You Are What You Tweet: Profiling Users by Past Tweets to Improve Hate Speech Detection

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Abstract. Hate speech detection research has predominantly focused on purely content-based methods, without exploiting other contextual data. We briefly critique pros and cons of this task formulation. We then investigate profiling users by their past utterances as an informative prior to better predict whether new utterances constitute hate speech. To evaluate this, we augment three Twitter hate speech datasets with additional timeline data, then embed this additional context into a strong baseline model. Promising results suggest merit for further investigation.

Keywords: hate speech · classification · modeling · profiles · twitter

1 Introduction

Online hate speech is a vast and continually growing problem [10, 12, 13, 18]. The detection task is most commonly framed as purely content-based: each utterance is classified without any additional context. However, history often repeats itself, and “A user who is known to write hate speech messages may do so again” [18]. Facebook researchers have also recently noted that “a user or group that has posted violating content in the past may be prone to do so more often in the future” [10]. This suggests that modeling of user priors may be highly informative and complementary to purely content-based detection models. We return to discussion of ethical considerations in Section 7.

To investigate user profiling, we augment three Twitter hate speech datasets [1, 5, 20] with additional recent timeline Tweets by each author, then embed this additional context into a strong baseline model [2] that was later further refined [1]. Results show strong improvement on one dataset, little benefit on another, and fairly consistent improvement on a third. Overall, results across experimental conditions and metrics suggest user modeling merits further work, though analysis is complicated by differences in annotation schemes and processes, as well as Twitter API limitations and data sharing policies.

2 Related Work

While most hate speech detection models have been content-oriented and non-contextual, there are notable exceptions. After Hovy [11] showed modeling value...
of demographics for classification tasks, Waseem and Hovy \cite{20} applied this to hate speech, inferring gender (by name) and location (by timezone) to classify hate speech with modest benefit: only gender raised hate detection accuracy, and it was statistically significant only when both gender and location were used. A challenge with demographics is that they are sensitive and often not widely available, if captured at all by the platform.

Rather than classify hateful utterances, other work has sought to classify hateful users. Assuming “birds of a feather flock together”, community detection \cite{8} has sought to identify hater communities. Ribeiro et al. \cite{17} and Mathew et al. \cite{14} analyze Twitter’s retweet graph to detect users likely to spread hateful content. Mishra et al. \cite{15} is the only work we are aware of to profile hateful users, via the follower graph, and then use these profiles to improve hate speech detection over baseline models.

Some hate speech datasets are heavily dominated by a few prolific haters. In Waseem and Hovy \cite{20}, all racist-labeled tweets came from 9 users. In fact, Arango et al. \cite{1} note that a single user generates 96% of all racist tweets, while another user produces 44% of all sexist tweets. Arango et al. aptly critique that benchmarking on such highly skewed datasets risks overfitting a few individuals rather than learning a broadly applicable model. Similar concerns have been voiced about over-fitting idiosyncrasies of a few annotators \cite{9}. We agree that datasets should have many diverse examples of the phenomena being modeled (i.e., hate speech examples from many users). However, dataset composition is orthogonal to model design: how can we best model historical context in prediction and fairly evaluate vs. context-free models?

Some past studies (cf., \cite{20,21}) have partitioned train/test data by utterance (i.e., by tweet), rather than by user. The consequence of such experimental design is that any model trained and tested in this manner can be expected to make better predictions on users found in both train and test splits. However, we should not confuse desirable user modeling with questionable experimental design in which user history is only captured haphazardly by whichever users happen to have some tweets in the training data, and the ratio of that user-specific history vs. training tweets from other users. Such a scheme does not reflect intentional design or controlled evaluation of user modeling.

An intuitive language-based approach is to model each user by a “document” of their past utterances. Such historical data is certainly available to social media companies, and often publicly via API or crawling. The closest work we are aware of on content-based modeling of haters is by Dadvar et al. \cite{4}, though they only considered the user’s past number of obscene words as a modeling feature.

