Fame and Ultrafame: Measuring and comparing daily levels of ‘being talked about’ for United States’ presidents, their rivals, God, countries, and K-pop

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When building a global brand of any kind—a political actor, clothing style, or belief system—developing widespread awareness is a primary goal. Short of knowing any of the stories or products of a brand, being talked about in whatever fashion—raw fame—is, as Oscar Wilde would have it, better than not being talked about at all. Here, we measure, examine, and contrast the day-to-day raw fame dynamics on Twitter for U.S. Presidents and major U.S. Presidential candidates from 2008 to 2019: Barack Obama, John McCain, Mitt Romney, Hillary Clinton, and Donald Trump. We assign “lexical fame” to be the number and (Zipfian) rank of the (lowercased) mentions made for each individual across all languages. We show that all five political figures have at some point reached extraordinary volume levels of what we define to be “lexical ultrafame”: An overall rank of approximately 300 or less which is largely the realm of function words and demarcated by the highly stable rank of ‘god’. By this measure, ‘trump’ has become enduringly ultrafamous, from the 2016 election on. We use typical ranks for country names and function words as standards to improve perception of scale. We quantify relative fame rates and find that in the eight weeks leading up the 2008 and 2012 elections, ‘obama’ held a 1000:757 volume ratio over ‘mccain’ and 1000:892 over ‘romney’, well short of the 1000:544 volume favoring ‘trump’ over ‘hillary’ in the 8 weeks leading up to the 2016 election. Finally, we track how one other entity has more sustained ultrafame than ‘trump’ on Twitter: The Korean pop boy band BTS. We chart the dramatic rise of BTS, finding their Twitter handle ‘@bts_twt’ has been able to compete with ‘a’ and ‘the’, reaching a rank of three at the day scale and a rank of one at the quarter-hour scale.

I. INTRODUCTION

> “It is silly of you, for there is only one thing in the world worse than being talked about, and that is not being talked about.”
>
> — Oscar Wilde, The Picture of Dorian Gray [1].

“Being talked about” is the essence of fame, a word that accurately encodes this most basic of sociological mechanisms as it traces back to the Latin fāma (“speak”) with φήμη (ph´ēmē, “talk”) as its Greek cognate.

Achieving widespread awareness is arguably the primary goal of any people-centric enterprise seeking to scale. Of course any such enterprise will want the valence of fame to be positive, and for “talk” to be self-sustaining. Examples abound. To take just one, in the sphere of sport, Lance Armstrong’s archetypal fall-from-grace followed a global expansion of awareness of cancer research, the Tour de France, and cycling. Armstrong himself became famous as an eight-fold kill-the-monster hero, first conquering cancer then the Tour seven times in a row, all ending with a televised confession of betrayal to Oprah.

We also know that fame is profoundly a social construct, a complex mix of system randomness, an individual’s luck, timing, history, and, to the extent that it exists at all in a given field, inherent quality [2–4]. From the perspective of collective evaluation of cultural entities, the existence and perceived importance of ranked lists of anything (wealthy individuals, songs, books, colleges, cities, countries) leaves social systems vulnerable to those unethical actors who would seek fame. Knowing that “getting the word out there” is the foundational work allows system-level manipulation by individuals or organizations pretending to be at or near the top of such lists by gaming myriad sociotechnical algorithms (many/some “people are saying” [5, 6], payola [7], “John Barron” [8–10]).

In politics, a key polling question concerns whether or not an interviewee has heard of a candidate *at all*—shorn of sentiment and story. While some polls show that increases in awareness correspond to increases in favorability, politicians trace out many paths in awareness-favorability space. For example, as we show in Fig. 1, a series of polls carried out by Monmouth University during the first five months of 2019 [11] revealed a strong correlation between awareness of and favorability toward 24 potential Democratic candidates for the 2020 presidential election (Spearman correlation coefficient: r_s=0.949). The awareness extremes were for Joe

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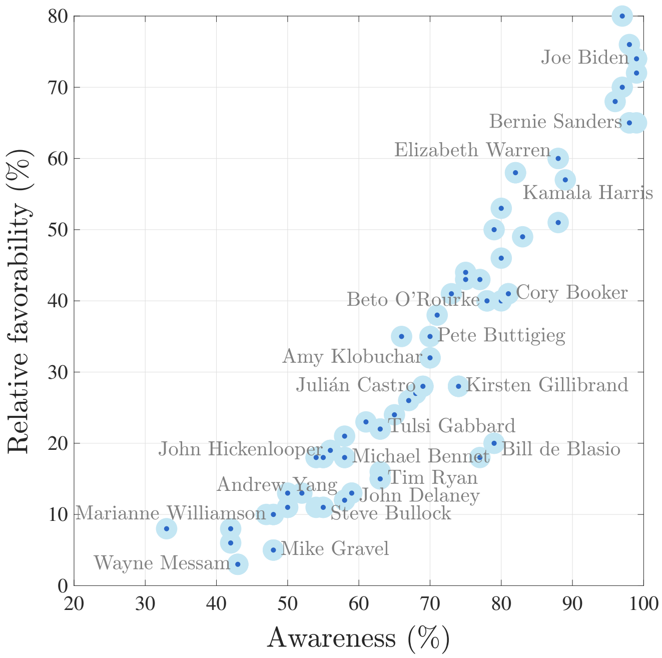

FIG. 1. Comparison of awareness and relative favorability for 24 democratic candidates for the democratic nominee in the 2020 US presidential election, showing a strong positive correlation (Spearman correlation coefficient: r_s=0.949). Details: The data comes from four polls carried out by Monmouth University from 2019/01 to 2019/05 [11]. We compute a candidate's relative favorability as normalized by the subset of respondents who have heard of that candidate. Not all candidates were included in all polls resulting in 58 data points (instead of 96). For readability, we only show a subset of unique names, and arrange these left and right so that one end of the text is close to the relevant data point. We acknowledge that the uneven repetition of candidates calls for a more sophisticated analysis than simple correlation, but our aim is simply to show a clear example of well correlated awareness and favorability (see Fig. 2 for a counter example).

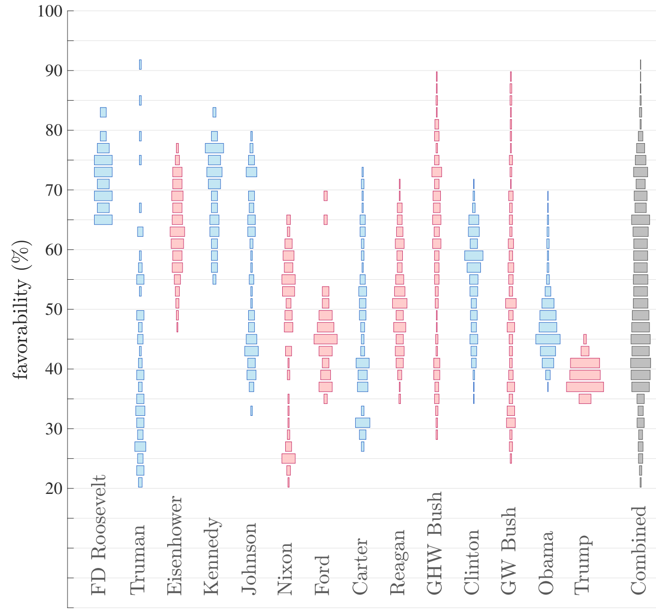

FIG. 2. Histograms of favorability ratings from Gallup polls for US presidents taken from Franklin Roosevelt through to Donald Trump [12]. The rightmost histogram represents a combined average with each president's ratings equally weighted. We do not have data for awareness levels but for US presidents we can reasonably assert that the percentage will be uniformly high. In contrast to the strong correlation between awareness and favorability in Fig. 1, we see that high-awareness political figures can certainly achieve a wide range of favorability ratings. With our focus in this paper on awareness—raw fame—we offer this figure as a tempering exhibit. Note: Polls run from 1941/07/22 through to 2018/10/08.

Biden, who registered 1% of those polled saying they had not heard of him (2019/05), and 67% saying the same of Marianne Williamson (2019/03). By contrast, as we show in Fig. 2, US presidents provide a powerful example as figures with extremely high global awareness levels while receiving a wide variation of approval over time and across demographics [12]. Nevertheless, achieving widespread awareness in politics is the order zero activity.

So, while exploring mechanisms, sentiment, narratives, and other aspects of fame are all necessary [2–4, 13–17], we will here concern ourselves with Wildean raw fame—the state of being talked about—for US presidents and their main rivals.

We focus on the major political figures involved in the last three US presidential elections held in 2008, 2012, and 2016, and the encompassing time frame: Barack Obama, John McCain, Mitt Romney, Hillary Clinton, and Donald Trump. As we will show, the Korean pop (K-pop) boy band BTS has enjoyed singularly transcendent fame—indeed what we will call lexical ultrafame—within our time period of interest, and we find that we are obliged to include them in our analyses. We list the five political figures in Tab. I.

There are many ways to gauge fame such as direct polls, mentions on social media, and rates of internet searches. While including an array of distinct measures would be ideal, we limit ourselves here to the social media enterprise that is Twitter. We will thus endeavor to perform our analyses with great care for one well-defined, if sprawling, realm of public discourse. For our purposes here, we will define lexical fame of any given entity by the daily counts and Zipfian ranks for 1-grams (words, hashtags, user handles, etc.) pertaining to that entity. For example, Barack Obama's lexical fame will be registered by counts and ranks for 'barack', 'obama', and '@barackobama'. For a few 1-grams on specific days, we will report on fame levels at the 15 minute time scale. We also limit ourselves to 1-grams, reserving full analyses of n-grams for $n \geq 2$ for future work, though we will mention a few observations for 2-grams for specific days.

We deliver the remainder of our paper as follows. In

Political figure:	Position:	1-grams (dominant 1-gram in **bold**):
Barack Obama	US president from 2009/01 to 2017/01	barack, **obama**, @barackobama
John McCain	Republican Party nominee in 2008	john, **mccain**, @sejohnmccain
Mitt Romney	Republican Party nominee in 2012	mitt, **romney**, @mittromney
Hillary Clinton	Democratic Party nominee in 2016	**hillary**, clinton, @hillaryclinton
Donald Trump	US president from 2017/01 to present	donald, **trump**, @realdonaldtrump

TABLE I. The five political figures whose fame we trace and compare via Twitter mentions. To quantify fame, we measure the rank and count dynamics for three 1-grams for each political figure: First name, last name, and Twitter handle. The 1-grams in bold are the on-average, unambiguous 1-gram with the highest count referring to the political figure. We also follow the lexical fame of the South Korean boy band BTS per their Twitter handle @bts_twt.

Sec. II we describe our Twitter data set and the data-wrangling part of our analysis, reserving details for Sec. V at the end. We present our core results in Sec. III. In Sec. III A, we first examine time series and histograms for ranks of Twitter mentions for our five political figures and the K-pop band BTS. In Sec. III B, we then make comparative analyses of mentions across figures and across calendar years and the eight weeks leading up to the US elections. Our work is observational and descriptive—a fundamental aspect of basic science—and we will not move toward prediction here. We close with concluding remarks in Sec. IV. We have also constructed our figures and captions to be as self-contained as possible for those readers who may not wish to read the main text, and by inclusion, this sentence.

II. DATA AND PREPARATORY TREATMENT

A. Description of Twitter data set and rationale for use

We measure the daily fame of political figures as reflected by mentions on the social media platform Twitter. We have collected roughly 10% of all public tweets starting on 2008/09/09 through to 2019/09/29, allowing us to explore fame dynamics around the last three US presidential elections.

Twitter has a number of well known benefits and drawbacks. First, a few of the stronger positives. We have essentially real-time temporal resolution for a massive scale of messages. Standardization of hashtags have made for powerful codifying of issues (e.g., #metoo), and formalization of retweets, favorites, and replies allow us to follow the reaction to individual tweets in detail. Though accounts can be made private, Twitter is by default public-facing and largely engaged with such an understanding by its users. The world's languages, and not just the dominant ones, are all present on Twitter, allowing for potentially rich cultural and linguistic explorations.

Negatives for Twitter are also on offer in good number. Geolocation and demographic features have typically been publically available for a small fraction of tweets (less than 1% for the former). Geolocation has been uneven in nature (latitude-longitude versus place name), and was removed entirely as a feature for users in 2019 though metadata in photos could still encode location. Twitter is not used uniformly by all people around the world with strong user bases in, for example, the US, Japan, and Brazil. Algorithmically generated content is prevalent (e.g., "bots") and problematic for the both the service and users [18]. The changing nature of how Twitter presents information to user through algorithmic feeds and trending story pages only adds further complexity.

In the middle lies the evident issue that tweets, and cleverly constructed subsets of tweets, do not perfectly represent all the ideas, viewpoints, and utterances of people of whatever category one may want to study. The collective voice of Twitter is a discordant symphony of the expressions, reactions, and amplifications of individuals, news outlets, corporations, fan bases, celebrities, and automatic accounts of all alignments. The amplification processes are rich-get-richer mechanisms [19, 20] made possible by follower networks, external media's embedding of tweets, and Twitter's own system of curating and presenting trending stories.

We know that as a whole Twitter strongly follows major events [21, 22] and can successfully be used as an indirect polling system [21, 23]. Twitter has also risen in prominence in the political sphere, particularly with the usage of the platform by the current US president, Donald Trump. In turbulent times, recalling what major events occurred and in what order temporally can be challenging. With daily (and sub-day) resolution of lexical fame, we find we are able, by inspection, to tie rank dynamics to specific events.

Like other global social media giants of today, Twitter has the potential to create real impact at all scales. Of many examples, one thematically related to our study here is the identification of President Trump's tweets as having an effect on prices of Treasury bonds, leading JP Morgan Chase to create a covfefe-fueled "Volfefe index" [24] (see also [25]). Entwining news, politics, markets, patriotism issues, and belief, a 2013 hacked tweet from the Associated Press's Twitter account suggesting that the White House had been bombed and Obama was injured, leading to an immediate drop in the market [26]. Although the story was quickly corrected, this one hacked tweet caused the evaporation of $136 billion in a few minutes. One more example, this time showing the power of a celebrity's off-handed remark: On February 21, Kylie Jenner, tweeted, and we quote, "sooo does anyone else not open Snapchat anymore? Or is it just me... ugh this is so sad" [27]. Because of this single tweet, Snapchat's shares deflated 6% in value ($1.3 billion).

In short, Twitter is a large-scale, temporally fine-grained source of written text containing meaningful signatures that can powerfully affect society and the world. Even shorter, Twitter is Twitter.

B. Preparation of Twitter data set for analysis

To explore raw fame and ultrafame, we take our entire Twitter corpus and process tweets into 1-grams. While keeping the parsing as simple as possible, we make some choices such as discarding emojis, excluding languages that do not use whitespace, and adjusting all letters to lower case for languages where two cases exist (e.g., counts for 'god' include counts for 'God', 'GOD', 'god', etc.) (see Methods for full details, Sec. V). Such parsing is evidently not an activity that humans could perform, and even if they could, reading (or perhaps more accurately, absorbing) a stream of 50 million tweets a day could well be harmful (we note that animal Twitter is generally uplifting though).

For each day, we determine usage frequency for all 1-grams appearing on that day. We also create the resultant Zipf distribution [28], ranking 1-grams by descending order of counts, denoting rank by r.

