



# Cross-lingual offensive language identification

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## Abstract

To be added.

## Keywords

Text classification, Hate speech classification

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## Introduction

Text classification is one of the most important and well researched tasks in Natural Language Processing. It represents a supervised learning approach whose goal is to classify an input text into the correct category, therefore each input example gets assigned a label and as such is used in wide range of applications. Applications that exploit text classification the most are document classification, web search, information retrieval, sentiment analysis and spam detection. Text classification breaks down to different levels of scope:

1. **Document level** - In the document classification algorithm, classifies document as a whole into the categories
2. **Paragraph level** - Classifies a portion of a document, a single paragraph into the required categories.
3. **Sentence level** - Obtains the categories of a portion of a paragraph, a single sentence.

In this paper we focus on online hate speech classification problem. Online hate speech classification has become a well researched part of NLP and an urgent need since human supervision is unable to handle an enlarging volume of online content. We further divide classification problem based on the number of target variables to be classified. At first we classify input text at a paragraph level into binary categories, while in the later phase we classify input text on multi-class labels. In this paper we will explore two types of models for binary classification problems. First, traditional machine learning models such as Logistic regression, SVM, Random forest and an Ensemble voting model are to be employed into classifying online hate speech. The later approach will rely on BERT, a transformer based machine learning

technique. In case of successfully validating our initial hypothesis of correctly classifying hate speech we will introduce a Slovene labeled hate speech data set consisting of Twitter tweets and news website comments. Additionally, we will transfer the knowledge from pre-trained multi-lingual models using one-shot transfer and evaluate introduced Slovene data set.

## Related work

With the enlarged amount of online content, the need and the focus of research has shifted towards online text classification, with a particular focus on content moderation. Within the early stages of text moderation number of methods utilizing shallow approaches have been proposed. Dao et al. [1] introduced methods which use feature vectors constructed with BoW language model. The main shortcomings of the introduced methods is that it suffers from data sparsity and that it typically leads to many false positives. Other approaches for feature spaces comprising of TF-IDF and character n-grams have been introduced. Waseem et al. [2] explore the traditional, feature-engineered machine learning models such as Logistic Regression and SVM for automatic content moderation.

In order to tackle the problem of data sparsity, number of approaches such as Word2Vec[3] and GloVe [4] have been introduced for better representation of words and sentences. These methods outshine sparse feature vectors since similar words are located closer together in the latent space and dense word representation produce better encoding of such features. Recent studies show that Neural Network based approaches are superior compared to the traditional machine learning methods. Advantage of neural network approaches lays in it's capability to model larger sequences of text. Sutskever et al. [5] show that gated RNNs are capable of capturing long

term dependencies in text leading to a better results in content classification.

The main shortcoming of NN based approaches lays in it's inability to catch global context of the words. A breakthrough in the field of NLP happened with introduction of BERT [6]. Bidirectional Encoder Representations from Transformers - BERT represents a SOTA approach in NLP. Compared to the other dense word representations BERT takes into account a larger left and right semantic space thus better modelling words with respect to the context around it. There are a number of pre-trained BERT models which can be fine tuned on various downstream NLP tasks. Furthermore, there are a number of available multilingual pre-trained BERT models, thus allowing a transfer of model knowledge to the less resourced languages.

## Methods

In this section we introduce used methods, data sets and pre-processing steps.

### Data

As aforementioned, we have subdivided speech classification task into two categories, a binary and a multi class label text classification. For both task categories we have used english and slovene data sets. For binary task we have used four publicly available english data sets that have been further processed and adopted in order to be combined into one uniform binary class data set. The dataset consists of hate-speech labelled with **1** while non-hate speech is annotated with **0**. While, for muticlass task we have used two english data sets which are then processed and adopted into one uniform multi-class dataset. Both tasks were tested on one slovene data set with additional hand collected comments from web.

### Binary english datasets

#### Dataset 1

First dataset represents a 1528 Fox news comments [7] which are manually classified into hate and non-hate categories. publicly available at [url](#). The original data set is a json file where each comment has an additional metadata and previous contextual comments. All the metadata have been removed, preserving only the text and the binary label. The dataset is highly imbalanced consisting of 435 hateful and 1093 non-hateful comments.

#### Dataset 2

Second dataset represents a 26581 comments [8] from Reddit posts which are manually classified into hate and non-hate categories, publicly available at [url](#). The original data set is a csv file where each comment has an additional metadata and previous contextual comments. All the metadata have been removed, preserving only the text and the binary label. The dataset is highly imbalanced consisting of 5257 hateful and 17052 non-hateful comments .

