TOWARDS COUNTERING HATE SPEECH AND PERSONAL ATTACKS IN SOCIAL MEDIA

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ABSTRACT

The damaging effects of hate speech in social media are evident during the last few years, and several organizations, researchers and the social media platforms themselves have tried to harness them without great success. Recently, following the advent of deep learning, several novel approaches appeared in the field of hate speech detection. However, it is apparent that such approaches depend on large-scale datasets in order to exhibit competitive performance. In this paper, we present a novel, publicly available collection of datasets in five different languages, that consists of tweets referring to journalism-related accounts, including high-quality human annotations for hate speech and personal attack. To build the datasets we follow a concise annotation strategy and employ an active learning approach. Additionally, we present a number of state-of-the-art deep learning architectures for hate speech detection and use these datasets to train and evaluate them. Finally, we propose an ensemble model that outperforms all individual models.

1 Introduction

Hate Speech is not a new phenomenon. However, before the advent of email, online comments and networking platforms, the threshold to utter it to any effect at all was much higher. People had to draft a letter, buy postage, and send their missive through the mail. Since then, the formulation and dissemination of hate speech have become easy, instant, potentially ubiquitous, public, and therefore much more damaging. In fact, it not only poisons and thus effectively undermines free and open discourse on the Internet, which is bad enough in itself, but also constitutes a real threat to the individuals and organizations it is directed at.

The increasing propagation of hate speech through social media has drawn the attention of governments and researchers. Several papers exist in the literature dealing with the problem of automatic hate speech detection. Hate speech detection methodologies aim to classify any social media post as hate speech or non-hate speech and some even try to derive the type of hate speech.

In this paper, some of the outcomes of DACHS1 (“A Data-driven Approach to Countering Hate Speech”) project will be described. DACHS studies hate speech, focusing on quality journalism as a test case. As professional arbiters

1https://hatedetection.com/
of the public sphere, journalists run afoul of hate speech originators practically by default, yet normally without the background or affiliation that usually triggers much of the destructive online communication. Journalists are multipliers of societal discourse, and a side effect of their relative prominence and high audience reach is that they help protect the smaller and weaker actors in the arena of opinions. The main goal of the project is to build an Alert Monitoring Platform that notifies journalists in cases where there is hate speech. The Alert Monitoring Platform allows journalists to monitor hate speech and is posted on social networks. The journalists can configure the threshold over which content with hate speech will be sent to them via mail as aggregated alert reports. Optionally, journalists can contribute to the dataset generation by further annotating such posts. During DACHS, hate speech against journalists in Twitter is studied in 5 languages, English, French, German, Spanish, and Greek. This paper presents ongoing work regarding automated hate speech and personal attack detection as well as the related datasets that were created.

This work’s contribution is twofold. First, it presents a concise annotation strategy used for the generation of publicly available multilingual hate speech and personal attack Twitter datasets. Second, it uses these datasets to train various state-of-the-art deep learning architectures, while at the same time, proposes an ensemble model and reports the evaluation results. To the best of our knowledge, this is the first effort that creates such a multilingual, diverse and large dataset for hate speech.

The paper is structured as follows. Section 2 includes a brief overview of the work that addresses hate speech detection and provides an overview of the current state of the art. In section 3 the definition of hate speech and personal attack is presented. Section 4 and 5 present the data collection and annotation methodology respectively. Section 6 describes the experimental study that was performed and demonstrates the results and outcomes of this work. In the last section, we conclude this work and present some future steps.

2 Related Work

2.1 Definitions

One of the challenges in studying negative online behavior and hate speech in particular, is the lack of a clear, common definition [1]. In recent literature, many authors studied cyberbullying [2,3]. Work in [4] employs the term personal attack to describe offensive online behavior, while other studies focus on offensive or abusive speech and online harassment [5,6,7]. The actual term hate speech is used in many previous works [8,9,10,11,12,13,14]. Even though these definitions share many common characteristics, in many cases, there are distinct differences even between definitions that use the same term to describe negative online behavior.

2.2 Datasets

With the advent of social media, research on hate speech was intensified especially during the last few years. A critical step to achieve further progress in the detection of online hate speech is the availability of large scale datasets. There have been relatively few efforts focusing on the creation of hate speech datasets from social media. Davidson et al. [6] collected Twitter data using a hate speech lexicon compiled with the help of Hatebase.org in English. They employed crowd-sourcing to label tweets into three categories: hate speech, offensive language, and those with neither. Waseem et al. [15,13] provide a hate speech dataset, which contains 16k tweets, and described the respective annotation procedure in which an initial manual search was conducted on Twitter in order to collect common slurs and terms pertaining to religious, sexual, gender, and ethnic minorities. Manual annotation of the dataset classified tweets whether they contain sexism, racism or neither. Sharma et al. [12] collected a set of 9k tweets containing harmful speech and they manually annotated them in three classes based on their degree of hateful intent. Another study [14] crawled data from a white supremacy forum to extract and manually annotate over 10k sentences classified as hate speech or not. Authors in [16] describe a multi-step classification process and provide a comprehensive hate speech dataset containing more than 28k tweets and capturing various types of hate such as sexual orientation, gender, ethnicity and other. Finally in older work, many researchers have relied on creating their own hand-coded hate speech datasets as in [11,8].

