Improving Hate Speech Classification on Twitter

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Abstract

Hate speech classifers struggle to correctly identify sentences that do not contain explicit hate speech terms as hate speech. We wanted to see if adding hand-built, fine-grained features into a Logistic Regression model increased both macro-average recall and the recall the "hate speech" class. Our primary concern was correctly classifying tweets that do not have explicit hate terms, as these can be difficult for classifiers to identfiy correctly. We chose to focus solely on a Logistic Regression model because LR models are easily interpreted out of the box. We found that a combination of hand-built features and sentence-level embeddings improves both metrics. We conducted an in-depth error analysis to determine if, even with the improvement in numbers, we actually correctly classified more tweets that did not have explicit hate terms.

1 Introduction

Hate speech and offensive language have begun to perpetuate online communities that were originally designed to foster community and bring people together. Both anonymity and the ease of spreading content online have made it easier for hateful speech to infiltrate large communities like Twitter. Unfortunately, it is difficult for social media companies to identify this sort of speech. Part of the problem is the vast amount of content that gets posted every day, and part of the problem is also in identifying when and how hate speech actually occurs. Many instances of hate speech occur in contexts where no explicit hate terms are used.

This problem could be helped by a Machine Learning classifier that identifies hate speech. However, until Davidson et al. (2017)'s research, all classifiers were binary, classifying speech as either offensive or not. Hate speech is a separate from category offensive speech because it targets individuals based on nationality, ethnicity, religion, gender, sexual discrimination, disability or class in an especially aggressive or demeaning manner (Tuckwood, 2017). Davidson et al. (2017) were the first to identify this field as needing at least three classes: Hate Speech, Offensive Language, or Neither.Davidson et al. (2017) identify classification of tweets without explicit hate speech as difficult to correctly classify. We attempted to take Davidson et al. (2017)'s research further by adding more robust features to the Logistic Regression model in order to better capture the context surrounding tweets that don't contain explicit hate terms and correctly classify them.

2 Related Work

2.1 Automated Hate Speech Detection and the Problem of Offensive Language

(Davidson et al., 2017) focused on the differentiation of hate speech and offensive speech with the aim to classify without relying on explicit hate keywords. The distinguishing factor between hate speech and offensive language is that while both may contain inappropriate or obscene language, only hate speech is intended to communicate a highly negative, and even aggressive, sentiment towards a person or group of people.

The features (Davidson et al., 2017) employed included uni/bi/trigrams weighted by its TF-IDF, binary and count indicators for hashtags, mentions, retweets, and URLs. To capture syntactic structure information they used NLTK and Penn Part-of-Speech (POS) taggings. They trained a logistic regression with L2 regularization model on the entire dataset and then used it to predict the label for each tweet using a one-versus-rest framework with: 0.91 precision, 0.90 recall, and .90 F1 score. However, almost 40% of hate speech was misclassified: the precision and recall scores for the hate class were 0.44 and 0.61 respectively which suggested that the model is biased towards classifying tweets as less hateful or offensive than the human coders.

The tweets with the highest predicted probabilities for hate speech contained multiple racial or homophobic slurs. Some tweets that should have been predicted as hate speech but did not contain explicit slurs so were mislabeled. Hateful tweets such as ”If some one isnt an Anglo-Saxon Protestant, they have no right to be alive in the US. None at all, they are foreign filth contains a negative term, filth but no slur against a particular group.” were incorrectly labeled as neither because do not contain hate or curse words, again showing the system's reliance on explicit hate words. The results showed that hate speech can be directly aimed at a person or group of people targeted, it can be espoused to no one in particular, and can be in a conversation between people. They suggest that future work should distinguish between these three cases and look more at the social context and conversations in which hate speech occurs. In addition, we must also study the people who use hate speech (their individual characteristics and motivations) and on the social structures they are embedded in.