#### Dataset 3

Third dataset represents a 38018 comments [8] from Gab posts which are manually classified into hate and non-hate categories, publicly available at [url](#). The original data set is a csv file where each comment has an additional metadata and previous contextual comments. All the metadata have been removed, preserving only the text and the binary label. Dataset consists of 14614 hateful comments and 19162 non-hateful comments.

#### Dataset 4

Fourth dataset represents a 10945 comments [9] from a white supremacists forum which are manually classified into hate and non-hate categories publicly available at [url](#). The original dataset consists of textual documents which hold each comment and a csv file marking whether a document is classified as a hateful or non-hateful one. The dataset has been processed into one csv shaped file consisting of comments and label categories. The dataset is highly imbalanced consisting of 1196 hateful comments and 9748 non-hateful comments.

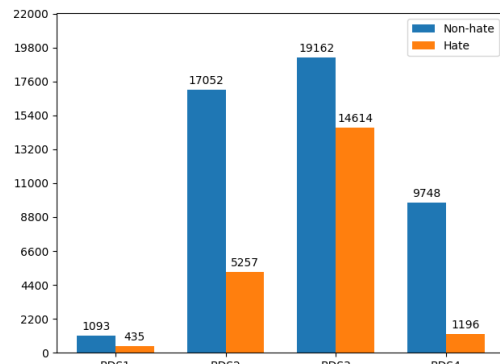


Figure 1. Distribution of classes in binary datasets.

### Multiclass english datasets

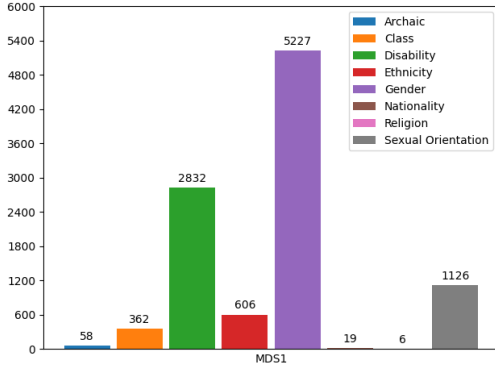
#### Dataset 1

First multiclass dataset consists of 10236 comments [10] from Twitter posts which are classified into 7 categories showed in table 1. The dataset tweet ids are publicly available at [url](#). The dataset was collected by searching the Twitter's 1% public stream from January 2016 to July 2017 for tweets containing hate keywords. Those tweets were then additionally checked with Perspective API developed by Jigsaw and the Google Counter-Abuse technology team. The API was used for checking tweet toxicity and attack on commenter property. The quality of dataset was tested by human annotators, which labeled 97.8% of tweets as hate speech with 92.8% agreement percentage.

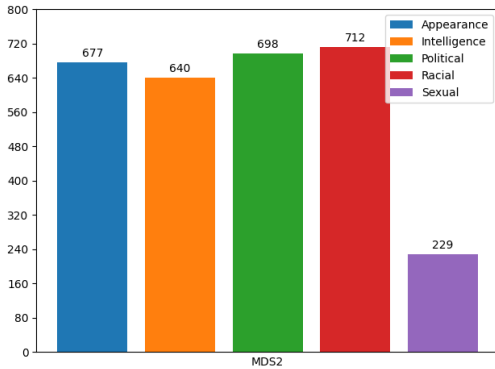
#### Dataset 2

Second multiclass dataset consists of 25000 comments [11] from Twitter posts which are classified into 5 categories showed in table 1. The dataset was collected by searching the Twitter from December 2016 to January 2017 for tweets

containing at least one hate keyword. After that additional 3 human annotators were used to annotate the presence of hate in fetched tweets, with agreement percentage of 80.6%. Of those 25000 tweets, only 2958 contain hate speech.



**Figure 2.** Distribution of classes in the 1. multiclass dataset.



**Figure 3.** Distribution of classes in the 2. multiclass dataset.

## Slovenian datasets

### Dataset 1

First dataset consists of Slovenian comments from two news websites 24ur.com and Nova24.si. We manually collected and annotated 141 comments into 6 hate classes: non hate, racism, sexual, intelligence, appearance, and other.

### Dataset 2

Second dataset consists of 60000 Slovenian tweets [12]. Tweets are classified into 4 hate speech types: appropriate, inappropriate, offensive, and violent. Tweets are also classified into 11 hate speech targets: racism, migrants, islamophobia, antisemitism, religion, homophobia, sexism, ideology, media, politics, individual, and other. Tweets were fetched from Twitter between December 2017 and August 2020. Tweets were annotated by ten annotators, with agreement percentage of 60%. We sample 673 violent and 3000 appropriate, inappropriate, and offensive (1000 each) tweets, for our needs in this project.