The majority of the studies for hate speech are focused in the English language. However, some other languages were considered by some authors, as in [17,18] were examples of dataset collection and related annotations in German, were presented, focusing in the specific topic of hate speech against refugees. Authors in [19] crawled Facebook comments from public Italian pages. Comments are annotated into a variety of hate categories to distinguish the kind of hate. In addition, there are a lot of datasets addressing offensive and toxic online behavior. Kaggle’s Toxic Comment Classification Challenge dataset [20] consists of 150k Wikipedia comments annotated for toxic behavior. Kaggle hosts additional large scale toxic speech datasets like [21,22]. Studies in [4,23] use crowdsourcing to provide abuse-related annotation on 100k English Wikipedia comments and 80k tweets respectively. Finally, smaller datasets as in [7,9] focus on the annotation of toxic versus clean online comments.
2.3 Detection methods

Existing hate speech detection methods address the problem as a supervised classification task \cite{24}. Traditional methods rely on manually designing and encoding features of textual data into feature vectors, that are used as inputs to algorithms such as Naive Bayes, Logistic Regression, SVM and Random Forest. These methods are adopted by numerous hate and offensive speech detection studies such as \cite{9, 6, 10, 11, 25, 8, 15, 13, 26, 27}. These studies experiment with various features including bag of word representation, character-level, and word-level n-gram features, syntactic features, linguistic features, and comment embedding features.

Following the more recent deep learning paradigm, several studies use neural networks to detect hateful and toxic content. Neural networks, learn abstract feature representations from input data through multiple stacked layers. The key difference from traditional models is that deep learning models automate the feature extraction process and the multi-layer structure provides more efficient feature representations. Many studies have shown that deep learning and neural network methods outperform traditional methods on hate speech detection tasks \cite{28, 5}. The most popular network architectures are Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN). In the context of hate speech classification, CNN extracts meaningful features from word or character combinations \cite{29, 28, 5, 30}, while RNN learns word or character dependencies in sequences of words \cite{27, 29, 19, 31}. Combinations of CNN and RNN models were applied in \cite{32}.

3 Definition

To consistently annotate a large Twitter corpus, there is a need for a clear and simple definition. Our purpose is to define hate speech in a way that would be easy for annotators to label tweets but also would be easy for other non-expert groups like journalists, to further enhance the dataset or provide feedback.

A team of experienced journalists after looking at hundreds of hateful tweets and several meetings, decided that the presence of hate speech should be concluded via answering to two simple key questions. These questions refer to the tweet content and they are presented below:

- Does it target a person or group?
- Does it contain a hateful attack?
  - Violent speech
  - Support for death/disease/harm
  - Statement of inferiority relating to a group they identify with (like LGBTQI)
  - Call for segregation

A positive answer to both bullets should make the annotator flag the post as hate speech. The second question can refer to any of the four subcategories that are listed above.

The following definition from \cite{4} is used for identifying personal attack:

- Does it contain a personal attack or harassment?
  - Targeted at the recipient of the message (i.e. you suck).
  - Targeted at a third party (i.e. Bod sucks).
  - Being reported or quoted (i.e. Bod said Henri sucks).
  - Another kind of attack or harassment.

4 Data collection

The main aim of this work is to create datasets of hate speech in a journalistic context and in English, French, German, Greek and Spanish. The first step of the data collection process consists of gathering a list of journalism-related Twitter accounts for each language, that are used as sources for tweet retrieval. A straightforward way to compose such a list was to manually identify a list of well-known accounts of journalists and news outlets and focus data collection on those accounts. However, preliminary experiments showed that the volume of data that could be collected following this approach is limited, at least by using the standard version of Twitter’s Search API\footnote{https://developer.twitter.com/en/docs/tweets/search/api-reference/get-search-tweets.html}, which does not provide historical data.
Twitter lists\footnote{3https://help.twitter.com/en/using-twitter/twitter-lists} are curated groups of Twitter accounts and are usually centered around specific themes. In order to find Twitter lists related to journalism, we collected the Twitter accounts of well-known news outlets and journalism-related organizations and automated the process of fetching all list members of lists including the original Twitter accounts. Despite the fact that the majority of the collected accounts belong to either journalists or news outlets, we also noticed the presence of non-journalistic accounts, which could potentially tamper with the journalistic focus of our data collection. To tackle this issue, we manually filtered the irrelevant accounts. Since annotating (for relevance with journalism) the full list of accounts would involve a considerable manual effort, we prioritized the annotation of the most followed accounts, since those accounts usually attract a larger number of tweets. In the first iteration of account collection, we annotated the accounts using the following classes: a) journalist, b) outlet, c) irrelevant. The initial seed consists of 200 manually collected journalism-related accounts for each language. Table \[T\] lists the number of journalism-related accounts per language.

