Spartans@LT-EDI-EACL2021: Inclusive Speech Detection using Pretrained Language Models

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Abstract
We describe our system that ranked first in Hope Speech Detection (HSD) shared task and fourth in Offensive Language Identification (OLI) shared task, both in Tamil language. The goal of HSD and OLI is to identify if a code-mixed comment or post contains hope speech or offensive content respectively. Our work extends that of (Arora, 2020a) as we use their strategy to synthetically generate code-mixed data for training a transformer-based model RoBERTa and use it in an ensemble along with their pre-trained ULMFiT.

1 Introduction
Language has the ability to build relationships and forge connections but it is equally liable for creating barriers and impacting someone’s sense of belonging. The language used on the internet has an impact on people across the globe. It is important to build language technology which makes everyone feel valued and included. We make contributions to this field by competing in two shared tasks:

1. Hope Speech Detection (HSD) at First Workshop on Language Technology for Equality, Diversity, Inclusion1 (LT-EDI-2021)
2. Offensive Language Identification (OLI) in Dravidian Languages at First Workshop on Speech and Language Technologies for Dravidian Languages2 (DravidianLangTech-2021)

Hope is considered significant for the well-being, recuperation and restoration of human life by health professionals. Hope speech reflects the belief that one can discover pathways to one’s desired objectives and become motivated to utilize those pathways (Snyder et al., 1991; Chang, 1998). The goal of HSD task is to identify whether a YouTube comment contains hope speech or not. The datasets are available in English, code-mixed Tamil-English and Malayalam-English. OLI task intends to identify offensive language content in datasets comprising of comments/posts in code-mixed Tamil-English, Malayalam-English and Kannada-English which are collected from social media. Both datasets have been annotated at a comment level wherein a comment could comprise of more than one sentence but on average it has a single sentence.

Our work is an extension of the work done in (Arora, 2020a) as we use their synthetic code-mixed dataset for Tamil and ULMFiT model trained on that dataset. We pre-train a transformer based model RoBERTa (Liu et al., 2019) from scratch on code-mixed data and build an ensemble using ULMFiT and RoBERTa to achieve:

• Weighted F1 score of 0.61 for Tamil HSD and Rank 1 amongst 30 participating teams
• Weighted F1 score of 0.75 for Tamil OLI and Rank 4 amongst 30 participating teams

We review some related work from literature before explaining the details of our approach and the results. All experiments described in the paper can be reproduced using the source code available on GitHub3.

2 Related Work
As noted on the LT-EDI 2021’s website4, this is the first shared task on HSD. Some work has been previously done for HSD (Palakodety et al., 2019),

1equal contribution
1https://sites.google.com/view/lt-edi-2021/home
2https://dravidianlangtech.github.io/2021/
3https://github.com/goru001/nlp-for-tanglish
4https://sites.google.com/view/lt-edi-2021
but we are not aware of any work for HSD in Tamil language. OLI has been an area of active research in both academia and industry for the past two decades. Recent work has been done for OLI in Dravidian languages in HASOC task at FIRE (Mandl et al., 2020). HASOC task, which attracted over 40 research groups, consisted of building Hate Speech and Offensive Language identification systems by using datasets prepared by extracting comments/posts from YouTube and Twitter. In this paper, we build classification models for HSD and OLI using Transfer Learning, details of which have been explained in Section 3.

3 Methodology

In this section we look at classification datasets, discuss details of RoBERTa and ULMFiT models and the classifiers which are trained on top of these language models.

3.1 Dataset

**Dataset for RoBERTa pre-training.** We use synthetically generated code-mixed data for Tamil\(^5\) prepared in (Arora, 2020a) to pretrain RoBERTa.

\(^5\)Pre-training dataset can be downloaded from https://github.com/goru001/mlp-for-tanglish

from scratch. The dataset is a collection of Tamil sentences written in Latin script. It was prepared by transliterating Tamil Wikipedia articles using Indic-Trans\(^6\) library.

**Classification datasets.** Table 1 shows statistics of datasets of both tasks. We observe that the statistics are fairly consistent across train, valid and test sets. Classification dataset for HSD (Chakravarthi, 2020) has 3 classes whereas that in OLI has 6 classes. Both the classification datasets have significant class imbalance depicting real-world scenarios. Additionally, they contain code-mixed comments/posts in both Latin and native scripts, making the tasks challenging.

