Panlingua-KMI MT System for Similar Language Translation Task at WMT 2019

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Abstract

The present paper enumerates the development of Panlingua-KMI Machine Translation (MT) systems for Hindi ↔ Nepali language pair, designed as part of the Similar Language Translation Task at the WMT 2019 Shared Task. The Panlingua-KMI team conducted a series of experiments to explore both the phrase-based statistical (PBSMT) and neural methods (NMT). Among the 11 MT systems prepared under this task, 6 PBSMT systems were prepared for Nepali-Hindi, 1 PBSMT for Hindi-Nepali and 2 NMT systems were developed for Nepali↔Hindi. The results show that PBSMT could be an effective method for developing MT systems for closely-related languages. Our Hindi-Nepali PBSMT system was ranked 2nd among the 13 systems submitted for the pair and our Nepali-Hindi PBSMT system was ranked 4th among the 12 systems submitted for the task.

1 Introduction

Automated translation between languages from the same family is a challenging task. While similarity among language pairs may seem to be an advantageous situation in terms of the possibility of developing better performing machine translation systems even with low quantity of resources (like low volume of parallel data), the challenge is to figure out how exactly the advantage can be leveraged and what could be the best method to do it.

The area of Statistical Machine Translation (SMT) has witnessed a continuous rise for the last two decades. The availability of open source toolkits, like Moses (Koehn et al., 2007), have also provided it an impetus. However, neural models have garnered much attention in recent times as they provide robust solutions to machine translation tasks. Their popularity is heightened further with the availability of Neural Machine Translation (NMT) open source toolkits such as OpenNMT (Klein et al., 2017), which provides an almost out-of-the-box solution for developing the first NMT systems as well as experimenting with different kinds of architectures and hyper-parameters (which is crucial for developing a good NMT system). Keeping in view the recent results obtained in MT developments, we experimented with both PBSMT as well as NMT models and evaluated how different models perform in comparison to each other. In general, NMT systems are extremely data-hungry and require huge amounts of parallel data to give a good system. The team was motivated to know if NMT could perform better than PBSMT systems even with low volume of data and without making use of monolingual data when the language pairs were closely-related.

Thus, the broad objectives behind conducting these experiments were,

a) to compare the performance of SMT and NMT in case of closely-related, relatively low-resourced language pairs, and

b) to find how SMT can be made to perform better for closely-related language pairs.

2 System Overview

This section provides an overview of the systems developed for the WMT 2019 Shared Task. In these experiments, the Panlingua-KMI team explored both phrase-based statistical (Koehn et al., 2003) method and neural method for Nepali-Hindi and Hindi-Nepali language pairs. For this purpose, 11 MT systems were developed including 6 Phrase-based Statistical Machine Translation (PBSMT) for Nepali-Hindi, 1 PBSMT for Hindi-Nepali, 2 NMT for Nepali-Hindi and 2 NMT for Hindi-Nepali.
Hindi-Nepali. The system details are provided in the following subsections.

2.1 Phrase-based SMT Systems

These systems were built on the Moses open source toolkit using the KenLM language model (Heafield, 2011) and GIZA++ aligner. ’Grow-diag-final-and heuristic’ parameters were used to extract phrases from the corresponding parallel corpora. In addition to this, KenLM was used to build 5-gram language models. The pre-processing was done to handle noise in data (for example, hyperlink, non-UTF characters etc), the details of which are provided below in section 3.1.

2.2 Neural Machine Translation System

OpeNMT (pytorch port of this toolkit) was used to build 2 NMT systems. The first system was built with 2 layers using LSTM model while the second system was built with 6 layers using the Transformer model. 500 hidden units were used.

2.3 Assessment

Assessment of these systems was done on the standard automatic evaluation metrics: BLEU (Papineni et al., 2002) and Translation Error Rate (TER) (Snover et al., 2006). TER was evaluated only for systems whose BLEU score was above 5. In addition to these, the errors of the developed systems were also analysed.

3 Experiments

This section briefly describes the experiment settings for developing the systems.

3.1 Corpus Size

The parallel dataset for these experiments was provided by the WMT Similar Translation Shared Task 1 organisers and the Nepali monolingual dataset was taken from WMT 2019 Shared Task: Parallel Corpus Filtering for Low-Resource Conditions2. The monolingual dataset for Hindi was procured from Workshop on Asian Translation Shared Task 2018 (Nakazawa et al., 2018). The parallel data was sub-divided into training, tuning and monolingual sets, as detailed in Table 1.

| Language Pair | Training | Tuning | Monolingual |
|---------------|----------|--------|-------------|
| Nepali ↔ Hindi| 65505    | 3000   | -           |
| Nepali        | -        | -      | 92296       |
| Hindi         | -        | -      | 104967      |

Table 1: Statistics of Parallel and Monolingual Sentences of the Nepali and Hindi Languages

tested on 2,000 and 1567 test sentences respectively.

3.2 Pre-processing

The following pre-processing steps were performed as part of the experiments:

a) Both corpora were tokenized and cleaned (sentences of length over 40 / 80 words were removed).

b) True-casing of Latin characters in the corpora was performed. Even though neither of the language pairs use Latin-based scripts, this was needed as the corpora for training as well as testing contained some Latin characters as well.

All these processes were performed using Moses scripts. However, the tokenization was done by the RGNLP team tokenizer (Ojha et al., 2018). This tokenizer was used since Moses does not provide tokenizer for Indic languages. Also the RGNLP tokenizer ensured that the canonical Unicode representation of the characters are retained.

3.3 Development of MT Systems

The pre-processed dataset was used to develop three MT models per language pair – two different phrase-based statistical machine translation system using different language models and one neural MT system using the encoder-decoder framework. Both of these are discussed in the following subsections.

