Topic and Tone on Twitter in U.S. Politics

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Abstract

I explore the use of social media by politicians. What types of tweeting behavior relates to a politician's electability? I find Democrats rally around key hashtags that improve their social media visibility and correlate with election day success; meanwhile, Republicans - particularly Republican women - fall comparatively short on this metric. I also find that, leading up to an election, the dominant tone that a politician expresses - fear, joy, disgust, etc. - is related to the fraction of votes they'll receive. This effect interacts with gender: women, more than men, are favored for pessimistic tones. One partial explanation is that women receive more retweets for these tones leading up to the election, getting their views out there more efficiently. Women, perhaps emboldened by the above, have only recently started outpacing men in the frequency with which they tweet.

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Introduction

We've seen a huge increase in the use of social media; on Twitter an estimated 500 million tweets are sent every day. Politicians use Twitter to mobilize support, attack opponents, share news that endorses their policy, and more. They can make their views more visible to the public when followers choose to retweet - copy the message - for their own followers to see.

A number of strategies on Twitter have been identified. Stieglitz and Dang-Xuan [2014] present a "methodological framework for social media analytics in political context," which includes content analysis, opinion mining, and social network analysis identify the political opinion leaders and the emerging political topics. Hellweg [2011] found that social media use, particularly if personal rather than professional in tone, can significanly enhance the perception followers have of a candidate. Going further with a tweet's tone, Proctor [2017] looked to identify differences in the amount of confidence, tentativeness, analyticalness, etc., that appear in male and female tweets. The study found no measurable difference by gender, but suggested followers might selectively retweet based on the tone of the message.

Also treating retweets as a measure of visibility, Nilizadeh et al. [2016] found a glass ceiling for visibility on Twitter: women at the highest levels of visibility fail to track against the most visible men in achieving retweets.

I ask how several of these identified strategies achieve different payoffs come election day. First I'll analyze the use of Twitter at the coarse level of tweet frequency - who's been adopting the medium over time, and why? Second, I find certain interprettable, polarized topics which help explain the draw to social media for different politicians. I then identify certain topics that, when tweeted about, have historically led to election success. Finally, I follow Proctor [2017] in analysis of tone, this time aligning the use of certain tones to election success.

Dataset Overview

Individuals

Metadata on recent U.S. politicians have been aggregated by individuals working in Frances Rosenbluth's lab at Yale. They used sources such as GovTrack, Vote Smart, and others to determine metadata characteristics of the 115th (2016 election) and 116th (2018 election) members of the U.S. congress (U.S. House and U.S. Senate). Columns include age, party, gender, senator or representative, polarization level via the dw nominate metric, and professional action characteristics such as the percentage of time they vote with their party.

Election data

For this metadata, I pull in information on their elections from 2010 to 2016 from the MIT Election Data Science Lab. Over these four elections we have a total of 1304 elections from 470 individuals. Although the metadata are harder to aggregate, in the future our lab will directly seek out losers of elections. For now, since most of the sitting congressmembers are incumbents from 2010 and through 2014, election success for an individual is treated comparatively as the fraction of votes they received in the election.

Tweets

Tweets from this data.world dataset. We have 1105660 tweets from 455 individuals in our metadata. In addition to the text of the tweet and when it was created (ranging from 2008-06-30 to 2017-04-07), they've pulled out hashtag entities, favorite counts, retweets, and urls.