In what follows, we first use 1-gram ranks. As such, we do not need to be concerned with the extremely heavy tails of frequency and Zipf distributions for Twitter, and concomitant worries about subsampling given our corpus's approximate 10%-of-all-tweets character. (i.e., we are, not unreasonably, not assured by Twitter that our subset is exactly 10% of all tweets). We note that rates of 1-gram appearance for 1-grams that are not too rare are quantities we can measure well by simple normalization of frequencies by the sum of all counts. The phrase "not too rare" would have to be considered carefully for studying very low fame 1-grams. But such rates are not of importance here as, again, we will only work with ranks, counts, and rates of a small set of prominent entities.

For the core of our analysis, we extract the ranks and counts for names and Twitter handles for our five political figures (see Tab. I), along with two 1-grams which will prove to be of value and interest: 'god' and the Twitter handle for the K-pop band BTS, '@bts_twt'.

The four male politicians are all dominantly referred to by their last names, while Hillary Clinton's strongest 1-gram referent is 'hillary'. One partial reasons for this would be that Clinton shares a last name with her husband, former US president Bill Clinton, and the use of at least her first name has long been a practical choice for clarity. But referring to a person by first name versus last name is a not uncommon instantiation of gender bias [29, 30], and has been identified in media coverage for Clinton in the 2008 democratic primary [31]. Still, for our present study, five is a small sample from which we cannot generalize (a separate comprehensive study certainly could be a topic of another paper); we want to be clear that we are simply taking what the data from Twitter gives us. We can at least note that this naming bias is not completely pervasive with major political figures. The 1-gram 'bernie' dominates for Bernie Sanders for example. A separate issue is McCain's first name John, which is a poor referent. As we will see, the movement of 'john' against a background level of the name is discernible, though this is a minor issue. In future work, we will be able to explore 2-grams and 3-grams but we set that analysis outside of our present scope.

To better help communicate 1-gram rank, we also determine median daily rank for two subsets of 1-grams in 2018: (1) Function words with median rank $r \leq 1000$; (2) Names of countries including identifiable component words (e.g., 'america') for $r > 1000$. We acknowledge that being based on Twitter as a whole, these ranks will tend toward a US-centric view of the world from a particular period of history, but we nevertheless believe they generally provide useful footholds for all readers. A few examples are:

'a' with r=1,

'and' with r=6,

'la' with r=16,

'there' with r=162,

'porque' with r=323,

'friend' with r=539,

'america' with r=990,

'england' with r=6,718,

'guatemala' with r=27,775,

'fiji' with r=104,091, and

'niue' with r=1,062,883, the least famous country with a four letter name [32].

Finally, we make a choice to demarcate a lexical ultrafame rank. We consider a 1-gram to have achieved lexical ultrafame if it is competing with the basic function words of languages. Upon inspection of the typical function words that tend to have the highest daily counts, we find a remarkably stable presence for one non-function word:

'god'. The rank for 'god' hovers around 300, showing very low volatility (see Sec. III A). Over the time period for our study (2008/09/09–2019/09/29), the median rank for 'god' is $r_{\text{god}} = 302$. The first and third quartiles for the rank of 'god' are 280 and 330, the 2.5% and 97.5% percentiles are 237 and 385, and the overall high and low ranks are 134 and 529.

We will ascribe lexical ultrafame to any 1-gram with rank $r \leq r_{\text{god}} = 302$.

III. RESULTS

A. Dynamics of lexical fame and ultrafame

We chart the 2008–2019 daily rank time series for our five political figures, '@bts_twt', and 'god' in Fig. 3, and show corresponding histograms and ultrafame rates in the companion figures, Figs. 4 and Fig. 5. Per Tab. I, the 1-grams we track for the political figures are 'obama', 'mccain', 'romney', 'hillary', and 'trump'. We discuss these three connected figures together.

We make a number of structural elements consistent across Figs. 3 and 4.

First, except Figs. 3H and 3I, we show all ranks on a logarithmic scale with limits of $r = 1$ and 10^6.

Second, in all nine plots of Fig. 3, we mark the threshold of lexical ultrafame using dotted horizontal lines at the median rank $r_{\text{god}} = 302$. We visually demonstrate the stability of 'god' in Fig. 3G, confirming that 'god' experiences little rank turbulence [33], as reported by the statistics at the end of preceding section. We similarly include a dotted line for the rank of 'god' in Fig. 4. We more roughly locate what we call the "lexical abyss" in Figs. 3 and 4. We suggest the lexical abyss begins to appear for ranks in the hundreds of thousands, where we have descended well below the levels populated by commonly misspelled words to find a wild ecology of strange lexical creatures.

Third, we indicate US presidential election dates by vertical dashed lines. In Figs. 3A–G, these are for 2008/11/04, 2012/11/06, and 2016/11/08. In Figs. 3H and 3I, the 'obama' and 'trump' rank time series are time-shifted for direct comparison and the day of the election is set as day number 0.

Fourth, in Figs. 3A–G, we annotate the date of the overall highest (most talked about) and lowest ranks for the reference 1-grams. These dates are also highlighted in Fig. 4, where we provide example 1-grams typically found at those ranks.

Fifth and last, in Appendix A, we provide tables of extreme dates for the political figures and BTS. We list the top 10 and bottom 5 rank days for the entire time span (Tab. A1) as well as at the scale of each calendar year (Tabs. A2– A7).

We discuss the time series and histograms for the five political figures and BTS as displayed in Figs. 3A–3F and Fig. 4 in order. We then remark on the comparison of time series for 'obama' and 'trump' in Figs. 3H and 3I.

Lexical fame dynamics for 'obama':

The lexical fame time series for 'obama' can be broken down into two main phases:

1. Starting from a lexical ultrafame heights of Obama's 2008 campaign and election, a gradual decline in being talked about into 2011; and

2. From the middle of 2011 to present, a largely steady state with an ultrafame shock for the 2012 election, and a minor, years-wide cusp centered around the 2016 election.

As our historical Twitter data set begins on 2008/09/09, we have on hand just short of two months of tweets leading up to the election of Obama for his first term. The time series for the 1-gram 'obama' starts high, achieving its highest ever rank of r=14—a level typically held by the word 'me'—attained on the date of Obama's first election, 2008/11/04 (Fig. 4).

At the sub-day time scale of quarter hours, 'obama' rose to be ranked first among all words, incredibly beating out 'the' and 'a'. This peak rank for 'obama' came in the 11:00 pm to 11:15 pm time frame on the night of the election (US Eastern Standard Time). To reach such heights in a Zipf distribution may seem unfathomable, and we will offer explanations later in the paper after we consider '@bts_twt'.

The overall lowest rank day for 'obama' was on Christmas Day in the third year of Obama's presidency (2011/12/25) where the 1-gram dropped to $r = 5,970$, about that of 'malaysia' (Fig. 4). (Generally, we see that major holidays take precedence over politics.) We see that after a gradual decay in rank, 'obama' resurges abruptly for the 2012 election, and even more abruptly collapses post re-election—a spike when viewed from the level of a decade. After level years in 2013 and 2014, 'obama' slowly increases in fame again, taking on import once again around 2016. Post the 2016 election, 'obama' has remained high in rank, showing no evident loss of fame.

In strong contrast to the four other political figures we examine here, lexical fame for 'obama' has proved steady, durable, and relatively high on Twitter, with a median rank of 1,720 akin to that of 'uk', and a unimodal histogram (Fig. 4). But in terms of ultrafame, 'obama' has been ranked above 'god' on only 3.0% of all days. Per Fig. 5, 'obama' was ultrafamous on 54.4% of the days in the last four months of 2008, 6.9% of all days in 2009, and then at most 2.2% for all subsequent years. Obama was talked about during what would be his year of re-election (2.2%, 2012) and then at the end of his second term (2.0%, 2016) and then the first year of Trump's presidency (2.2%, 2017). From there, the gradual decline in the rank of 'obama' (Fig. 3A), has meant that in 2019 (2009/01/01 through to 2019/09/29), 'obama' has not

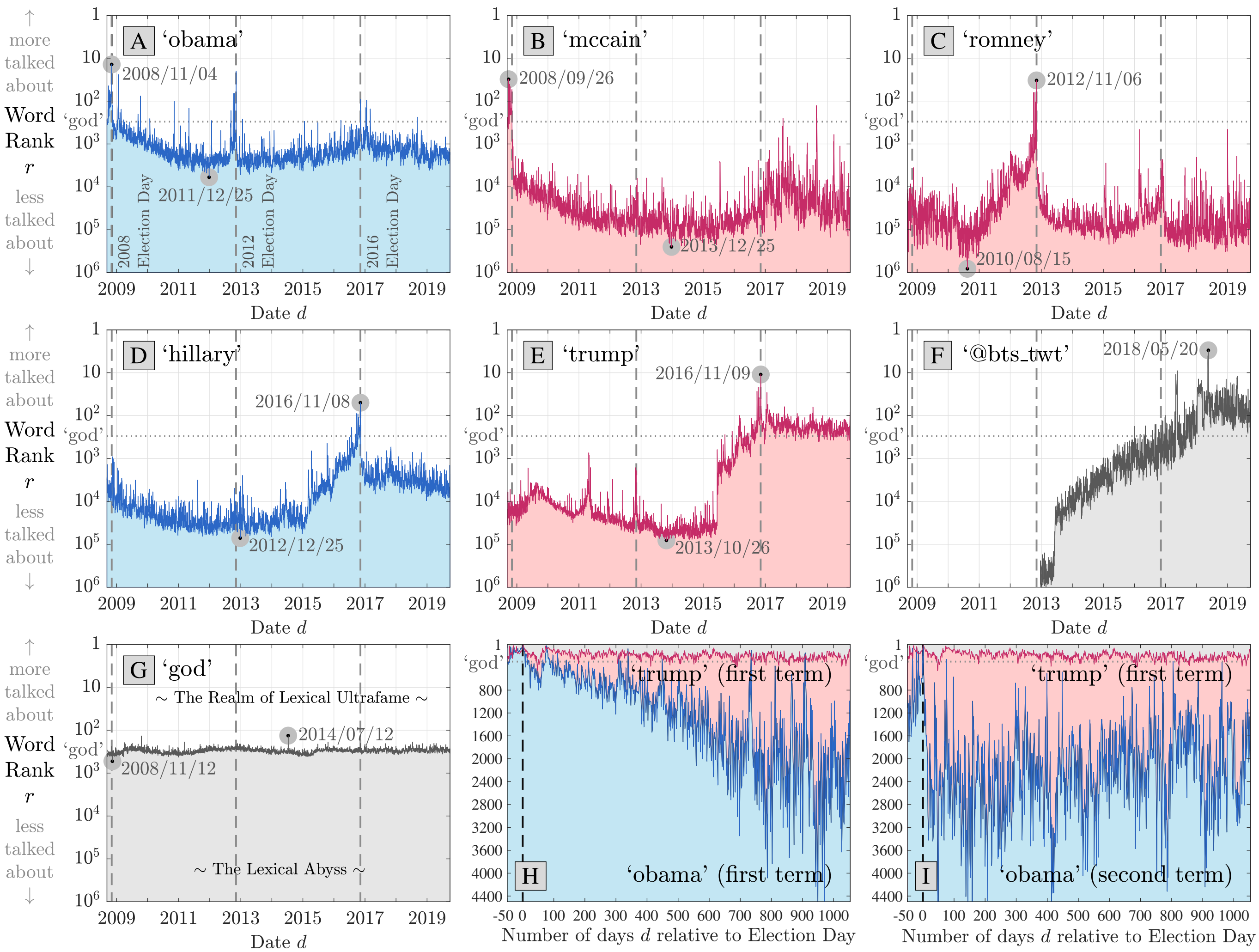

FIG. 3. **A–G. Temporal lexical fame on Twitter at the day scale for US presidents, US presidential candidates, the K-pop boy band BTS, and the word 'god' for the time period 2008/09/09 through to 2019/09/29.** We define the lexical fame of a word as its Zipfian rank r based on descending raw usage frequency (see Data and Methods, Secs. II and V). We display lexical fame on a logarithmic scale covering six orders of magnitude. For the presidents and presidential candidates, we show time series of the most dominant word used to refer to them out of their first name, last name, and Twitter handle (see Sec. III B and Figs. 6 and 7 for relative usage rates). See Fig. 4 for violin plots corresponding to time series in **A–F**. We indicate the three US presidential elections occurring within the time period by vertical dashed lines, and the dates of the highest and lowest lexical fame on all time series. In all panels **A–I**, the dotted horizontal line at a word rank of $r = 302$ registers the global median rank for the word 'god' (panel **G**), and we consider ranks above to be in the realm of lexical ultrafame. The time series are varied: 'obama' has remained relatively famous throughout; 'mccain' and 'romney' have low, noisy fame outside of their candidacy periods; 'hillary' has remained high post the 2016 election; and 'trump' has achieved enduring lexical ultrafame, competing with basic function words. The band BTS, which most often appears through their Twitter handle, @bts_twt, has followed an exponential climb into a class of lexical ultrafame unto itself, exceeding even that of 'trump'. **H. Comparison of the lexical fame of 'obama' and 'trump' on Twitter relative to the date of the first election of Presidents Obama, as marked by the vertical dashed line at $d = 0$. I**. Same as **H** but now showing Obama's second term relative to his 2012 re-election. Because 'obama' and 'trump' are so prominent on Twitter during these time periods, we are able to display word rank r on a linear scale, rather than the logarithmic one of panels **A–G**. The 1-gram 'trump' is remarkable for both its ultrafame level of rank (median of 194, 2016/06/01–2019/09/29) and consistency. Post inauguration, 'trump' never falls below a rank of $r = 405$ (which occurred on 2018/09/23). The word 'obama' slowly drops in rank in the first few years of Obama's presidency before stabilizing, and overall shows a great deal more volatility in linear rank than 'trump'.

