LPS@LT-EDI-ACL2022:An Ensemble Approach about Hope Speech Detection

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Abstract

The task shared by sponsor about Hope Speech Detection for Equality, Diversity, and Inclusion at LT-EDI-ACL-2022.The goal of this task is to identify whether a given comment contains hope speech or not,and hope is considered significant for the well-being, recuperation and restoration of human life.Our work aims to change the prevalent way of thinking by moving away from a preoccupation with discrimination, loneliness or the worst things in life to building the confidence, support and good qualities based on comments by individuals. In response to the need to detect equality, diversity and inclusion of hope speech in a multilingual environment, we built an integration model and achieved well performance on multiple datasets presented by the sponsor and the specific results can be referred to the experimental results section.

1 Introduction

In the age of multimedia information technology, massive network data is a symbol of people's freedom of speech,and these messages contain a lot of positive or negative sentiments.Past research has mostly focused on sentiment analysis, or negative detection of insults,aggression and hate speech[1] (Chakravarthi et al., 2020, 2021, 2022b; Sampath et al., 2022; Ravikiran et al., 2022; Bharathi et al., 2022; Priyadharshini et al., 2022). Instead,the goal of this task(Chakravarthi et al., 2022a) shared at LT-EDI 2022- ACL 2022[2] is to determine whether a given comment contains hope speech or not in Tamil, Malayalam, Kannada, English and Spanish. Tamil, Malayalam, and Kannada belongs to Dravidian languages (Subalalitha, 2019; Srinivasan and Subalalitha, 2019; Narasimhan et al., 2018). Tamil is an official language of the Indian state of Tamil Nadu, the sovereign nations of Sri Lanka and Singapore, and the Union Territory of Puducherry (Sakuntharaj and Mahesan, 2021, 2017, 2016; Thavareesan and Mahesan, 2019, 2020a,b, 2021). The Dravidian languages are first attested in the 6th century BCE as Tamili (also called Tamil-Brahmi) script inscribed on the cave walls in the Madurai and Tirunelveli districts of Tamil Nadu (Anita and Subalalitha, 2019b,a; Subalalitha and Poovammal, 2018).

Research should take a positive reinforcement approach.The aim is to change the prevailing mindset by moving away from focusing on discrimination,loneliness or the worst things in life to building confidence,support and good character based on personal comments(Chakravarthi et al., 2022a).Therefore,we built an ensemble model to detect user-generated comment sentences from the social media platform (YouTube) that contained hope speech or not, and our model achieves good results on relevant data sets[3].This is a study of a speech of hope that interprets equality, diversity and inclusion in a multilingual environment. We have open-sourced our code implementations on GitHub [4].

2 Related Work

The study found that in the past, people mainly focused on the sentiment analysis of monolingual (English)(A. Al Shamsi et al., 2021),or the negative detection of insult, attack and hate speech in mixed or multilingual languages.While there were few studies on the hope speech detection of equality, diversity and inclusion in multilingual environments(as (Ghanghor et al., 2021)). In particular, studies that use positive reinforcement methods to build people's confidence, support and

[1] https://competitions.codalab.org/competitions/25295
[2] https://competitions.codalab.org/competitions/36393
[3] https://competitions.codalab.org/competitions/36393/result
[4] https://github.com/TroubleGilr/Hope-Speech-Detection-for-Equality-Diversity-and-Incl

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May 27, 2022

Data	Class	English	Spanish	Kannada	Malayalam	Tamil
Training	Non_hope_speech	20778	499	3241	6205	7872
	Hope_speech	1962	491	1699	1668	6327
Development	Non_hope_speech	2569	161	408	784	998
	Hope_speech	272	169	213	190	757
Test		2843	330	618	1071	1761
Total		28424	1650	6176	9918	17715