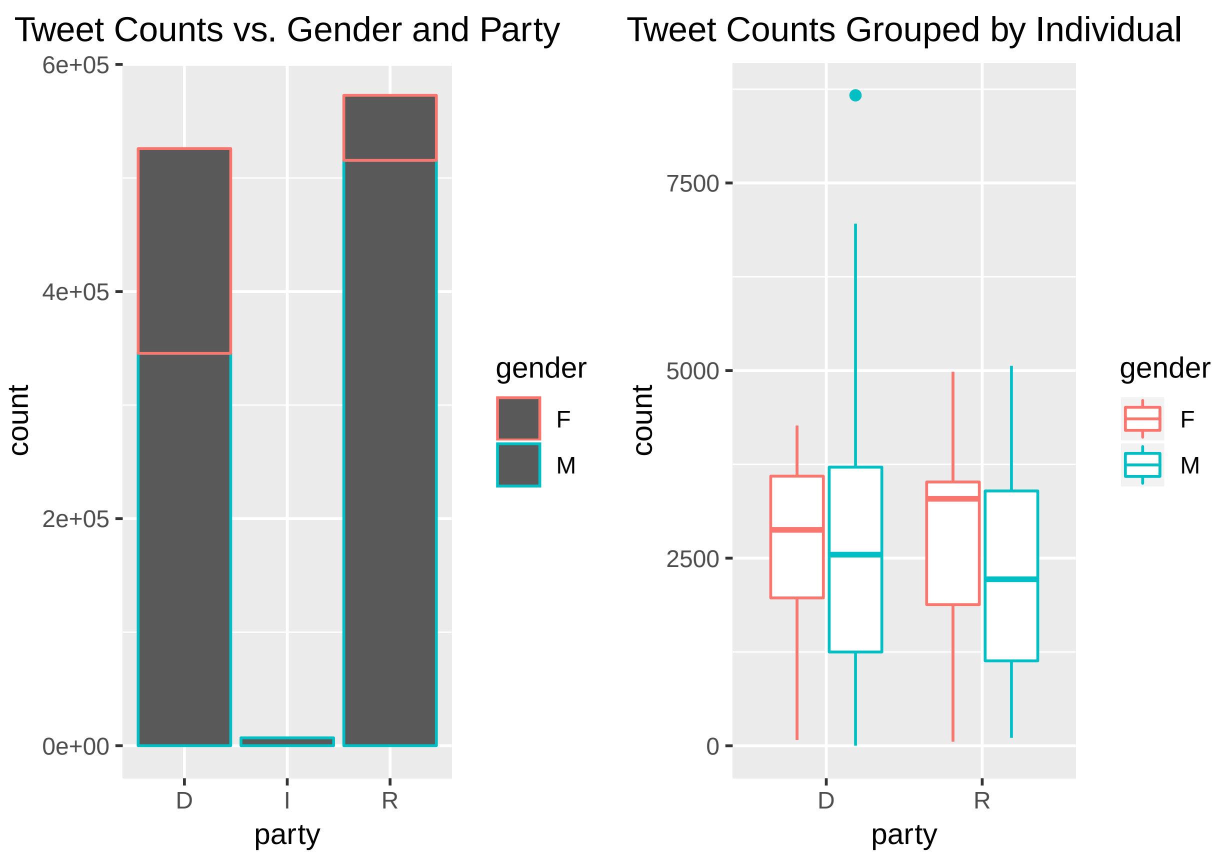
Tones

There has been a lot of work done on the text classification task of tones - the style with which someone makes an utterance. IBM Watson, the same that won Jeopardy in 2011, now has a feature of tagging tones in text, including specifically in Tweets. The tones tagged by IBM are Anger, Disgust, Fear, Joy, Sadness, Analytical, Confident, Tentative, Openness, Conscientiousness, Extraversion, Agreeableness, Emotional Range. Underneath the hood a neural net is used to classify the text. To understand this model, we can draw analogies from open-source efforts. The most successful open-source models for text classification on Tweets were submitted to the SemEval 2018 "Affect in Tweets" competition authored by Mohammad et al. [2018].

