Abstract

In this paper, we describe our submissions for Similar Language Translation Shared Task 2020. We built 12 systems in each direction for Hindi ⇐⇒ Marathi language pair. This paper outlines initial baseline experiments with various tokenization schemes to train statistical models. Using optimal tokenization scheme among these we created synthetic source side text with back translation. And prune synthetic text with language model scores. This synthetic data was then used along with training data in various settings to build translation models. We also report configuration of the submitted systems and results produced by them.

1 Introduction

Machine Translation systems are models which aim to translate text from one language into another. There are multiple ways of building such a model (Rule Based, Data driven, Hybrid etc.). In this system description paper, we use data driven techniques to build MT systems. As the name suggests, data driven MT systems make use of parallel sentences (i.e. \(x^{th}\) sentence in two languages have same meaning). We make use of statistical (Koehn et al., 2003) and neural (Bahdanau et al., 2014) methods to build systems for Hindi-Marathi pair. Hindi-Marathi language pair comes under purview of similar languages. Similar Languages are languages which exhibit lexical and structural similarities (Kunchukuttan et al., 2014a). This can be due to common ancestry or being in close proximity for long time. In current digital age communication, translation between similar language is a justifiable requirement. But there is a scarcity of good quality bitext for many language pairs, as is the case of Hindi-Marathi. Hence, we used characteristics displayed by similar languages (in this case Hindi and Marathi) like similar form of spelling, pronunciation etc. Following Kunchukuttan and Bhattacharyya (2017) and Kunchukuttan et al. (2014b) we made use of byte pair encoding (Sennrich et al., 2016b) and morfessor toolkit (Virpioja et al., 2013) respectively as part of preprocessing step before training. Using cues from Koehn and Knowles (2017) and looking at the size of training data provided, we use statistical method to build initial models. To further salvage similarity between this language pair we made use of backtranslation (Sennrich et al., 2016a) to generate more synthetic data for further training using both neural and statistical methods.

For this shared task we developed 12 translation systems in each direction (Hindi ⇐⇒ Marathi). To rank systems, we went through some test instances subjectively and also compared our BLEU scores with another Translation system. And chose top 2 systems in both direction using both subjective examination and detoknized BLEU scores. Subsequent sections give more detailed overview of systems developed.

2 Seed MT systems using different tokenization schemes

Experiments in Koehn and Knowles (2017) show that Statistical Machine Translation model fairs better when compared to Neural model in case of low resource setting. So, we make use of SMT model to make initial baseline systems using various tokenization schemes. We use these systems as seed system, used to create synthetic dataset for further training by back translation.

2.1 Data

For our initial experiments we just used parallel and monolingual corpora shared by the organizers. We include training data to monolingual corpus for each language (LM corpus) to make language model. Parallel text consisted of bitext from 3
Table 1: Total number of Tokens in each file after various tokenization schemes, last sub-column in both languages column denotes total number of lines in respective corpus

| Corpus/Language | Hindi | Marathi |
|-----------------|-------|---------|
| # of Tokens     | basicTok | BPE | Morf | basicTok | BPE | Morf |
| Train           | 840863 | 977742 | 38246 | 38246 | 638467 | 867968 | 851394 | 38246 |
| Dev             | 32106 | 36482 | 34600 | 1411 | 25552 | 33997 | 33828 | 1411 |
| Monolingual     | 1455510657 | 1760885875 | 1629220967 | 77722389 | 4834280 | 6715047 | 6526439 | 369403 |

2.2 Preprocessing

We used the IndicNLP toolkit\(^1\) to tokenize all corpora as first preprocessing step. Then we made use of a BPE (Sennrich et al., 2016b) model trained with 10000 merge operations on the LM corpus for both Hindi and Marathi. The resultant model was used to tokenize words to subwords in sentences for all texts. Morfessor (Virpioja et al., 2013) was also used as another alternative preprocessing step. We trained a morfessor model on the full LM corpus of Marathi and an equally sized Hindi Corpus. And taking cue from IndicNLP toolkit, we used ‘+’ as delimiter when segmenting words into segments i.e. a word $xyz$ which was to segment as $x \ yz$ will segment as $x+ \ yz$. Table 1 shows statistics of preprocessed data. We used all possible combinations of tokenization schemes while training initial models, these tokenization schemes were,