2.2 Fine-Grained Hate Speech Detection

Wang (2018) outlines fine-grained hate speech detection as a classification task that splits Tweet sentiment into three categories: hate speech, offensive speech, or neither. Wang (2018) describes methodology in the current literature for classifying tweets in this manner, identifying Bag Of Words as the most common approach with unigrams being the most effective feature for identifying tweets with hate speech, except when explicit hate terms aren't present. Wang (2018) also finds that Deep architectures are effective without needing manual feature extraction. Wang (2018) finds the use of an LSTM effective and incorporates the Hatebase lexicon into the embedding layer in order to learn representations for each tag found, which helps to improve performance on all the models she tested except Davidson et al. (2017)'s original model. In Wang (2018)'s conclusion, explainability of models is identified as being an important area of future research, since it could show bias that conflates hateful intent with the vernacular of communities that are not inherently hateful.

2.3 Comparative Studies of Detecting Abusive Language

Lee et al. (2018) performed the first comparative study of applications of deep learning methods to a 100K example data set of tweets labeled for hateful speech. They classify tweets according to the following labels: normal, spam, hateful, or abusive. They were also able to use context tweets, which has been a step missing in much of prior research. Including context is important because, as humans, it is much easier to identify the offensiveness of a statement if we know the context within which the statement was being made, and Lee et al. hypothesized that this would also help a classifier. They found that the best-performing models (in terms of macro F1 score) were an RNN using word-level features and an RNN using Latent Topic Clustering, which is used to extract topic information from the hidden states of RNN which can be used in classification. They found that including context tweets did not improve model accuracy. This paper shows the efficacy of deep learning models on the classification task at hand.

3 Data and Methodology

3.1 Data

The data was obtained by first collecting a hate speech lexicon comprised of words and phrases from *Hatebase.org* (Tuckwood, 2017), an online, crowd-sourced repository of structured, multilingual, usage-based hate speech. Then, the Twitter API was used to obtain 85.4 million tweets from 33,548 users, of which 24,783 tweets were selected to make up the final dataset. To obtain ground truth labels for these data, a crowd-sourcing website was used. Annotators were provided with a formal definition of hate speech and asked to label each tweet as hate speech, offensive but not hate speech, or neither offensive nor hate speech. Every tweet was labeled by at least three annotators, and mean inter-annotator agreement was 92%.

3.2 Training

We trained all models using a set of 19K tweets from the dataset. Each model had a feature set concatenated with the baseline features.

These models were then run through 5-fold cross-validation grid search on a Logisitic Regression model.

3.3 Features

We implemented a number of hand-built features and utilized Flair embeddings Akbik et al. (2018) as well. These were used in conjunction with the baseline feature set.

3.3.1 Baseline Features

We utilized Davidson et al. (2017)'s feature set as our baseline. These features included uni/bi/trigrams weighted by TF-IDF, binary and count indicators for hashtags, mentions, retweets, and URLs. To capture syntactic structure information they used NLTK and Penn Part-of-Speech (POS) taggings

3.3.2 Hand Built Features

We built a lexicon of ethnic and group membership words and treated tweets containing keywords indicating group membership differently. We used this lexicon to create a binary feature capturing if a tweet contains a statement targeting a specific group of people, i.e. ”all you Asians” or ”every Mexican.” This could possibly capture the nuance of a statement that isn't explicitly hateful. Similarly, we tried to identify tweets where the name of a group was followed by a modal verb like ”should” or ”can.” We also tried to capture self-reference when an allusion to specific group was made by implementing a feature that looked for first person pronouns followed by a word indicating group membership.

We implemented an indicator feature for offensive / hate speech geared towards women. We sourced gendered insults towards women to form a lexicon, where terms were scraped from a crowd-sourced post (sac, 2018). We also included popular terms that were used by Trump supporters targeting Megyn Kelly (Crockett, 2016). This context-based feature was performed in two-steps: first, identify if a tweet is aimed at a female (as indicated by pronouns). Second, check if the tweet has a gendered insult. This differs from a simple 'contains check' because many female-specific insults like ”feisty”, ”bossy”, etc. are offensive only in the context of being aimed at a woman. We also used the Words that Hurt Lexicon (wor, 2018) to augment this feature.

Slang is an important characterization of tweets, so we wanted to capture the meaning behind slang words instead of ignoring them. To decode slang terms, we mapped common Twitter slang terms to their definitions and replaced any instance of slang with its definition. After replacing the slang, we extracted the sentiment of the tweet (positive, negative, or objective). We utilized the Marcus et al. (1993) PennTreebank to convert tweets to Wordnet tags (Miller, 1995) to get the sentiment of tweets with slang replaced with their definition.