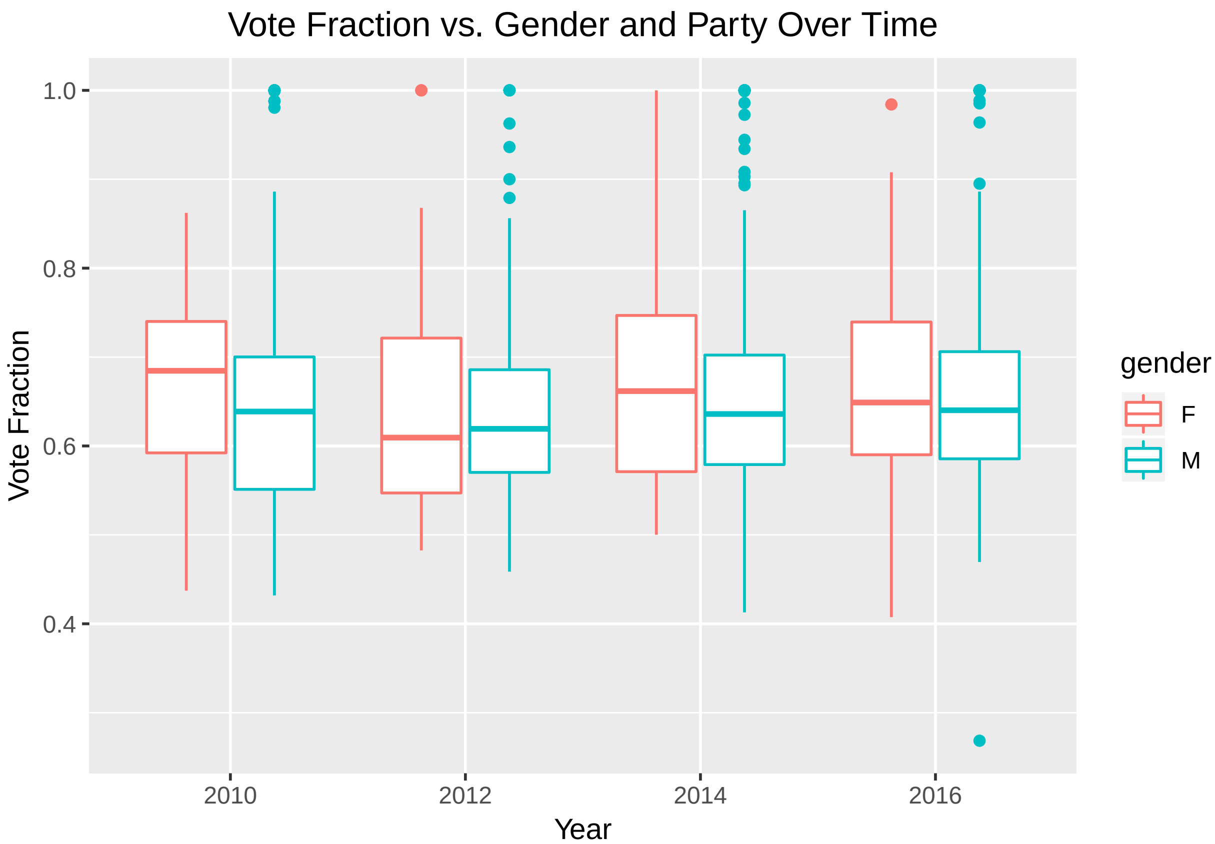
Data Exploration

Balance and Limitations of the Data

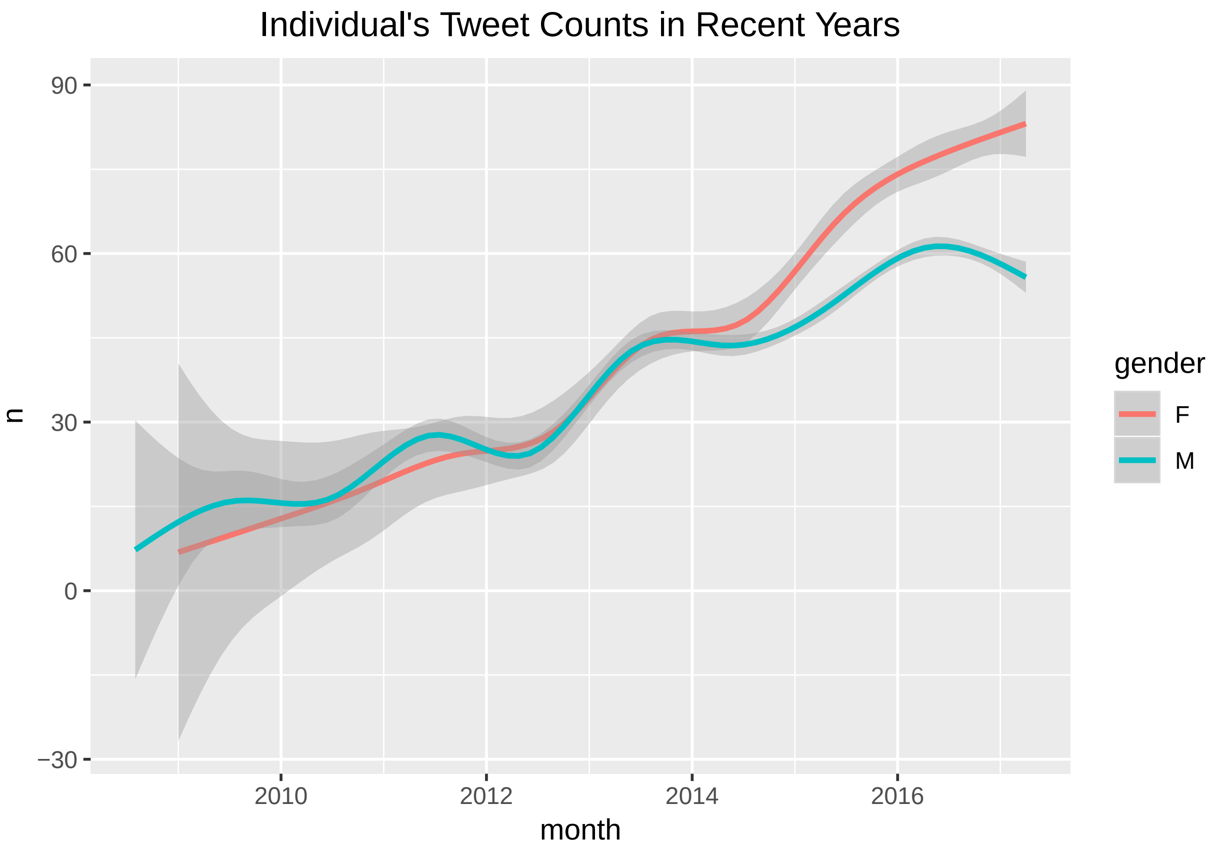
First we'll consider several ways in which the data is balanced (and some ways it's not), so that the more nuanced effects we find later aren't trivially explained by a biased dataset. On the left, we see the tweets broken down by gender and party. For most of the analysis, I'll be doing comparative work, choosing to drop independents. The breakdown of tweets is roughly proportional to the number of individuals in each category. Thus, when we take tweets per individual, shown at right, the distributions are pretty similar between groups. We are somewhat limited by the real-world issue of having so few Republican women.



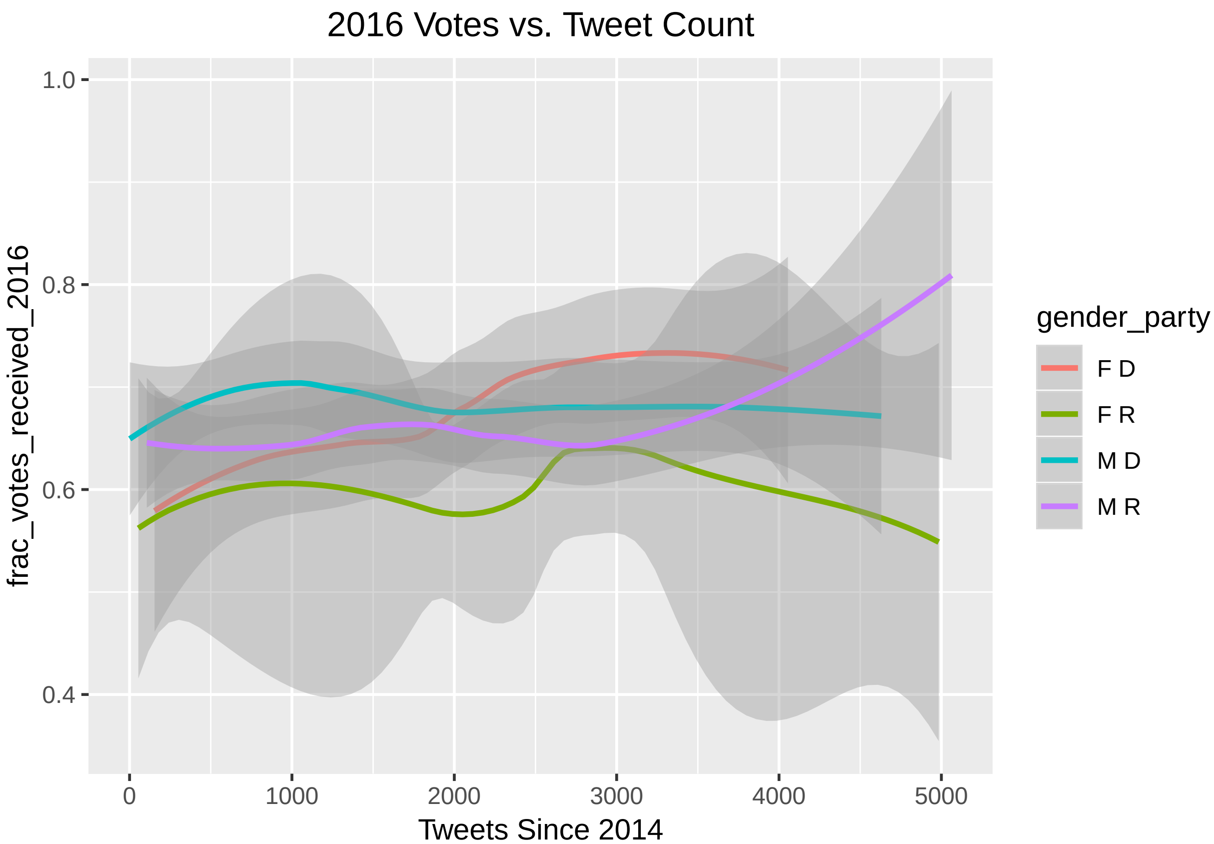
Next we turn to our election data. The dataset is unbalanced in that most individuals have won their elections. However, vote fraction received is still interesting; we see the between gender and party there is relative balance over the recent elections.