Table 1: Data Distribution

good character based on news comments.In particular, the positive reinforcement study methods, are used to help people get rid of negative attitudes to building the confidence, support and good qualities based on comments by individuals.So some groundbreaking work is easy to catch people's attention. Chakravarthi et al.(Chakravarthi, 2020a) have constructed a Hope Speech dataset for Equality, Diversity and Inclusion (HopeEDI) and determined that the inter-annotator agreement of their dataset using Krippendorff's alpha. Ghanghor et al.(Ghanghor et al., 2021) submitted the result about hope speech detection in Dravidian languages shared task organized by LT-EDI 2021. In the same task, Mahajan et al.(Mahajan et al., 2021) also made contributions.Their approach fine-tunes RoBERTa for Hope Speech detection in English and fine-tune XLM-RoBERTa for Hope Speech detection in Tamil and Malayalam, two low resource Indic languages.Although some people have done pioneering work, the research in this area still needs more energy from researchers, which is why we are working hard to do research and write this paper.

3 Dataset

The dataset(Chakravarthi, 2020b) is provided by ACL 2022 contains 59,354 comments from the famous online video sharing platform YouTube out of which 28,424 are in English, 1,650 in Spanish, 6,176 in Kannada(Hande et al., 2021), 9,918 in Malayalam, and 17,715 comments are in Tamil (Table 1). This is a comment or post level classification task. Given a YouTube comment, we should classify it into 'Hope speech' and 'Not hope speech'. A comment / post may contain more than one sentence but the average sentence length is 1. The annotations are made at a comment / post level[5], and the test set is not annotated of label.

It is observed that the sentence of data is in a code-mixed format (a mixture of Native type and Roman type), and contains a lot of @ names, repeated words or letters, useless symbols, expressions, etc.Before feeding the raw tweets to any training stage,we will do a simple data preprocessing.

1.No translation processing is done for texts code-mixed with native and Roman type and Keep the sentence length at 50.

2.Remove unwanted information,like: Usernames (annotated as @names),URLs,and useless symbols present in the tweets are removed altogether,while hashtags (annotated as hashtag) are left as it is.But emoticons remain, and they contain in some sense our sentiment expression.

3.Stopwords processing

After the above simple preprocessing, it is directly input to the model for training.In addition, it can be found that the data set is unbalanced, which we will address in future work, and our model does not use any external data.

4 Model Framework and Experimental Results

This section introduces the structure of our model and experimental results.

4.1 Model Framework

All the data we submitted came from the same model framework and the architecture of the proposed system is shown in Figure 1, which is an ensemble model consisting finallyof three parts.There are LSTM(Greff et al.), CNN+LSTM(Yenter and Verma)and BiLSTM(**?**), respectively.Finally, add an attention layer before ensemble the three-part results.

LSTM:this part includes an LSTM layer and two Dense layers.Units of LSTM layer are 264, and the activation function used is Tanh. Units and activation functions in the two dense layers are 64, 2 and Tanh and Softmax, respectively.LSTM is a

[5]https://drive.google.com/file/d/1uOxyblVUCOFaofuw56KJKlx-t_nL4mLf/view

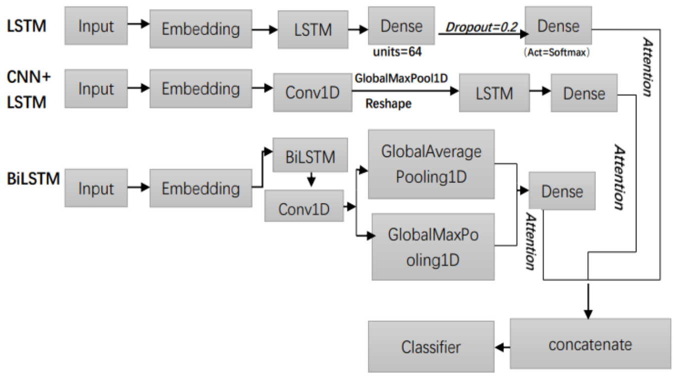

Figure 1: Ensemble model structure diagrams and related model parameters

Model	Embedding	BiLSTM	Conv1D	LSTM	Dense	Other
LSTM	vocab_size=20000 embed_size=128			units=264 Act=tanh	units=2 Act= Softmax	epochs=6 batch_size=128
CNN+ LSTM	vocab_size=20000 embed_size=128		Filters=64 kernel=3	units=64 Act=tanh	units=2 Act= Softmax	epochs=5 batch_size=128
BiLSTM	vocab_size=20000 embed_size=128	units=128 Act=tanh	Filters=64 kernel=3		units=2 Act= Softmax	epochs=7 batch_size=128

Figure 2: Parameters of the model

special RNN type that can learn long-term dependency information which increases the complexity of RNN units, models more carefully, has more constraints, makes training easier, and solves the problem of gradient dissipation of RNN.