Having a validated list of journalism-related Twitter accounts for each language, the next step consisted of setting up a mechanism to collect data (tweets) from the feeds of these accounts. To this end, the free Twitter Search API was used, which returns a sample of recent Tweets published in the past 7 days. The API is rate-limited at 180 requests per 15-min window when user authentication is used and at 450 requests per 15-min window when application authentication is used. In our case, we used application authentication having also in mind that each call can return a maximum of 100 tweets (by appropriately setting the ‘count’ request parameter). This means that a maximum of 45,000 distinct tweets could be collected within 15 minutes. Despite these limitations, by effectively utilizing the API within the imposed call rate limitations, we managed to collect a very large number of tweets that was sufficient for creating a sizeable, journalism-oriented hate speech database. Typically, the free Twitter’s Search API query consists of a series of keywords that should be contained in the set of returned tweets, along with account-based search operators. We opted for using search queries that do not restrict the tweet contents and only used account-based search operators to limit results. More specifically, we used the “to:” (e.g., to:journalisticAccount) and the “@” (e.g. @journalisticAccount) operators in order to collect tweets authored in reply to and tweets mentioning those specific accounts.

Specifically, every 15 minutes, the module sequentially performed $N = 450 - N_{safe}$ API requests, evenly distributed across the 15-minute window. $N_{safe}(0, 450)$ corresponds to a safety parameter that is used to avoid pushing the API to its limits. Currently $N_{safe} = 200$ was used and thus a maximum of $N = 250$ calls were performed per every 15-min window. Since each call is associated with one account and the number of calls that can be performed within each 15-min window is much smaller than the pool of target accounts, an account prioritization/selection mechanism was implemented. A naive approach would consist of sequentially iterating over the list of accounts in batches of $N$ accounts per time window and fetching the latest 100 tweets that each account has received using the $count = 100$ and the $result_type = recent$ call parameters. This approach would ensure that content from all accounts would be regularly fetched in even time intervals but had the disadvantage that it is rate-agnostic (i.e., ignored the fact that each account could receive tweets at a different rate) and would, therefore, result in performing many requests that return much fewer tweets than the maximum of 100 tweets per request. A better approach would be to limit the pool of target accounts to the $K$ most followed ones, under the assumption that the number of followers is indicative of the rate at which an account receives new tweets. Although this approach would improve the effectiveness of the calls, it would have two disadvantages: a) it would limit the data collection to only $K$ instead of $N$ accounts and b) it would assume a static incoming tweet rate for each account while the rate is highly dynamic.

To overcome these limitations, we developed a more elaborate account prioritization approach that fetched data from all accounts and measured an estimate of the rate of incoming tweets. Using this estimate, the available API calls were distributed on accounts which were expected to have received a sufficient number of new tweets since the last time that they were queried. Specifically, whenever a new API call was performed, an estimated number of available new tweets was calculated for each account based on the account’s estimated incoming tweet rate and the time that has passed since the last time it was fetched. Then, one account was randomly selected among those whose estimated number of available new tweets was larger than a user-specified threshold (for which reasonable values should lie close to 100, the maximum number of results per request). After a call is performed, the incoming tweet rate for each account was updated by dividing the number of returned tweets with the time difference between the newest and the oldest tweet (a very low rate was assigned in case a call returns zero results). Moreover, the last fetched timestamp was recorded to facilitate the calculation of the estimated number of incoming tweets. Initially, all accounts were assigned a fixed, high incoming tweet rate to ensure that all accounts will be fetched at least once. This approach ensured that all accounts were queried proportionally to their actual, dynamic incoming tweet rate, thus maximizing the amount of tweets that can be collected.
Table 1: Total number of journalism-related Twitter accounts and total number of tweets retrieved per language

| Language | Accounts | Tweets     |
|----------|----------|------------|
| EN       | 12,306   | 92,324,248 |
| DE       | 3,436    | 12,436,132 |
| ES       | 1,765    | 49,453,601 |
| FR       | 2,794    | 34,118,951 |
| GR       | 3,577    | 2,147,668  |

We applied this approach for every language using the corresponding pool of Twitter accounts. For every language, we stored retrieved tweets in a mongoDB database. To ensure that tweets language matches the language of the accounts we used to retrieve them, we checked the tweet’s metadata information that is available by Twitter API.

The total number of collected unlabeled tweets per language is listed in Table 1. Notice that there are significant differences in the number of tweets retrieved per language. This is expected due to the different number of source accounts used to retrieve tweets, each language popularity, but also depends on the Twitter usage per country. The total duration of tweet collection was approximately 6 months (1/10/2018 - 8/5/2019).

5 Annotation process

The annotation task is always crucial. We opted for a comprehensive process that ensured high-quality annotations but also taking into account the need to create large datasets.

5.1 Description

There are many ways to annotate a large corpus of data in related literature. For this work, we follow the findings reported in [33], which claims that it is better to allocate the annotation budget to label as many examples as possible, when the annotation quality is above a threshold. Based on the above and the fact that we used experienced annotators proficient in the corresponding languages and acquainted with the colloquial nature of social media, it was decided to proceed to the annotation task with one annotation per tweet, following a string quality assurance methodology and utilizing the annotation budget in order to annotate as many tweets as possible.

The supervisor and annotators of each language performed preliminary annotations to make sure that the definitions of hate speech and personal attack were correctly understood. This process also included discussions about any particularities of each language. For each language, the corresponding annotator was asked to flag hate speech and personal attack in tweets with a yes/no answer. Annotating hate speech and personal attack were two separate tasks and were annotated independently. For each tweet in the datasets, the annotator made two separate binary annotations. In case the annotator was unsure about the answer, he/she could flag the tweet as indecisive, and on a second stage, this post would be discussed with the supervisor.