Another way the dataset is unbalanced is when it comes to tweet frequencies over time: there are many more in recent years. This is due to the increased popularity in the medium. Standardized to individual, when we brek tweet frequency down by gender, we see that women only recently have started outpacing men.



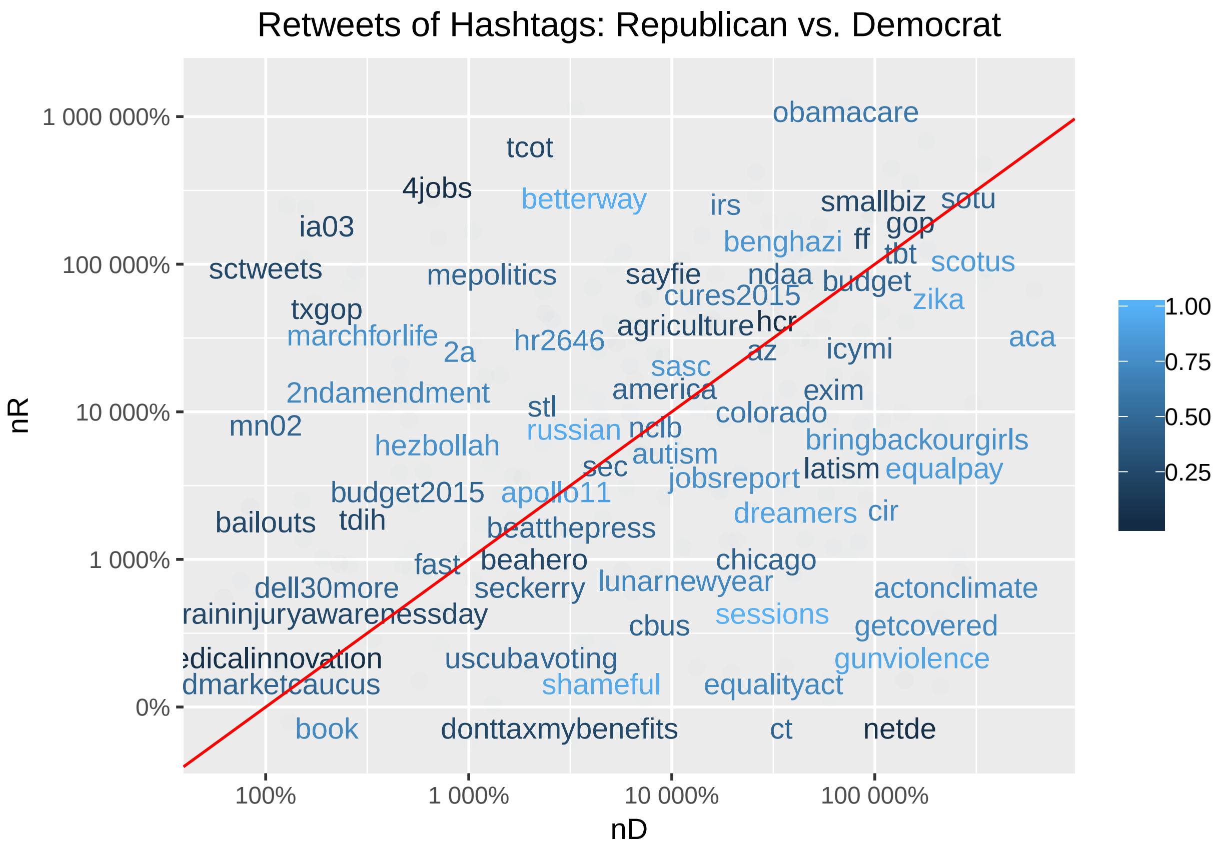
Tweet frequency does not seem to correspond much to greater election success for any combination of party and gender (below). Not shown, receiving more retweets also is largely uncorrelated.