## Datasets combining

We combine all English datasets into one final binary and one final multiclass dataset. Those two datasets are then used for training the classification models. The final binary dataset is obtained by combining binary datasets and multiclass datasets, which were converted to binary by grouping all hate classes into one class. The final multiclass dataset is obtained by mapping different classes from each multiclass dataset into a predefined 6 final classes, and additional non-hate classes from binary datasets. The class mapping rule is shown in Table 1.

Slovene datasets were also combined into one binary and one multiclass dataset. Binary dataset is obtained by merging all hate classes into one hate class, and combining it with non-hate classes. Multiclass dataset is obtained by merging dataset 1, which was already collected with the correct classes, and mapped dataset 2. Class mapping is shown in Table 2.

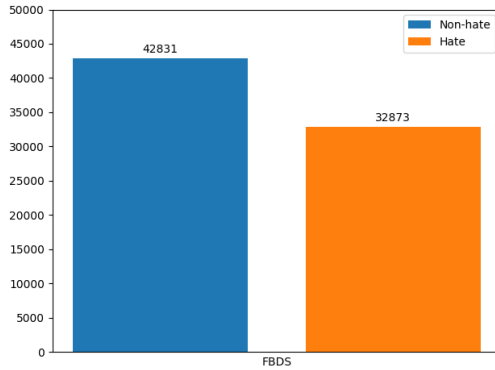
The final classes for binary dataset: Non-hate (0), Hate (1). The final classes for multiclass dataset: Non-hate (0), Racism (1), Sexual (2), Intelligence (3), Appearance (4), Other (5).

**Table 1.** English multiclass datasets classes (left columns) and mapping rule for creating the final dataset of 6 classes.

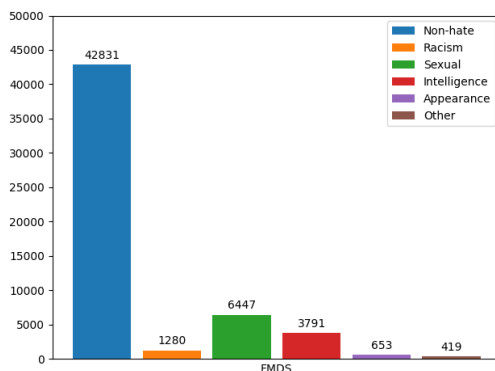
DS1	Final DS	DS2	Final DS
Archaic	Other	Racial	Racism
Ethnicity	Racism	Appearance	Appearance
Nationality	Racism	Intelligence	Intelligence
Class	Intelligence	Political	Other
Disability	Intelligence	Sexual	Sexual
Gender	Sexual		
Sex	Sexual		
Religion	Other		

**Table 2.** Slovene multiclass 2. dataset classes (left columns) and mapping rule for creating the final dataset of 6 classes.

DS2	Final DS
Non hate	Non hate
Racism	Racism
Migrants	Other
Islamophobia	Other
Antisemitism	Racism
Religion	Other
Homophobia	Sexual
Sexism	Sexual
Ideology	Other
Media	Other
Politics	Other
Individual	Other
Other	Other



**Figure 4.** Distribution of classes in the combined binary dataset.



**Figure 5.** Distribution of classes in the combined multiclass dataset.

## Preprocessing

Preprocessing is applied to all the instances of each dataset that the classifier could predict class for. Preprocessing is conducted through eight steps. Since our datasets are collected mainly from the social media or news media comments there are high number of occurrences of emoticons. With step 1 all the emoticons are removed. Same reasoning is behind step 2 and 3 where all twitter urls, hashtags and @name mentions are removed. Steps 4 and 5 remove all non-alphabetical characters and lower down all words. Step 6 tokenizes each input comment with nltk function `word_tokenize` which first tokenizes text into sentences than it further tokenizes it into tokens. Lemmatization is performed in step 7 in order to get word in a canonical form and get higher frequency of similar words. Nltk WordNetLemmatizer is used for converting a word into lemmas. Additionally, step 8 combines english stop words removal as well as filtering out words of length 1. Lemmatization and stop words removing is performed only before training on traditional methods. On BERT training, no lemmatization and stop words removing is applied because that may remove context from the text, which may lower the performance of fine-tuned BERT models.

## Features

For the feature extraction in our baseline model we have used sparse-word embeddings. Moreover, we have combined sparse-word embedding language models such as BoW and tf-idf with topic-modelling features constructed from the given data sets with Latent Dirichlet Allocation - LDA. First, we have extracted ten topic categories from the data and one-hot encoded each comment to the belonging category which are then combined with BoW or tf-idf features as aforementioned. With both approaches we have used unigrams and bigrams while using Sklearn implementations of `CountVectorizer` and `TfidfVectorizer` respectively, with using `gensim` implementation of LDA.