For quality assurance, the quality control methodology as described in ISO 2859 and ANSI/ASQ Z1.4-2003 was followed. We used level II, i.e., the normal severity level, and thus a lot of 1,000 annotations would be considered of acceptable quality if the error rate did not exceed 4%. To determine this, a single sampling size of 80 annotations out of 1,000 was used. The supervisor of the process with external third parties evaluated the annotations, and if more than 7 annotations (out of the 80) were erroneous, the whole lot would be rejected, and careful instructions are given to the annotator.

5.2 Initial annotation batches

The annotation was performed in batches of tweets. Namely, the annotators responsible for the respective languages were given a relative small number of tweets for annotation. After conducting a brief preliminary annotation round in various languages using random tweets from the journalist-related pool, we observed an apparent scarcity of hateful content among annotated tweets. Table 2 shows that there are only 8 tweets that annotated as hate speech in a total of 2000 annotated tweets that were randomly retrieved from the English database. Based on this observation, it is evident that we needed to develop a process, which would generate annotation batches with a higher percent of tweets that express hate.

To mitigate the lack of hateful content, we chose and used some publicly available Twitter hate speech or offensive language datasets which were used to train baseline models for detecting hateful or offensive tweets. In some languages, there was none or minimal resources in order to create such models. For these cases, we created a comprehensive list of
keywords that could potentially be offensive, discriminative, or insulting with purpose to retrieve tweets containing such words, following the example of [6]. Additionally, to avoid bias introduced by the methods above, we also add an equal proportion of random tweets in the annotation batches.

Specifically, for the English language, we used the dataset presented in [6]. The dataset contains 25000 English tweets, which are divided into 19200 offensive, 1500 hate speech, and 4200 other tweets. Although their definition of hate speech differs from the one described in this work, we used this dataset to create an initial hate speech detection model. For our binary classification task, we merged the classes offensive and other into one class. Additionally, we used the dataset reported in [4], which contains 100k Wikipedia comments and corresponding personal attack annotations. We used these datasets to train CNN models. CNN model is described later in section 6.2. Using these models in a way we describe in the following paragraphs, we achieve a much higher hate speech concentration of hate speech in our annotation batches.

For the case of the German language, two different datasets were combined. The first dataset [17], included tweets referring to refugees and included binary hate speech annotations. Most of the hate speech in this dataset was focused on racist expressions. Additionally the GermEval 2018 dataset [18] was used, which is a series of shared task evaluation campaigns that focused on natural language processing for the German language. This dataset contained tweets that are divided into offensive and not offensive. The two datasets were merged, creating a dataset of 9010 tweets, and on a binary classification setup, offensive tweets from the second dataset were treated as hate. Just like the previous case, a CNN model was trained using this dataset.

For the rest of the languages (Spanish, French, Greek), we employed similar keyword based methodologies. A small list of such keywords can introduce high bias in the resulting dataset, because they probably capture specific types of hate speech. To avoid bias, a large list of keywords were created for these languages, including 500 to 1000 keywords depending on the language. These lists included offensive slang, phrases and words that could potentially express hate when used in the appropriate context and keywords related to several kinds of possible discrimination (religion, gender, refugees etc).

To generate the first annotation batch, the following process was used (for each language) with a goal to increase the probability of retrieving a tweet with hate speech in comparison with random selection. If a hate speech detection model could be obtained by using available datasets for the each language, we applied it to the corresponding pool of unlabeled tweets calculating a hate speech probability for each unlabeled tweet. Then 8000 tweets were randomly retrieved corresponding to a wide range of hate speech probability [0.2-1.0]. This wide range was chosen to reduce the bias of the generated batch. Note that for the case of English we had 2 available models, so we applied them both to the pool of unlabeled tweets and we retrieved those which satisfy the hate speech probability constraint for both models. If a hate speech detection model could not be created, a keyword list as described in the previous paragraph was used to fetch up to 8000 tweets. For both cases, 2000 randomly selected tweets were added to the batch, in order to further mitigate bias imposed by the model or keyword methodology. Note that each tweet that was retrieved from the database of unlabeled tweets was marked, in order not be retrieved again during the creation of the next annotation batches.