### 3 Datasets

We adopt the same three datasets studied by Arango et al. \cite{1}: see statistics in Table 1. As is common in other problem domains, each hate speech dataset has various limitations; by evaluating across several datasets, we test across varying data conditions.
Fig. 1. Log-log distribution of tweets per user (top) and hate tweets per user for users producing 1 or more hate tweets (bottom), for all three datasets. The y-axis indicates the number of tweets while the x-axis simply enumerates users in descending order of activity.

Waseem and Hovy [20] (W&H) label 16K tweets for 3 classes: Racism, Sexism and Neither. After author labeling, tweets labeled as hate speech were reviewed by a 25-year old female “studying gender studies and a nonactivist feminist”. Agreement between author and reviewer was $\kappa = 0.84$, with 85% of disagreements on sexist labels, and 98% of these changed to neither. Tweet IDs and labels were shared, with tweets obtained via the Twitter API. Since tweets and user accounts are often deleted, 15K tweets are found in [1]. We find 10K tweets (and only 6 racist ones) over 1,458 users.

Davidson et al. [5] crowd-label 25K tweets for 3 classes: Hate, Offensive and Neither. Majority voting over 3 or more workers was used for label aggregation. 200 tweets were discarded with no majority over the 3 classes. For hate, only 5% were labeled by 2/3 and only 1.3% by 3/3. Most were labeled offensive (76% at 2/3, 53% at 3/3) and the rest non-offensive (16.6% at 2/3, 11.8% at 3/3). We find 18K tweets (~75%) from 741 users.

Arango et al. [1] identify three issues: 1) W&H has few haters; 2) those haters are prolific; and 3) train/test splits by utterance mean the same hater often appears in both train and test splits. To address this, they 1) add to W&H all hate-labeled tweets from DAVIDSON; 2) restrict to at most 250 tweets per user per class; and 3) perform train/test split by user rather than by utterance. Their fused dataset had 7K tweets, collapsing labels to simple binary hate vs. non-hate. We find 5.4K over 1746 users.

[Figure 1] shows the distribution of tweets per user across datasets. For all users who produce 1 or more hate tweet (W&H: 443 users, Davidson: 566, Arango: 734), we also plot the number of hate tweets from each such “hater”.

4 Profiling Users by Past Tweets

As a strong baseline, we adopt Badjatiya et al. [2]’s 2-phase model, using [1]’s corrected version in which word embeddings are derived only from training data. An LSTM classifier is first trained to predict the label. Each word is converted
to a dense vector representation using a word embedding matrix initialized with pretrained GloVe embeddings [16]. The final vector from the LSTM is followed by a fully connected layer and a softmax or sigmoid layer for obtaining prediction probability. The network is trained with cross entropy loss with Adam optimizer. Once training of LSTM is done, the first layer is extracted, i.e. word embedding matrix fine tuned on the training set. In the second phase, a tweet is converted to a fixed sized vector by averaging the embedding vectors of its tokens using the trained embeddings from the previous phase. Representing the tweet by this vector, a Gradient Boosted Decision Tree (GBDT) is trained for classification.

Given a tweet ID, we use the Twitter API to retrieve the author’s timeline[1] their latest 20 tweets. This size of 20 reflects an API maximum, but it would be interesting in future work to model longer histories. Given this history, we augment existing public datasets (section 3) with these timelines. W&H includes tweet IDs, and Davidson kindly shared their tweet IDs with us upon request. In practice, timeline tweets should precede tweets being classified; here we use existing datasets. By augmenting existing datasets, we can assess the relative benefit with and without user profiling on hate speech datasets that are already familiar to the research community.

We utilize these user profiles in (Arango et al. [1]’s corrected version of) [2]’s model as follows. Given a tweet, the author’s timeline is averaged using the same trained word embedding used for tweet representation. Following this, both tweet representation and timeline representation are concatenated and used to train the GBDT classifier. In general, a history-informed prior of the user ought to complement any content-based model of the tweet alone. We expect future work will continue to benefit from exploiting such a prior-informed modeling architecture, irrespective of the specific model.

