A3-108 Machine Translation System for Similar Language Translation
Shared Task 2021

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Abstract

In this paper, we describe our submissions for the Similar Language Translation Shared Task 2021. We built 3 systems in each direction for the Tamil ⇐⇒ Telugu language pair. This paper outlines experiments with various tokenization schemes to train statistical models. We also report the configuration of the submitted systems and results produced by them.

1 Introduction

Machine translation is a process of translating text from a source to a target language. There are multiple ways of building such a system - Rule-based, Data-driven, Hybrid etc. In this shared task, we use data-driven method to create machine translation system for Tamil ⇐⇒ Telugu. Due to low-resource setting of this language pair in the shared task, we use Statistical Machine translation method (Koehn et al., 2003), (Koehn and Knowles, 2017) to build systems.

Tamil Telugu language pair comes under the bracket of similar languages. Similar languages show similarity in their lexical and syntactical properties (Kunchukuttan et al., 2014a). This may be due to them being in close proximity of each other for long time. This can also be due to common ancestry. In the current digital context, translation between similar languages is of importance. But there can be scarcity of good quality parallel text. In the current shared task, we have a language pair which is morphologically rich and with ≃39K parallel sentences. So, following Kunchukuttan and Bhattacharyya (2017) and Kunchukuttan et al. (2014b) we use sentencpiece (Kudo and Richardson, 2018) and morfessor (Virpioja et al., 2013) to segment tokens in the dataset into subwords. And due to the size of parallel text (≃39K parallel text) coming under purview of low resource, we make use of Moses (Koehn et al., 2007) to create statistical machine translation models (Koehn and Knowles, 2017).

For this shared task we developed 3 translation systems (1 Primary and 2 Contrastive) in each direction Tamil ⇐⇒ Telugu. For each output we post-processed and detokenized translation output depending on the tokenization scheme for target language. To choose a primary and 2 contrastive systems, we compared BLEU (Papineni et al., 2002) scores on output of development dataset for each system using sacrebleu (Post, 2018). The following sections give more details about the systems developed.

2 SMT systems using different schemes

We used various tokenization schemes to build translation systems. Evaluated these systems on the development dataset. After post-processing, detokenizing and scoring each translation output, we submit output systems as primary and contrastive submissions accordingly.

2.1 Data and preprocessing

We used parallel data provided by the organizers to train all the models. IndicNLP (Kunchukuttan, 2020) was used to normalize and tokenize datasets. 2 Subword models were trained on tokenized text for each language. Sentencepiece (Kudo and Richardson, 2018) was used to prepare a subword tokenizer model with vocabulary size set to 32000 and character coverage set to 0.9995. Another alternative tokenization model was trained on morfessor (Virpioja et al., 2013). To create 3 systems for each translation direction, we used the

1https://github.com/google/sentencpiece
2https://github.com/aalto-speech/morfessor
3https://github.com/moses-smt/mosesdecoder
4https://github.com/mjpost/sacrebleu
5https://github.com/anoopkunchukuttan/indic_nlp_library
Table 1: Statistics of Tamil and Telugu datasets

| Dataset with tokenization | Tamil | Telugu | Total number of Lines |
|---------------------------|-------|--------|----------------------|
|                           | Total Token Count | Total Unique Token | Avg Token Per line | Total Token Count | Total Unique Token | Avg Token Per line |
| Train.basicTok            | 691433 | 74341  | 17.22                | 725365 | 72949  | 18.06                | 39836 |
| Dev.basicTok              | 30017  | 9683   | 23.80                | 30359  | 9467   | 24.07                | 1261  |
| Train.spm                 | 770632 | 31674  | 19.63                | 956023 | 31782  | 24.35                | 39246 |
| Dev.spm                   | 36672  | 8647   | 29.08                | 41779  | 9112   | 33.13                | 1261  |
| Train.morf                | 956485 | 13956  | 24.47                | 947463 | 17823  | 24.24                | 39081 |
| Dev.morf                  | 45279  | 5496   | 35.90                | 43602  | 6380   | 34.57                | 1261  |

Table 1 shows the statistics of the Tamil and Telugu dataset for each tokenization scheme after using clean-corpus-n.perl script with 1,70 as min,max line length for training text. No additional monolingual dataset was used in building any of the models.