By using the methodology mentioned above, more tweets that express hate speech and personal attack were collected (see Table 2) - comparing the preliminary annotation round (random sampling) to the initial generated batch. Similar increases were evident in all the other languages.

| lang | class | Batch type | preliminary | initial | AL first batch |
|------|-------|------------|-------------|---------|----------------|
| EN   | HS    |            | 0.4%        | 1.9%    | 6.33%          |
|      | PA    |            | 7.3%        | 26.20%  | 29.10%         |
| DE   | HS    |            | 0.2%        | 1.13%   | 3.47%          |
|      | PA    |            | 1.3%        | 2.88%   | 9.19%          |
| ES   | HS    |            | 0.12%       | 0.89%   | 2.51%          |
|      | PA    |            | 0.9%        | 1.87%   | 5.55%          |
| FR   | HS    |            | 0.3%        | 2.36%   | 7.37%          |
|      | PA    |            | 4.3%        | 7.42%   | 25.34%         |
| GR   | HS    |            | 0.13%       | 0.70%   | 1.32%          |
|      | PA    |            | 2.3%        | 5.91%   | 19.59%         |

Table 2: Percentage of hate speech (HS) and personal attack (PA) tweets in different annotation batches.
5.3 Active learning

After annotating the initial batch of tweets for each language, new models could be trained with the annotated datasets, thus focusing on our definition of hate speech. For every subsequent annotation batch, the process applied in the previous subsection for the case of English and German language was used. Namely, the latest annotated dataset of each language was used to create models and these models were applied to the pool of all unlabeled tweets. Subsequently, new annotation batches were created, by choosing tweets from a hate probability range and merging them with random selection.

Although this is a valid process, it does not guarantee that the retrieved tweets will add additional value to the models. For instance, if a classifier is highly confident that a tweet contains hate speech or the opposite, then this tweet will not contribute to the learning process and might even hurt generalization performance. Motivated by this assumption, an active learning mechanism was created to generate annotation batches of tweets that would eventually contribute to the ability of the models to learn.

Pool-based active learning [34] relies on an initial small set of labeled instances \( L \), and a larger set of unlabeled ones \( U \). Batches of informative training samples are iteratively selected from \( U \) and added to \( L \), with respect to some selection mechanism, after a query about their actual label to an annotator. This approach is motivated in many modern machine learning applications, where unlabeled data may be abundant, but labels are difficult or expensive to obtain.

Initially, uncertainty sampling [34] was used as a selection mechanism. In this setup, an active learner queried the tweets about which it was the most uncertain of how to label. This approach is very straightforward for probabilistic learning models. In our binary classification model, uncertainty sampling selected tweets whose posterior probability was near to 0.5. This approach proved problematic for our scenario, since hate speech datasets are imbalanced, and thus the probability distributions are skewed towards the dominant class. Having this in mind and also the fact that multiple deep learning models would be trained for comparison and evaluation, the best approach proved to be the query by committee [35] algorithm. The query-by-committee approach involves maintaining a committee \( C = \{ \theta^{(1)}, ..., \theta^{(c)} \} \) of models which are all trained on the current labeled set \( L \), but represent competing hypotheses. This is applicable to our scenario since each deep learning model architecture captures different semantic and syntactic components of the tweet, even if they are trained using the same dataset. Then each committee member is allowed to vote on the labels of query candidates. The most informative tweet to be sent to annotators is considered to be the instance that committee members disagree the most. The average Kullback-Leibler (KL) divergence [36]:

\[
x^*_{KL} = \arg\max_x \frac{1}{C} \sum_{c=1}^{C} D(P_{\theta^{(c)}}(x)||P_C(x)),
\]

where:

\[
D(P_{\theta^{(c)}}(x)||P_C(x)) = \sum_i P_{\theta^{(c)}}(y_i|x) \log \frac{P_{\theta^{(c)}}(y_i|x)}{P_C(y_i|x)}
\]

was used for measuring the level of disagreement among the classifiers. Here \( \theta^{(c)} \) represents a particular model in the committee, and \( C \) represents the whole committee, thus \( P_C(y_i|x) = \frac{1}{C} \sum_{c=1}^{C} P_{\theta^{(c)}}(y_i|x) \) is the “consensus” probability that \( y_i \) is the correct label. KL divergence [37] is an information-theoretic measure of the difference between two probability distributions. So this disagreement measure considers the most informative query to be the one with the largest average difference between the label distributions of any one committee member and the consensus.

The active learning approach that was followed is summarized in the following bullet points and can be seen in Figure 1.

- For each language, the initial batch of annotated tweets was used to train models as described in Section 6.2 and generate the committee of our classifiers.
- The committee was applied to the unlabeled pool of tweets \( U \) calculating the probabilities for every classifier on each tweet.
- The average KL divergence for every tweet was computed and tweets with the highest score were chosen.
- Furthermore, we applied the ensemble model (described in Section 6.2) in order to increase tweets from the hate speech class. Similarly with subsection 5.2, 8000 tweets with 0.2 or higher hate speech probability were kept.
- 2000 randomly selected tweets were added to the batch.
- A new batch of 10000 tweets were submitted for annotation.
- After the annotation of the batch is completed, it was added to the pool of annotated tweets \( L \).
Figure 1: A schematic representation of the annotation process (dotted arrows used only for the initial batch generation)

| Train dataset | Test dataset | macro-F1 |
|---------------|--------------|----------|
| Initial       | Additional   |          |
| 8000          | -            | 2000     | 0.43     |
| 8000          | 2000 (random)| 2000     | 0.43     |
| 8000          | 2000 (hate probability)| 2000 | 0.45     |
| 8000          | 2000 (active learning)| 2000 | 0.47     |

Table 3: Different evaluation experiments in English language. We evaluate models created with an initial train set and additional sets generated with different techniques.

- The process was repeated using $\mathcal{L}$ to retrain the classifiers and generate the next batch for annotation.