CNN+LSTM:this section consists of three different layers,a convolution layer, an LSTM layer, and a Dense layer.In the LSTM layer, units=64, the activation function and dense layer were the same as the former(LSTM) model.Convolutional layer have 64 of the filter siensembleze and 3 kernel size ,followed by a global maximum pool layer.In the task of short text analysis, CNN has a significant effect in dealing with this kind of problems due to the limited length of sentences, compact structure and independent expression of meaning.

BiLSTM: it consists of a BiLSTM layer, a Convolution layer and a Dense layer.BiLSTM layer contains two parameters (units=128, activation=tanh).The parameters of the convolution layer are units=128,activation=tanh,followed by a global maximum pool layer and global average pool layer.The final dense layer is the same as the two above.It is worth mentioning that the epochs of the three parts are 6, 5 and 7 respectively. All three model use same Optimizers:Adam of learning rate=0.01. Sparse-categorical-crossentropy is used as the loss function.Cross entropy is used to evaluate the difference between the current training probability distribution and the real distribution. It describes the distance between the actual output (probability) and the expected output (probability), that is, the smaller the value of cross entropy, the closer the two probability distributions will be. The difference is that sparse-categorical-crossentropy accepts discrete values. All parameters of the mode shown in the table in Figure 2.

Attention: before ensemble the three models, we used the attention mechanism(Petersen and Posner, 2012). The introduction of attention mechanism can not only help the model to make better use of the effective information in the input, but also provide some ability to explain the behavior of the neural network model.

In the basic neural network model, "attention" is not obtained in the process of decoding,Encoder-Decoder framework transforms input X into semantic representation C,resulting in the translated sequence in which each word takes into account the equal weight of all words in the input. After the attention mechanism is introduced, there are different hidden layer states at different decoding time. Therefore, we use the state of the decoder hidden layer at a certain moment and the state of the encoder at each moment to carry out matching calculation, and get their respective weights. At this

Lang	M Precision	M Recall	M F1 score	W Precision	W Recall	W F1	Rank/total
Eng	0.43	0.39	0.4	0.88	0.9	0.88	7/20
Spa	0.77	0.76	0.76	0.77	0.76	0.76	4/6
Kan	0.45	0.45	0.45	0.71	0.71	0.71	3/8
Mal	0.45	0.49	0.47	0.69	0.76	0.72	4/9
Tam	0.29	0.34	0.31	0.39	0.44	0.41	2/7

Table 2: The experimental results of our model

Language	English	Spanish	Kannada	Malayalam	Tamil
LSTM	0.34/0.67	0.60/0.62	0.32/0.57	0.30/0.64	0.2/0.30
CNN	0.30/0.59	0.55/0.59	⋆	0.29/0.55	⋆
CNN+LSTM	0.35/0.70	0.62/0.65	⋆	0.34/0.66	⋆
BiLSTM	0.35/0.71	0.61/0.67	⋆	0.33/0.64	⋆
CNN+BiLSTM	0.37/0.75	0.65/0.70	⋆	0.33/0.66	⋆
LSTM+BiLSTM	0.37/0.80	0.70/0.72	⋆	0.40/0.70	⋆
Our approach	0.40/0.88	0.76/0.76	0.45/0.72	0.47/0.72	0.31/0.41