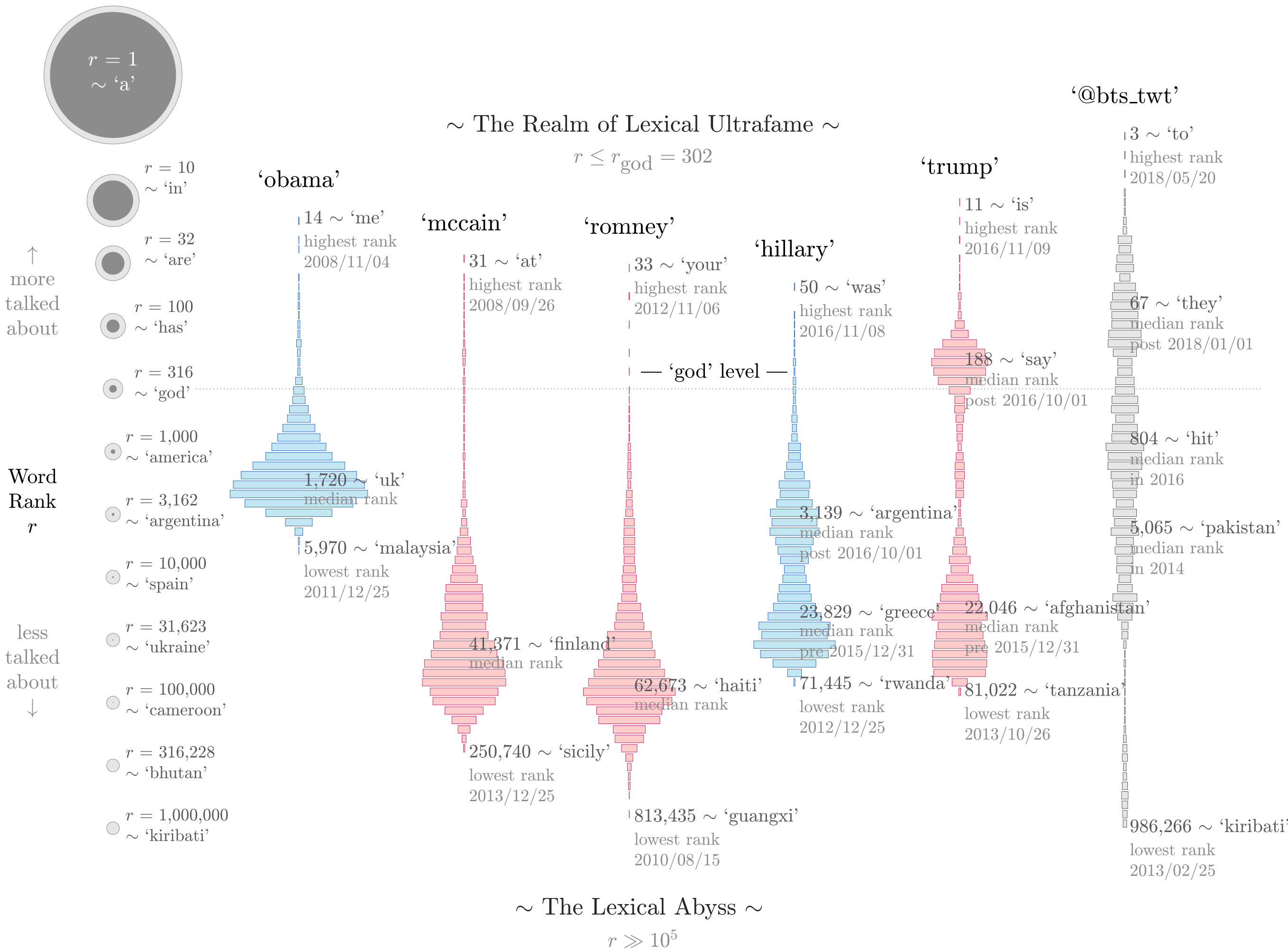

FIG. 4. **Violin plots of lexical fame for US presidents, US presidential candidates, and the K-pop boy band BTS,** summarizing the time series of Fig. 3. The disks on the left provide a scale for word rank at half decades, with the internal dark gray area proportional to inverse rank. As a guide, the example words for each disk are aligned with their approximate median word rank for the year 2018, and switch from function words ('a', 'in', . . .) to country or region names ('america', 'argentina', . . .). Consistent with Fig. 3, we mark the the lexical ultrafame threshold with a dotted line at the rank of 'god' (note that $r = [10^{5/2}] = 316$ is close to $r_{\text{god}} = 302$). We indicate the highest and lowest ranks along with the dates they were attained. We annotate medians for the whole time period, with the exception of the terms 'hillary' and 'trump', for which we show medians for before 2015/12/31 and after 2016/06/01, end dates included. For high, low, and median ranks, we show either function or country words which had similar median ranks in 2018. For Presidents and candidates, only 'trump' maintains lexical ultrafame (median 194, post 2016/06/01). The highest lexical fame achieved was by the Twitter handle of the band BTS, @bts_twt, reaching a rank of 3 on 2018/05/20, matching the 2018 median rank of the word 'to'.

Ultrafame—Percentage of days per year ranked above ‘god’

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
‘barack’	1.8%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
‘obama’	54.4%	6.9%	0.5%	0.6%	2.2%	0.3%	0.0%	0.3%	2.0%	2.2%	0.5%	0.0%
‘@barackobama’	0.0%	0.0%	0.0%	0.0%	0.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
‘john’	3.5%	0.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.3%	0.8%	0.0%
‘mccain’	39.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.3%	1.1%	0.0%
‘@senjohnmccain’	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
‘mitt’	0.0%	0.0%	0.0%	0.0%	0.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
‘romney’	0.0%	0.0%	0.0%	0.0%	1.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
‘@mittromney’	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
‘hillary’	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	10.7%	0.0%	0.0%	0.0%
‘clinton’	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	7.9%	0.0%	0.0%	0.0%
‘@hillaryclinton’	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.1%	0.0%	0.0%	0.0%
‘donald’	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	2.8%	0.6%	0.0%	0.0%
‘trump’	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.6%	49.0%	98.3%	93.4%	91.4%
‘@realdonaldtrump’	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	2.8%	26.5%	41.1%	58.4%
‘@bts_twt’	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.6%	8.2%	50.6%	100.0%	100.0%

FIG. 5. **Annual levels of ultrafame: Percentage of days per calendar year each 1-gram was ranked above (or equal to) $r_{\mathrm{god}} = 302$.** Sustained ultrafame is rare. Only 1-grams associated with Trump and BTS have achieved enduring ultrafame across years. We round percentages to the nearest 0.1 percent, and render 0.0% in a light gray. Both 2008 and 2019 are for part of those years only (2008/09/09 on and through to 2019/09/29).

once been ultrafamous. Fig. 5 gives a first glimpse of the relative dominance of first names, last names, and Twitter handles. We see that ‘barack’ and ‘@barackobama’ are well behind the ultrafame of ‘obama’ with only ‘barack’ registering in 2008 and 2009.

The overall top 10 dates for ‘obama’ (listed in Tab. A1) all fall on or close to election dates and inauguration dates. High points at year scales for ‘obama’ (Tab. A2) are largely tied to political events even when Obama was not the central actor (e.g., Trump’s election in 2016 and inauguration in 2017). In 2018, Obama’s high ranks occurred on September 7, 8, and 9, and were due to a speech he gave at the University of Illinois at Urbana-Champaign where he appeared to attack President Trump (“How hard can that be? Saying that Nazis are bad.”) [34].

At the not-being-talked-about end of the spectrum, the lowest two days for ‘obama’ fell on New Year’s Day in 2014 and 2015 (r=5,254 and 5,970). Consistently across 1-grams, we see low rank days often occur on dates of major holidays or non-political events (Tab. A2).

Lexical fame dynamics for ‘mccain’:

We see in Fig. 3B that the time series for ‘mccain’ encompasses four main phases:

1. Candidate for president in 2008;
2. US senator;
3. Trump presidency; and
4. Death and legacy.

The rank for ‘mccain’ is highest around the 2008 election, with a top rank of r=31 (equivalent to the usual rank of the function word ‘at’). Occurring on 2008/09/26, this high water mark for ‘mccain’ was due to interest in the first presidential debate, held at the University of Mississippi. In 2008, ‘mccain’ was ultrafamous on 39.5% of recorded days (c.f., 54.4% for ‘obama’, Fig. 5). On election day, ‘mccain’ was still easily ultrafamous but it would be only the 1-gram’s fourth-most talked about date of the year (2008/11/04, r=54).

Across the entire time frame, McCain’s 1-gram fame level is similar to that of ‘finland’ (r=41,371) with a low point on par with ‘sicily’ (2013/12/25, r=250,740)

(Fig. 4). Like 'obama', the lexical fame of 'mccain' collapsed over time renders a unimodal histogram. Ranking above 'god' on only 1.3% of all days, outside of 2008 'mccain' was briefly ultrafamous again in only 2017 and 2018 with rates of 0.3% and 1.1%.

Immediately post election, we see a sharp drop for 'mccain' followed by a slow decay in rank over the ensuing second-phase years, flattening out through 2013–2015. The lowest-highest rank for 'mccain' in a calendar year was 12,988 in 2014 (Tab. A3). Throughout the Obama presidency, McCain was often talked about when he spoke out about decisions made by the Obama administration. For example, the second most talked about day for 'mccain' in 2016 arose on 2016/06/16 when McCain suggested that Obama's foreign policy led to the Pulse nightclub shooting Orlando (r=3,491; Tab. A3).

Starting in 2015, leading up to and elevating through the 2016 election, the time series for 'mccain' enters a third stage which is one of high fluctuations as it begins to track McCain's increasingly antagonistic relationship with President Trump. The incipient event appears to have been Trump's dismissal of McCain's record as prisoner of war in Vietnam [35]—"He's not a war hero. He's a war hero because he was captured. I like people who weren't captured"—which led to the most talked about sequence of days in 2015 for 'mccain' (peak: 2015/07/18, $r = 2,557$). (We note that some of the later mentions of 'mccain' will be due to McCain's daughter Meghan McCain, a public figure herself by this time.)

Marking the transition into a fourth phase, the highest rank for 'mccain' in 2016 fell on Election Day (2016/11/08, r=2,383). McCain had won re-election to the US senate himself, and his withdrawn support for Trump took on heightened salience with Trump's win.

In 2017, McCain's thumbs-down vote against in the senate to defeat a bill to end the Affordable Care Act generated a return to the realm of lexical ultrafame for the first time since 2008 (2017/07/28, r=252; Tab. A3).

In 2018, his death on August 25 led to a series of lexical ultrafame days (2018/08/25, r=190; 2018/08/26, r=128). The only top-10 day in 2018 that was not related to McCain's passing came on 2018/05/11 when Kelly Sadler, a White House aide, was reported to have said that McCain's opinion on Gina Haspel's nomination for CIA director was irrelevant because "he's dying anyway."

After McCain's death, 'mccain' has remained a Twitter 1-gram staple, in part due to Trump maintaining what had emphatically become an argument in which only one side could engage. The high rank of r=603 on 2019/03/20 was due to Trump [36] who took aim at McCain in a speech on manufacturing jobs: "I have to be honest: I've never liked him much" [36].

Lexical fame dynamics for 'romney':

As we did for 'mccain', we can identify four phases for the time series for 'romney' in Fig. 3C:

1. Abiding in the lexical abyss: Low fame through to the end of 2010;
2. A mostly steady build to the 2012 election;
3. Through to the 2016 election, a regime of fame higher and less volatile than the first phase; and
4. A return to the lexical abyss, characteristic of the first phase.

Romney's 1-gram has the lowest overall median rank of the five political figures, tantamount to that of 'haiti' and again produces a unimodal histogram (r=62,673, Fig. 4). The low and high points for 'romney' bookend the two-year-long second phase of his fame time series. Romney's 1-gram rose from the lexical abyss dwelling of r=813,435 (similar to 'guangxi') on 2010/08/15 to an ultrafamous r=33 (similar to the function word 'your') on the 2012 election day (2012/11/06).

The 1-gram 'romney' was ultrafamous on 0.2% of all days in our study—a total of only 6 days with $r_{\text{romney}} \leq r_{\text{god}} = 302$. Per Fig. 5 and Tab. A1, all of these days occurred around the 2012 election (1.7% of 2012).

In the third phase of the time series, 'romney' slowly gains fame as the 2016 election approaches, spiking on a few isolated occasions, and then once again in 2019. Unlike 'obama' and 'mccain', two of the top 10 overall days for 'romney' do not fall around election dates directly involving Romney. In Tab. A1, the 9th and 10th ranked days for 'romney' are 2019/01/02 (r=457) and 2016/03/03 (r=460). Further, outside of 2012, these are the only two days on which 'romney' was ranked in the top 1000 1-grams.

Like McCain, Romney had had contentious public interactions with Trump, and we see the cause of both of these two major spikes was Romney speaking out against Trump. On 2016/03/03, Romney gave a speech at the University of Utah in which he attacked (then potential nominee) Trump calling him a 'fraud' and asked voters to strategically vote against him [37]. Almost three years later on 2019/01/01, having been elected a senator for Utah two months prior, Romney published a stir-causing opinion piece in the Washington Post regarding his negative view of Trump's character [38]. Both of these spikes evaporated, leaving no evident residual.

Lexical fame dynamics for 'hillary':

The lexical fame time series for Hillary Clinton's dominant 1-gram 'hillary' in Fig. 3D traverses three major phases:

1. A gradual initial decay to a stable moderate lexical fame through the end of 2014;
2. Two year build towards the 2016 election;
3. A new stable lexical fame regime, above that of the first phase.

Our time frame begins after Clinton's unsuccessful campaign for the Democratic presidential nomination for the 2008 election, and the starting point for 'hillary' comes part way into a consequent drop in lexical fame. As Obama's Secretary of State during his first term, Clinton maintained a degree of public prominence that slowed a fall towards the lexical abyss. Until the year 2015, 'hillary' was ranked in the top 1000 on a solitary day, the one on which the possibility of her becoming Secretary of State was made public (2008/11/14, r=910, Tab. A5). The nadir for the 1-gram 'hillary' landed on 2012/12/25, Christmas Day (r=71,445, similar to that of 'rwanda'; Fig. 4 and Tab. A5).

The second phase for 'hillary' is a two-year linear ascent in $\log_{10} r$ starting 2015/01. There are a few spikes during this period, notably the day Clinton declared her candidacy (2015/04/12, r=662, Tab. A5; and the first Democratic debate (2015/10/13, r=446, Tab. A5)

After a vacation lull at the end of 2015, the first half of 2016 saw 'hillary' jump and maintain a high fame level of around a rank of r=1,000. Once Clinton became the Democratic nominee, 'hillary' once again began to climb in rank. The first presidential debate (held at Hofstra University) between Clinton and Trump led to the third highest rank overall for 'hillary' and the first time Clinton's 1-gram had achieved lexical ultrafame (2016/09/26, r=89, Tab. A1).

The second phase for 'hillary' ends with Clinton's loss in the 2016 election, the date of which would prove to be the all-time top rank for 'hillary' (2016/11/08, r=50, Tab. A1). A rank of 50—the typical return for the word 'was' (Fig. 5)—is lower than that achieved by both 'mccain' and 'romney', and is possibly in part to 'hillary' being one of several 1-gram's used to refer to Clinton. Indeed, the day of the 2016 election would be the high rank for 'clinton' over the entire time frame (r=99).

The year 2016 is the only year in which 'hillary' would achieve any level of lexical ultrafame (10.7% of all days in 2016, Fig. 5). Both 'clinton' and '@hillaryclinton' were also ultrafamous (7.9% and 1.1%). All told, 'hillary' was ultrafamous on 1.0% of all days over the entire period of study, all of them contained in 2016.

After the election, 'hillary' falls abruptly, a shock transition to the third phase of Clinton's lexical fame. In the three following years, 'hillary' trends gradually downwards, reflected in the high ranks for 2017, 2018, and 2019: r=536 on 2017/11/03, following book-delivered accusations by Donna Brazile that Clinton controlled the Democratic National Committee; r=713 on 2018/07/16, apparently due to remarks by Russian President Vladimir Putin in a meeting with Trump in Helsinki, in which he stated that he wanted Trump to win; and r=1,394 on 2019/04/24, arising from Clinton's opinion piece in the Washington Post on the Mueller Report and impeachment [39].

But Clinton's lexical fame moved to a substantially higher level relative to the first phase. The typical ranks for the first and third phases for 'hillary' roughly differ by an order of magnitude. Before 2015/12/31, the median rank for 'hillary' was r=23,829, on par with 'greece'. Post 2016/10/01, the median rank has elevated to 3,139, matching the level of 'argentina'.

Such a clear shift in levels of being talked about is not what we saw for 'romney' for which we have before- and after-election phases that match in statistical character (we do not have data for 'mccain' prior to the 2008 election). Clinton has been talked about much more in a stage of her career where she has no public position than an earlier one where she was Secretary of State for the US.