We utilized the NRC Emotion Lexicon (Mohammad and Turney, 2013) to count the number of tokens in a tweet referring to a specific emotion (anger, anticipation, disgust, fear, joy, sadness, surprise, and trust). We used the count for each emotion as its own separate feature.

In addition to contextual features, we included some lexical features. The (Davidson et al., 2017) model utilizes a porter stemmer when processing the tweets; we included a feature that did not stemming the words in tweets when creating tfidf weightings to see if that helped capture sentiment in tweets that may not be explicitly offensive. We also included a few indicator features. First, a feature indicating if a tweet referenced immigrants directly. Second, a feature that searched for a group membership word inside of quotes.

3.3.3 Flair

We wanted to include contextual string embeddings to better capture sentence-level context, since we were interested in capturing the nuanced context of a tweet that contains hateful speech without being explicit. Akbik et al. (2018) created an embedding library called **Flair** that provides word and sentence-level pre-trained embeddings. One of their word-level embeddings was trained using Twitter. We chose to use this set of embeddings converted to sentence level, which Akbik et al. (2018) call ”Document Pool” embeddings. We also utilized Flair's contextual string embeddings, one of which was BERT embeddings (originally developed by Devlin et al. (2018)). The second set of embeddings was trained on a 1 billion word corpus from the news. We trained models using Twitter on its own as well as in combination with the news and BERT embeddings. Akbik et al. (2018) recommend ”stacking” word and string embeddings for the best results.

3.3.4 Combined Features

We wanted to compare the performance of our hand-built features with the embeddings both separately and combined. We concatenated the embedding features first with the baseline set of features and trained the model on those feature sets. We did the same for the baseline features plus our hand built features. After training separate models for these, we combined the hand-built features with the Twitter embeddings and the combined news, BERT, and Twitter embeddings.

	Precision	Recall	F1-score
Hate Speech	0.30	0.45	0.36
Offensive	0.94	0.86	0.90
Neither	0.66	0.81	0.73
Micro avg	0.83	0.83	0.83
Macro avg	0.64	0.71	0.66
Weighted avg	0.86	0.83	0.84

Table 1: Davidson et al. (2017) Logistic Regression Baseline

	Precision	Recall	F1-score
Hate Speech	0.25	0.35	0.29
Offensive	0.92	0.87	0.90
Neither	0.68	0.75	0.71
Micro avg	0.83	0.83	0.83
Macro avg	0.62	0.66	0.63
Weighted avg	0.84	0.83	0.83

Table 2: Twitter Embeddings

	Precision	Recall	F1-score
Hate Speech	0.31	0.47	0.38
Offensive	0.95	0.88	0.91
Neither	0.74	0.85	0.79
Micro avg	0.86	0.86	0.86
Macro avg	0.67	0.74	0.69
Weighted avg	0.88	0.86	0.87

Table 3: News, Twitter, and BERT Embeddings

	Precision	Recall	F1-score
Hate Speech	0.24	0.36	0.29
Offensive	0.91	0.86	0.89
Neither	0.65	0.71	0.68
Micro avg	0.81	0.81	0.81
Macro avg	0.60	0.64	0.62
Weighted avg	0.83	0.81	0.82

Table 4: Hand-Built Features

	Precision	Recall	F1-score
Hate Speech	0.27	0.38	0.32
Offensive	0.92	0.87	0.90
Neither	0.68	0.75	0.71
Micro avg	0.83	0.83	0.83
Macro avg	0.62	0.67	0.64
Weighted avg	0.85	0.83	0.84

Table 5: Hand-Built Features with Twitter Embeddings

	Precision	Recall	F1-score
Hate Speech	0.31	0.47	0.38
Offensive	0.95	0.89	0.92
Neither	0.74	0.84	0.79
Micro avg	0.86	0.86	0.86
Macro avg	0.67	0.73	0.69
Weighted avg	0.88	0.86	0.87

Table 6: Hand-Built Features with News, BERT, and Twitter Embeddings

4 Results

4.1 Model Performance

Final results were reported after all models were run on a held-out test set comprised of 5K tweets. We used 5-fold cross-validation grid search on a Logisitc Regression model to find the optimal parameters for each model. Our best performing model (Table 3) outperformed the baseline model (Table 1) by 2% in recall of the Hate Speech class and by 3% in macro averaged recall. Interestingly, hand built features did not seem to increase classification recall on the currently labeled data set. However, as will be explored in the error analysis, this does not necessarily mean that the hand-built features are in reality worse at correctly identifying hate speech.

