Predicting the Year of Trump Tweets

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1 Introduction

Donald Trump's 2016 election campaign and presidency were characterized by his prolific posting on Twitter, until his ban from the platform following January 6th. Since his account's creation in 2009, his posts have gone from PR-written advertisements for his television appearances to erratic, snappy posts written by Trump that have fueled his political career. The goal of this project is to analyze how the @realdonaldtrump account's posts have changed over time using different machine learning models.

2 Data

This project uses a dataset of every tweet posted by @realdonaldtrump since the account's creation in 2009 (excluding those deleted before September 2016) until the suspension of his account following the events of January 6th. This data comes from the Trump Twitter Archive. It was loaded into a Pandas DataFrame,[1] which was used for all later operations. The data set includes nine fields: 'id', 'text', 'isRetweet', 'isDeleted', 'device', 'favorites', 'retweets', 'date', and 'isFlagged'. The 'id', 'isDeleted', and 'isFlagged' fields have been disregarded, as the former is arbitrary and the latter two are irrelevant. The 'retweets' and 'favorite' features have also been discarded, as they grow with Trump's popularity, distracting from the contents of his tweets, which are meant to be the primary input. For similar reasons, the day and time of the tweet are dropped. Retweets are not used, as they were not written by Trump. Tweets that contain media such as images and videos are also dropped, as the text portions of these tweets are often short captions that do not contain the full meaning of the tweet. The remaining tweets show an uneven distribution between years, shown in Figure 1. 2009-2011 are heavily underrepresented, as they seem to primarily feature tweets written by a PR team promoting Trump's television appearances and shows. In addition, 2021 has very few tweets, as Trump's account was banned early in the year. These years are dropped because they do not provide enough data to make reasonable predictions based on them, leaving 37,144 tweets from nine years remaining.

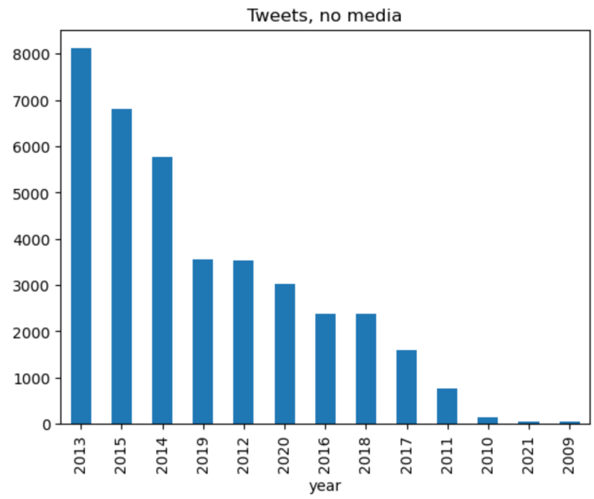

Figure 1: Bar chart showing the distribution of years in the tweet data set after dropping retweets and media tweets. 2009-2011 and 2021 are vastly underrepresented, so they are excluded from testing.

3 Methodology

Several models were trained on the remaining Trump tweets, using the scikit-learn Python Module.[2] The text of the tweets was transformed into a bag-of-words embedding, then passed into the models for training. Naive Bayes, Random Forest, and Multi-layer Perceptron models were used in order to show a wide range of classifiers that may provide different results.

The Naive Bayes and Random Forest results were obtained using scikit-learn's

[1] Pandas. https://github.com/pandas-dev/pandas

[2] scikit-learn. https://github.com/scikit-learn/scikit-learn

	precision	recall	f1-score	support
2012	0.66	0.36	0.47	3522
2013	0.50	0.58	0.54	8114
2014	0.43	0.35	0.39	5769
2015	0.45	0.48	0.46	6810
2016	0.54	0.16	0.25	2382
2017	0.57	0.02	0.04	1585
2018	0.35	0.30	0.32	2375
2019	0.33	0.73	0.46	3557
2020	0.53	0.56	0.54	3030
accuracy			0.45	37144

Figure 2: Accuracy scores for Naive Bayes on a year-by-year basis. The model had an extremely poor recall score for 2017, leading to a much lower f-1 score than other years.

cross_val_predict method, yielding more holistic predictions than a typical train/test split. However, using this method with Multi-layer Perceptron took far too long, so a single train/test split was used instead.

