Natural Language Processing Project

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Abstract

Hate speech detection of tweets as a classification problem has become a popular research topic in NLP. While hate speech online has become a worldwide problem, the focus has been primarily on detecting hate speech in English. With the absence of large, pre-trained models in non-English languages, and with the problem of ambiguity of what classifies as hate speech, training an effective, non-English hate speech model is difficult. In this project, we successfully train an Italian hate speech detecting transformer. We compare monolingual models in both Italian and English (where the Italian dataset is translated into English) and a multilingual model, and show that the multilingual model outperforms monolingual models on this classification task.

Contents

1 Problem definition

In the age of social media, the ability to automatically detect hate speech has become a crucial task for social media giants such as Twitter. However, due to a variety of reasons, it is often a complex NLP task. Tweets often contain grammatical and spelling errors, slang, and lack context. Furthermore, the criteria for what constitutes as hate speech is ambiguous, even under human evaluation. The absence of large pretrained models and fewer datasets, further compounds the problem for non-English languages. Therefore, it is a challenging and important problem for NLP researchers to tackle this major issue.

For this project, we utilised the Italian Hate Speech Corpus[8] for a transformer based approach to detecting Italian hate speech on Twitter. We compare the Italian monolingual model, the multilingual model, and the English model with the translated dataset and show which technique can be useful technique for low-resource languages.

1.1 Related Works

Research into low-resource languages have seen a variety of monolingual and multilingual approaches. A multilingual approach was proposed by Aluru et al.[1] for multi-lingual embeddings in 9 different languages. In Italian in particular, Nozze et al.[6] presented a new hate speech dataset, along with a set of multi language models, showing that multilingual models outperform monolingual models trained solely on Italian datasets.

With regards to Italian datasets, aside from Sanguinetti et al.[8] which is a popular dataset for hate speech, Fersini et al.[3] and Bosco et al.[2] are also popular for hate speech related to misogyny.

Hate speech datasets have been criticised for their binary nature, such as by Vidgen et al.[9], who has built datasets with more descriptive labels than hate and non-hate. However, as the additional labels proposed by researchers are not normalized, it is difficult to join such datasets together.

2 Dataset

The dataset employed is the Italian Hate Speech Corpus[8]. It is a corpus of hate speech on Twitter towards migrants and ethnic and religious minorities (Roma and Muslims in particular).

The labels are highly unbalanced:

	Number of tweets	Percentage
Positive	811	15.7%
Negative	4345	84.3%
Total	5156	100%

Given this class unbalance, the results of the classifier would be skewed in favor of the minority class and hence potentially lead to misclassification which is one major problem of the dataset.

Every tweet was annotated for the categories of hate speech, aggressiveness, offensiveness, irony and stereotype, however for the purposes of this project, we only use hate speech as a label.

2.1 Preprocessing

Due to the short structure of tweets, users will typically compress semantic information using emojis or abbreviations. As such, it is necessary to pre-process the text to create a clearer semantic structure. Each tweet was pre-processed using the following methods:

- Remove the reference to twitter users, links and hashtags.
- Normalise sequences of at least 3 repeated characters with a maximum of two letters (e.g. heeeeeey $\rightarrow$ heey).
- Remove numbers.
- Remove punctuations.
- Transform emojis into their aliases.
- Remove extra white spaces.
- Remove any left or right spacing

The cleaned Italian dataset is then divided and shuffled into training, validation and test sets in the following way:

	Number of tweets	Percentage
Training set	3608	70%
Validation set	516	10%
Test set	1032	20%

3 Methods

We analyze different approaches to solve the aforementioned problems of lack of large pre-trained models and small number of datasets in the field of hate speech detection for non-English languages. First, we examine the monolingual transformer to detect hate speech in Italian. Second, we examine multilingual methods that use a larger English dataset to train a model for detecting hate speech in Italian texts using cross-language information transfer techniques. Finally, we examine a standard transformer for hate speech detection in English, applied to a dataset translated into English using Google Translate.

To model the data, 3 different transformer models were chosen: Italian Bert model, Twitter XLM Roberta Base and Bertweet Base Sentiment Analysis. Encoding was done with the pretrained encoders for each model.

For the transformer models, a low learning rate and a large batch size proved to be the most effective. We used a learning rate of 1e-5, a batch size of 128, with up to 7 epochs of training. The best model was evaluated using the F1 score, due to the unbalanced nature of the Italian dataset. Weight biasing was also tested with a 1:1.5 bias for non-hate and hate respectively, for the same reason. A confusion matrix was also plotted for each model to better visualise the predictions and errors.

3.0.1 Italian Monolingual model

For the monolingual Italian model we use a pre-trained cased Italian Bert model [4]. The source data for the Italian BERT model consists of a recent Wikipedia dump and various texts from the OPUS corpora collection.

3.0.2 Multilingual model

For the multilingual model, we used Twitter XLM Roberta Base [5], a Roberta model trained on multilingual Twitter dataset.