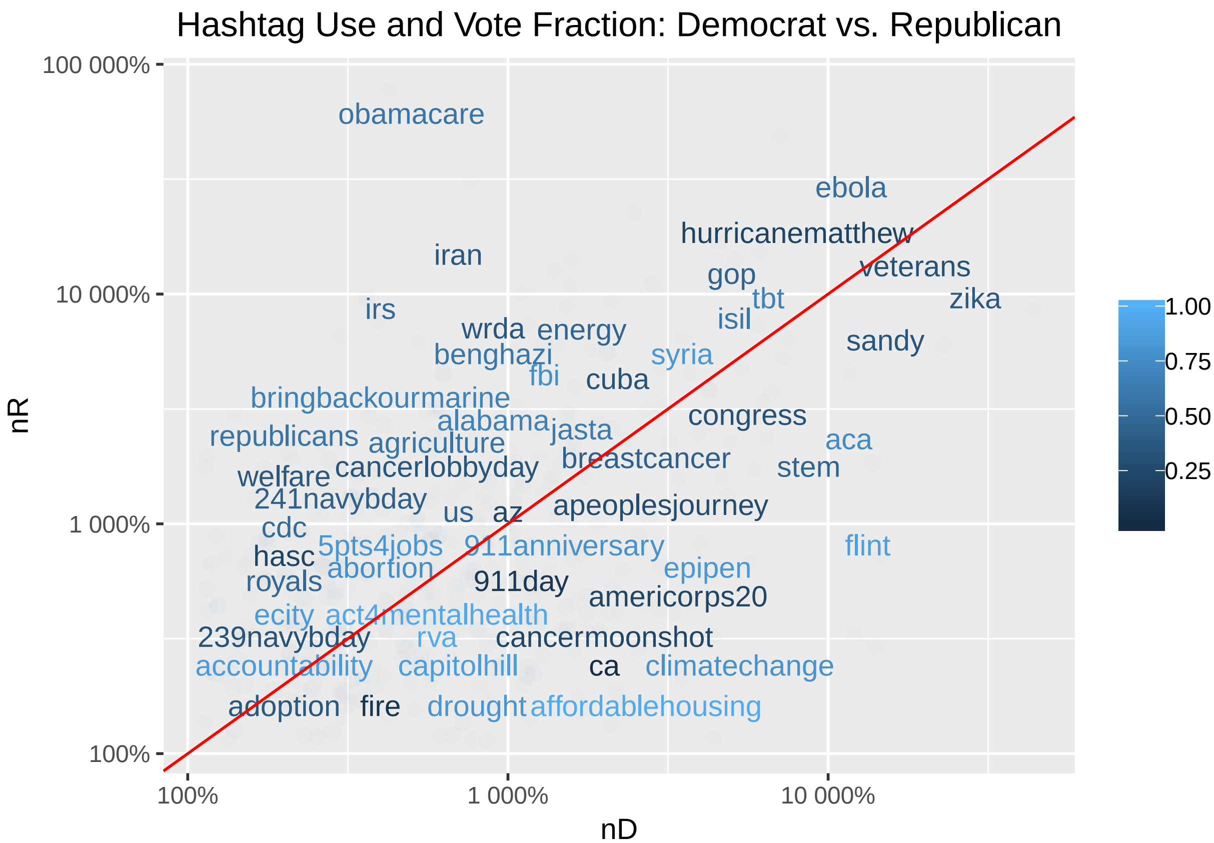
Tweet Topics: Hashtags

Hashtags are a way for users to self-identify topics that relate to their tweets, so it's a good place to start when doing any content analysis on tweets.

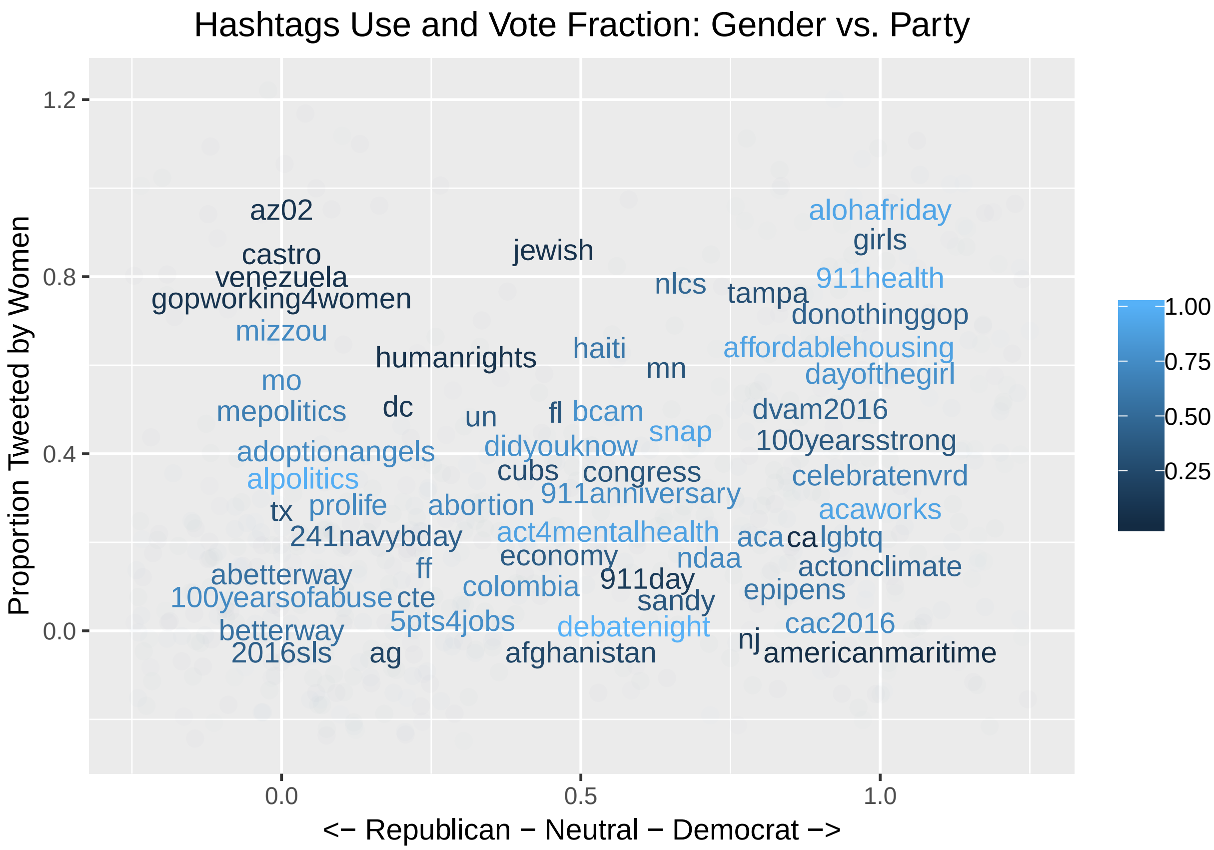
Different parties focus on different issues, and this comes across in their use of hashtags. The reception of these issues also differs on different topics. Inspired by a layout at https://www.tidytextmining.com/twitter.html, In the below, we place the hashtag on the x axis based on how much (log base 10) it gets used by democrats, y axis for republicans, and then we color the points by the (zero to one) percentile of retweets it gets. Democrats seem to be getting slightly better retweet visibility for their more commonly used hashtags vs. that which Republicans receive for theirs.