The two distinct steady state regimes for 'hillary' lead to a bimodal histogram in Fig. 4, in contrast to the unimodal histograms of 'obama', 'mccain', and 'romney'.

Lexical fame dynamics for 'trump':

The top 10 ranked dates for 'trump' fall, as we might expect, on or adjacent to the presidential debates in 2016, the 2016 election, and Trump's 2017 inauguration (Tab. A1). There is however much other structure to discern, and we work through the rich details of the lexical fame time series for 'trump', which has four major phases (Fig. 3E):

1. A brief initial increase in lexical fame reaching a cusp centered around August of 2009;
2. A slow, birtherism-punctuated descent into the lexical abyss running into 2015;
3. Starting with a shock transition on 2015/06/15, an upward trajectory until the 2016 election;
4. The Trump presidency, a period where the word 'trump' has established an enduring level of lexical ultrafame.

The first phase for 'trump' sees a rise to a cusp point with ranks in the 3000s. Of the one-day spikes (see Fig. 3E and Tab. A1), stories that failed to persist, we see a range of causes that are political and business-related.

On 2008/10/15, 'trump' reached a high for 2008 of r=5,249, following his statement in a CNN interview with Wolf Blitzer that Nancy Pelosi should have impeached President George W. Bush over the Iraq War [40] (Trump was a registered Democrat into 2009).

The highest point for 'trump' over the first few years fell on 2009/05/12, when the 1-gram reached r=1,668 after Trump asserted that Carrie Prejean could keep her title, Miss California USA, after she publically said she did not support same-sex marriage enraging pageant judge Perez Hilton and, more broadly, the internet [41]. Less than a month later, Trump would be involved in firing Prejean for shirking duties set out by her contract [42], making for another spike (r=3,670, 2009/06/10).

The second highest rank for 'trump' in 2009, r=3,227, came on what was very much a bad news day: On 2009/02/17, Trump Entertainment Resorts and nine related Trump companies all filed for bankruptcy [43].

The cusp marking the transition from the first to the second phase for 'trump' appears to match with the 2008

Miss Universe pageant held in the Bahamas. (r=3,617, 2009/08/23). After this point, 'trump' goes into a long, slow descent, interrupted by occasional spikes and one strong resurgence which traces Trump's major role in the birther conspiracy theory movement which claimed that Obama was not born in the United States [44], and his non-unconnected consideration of a presidential run for the 2012 election.

In Fig. 3E we see 'trump' break from its downward trend in the second half of 2010, build rapidly to a high rank of r=734 on 2011/04/27, (the day on which Obama released his long form birth certificate), and then drop sharply shortly thereafter. The rank r=734 would be the highest overall for 'trump' until 2015.

On 2011/04/30, Trump was extensively mocked at the White House Correspondents' Dinner by president Obama and the host Seth Meyers. The following day, 2011/05/01, the rank for 'trump' reached back up to r=829, the only other date 'trump' would make the top 1000 until 2015.

A few weeks later, on 2011/05/16, Trump announced that he would not seek the republican nomination; 'trump' jumped back up to r=1,629, and then fell back into what would become an ambient six-year long downward trend. Looking back, 'trump' had enjoyed half a year of being talked about more and more, albeit with strongly disjoint story frames of successful tycoon or blustering buffoon.

From mid 2011 to mid 2015, 'trump' inhabited the lexical abyss, finding a 'tanzania'-equivalent low point of r=81,022 on 2013/10/26. The lack-of-fame problems for 'trump' were strongest in 2014 where the highest rank for the untalked-about 'trump' was r=13,069 on 2014/09/29 (Tab. A6). There were a few spikes for 'trump' during this time period, two of note around the 2012 election (r=1,627 on 2012/10/24 and r=1,921 on 2012/11/07).

The third phase begins with a shock transition on 2015/06/16, the day Trump announced his candidacy. The 1-gram 'trump' jumped from r=24,772 the day before up to r=621. Just five days before, 'trump' was at r=41,090. From not being able to break into the top 10,000 1-grams in 2014, 'trump' now reached well inside the top 1,000 on many dates in 2015. On 2015/12/08, 'trump' was ranked 231. Having been ranked as low as 70,230 in 2015, 'trump' would not fall below 1,297 in 2016 (Tab. A6).

Post declaration of candidacy, 'trump' rises steadily for the next 17 months, peaking at $r = 12$—normally where the word 'is' is—the day after the 2016 election (2016/11/09).

In 25 of 192 quarter hour intervals on 2016/11/08 and 2016/11/09, 'trump' was ranked a staggering 4th overall, mostly in the late hours of election day and early morning hours of the following day. The highest rank 'hillary' achieved during these two days was 22nd. This peak came in the quarter hour starting at 9 pm on the night of the election (2016/11/08), before 'hillary' began to drop down as Trump started to become perceived as the likely winner.

After a minor relative draw down post election, 'trump' surges again at Trump's inauguration (r=20, 2017/01/20). The time series for 'trump' then settles into an a scoreboard-shattering fourth phase, a stable, low-volatility ultrafamous regime (Fig. 3E).

During the fourth phase, Trump's presidency, a few dates have stood out (Tab. A6). These dates have largely been highly controversial, diverse in nature, and of course, generative of enormous coverage and reaction. We will report on distinct events that lifted 'trump' to the top 10 rank for each calendar year.

In 2017, the 8th most talked about day for 'trump' and the only non-inauguration related day in the top 10 for that year (2017/08/15, r=62), fell on the Tuesday after the Charlottesville white supremacist rally on August 11 and 12, and the death of protester Heather Heyer on August 12. On that Tuesday, Trump presented what would be a third statement of his regarding the violence, a walking back of a walking back, best captured by his assertion that there were "very fine people on both sides".

In 2018, 'trump' peaked at r=63 on 2018/07/16, the date of the Russian-United States summit in Helsinki when Putin expressed his preference for Trump.

On 2018/01/12, a rank of r=89 (4th highest for 2018), followed from Trump being reported as saying that fewer immigrants should come from "shithole" countries, and more from places like Norway [45].

On 2018/06/20 (r=92, 5th highest for 2018), Trump signed an Executive Order to end forced separation of migrant families.

The North Korea-United States summit in Singapore was held on 2018/06/12, delivered 'trump' to a rank of r=95, the 6th highest for 2018.

Trump's first State of the Union address on 2018/01/30 elevated 'trump' to r=105, 9th highest for the year.

The highest rank day in 2019 (through 2019/09/29) was 2019/09/25 (r=84), and the second highest the day before (r=105). On 2019/09/24, Nancy Pelosi, the Speaker of the House, announced that impeachment proceedings would begin against Trump. Three relevant 1-grams that had their highest ever ranks to date on 2019/09/25 were 'ukraine' (r=264), 'transcript' (r=306), and 'whistleblower' (r=700).

Earlier in the year on 2019/01/25, Trump signed a bill to reopen government after a prolonged shutdown, backing down over demands to fund the US-Mexico border wall. On that day, 'trump' reached a high that would last until the impeachment inquiry with r=112. Three other related dates in January were also days of high ranks for 'trump'.

The start of a second summit with Kim Jong Un, this time in Hanoi, provided the another high ranked day on 2019/02/27 (r=114).

Trump's attacks on four congresswomen, coupled with "Send her back" chants at his rallies, provided the further highly ranked days of 2019 (2019/07/18, r=122).

One relatively low controversy date that stood out was

2019/02/05 on which Trump gave his second State of the Union address, leading to a rank of 125 for 'trump'.

For the whole time span, 'trump' has been ultrafamous on 28.1% of all days. After first experiencing lexical ultrafame in 2015 (0.6%), the 'trump' shock in 2016 lead to 49.0% of days being ultrafamous in that year (Tab. A6). In 2017, 2018, and 2019, 'trump' stayed extremely high, with ultrafame rates of 98.3%, 93.4%, and 92.1%. Trump's low ranks during his presidency help show the persistence of fame: r=384 on 2017/12/25, r=405 on 2018/09/23, and r=385 on 2019/09/01. We also see the rise of @realdonaldtrump, with ultrafame levels in 2017, 2018, and 2019 of 26.5%, 41.1%, and 60.7%. Trump's Twitter handle is the only one for the five political figures that ever earns sustained ultrafame. We discuss how Twitter handles function further below when we make sense of the fame of @bts_twt.

As an aside, we have made a preliminary analysis of Zipf distributions for a day of Twitter versus the same day with retweets excluded. While removing retweets dropped 'trump' in rankings, we observed the opposite for '@realdonaldtrump'. Trump's Twitter handle appears then to be involved more strongly in replies and fresh mentions than retweets.

Like 'hillary', the histogram for 'trump' is bimodal (Fig. 4). Before 2015/12/31, the median rank for 'trump' was r=22,046, the level of 'afghanistan'.

But unlike 'hillary' or any of the other political figures, the level 'trump' reaches and holds in the fourth phase of the fame time series is that of ultrafame. Post 2016/10/01, the median rank for 'trump' has been r=188. Beyond the scales of country 1-grams, such a rank is typical of the function word 'say'.

Lexical fame dynamics for '@bts_twt':

We come to the extraordinary lexical fame time series for the seven-member K-pop band BTS, as carried by their Twitter handle, '@bts_twt' (Fig. 3F). BTS's emergence, fame, and now central role in the K-pop industry has been studied from a few angles by others [46–49]. BTS's fame has translated into real money, and they have substantially impacted the South Korean economy as well as sales for the global music industry [49].

The three main phases for BTS's lexical fame are:

1. Spending the first half of 2013 in the lexical abyss;
2. A ruthless march towards the realm of lexical ultrafame from mid 2013 through to the end of 2017;
3. Unstoppable lexical ultrafame from the start of 2018 to 2019/09/29.

After breaching the top 10^6 of 1-grams on 2012/12/22, '@bts_twt' remained in the lexical abyss and did not break the r=10^5 mark until around the time BTS released their debut album '2 Cool 4 Skool' and single 'No More Dream' on 2013/06/12.

Though the reception of BTS's first album and singles did not much portend for global success—on Korean charts, '2 Cool 4 Skool' reached #5, the lead song would only reach #124, and the band's second single failed commercially [50]—the band had entered what would become the second phase of their lexical fame. The ascent of '@bts_twt' to lexical ultrafame is linear in $\log_{10} r$ and thus exponential in r (Fig. 3F).

In 2014, the median rank for '@bts_twt' was at the level of 'pakistan' (r=5,065, Fig. 4). By 2016, the median rank had climbed to 804, on par with the word 'hit'. For 2018 and 2019, the third phase of '@bts_twt', BTS's handle stabilized around a standard usually held by the word 'they' (r=67).

The highest ranks for '@bts_twt' for each calendar year even more strongly show the explosion of BTS's lexical fame (Tab. A7): r=967 on 2014/12/31, r=176 on 2015/12/29, r=99 on 2016/12/29, r=9 on 2017/05/21, to the almost incomprehensible r=3 on 2018/05/20. For comparison, the function word 'of' is on average ranked 9th, and 'to' is on average ranked 3rd, with only 'a' and 'the' above at ranks 1 and 2.

If we descend below the day scale, we find that at the level of fifteen minute time intervals on 2018/05/20, '@bts_twt' was in fact ranked first overall in 17 out of 96 quarter hours. perhaps a reflection of a truly global dedicated fan base, perhaps a testament to the gameability of Twitter, it remains that a non-function word being able to beat out all other 1-grams for lexical fame on a global social media platform with myriad competing entities is a truly remarkable phenomenon.

For 2019, the highest rank for '@bts_twt' slipped to r=12 (2019/05/01). Overall, BTS's handle has been ranked in the top 10 1-grams on 6 days (Tab. A1).

The calendar year lexical ultrafame rates for '@bts_twt' again show their astonishing rise (Fig. 5): 0.6% in 2015, 8.2% in 2016, 50.6% in 2017, and 100% in both 2018 and 2019. The lowest ranks in 2018 and 2019 for '@bts_twt' were 267 and 257 (Tab. A7). Running from 2012/12/22 to 2019/09/29, '@bts_twt' was ultrafamous on 35.5% of all days.

How can an entity compete against the most basic function words of a language? While Coke did once assert itself to be 'it', a marketing goal of making the word 'coke' be used as much as the word 'it' would be (hopefully) laughed out the door. A rank of 3 for a non-function word would not be normal for, say, a typical book. In Moby Dick, a deeply cetacean-rich text, 'whale' is the most frequent non-function word and is ranked 28th.

But Twitter is a complicated melange of text. At times, sub-populations take on the character of a chanting, echoing crowd. In general, retweets, replies, and mentions all combine to drive up counts of Twitter handles. Fandoms are especially capable of harnessing the mechanisms of social media [51, 52]. BTS's fan club, ARMY, is a globally formidable following, and most tweets from the account @bts_twt rapidly garner massive numbers of interactions, far exceeding that of US political figures.

While some degree of the activity around @bts_twt may be algorithmic in nature—as is true for any major figures on Twitter—we leave such quantification to other work as we are focused on the overall observables of the system.

The high ranks of 9, 3, and 12 for '@bts_twt' in 2017, 2018, and 2019 are tied to the annual Billboard Music Awards. BTS won Top Social Artist in each of these three years, ending Justin Bieber's winning streak from the award's inception in 2011 to 2016. (Three of the five nominees in 2019 were K-pop bands.) On the day '@bts_twt' was ranked 3rd (2018/05/20), the hashtag '#ivotebtsbbmas' reached r=7 (bbmas = Billboard Music Awards), reflecting the efforts of ARMY. In 2019, BTS won Billboard's music award for Top Duo/Group, the first year in which they were nominated.

Lexical fame dynamics for 'obama' vs. 'trump':

In bridging to the next section on relative fame rates, we move on from our discussion of individual fame dynamics by returning to Fig. 3 to consider two side-by-side comparisons of 'obama' and 'trump'.

In Fig. 3H, we overlay the lexical fame time series for 'obama' and 'trump' with the first term election days for both presidents shifted to day number 0. In Fig. 3I, we plot 'obama' for the second term of Obama's presidency against 'trump' for Trump's first term. For both plots, we show rank on a linear scale rather than logarithmic, and include the 'god' line for ultrafame once again.

Both figures show that 'obama' and 'trump' follow time series of divergent character. Per our analysis of 'trump', the 1-gram 'trump' remains ultrafamously high through 1000 days, falling below 'god' on less than 10% of days, and showing very little volatility on a linear scale. By contrast, 'obama' falls away steadily through Obama's first term, and shows much greater fluctuations. We see that 'trump' is constantly a dominant feature of Twitter's story-space, whereas 'obama', while 'uk'-level famous, experiences a much more variable intensity. There are days off for 'obama' but not for 'trump' (and never for '@bts_twt').

B. Direct comparisons of lexical fame

We turn now to lexical fame comparisons of 1-grams with each other and themselves, within and across time frames. To do so, we must move to considering normalized counts rather than ranks. Our aim is to be able to estimate relative numbers of mentions. For example, in processing tweets from 2016, we want to be able to determine how many mentions of 'hillary' we should expect for every 1000 mentions of 'trump', and what would be equivalent number of mentions of 'obama' and 'mccain' in 2008, '@bts_twt' in 2018, and so on.