- Basic tokenization denoted as BasicTok in Table 1 which make use of IndicNLP toolkit.
- BPE which tokenize words into subword and is denoted as BPE.
- Tokenization using Morfessor, which is denoted as Morfes.

2.3 Machine Translation Model

We made use of Moses toolkit (Koehn et al., 2007) to build statistical models trained with tokenized bitext. We also use GIZA++ (Och and Ney, 2003) to find alignments between parallel text and grow-diag-final-and method (Koehn et al., 2003) to extract aligned phrases. And utilize KenLM (Heafield, 2011) to train a trigram model with kneser ney smoothing on monolingual corpus of both languages. MERT (Och, 2003) is used for tuning the trained models. We evaluated these models on dev set. Results are given in Table 2.

2.4 Using back-translation to augment training data

Based on the results in Table 2 we make use of following tokenization schemes depending on direction of translation,

- BPE as tokenization preprocessing scheme on both languages when translation direction is from Hindi to Marathi.
- Morf as tokenization scheme for Marathi and Basic tokenization for Hindi when translating from Marathi to Hindi.

After translating monolingual corpus, we did the following post processing based on direction of translation,

- In case of Marathi to Hindi translation, in post processing we remove ’+’ delimiter. This is due to Marathi being morphological richer than Hindi.
- For Hindi to Marathi, we simply joined the subwords in text translated.

Due to time constraint we translated some part of Hindi monolingual corpus (Authentic\(_{Hindi}\)) to Marathi (Synthetic\(_{Marathi}\)). We used beam search with default setting in Moses for this translation. We used already trained LM from Section 2.3 to learn average LM score of BPE tokenized Marathi monolingual corpus. Synthetic\(_{Marathi}\) is than pruned (SyntheticPruned\(_{Marathi}\)) by keeping back-translated sentences which have LM score higher than average LM score on aforementioned Corpus. Same process is followed while translating Authentic\(_{Marathi}\) to Synthetic\(_{Hindi}\) and further pruning to get SyntheticPruned\(_{Hindi}\). Statistics related to back-translated data and resultant pruned corpus is given in Table 3.

\(^1\)http://anoopkunchukuttan.github.io/indic_nlp_library/
Table 2: BLEU Scores on dev dataset when we use SMT models which are trained in all combinations of 3
tokenization schemes.

| Experiment | Tokenization Based Exp | Hin To Mar | Mar To Hin |
|------------|------------------------|------------|------------|
| 1          | Hindi BasicTok – Mar BasicTok | 19.937     | 24.542     |
| 2          | Hindi BPE – Mar BasicTok  | 19.225     | 23.13      |
| 3          | Hindi Morfes. - Mar BasicTok | 19.1327    | 23.44      |
| 4          | Hindi BasicTok – Mar BPE  | 19.02      | 25.836     |
| 5          | Hindi BPE – Mar BPE       | 20.06      | 26.07      |
| 6          | Hindi Morfes. - Mar BPE   | 19.43      | 25.45      |
| 7          | Hindi BasicTok – Mar Morfes. | 19.37     | 26.282     |
| 8          | Hindi BPE – Mar Morfes.   | 19.49      | 25.30      |
| 9          | Hindi Morfes. - Mar Morfes. | 19.33     | 26.03      |