## Models

Figures 1, 2 and 3 show that data sets are highly imbalanced which can lead to classification algorithms having low accuracy towards the minority classes. In order to tackle the problem of imbalanced datasets we have tested under-sampling and over-sampling on training data as well as adjusting class weights.

### Traditional ML models

For the baseline models we have selected SKlearn implementation of Logistic regression, Support-Vector Machine and and Ensemble voting classifier - XGBoost.

**Logistic regression** - We have used sklearn implementation of Logistic Regression classifier. For the model parameter tuning the GridSearchCV is used to choose the best model for predicting classes of each dataset as well as predicting classes for a dataset that is a concatenation of all datasets. Best performant model is using `solver=lbfgs`, `max_iter=5000`, `class_weight=balanced`, `C=1` with `penalty=L2`.

**Support-Vector Machine** - We have used sklearn implementation of Support-Vector Machine classifier. For the model parameter tuning the GridSearchCV is used to choose the best model for predicting classes of each dataset as well as predicting classes for a dataset that is a concatenation of all datasets. Best performant model is using `kernel=rbf`, `class_weight=balanced` with `C=1`.

### Ensemble models

**XGBoost** - We have used XGBoost ensemble model for classifying comments data. The boosting algorithm is used with a `learning_rate = 0.05`, `initial_n_estimators=300`.

### Transformer ML models

**BERT** - In order to utilize BERT for text classification we have used `BertForSequenceClassification` model with classification head from <https://huggingface.co/transformers/> library. In the experiments classification head is based on either `mBert` or `CroSloEngualBert`. Both models are pre-trained on a large corpora of multilingual data and are suitable for cross-language knowledge transfer. The model fine-tuning is powered by <https://pytorch.org/> framework.

## Experiments and Results

### Traditional ML models

In the first pass all the models are trained and evaluated on each individual english data set for both, binary and multiclass task. The process of training and testing is conducted via stratified K-fold validation with  $K = 5$  on both feature sets composed from BoW or tfidf. In the each pass, the data is split on training and testing data with 80 – 20% ratio. In the second pass the same procedure is repeated on afore described combined dataset for both binary and multiclass tasks.

As stated above, our data is highly imbalanced. Since in our data we have a dominant majority class, which is non-hate class, a natural effect would be that trained traditional models would be biased towards minority class, thus the model would have a low accuracy on minority class. In order to stimulate the models to focus and reduce the error on minority class, we adjust class weights, giving more weightage to the minority class in the cost function. As afore mentioned, due to the data being imbalanced model would mostly predict the majority class, thus having a high overall accuracy while having poor results on minority class. Therefore, for evaluation metric we chose weighted f1-score which presents the weighted harmonic mean of precision and recall.

Table 3 shows model evaluation results on binary class data set. Both models, LR and SVM have the worst performance on the first dataset. The reason behind such a performance lays in data. The data collected from news comments represent a short comments on average, with a fair share of emoticons and stop words. After the removal of such in the preprocessing step the data remains even shorter, thus there is a little context that the model can learn on. It is shown that the both models have a remarkable performance on the combined dataset with feature spaces composed from tfidf vectors.

The same reasoning for the class weights and evaluation metric selection lays behind the choice for the multiclass data sets. Table 4 shows model evaluation results on multi class data set. Both models have a remarkable result on both data sets as well as on combined one.

**Table 3.** Model classification weighted f1-score on binary class labels

Imbalanced					Model
DS 1	DS 2	DS 3	DS 4	DS 1-4	
0.749	0.845	0.792	0.934	0.883	LR
0.784	0.865	0.823	0.912	0.899	SVM

### Transformer ML models

#### BERT

For BERT fine-tuning we first used the CroSloEng pretrained model with Transformers library and BertForSequenceClassification architecture, which adds a single classification linear layer on top of BERT architecture. Before training we removed

**Table 4.** Model classification weighted f1-score on multi class labels

Imbalanced			Model
DS 1	DS 2	Combined DS	
0.931	0.897	0.929	LR
0.942	0.901	0.943	SVM

30000 non-hate comments from the multiclass dataset, so that the training dataset will be more balanced. Max input text length for BERT models is 512, so we had to modify our datasets a bit. We just filtered out text that is longer than 512. With this approach we filtered out 4.15% text on binary data and 2.59% text on multiclass data. We then prepared our dataset for training with passing it into a BertTokenizer, which uses WordPiece algorithm for tokenization. First the text is tokenized and special tokens are added. For marking the task as classification [CLS], for splitting the sentences [SEP], for padding the text if its shorter than max input text length [PAD], and for marking if the token is not in the pre-trained vocabulary [UNK]. If the token is not in pre-trained vocabulary, the token is split into several subwords. After tokenization all the tokens are converted into ids according to the token position in vocabulary. Additional attention mask token is computed to tell the model which token should be attended to.