We take some care to address the complications arising from the extremely heavy-tailed Zipf distributions produced by Twitter. With ranks, we did not have to

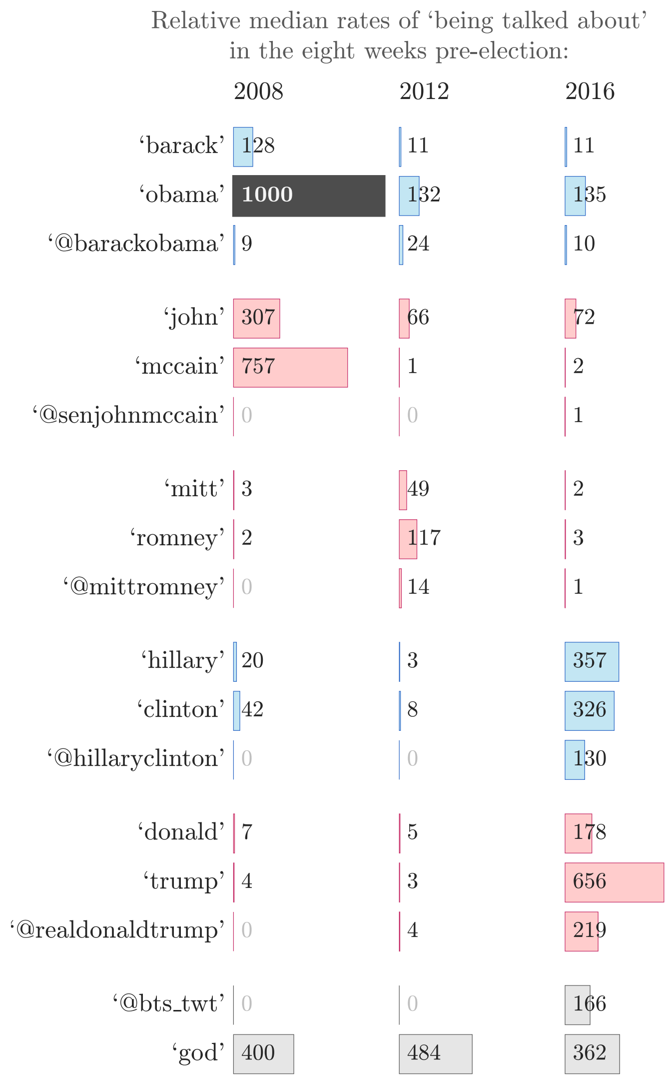

FIG. 6. **Relative median rates of lexical fame for presidents and major candidates in the eight weeks leading up to the 2008, 2012, and 2016 elections**, normalized across terms and years using a 'god' as an anchor (see Sec. III B). By median rate, the most talked about relatively was 'obama' in 2008. We choose to set 'obama' in 2008 to have an anchoring base rate of 1000 (light text, dark gray bar). In processing a stream of tweets in a given time frame, for every 1000 'obama's encountered in 2008, all other numbers show the relative median rate of the number of expected mentions. For example, a relative count of 'mccain' in 2008 shows 'obama' had a roughly 4:3 advantage on Twitter (1000:757). The 2012 election was much less talked about with 'obama' dropping to 141, with roughly a 9:8 advantage over his opponent 'romney' (132:117). In 2016, 'trump' outpaced 'hillary' by a much stronger ratio of nearly 2:1 (656:357). At a relative median rate of 656, 'trump' in 2016 was relatively less talked about than 'obama' in 2008 pre-election, in part due to the much increased volume of Twitter. Over the three elections, only in 2016 did the handles of the candidates, '@hillaryclinton' and '@realdonaldtrump', garner substantial mentions. We include '@bts_twt' and 'god' for comparisons.

Relative median rates of ‘being talked about’ per year:

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
‘barack’	150	38	17	9	10	7	8	11	13	15	14	14
‘obama’	898	379	152	88	97	79	91	104	156	160	129	104
‘@barackobama’	10	7	11	10	17	15	16	13	13	17	17	13
‘john’	405	274	188	126	117	104	113	121	118	129	128	107
‘mccain’	579	11	4	2	2	2	1	1	3	15	7	4
‘@senjohnmccain’	0	2	1	0	0	1	1	1	1	9	2	0
‘mitt’	5	8	5	6	25	6	5	4	4	2	2	3
‘romney’	3	1	1	4	43	2	1	1	4	1	1	2
‘@mittromney’	0	0	0	0	5	0	0	0	1	0	0	1
‘hillary’	28	10	5	3	3	4	6	30	170	72	61	41
‘clinton’	62	25	16	10	8	6	8	27	141	65	62	43
‘@hillaryclinton’	0	0	0	0	0	0	1	11	72	22	19	18
‘donald’	11	17	11	11	8	6	7	45	168	146	114	100
‘trump’	7	20	10	7	4	3	3	80	592	1000	865	772
‘@realdonaldtrump’	0	0	0	1	2	3	2	32	221	469	555	628
‘@bts_twt’	0	0	0	0	0	5	36	124	243	587	2489	1935
‘god’	666	851	687	695	792	719	608	615	601	591	613	617

FIG. 7. **Relative median rates of lexical fame for Presidents Obama and Trump and major candidates at the level of years.** Using the same approach as Fig. 6, we determine ‘trump’ in 2017 to have the highest median rate and set that term to be the standard with a rate of 1000 (light text, dark gray bar). In 2018, the second year of his presidency, ‘trump’ declined modestly to 873. The corresponding years for ‘obama’ give 367 and 151, both well below ‘trump’ and showing a steep first year to second year decline. We again include ‘@bts_twt’ and ‘god’. After Twitter’s early growth, we see ‘god’ stabilize from 2014 on. The rapid growth of ‘@bts_twt’ brings the handle to a median relative median rate of 2489 in 2018, registering an almost 3:1 ratio over ‘trump’ in the same year (2489:865). We note that this relative median rate comparison figure may seem similar in appearance to that of Fig. 5, but the conception and underlying calculations are different, and are worth examining separately.

concern ourselves with the nature of the rare, that is, the tails of highly skewed distributions. (We of course derived ranks from counts which are less informative than properly normalized relative frequencies.) We argue that we can meaningfully interpret normalized counts as rates rather than probabilities.

To measure rates of 1-grams, we would seem to need the total number of 1-grams per time interval of interest, which we will continue to take here to be the day scale. We would appear to have a problem in that we do not know these overall counts of all 1-grams as we only know that our data set comprises approximately, and not exactly, 10% of all tweets per day. But again this is only a problem for the tail of our distributions. For non-rare words, we are able to accurately compute rates by normalizing counts by the total number of 1-grams we find we have on hand per day. More data will only modify the tails of the distributions that we are able to deduce for our subset of all tweets (we note that the hapax legomena for our daily Twitter Zipf distributions are largely Twitter handles). There are substantive ramifications here for computing fundamental whole-distribution measures, from simple statistics such as moments to quantities such as the Gini coefficient and Shannon’s entropy [53]. Here, we are able to continue on our way with our focus being on 1-grams that are for the most part non-rare.

We generate our rate analysis in two steps. We explain how as we present our last two main figures. In Fig. 6, for the 8 weeks leading up to the last three elections, we show relative median rates for the first name, last name, and Twitter handle of all five political figures, BTS’s Twitter handle, and ‘god’. In Fig. 7, we show relative rates for the same 1-grams at the scale of the calendar years 2008 through to 2019, inclusive, and for days on which we have data.

We introduce some notation to aid our explanation.

On date d, we write the number of counts of term τ as

$$N_{\tau,d}, \tag{1}$$

and the rate of term τ, the normalized count, as:

$$R_{\tau,d} = \frac{N_{\tau,d}}{\sum_{\tau'} N_{\tau',d}}, \tag{2}$$

where the sum is over all unique terms observed on date d. In general, we will use D to represent a set of days with a suitable subscript. For example, we write D_y for the set of days in year y. So, for the year 2018, $D_{2018} = \{2018/01/01, 2018/01/02, \ldots, 2018/12/31\}$. For the 8 weeks leading up the US presidential election in 2016, we would write $D_{8w\text{ pre-2016 election}} = \{2016/09/13, 2016/09/14, \ldots, 2016/11/07\}$.

For each 1-gram τ and each time frame D, we compute the median daily rate. (We note that the median is invariant under logarithmic transformation.) For example, for 'trump' in 2017, we would determine

$$\mathrm{med}_{d \in D_{2017}} R_{\text{`trump'},d}, \tag{3}$$

where we use med to denote the median operator.

To now make comparisons across time periods interpretable, we renormalize all values so that the maximum median rate for all political figure 1-grams is 1000, rounding to the nearest integer. The maximum median rate is

$$R^{\max} = \max_{\tau, D} \mathrm{med}_{d \in D} R_{\tau,d}, \tag{4}$$

where τ and D range across the political figures' 1-grams and the time frames being compared. So, for example, the relative median rate for 'trump' in 2019 would be:

$$R^{\text{rel}}_{\text{`trump'},D_{2019}} = \frac{1000}{R^{\max}} \mathrm{med}_{d \in D_{2019}} R_{\text{`trump'},d}. \tag{5}$$

We add that if we were interested only in comparing median rates of 1-grams within the same time frame, we could do so without computing rates at all. For example, for a time frame D, we could compute the median of daily ratios of counts for any two 1-grams. It is only when we want to compare across different time ranges that we must properly include rates.

We can now properly discuss Figs. 6 and 7. The lexical fame balance for the three pre-election periods in Fig. 6 have distinct characteristics. For 2008, 'obama' held a 1000:757 advantage over 'mccain' (roughly 4:3) and both were relatively more talked about than any other political figure later on (first column of Fig. 6). (We note that the common name 'john' was inflated by McCain's fame.) We may speculate that 'obama' led all three pre-elections in fame in part because Twitter had a smaller user base in 2008 than in 2012 and 2016, and so there was less competition for lexical fame across all topics. Automatically generated content due to bots was also likely less prevalent.

For the 2012 election, 'obama' again had an advantage of lexical fame, trimmed somewhat to 132:117 over 'romney' (equivalently 1000:892, roughly 9:8, second column of Fig. 6). A much stronger distinction is that both 'obama' and 'romney' consumed far less lexical fame space, with a relative median rate of 1000 dropping to 132 for 'obama', a factor of more than 7 lower than before the 2008 election.

Pre-election Twitter for 2016 shows 'trump' outpacing 'hillary' and 'clinton' by almost a 2:1 ratio at 656:357 (equivalently 1000:544, third column of Fig. 6). Both Clinton and Trump's Twitter handles also rise in lexical fame, in strong contrast to the handles of the other three political figures, an effect of increased mentions and retweeting.

In short, while 'trump' was relatively less talked about than 'obama' in the lead up to their respective first elections by a 656:1000 ratio (roughly 2:3), references to Trump dominated those of his opponent Clinton well ahead of the smaller margins held by references to Obama over McCain and Romney.

In Fig. 7, we expand the same analysis out to the full time span of our Twitter data set, broken into calendar years. While for the full data set, we have established much with the time series in Fig. 3 and the histograms in Fig. 4, the relative median rates in Fig. 7 allow us to gather further insight with hard numbers.

For political figures, the most prevalent 1-gram is now 'trump' in 2017, the first year of Trump's presidency, and we set that median rate to a standard of 1000.

Overall, we again see the overwhelming dominance of 'trump' against the 1-grams of the other four political figures. In the final months of 2008, 'obama' performs strongly with a relative median rate of 898, carries a relative median rate of 379 through 2009, but then falls and holds around a relative median rate 100 to 150 thereafter, well below 'trump'. In 2016 as a whole, 'trump' outweighed 'hillary' in mentions by a ratio of nearly 7:2 (592:170).

From 2015, Trump's Twitter handle '@realdonaldtrump' has continued to rise in lexical fame, even while 'trump' has gradually waned from the 2017 peak. Barely apparent in 2014 with a relative median rate of 2, '@realdonaldtrump' reaches 627 in 2019, nearing the level of 'trump' at 768. Due to increases in mentions, retweets, and replies, we suggest that changes in user norms and modifications in Twitter's platform mechanisms are two possible aspects of what might explain such a shift in how users reference Trump on Twitter.

Trump's abrupt rise out of the lexical abyss is again on display in Fig. 7. From a low peak relative median rate of 20 in 2009 (relative to 1000 'trump's in 2017), 'trump' fell to 4, 3, and 3 in 2012, 2013, and 2014, barely a blip. If the Trump's campaign goal was to Make America talk about Donald Trump Again, then it has been a great success.

Finally, while Trump's lexical fame is clear, BTS soundly beats all with relative median rates of '@bts_twt' reaching nearly 2,500 in 2018 and just below 2,000 in 2019 (in netspeak, '@bts_twt' >>> 'trump').

IV. CONCLUDING REMARKS

We have explored in depth the daily lexical fame for five major US political figures—Barack Obama, John McCain, Mitt Romney, Hillary Clinton, and Donald Trump—from 2008 to 2019 covering three presidential elections. Because of the extraordinary being-talked-about levels that US political figures have achieved, most especially Trump, we have found that we needed to conceive of lexical ultrafame, above 'god' fame. From a branding and language point of view, our findings that 'trump' has been competing with function words over the last few years should be shocking. As we suggested in the main text, an advertising company promising that their campaign will elevate a brand to the level of the word 'say' or 'they' (par medians for 'trump' and '@bts_twt' in the last few years)—and have days rising to compete with the word 'is' and 'to'—would, we would hope, struggle to be taken seriously.

It should seem preposterous—even in the face of a global fan club, even with the possible use of bots and algorithmic manipulation of Twitter—that any non-function word could be ranked third on a single day, as famous as the word 'to'. But '@bts_twt' did just this on May 20 in 2018, even rising to be ranked first within quarter hour periods of the day. The collective text of Twitter and similar kinds of social media is distinguished from that of other kinds of corpora because of explicit referencing and amplification processes. For Twitter, these processes are automatically hyperlinked handles and retweets. The retweet mechanism builds in social contagion and is adjacent to renown (to name again) and reclaim (to shout again).

We have focused on one major source in Twitter for two major reasons, and which we can now better defend. First, Twitter provides for a measurable reflection of global events and trends, as our ready identifications of many major events in lexical fame time series demonstrates. Twitter is, however imperfectly, entrained with aspects of the real world. Music and sport arguably dominate—indeed they seem to form part of a resting state of the Twitterverse—but politics and world events are richly represented.

Second, with Twitter we have temporal resolution available in principle at the level of a second, though here the day scale has served as our ideal time scale for a time frame lasting over a decade. In contrast to traditional polls, which we are in no way endeavoring to replace but rather complement, we have a massive time series database to draw on, which we consequently feel is deserving of a focused analysis.

In terms of future work, we have examined in depth only lexical fame at a daily resolution for a small set of 1-grams; much more can be done. Detailed investigations of thoughtfully curated sets of competing 1-grams will always be on offer. Other clear directions to follow would be analogous to those taken for search terms by, for example, Google Trends (https://trends.google.com/trends/?geo=US).

Considering 2-grams and 3-grams is also a natural next step, though we caution that 2-grams and 3-grams will not immediately solve issues of name disambiguation. Famous individuals are referred to in a range of ways and comparing 1-grams with, say, 2-grams is work that must be done with care. Ideally, we would break language into semantically intact phrases but we do not yet have a commonly agreed upon approach [54]. For the present work, we have sought to overcome the limitations of 1-grams by considering three essential ones for each individual: first name, last name, Twitter handle.

We have here taken the content of all tweets in our database as being of equal weight. Separating out algorithmically generated tweets would be of evident value [18, 55, 56], as would separating retweets from "fresh" tweets, and dividing tweets up by language, and any combination of these factorings.