5 Experimental Setup

We build on Badjatiya et al. [2]’s and Arango et al. [1]’s shared source code. We use 10-fold cross validation with default hyperparameters for [2]’s model. The LSTM word embeddings are initialized with 200 dimensional pretrained GloVe embeddings, and the size of the LSTM representation is 200. We also add dropout of 0.25 and 0.5 after the word embedding layer and the LSTM, respectively. We train the LSTM based architecture for 10 epochs, and then train the GBDT using the final word embeddings.

With nearly all racism tweets in W&H deleted, we train it as a binary classifier: sexism vs. none. For DAVIDSON, we train a ternary classifier over its three classes. ARANGO fuses W&H and DAVIDSON label sets by collapsing classes into simple binary classification of hate vs. non-hate.

Tweet deletions make comparison to prior published results more difficult, with only 2/3 of W&H and 3/4 of DAVIDSON datasets still available, and nearly all W&H racist tweets deleted. Arango et al. [1] note that partitioning train/test

1 https://developer.twitter.com/en/docs/tweets/timelines/
by tweet, as in past studies, results in prolific tweeters appearing in both splits. The risk this poses is potentially overfitting to particular users. Instead, they argue for splitting train/test by user. To be as comprehensive as possible, we report results both ways for completeness.

6 Results

Table 1 compares model performance with and without user timeline history across the three datasets and the two train/test data partitions: by tweet vs. by user. With regard to testing baseline vs. timeline results, splitting by user is cleaner because for any users appearing in the test data, there are no tweets from that user in the training set.

Results show strong improvement on W&H but little change on DAVIDSON. We do see split-by-tweet shows modest improvement for DAVIDSON on the Hate category, but not on other categories or for split-by-user. Between W&H and DAVIDSON extremes, we see more modest but fairly consistent improvement on Arango et al.’s dataset, which fuses W&H and DAVIDSON by adding to W&H all hate-labeled tweets from DAVIDSON and down-sampling to at most 250 tweets per user per class to reduce skew. Consistent with Arango et al. [1], we see much higher results on W&H and their fused dataset when splitting by tweet rather than by user (Arango et al. do not report on DAVIDSON).

Given the difference in model performance across the datasets, what explains this? Table 1 and Figure 1 show important differences in data scale and distribution across different datasets. The classes being annotated also differ, as does the method of annotation: W&H uses traditional annotators while DAVIDSON relies on crowd annotators. Such differences highlight several dimensions of ongoing debate in hate speech research surrounding differing approaches to annotation categories and processes [3, 7, 19].
| Dataset | Size | Timeline Tweets | Baseline P | Baseline R | Baseline F | With Timeline P | With Timeline R | With Timeline F |
|---------|------|----------------|------------|------------|------------|----------------|----------------|----------------|
| W&H     | 0-5  | 58             | 78.2       | 74.1       | 75.8       | 68.8           | 67.4           | 68.0           |
|         | 6-10 | 18             | 47.1       | 47.1       | 47.1       | 75.0           | 97.1           | 81.8           |
|         | 11-15| 34             | 60.0       | 54.7       | 53.0       | 50.5           | 50.2           | 46.0           |
|         | 16-20| 9,991          | 82.2       | 79.0       | 80.1       | 88.3           | 87.4           | 87.9           |
| DAVIDSON| 0-5  | 4,943          | 76.6       | 66.6       | 69.6       | 76.3           | 66.4           | 69.4           |
|         | 6-10 | 22             | 96.5       | 72.2       | 80.4       | NAN            | 0              | NAN            |
|         | 11-15| 287            | 66.0       | 58.8       | 61.5       | 58.5           | 54.0           | 55.8           |
|         | 16-20| 12,775         | 76.9       | 67.5       | 70.1       | 77.2           | 67.6           | 70.3           |
| ARANGO  | 0-5  | 59             | 76.5       | 75.4       | 75.9       | 70.0           | 70.0           | 70.0           |
|         | 6-10 | 20             | 100.0      | 100.0      | 100.0      | 97.2           | 83.3           | 88.6           |
|         | 11-15| 49             | 81.2       | 80.3       | 79.5       | 77.0           | 76.2           | 75.4           |
|         | 16-20| 5,341          | 83.0       | 81.3       | 82.0       | 86.1           | 84.0           | 84.9           |
| ARANGO  | 0-5  | 59             | 81.9       | 77.8       | 79.4       | 85.3           | 78.9           | 81.3           |
| (split by user) | | | | | | | | |
|         | 6-10 | 20             | 97.2       | 83.3       | 88.6       | 97.2           | 83.2           | 88.6           |
|         | 11-15| 49             | 84.9       | 80.8       | 79.2       | 84.9           | 80.8           | 79.2           |
|         | 16-20| 5,341          | 78.3       | 76.1       | 76.9       | 78.2           | 77.1           | 77.6           |

