Mixed Signals:
The Limitations and Potential for Twitter Sentiment Analysis as a Supplement for Poll Data

Trevor Laity
UC Berkeley

Sociology 105

Abstract

In an effort to explore the use of social media and tweets as a data source for interpreting public opinion, this study correlates aggregated sentiments via a selection of relevant tweets, unweighted and weighted by likes and retweets, against various daily poll data of presidential approval ratings for Donald Trump. While the results were mixed between weak, insignificant correlations and strong, significant relationships, sentiment analysis as a proxy for public opinion remains a very distant, promising data source.

Introduction

Polls have always been the paramount tool in electoral analysis. Historically, polls have had excellent accuracy and have been more than reliable -- Gallup, Inc.'s poll correctly predicted the general presidential election for 16 of the past 20 cycles (Gallup, 2012). Pundits have consistently used polls to shape their analysis and interpretation of the electoral race, and internal polling done by candidate campaigns has long held significant weight in designating battleground states and deciding where to devote campaign resources. That stark confidence in polling has led to some notable surprises, including the infamous "Dewey Beats Truman" race of 1948. The Chicago Daily Tribune relied heavily on early poll data to make a premature prediction in favor of Governor of New York Thomas Dewey over incumbent President Harry S. Truman and sorely embarrassed everyone involved (Lester, 1998). According to many analyses, overreliance on and misinterpretation of poll data also led to the monumental, unexpected defeat of Hillary Clinton by Donald Trump in the 2016 election. The night before the election, everyone expected to watch a Clinton acceptance speech-- famed FiveThirtyEight analyst Nate Silver gave Hillary Clinton a 71.4% chance of victory the day before the election, and his was the most cautious of all leading polls; betting markets gave Clinton an 82.1% chance, and the New York Times' multi-poll model declared Clinton the 85% favorite (Silver, 2016; Katz, 2016; Silver, 2017). On November 8, Clinton ended up winning the overall popular vote, netting 46% of the vote to Trump's 48%; yet in crucial states the Clinton campaign fell short, losing the presidency in one of the most shocking elections in recent history. While the official campaign threw blame in every direction but their own, sources from inside the campaign placed significant fault on a central obsession with internal modeling and polling conducted by the campaign headquarters in Brooklyn: despite field offices' repeated warnings that the race appeared closer than estimated, top level brass held to their interpretation of their collected data and refused to adjust to the reality of the Midwestern political landscape (Dovere, 2016). Clinton's campaign believed they had a resilient white, middle-class firewall based on their polling, but we all know how that story ends.

Polls are correct fairly often, but equally as often pollsters arrive at those conclusions for what turn out to be the wrong reasons. Polls are extremely vulnerable to biases, whether from inaccuracies inherent to self-report measures; dishonesty from the social desirability effect; and other depth and control issues due to survey methodology (a lack of consistency and enforcement, holistic considerations and partial responses, etc.). Not only is the collected data itself often flawed, but flexibility in data interpretation can lead to different conclusions from the same data by different people with varying accuracy -- and even within those interpretations there exist countless biases. When campaigns choose the wrong model, or even misinterpret the right one, they can make fatal, sometimes Michigan-sized mistakes.

This researcher's primary critique of polling (and all lab-based research) is the attempted recreation of a natural, organic affect, behavior or cognition in a non-natural, controlled, measured setting, which intrinsically introduces error and variance. For as long as we as scientists have recognized this, we have been resigned to accepting the inescapable presence of the observer effect, minimizing it as best we can through methodological design, complicated corrections, and intricate controls (not all of which can completely neutralize bias in polling responses -- hello, social desirability!). But with the advent of social media, people all over the world are volunteering this same level of data via Facebook, Instagram, and Twitter as a means of self-expression. Researchers have successfully used social media to predict depression, friendship networks, disease outbreaks, and even stock market valuations from assortments of likes, statuses, locations, and interactions with other social media users (De Choudhury et al., 2013; Aiello et al., 2012; Schmidt, 2012; Chen et al., 2014). If we can extrapolate and predict these complex behavioral patterns from digital behavior, it stands to reason we may be able to estimate popular opinion on a given topic based on social media posts.