3.0.3 English model with translated dataset

For the English model we use Bertweet Sentiment Analysis [7] a RoBERTa model trained on English tweets.

The entire dataset has been translated using Google Translate document translation provided by Google Cloud Translation.

4 Results

The test set is unbalanced as there are few hate examples. We thus show the performance of the models for both hate and not-hate classes.

	Precision		Recall		F1 Score	
	hate	not-hate	hate	not-hate	hate	not-hate
Italian Transformer	67%	87%	21%	98%	31%	92%
Multilingual transformer	58%	90%	35%	96%	44%	92%
English transformer with translated dataset	21%	88%	45%	70%	28%	78%

Below are the confusion matrices of the models with the best hyperparameters.

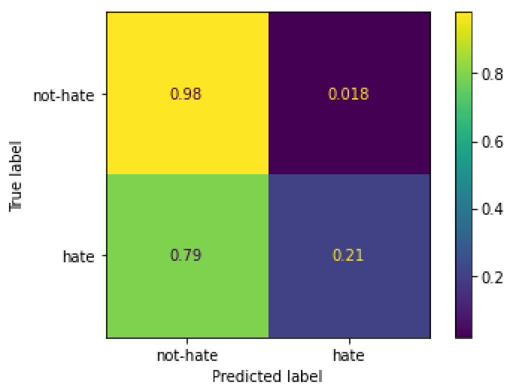

Figure 1: Confusion matrix of the Italian Transformer

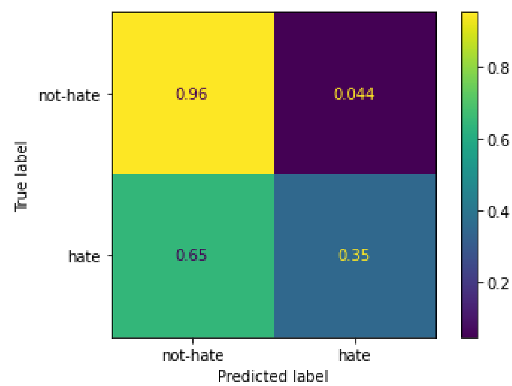

Figure 2: Confusion matrix of the multilingual Transformer

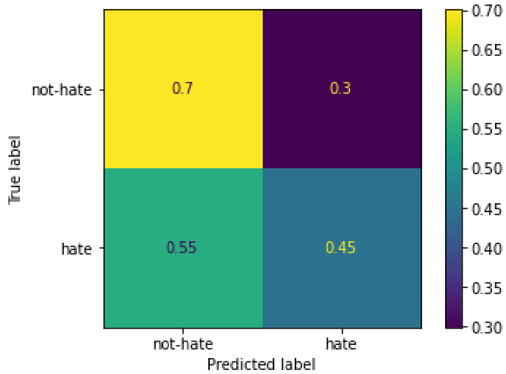

Figure 3: Confusion matrix of the English Transformer

Based on our achieved results, we note certain interesting findings. Firstly, we note that the multilingual model has the best overall results. The monolingual model has comparable results, although the F1 score for the hate speech class is lower. The English model with the translated dataset has the worst results, which we hypothesise is due to the added error introduced through the translation. Overall, all models struggled with false positives in the hate class, which is to be expected in a highly unbalanced dataset.

To combat the unbalanced nature of the dataset, weight biasing was tested, however it gave mixed results. While applying a weight bias to the under-represented label (1:2 to no-hate, hate) gave better performance for the hate class, it inhibited the results of the no-hate class. Below is the confusion matrix for the multilingual transformer with a weight bias. While the number of false positives for the hate label goes down, the number of false positives for the non-hate label, goes up. In a real-world situation, we assume that precision in the hate speech class is more important, as the aim would be to remove all hate speech off social media platforms.

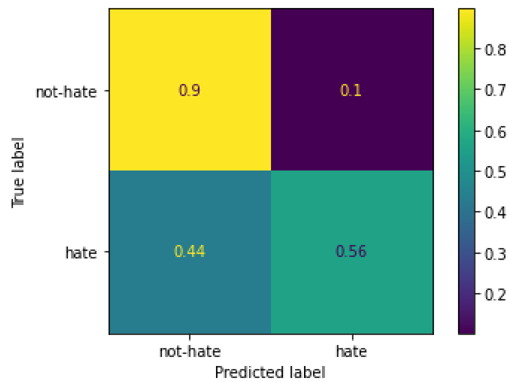

Figure 4: Confusion matrix of the Multilingual Transformer with a weight bias of 1:2

5 Conclusion

In this project, we compared the Italian monolingual model, the multilingual model, and the English model for a binary hate speech classification task. We found that multilingual models gave the highest results, even when the model is trained on languages other than the target language. Overall, this shows that multilingual models can improve the performance of the model when faced with relatively limited training data. We hope that this work helps research in other low-resource languages, and to reach comparable results in these languages, as English.

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