4.2 Error Analysis

Error analysis with this dataset proved difficult because not all examples of tweets labeled as hate speech are truly hate speech. Some examples include :

”I’m the biggest redskins dam right now if they get this stop”

”I’m not really a phone kinda guy.. I actually hate talking on the phone amp; texting kinda trash to me also.”

”Whipped out some french in front of some babes at the post office. winning”

The Hand-Built Features with News, BERT, and Twitter Embedding (Table 6) model had 591 misclassified tweets. Of these, 88 were in the hate speech class, 99 in the neither class, 404 in the offensive class.

The News, Twitter, and BERT Embeddings ((without our hand built features)) model had 489 misclassified tweets. Of these, 32 were in the hate speech class, 82 neither, and 375 offensive. Out of the 489 misclassified tweets we do not agree with the labeling of 12% of the tweets with 36% of those both wrongly classified by our model and wrongly labeled and 64% correctly predicted by our model.

In the following sections we take a deep dive comparing the models Hand-Built Features with News, BERT, and Twitter Embedding (Table 6) and News, Twitter, and BERT Embeddings (Table 3).

4.3 Hand-Built Features with News, BERT, and Twitter Embedding model Class: Hate Speech

In the Hand-Built Features with News, BERT, and Twitter Embedding model we found 29 instances of tweets that we believe were incorrectly labeled. That’s 35% of all missed tweets in the hate speech category. Of those, 3% of the tweets were both incorrectly labeled and incorrectly predicted by our model, leaving 32% of tweets in the hate speech class that our model correctly predicted.

Amongst the hate speech labels we agree with, the targeted groups were:

- 25% Female with one instance threatening violence and another suggesting the target commit suicide. 73% of these were predicted as offensive showing a bias towards the offensive class when concerning women and variations of the terms ’hoe’ and ’bitches’.
- 20% Gay Community. The diverse variations and spellings of the term ’fag’ make it difficult to weight it towards hate speech. One possible feature could be a regex for the term ’fag’ or gay in conjunction with a swear word.
  - 6/12 targeting males as a means to emasculate
  - 4/12 targeting women
  - 1/12 targeting males
  - 1/12 targeting the gay community in general
- $<$ 14% Males with six instances including insults meant to emasculate with three of those also including threats of violence. A feature looking at males as a target and the usage of terms ’bitch’ and ’pussy’ could weigh it from offensive to hate speech.
- $<$ 12% African American; with most of the tweets having hard to discern context identifying them as hate speech such as a link to an article, usage of the n word in different spellings, and one tweet where the hate speech was in quotes making it difficult to know if it was commentary condemning it or agreeing with it.
  - 1/7 targeting African American females
  - 6/7 targeting African Americans in general
- $<$ 12% White people with one threat of violence and two including politics. The term ’white trash’ was in almost every instance. When running our features, we ran them over each token so a possible feature is to do a regex for the term and format it as one token.
- 8% Asian; with every instance targeting Chinese people including some variation of the term ’chink’, making it hard to understand why our model failed to flag it as hate speech

especially since half of these instances were predicted to the class 'neither' by the model. One possibility is the low number of hate speech in the training class making use of the term and the alternate definition of chink meaning "a narrow opening or crack, typically one that admits light."

  - 4/5 Chinese
  - 1/5 Asians and the gay community as a means to emasculate

- 2/59 Politics, 1/59 general racist, 1/59 Jewish, 1/59 Latinos

  Many of the tweets included masked swear or hate words surrounded by hash tags, or html tags. Making a regex for these terms could help identify the intent.

4.4 News, BERT, and Twitter Embedding model Class: Hate Speech

For the News, Twitter, and BERT Embeddings model, we found 4 instances of tweets that we disagree are hate speech. Three of these were correctly predicted by our model and one tweet was both incorrectly labeled and wrongly predicted by our model.