Twitter has long been used to indirectly or directly express an opinion or other emotions about someone or something. As a microblogging platform, Twitter nominally exists for this use case: it is a space for users to tell the world (or at least their followers) how they feel -- about something, nothing, or anything. Even the default text prompt for users to write tweets asks “What’s happening?” It then stands to reason that a tweet by a user should map directly to a hyperfocused, time-sensitive distillation of their opinion about the topic of the tweet. Therefore an aggregation of a large enough sample of topical tweets should provide a general estimate of the population’s aggregate opinion.

Researchers have reliably conducted sentiment analysis on publicly available tweets with impressive accuracy (Go et al., 2009). If these online sentiments are consistent and congruous with offline opinions, Twitter and other microblogging platforms may prove to be a better data source for public opinion than polls. The relationship between personally held political opinions and digitally shared sentiments has already been explored in the

Greek political system (Tumasjan et al., 2010) -- if a readily-available, data-rich, raw and unimproved source has similar accuracy to a cost- and effort-intensive, tricky technique that the field has struggled with for decades, why not start using and improving it?

Hypotheses

Our hypotheses are as follows:

H_0 There is no significant relationship between average sentiment extracted from tweets and approval ratings from various polls.

H_1 The percentage of positive tweets for a given range of dates will be correlated with approval ratings from various polls.

H_2 The percentage of positive tweets for a given range of dates, weighted according to the given tweets' likes, will be correlated with approval ratings from various polls.

H_3 The percentage of positive tweets for a given range of dates, weighted according to the given tweets' retweets, will be correlated with approval ratings from various polls.

H_4 The percentage of positive tweets for a given range of dates, weighted according to the given tweets' likes and retweets, will be correlated with approval ratings from various polls.

Methods

All tweets analyzed were sourced from Twitter's free developer API to scrape and collect tweets based on a given query, which for this study was simply the word 'trump' (Figure 1).

```
In [ ]: auth = tweepy.AppAuthHandler(consumer_key, consumer_secret)
        api = tweepy.API(auth, wait_on_rate_limit=True,
                         wait_on_rate_limit_notify=True)

In [ ]: searchQuery = 'trump'  # this is what we're searching for
        maxTweets = 10000000 # Some arbitrary large number
        tweetsPerQry = 100  # this is the max the API permits
        fName = 'tweets_archive.csv' # We'll store the tweets in a text file.

        # all_tweets = pd.DataFrame()

        print("Downloading max {0} tweets".format(maxTweets))
        with open(fName, 'w') as f:
            while tweetCount < maxTweets:
                try:
                    #### search
                    if (max_id <= 0):
                        if (not sinceId):
                            new_tweets = api.search(q=searchQuery, count=tweetsPerQry)
                        else:
                            new_tweets = api.search(q=searchQuery, count=tweetsPerQry,
                                                    since_id=sinceId)
                    else:
                        if (not sinceId):
                            new_tweets = api.search(q=searchQuery, count=tweetsPerQry,
                                                    since="2017-03-13")
                        else:
                            new_tweets = api.search(q=searchQuery, count=tweetsPerQry,
                                                    max_id=str(max_id - 1),
                                                    since_id=sinceId)
                    if not new_tweets:
                        print("No more tweets found")
                        break
```

Figure 1. Twitter scraper logic.

More sensitive, specific queries (perhaps containing the keywords 'president' or various relevant hashtags) were not favored as tweets returned by these keywords may not be relevant to the analysis at hand and may introduce noise, either from unrelated content or from a biased sample (i.e. a given hashtag may be used more by conservatives than by liberals, or vice versa). While fewer query terms might exclude some relevant tweets, this analysis favored a (relatively) smaller sample from a narrower slice of available tweets in hopes that a simpler sample may remain objective and better capture the zeitgeist of the Twitter/Trump relationship.