Table 2. Detection accuracy on user subgroups, based on amount of Twitter timeline available per user (0-20 most recent tweets). Train/test partition of data is by tweet unless noted otherwise.

We also conducted a further analysis to assess whether the amount of timeline history per user varied significantly across datasets. Results appear in Table 2, where we bin users by the count of timeline tweets found: 0-5, 6-10, 11-15, or 16-20. We see that the vast majority of users have 16-20 past timeline tweets, and for this category we see consistent improvement across datasets and train/test split conditions, driving scores.

Crucially, however, on DAVIDSON we see nearly 5K tweets (~28%) from users with only 0-5 timeline tweets available, where we expect small to no improvement from timelines due to lack of history. This holds across datasets when splitting by tweet, including DAVIDSON, which indeed drives down overall results on this dataset. When splitting by user on ARANGO, we do see increased accuracy even with 0-5 timeline tweets, though the sample size is quite small to draw conclusions.

Further limited qualitative analysis helped give us a sense of examples where profiling a user created an informative prior for correctly classifying tweets that might have been missed otherwise. We explored most prolific tweeters in W&H for evidence of sexist timeline tweets. As an example, one user made a possibly sexist tweet “.@USER1 @USER2 when was she good? i confuse her and ten other women, which is why their pay is lower btw. supply vs. demand.” which was easier to predict by their earlier timeline tweet “#FeminismIsAwful”. Use of the timeline correctly predicts the ‘sexist’ label, and increases overall detection accuracy for this user from 53% to 87%.
7 Ethical Considerations

While user modeling is common in personalized ranking and recommendation systems (e.g., Google or Netflix), some users may wish to opt-out, and GDPR allows “the right to be forgotten”. User modeling to prevent fraud and abuse, while equally common in commercial systems, may raise different sorts of ethical and legal questions. We know that social media platforms already do monitor user accounts for terms of service violations, suspending accounts demonstrating repeated abusive behaviors [10]. Given the vast scale and expense of commercial content moderation, and extensive user histories available, platforms cannot afford to ignore such a strong predictive signal.

However, what challenges may arise? Would a reformed hater have difficulty overcoming his/her past profile a model had learned? One idea would be to decay weight assigned to past tweets by age, or to completely restrict history to a recent window (e.g., our current timeline of past 20 tweets). In fact, the opposite problem is significant on platforms today: a bad actor who is suspended often circumvents this by creating a new account, with a cycle of continuing abusive behaviors by re-entrant bad actors.

8 Conclusion

Producers of hate speech are often repeat offenders, yet we know of no prior work explicitly profiling users by their past tweets to improve hate speech detection accuracy. We collect Twitter timeline data toward this end to augment existing hate speech datasets. Results on several datasets, metrics, and experimental settings are encouraging, but confounds remain. Future work might explore better modeling (e.g., via BERT [6]), collecting more user history, and combining with other profiling approaches [15]. Other approaches may explore adding other features extracted from user twitter timeline, such as hate speech tweet frequency, number of hate speech retweets, etc.