### Table 1: Dataset statistics for OLI and HSD tasks

| Metric                              | Offensive Language Identification | Hope Speech Detection |   |
|-------------------------------------|-----------------------------------|-----------------------|---|
| Number of classes                  | 6                                 | 3                     |   |
| Dataset size                        | Train: 35139 Valid: 4388 Test: 4392 | Train: 16160 Valid: 2018 Test: 2021 |   |
| %age of examples containing only Roman characters | 80.4% Valid: 81% Test: 81.2% | Train: 83.9% Valid: 83.8% Test: 84.8% |   |
| min. no. of examples in a class     | 454 Valid: 65 Test: - | Train: 1961 Valid: 263 Test: - |   |
| max. no. of examples in a class     | 25425 Valid: 3193 Test: - | Train: 7872 Valid: 998 Test: - |   |
| avg. no. of examples in a class     | 5856.5 Valid: 731.33 Test: - | Train: 5386.67 Valid: 672.67 Test: - |   |
| min no. of tokens in an example     | 1 Valid: 2 Test: 1 | Train: 1 Valid: 1 Test: 2 |   |
| max no. of tokens in an example     | 183 Valid: 93 Test: 138 | Train: 204 Valid: 159 Test: 187 |   |
| avg no. of tokens in an example     | 12.04 Valid: 12.03 Test: 11.89 | Train: 9.57 Valid: 9.97 Test: 11.07 |   |
| median no. of tokens in an example  | 9 Valid: 9 Test: 9 | Train: 7 Valid: 7 Test: 8 |   |

### Table 2: Validation set perplexity of RoBERTa and ULMFiT

| Model Architecture | Perplexity | Vocab size |
|--------------------|------------|------------|
| RoBERTa            | 8.4        | 10000      |
| ULMFiT             | 37.50      | 8000       |

### Table 2: Validation set perplexity of RoBERTa and ULMFiT

3.2 Modeling Details

We take a two-step approach to the problem by pretraining ULMFiT (Howard and Ruder, 2018) and RoBERTa (Liu et al., 2019) models on synthetically generated code-mixed language followed by an ensemble of two classifiers which are trained on top of ULMFiT and RoBERTa language models respectively.

3.2.1 ULMFiT Model

We use pre-trained ULMFiT model for code-mixed Tamil similar to the one used in (Arora, 2020b). Its embedding size is 400, number of hidden activations per layer are 1152 and the number of layers are 3. Two linear blocks with batch normalization and dropout have been added as custom head for the classifier with rectified linear unit activations for the intermediate layer and a softmax activation
| Dropout Multiplicity | Batch Size | Epochs | Learning Rate | Adam Beta1 | Adam Beta2 | Adam Epsilon | LR Scheduler Type |
|----------------------|------------|--------|---------------|------------|------------|--------------|-------------------|
| 0.1                  | 8          | 3      | 5e-05         | 0.9        | 0.999      | 1e-08        | LINEAR            |

Table 3: RoBERTa Classification Model Hyperparams for OLI

| Model               | Precision | Recall | F1 Score | Accuracy |
|---------------------|-----------|--------|----------|----------|
| Baseline KNN        | 0.62      | 0.72   | 0.65     | 0.72     |
| ULMFit              | 0.73      | 0.78   | 0.73     | 0.78     |
| RoBERTa             | 0.74      | 0.77   | 0.75     | 0.77     |
| Ensemble            | **0.75**  | **0.79** | **0.76** | **0.79** |

Table 4: Validation set results for OLI

| Model                  | Precision | Recall | F1 Score | Accuracy |
|------------------------|-----------|--------|----------|----------|
| Baseline KNN Model     | 0.53      | 0.53   | 0.53     | 0.53     |
| ULMFit                 | 0.63      | 0.63   | 0.63     | 0.63     |

Table 5: Validation set results for HSD

at the last layer.