A scraper program written in Python collected tweets matching the query starting on March 1, 2017. The scraper extracted various metadata for each tweet including the number of likes, number of retweets, the time of tweet creation and publishing, and the stripped text of the tweet itself. To determine the sentiment of each collected tweet, each tweet's text was run through the sentiment analysis algorithm provided in the TextBlob

Python library. TextBlob relies on an internal dictionary that maps words against their rated sentiment value via an internal dictionary, and can scale this interpretation up to interpret multi-word phrases and sentences. TextBlob's sentiment analysis algorithm is far from infallible in reading abstract, complex linguistic nuances like sarcasm, insinuations, and context-specific references, but for our purposes, simply being able to consider the sentiment of phrases of words is a large step up in comprehension from the capabilities used in most published literature on the subject, which normally construe sentiment of bodies of text by simply averaging out the individual sentiments of each word in the text (which often misses the majority of a given passage of text's sentiment, as language is inherently constructive and all words take on different meanings within the context of the words around them). TextBlob's assessment of sentiment can be seen below in Figure 2.

```
for index, row in test.sample(5).iterrows():
    print 'sentiment: {0}'.format(row['sentiment'])
    print row['text'], '\n\n'
```

```
sentiment: 0.0
"if donald trump isnt your president then get out of this country!"
me:  https://t.co/jgxYohkfcy


sentiment: -0.388888888889
Trump taking credit for jobs he didn't create is the worst example of a white president appropriating black president
 culture I've ever seen



sentiment: 0.0
As #pollutingPruitt guts #EPA &amp; #regulations the Trump's will make millions designing your gas masks. #Climate… h
ttps://t.co/cdrBdSj2mh


sentiment: -0.366666666667
Trump was surprised health care was so complicated. Maybe this will help him get why the GOP bill is so disastrous. h
ttps://t.co/XSgVZ9LSmj
```

Figure 2. TextBlob sentiment extraction.

From Twitter, we obtain tweet texts, likes, retweets, and dates; from TextBlob we obtain tweets' sentiment on two dimensions: an estimate of the magnitude of the text's sentiment polarity (-1 to 1, negative text to positive text) and subjectivity (0 to 1, the degree of confidence TextBlob holds in the corresponding polarity estimate). For the sake of simplicity, polarity was coded to three one-hot variables: positive_dummy if the value was greater than zero, neutral_dummy if the value was equal to zero, and negative_dummy if the value was less than zero.

```
test.sample(5)
```

	sentiment	positive_dummy	neutral_dummy	negative_dummy	subjectivity	retweets	likes	timestamp	text
0	-0.125000	0	0	1	0.125000	86	74	2017-03-10 23:57:59	Trump did not know Flynn would have to registe...
0	0.000000	0	1	0	0.000000	380	529	2017-03-09 20:55:55	🇺🇸President Donald J. Trump Rally!\n 💥Nashvi...
0	0.000000	0	1	0	0.000000	55250	95004	2017-03-09 15:57:32	"if donald trump isnt your president then get ...
0	0.357143	1	0	0	0.571429	2382	3347	2017-03-10 14:05:00	Even Democrat Senators are beginning to be in ...
0	0.000000	0	1	0	0.000000	0	1	2017-03-10 23:59:57	@FoxNews @LisaMarieBoothe And have been 4 mont...

Figure 3. Sample data

To find an estimate of aggregate sentiment for the day, we group tweets by the date they were published and derive the percentage of all sentimentally charged tweets for the day that is positive or negative. This study posits the percentage of positive tweets for a given day corresponds to a poll's daily approval rating.

The difference of these two percentages yield a margin. We can calculate different margins by indexing ratings by raw tweet total (purely the percentage of sentiment tweets deemed to be positive), as well as using the number of likes and/or retweets as weights to give more consideration to tweets with more likes and retweets to account for degrees of collective agreement.

In [18]:
```
grouped = past_copy_slim.groupby('timestamp date').mean()
grouped['tweet margin'] = grouped['positive_dummy'] - grouped['negative_dummy']
grouped['lw margin'] = grouped['lw_positive'] - grouped['lw_negative']
grouped['rw margin'] = grouped['rw_positive'] - grouped['rw_negative']
grouped['lrw margin'] = grouped['lrw_positive'] - grouped['lrw_negative']

grouped.head()
```

Out[18]:

ment	...	lw_neutral	rw_neutral	lrw_neutral	lw_negative	rw_negative	lrw_negative	tweet margin	lw margin	rw margin	lrw margin
5	...	1605.106109	655.051447	2260.157556	354.289389	180.890675	535.180064	0.090032	1292.807074	840.308682	2133.115756
958	...	678.752089	557.264624	1236.016713	260.175487	214.395543	474.571031	0.075209	1141.002786	499.367688	1640.370474
6795	...	8635.747592	3623.618497	12259.366089	8213.788054	3040.414258	11254.202312	-0.019268	-7691.156069	-2783.142582	-10474.298651
38	...	2042.978218	2045.677228	4088.655446	523.574257	353.289109	876.863366	0.154455	101.558416	13.376238	114.934653
458	...	3135.610236	1377.385827	4512.996063	554.988189	293.803150	848.791339	0.062992	548.649606	235.383858	784.033465

Figure 4. Illustration of margins.