For the News, Twitter, and BERT Embeddings model (without our hand built features), out of the 12% of the tweets that were incorrectly labeled, 36% of those were both wrongly classified by our model and wrongly labeled and 64% correctly predicted by our model.

In the hate speech class, our model correctly predicted three instances labeled as hate speech as offensive and neither.

It also correctly predicted 17 instances as hate speech:

- 76% were incorrectly labeled as offensive speech
- 18% were incorrectly labeled as neither
- While some of the following target groups are represented in the same tweet, instances include:
  - 11% African Americans; 28% Female; 28% male with three instances aiming to emasculate men; 22% gay community in general; 5% Asian; and 5 % White people

We note that this model improved our recall for hate speech targeting African Americans and White people compared to the combined usage of the hand built features. It would be useful to comment out certaing features to see what is reducing performance.

Our model missed 28 instances of hate speech our model incorrectly predicted 39% into the neither class, and 61% of tweets into the offensive class.

Of the 17 instances incorrectly predicted as offensive:

- 35% female with two of those encouraging suicide;
- 24% gay community;
- 24% male with three including threats of sexual violence / general violence;
- 12% targeted African Americans; and
- the remaining targeting politics and using the term 'retarded'.

We notice a reduction of overall missed classifications over all groups and a removal of missed hate speech tweets targeting Latinos and Asians. This provides us with a starting point of inspecting the ethnic group feature that focuses on Latinos and Asians (although also African Americans).

Of the 11 instances that were classified in the neither class:

- 36% African American with one including threat of violence
- 27% gay community with one including encouragement of suicide and the rest emasculation of males
- the remaining targeting Chinese, and White people.

We notice that the number of missed instances targeting African Americans, White people, and Asians rises showing a bias of this model to classify as neither. It should be noted that there are no missed instances targeting females.

4.5 Hand-Built Features with News, BERT, and Twitter Embedding model Class: Offensive

Out of the 403 Offensive class using the Hand-Built Features with News, BERT, and Twitter Embedding model, we disagree with 45% of the tweets ad believe they are incorrectly labeled, 7% of which our model also incorrectly predicted the label. The remaining 28% of the tweets were correctly predicted by our model.

Of the 28% tweets where we believe our model correctly predicted the label, 68% of the tweets should be labeled as hate speech. Within these, the targeted communities are:

- 26% gay community; 11 instances where it was used as a means to emasculate men and the remaining targeting the gay community in general
- 22% African American; this continues to be difficult as variations of 'nigga', 'nigguh', 'nig', 'niglet' are used both as an in-group and by other parties as part of an insult.
- 15% female; three instances including violence / sexual violence
- 14% male; 3 emasculating
- 8% used the term 'retarded'; a possible feature capturing instances of [What / He's][a][retard/ed] to weigh them towards the offensive class could reduce the errors.
- 8% White people
- 4% Latinos; an interesting insight as that all instance in the missed tweets mentioning Latinos were either offensive or hate speech. A feature to capture more of these instances would be to decode masked hate words, e.g. 'buck all the beaners', in fact almost all tweets targeting Latinos included a variation of the term beaner so a feature checking for the term along with swear words would properly flag it as hate.
- The remaining 3% were generally offensive

32% should be labeled as class neither. Our model appropriately captured self-referential statements and usage of terms that were used in a self-affirmative manner, such as:

- RT @kaitlyn_lardi: "@17Seniors: so i basically become a fearless bitch when i'm mad"
- RT @G0ldenG0ddess: Turn up about to be real , marriott with my bitches for the weekend , mansion tonight , adult swim tomorrow 128131;

Of the 7% of tweets that were both incorrectly labeled and incorrectly predicted by our model and whose class should be hate speech, there were the following instances targeting: 3 female, 3 African American; 1 Latino; 1 using the term retarded.

Of the missed predictions to true class offensive, the tweets were not targeted and were said as a statement as opposed to an attack. The terms hoe, pussy, and variations of nigga were common. Making use of our targeted features could help to capture these tweets by toggling the targeted to off.

4.6 News, BERT, and Twitter Embedding model Class: Offensive

Of the 331 missed tweets in the offensive class, we only disagree with the labeling of 8 tweets. Five targeted males, showing a higher bias towards labeling male offensive speech as hate speech. 3 targeted the gay community and 1 was generally racist.