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http://goodsystems.utexas.edu/
Bibliography

[1] Arango, A., Pérez, J., Poblete, B.: Hate speech detection is not as easy as you may think: A closer look at model validation. In: Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval. pp. 45–54 (2019), https://github.com/aymeam/user_distribution_experiments

[2] Badjatiya, P., Gupta, S., Gupta, M., Varma, V.: Deep learning for hate speech detection in tweets. In: Proceedings of the 26th International Conference on World Wide Web Companion. pp. 759–760 (2017), https://github.com/pinkeshbadjatiya/twitter-hatespeech

[3] Balayn, A., Bozzon, A.: Designing evaluations of machine learning models for subjective inference: The case of sentence toxicity. arXiv preprint arXiv:1911.02471 (2019)

[4] Dadvar, M., Trieschnigg, D., Ordelman, R., de Jong, F.: Improving cyberbullying detection with user context. In: European Conference on Information Retrieval. pp. 693–696. Springer (2013)

[5] Davidson, T., Warmsley, D., Macy, M., Weber, I.: Automated hate speech detection and the problem of offensive language. In: Eleventh international aaai conference on web and social media (2017), https://github.com/t-davidson/hate-speech-and-offensive-language

[6] Devlin, J., Chang, M.W., Lee, K., Toutanova, K.: Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805 (2018)

[7] Fortuna, P., Soler, J., Wanner, L.: Toxic, hateful, offensive or abusive? what are we really classifying? an empirical analysis of hate speech datasets. In: Proceedings of The 12th Language Resources and Evaluation Conference. pp. 6786–6794 (2020)

[8] Fortunato, S.: Community detection in graphs. Physics reports 486(3-5), 75–174 (2010)

[9] Geva, M., Goldberg, Y., Berant, J.: Are we modeling the task or the annotator? an investigation of annotator bias in natural language understanding datasets. In: Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP). pp. 1161–1166 (2019)

[10] Halevy, A., Ferrer, C.C., Ma, H., Ozertem, U., Pantel, P., Saeidi, M., Silvestri, F., Stoyanov, V.: Preserving integrity in online social networks. arXiv preprint arXiv:2009.10311 (2020)

[11] Hovy, D.: Demographic factors improve classification performance. In: Proceedings of the 53rd annual meeting of the Association for Computational Linguistics and the 7th international joint conference on natural language processing (volume 1: Long papers). pp. 752–762 (2015)
[12] Jurgens, D., Chandrasekharan, E., Hemphill, L.: A just and comprehensive strategy for using nlp to address online abuse. arXiv preprint arXiv:1906.01738 (2019)
[13] MacAvaney, S., Yao, H.R., Yang, E., Russell, K., Goharian, N., Frieder, O.: Hate speech detection: Challenges and solutions. PloS one 14(8) (2019)
[14] Mathew, B., Dutt, R., Goyal, P., Mukherjee, A.: Spread of hate speech in online social media. In: Proceedings of the 10th ACM Conference on Web Science. pp. 173–182 (2019)
[15] Mishra, P., Del Tredici, M., Yannakoudakis, H., Shutova, E.: Author profiling for abuse detection. In: Proceedings of the 27th International Conference on Computational Linguistics. pp. 1088–1098 (2018)
[16] Pennington, J., Socher, R., Manning, C.D.: Glove: Global vectors for word representation. In: Empirical Methods in Natural Language Processing (EMNLP). pp. 1532–1543 (2014), http://www.aclweb.org/anthology/D14-1162
[17] Ribeiro, M.H., Calais, P.H., Santos, Y.A., Almeida, V.A., Meira Jr, W.: Characterizing and detecting hateful users on twitter. In: Twelfth international AAAI conference on web and social media (2018)
[18] Schmidt, A., Wiegand, M.: A survey on hate speech detection using natural language processing. In: Proceedings of the Fifth International Workshop on Natural Language Processing for Social Media. pp. 1–10 (2017)
[19] Waseem, Z.: Are you a racist or am i seeing things? annotator influence on hate speech detection on twitter. In: Proceedings of the first workshop on NLP and computational social science. pp. 138–142 (2016)
[20] Waseem, Z., Hovy, D.: Hateful symbols or hateful people? predictive features for hate speech detection on twitter. In: Proceedings of the NAACL student research workshop. pp. 88–93 (2016), https://github.com/zeerakw/hatespeech
[21] Xiang, G., Fan, B., Wang, L., Hong, J., Rose, C.: Detecting offensive tweets via topical feature discovery over a large scale twitter corpus. In: Proceedings of the 21st ACM international conference on Information and knowledge management. pp. 1980–1984 (2012)