2.2 MT Systems

We build a trigram language model with kneser ney smoothing for each language in each tokenization scheme using KenLM (Heafield, 2011). And used Moses (Koehn et al., 2007) to train an SMT system. MERT (Och, 2003) is used for tuning the trained model on development datasets. The performance of all systems, for each language direction on respective tokenized development datasets, is given in Table 2. For this shared task, we submit 3 systems:

- A3-108_TE_TA_PRIMARY.txt: basicTok Telugu -> basicTok Tamil system - trained using SMT model - tokenized using indic nlp library.
- A3-108_TE_TA_CONTRASTIVE1.txt: morf Telugu -> morf Tamil system - trained using SMT model - tokenized using morfessor into subwords for training
- A3-108_TE_TA_CONTRASTIVE2.txt: spm Telugu -> spm Tamil system - trained using SMT model - tokenized using sentencepiece into subwords for training

- For Tamil to Telugu,
  - A3-108_TA_TE_PRIMARY.txt: morf Tamil -> morf Telugu system - trained using SMT model - tokenized using morfessor into subwords for training
  - A3-108_TA_TE_CONTRASTIVE1.txt: basicTok Tamil -> basicTok Telugu system - trained using SMT model - tokenized using indic nlp library.
  - A3-108_TA_TE_CONTRASTIVE2.txt: spm Tamil -> spm Telugu system - trained using SMT model - tokenized using sentencepiece into subwords for training

2.3 Results

This subsection compares the results of our systems, which we received from organizers, in terms of BLEU scores. Table 3 shows the BLEU scores for Telugu to Tamil systems. In comparison with other systems, all of our system outputs score highest. We were hoping that, in test cases, models using subwords for training and translating would prove to be better than basicTok, but that was not the case. Instead models trained on basicTok fared better.

Table 2: BLEU score on development dataset for each system

| Tamil ->Telugu | Telugu ->Tamil |
|----------------|----------------|
| basicTok       | 7.7            | 9.9            |
| spm            | 5.2            | 9.0            |
| morf           | 7.7            | 9.8            |
Table 3: Scores on test dataset for each Telugu to Tamil system

| System Type          | BLEU | RIBES | TER   |
|----------------------|------|-------|-------|
| PRIMARY (basicTok)   | 8.37 | 43.55 | 95.884|
| CONTRASTIVE1 (morf)  | 7.89 | 46.24 | 95.627|
| CONTRASTIVE2 (spm)   | 7.43 | 42.54 | 94.964|

Table 4 shows the BLEU score we received for Tamil to Telugu systems. Our system outputs from

| System Type          | BLEU | RIBES | TER   |
|----------------------|------|-------|-------|
| CONTRASTIVE1 (basicTok) | 5.54 | 40.58 | 98.082|
| PRIMARY (morf)       | 5.23 | 42.37 | 98.662|
| CONTRASTIVE2 (spm)   | 3.32 | 34.42 | -     |

Table 4: Scores on test dataset for each Tamil to Telugu system

CONTRASTIVE1 and PRIMARY submission are in the top 3 in comparison with other systems. Here again, we see basicTok model fared a bit better than model trained on morf segmented dataset. And sentencepiece model was ≃2 BLEU points behind both the systems. These BLEU scores (CONTRASTIVE1, PRIMARY) are in the top 3. Again, we were hoping, that in test cases, models using subwords for training and translating would prove to be better. But as was case in Telugu to Tamil, here also models trained on basicTok dataset fared better, followed by models trained on morfessor segmented dataset.

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