HATEMINER at SemEval-2019 Task 5: Hate speech detection against Immigrants and Women in Twitter using a Multinomial Naive Bayes Classifier

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Abstract
This paper describes our participation in the SemEval 2019 Task 5 - Multilingual Detection of Hate. This task aims to identify hate speech against two specific targets, immigrants and women. We compare and contrast the performance of different word and sentence level embeddings on the state-of-the-art classification algorithms. Our final submission is a Multinomial binarized Naive Bayes model for both the subtasks in the English version.

1 Introduction
Twitter is a micro-blogging platform where people exchange ideas using short messages called tweets. Users can propagate their notions, including hatred against an individual or a group, to the entire global population with a latency of a few seconds. This poses a unique challenge of developing systems that can automatically identify and mitigate hate speech. Although twitter condemns hate speech through its hateful conduct policy¹, enforcing it is difficult. There are several reasons for this. Tweets often contain emoticons, emojis, language slangs, hashtags and other noisy data. Often, offensive and abusive language may be erroneously perceived as hate speech and hence it is important to distinguish offensive, abusive and hateful languages (Davidson et al., 2017; Waseem and Hovy, 2016). These problems are exacerbated by the fact that even humans find it difficult to delineate offensive and hateful language.

Many approaches have been put forward to detect hate speech. Bag of words and ngram features are effective in hate speech detection (Burnap and Williams, 2015; Warner and Hirschberg, 2012) as well as the detection of abusive and offensive content (Nobata et al., 2016). Gitari et al. (2015) used lexical resources to look up certain words that contribute significantly to hate speech but such features, when used in isolation may not be very effective. SVM (Burnap and Williams, 2015), Naive Bayes (Kwok and Wang, 2013) and Logistic Regression (Davidson et al., 2017) are some of the classifiers used in this domain.

Most of the above methods are targeted to detect general hate speech. Through this task, we aim to identify hate speech, specifically against immigrants and women. Frenda et al. (2018) used lexicon resources to identify misogynistic comments. Ahluwalia et al. (2018) used an ensemble of random forest, gradient boosting and logistic regression with bag of words, ngram and lexical features to discern hatred against women. We did not find significant work in detection of hate speech in English against immigrants.

2 Shared Task Description
The SemEval 2019 Task 5 is divided into two subtasks.

1. Subtask A, where systems must predict whether a tweet is hateful (HS=1) against immigrants and women.

2. Subtask B, where systems must first classify hateful tweets as aggressive (AG=1) or not, and secondly to identify the target harassed as an individual (TR=1) or generic.

We used the datasets provided by the organizers. Table 1 describes the composition of the dataset. Further details of the task are available in the task description paper (Basile et al., 2019).

3 System Description
3.1 Pre Processing
We perform the following pre-processing operations on the text before feature engineering.
|        | HS=1 | TR=1 | AG=1 |
|--------|------|------|------|
| Train  | 57.9%| 17.3%| 14.9%|
| Dev    | 42.7%| 20.4%| 21.9%|

Table 1: Dataset composition. HS: Hate Speech TR: Target AG: Aggressiveness

- All text is converted to lower case.
- All URLs, mentions, emojis and smileys are removed from the tweets. We used a python package tweet-preprocessor\(^2\) to achieve this.
- All contractions are replaced with their full form. For example, *don’t* will be replaced by *do not* and *can’t* will be replaced by *can not*.
- All punctuation marks are removed.
- All numerical sequences are removed from the text.
- **Hashtag segmentation and spell correction:** Hashtags provide insights about a specific ideology by a group of people. These notions provide vital information for text classification, especially in the case of hate speech against immigrants and women. For example, hashtags like *#endimmigration*, often come from a group of people who are against immigrants. Segmentation (Segaran and Hammerbacher, 2009) of the hashtags is essential to allow the classifier to treat *#buildthatwall, #buildthewall, #buildthedamnwall, #buildwall*, etc with the same importance. After segmentation, *#buildthatwall* becomes *build that wall*, *#buildthedamnwall* becomes *build the damn wall* etc. Many tweets contain abusive words in elongated form, such as *f****kkkk*. We perform spell corrections (Jurafsky and Martin, 2018) on these words to reduce the vocabulary size and to account for better results. Text8\(^3\) is utilized to generate unigram and bigram word statistics with ekphrasis (Baziotis et al., 2017) to perform both these operations.
- **Stemming:** Stemming is the process of reducing a word to its base root form. We used Porter Stemmer\(^4\) from NLTK (Steven Bird and Loper, 2009) to stem. Stemming is used in combination with the Naive Bayes classifier. For other classifiers, pretrained word embeddings without stemming are used.

### 3.2 Feature Engineering

The following features are considered in our experiments.

- **Bag of words (BoW):** Bag of words is used to represent the presence of word n-grams.
- **Word Embeddings:** Glove840B - common crawl, GloveTwitter27B - twitter crawl (Pennington et al., 2014) and fasttext - common crawl (Mikolov et al., 2018) pre-trained word embeddings are used to analyze their impact on the classification.
- **Sentence Embeddings:** InferSent (Conneau et al., 2017) is used to produce sentence level embeddings. InferSent is a sentence embedding method that provides semantic representations for English sentences. It is trained on natural language inference.