We can also ask how tweeting about different topics pays off come election day. To do this, we focus on tweets immediately preceding an election. Per individual, I randomly selected up to fifty tweets in the two months preceding each election. It seems that Democrats might be able to differentially find hashtags that correlate with election success.

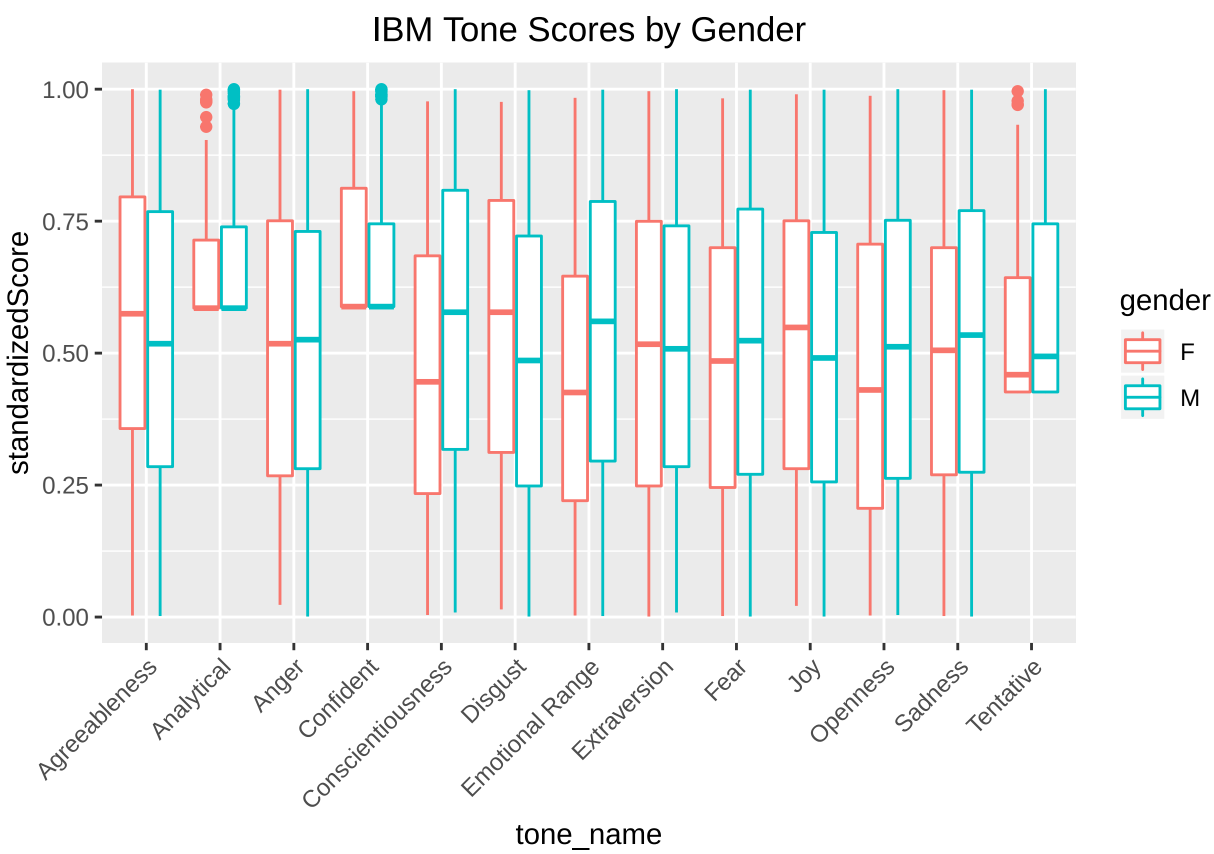


To add a dimension of gender, I collapse the prior axes by computing the fraction of democrats using the tweet (the rest are republican), and the fraction of women (the rest are men). This roughly creates an area for hashtags most used by Republican women (top left), Republican men (bottom left), Democrat women (top right), and Democrat men (bottom right). We see that while Democrat women are finding winning hashtags, republican women are lagging even behind Republican men. One possible explanation would be if Republican women, being such a minority, feel pressure to take the lead on topics initialized by Republican men, not coming up with as many winning topics of their own.