This analysis first correlates these margins against the margins of various polls' approval ratings for each corresponding date, using like- and retweet-based weights for more complex models (H_{1-4}). We will discuss the results of these tests below in the next section.

Descriptive Statistics & Results

Our sample consists of 2117867 tweets across 20 dates, with an average of 41556.47 tweets per day. We indexed our Twitter-sourced margins across four separate polls: the Rasmussen Reports' Approval Index, the RealClearPolitics Trump Job Approval Poll, Gallup Inc.'s daily Trump Job Approval poll, and the Presidential Job Approval poll from UC Santa Barbara's American Presidency Project (Appendix 1).

Our results were mixed: we found no clear relationship between tweets and the Rasmussen and RCP polls, but found statistically significant correlations between our collected tweets and both the Gallup and UCSB polls. This mix of correlations extended across models: Gallup and UCSB poll results consistently correlated strongly with our Twitter estimates with statistical significance (r = .812-.980, p = .02-.187; r = .559-.635, p =

.027-.059) but the Rasmussen and RCP polls had weak correlations that were not statistically significant (r = -.128-.023, p = .809-.973; r = .089-.204, p = .464-.754) -- even when accounting for likes and retweets.

model: raw avg tweet %

	rasmussen	aggregate	gallup	ucsb
margin	tweet_margin	tweet_margin	tweet_margin	tweet_margin
correlation	-0.128069	0.204526	0.812627	0.634674
p value	0.808946	0.464663	0.187373	0.026622

model: avg tweet %, weighted by likes

	rasmussen	aggregate	gallup	ucsb
margin	like_weight_margin	like_weight_margin	like_weight_margin	like_weight_margin
correlation	0.0228929	0.0887661	0.977518	0.612605
p value	0.965667	0.753076	0.0224822	0.0342004

model: avg tweet %, weighted by retweets

	rasmussen	aggregate	gallup	ucsb
margin	retweet_weight_margin	retweet_weight_margin	retweet_weight_margin	retweet_weight_margin
correlation	-0.0181568	0.152645	0.969629	0.559339
p value	0.972768	0.587058	0.0303706	0.0586454

model: avg tweet %, weighted by likes and retweets

	rasmussen	aggregate	gallup	ucsb
margin	like_retweet_weight_margin	like_retweet_weight_margin	like_retweet_weight_margin	like_retweet_weight_margin
correlation	-0.0181568	0.10523	0.98031	0.598533
p value	0.972768	0.708974	0.0196895	0.039772

This mix of results does not produce an interpretable analysis -- there are no other included predicting variables that could account for why some polls correlate with Twitter data and some do not. Inconsistent results is not a promising finding -- unfortunately, we cannot derive any meaningful conclusions from this data.

It is interesting that some models are highly correlated ($r = .98$, $p < .02$), with some not at all ($r = -.01$, $p > .972$). If there were less disparity between the correlations, that would indicate a fault in the internal validity of our hypotheses; however, the extreme polarity appears to support an inconsistency or inadequacy in our data and analysis. We will discuss these potential inconsistencies below.

Constraints and Limits

Many things could have affected our analysis, and there are many areas in which unnecessary error could have been introduced. Our data is likely not fully representative of the population we want to measure. There is no guarantee that users who are more likely to tweet are likely voters or likely poll participants, nor that these tweets are solely US-based (the overwhelming majority of tweets did not have a location attribute); our estimation may be more representative of global aggregate opinion, instead of US likely voters. I had hoped the law of large numbers would smooth out any noise with over a few million data points, but we cannot be sure -- we cannot even be sure a few million data points is an adequate sample. How many tweets were made about Trump in our given period of time, and how many must we collect to accurately, randomly select a representative sample? Additionally, as most of these polls' approval ratings span across multiple days, aggregating tweets into day averages and then multi-day averages reduce the data points for which we can compare values, which reduces the power with which we can conduct our analysis.