- 48% of the tweets were incorrectly predicted as neither; about 90% of the missed tweets referenced offensive speech towards women. This provides a case for our hand built feature that checks if a tweet is offensive to women and we look forward to doing additional manipulation of combining our features to improve performance.
- 52% predicted as hate speech; the overwhelming majority were offensive to women and then African Americans showing a bias our model has towards labeling offensive speech targeting these groups as hate speech. The tweets also included heavy usage of slang, hinting that our slang decoder does help in contextualizing the tweet to capture more information.

4.7 Hand-Built Features with News, BERT, and Twitter Embedding model Class: Neither

26% of the 99 missed tweets in the class neither should have alternate labels. Our model correctly predicted the label for 21% of the tweets with the remaining 5% both wrongly labeled and incorrectly predicted by our model.

Our model incorrectly classified 41% of tweets as offensive. The upside is that not many included slang outside as terms 'nig' and variations thereof, meaning that our slang decoder seemed to help minimizing previous biases that labeled tweets with slang as offensive. The majority of the tweets included pronouns, which may have triggered our pronouns checker feature to label these as offensive. We could fine tune that feature by noting if the tweet is a question, that it may not be offensive. Checking to see if ther tweet is commentary that flips the negative sentiment could be helpful in correctly labeling tweets as neither, e.g. 'RT @MobJoe: Word. And it don't make u a hoe RT @100granHman: It's okay to have sex on first date long as the feeling is mutual'.

More concerning is that our model labeled 32% of the missed tweets in the neither class as hate speech. Many of the tweets combined the term 'trash' with a noun. Capturing the term 'white trash' could down weigh and other instances of the term trash just by itself. The use of the term 'Jihadis' created a strong bias towards labeling the tweet offensive, even when in the context of reporting news. We could create a feature where it searched for the term 'Jihad' along with profanity to differentiate it from the term 'Jihad' just by itself.

4.8 News, BERT, and Twitter Embedding model Class: Neither

We disagree with the labeling of 47% of the missed tweets in the neither class. And of these we believe our model correctly predicts 65% of these tweets and 35% of these tweets were both incorrectly labeled and incorrectly predicted by our model.

Our model correctly identified 19 instances of hate speech targeting:

- 26% female; 26% male; 21% gay community; 11% African Americans; and the remaining 16% evenly distributed targeting Asians, general racist, and White people.

Of the instances where both the labeling and predictions were incorrect, 7 were hate speech targeting:

- 36% African Americans
- 36% female
- 28% gay community

Of our model's incorrect predictions of neither into the offensive class, the model failed to pick up on self-referential and in-group tweets highlighting the need for these hand built features. For the tweets that were incorrectly predicted as hate speech, the NRC emotions feature may help capture more nuanced information about the tone of the tweet.

Overall we hope to have highlighted how difficult it is to gauge model performance when dealing with a dataset that is almost 2/3 offensive and with which we feel a great disagreement in the labeling process. We look forward to continuing our work in this space as we have just received academic research API access from Twitter and plan to work on creating new labeled multi-class datasets available to everyone and to test our current and future models.

5 Future Work

The field of multi-class hate speech detection is fairly new. Thus, the only dataset (with the three class labeling system) available is Davidson et al. (2017)'s. As briefly discussed previously, this dataset has limitations. It is relatively small, with 25K samples. Additionally, the data is heavily weighted toward offensive speech. Davidson et al. (2017) also recognize that while there was agreement in judgement amongst labelers, the researchers themselves did not fully agree with all of the labels generated. Thus it would be beneficial to have the dataset relabeled and verified by a hate speech expert. As pointed out in the error analysis, the dataset is littered with tweets that are labeled as hate speech but are in fact benign. For more progress to be made in this field, better labeled data needs to be made available.

(Davidson et al., 2017) just used a Logistic Regression model, as did we. This task would benefit from other models (LSTMs, NNs) being run on larger, more accurately labeled datasets, as Wang (2018) began to explore.

6 Authorship Statement

Equal authorship on the video, literature review, and experimental protocol. Susana wrote all but one of the hand-built features and conducted the error analysis, writing that part of the paper. Andrew implemented the Flair library and ran all of the models.

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