In Table 3, it is evident that the first annotation batch created with active learning approach (AL first batch) had a higher percent of hate speech compared to the initial batch.

Table 3 shows some experiments conducted to validate this process. In this experimental setting, the initial annotated batch of English tweets were split to 8000 training and 2000 testing tweets. A simple CNN model was trained using the training set and the macro average F1 score was calculated for the test set. This process was repeated 3 times using different additional annotated sets to train the classifier. The first set consisted of 2000 randomly sampled tweets, the second set consisted of 2000 tweets sampled from the [0.2-1.0] hate speech probability interval, and the third contained 2000 tweets sampled using the active learning approach. Random sampling did not improve the evaluation results at all. On the other hand, both hate probability and active learning approaches improved the macro-F1 evaluation with the latter being the best approach. Active learning improved the learning process of the classifier by choosing the most appropriate tweets for annotation.

5.4 Datasets

The final datasets for English, German, Spanish, French and Greek languages are hosted on Zenodo platform and are available after request. Each dataset contains tweets ids and their corresponding annotations for hate speech and personal attack class. Table 4 shows the individual dataset statistics for each language. The datasets are provided in train/test sets, preserving the proportion of negative and positive samples.

4https://zenodo.org/record/3520152#.XcL0OnUzY5k
5https://zenodo.org/record/3520148#.XcL04XUzY5k
6https://zenodo.org/record/3520150#.XcL1C3UzY5k
7https://zenodo.org/record/3520156#.XcL1GHUzY5k
8https://zenodo.org/record/3520157#.XcL1G3UzY5k
### Table 4: Dataset statistics

| lang | dataset | Hate speech | | | | Personal Attack | | |
|------|---------|-------------|---|---|---|---|---|---|
|      |         | positive  | negative | positive | negative | positive  | negative |
| EN   | train   | 5804       | 68051     | 22665     | 50046     | 7159      | 84863     | 28336     | 62556     |
|      | test    | 1355       | 16812     | 5671      | 12510     | 1702      | 42033     | 4639      | 39095     |
| DE   | train   | 1361       | 33626     | 3711      | 31276     | 795       | 29355     | 1697      | 28453     |
|      | test    | 340        | 8707      | 928       | 7819      | 199       | 7339      | 424       | 7114      |
| ES   | train   | 795        | 36694     | 2121      | 35567     | 994       | 36694     | 2121      | 35567     |
|      | test    | 541        | 7281      | 2439      | 5383      | 340       | 8707      | 928       | 7819      |
| FR   | train   | 2163       | 29124     | 9755      | 21532     | 2704      | 26405     | 12194     | 26915     |
|      | test    | 541        | 7281      | 2439      | 5383      | 228       | 12069     | 2764      | 9533      |
| GR   | train   | 913        | 48271     | 11055     | 38129     | 1141      | 60340     | 13819     | 47662     |
|      | test    | 228        | 12069     | 2764      | 9533      |           |           |           |           |

### 6 Experimental study

In this section, the experimental pipeline that was used to train and evaluate the hate and personal attack models using the datasets described in the previous Section is described.

#### 6.1 Tweet pre-processing

Due to the colloquial nature of the Twitter data, there is a lot of noise among words. For example, posted links or mentions do not provide any useful information and need to be normalized, since the focus is only on textual data. To achieve this, a state of the art tweet normalization tool [38] was used, to tokenize and transform each tweet into a sequence of words. The process involves Twitter handles normalization (e.g. @random_user becomes <user>), emoji transformation (e.g. :( becomes <sad>), lower casing, as well as, URL, email and number removal. Furthermore, only basic punctuation was retained (e.g. ..?,;”).

#### 6.2 Models

Following the latest trend in the literature, that shifts towards the adoption of deep learning based methods, some of the latest state of the art models for text classification were used. Deep learning models are found to perform better than traditional methods in most NLP tasks, including hate speech detection tasks [28, 5]. Furthermore, an ensemble learning architecture is proposed, since it combines the predictive power of each individual classifier. Below as small description of the deep learning architectures that were used is provided.

**CCN.** A simple Convolutional Neural Network model described in [30] acts as n-gram feature extractor. Using windows sizes of 2, 3 and 4 this CNN model can extract bi-gram, tri-gram and quad-gram features. The output of each CNN is then further down-sampled by a 1D max pooling layer with a pool size of 4 and a stride of 4 for further feature selection. After the concatenation of pooling layers, another 1D max pooling layer is added and the output is fed to the final fully connected layer.

**Skipped CNN (sCNN).** Extending the base CNN model in order to capture features of words that are not next to each other zhang et al. [30] proposed Skipped CNN layer. Skipped CNN applies a mask to a kernel window, skipping intermediate words and associating words that are not directly near. According to the authors, skipped CNNs can be considered as extractors of ‘skip-gram’ like features.

**CNN + GRU.** Work in [32] added a GRU layer followed by a global max pooling layer on top of CNN model. The GRU layer captures sequence feature relations and learns to identify dependencies between n-gram features.