We emphasize that daily ranks give lower bounds on ranks for sub-day time scales. BTS's handle '@bts_twt' was ranked 3rd on 2018/05/20 but may have, absurdly, held the silver or even gold medal for some period of time during that day. More generally, a full exploration of time series at, say, minute, 15 minutes, or hour scales for whatever topics of interest would generate another level of fame dynamics resolution.

Finally, our work here is but one contribution to what we believe is an emerging, post-disciplinary, data-driven science of stories. Faithfully determining what was talked about years after the fact is an enormously challenging enterprise in itself, and the difficulty of such enables the intentional creation and uncontrolled emergence of false narratives. Here, we have been able to examine a elementary part of history by following raw Wildean fame—albeit extruded though Twitter—and thereby quantify how much and for how long events mattered. In the lexical fame time series of political figures, we have seen some fundamental types of the shapes of history, the signatures of sociotechnical time series: stasis, noise, spikes, cusps, and shocks [57]. A data-driven categorization of the shapes and motifs of the full ecology of rank time series for Twitter would hold much promise for understanding and possibly predicting sociotechnical time series, and in the long run, stories.

V. DATA AND METHODS

Our Twitter database comprises roughly 10% of all tweets from spans 2008/09/09–2019/09/29. We separate tweets into 1-grams by breaking at whitespace using a regular expression. Certain edge cases may result in the production of 1-grams from non-whitespace delimited sequences; these cases are relatively rare and we did not find them to significantly affect the quality of our parsed data.

We found we were obliged to filter out scriptio conintua languages (languages that do not use spaces to delineate words). we removed common characters from Japanese, Thai, Chinese, and Korean.

After preliminary testing, we found Chinese and Japanese characters to present the biggest challenges in terms of the high number of unique, very long (> 100 characters) strings. We accomplished the removal of these characters by running a regular expression to find characters in the unicode ranges for the most commonly used Japanese and Chinese characters. Because character ranges for Chinese, Japanese, and Korean (CJK) are shared, we found it necessary to remove the whole CJK range. The regular expression we used for this step was:

```
[\u2E80-\u2FD5\u3190-\u319f\u3400-\u4DBF
\u4E00-\u9FCC\u4E00-\u9FFF\u3000-\u303F
\u3040-\u309F\u30A0-\u30FF\u0E00-\u0E7F]+
```

For this study, we also discarded emojis.

We then parse tweet bodies using a regular expression designed to capture semantically meaningful 1-grams in a principled manner, while limiting the artifacts of our design choices in the resulting data set. Our regular expression for breaking on whitespace was:

```
(https?:\/\/\w+\.\S+)|
([\w\@\#\'\'\&\]\*\-\/\[\=]+)
```

The expression breaks down into two groups. The first group of the regular expression is for capturing URLs. This group captures http and https links with arbitrary characters after the domain name extension. The results of the URL group capture retain case sensitivity since many links (especially those from link shortening services) are case sensitive. The second group captures words, hashtags, handles, and similar collections of characters. Hyphenated words/phrases, contractions, and expressions with slashes are allowed (thus, including many common date formats as 1-grams). We do not impose restrictions on the number of times allowed punctuation can repeat (e.g. "state-of-the-art" will be considered a 1-gram). The results of the second group are all converted to lowercase before counting their occurrence.

With 1-grams extracted, we converted all Latin letters in 1-grams to lowercase. Finally we removed the 1-grams 'rt', 'https', 'http', '//t', '-', and 't'.

We take days as based on US Eastern Standard Time. For each day, we construct Zipf distributions by ranking 1-grams in order of descending counts [28].

As we discuss in Sec. II B, because an entity may be referred to in more than one way, and sometimes in many ways, our simple measure of lexical fame affords a lower bound. For example, during his two terms in office, Obama would be indicated by 'obama', '@barackobama', '#obama', 'potus', or '#presidentobama'. Here, we take the most common single word for each person or entity of interest. Evidently, working with n-grams beyond individual terms would allow for more complete measures of fame, and would be necessary for names that are ambiguous referents (e.g., 'bush').

For all figures, we used MATLAB (or, the Laboratory of the Matrix), Release R2019a.

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Appendix A: Extreme dates

The following pages present tables showing the top 10 and bottom 5 dates for the ranks of the main 1-grams we study, first overall (Tab. A1) and then at the year scale for each 1-gram (Tabs. A2–A7).

All tables are based on Twitter data in the time range 2008/09/09–2019/09/29.

'obama'	'mccain'	'romney'
1. 2008/11/04: 14	1. 2008/09/26: 31	1. 2012/11/06: 33
2. 2008/11/05: 15	2. 2008/10/07: 40	2. 2012/10/03: 63
3. 2012/11/06: 20	3. 2008/10/15: 46	3. 2012/10/16: 63
4. 2009/01/20: 24	4. 2008/11/04: 54	4. 2012/10/22: 104
5. 2008/09/26: 44	5. 2008/09/27: 74	5. 2012/11/07: 170
6. 2008/11/03: 44	6. 2008/10/16: 84	6. 2012/11/05: 250
7. 2012/11/07: 52	7. 2008/10/08: 94	7. 2012/10/04: 328
8. 2008/10/07: 55	8. 2008/11/02: 94	8. 2012/10/17: 389
9. 2008/11/01: 55	9. 2008/09/24: 99	9. 2019/01/02: 457
10. 2008/11/02: 57	10. 2008/11/03: 106	10. 2016/03/03: 460
...	...	...
3951. 2013/04/13: 4,802	3951. 2013/12/27: 220,687	3941. 2010/10/23: 449,099
3952. 2013/03/24: 5,086	3952. 2014/05/26: 222,288	3942. 2010/05/30: 451,241
3953. 2013/12/29: 5,132	3953. 2014/02/09: 235,769	3943. 2017/10/01: 464,323
3954. 2014/01/01: 5,254	3954. 2014/08/06: 240,792	3944. 2008/09/19: 540,384
3955. 2015/01/01: 5,970	3955. 2014/04/19: 250,740	3945. 2010/10/25: 813,435

'hillary'	'trump'	'@bts_twt'	'god'
1. 2016/11/08: 50	1. 2016/11/09: 11	1. 2018/05/20: 3	1. 2014/07/12: 134
2. 2016/11/09: 77	2. 2016/11/08: 15	2. 2018/05/15: 4	2. 2009/10/20: 136
3. 2016/09/26: 89	3. 2016/11/10: 19	3. 2018/05/14: 6	3. 2011/03/11: 188
4. 2016/10/09: 91	4. 2016/10/09: 22	4. 2018/05/16: 8	4. 2015/10/24: 188
5. 2016/10/19: 110	5. 2016/09/26: 27	5. 2018/05/18: 8	5. 2018/07/13: 188
6. 2016/09/27: 127	6. 2017/01/20: 29	6. 2017/05/21: 9	6. 2009/03/31: 194
7. 2016/11/07: 130	7. 2017/01/21: 37	7. 2017/05/01: 11	7. 2009/07/04: 202
8. 2016/10/20: 132	8. 2016/10/19: 38	8. 2018/05/17: 11	8. 2019/03/24: 202
9. 2016/10/10: 138	9. 2016/11/11: 40	9. 2018/05/19: 11	9. 2016/11/09: 204
10. 2016/11/10: 157	10. 2016/10/08: 45	10. 2019/05/01: 12	10. 2012/11/22: 205
...	...	...	...
3951. 2013/04/22: 64,733	3951. 2013/11/28: 76,435	2373. 2013/01/23: 882,731	3951. 2008/12/04: 413
3952. 2011/11/24: 64,804	3952. 2014/05/11: 77,186	2374. 2013/03/06: 882,966	3952. 2008/09/19: 415
3953. 2013/07/07: 66,346	3953. 2014/08/10: 78,219	2375. 2013/05/13: 929,849	3953. 2015/03/07: 417
3954. 2011/11/26: 67,635	3954. 2014/11/30: 79,322	2376. 2013/03/12: 952,557	3954. 2015/01/30: 424
3955. 2011/08/27: 71,445	3955. 2014/02/08: 81,022	2377. 2013/04/28: 986,266	3955. 2008/12/29: 529

TABLE A1. **Overall top 10 and bottom 5 rank days for main 1-grams.**

'obama': 2008	**'obama': 2009**	**'obama': 2010**	**'obama': 2011**
1. 2008/11/04: 14	1. 2009/01/20: 24	1. 2010/11/09: 101	1. 2011/05/02: 148
2. 2008/11/05: 15	2. 2009/01/21: 57	2. 2010/01/27: 256	2. 2011/05/01: 179
3. 2008/09/26: 44	3. 2009/10/09: 76	3. 2010/01/28: 417	3. 2011/01/25: 376
4. 2008/11/03: 44	4. 2009/01/22: 98	4. 2010/03/22: 439	4. 2011/03/19: 528
5. 2008/10/07: 55	5. 2009/01/19: 105	5. 2010/11/08: 455	5. 2011/03/20: 608
6. 2008/11/01: 55	6. 2009/01/18: 137	6. 2010/11/10: 484	6. 2011/04/27: 671
7. 2008/11/02: 57	7. 2009/01/23: 142	7. 2010/03/23: 516	7. 2011/05/04: 684
8. 2008/11/06: 58	8. 2009/01/17: 155	8. 2010/01/29: 543	8. 2011/03/21: 691
9. 2008/10/15: 61	9. 2009/02/24: 155	9. 2010/03/21: 585	9. 2011/05/03: 714
10. 2008/10/29: 64	10. 2009/01/24: 172	10. 2010/11/03: 585	10. 2011/03/18: 880
...	...	...	...
110. 2008/12/29: 673	342. 2009/12/27: 1,391	361. 2010/12/26: 3,191	356. 2011/11/25: 4,626
111. 2008/11/29: 705	343. 2009/11/22: 1,394	362. 2010/12/24: 3,204	357. 2011/12/24: 4,777
112. 2008/12/31: 721	344. 2009/11/29: 1,442	363. 2010/10/03: 3,347	358. 2011/11/27: 4,802
113. 2008/11/28: 767	345. 2009/12/26: 1,508	364. 2010/12/25: 3,580	359. 2011/12/26: 5,132
114. 2008/12/25: 800	346. 2009/12/25: 1,538	365. 2010/12/31: 4,085	360. 2011/12/25: 5,970

'obama': 2012	**'obama': 2013**	**'obama': 2014**	**'obama': 2015**
1. 2012/11/06: 20	1. 2013/01/21: 262	1. 2014/01/28: 484	1. 2015/01/20: 297
2. 2012/11/07: 52	2. 2013/12/10: 511	2. 2014/11/20: 574	2. 2015/06/26: 320
3. 2012/10/03: 66	3. 2013/02/12: 572	3. 2014/12/17: 622	3. 2015/04/11: 473
4. 2012/10/16: 66	4. 2013/08/31: 678	4. 2014/11/21: 682	4. 2015/11/16: 558
5. 2012/10/22: 115	5. 2013/10/01: 741	5. 2014/11/05: 738	5. 2015/01/21: 631
6. 2012/09/06: 167	6. 2013/09/10: 769	6. 2014/09/10: 752	6. 2015/12/06: 722
7. 2012/11/05: 176	7. 2013/01/16: 971	7. 2014/12/19: 837	7. 2015/11/13: 746
8. 2012/01/24: 285	8. 2013/04/15: 993	8. 2014/08/14: 907	8. 2015/11/18: 798
9. 2012/09/04: 334	9. 2013/01/22: 1,101	9. 2014/09/11: 963	9. 2015/01/25: 852
10. 2012/10/04: 356	10. 2013/09/04: 1,156	10. 2014/12/18: 1,026	10. 2015/01/27: 872
...	...	...	...
354. 2012/02/12: 3,853	354. 2013/04/13: 4,475	352. 2014/04/20: 3,971	349. 2015/05/02: 3,834
355. 2012/12/23: 4,132	355. 2013/06/02: 4,475	353. 2014/04/05: 4,041	350. 2015/05/07: 3,911
356. 2012/04/08: 4,643	356. 2013/03/31: 4,595	354. 2014/11/28: 4,042	351. 2015/01/03: 4,076
357. 2012/12/24: 4,694	357. 2013/12/25: 4,673	355. 2014/12/14: 4,051	352. 2015/05/03: 4,243
358. 2012/12/25: 5,254	358. 2013/04/14: 5,086	356. 2014/01/01: 4,340	353. 2015/01/01: 4,318

'obama': 2016	**'obama': 2017**	**'obama': 2018**	**'obama': 2019**
1. 2016/11/09: 90	1. 2017/01/20: 95	1. 2018/09/07: 237	1. 2019/08/06: 685
2. 2016/11/10: 136	2. 2017/01/10: 143	2. 2018/09/08: 263	2. 2019/02/19: 815
3. 2016/11/08: 155	3. 2017/01/11: 148	3. 2018/09/09: 381	3. 2019/03/26: 843
4. 2016/11/11: 161	4. 2017/03/04: 153	4. 2018/07/17: 448	4. 2019/02/18: 902
5. 2016/11/12: 260	5. 2017/03/05: 220	5. 2018/09/10: 483	5. 2019/08/05: 902
6. 2016/11/13: 272	6. 2017/01/21: 230	6. 2018/10/24: 485	6. 2019/04/26: 971
7. 2016/03/23: 282	7. 2017/01/12: 236	7. 2018/02/07: 543	7. 2019/04/11: 1,056
8. 2016/11/14: 325	8. 2017/01/19: 257	8. 2018/09/01: 570	8. 2019/03/25: 1,065
9. 2016/07/27: 343	9. 2017/01/17: 314	9. 2018/07/18: 572	9. 2019/04/10: 1,079
10. 2016/07/28: 343	10. 2017/01/18: 363	10. 2018/07/14: 573	10. 2019/04/22: 1,099
...	...	...	...
351. 2016/05/31: 2,443	354. 2017/11/10: 2,502	361. 2018/02/26: 3,221	263. 2019/02/12: 3,592
352. 2016/02/28: 2,613	355. 2017/05/14: 2,557	362. 2018/09/29: 3,423	264. 2019/01/20: 3,611
353. 2016/04/08: 2,619	356. 2017/04/16: 2,573	363. 2018/09/23: 3,471	265. 2019/02/06: 3,818
354. 2016/04/17: 2,867	357. 2017/09/11: 3,003	364. 2018/09/27: 3,595	266. 2019/03/03: 3,928
355. 2016/04/09: 2,983	358. 2017/09/10: 3,285	365. 2018/09/28: 3,981	267. 2019/01/31: 4,092