Dataset is then split into 80%-20% training and testing sets. And training set is additionally split into 90%-10% training and validation sets, for tracking the training loss and checking for overfitting.

Adam with weight decay fix optimizer is used for training, with parameters: learning rate  $5e-5$ , epsilon  $1e-6$ , betas (0.9, 0.999), no weight decay and with bias correction. Learning rate is set to linearly decrease from initial learning rate to 0 during the training.

As the BERT model is quite large and we use the max text length, we had to freeze the embeddings and first 8 encoder layers in BERT. This gives us 4 encoding BERT layers and 1 classification layer for training. The batch size during training was 20 and we trained each model for 3 epochs.

Tables 5 and 6 show the performance of the fine-tuned CroSloEng BERT model on English data. The performance on English data is good for both tasks. Multiclass model performs better probably because the multiclass datasets were queried by a limited number of hate keywords and so the model can more easily learn the differences between classes. Also multiclass datasets doesn't include the hate data from binary datasets, so the results are different.

When we test the models on Slovene data, the performance drops massively. Tables 7 and 8 show the performance of the fine-tuned CroSloEng BERT model on Slovene data. On binary data some small percentage of hate text was classified correctly, but majority was classified as non hate. While on multiclass data practically all hate text was classified as

non-hate. The performance on Slovene data is poor, which indicates that additional training on Slovene data must be performed to get acceptable results.

**Table 5.** Performance metrics from fine-tuned CroSloEng BERT on English data, tested on English binary classification.

Rows - Actual		Columns - Predicted	
	0	1	
0	51.22	4.37	55.59
1	4.25	40.16	44.41
	55.47	44.53	
Majority Class: 0.5559			
Accuracy: 0.9138			
F1 Score: 0.9224			

**Table 6.** Performance metrics from fine-tuned CroSloEng BERT on English data, tested on English multiclass classification.

Rows - Actual		Columns - Predicted						
	0	1	2	3	4	5		
0	45.76	0.45	0.69	0.45	0.10	0.10	47.55	
1	0.49	4.24	0.20	0.22	0.02	0.00	5.18	
2	0.24	0.04	26.29	0.10	0.14	0.02	26.84	
3	0.33	0.69	0.14	14.53	0.04	0.10	15.84	
4	0.08	0.06	0.02	0.02	2.61	0.00	2.79	
5	0.20	0.06	0.06	0.49	0.00	0.98	1.79	
	47.11	5.54	27.42	15.82	2.91	1.20		
Majority Class: 0.4755								
Accuracy: 0.9442								

**Table 7.** Performance metrics from fine-tuned CroSloEng BERT on English data, tested on Slovene binary classification.

Rows - Actual		Columns - Predicted	
	0	1	
0	54.06	2.08	56.15
1	39.33	4.52	43.85
	93.39	6.61	
Majority Class: 0.5615			
Accuracy: 0.5858			
F1 Score: 0.7230			

**Table 8.** Performance metrics from fine-tuned CroSloEng BERT on English data, tested on Slovene multiclass classification.

Rows - Actual		Columns - Predicted						
	0	1	2	3	4	5		
0	54.56	0.40	0.62	0.16	0.03	0.16	55.93	
1	1.56	0.00	0.00	0.00	0.00	0.00	1.56	
2	1.43	0.00	0.00	0.00	0.00	0.00	1.43	
3	0.59	0.00	0.03	0.00	0.00	0.00	0.62	
4	0.24	0.00	0.00	0.00	0.00	0.00	0.24	
5	39.48	0.24	0.16	0.24	0.00	0.08	40.21	
	97.87	0.65	0.81	0.40	0.03	0.24		
Majority Class: 0.5593								
Accuracy: 0.5464								

future work

- Classify binary hate text with hate keywords, which were used in multiclass dataset fetching from the net. Plan to extend multiclass dataset with additional hate classes. Should be save to use, as the binary datasets were already annotated for hate.
- Addition bert fine-tuning training on Slovene data.
- Try a basic idea: extract keywords from each class using, for example Tf-idf. Manually translate the keywords into slovene. And then check slovene text for slovene keywords, compute distances, use traditional machine learning.

## Conclusion

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