**LSTM.** A bidirectional LSTM model was created. After the embedding layer, spatial dropout was introduced, which randomly masked 20% of the input words. To process the sequence of word embeddings, an LSTM layer was used, with 128 units. Next, a global max pooling and an average max pooling layer was concatenated, flattening the output space by taking the highest and the average value in each timestep dimension, respectively. The produced feature vector was fed into the final fully connected layer.
LSTM + Attention (aLSTM). Attention mechanism is used with success in many NLP tasks like in [39]. Intuitively, attention is a mechanism that learns to favor features that are more relevant to the classification task, by assigning weights. This means that features that are not important to the task are multiplied by smaller weights, while predictive features are multiplied by higher weights. The attention layer was implemented based on [40] and was applied to the LSTM model. Instead, of taking the max and average features in each timestep, an Attention layer with 100 units was used, to extract the important features of the LSTM layer. The output of the attention layer was then fed to the output layer.

Ensemble (E). Aken et al. [41] proposed an ensemble model based on the assumption that classification methods vary in their predictive power and may conduct specific errors. The ensemble model in [41] was trained with gradient boosting decision trees. We used a simple dense neural network ensemble architecture, forwarded the output predictions of the models as inputs to a dense layer with 20 neurons, applied a dropout layer with a ratio of 0.2 and finally the outputs features were forwarded to the final output layer. Intuitively, this small neural network learns to apply a weighted average based on the prediction probability of each individual classifier.

6.3 Implementation details

For all methods discussed in this work, we use Keras [42] with Tensorflow [43] backend and the scikit-learn [44] library. Each model was trained for 10 epochs and a mini-batch of 64 tweets as used. Keras requires static input sequences, meaning that the max number of words in a tweet had to be predefined. Thus the max sequence of words for a tweet was set to 50 since after experimentation, it was found that it does not affect performance. Zero padding was used for sentences with less than 50 words. The first layer for every model is an embedding layer. We initialize the embedding layer using pre-trained word vectors for each language. After conducting some preliminary experiments, the best pre-trained embedding choice for Greek and French language was using fastText embeddings [45], trained on Common Crawl and Wikipedia. For English, Spanish and German language Glove embeddings [46] achieved better evaluation results. Word2vec [47] pre-trained embeddings were also tested. Note that the evaluation results among different embedding approaches do not exhibit significant differences. Word vectors that did not exist in the pre-trained embeddings were randomly initialized, and the embedding layer was further fine-tuned during the training process. To represent a padding token, a word vector initialized with zeros was used. For every model, the default parameters were used, as provided by the corresponding authors unless stated otherwise. The l2 regularization parameter was chosen to be $1e^{-3}$ for every layer. Hate speech and personal attack detection were treated as two separate binary classification problems. The final fully connected layer has a sigmoid activation and makes the prediction for each binary classification task. Binary cross-entropy loss function and the Adam optimizer was used to train the models.

6.4 Evaluation setup

In related literature, evaluation of the performance of hate speech detection typically adopts the classic Precision, Recall and F1 metrics. Precision measures the percentage of true positives among the predicted hate speech tweets. Recall measures the percentage of true positives among the ground truth hate speech tweets, and F1 calculates the harmonic average of the two. The three metrics are applied to each dataset class and an aggregated result is computed either using micro-average or macro-average. The first approach sums up the individual true positives, false positives, and false negatives identified by a model, not taking into consideration different classes to calculate overall Precision, Recall and F1 scores. The second approach takes the average of the Precision, Recall and F1 on different classes. Existing studies on hate speech detection have primarily reported their results using micro-average Precision, Recall and F1 [29, 28, 5, 15, 32].

As stated in [30] and is obvious in our dataset statistics shown in Table 4, a usual observation in hate speech datasets is their highly imbalanced nature. In imbalanced datasets, like the ones discussed in this paper, micro-averaging can inherently hide the real performance of minority classes. Thus a significantly lower or higher F1 score on a minority class is unlikely to cause a significant change in micro-F1 on the entire dataset. In a practical application like hate speech detection, reporting micro-F1 on the entire dataset will not properly reflect a models’ performance on hateful content as opposed to non-hate. Motivated by these observations, we use the standard Precision (P), Recall (R) and F1 measures for evaluation and report their macro averages(m-P, m-R, m-F1). Additionally, we provide F1 obtained on hate speech class (h-F1) and personal attack class (pa-F1).

To train and evaluate the models for hate speech and personal attack, we used the training and test dataset reported in Table 4 respectively. Two separate models were trained - one for hate speech and one for personal attack.
6.5 Results

Table 5 shows the evaluation results for the hate speech class in each language. A first observation that highlights the imbalance between classes is that F1 score for the hate class is significantly lower compared to the macro F1 scores. This is expected because the number of non-hate tweets in the test dataset is significantly larger than hate tweets, as displayed in Table 4.