But even if we presume our data is perfect, the analysis used here still allows much room for error. Our method of determining sentiment may be too lacking to get an adequate interpretation of a tweet's positivity or negativity -- as mentioned before, our algorithm lacks the ability to account for complex sentiments or rhetorical devices like sarcasm, references and inferences, or hyperbole. To top it all off, the model used here is very simple, accounting only for aggregate number of tweets, likes, and retweets, with no further parameter tuning or weight adjustments. A more complex, scaled, and nuanced model may account for significantly more variation than we are able to in this study.

Conclusion

Previous literature warned against putting much faith in predicting polls from Twitter data, and this researcher is inclined to agree. Mixed predictive success indicates is not to say our initial assumption is invalidated: considering its limitations, it is not wise to interpret this study as discouraging the hypothesis that social media behavior is not indicative of offline behavior, affect, or opinion -- I believe the lack of consistent significance seen here is more representative of deficiencies in the data and limitations in our analysis than of an absence of an effect , with our inability to fully account for variance coming mainly from the shortcomings listed above.

While researchers are hesitant to delve into this area of data analysis, results like this ought to encourage, rather than discourage, exploration. As a field, we are now more equipped to interpret this data than ever before, especially in comparison to researchers' first foray into Twitter sentiment analysis -- our sentiment analysis capability has made leaps and bounds, and neural nets powered by machine learning allows for more and more complex analyses of terabytes of data. With more complex, nuanced approaches (and potentially a more concrete research question), this researcher is confident one can successfully derive truths about our offline world from our online world.

References

Aiello, L. M., Barrat, A., Schifanella, R., Cattuto, C., Markines, B., & Menczer, F. (2012). Friendship prediction and homophily in social media. *ACM Transactions on the Web (TWEB)*, *6*(2), 9.

Chen, H., De, P., Hu, Y. J., & Hwang, B. H. (2014). Wisdom of crowds: The value of stock opinions transmitted through social media. *Review of Financial Studies*, *27*(5), 1367-1403.

De Choudhury, M., Gamon, M., Counts, S., & Horvitz, E. (2013, July). Predicting Depression via Social Media. In *ICWSM* (p. 2).

Gallup. (2012). *Election Polls -- Accuracy Record in Presidential Elections*. [Data set]. Gallup [Distributor]. Retrieved from: http://www.gallup.com/poll/9442/election-polls-accuracy-record-presidential-elections.aspx.

Go, A., Huang, L., & Bhayani, R. (2009). Twitter sentiment analysis. *Entropy*, *17*, 252.

Gosling, S. D., Augustine, A. A., Vazire, S., Holtzman, N., & Gaddis, S. (2011). Manifestations of personality in online social networks: Self-reported Facebook-related behaviors and observable profile information. *Cyberpsychology, Behavior, and Social Networking*, *14*(9), 483-488.

Lester, W. (1998, November 1). 'Dewey Defeats Truman' Disaster Haunts Pollsters. *Los Angeles Times*. Retrieved from http://articles.latimes.com/1998/nov/01/news/mn-38174.

Dovere, E. (2016, December 14). How Clinton List Michigan -- and blew the election. *Politico*. Retrieved from http://www.politico.com/story/2016/12/michigan-hillary-clinton-trump-232547.

Katz, J. (2016, November 8). Who Will Be President? *The New York Times*. Retrieved from https://www.nytimes.com/interactive/2016/upshot/presidential-polls-forecast.html?_r=0

Pak, A., & Paroubek, P. (2010, May). Twitter as a Corpus for Sentiment Analysis and Opinion Mining. In *LREc* (Vol. 10, No. 2010).

Schmidt, C. W. (2012). Using social media to predict and track disease outbreaks. *Environmental health perspectives*, *120*(1), A31.

Silver, N. (2016, November 7). Who will win the presidency? *FiveThirtyEight: 2016 Election Forecast*. Retrieved from https://projects.fivethirtyeight.com/2016-election-forecast/.

Silver, N. (2017, January 19). The Real Story of 2016. *FiveThirtyEight*. Retrieved from http://fivethirtyeight.com/features/the-real-story-of-2016/.

Tumasjan, A., Sprenger, T. O., Sandner, P. G., & Welpe, I. M. (2010). Predicting elections with twitter: What 140 characters reveal about political sentiment. *ICWSM*, *10*(1), 178-185.