Another experiment was run that involved splitting the data set by whether a tweet was posted before or after the beginning of a given year. Each model was then fit to use these altered classes and predicted if a given tweet was from before the year or not. The results of this experiment are detailed in Section 4.5.

4 Results

4.1 Naive Bayes

The Naive Bayes model was able to achieve an overall accuracy of 0.45, well above that of a random predictor's 0.11. As can be seen in Figure 2, most years did around the same, except for 2017. This phenomenon will be discussed further in Section 4.4.

4.2 Random Forest

The Random Forest model performed slightly worse than the Naive Bayes model, garnering a score of 0.43. Interestingly, it also performed poorly when predicting the year of 2017 tweets, as seen in Figure 3.

4.3 Multi-layer Perceptron

The Multi-layer Perceptron model performed significantly better than its peers, achieving an accuracy score of .56. Recall was better across the board, particularly for 2017, although that year still had a lower accuracy than other years, as seen in Figure 4.

	precision	recall	f1-score	support
2012	0.64	0.40	0.49	3522
2013	0.38	0.64	0.47	8114
2014	0.39	0.26	0.31	5769
2015	0.41	0.49	0.45	6810
2016	0.53	0.24	0.34	2382
2017	0.34	0.10	0.16	1585
2018	0.48	0.19	0.28	2375
2019	0.46	0.57	0.51	3557
2020	0.58	0.40	0.47	3030
accuracy			0.43	37144

Figure 3: Accuracy scores for Random Forest model. It did slightly worse than Naive Bayes overall, but continued the trend of 2017 being difficult to predict.

	precision	recall	f1-score	support
2012	0.61	0.59	0.60	841
2013	0.60	0.59	0.60	2023
2014	0.51	0.52	0.51	1428
2015	0.61	0.61	0.61	1673
2016	0.53	0.50	0.51	633
2017	0.37	0.36	0.37	419
2018	0.47	0.47	0.47	607
2019	0.53	0.58	0.55	888
2020	0.60	0.60	0.60	774
accuracy			0.56	9286

Figure 4: Accuracy scores for Multi-layer Perceptron model. It achieved an accuracy above 50%, showing that this kind of model is well suited for this kind of classification.

4.4 Classifying 2017

All three models had a great deal of difficulty in correctly classifying tweets from 2017 compared to other years, often misclassifying posts from that year, leading to low recall scores. Figure 5 shows the predicted years of 2017 tweets for each model. The incorrect predictions for the Naive Bayes model were particularly interesting, as the vast majority were from after 2017, in the midst of Trump's presidency. This trend continues in the other models, albeit less strongly, suggesting that Trump's tweets from 2017 concerned subjects that were common across the rest of his presidency. Looking at the correctly predicted tweets from 2017 seems to confirm this theory, as the most common words in those tweets pertain to events that were unique to that year, such as Trump's support for Luther Strange in the 2017 Alabama Senate Pri-

	NB	RF	MLP
pred			
2012	2	32	7
2013	71	644	27
2014	17	45	12
2015	96	155	18
2016	26	82	30
2017	37	162	152
2018	316	80	68
2019	782	228	59
2020	238	157	46

Figure 5: Accuracy scores for Multi-layer Perceptron model. It achieved an accuracy above 50%, showing that this kind of model is well suited for this kind of classification.

mary, the attempt to repeal the Affordable Care Act, and the 2017 Tax Cuts and Jobs Act.

4.5 Bisecting by Year

Using Naive Bayes, we split the data set by each year, in order to find which division was best suited for prediction. The years at the edge of the dataset (2012 and 2020) had the highest accuracies, which makes sense when considering that the model was essentially predicting whether a tweet was from a given year or not, which is an easier task. Out of the other years, 2017 provided the best results, with an accuracy of .88. This suggests that tweets from before this year are significantly different than those posted during and after. This would mean that Trump's presidency changed his tweeting behavior significantly. Other models performed similarly well when splitting by 2017, with Random Forest achieving an accuracy of 0.89 and the Multi-layer Perceptron model reaching 0.92.

5 References

Trump Twitter Archive. 2021.