| metric | CNN | sCNN | CNN + GRU | LSTM | aLSTM | E |
|--------|-----|------|-----------|------|-------|---|
| EN     | m-P | 0.81 | 0.83      | 0.80 | 0.77  | 0.79 | 0.80 |
|        | m-R | 0.78 | 0.78      | 0.80 | 0.78  | 0.79 | 0.82 |
|        | m-F1| 0.79 | 0.80      | 0.80 | 0.77  | 0.79 | 0.81 |
|        | h-F1| 0.61 | 0.64      | 0.63 | 0.58  | 0.61 | 0.65 |
| DE     | m-P | 0.64 | 0.67      | 0.68 | 0.65  | 0.67 | 0.67 |
|        | m-R | 0.67 | 0.71      | 0.68 | 0.65  | 0.66 | 0.71 |
|        | m-F1| 0.65 | 0.69      | 0.68 | 0.65  | 0.66 | 0.69 |
|        | h-F1| 0.34 | 0.40      | 0.38 | 0.32  | 0.35 | 0.40 |
| ES     | m-P | 0.69 | 0.69      | 0.70 | 0.74  | 0.68 | 0.70 |
|        | m-R | 0.71 | 0.75      | 0.72 | 0.68  | 0.68 | 0.73 |
|        | m-F1| 0.70 | 0.72      | 0.71 | 0.70  | 0.68 | 0.72 |
|        | h-F1| 0.42 | 0.45      | 0.44 | 0.42  | 0.38 | 0.44 |
| FR     | m-P | 0.81 | 0.81      | 0.83 | 0.80  | 0.80 | 0.84 |
|        | m-R | 0.81 | 0.82      | 0.81 | 0.77  | 0.82 | 0.81 |
|        | m-F1| 0.81 | 0.82      | 0.82 | 0.78  | 0.81 | 0.83 |
|        | h-F1| 0.65 | 0.66      | 0.66 | 0.64  | 0.64 | 0.67 |
| GR     | m-P | 0.78 | 0.87      | 0.87 | 0.86  | 0.86 | 0.87 |
|        | m-R | 0.78 | 0.77      | 0.75 | 0.75  | 0.75 | 0.78 |
|        | m-F1| 0.79 | 0.81      | 0.80 | 0.80  | 0.80 | 0.82 |
|        | h-F1| 0.59 | 0.63      | 0.60 | 0.60  | 0.60 | 0.65 |

Table 5: The evaluation results for hate speech class

By inspecting each language separately, we notice that there are no significant performance differences between all models in terms of macro F1. However, in terms of individual models, the sCNN model seems to generally exhibit the best performance. Some exceptions are observed, as in the case of the Spanish language where the LSTM model performs better in terms of macro Precision, and in the Greek language, where the CNN model has better macro Recall evaluation. sCNN seems to be the most compelling feature extractor for hate speech as it achieves the best F1 score for hate class, among individual models. This also translates to overall better macro F1 by sCNN compared to other methods. For the case of the French language, CNN+GRU model performs on par with sCNN model.

Additionally, the combination of all individual models in the ensemble model (E) yielded even better results in terms of macro F1. Ensemble model had the best macro F1 score, as it manages to perform well both in terms of macro Precision and macro Recall. The ensemble model also exhibits the best performance in terms of hate speech F1 score. The only exception is observed in the Spanish language, where sCNN model scores a higher F1 score for the hate speech class.

Another observation is that the evaluation for English, Fresh and Greek, specifically in terms of F1 score in the positive class, is significantly better when compared with the Spanish and the German languages. This is potentially due to the fact that there are less positive samples in these datasets. Our goal is to continue expanding the dataset and specifically address the issue for these languages.

Table 6 displays the evaluation for personal attack. It is evident that F1 scores among personal attack (PA) and macro F1 are closer to each other compared to hate speech dataset evaluation. More specifically, F1 scores in positive class are much better in personal attack dataset compared to hate speech dataset. Intuitively, this can be justified with the fact that the personal attack dataset, as shown in Table 4, is not so highly imbalanced in contrast with the hate speech dataset.

Following the hate evaluation paradigm, we do not notice significant performance differences between all models in terms of macro F1. sCNN is the best performing individual model. There are cases where CNN+GRU model exhibit equivalent or even better performance (EN,DE) Ensemble model however, does not perform better than individual models in the personal attack dataset and produces similar results with various other models. One potential reason for this could be that individual models fail to capture diverse features in the personal attack scenario because of the more general nature of personal attack definition.
## 7 Conclusion

In this work, five new Twitter datasets in the English, French, German, Spanish and Greek language are presented, and state of the art deep learning architectures were applied to detect hate and personal attacks. To annotate this set, we focused on a simple and consistent definition for hate speech and personal attack in order to provide high-quality labeling and mitigate the personal bias of annotators. We also devised a comprehensive methodology to generate meaningful batches of tweets for annotation. Our primary goal was to provide large scale datasets in order to contribute to the improvement of methods for identifying hateful and offensive content on social media.

We also employed some state of the art deep learning architectures and used our datasets to train and evaluate them. Despite the imbalanced nature of the datasets these methods can efficiently capture hate speech and personal attack features and exhibit good results in both cases.

As future steps, we plan to keep expanding the datasets with new tweets. We have developed an Alert Monitoring Platform for journalists that supports further annotation of tweets and we plan to retrain our models frequently. Additionally, we aim to use active learning techniques in order to choose more informative tweets for the learning procedure of the models. Another issue we will focus on is the imbalance between the positive and negative classes. To alleviate this, we will use smart ways to fetch more unbiased hateful content. Finally, we will experiment with some state of the art deep learning architectures for natural language processing like BERT [48] or ULMFiT [49].

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