TABLE A2. **Overall top 10 and bottom 5 rank days per year for 'obama'.**

‘mccain’: 2008	**‘mccain’: 2009**	**‘mccain’: 2010**	**‘mccain’: 2011**
1. 2008/09/26: 31	1. 2009/01/20: 2,219	1. 2010/02/25: 2,844	1. 2011/04/22: 5,475
2. 2008/10/07: 40	2. 2009/03/09: 2,308	2. 2010/03/26: 4,335	2. 2011/01/25: 7,719
3. 2008/10/15: 46	3. 2009/03/16: 2,676	3. 2010/01/21: 4,431	3. 2011/07/30: 11,911
4. 2008/11/04: 54	4. 2009/02/24: 2,677	4. 2010/12/18: 5,021	4. 2011/07/28: 12,222
5. 2008/09/27: 74	5. 2009/01/19: 2,774	5. 2010/08/25: 5,719	5. 2011/05/12: 12,533
6. 2008/10/16: 84	6. 2009/03/17: 3,368	6. 2010/01/20: 6,022	6. 2011/09/19: 13,909
7. 2008/10/08: 94	7. 2009/09/09: 3,510	7. 2010/01/27: 7,261	7. 2011/06/21: 15,102
8. 2008/11/02: 94	8. 2009/03/03: 4,026	8. 2010/02/15: 7,263	8. 2011/01/08: 15,669
9. 2008/09/24: 99	9. 2009/01/23: 4,069	9. 2010/01/23: 7,712	9. 2011/07/27: 16,520
10. 2008/11/03: 106	10. 2009/08/25: 4,204	10. 2010/03/22: 7,763	10. 2011/05/14: 16,907
...	...	...	...
110. 2008/11/28: 11,208	342. 2009/12/31: 32,733	361. 2010/12/29: 74,177	356. 2011/09/05: 109,745
111. 2008/12/17: 11,604	343. 2009/12/29: 33,107	362. 2010/12/30: 77,260	357. 2011/07/23: 111,659
112. 2008/12/24: 11,895	344. 2009/10/07: 38,820	363. 2010/11/26: 78,685	358. 2011/07/24: 112,608
113. 2008/12/23: 12,083	345. 2009/11/27: 38,847	364. 2010/10/24: 79,385	359. 2011/10/08: 118,100
114. 2008/12/25: 16,193	346. 2009/12/25: 59,496	365. 2010/12/26: 82,727	360. 2011/12/25: 133,236

‘mccain’: 2012	**‘mccain’: 2013**	**‘mccain’: 2014**	**‘mccain’: 2015**
1. 2012/11/14: 6,259	1. 2013/09/03: 6,075	1. 2014/09/10: 12,988	1. 2015/07/18: 2,557
2. 2012/11/15: 6,426	2. 2013/03/07: 6,247	2. 2014/06/13: 15,370	2. 2015/07/20: 2,702
3. 2012/01/04: 8,612	3. 2013/09/04: 6,361	3. 2014/09/11: 16,018	3. 2015/07/19: 2,722
4. 2012/11/06: 9,202	4. 2013/03/08: 9,548	4. 2014/08/12: 18,260	4. 2015/07/21: 6,959
5. 2012/01/24: 9,270	5. 2013/09/25: 10,319	5. 2014/01/10: 18,870	5. 2015/10/12: 12,697
6. 2012/08/29: 9,352	6. 2013/09/06: 12,454	6. 2014/12/09: 22,078	6. 2015/07/22: 15,497
7. 2012/03/05: 12,163	7. 2013/09/02: 13,242	7. 2014/06/14: 24,667	7. 2015/01/29: 16,241
8. 2012/11/07: 12,427	8. 2013/01/31: 13,297	8. 2014/03/03: 25,663	8. 2015/10/13: 17,308
9. 2012/11/16: 12,655	9. 2013/09/19: 13,541	9. 2014/07/17: 26,036	9. 2015/07/25: 19,278
10. 2012/11/27: 13,511	10. 2013/05/27: 13,801	10. 2014/02/18: 26,102	10. 2015/07/23: 21,117
...	...	...	...
354. 2012/05/13: 142,257	354. 2013/11/28: 204,083	352. 2014/12/26: 188,132	349. 2015/03/28: 176,686
355. 2012/07/01: 145,447	355. 2013/11/30: 208,817	353. 2014/05/24: 192,300	350. 2015/05/03: 176,827
356. 2012/12/23: 148,507	356. 2013/12/08: 209,145	354. 2014/12/24: 197,104	351. 2015/05/17: 209,434
357. 2012/12/24: 167,073	357. 2013/12/26: 212,893	355. 2014/04/20: 235,769	352. 2015/03/07: 209,811
358. 2012/12/25: 220,687	358. 2013/12/25: 250,740	356. 2014/05/25: 240,792	353. 2015/06/07: 222,288

‘mccain’: 2016	**‘mccain’: 2017**	**‘mccain’: 2018**	**‘mccain’: 2019**
1. 2016/10/08: 2,383	1. 2017/07/28: 252	1. 2018/08/26: 128	1. 2019/03/20: 603
2. 2016/06/16: 3,491	2. 2017/07/25: 386	2. 2018/08/25: 190	2. 2019/03/21: 698
3. 2016/08/01: 4,304	3. 2017/07/20: 609	3. 2018/08/27: 227	3. 2019/03/17: 871
4. 2016/12/12: 4,431	4. 2017/07/19: 677	4. 2018/09/01: 258	4. 2019/05/30: 1,122
5. 2016/08/02: 4,611	5. 2017/09/22: 699	5. 2018/09/02: 483	5. 2019/03/19: 1,699
6. 2016/12/11: 5,138	6. 2017/06/08: 715	6. 2018/08/28: 703	6. 2019/03/22: 1,711
7. 2016/05/03: 5,541	7. 2017/07/26: 1,057	7. 2018/05/11: 946	7. 2019/03/18: 1,816
8. 2016/10/11: 5,998	8. 2017/10/17: 1,102	8. 2018/09/03: 1,097	8. 2019/07/18: 2,569
9. 2016/10/09: 6,712	9. 2017/07/29: 1,269	9. 2018/08/31: 1,105	9. 2019/03/16: 2,667
10. 2016/12/31: 7,374	10. 2017/02/19: 1,404	10. 2018/08/24: 1,118	10. 2019/06/14: 2,690
...	...	...	...
351. 2016/04/24: 124,361	354. 2017/04/28: 58,729	361. 2018/12/08: 97,532	263. 2019/08/11: 108,050
352. 2016/01/02: 124,848	355. 2017/04/22: 61,945	362. 2018/11/24: 97,581	264. 2019/02/02: 113,129
353. 2016/04/16: 125,016	356. 2017/07/08: 68,297	363. 2018/10/14: 103,733	265. 2019/09/01: 131,454
354. 2016/10/02: 126,921	357. 2017/05/07: 88,681	364. 2018/01/26: 105,016	266. 2019/09/02: 141,429
355. 2016/04/17: 133,408	358. 2017/04/29: 102,715	365. 2018/11/25: 109,784	267. 2019/02/03: 151,097

TABLE A3. **Overall top 10 and bottom 5 rank days per year for ‘mccain’.**

'romney': 2008	**'romney': 2009**	**'romney': 2010**	**'romney': 2011**
1. 2008/11/19: 3,575	1. 2009/02/28: 5,911	1. 2010/02/19: 8,488	1. 2011/10/11: 2,628
2. 2008/11/20: 8,512	2. 2009/03/01: 8,691	2. 2010/02/18: 9,627	2. 2011/10/18: 2,817
3. 2008/10/15: 8,557	3. 2009/02/06: 10,400	3. 2010/04/10: 10,361	3. 2011/12/15: 3,228
4. 2008/09/29: 10,771	4. 2009/02/27: 11,300	4. 2010/02/20: 11,730	4. 2011/06/02: 3,857
5. 2008/11/03: 10,931	5. 2009/07/20: 12,086	5. 2010/02/16: 13,215	5. 2011/08/11: 3,941
6. 2008/11/01: 11,283	6. 2009/07/03: 12,430	6. 2010/03/03: 14,000	6. 2011/09/22: 3,957
7. 2008/09/15: 11,535	7. 2009/09/19: 12,884	7. 2010/01/19: 15,319	7. 2011/12/10: 4,085
8. 2008/12/08: 11,817	8. 2009/06/14: 13,042	8. 2010/04/11: 15,550	8. 2011/09/12: 4,203
9. 2008/12/14: 13,154	9. 2009/06/01: 14,343	9. 2010/03/02: 15,638	9. 2011/11/22: 4,704
10. 2008/09/09: 14,239	10. 2009/08/20: 15,042	10. 2010/02/23: 16,092	10. 2011/06/13: 4,750
...	...	...	...
109. 2008/12/02: 237,233	334. 2009/10/25: 248,997	360. 2010/08/08: 449,099	356. 2011/02/20: 164,043
110. 2008/12/30: 289,261	335. 2009/01/06: 272,074	361. 2010/11/26: 451,241	357. 2011/01/15: 171,409
111. 2008/09/20: 300,879	336. 2009/03/08: 279,411	362. 2010/09/03: 464,323	358. 2011/01/08: 183,393
112. 2008/09/10: 317,501	337. 2009/12/09: 287,444	363. 2010/08/11: 540,384	359. 2011/01/18: 183,978
113. 2008/09/19: 331,363	338. 2009/12/22: 301,241	364. 2010/08/15: 813,435	360. 2011/01/01: 228,408

'romney': 2012	**'romney': 2013**	**'romney': 2014**	**'romney': 2015**
1. 2012/11/06: 33	1. 2013/01/21: 4,594	1. 2014/01/05: 18,801	1. 2015/01/30: 2,789
2. 2012/10/03: 63	2. 2013/03/03: 9,049	2. 2014/01/25: 22,539	2. 2015/01/09: 9,052
3. 2012/10/16: 63	3. 2013/02/03: 12,687	3. 2014/10/14: 23,710	3. 2015/05/16: 9,571
4. 2012/10/22: 104	4. 2013/03/04: 13,646	4. 2014/03/03: 24,007	4. 2015/06/20: 9,675
5. 2012/11/07: 170	5. 2013/03/15: 14,344	5. 2014/06/15: 24,555	5. 2015/01/13: 10,657
6. 2012/11/05: 250	6. 2013/02/12: 15,865	6. 2014/09/07: 25,752	6. 2015/05/15: 11,431
7. 2012/10/04: 328	7. 2013/03/13: 18,537	7. 2014/05/09: 27,123	7. 2015/01/17: 12,105
8. 2012/10/17: 389	8. 2013/12/31: 19,357	8. 2014/01/24: 27,728	8. 2015/01/14: 13,445
9. 2012/10/23: 540	9. 2013/11/03: 19,607	9. 2014/03/18: 28,216	9. 2015/01/31: 14,881
10. 2012/11/04: 587	10. 2013/01/01: 20,268	10. 2014/06/12: 28,294	10. 2015/01/16: 15,326
...	...	...	...
354. 2012/12/29: 29,452	354. 2013/11/28: 120,308	352. 2014/09/20: 163,954	349. 2015/03/08: 179,715
355. 2012/12/28: 29,474	355. 2013/12/22: 122,178	353. 2014/05/25: 166,930	350. 2015/05/02: 183,777
356. 2012/12/22: 29,868	356. 2013/12/24: 123,132	354. 2014/11/25: 168,038	351. 2015/05/24: 192,989
357. 2012/12/15: 32,601	357. 2013/12/28: 123,181	355. 2014/09/21: 169,677	352. 2015/05/03: 212,805
358. 2012/12/25: 35,184	358. 2013/12/23: 133,922	356. 2014/11/23: 179,574	353. 2015/03/09: 220,302

'romney': 2016	**'romney': 2017**	**'romney': 2018**	**'romney': 2019**
1. 2016/03/03: 460	1. 2017/08/18: 3,572	1. 2018/01/02: 2,052	1. 2019/01/02: 457
2. 2016/03/04: 2,155	2. 2017/08/16: 5,431	2. 2018/02/16: 3,802	2. 2019/01/03: 1,520
3. 2016/11/25: 2,296	3. 2017/12/06: 6,058	3. 2018/02/20: 4,305	3. 2019/04/20: 1,951
4. 2016/11/08: 2,302	4. 2017/11/10: 6,373	4. 2018/04/22: 4,445	4. 2019/04/19: 2,935
5. 2016/11/23: 2,549	5. 2017/12/05: 6,686	5. 2018/01/03: 4,469	5. 2019/01/01: 3,040
6. 2016/11/30: 2,735	6. 2017/08/19: 8,083	6. 2018/04/24: 7,071	6. 2019/05/19: 5,181
7. 2016/11/09: 3,221	7. 2017/12/04: 8,663	7. 2018/03/05: 7,171	7. 2019/09/25: 5,296
8. 2016/11/24: 3,291	8. 2017/08/17: 9,728	8. 2018/02/19: 8,576	8. 2019/09/26: 5,636
9. 2016/03/02: 3,381	9. 2017/11/11: 14,285	9. 2018/06/27: 9,871	9. 2019/01/04: 5,928
10. 2016/11/27: 3,487	10. 2017/09/11: 18,114	10. 2018/02/17: 10,717	10. 2019/04/21: 6,075
...	...	...	...
351. 2016/12/24: 138,293	354. 2017/05/21: 253,351	361. 2018/07/29: 281,189	263. 2019/07/10: 212,718
352. 2016/12/27: 139,817	355. 2017/10/03: 268,755	362. 2018/08/05: 286,269	264. 2019/02/13: 213,194
353. 2016/12/29: 143,017	356. 2017/10/14: 282,555	363. 2018/12/28: 317,186	265. 2019/09/01: 225,726
354. 2016/01/02: 143,955	357. 2017/12/25: 290,062	364. 2018/12/05: 318,783	266. 2019/04/03: 235,546
355. 2016/12/25: 145,813	358. 2017/10/01: 331,807	365. 2018/12/09: 321,224	267. 2019/04/14: 246,341

TABLE A4. **Overall top 10 and bottom 5 rank days per year for 'romney'.**

'hillary': 2008	**'hillary': 2009**	**'hillary': 2010**	**'hillary': 2011**
1. 2008/11/14: 910	1. 2009/01/13: 1,669	1. 2010/01/21: 5,180	1. 2011/08/14: 3,161
2. 2008/11/21: 1,016	2. 2009/01/21: 1,925	2. 2010/03/03: 5,985	2. 2011/01/01: 7,674
3. 2008/12/01: 1,213	3. 2009/01/22: 2,049	3. 2010/01/16: 6,319	3. 2011/08/15: 8,249
4. 2008/09/14: 1,383	4. 2009/03/02: 2,870	4. 2010/03/02: 7,268	4. 2011/06/09: 9,181
5. 2008/11/18: 1,780	5. 2009/01/20: 3,001	5. 2010/02/15: 7,430	5. 2011/01/30: 9,349
6. 2008/11/12: 1,795	6. 2009/08/11: 3,190	6. 2010/11/29: 9,087	6. 2011/03/16: 9,600
7. 2008/09/13: 2,030	7. 2009/03/07: 3,297	7. 2010/01/22: 9,321	7. 2011/01/28: 9,679
8. 2008/11/13: 2,297	8. 2009/02/20: 3,586	8. 2010/02/24: 9,342	8. 2011/05/09: 10,093
9. 2008/11/17: 2,535	9. 2009/02/24: 3,659	9. 2010/01/13: 9,542	9. 2011/11/01: 10,234
10. 2008/09/10: 2,622	10. 2009/01/23: 3,763	10. 2010/03/22: 9,646	10. 2011/02/27: 10,348
...	...	...	...
110. 2008/11/28: 14,023	342. 2009/11/28: 31,050	361. 2010/12/21: 48,726	356. 2011/11/26: 57,923
111. 2008/12/25: 14,474	343. 2009/12/25: 33,335	362. 2010/11/24: 49,149	357. 2011/11/24: 58,329
112. 2008/12/20: 14,975	344. 2009/12/23: 34,341	363. 2010/11/14: 51,234	358. 2011/12/25: 59,738
113. 2008/12/21: 15,603	345. 2009/11/23: 36,036	364. 2010/11/25: 52,996	359. 2011/11/06: 59,801
114. 2008/12/13: 18,477	346. 2009/11/26: 42,087	365. 2010/12/24: 61,848	360. 2011/10/09: 64,733