### 4 Experiments

In this section, we describe the experimental settings used in our research. All our code is publicly available in a github repository.\(^5\)

#### 4.1 Evaluation Metrics

The evaluation metrics for subtask A are precision(HS), recall(HS) and F\(_1\)-score(HS). Macro averaged F\(_1\)-score(HS,TR,AG) and Exact Match Ratio (EMR) are the evaluation metrics for subtask-B. Submissions are ranked based on F\(_1\)-score(HS) and EMR for subtask-A and subtask-B, respectively.

#### 4.2 Methodology

All the experiments are developed using the Scikit-Learn (Pedregosa et al., 2011) machine learning library. Five-fold cross validation score on the train set used to evaluate our models. We ran several experiments on various classification algorithms. The best performing classifiers were Naive Bayes, logistic regression, SVM and XGBoost. The following are the details of the classifier settings.

\(^2\)https://github.com/s/preprocessor

\(^3\)http://mattmahoney.net/dc/textdata.html

\(^4\)https://tartarus.org/martin/PorterStemmer/

\(^5\)https://git.io/fhFGR
### Table 2: Pretrained word and sentence embeddings results. For each classifier family, the best score is made bold.

| WordVector     | Logreg | SVM     | XGB     |
|----------------|--------|---------|---------|
|                | $F_{avg}(HS)$ | $F_{avg}(HS,TR,AG)$ | EMR | $F_{avg}(HS)$ | $F_{avg}(HS,TR,AG)$ | EMR | $F_{avg}(HS)$ | $F_{avg}(HS,TR,AG)$ | EMR |
| glove          | 0.58   | 0.57    | 0.49    | 0.54 | 0.54    | 0.45 | 0.61 | 0.56    | 0.44 |
| fasttext       | 0.58   | 0.56    | 0.53    | 0.55 | 0.52    | 0.45 | 0.61 | 0.56    | 0.43 |
| glove twitter  | 0.69   | 0.67    | 0.48    | 0.69 | 0.61    | 0.45 | 0.69 | 0.65    | 0.44 |
| glove + infersent | **0.73** | **0.70** | 0.47    | 0.66 | 0.64    | 0.46 | 0.72 | 0.68    | 0.46 |

### Table 3: Multinomial Naive Bayes Classifier results with word ngram range, stemming and binarization

| Word ngrams | Stem | Binary | $F_{avg}(HS)$ | $F_{avg}(HS,TR,AG)$ | EMR |
|-------------|------|--------|---------------|---------------------|-----|
| 1,2         | false | true   | 0.69          | 0.66                | 0.45 |
| 1,2         | false | false  | 0.68          | 0.66                | 0.45 |
| 1,2         | true  | true   | **0.69**      | 0.67                | **0.47** |
| 1,2         | true  | false  | 0.68          | 0.66                | 0.45 |
| 1,3         | true  | true   | 0.69          | 0.66                | 0.45 |
| 1,4         | true  | true   | 0.69          | 0.66                | 0.45 |
| 1,4         | true  | true   | 0.69          | 0.66                | 0.45 |

### Table 4: Results on the dev set

| Classifier                  | $F_1(HS)$ | $F_1(HS,TR,AG)$ | EMR |
|-----------------------------|-----------|-----------------|-----|
| glove twitter+logreg        | 0.70      | 0.70            | 0.48 |
| glove twitter+XGB           | 0.69      | 0.66            | 0.55 |
| glove+infersent+XGB         | 0.72      | 0.72            | 0.53 |
| glove+infersent+logreg      | 0.72      | 0.72            | 0.53 |
| NB binarized+word-ngrams(1.2) | **0.74** | **0.73**        | **0.57** |

### 5 Results and Analysis

We wanted to submit a single system for both the subtasks. Hence, our goal was to maximize all three metrics: $F_1(HS)$, $F_1(HS,TR,AG)$ and EMR. The results show that there is no single variation that defeats the others in all the metrics combined. Logistic regression with glove and infersent performed the best in $F_1(HS)$ and $F_1(HS,TR,AG)$, but only with an acceptable EMR. Regarding the XGBoost family, glove with infersent version outperforms the rest in all the metrics. Stemmed-binarized Naive Bayes classifier with ngram range (1,2) performed better in $F_1(HS)$ and EMR in the Naive Bayes family. The Glove-Twitter version of logreg and XGBoost aren’t too far behind as well. We applied all these high performing models on the dev set to analyse their performance further. The results are shown in Table 4. Naive Bayes comfortably achieved the highest score on the dev set on all the three metrics as shown in Table 4. Hence, we finalized the Naive Bayes model as our official submission. This submission scored an $F_1(HS)$ of 0.405 in subtask-A, $F_1(HS,TR,AG)$ of 0.54 and EMR of 0.296 in subtask-B.
6 Conclusion and Future Work

The aim of this research was to detect hate speech against two specific targets, immigrants and women. We described a naive bayes classifier system and also elucidated our trials of using different pre-trained word and sentence level embeddings on the state-of-the-art classification algorithms. In the future, we would like to include lexicon-based, Parts Of Speech features to further investigate the performance of these classifiers. We would also like to evaluate how deep learning approaches respond to this task.

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