### 3.2.2 RoBERTa Model

RoBERTa model builds on BERT (Devlin et al., 2019) and modifies BERT’s key hyperparameters, removes the next-sentence pre-training objective and trains with much larger mini-batches and learning rates. RoBERTa has the same architecture as BERT but it uses a different pre-training scheme and tokenizes text using Byte-Pair Encoding (Sennrich et al., 2016). We use implementation of RoBERTa in Huggingface’s Transformers library\(^7\) to pre-train the model from scratch. We train it for 7 epochs using a learning rate of 5e-5 and a dropout of 0.1 for attention and hidden layers. Table 2 compares perplexity of our pre-trained RoBERTa model with that of ULMFiT model which is also trained on the same code-mixed data.

### 3.3 Classification data pre-processing

We pre-process the classification datasets of both tasks by transforming comments in native script into Latin script using Indic-Trans library. This step is required because both of our pre-trained language models, ULMFiT and RoBERTa, are trained on code-mixed data in Latin script. We also perform other basic pre-processing steps like lower-casing and removing @username mentions. We did not apply other pre-processing steps such as stop words removal or removal of words that are too short since both of our pre-trained language models are trained on complete sentences and we wanted the model to figure out on its own if stop/short words are important for classification or not.

### 4 Experiment and Results

In this section we discuss details and results of our baseline model, classification models and ensemble strategy.

#### 4.1 Experiment Details

##### 4.1.1 OLI Task

**Baseline Model.** Our baseline uses KNN classifier on embeddings generated using code-mixed ULMFiT model from iNLTK\(^8\) (Arora, 2020b). We set k=5 for all our experiments with uniform weighting on neighbors.

**Ensemble.** Our final model is a weighted ensemble of two classifiers where their weights sum to 1. Training of classifiers happens in two steps. First we fine-tune our language model on the downstream task of OLI and then train a classifier on the fine-tuned language model. Table 3 contains details of hyperparameters of the first classifier which is trained on our pre-trained RoBERTa. We train the second classifier using fine-tuned ULMFiT language model which is available in iNLTK. We experiment with different weights of classifiers in the ensemble. Best results on the validation set are obtained by setting a weight of 0.5 for both classifiers. Figure 1 shows the variation of weighted F1 score

\(^7\)https://huggingface.co/transformers/model_doc/roberta.html  
\(^8\)https://github.com/goru001/inltk
by changing weights of RoBERTa based classifier.

![Figure 1: Change in Tamil OLI validation set F1 score on y-axis with change in RoBERTa weight shown on x-axis](image)

### 4.1.2 HSD Task

We use a similar approach as that used for OLI task. Baseline model is built using the KNN algorithm and the final model is a classifier trained on a fine-tuned ULMFiT language model. Due to time and resource constraints, we weren’t able to train RoBERTa based classifier.

### 4.2 Results

In both tasks weighted averaged Precision, weighted averaged Recall and weighted averaged F-Score are used as evaluation and ranking criteria. We participated in sub-task for Tamil and got Rank 4 in OLI task and Rank 1 in HSD task (Chakravarthi and Muralidaran, 2021). Table 4 shows the performance of different models on the validation set of former task. Best F1 score of 0.76 is obtained by using the ensemble of classifiers trained on RoBERTa and ULMFiT model which are pre-trained on code-mixed data. Table 5 contains results of models on the validation set of the latter task. We obtain an F1 score of 0.63 with ULMFiT based classifier. Results on the test-set for both the tasks have been shown in Table 6.

| Offensive Language Identification | | Hope Speech Detection | | |
|----------------------------------|---|----------------------|---|---|---|---|
| Precision | Recall | F1 Score | Rank | | Precision | Recall | F1 Score | Rank |
| 0.74 | 0.78 | 0.75 | 4/30 | 0.62 | 0.62 | 0.61 | 1/30 |

Table 6: Test set results for OLI task and HSD task

We got Rank 4 in the former task using an ensemble of classifiers trained on RoBERTa and ULMFiT and Rank 1 in the latter task using classifier based on ULMFiT. In future research we will explore other transformer architectures like BERT (Devlin et al., 2018), T5 (Raffel et al., 2020), XLM (Conneau et al., 2019). We will work on improving code-mixed data generation strategies. We plan to create a dataset using a combination of native Tamil sentences, their transliterations and translations in English.

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