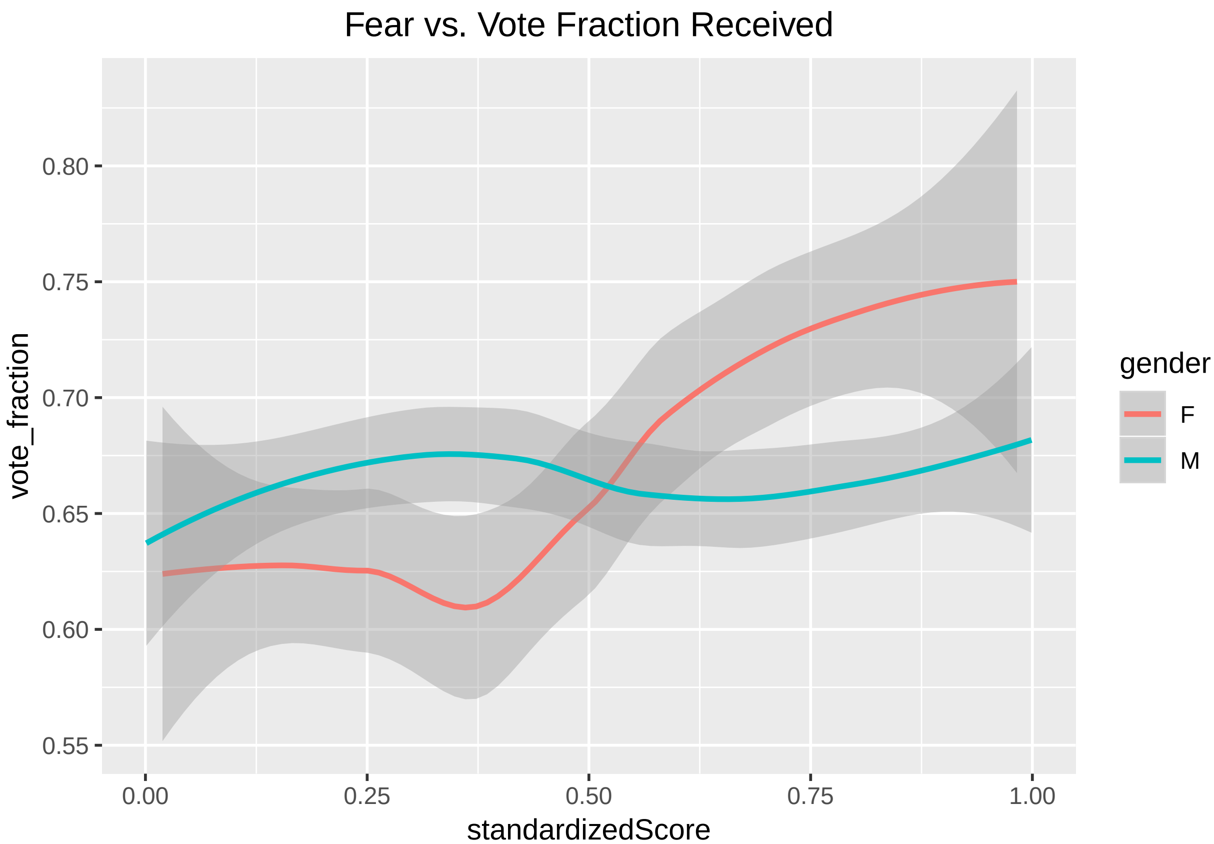


Tweet Tone

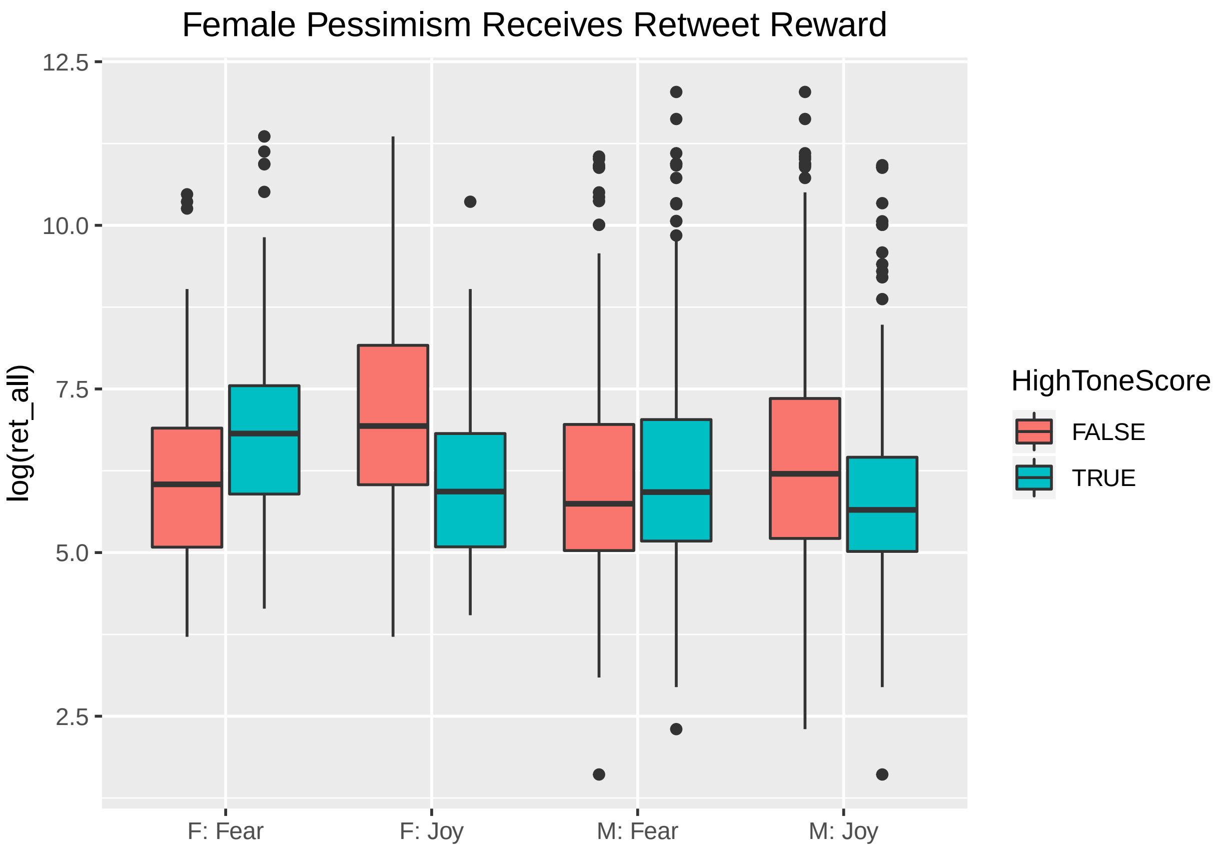
Now we turn to the tones that appear in the tweets. Similar to Proctor [2017], I find that the tone data is balanced in the sense that on aggregate there are no measurable effects of gendered tonal differences.