Appendices

Appendix 1: Poll Data

Rasmussen Reports' Approval Index

Date	Approval Index	Strongly Approve	Strongly Disapprove	Total Approve	Total Disapprove	Margin
4/18/2017	**-7**	**0.32**	**0.39**	**0.50**	**0.50**	0.00
4/17/2017	**-9**	**0.30**	**0.39**	**0.50**	**0.50**	0.00
4/14/2017	**-12**	**0.30**	**0.42**	**0.48**	**0.52**	-0.04
4/13/2017	**-13**	**0.29**	**0.42**	**0.48**	**0.52**	-0.04
4/12/2017	**-14**	**0.29**	**0.43**	**0.47**	**0.53**	-0.06
4/11/2017	**-15**	**0.28**	**0.43**	**0.47**	**0.53**	-0.06
4/10/2017	**-19**	**0.27**	**0.46**	**0.44**	**0.56**	-0.12
4/7/2017	**-17**	**0.28**	**0.45**	**0.45**	**0.55**	-0.10
4/6/2017	**-18**	**0.27**	**0.45**	**0.46**	**0.54**	-0.08
4/5/2017	**-15**	**0.28**	**0.43**	**0.46**	**0.54**	-0.08
4/4/2017	**-19**	**0.27**	**0.46**	**0.43**	**0.57**	-0.14
4/3/2017	**-19**	**0.27**	**0.46**	**0.42**	**0.58**	-0.16
3/31/2017	**-19**	**0.28**	**0.47**	**0.43**	**0.57**	-0.14
3/30/2017	**-17**	**0.27**	**0.44**	**0.44**	**0.56**	-0.12
3/29/2017	**-17**	**0.27**	**0.44**	**0.44**	**0.56**	-0.12
3/28/2017	**-17**	**0.27**	**0.44**	**0.45**	**0.55**	-0.10
3/27/2017	**-16**	**0.28**	**0.44**	**0.45**	**0.54**	-0.09
3/24/2017	**-17**	**0.29**	**0.46**	**0.44**	**0.56**	-0.12
3/23/2017	**-14**	**0.30**	**0.44**	**0.47**	**0.53**	-0.06
3/22/2017	**-14**	**0.30**	**0.44**	**0.46**	**0.54**	-0.08
3/21/2017	**-7**	**0.33**	**0.40**	**0.50**	**0.50**	0.00
3/20/2017	**-7**	**0.35**	**0.42**	**0.49**	**0.51**	-0.02
3/17/2017	**-9**	**0.34**	**0.43**	**0.48**	**0.52**	-0.04
3/16/2017	**-13**	**0.31**	**0.44**	**0.47**	**0.53**	-0.06
3/15/2017	**-16**	**0.28**	**0.44**	**0.45**	**0.54**	-0.09
3/14/2017	**-13**	**0.30**	**0.43**	**0.46**	**0.53**	-0.07
3/13/2017	**-11**	**0.31**	**0.42**	**0.47**	**0.53**	-0.06
3/10/2017	**-11**	**0.32**	**0.43**	**0.48**	**0.52**	-0.04

3/9/2017	**-8**	**0.33**	**0.41**	**0.49**	**0.51**	-0.02
3/8/2017	**-7**	**0.35**	**0.42**	**0.49**	**0.51**	-0.02
3/7/2017	**-1**	**0.37**	**0.38**	**0.51**	**0.49**	0.02
3/6/2017	**-1**	**0.37**	**0.38**	**0.52**	**0.48**	0.04
3/3/2017	**1**	**0.37**	**0.36**	**0.53**	**0.47**	0.06
3/2/2017	**-3**	**0.36**	**0.39**	**0.52**	**0.48**	0.04
3/1/2017	**-6**	**0.34**	**0.40**	**0.50**	**0.50**	0.00