'hillary': 2012	**'hillary': 2013**	**'hillary': 2014**	**'hillary': 2015**
1. 2012/12/30: 4,402	1. 2013/01/23: 2,475	1. 2014/06/10: 3,594	1. 2015/10/13: 446
2. 2012/10/16: 4,950	2. 2013/01/24: 6,883	2. 2014/04/11: 5,182	2. 2015/04/12: 662
3. 2012/12/31: 5,116	3. 2013/02/01: 6,998	3. 2014/06/17: 5,304	3. 2015/10/22: 854
4. 2012/12/15: 5,946	4. 2013/03/18: 7,251	4. 2014/06/09: 5,670	4. 2015/04/13: 1,068
5. 2012/10/15: 7,809	5. 2013/01/02: 7,539	5. 2014/06/11: 7,058	5. 2015/10/14: 1,170
6. 2012/09/03: 8,595	6. 2013/05/08: 7,955	6. 2014/04/10: 7,680	6. 2015/04/14: 1,533
7. 2012/09/05: 9,213	7. 2013/01/29: 10,952	7. 2014/06/18: 7,740	7. 2015/11/14: 1,687
8. 2012/10/26: 9,807	8. 2013/05/09: 11,133	8. 2014/06/12: 8,454	8. 2015/04/21: 1,782
9. 2012/01/24: 10,062	9. 2013/05/10: 11,209	9. 2014/06/23: 8,770	9. 2015/12/20: 1,804
10. 2012/09/04: 10,337	10. 2013/01/25: 11,236	10. 2014/06/16: 8,874	10. 2015/10/23: 1,807
...	...	...	...
354. 2012/02/11: 60,841	354. 2013/12/07: 60,608	352. 2014/03/27: 49,541	349. 2015/01/17: 40,311
355. 2012/02/09: 62,126	355. 2013/03/03: 60,786	353. 2014/10/04: 49,691	350. 2015/01/18: 41,476
356. 2012/03/25: 62,879	356. 2013/04/19: 62,263	354. 2014/12/27: 51,427	351. 2015/01/04: 41,824
357. 2012/12/24: 67,635	357. 2013/03/02: 64,804	355. 2014/12/26: 56,748	352. 2015/01/02: 44,119
358. 2012/12/25: 71,445	358. 2013/12/25: 66,346	356. 2014/12/25: 56,900	353. 2015/01/25: 44,401

'hillary': 2016	**'hillary': 2017**	**'hillary': 2018**	**'hillary': 2019**
1. 2016/11/08: 50	1. 2017/11/03: 536	1. 2018/07/16: 713	1. 2019/04/24: 1,394
2. 2016/11/09: 77	2. 2017/10/30: 605	2. 2018/10/24: 723	2. 2019/09/25: 1,433
3. 2016/09/26: 89	3. 2017/09/13: 654	3. 2018/01/29: 906	3. 2019/09/29: 1,570
4. 2016/10/09: 91	4. 2017/11/02: 670	4. 2018/02/02: 1,048	4. 2019/03/05: 1,621
5. 2016/10/19: 110	5. 2017/10/25: 688	5. 2018/10/10: 1,049	5. 2019/03/24: 1,703
6. 2016/09/27: 127	6. 2017/01/20: 696	6. 2018/07/17: 1,057	6. 2019/03/25: 1,770
7. 2016/11/07: 130	7. 2017/11/04: 708	7. 2018/03/13: 1,100	7. 2019/07/24: 1,822
8. 2016/10/20: 132	8. 2017/10/26: 709	8. 2018/06/14: 1,165	8. 2019/01/26: 1,861
9. 2016/10/10: 138	9. 2017/09/12: 801	9. 2018/06/15: 1,197	9. 2019/03/13: 1,886
10. 2016/11/10: 157	10. 2017/06/01: 859	10. 2018/12/05: 1,239	10. 2019/03/23: 1,928
...	...	...	...
351. 2016/12/26: 3,710	354. 2017/07/01: 5,435	361. 2018/12/24: 6,619	263. 2019/07/22: 8,125
352. 2016/12/25: 3,734	355. 2017/04/27: 5,437	362. 2018/12/20: 6,649	264. 2019/07/17: 8,243
353. 2016/01/01: 3,969	356. 2017/04/16: 5,618	363. 2018/12/23: 6,709	265. 2019/08/06: 8,288
354. 2016/12/30: 4,231	357. 2017/08/22: 5,647	364. 2018/11/02: 6,727	266. 2019/09/04: 8,362
355. 2016/12/29: 4,375	358. 2017/05/01: 6,683	365. 2018/12/25: 9,619	267. 2019/08/04: 8,653

TABLE A5. **Overall top 10 and bottom 5 rank days per year for 'hillary'.**

'trump': 2008	**'trump': 2009**	**'trump': 2010**	**'trump': 2011**
1. 2008/10/15: 5,249	1. 2009/05/12: 1,668	1. 2010/01/08: 4,954	1. 2011/04/27: 734
2. 2008/09/18: 5,969	2. 2009/02/17: 3,227	2. 2010/09/09: 6,602	2. 2011/05/01: 829
3. 2008/12/01: 7,074	3. 2009/08/23: 3,617	3. 2010/01/09: 6,717	3. 2011/05/02: 1,097
4. 2008/11/03: 9,773	4. 2009/08/10: 3,663	4. 2010/01/01: 7,233	4. 2011/04/28: 1,533
5. 2008/10/29: 10,238	5. 2009/06/10: 3,670	5. 2010/08/23: 7,252	5. 2011/05/16: 1,629
6. 2008/10/01: 10,608	6. 2009/06/16: 3,709	6. 2010/02/04: 7,384	6. 2011/04/30: 2,235
7. 2008/09/29: 10,651	7. 2009/09/06: 3,729	7. 2010/01/02: 7,728	7. 2011/04/29: 2,402
8. 2008/09/24: 11,086	8. 2009/06/22: 3,746	8. 2010/01/04: 7,758	8. 2011/04/07: 2,991
9. 2008/11/04: 11,534	9. 2009/08/11: 3,799	9. 2010/01/03: 7,947	9. 2011/04/26: 3,337
10. 2008/12/18: 11,588	10. 2009/09/05: 3,882	10. 2010/01/10: 8,007	10. 2011/04/19: 3,422
…	…	…	…
110. 2008/09/10: 32,204	342. 2009/01/31: 24,889	361. 2010/11/15: 24,274	356. 2011/10/09: 32,002
111. 2008/09/14: 32,486	343. 2009/01/16: 28,079	362. 2010/11/14: 24,470	357. 2011/11/12: 32,245
112. 2008/09/13: 34,699	344. 2009/02/03: 28,736	363. 2010/10/31: 25,056	358. 2011/11/10: 32,355
113. 2008/10/05: 35,238	345. 2009/01/17: 30,325	364. 2010/10/03: 26,500	359. 2011/11/26: 33,796
114. 2008/12/23: 36,433	346. 2009/01/01: 32,208	365. 2010/10/22: 30,992	360. 2011/11/11: 35,165

'trump': 2012	**'trump': 2013**	**'trump': 2014**	**'trump': 2015**
1. 2012/10/24: 1,627	1. 2013/01/31: 9,358	1. 2014/09/29: 13,069	1. 2015/12/08: 231
2. 2012/11/07: 1,921	2. 2013/08/26: 11,411	2. 2014/12/07: 16,983	2. 2015/09/16: 277
3. 2012/02/02: 3,081	3. 2013/08/25: 13,078	3. 2014/09/09: 18,183	3. 2015/12/09: 319
4. 2012/10/25: 3,672	4. 2013/02/27: 17,309	4. 2014/04/15: 20,071	4. 2015/08/06: 356
5. 2012/11/06: 3,936	5. 2013/03/06: 17,694	5. 2014/12/17: 21,503	5. 2015/12/15: 377
6. 2012/05/29: 5,487	6. 2013/06/01: 18,782	6. 2014/10/17: 21,529	6. 2015/08/26: 473
7. 2012/12/19: 7,474	7. 2013/02/25: 19,323	7. 2014/12/16: 22,067	7. 2015/12/11: 515
8. 2012/11/08: 7,483	8. 2013/02/01: 19,789	8. 2014/03/06: 22,330	8. 2015/12/07: 527
9. 2012/05/30: 7,764	9. 2013/03/19: 19,940	9. 2014/09/16: 23,032	9. 2015/08/25: 594
10. 2012/10/26: 7,876	10. 2013/05/03: 20,647	10. 2014/04/01: 23,090	10. 2015/08/07: 609
…	…	…	…
354. 2012/09/02: 53,328	354. 2013/08/03: 73,434	352. 2014/05/25: 74,344	349. 2015/04/03: 59,988
355. 2012/12/23: 53,439	355. 2013/11/24: 75,049	353. 2014/07/19: 75,600	350. 2015/05/24: 60,385
356. 2012/12/30: 55,196	356. 2013/11/17: 78,219	354. 2014/07/25: 75,672	351. 2015/02/08: 64,066
357. 2012/12/16: 56,494	357. 2013/11/16: 79,322	355. 2014/08/23: 76,435	352. 2015/03/29: 67,198
358. 2012/10/06: 57,032	358. 2013/10/26: 81,022	356. 2014/07/27: 77,186	353. 2015/04/04: 70,230

'trump': 2016	**'trump': 2017**	**'trump': 2018**	**'trump': 2019**
1. 2016/11/09: 11	1. 2017/01/20: 29	1. 2018/07/16: 63	1. 2019/09/25: 84
2. 2016/11/08: 15	2. 2017/01/21: 37	2. 2018/07/13: 87	2. 2019/09/24: 105
3. 2016/11/10: 19	3. 2017/01/30: 55	3. 2018/07/17: 87	3. 2019/01/25: 112
4. 2016/10/09: 22	4. 2017/01/29: 58	4. 2018/01/12: 89	4. 2019/02/27: 114
5. 2016/09/26: 27	5. 2017/01/22: 60	5. 2018/06/20: 92	5. 2019/09/26: 115
6. 2016/10/19: 38	6. 2017/01/28: 61	6. 2018/06/12: 95	6. 2019/01/18: 119
7. 2016/11/11: 40	7. 2017/01/25: 62	7. 2018/11/07: 100	7. 2019/07/18: 122
8. 2016/10/08: 45	8. 2017/08/15: 62	8. 2018/06/11: 104	8. 2019/07/24: 123
9. 2016/10/10: 48	9. 2017/01/26: 63	9. 2018/01/30: 105	9. 2019/01/08: 125
10. 2016/09/27: 54	10. 2017/01/31: 63	10. 2018/07/18: 108	10. 2019/02/05: 125
…	…	…	…
351. 2016/01/04: 1,120	354. 2017/01/01: 320	361. 2018/02/25: 362	263. 2019/03/13: 352
352. 2016/01/06: 1,143	355. 2017/09/09: 326	362. 2018/12/31: 364	264. 2019/02/10: 371
353. 2016/01/10: 1,143	356. 2017/09/10: 335	363. 2018/09/29: 392	265. 2019/03/16: 371
354. 2016/01/01: 1,276	357. 2017/05/06: 343	364. 2018/09/28: 397	266. 2019/09/14: 376
355. 2016/01/11: 1,297	358. 2017/12/25: 384	365. 2018/09/23: 405	267. 2019/09/01: 385

TABLE A6. **Overall top 10 and bottom 5 rank days per year for 'trump'.**

'@bts_twt': 2013	'@bts_twt': 2014	'@bts_twt': 2015
1. 2013/12/03: 4,217	1. 2014/12/31: 967	1. 2015/12/29: 176
2. 2013/12/31: 4,384	2. 2014/12/29: 979	2. 2015/12/31: 260
3. 2013/11/30: 4,393	3. 2014/12/23: 1,357	3. 2015/12/30: 359
4. 2013/12/29: 4,559	4. 2014/12/26: 1,405	4. 2015/12/03: 368
5. 2013/11/14: 5,778	5. 2014/08/31: 1,417	5. 2015/12/11: 368
6. 2013/10/12: 5,842	6. 2014/12/07: 1,454	6. 2015/11/07: 386
7. 2013/11/27: 5,883	7. 2014/12/03: 1,471	7. 2015/09/11: 414
8. 2013/11/28: 6,129	8. 2014/12/20: 1,474	8. 2015/12/21: 415
9. 2013/12/02: 6,296	9. 2014/12/24: 1,482	9. 2015/10/12: 416
10. 2013/12/01: 6,413	10. 2014/10/12: 1,575	10. 2015/11/29: 420
...	...	...
312. 2013/04/27: 882,731	352. 2014/01/22: 20,076	349. 2015/04/09: 6,064
313. 2013/01/20: 882,966	353. 2014/04/18: 21,239	350. 2015/04/14: 6,657
314. 2013/02/10: 929,849	354. 2014/04/23: 21,270	351. 2015/04/16: 6,805
315. 2013/01/09: 952,557	355. 2014/04/19: 22,663	352. 2015/02/21: 6,899
316. 2013/02/25: 986,266	356. 2014/04/20: 25,221	353. 2015/04/13: 7,150

'@bts_twt': 2016	'@bts_twt': 2017	'@bts_twt': 2018	'@bts_twt': 2019
1. 2016/12/29: 99	1. 2017/05/21: 9	1. 2018/05/20: 3	1. 2019/05/01: 12
2. 2016/12/26: 110	2. 2017/05/01: 11	2. 2018/05/15: 4	2. 2019/04/22: 13
3. 2016/11/19: 127	3. 2017/05/20: 13	3. 2018/05/14: 6	3. 2019/04/24: 15
4. 2016/12/02: 134	4. 2017/05/02: 14	4. 2018/05/16: 8	4. 2019/02/10: 17
5. 2016/12/30: 137	5. 2017/05/04: 14	5. 2018/05/18: 8	5. 2019/03/16: 18
6. 2016/09/11: 158	6. 2017/05/05: 15	6. 2018/05/17: 11	6. 2019/04/28: 18
7. 2016/08/31: 162	7. 2017/05/03: 16	7. 2018/05/19: 11	7. 2019/04/29: 18
8. 2016/05/12: 173	8. 2017/05/06: 18	8. 2018/01/25: 14	8. 2019/03/02: 19
9. 2016/05/07: 174	9. 2017/05/19: 18	9. 2018/12/14: 14	9. 2019/04/25: 19
10. 2016/05/13: 204	10. 2017/05/07: 19	10. 2018/02/25: 15	10. 2019/04/26: 19
...	...	...	...
351. 2016/02/25: 2,770	354. 2017/02/10: 1,347	361. 2018/03/27: 215	263. 2019/02/25: 202
352. 2016/09/28: 2,869	355. 2017/03/15: 1,394	362. 2018/03/29: 222	264. 2019/03/15: 211
353. 2016/09/29: 2,893	356. 2017/01/11: 1,506	363. 2018/01/03: 234	265. 2019/03/06: 224
354. 2016/04/12: 3,209	357. 2017/03/16: 1,783	364. 2018/01/08: 255	266. 2019/08/22: 233
355. 2016/09/27: 3,210	358. 2017/01/31: 1,893	365. 2018/01/05: 267	267. 2019/08/28: 257

TABLE A7. **Overall top 10 and bottom 5 rank days per year for '@bts_twt', for 2013–2019.**