by the NL-PRL team for the Hindi – Marathi Similar Translation Task at WMT 2020. We apply the Transformer-based Neural Machine Translation (NMT) approach on both translation directions for this language pair. The trained model is evaluated on the corpus provided by shared task organizers, using BLEU, RIBES, and TER scores. There were a total of 23 systems submitted for Marathi to Hindi and 21 systems submitted for Hindi to Marathi in the shared task. Out of these, our submission ranked 6th and 9th, respectively.

1 Introduction
In the last decade and a half, neural machine translation (NMT) (Sutskever et al., 2014) has achieved great success in automatically translating human language text, outperforming statistical machine translation (SMT) (Koehn et al., 2003). Both the system require very large corpus sizes to train and evaluate the results. They, however, don’t work very well for low resource data (He et al., 2016; Koehn and Knowles, 2017; Dowling et al., 2018). Translation from or to low resource languages is the major challenges faced by today’s NMT systems.

Different methods have been proposed to overcome the data sparsity problem for low resource languages by researchers around the world. These include using monolingual data (Wu et al., 2019), fine-tuning (Miceli Barone et al., 2017) the high resource monolingual and parallel data on low resource data, back translation (Hoang et al., 2018), etc. They succeed up to some extent, but the success is limited, as the reported results show when compared to those for resource rich languages.

In this paper, we use the Transformer network-based NMT system (Vaswani et al., 2017) because it is among the state of the art models for machine translation. The work reported for this shared task is an extension of the work done by (Kumar and Singh, 2019) for similar languages task for 2019, which had also used a transformer based NMT system.

2 Similar Languages
Two languages are considered similar or closely related if they are close relatives in terms of the linguistic family of the linguistic family tree (or forest), or if the speakers of the two languages are in close contact over a long period of time. Contact over a long period leads to the exchange of cognates and loanwords between the speakers, sometimes even grammatical constructs.

Leveraging the close similarity of languages is one way to overcome the problem of data scarcity. Using similar features between such languages and improving translation is one of the directions for research for low resource machine translation.

For this submission, the motives behind conducting the shared task experiments are:

- To find out whether it is advantageous to use transformer-based NMT for similar languages.
- Whether using the SentencePiece library without tokenization is beneficial for translation between similar languages or not.

3 Submitted System
We submitted two systems, namely, Marathi→Hindi and Hindi→Marathi. Both are the NMT systems trained on a Transformer (Vaswani et al., 2017) network. In this experiment, we did not tokenize data using any tokenizer. We directly applied SentencePiece library on the corpus. We found that directly applying

1https://github.com/google/sentencepiece
SentencePiece for preprocessing of data gives a better result. Since both the languages come under the category of morphologically rich and similar languages, directly applying SentencePiece on their corpus is advantageous. SentencePiece breaks the sentences into morphemes and phonemes. It extracts loanwords and cognate pairs. Breaking of sentences into subwords helps the neural translation network to learn better translations, and to generalize this knowledge to translate and produce unseen words, partly due to jointly developing the subword vocabulary.

| Parameters                              | Value  |
|-----------------------------------------|--------|
| Encoder and decoder layers             | 5      |
| Encoder embedding dimension            | 512    |
| Decoder embedding dimension            | 512    |
| Encoder attention heads                | 2      |
| Decoder attention heads                | 2      |
| Dropout                                 | 0.4    |
| Attention dropout                      | 0.2    |
| Optimizer                               | Adam   |
| Learning rate scheduler                | inverse sqrt |
| Learning rate                          | 1e-3   |
| Minimum learning rate                  | 1e-9   |
| Adam-betas                             | (0.9, 0.98) |
| Number of epochs                       | 100    |

Table 1: Hyperparameters used in our experiment

4 Data

We trained the model on total 49434 number of Hindi - Marathi parallel corpus which belongs to three domains: News, PM India and Indic WordNet. Validation is done on total 1411 sentences. For testing, a total of 1941 sentences were used.

5 Experiment setup

We used fairseq \(^2\) sequence to sequence encoder-decoder framework to train and evaluate the system. For hyper-parameter settings, we used the settings reported by (Guzmán et al., 2019) as these setting work well on low resource languages. Table 1 gives the hyper-parameter settings.

6 Results

Task organizers evaluate the systems using three evaluation metric: BLEU (Papineni et al., 2002), RIBES (Isozaki et al., 2010) and Translation Error Rate (TER) (Snover et al., 2006). We report the evaluation scores in table 2.

| system                   | BLEU  | RIBES | TER    |
|--------------------------|-------|-------|--------|
| Marathi → Hindi          | 20.72 | 64.46 | 71.04  |
| Hindi → Marathi          | 12.5  | 58.66 | 76.86  |

Table 2: Scores of our system evaluated by task organizers

7 Conclusion

In this paper, we perform experiments for translation between two similar languages: Hindi and Marathi. We submitted two systems: Marathi→Hindi and Hindi→Marathi, which were evaluated using BLEU, RIBES and TER. We found that SentencePiece works well for similar languages because it helps the Transformer in capturing the relations between two languages by providing morphemes, phonemes, cognate pairs, loanwords, etc. There were a total 23 systems submitted for Marathi → Hindi and 21 systems submitted for Hindi → Marathi in the shared task. Out of these, our system ranked 6th and 9th for Marathi → Hindi and Hindi → Marathi, respectively, considering the BLEU scores.

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\(^2\)https://github.com/pytorch/fairseq
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