RealClearPolitics Trump Job Approval Poll

Poll	Start Date	End Date	Sample	Approve	Disapprove	Margin
RCP Average	**4/3/2017**	**4/17/2017**	**--**	**0.425**	**0.505**	**-0.08**
Gallup	**4/14/2017**	**4/17/2017**	1500 A	0.41	0.52	-0.11
Rasmussen Reports	**4/13/2017**	**4/17/2017**	1500 LV	0.5	0.5	0
Reuters/Ipsos	**4/13/2017**	**4/17/2017**	1843 A	0.43	0.52	-0.09
Marist	4/11/2017	4/12/2017	869 RV	0.39	0.49	-0.1
Economist/YouGov	4/10/2017	4/11/2017	1330 RV	0.43	0.52	-0.09
CBS News	4/7/2017	4/9/2017	1006 A	0.43	0.49	-0.06
Pew Research	4/5/2017	4/11/2017	1243 RV	0.42	0.52	-0.1
CNBC	4/3/2017	4/6/2017	804 A	0.39	0.48	-0.09
Gallup	4/2/2017	4/4/2017	1500 A	0.42	0.52	-0.1
Rasmussen Reports	4/2/2017	4/4/2017	1500 LV	0.46	0.54	-0.08
Economist/YouGov	4/2/2017	4/4/2017	1331 RV	0.43	0.5	-0.07
Reuters/Ipsos	3/31/2017	4/4/2017	2149 A	0.46	0.5	-0.04
Quinnipiac	3/30/2017	4/3/2017	1171 RV	0.35	0.57	-0.22
PPP (D)	3/27/2017	3/28/2017	677 RV	0.4	0.53	-0.13
IBD/TIPP	3/24/2017	3/30/2017	904 A	0.34	0.56	-0.22
Gallup	3/26/2017	3/28/2017	1500 A	0.35	0.59	-0.24
Rasmussen Reports	3/26/2017	3/28/2017	1500 LV	0.44	0.56	-0.12
Economist/YouGov	3/26/2017	3/28/2017	1271 RV	0.45	0.5	-0.05

CBS News	3/25/2017	3/28/2017	1088 A	0.4	0.52	-0.12
Reuters/Ipsos	3/24/2017	3/28/2017	1646 A	0.44	0.49	-0.05
McClatchy/Marist	3/22/2017	3/27/2017	906 RV	0.38	0.51	-0.13
Gallup	3/19/2017	3/21/2017	1500 A	0.4	0.55	-0.15
Rasmussen Reports	3/19/2017	3/21/2017	1500 LV	0.46	0.54	-0.08
Economist/YouGov	3/19/2017	3/21/2017	1296 RV	0.44	0.49	-0.05
Reuters/Ipsos	3/17/2017	3/21/2017	1606 A	0.47	0.47	0
Quinnipiac	3/16/2017	3/21/2017	1056 RV	0.37	0.56	-0.19
Economist/YouGov	3/13/2017	3/14/2017	1320 RV	0.44	0.49	-0.05
FOX News	3/12/2017	3/14/2017	1008 RV	0.43	0.51	-0.08
Gallup	3/12/2017	3/14/2017	1500 A	0.4	0.54	-0.14
Rasmussen Reports	3/12/2017	3/14/2017	1500 LV	0.45	0.54	-0.09
Reuters/Ipsos	3/10/2017	3/14/2017	1750 A	0.45	0.49	-0.04
PPP (D)	3/10/2017	3/12/2017	808 RV	0.43	0.5	-0.07
Economist/YouGov	3/6/2017	3/7/2017	1359 RV	0.44	0.5	-0.06
Gallup	3/5/2017	3/7/2017	1500 A	0.42	0.53	-0.11
Rasmussen Reports	3/5/2017	3/7/2017	1500 LV	0.49	0.51	-0.02
Reuters/Ipsos	3/3/2017	3/7/2017	1662 A	0.48	0.46	0.02
Quinnipiac	3/2/2017	3/6/2017	1283 RV	0.41	0.52	-0.11
Monmouth	3/2/2017	3/5/2017	722 RV	0.44	0.46	-0.02
USA Today/Suffolk	3/1/2017	3/5/2017	1000 RV	0.47	0.44	0.03
CNN/ORC	3/1/2017	3/4/2017	1025 A	0.45	0.52	-0.07

Gallup Inc.'s Trump Job Approval Poll

Start Date	End Date	Approve	Disapprove	No opinion	Margin
4/10/2017	4/16/2017	0.4	0.54	0.06	-0.14
4/3/2017	4/9/2017	0.4	0.53	0.07	-0.13
3/27/2017	4/2/2017	0.38	0.57	0.05	-0.19
3/20/2017	3/26/2017	0.39	0.56	0.06	-0.17