Table 3: Compare with baseline model

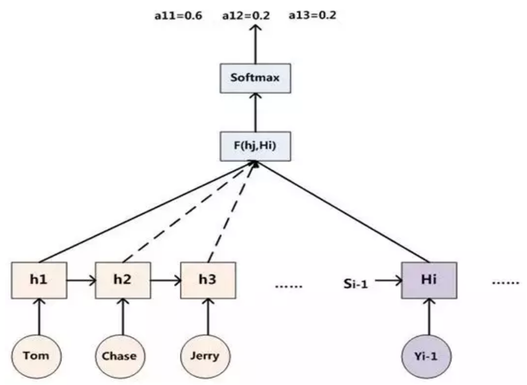

Figure 3: The structure diagram of weight a_{ij}

point, the semantic code C is no longer the direct encoding of input sequence X, but the weighted sum of each element according to its importance, as extra attentions, namely formula 1:

$$C_i = \sum_{j=0}^{T_x} a_{ij} f(x_j) \qquad (1)$$

In formula (1), parameter i represents the moment, j represents the j^{th} element in the sequence, T_x represents the length of the sequence, and f() represents the encoding of element x_j . a_{ij} can be seen as a probability reflecting the importance of element h_j to C_i and can be expressed by Softmax:

$$a_{ij} = \frac{exp(e_{ij})}{\sum_{k=1}^{T_x} exp(e_{ik})} \qquad (2)$$

Here e_{ij} just reflects the matching degree between the element to be encoded and other elements. When the matching degree is higher, it indicates that the element has greater influence on it, and the value of a_{ij} is also higher.Therefore, the process of obtaining a_{ij} is shown in Figure 3: Where, h_i represents the conversion function of Encoder, and $F(h_j,H_i)$ represents the matching scoring function of prediction and target.

Finally, concatenation the output after assigning attention weight. In the ensemble model, Soft Voting Classifier(Taylor and Kim, 2011) method is used: the average probability of the predicted samples of the three models for a certain category is taken as the standard, and the corresponding type with the highest probability is the final predicted result.

4.2 Experimental Results

We have submitted the results for each language(including:*English,Spanish,Kannada, Malayalam and Tamil*) given by the sponsor, and table 2 shows the detailed results.Which score is given in 6 methods,there are *M-Precision,M-Recall, M-F1-score,W-Precision,W-Recall,and W-F1-score*,respectively.The table also shows our team submission ranking and the total number of submission teams.Classification system's performance will be measured and ranked in terms of macro averaged Precision, macro averaged Recall and macro averaged F-Score across all the classes. Note: The follow number of rank indicates total of the teams submitted.

The data in the table 2 shows that our results are pretty performance in all languages except for Tamil, all teams performance poor in Tamil language. The first ranked team, Ablimet, submitted a M-F1 score of 0.32 and w-F1-score of 0.42. We will find and solve the specific reason in the future work. The results of our ensemble model were further compared with the baseline model in both macro average F1-score and weighted average F1-score in same dataset. Table 3 gives details of the corresponding results, where each option has two data points, macro average F1-score on the left and weighted average F1-score on the right.Observation carefully,all baseline models, or any combination of two of them, end up performing worse than our ensemble model

5 Conclusion

The ensemble model our submitted consisted of three parts:LSTM,CNN+LSTM and BiLSTM. Among them,CNN,to some extent,takes into account the ordering of the words and the context in which each word appears. Using the LSTM model can better capture long distance dependencies. Because LSTM can learn what to remember and what to forget through the training process,but LSTM doesn't take into account the sequential order of words in a sentence.LSTM has problems with ambiguous affective words in finer - grained classification. Therefore, BiLSTM can better capture the bidirectional semantic dependencies, taking into account the reverse information.Finally, on this basis, attention mechanism is introduced to highlight the key information. In other words, by adjusting a series of weight parameters, it can be used to emphasize or select the important information of the target processing object and suppress some irrelevant details, so as to make the classification more accurate.The model we submitted has achieved performance well, but there is still a lot of room for improvement in both pre-processing and model framework design in the future.

Acknowledgements

First of all, I would like to thank various technical associations and research institutes for providing research platforms. Secondly, I would like to thank every student volunteer for their dedication,and thank my teacher and partner for their encouragement and support,finally.

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