3.3.1 Training and Development of PBMST Systems

As mentioned above, we used the Moses open source toolkit for the development of the PBMST system. The translation model (TM) and language models (LM) were trained independently and combined in a log-linear scheme where both the models were assigned a different weight using the Minimum Error Rate (MERT) Training tuning algorithm (Och and Ney, 2003). In addition, 3,000
parallel sentences were used for Nepali-Hindi and Hindi-Nepali language pairs to tune the systems. The details of the experiments are as follows:

I) Nepali-Hindi PBSMT - 6 different experiments (3 each for dataset with sentences of length up to 40 words and 80 words) were conducted for Nepali-Hindi PBSMT system. The difference among the experiments were only with respect to pre-processing alterations. It was used to gauge the effect of different pre-processing steps on the performance of MT system for closely-related languages. The following pre-processing alterations were used -

a experiments without lowercasing
b experiments without removing utterances with non-UTF characters
c experiments with complete pre-processing including lowercasing and getting rid of utterances with non-UTF characters.

II) Hindi-Nepali PBSMT - Based on our experience with Nepali-Hindi system, we developed only one system for Hindi-Nepali pair, using the dataset with complete pre-processing including lowercasing and getting rid of utterances with non-UTF characters.

3.3.2 Training and Developments of NMT Systems

The OpenNMT toolkit was used to develop the NMT systems. The training was done on two layers of LSTM network with 500 hidden units at both, the encoder and decoder models for 1,00,000 epochs. The variability of the parameters was limited with the use of default hyper-parameters configuration. Any unknown words in the translation were replaced with the word in the source language bearing the highest attention weight. All the NMT experiments were carried out only with a dataset that contained sentences with length of up to 40 words.

The hyper-parameters and details of the architecture used for the experiments are as below.

a LSTM Model - This system was built using 2-layer LSTM model (Hochreiter and Schmidhuber, 1997). Our settings followed the Open-NMT training guidelines that indicate that the default training setup is reasonable for training of any language pairs.

b Transformer Model - Another NMT system was developed using the Transformer model (implemented in pytorch port of OpenNMT) with 6 layers. The Nepali-Hindi system was trained for 20,000 epochs and Hindi-Nepali for 10,000 epochs. All other hyper-parameters were kept at default values in the OpenNMT implementation.

3.4 Post-processing

In the end, the translations of the test data using PBSMT systems were post-processed using methods including de-tokenization, de-truecasing for English tokens to improve the accuracy rate of the translated outputs.

4 Evaluation and Error Analysis

This section discusses the results of automatic evaluation, human evaluation, and comparative analysis of the PBSMT and NMT systems.

4.1 Automatic Evaluation Results

Both the PBSMT and NMT systems were evaluated using the reference set provided by the shared task organizers. The standard MT evaluation metrics, BLEU (Papineni et al., 2002) score and TER (Snover et al., 2006), were used for the automatic evaluation. These results were prepared on the Primary and Contrastive system submission which are depicted in the graph provided below as *.P and *.C, where P stands for Primary and C stands for Contrastive, respectively. The results of only the highest scoring system across both language pairs are presented in this paper. It gives a quantitative picture of particular differences across different teams, especially with reference to evaluation scores (Figure 1 and 2).

The Panlingua-KMI PBSMT system produced fourth and second best results for Nepali-Hindi and Hindi-Nepali language pair respectively, across 6 teams and 12-13 systems. Also for PBSMT systems, the Hindi-Nepali language pair

The model is trained on 1,00,000 epochs, using Adam with a default learning rate of 0.002 and mini-batches of 40 with 500 hidden units. Vocabulary size of 32308 and 32895 for Nepali-Hindi and Hindi-Nepali language pairs respectively was extracted. A static NMT-setup was maintained with the use of same hyper-parameters setting across two language pairs.
showed better results in terms of both the metrics (11.5 in BLEU, 79.1 in TER) while the Nepali-Hindi language pair scored 9.8 in BLEU, 91.3 in TER.

4.2 Comparative Analysis of the PBSMT and NMT Systems

Across both the language pairs, PBSMT performed better than NMT as its accuracy rate was higher in BLEU and lower in TER metrics as shown in Figures 1 and 2. On further manual inspection of the outputs produced by Nepali-Hindi and Hindi-Nepali PBSMT, NMT-LSTM and
NMT-Transformer systems, we found that the outputs produced by the PBSMT seemed better than those produced by the NMT systems (shown in Figures 3 and 4).

Figure 3: Comparative Analysis of Nepali-Hindi PB-SMT, NMT and NMT-Transformer MT’s Output

Figure 4: Comparative Analysis of Hindi-Nepali PB-SMT, NMT and NMT-Transformer MT’s Output

5 Conclusion

The entire series of experiments revealed several aspects of developing NMT system for closely-related languages. It may seem that NMT performs better than SMT on fluency level (3 and 4) but the relation between source and target language is erroneous, thereby, resulting in poor BLEU score and higher TER. Also, alterations at pre-processing stage do not render any improvement in SMT system, thus, strengthening the importance of lower casing and excluding non-UTF characters from the data sets. It was also observed that datasets with maximum length of sentences up to 40 words performed better than those with up to 80 words.

The larger picture, based on these experiments, reveal that similarities between two languages did not yield any advantage, as expected at the initial stage. Thus it could be concluded that similar features shared between two languages do not have any significant effect on the performance of the MT systems, at least, as long as the standard methodologies are employed for developing the systems. In order to make use of the similarity in between the language pairs, some more sophisticated methods need to be explored and is a matter of further research.

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