However, I find that women seem to be rewarded more for fear when it comes to election day success. The effect is similar for disgust (not shown), suggesting that pessimism in general is differentially rewarded for women.



One partial explanation for the above is that women are retweeted more when they are expressing these pessimistic tones, below.



Analysis

Tweet Frequency

We saw earlier that female individuals are tweeting more than men, only recently. This effect can be approximated by a linear model fitting tweet count over time versus gender. The effect suggested by the plot is statistically significant. As time goes by, the fitted model has men losing in frequency versus women.

Table 1: Fitting linear model: n ~ month * gender

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-456	21	-22	2.5e-107
month	3.6e-07	1.5e-08	25	1.3e-135
genderM	206	22	9.3	2e-20
month:genderM	-1.5e-07	1.6e-08	-9.7	3e-22

Hashtags

We know that the dataset is balanced in that tweeting more or receiving more retweets does not straight-forwardly interact with party, gender, or election success. Therefore, the nuance we add by honing in on specific hashtags is interesting.

The first effect we identified graphically was that Democrats, more than Republicans, find hot-button topics that go more viral with retweets. To test this, we assess an additive fit linear model in which log retweet count is predicted by the number of Republicans and Democrats who tweeted about it. If the effect of more Democrats is larger than Republicans, the thesis is validated, which is what we find, below:

Table 2: Fitting linear model: log(1 + medianRetCount) ~ nD + nR

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.665	0.05354	31.11	2.165e-102
nD	0.0002156	7.748e-05	2.783	0.005685
nR	-7.82e-05	4.229e-05	-1.849	0.06528

An analogous model is used when we look at success versus a party's common hashtags. Again, Democrats use more hashtags predictive of election day success than do Republicans.

Finally, we presented a thesis that Republican women in particular struggle with tweeting hashtags that correlate with vote fraction. When we interact the fraction of women with the fraction of Democrats with the vote fraction outcome variable, we find the interaction is statistically significant, endorsing the hypothesis.

Tone

I also find that the effect of tone expressed before elections on election outcome is statistically significant. Again we use a linear model to approximate the effect of standardized tone score interacted with gender.

Table 3: Fitting linear model: vote_fraction ~ standardizedScore * gender

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.59	0.022	27	1e-101
standardizedScore	0.16	0.039	4.1	5.6e-05
genderM	0.065	0.025	2.7	0.0082
standardizedScore:genderM	-0.15	0.044	-3.4	0.00071

Confounding Factors

Dataset limitations

As mentioned earlier, this dataset lacks balance between election winners and losers; most elections our politicians ran in they won. This leads to an inherent confounder: if more of X (e.g. tone of Fear, using a certain hashtag) relates with higher vote fraction, maybe this just indicates that sure-win candidates feel emboldened/consequence free to use X. This is a particularly salient correlation-causation, "chicken-and-egg" problem with this approach.

Real-world limitations

We know that politicians at the highest level have campaign teams to manage their social media accounts; the question of "who is actually tweeting?" is hard to answer. Both candidates and social media teams have payoff models and concious strategies for their tweeting. Thus, tweet strategies and election payoffs are confounded together to the extent that the best-funded, incumbent, and/or more-likely-to-win candidates have the best social media teams, quickest to identify and adopt a predicted-successful social media strategy.

In addition to the question of who is tweeting, we should also ask who is viewing these tweets and/or retweeting. Barberá et al. [2015] analyzes to the extent that social media is an echo chamber vs. a national conversation. If social media is more of an echo chamber, more extreme "rally-the-base" style strategies should be seen. Therefore, women might still experience gendered language pressures that are not exposed in their tweets.

Conclusion and Future Work

Through three main pillars of analysis, tweet frequency, tweet (hashtag) topic, and tweet tone, I sought to characterize some of the relationship between strategy on Twitter and election day success. Straightforward explanations for who receives more visibility through retweets or votes on election day are not apparent - the dataset is balanced in that sense, calling for more nuanced approaches. I found a relationship between certain key hashtag topics and election day success; Democrats, more than Republicans, and especially more than Republican women, aligned their tweets with these key hashtags. When it came to tone, women who expressed fear before elections were rewarded more; similarly for disgust.

Future work would seek to learn topics on tweets, above just treating hashtags as topics. Some research has suggested that women feel more comfortable advocating for marginalized groups, so aligning topics to tones is an important next step. Learning topics on tweets is hard because of the shortness of these documents; topics rely on repeated document co-occurences of words. But Sharifirad et al. [2018] find that language models learned on tweets concatenated together with metadata characteristics of who is tweeting can achieve greater accuracy and data efficiency; this dataset is ripe for a similar approach.

Similar analysis applied to richer metadata might yield interesting results. Do effects that are seen at the highest level also apply at state and local levels of government? What about for NGO and business leaders? Treating even more recent tweets, and looking more specifically at movements such as #metoo, #blacklivesmatter, etc., could motivate novel vignettes.

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