Table 3: Statistics of back translated data

| Back Translation direction L1 to L2 | Hindi to Marathi | Marathi to Hindi |
|-------------------------------------|------------------|------------------|
| Sentences translated                | 456106           | 369403           |
| Average KenLM Score of Monolingual data in L2 | 62.66 | 42.25 |
| Sentences which are above this LM score | 283043 (62.05%) | 215417 (58.31%) |
| Average Sentence length of pruned corpus with standard deviation | 10.25, 4.80 | 11.57, 4.52 |

3 MT models using augmented bitext

For augmented data experiments we had following datasets available for training,

- Original training text
- Synthetic Marathi and Authentic Hindi
- Synthetic Pruned Marathi and Authentic Pruned Hindi
- Synthetic Hindi and Authentic Marathi
- Synthetic Pruned Hindi and Authentic Pruned Marathi

We ran experiments on following dataset combinations, for Hindi to Marathi Systems with BPE
tokenization on both Hindi and Marathi,

1. Original training text + Synthetic Marathi and Authentic Hindi + Synthetic Hindi and Authentic Marathi
2. Original training text + Synthetic Pruned Marathi and Authentic Pruned Hindi + Synthetic Pruned Hindi and Authentic Pruned Marathi
3. Original training text + Synthetic Marathi and Authentic Hindi + Synthetic Hindi and Authentic Marathi
4. Original training text + Synthetic Pruned Hindi and Authentic Pruned Marathi

And for Marathi to Hindi System, we ran following dataset combinations with morfessor model toke
nization on Marathi and Basic Tokenization on Hindi,

1. Original training text + Synthetic Hindi and Authentic Marathi + Synthetic Marathi and Authentic Hindi
2. Original training text + Synthetic Pruned Hindi and Authentic Pruned Marathi + Synthetic Pruned Marathi and Authentic Pruned Hindi
3. Original training text + Synthetic Marathi and Authentic Hindi
4. Original training text + Synthetic Pruned Marathi and Authentic Pruned Hindi

All these dataset combinations were used to train following methods to build MT models with respective
default configurations available in respective toolkits,

- SMT model using Moses toolkit (Koehn et al., 2007)
- NMT model with attention using Opennmt toolkit (Klein et al., 2017)
- NMT model with attention and copy attention (See et al., 2017) using Opennmt toolkit, to make use of similarity between Hindi Marathi language pair
4 Result

To submit two best systems out of 12 in each direction as directed by shared task, we did two evaluations. Firstly, we compared our system outputs to output of another publicly available translation model. Second, we went through some random outputs of all system outputs. We found that in most systems synthetic-authentic dataset which was not pruned with LM scores along with original training set performed better than pruned augmented bitext and original corpus. Following this, we selected following system outputs as our submission,

- Hindi to Marathi System:
  - Primary Submission: NMT with Attention + Original parallel text + SyntheticHindi_AuthenticMarathi
  - Contrastive Submission: NMT with Attention and CopyAttention + Original parallel text + SyntheticMarathi_AuthenticHindi + SyntheticHindi_AuthenticMarathi

- Marathi to Hindi System:
  - Primary Submission: NMT with Attention + Original parallel text + SyntheticMarathi_AuthenticHindi + SyntheticHindi_AuthenticMarathi
  - Contrastive Submission: SMT + Original parallel text + SyntheticMarathi_AuthenticHindi + SyntheticHindi_AuthenticMarathi

Table 4 gives the scores we received for these systems.

| Language Direction | Submission Type | BLEU | RIBES | TER |
|--------------------|----------------|------|-------|-----|
| Hindi to Marathi   | Primary        | 11.41| 57.2  | 79.96|
| Hindi to Marathi   | Contrastive    | 10.21| 55.17 | 82.01|
| Marathi to Hindi   | Primary        | 18.32| 59.31 | 77.35|
| Marathi to Hindi   | Contrastive    | 14.11| 60.76 | 77.28|

Table 4: Scores for our systems

Both of our Hindi to Marathi Systems were somewhere in the middle compared to the other submissions. On the other hand Marathi to Hindi Contrastive submission (which was trained using SMT) was in top 5 standings.

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