3/13/2017	3/19/2017	0.4	0.55	0.05	-0.15
3/6/2017	3/12/2017	0.42	0.52	0.06	-0.1
2/27/2017	3/5/2017	0.43	0.51	0.06	-0.08
2/20/2017	2/26/2017	0.42	0.53	0.05	-0.11
2/13/2017	2/19/2017	0.4	0.54	0.05	-0.14
2/6/2017	2/12/2017	0.41	0.53	0.06	-0.12
1/30/2017	2/5/2017	0.43	0.52	0.05	-0.09
1/20/2017	1/29/2017	0.45	0.47	0.08	-0.02

Presidential Job Approval poll from UC Santa Barbara's American Presidency Project

Start Date	End Date	Approve	Disapprove	unsure/no data	Margin
4/14/2017	4/17/2017	0.41	0.52	0.07	-0.11
4/13/2017	4/15/2017	0.41	0.53	0.06	-0.12
4/12/2017	4/14/2017	0.39	0.55	0.06	-0.16
4/11/2017	4/13/2017	0.4	0.55	0.05	-0.15
4/10/2017	4/12/2017	0.4	0.54	0.06	-0.14
4/9/2017	4/11/2017	0.41	0.52	0.07	-0.11
4/8/2017	4/10/2017	0.4	0.54	0.06	-0.14
4/7/2017	4/9/2017	0.4	0.53	0.07	-0.13
4/6/2017	4/8/2017	0.4	0.54	0.06	-0.14
4/5/2017	4/7/2017	0.4	0.54	0.06	-0.14
4/4/2017	4/6/2017	0.4	0.54	0.06	-0.14
4/3/2017	4/5/2017	0.41	0.53	0.06	-0.12
4/2/2017	4/4/2017	0.42	0.52	0.06	-0.1
4/1/2017	4/3/2017	0.39	0.55	0.06	-0.16
3/31/2017	4/2/2017	0.38	0.57	0.05	-0.19
3/30/2017	4/1/2017	0.38	0.57	0.05	-0.19
3/29/2017	3/31/2017	0.4	0.56	0.04	-0.16
3/28/2017	3/30/2017	0.38	0.56	0.06	-0.18
3/27/2017	3/29/2017	0.38	0.57	0.05	-0.19
3/26/2017	3/28/2017	0.35	0.59	0.06	-0.24

3/25/2017	3/27/2017	0.36	0.56	0.08	-0.2
3/24/2017	3/26/2017	0.36	0.57	0.07	-0.21
3/23/2017	3/25/2017	0.4	0.54	0.06	-0.14
3/22/2017	3/24/2017	0.41	0.54	0.05	-0.13
3/21/2017	3/23/2017	0.41	0.54	0.05	-0.13
3/20/2017	3/22/2017	0.39	0.56	0.05	-0.17
3/19/2017	3/21/2017	0.4	0.55	0.05	-0.15
3/18/2017	3/20/2017	0.39	0.56	0.05	-0.17
3/17/2017	3/19/2017	0.39	0.55	0.06	-0.16
3/16/2017	3/18/2017	0.37	0.58	0.05	-0.21
3/15/2017	3/17/2017	0.4	0.55	0.05	-0.15
3/14/2017	3/16/2017	0.41	0.54	0.05	-0.13
3/13/2017	3/15/2017	0.42	0.53	0.05	-0.11
3/12/2017	3/14/2017	0.4	0.54	0.06	-0.14
3/11/2017	3/13/2017	0.39	0.55	0.06	-0.16
3/10/2017	3/12/2017	0.42	0.51	0.07	-0.09
3/9/2017	3/11/2017	0.45	0.49	0.06	-0.04
3/8/2017	3/10/2017	0.44	0.49	0.07	-0.05
3/7/2017	3/9/2017	0.42	0.52	0.06	-0.1
3/6/2017	3/8/2017	0.41	0.53	0.06	-0.12
3/5/2017	3/7/2017	0.42	0.53	0.05	-0.11
3/4/2017	3/6/2017	0.43	0.51	0.06	-0.08
3/3/2017	3/5/2017	0.44	0.5	0.06	-0.06
3/2/2017	3/4/2017	0.43	0.5	0.07	-0.07
3/1/2017	3/3/2017	0.43	0.51	0.06	-0.08