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Tampering with Twitter's Sample API

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Abstract

Social media data is widely analyzed in computational social science. Twitter, one of the largest social media platforms, is used for research, journalism, business, and government to analyze human behavior at scale. Twitter offers data via three different Application Programming Interfaces (APIs). One of which, Twitter's Sample API, provides a freely available 1% and a costly 10% sample of all Tweets. These data are supposedly random samples of all platform activity. However, we demonstrate that, due to the nature of Twitter's sampling mechanism, it is possible to deliberately influence these samples, the extent and content of any topic, and consequently to manipulate the analyses of researchers, journalists, as well as market and political analysts trusting these data sources. Our analysis also reveals that technical artifacts can accidentally skew Twitter's samples. Samples should therefore not be regarded as random. Our findings illustrate the critical limitations and general issues of big data sampling, especially in the context of proprietary data and undisclosed details about data handling.

Keywords: Twitter Data; Sampling; Manipulation; Experiments

1 Introduction

Social media are perceived as central platforms for opinion formation, public participation and triggering political and societal change [1, 2]. Therefore, social media data is of great importance not only to social researchers but also to decision makers [3] in the context of political opinion formation [4], crisis management [5, 6], information quality [7], geopolitical events [8] or security concerns [9]. However, analyzing social media data to describe human behavior is complicated by several challenging factors, first and foremost related to the representation of human populations and human behavior, as well as by methodological issues [10–12].

In sharing its data, Twitter has become one of the most important data suppliers, providing a main source of data for social media analysis to journalists, policy makers and businesses alike. Twitter allows data access via three different Application Programming Interfaces (APIs): Filter API, Sample API, and REST API (Representational State Transfer API). For studying trends and emerging topics, Twitter's Sample API provides 1% of all Tweets worldwide. Most academic researchers rely on one of these freely available data sources, whereas social analytics industries and government entities buy in to get elevated access, e.g. to 10% of the overall Twitter data, also known as the *Decahose*.

Almost all of Twitter (and other social media) analyses depend on access to samples. Twitter does not reveal in detail how data sampling is handled. The API has to be regarded as an unavoidable "black box" [13, 14], which is sitting between the researcher and the data source. Consequently, the use of Twitter data is regarded as highly problematic, especially in the social sciences [15–17]. Because sampling is so prevalent, we need to question its validity [10, 18] and better understand platform mechanisms and possible biases in the resulting data [19–22].

Our work builds on a body of literature that opens up and reverse engineers this black box. The goal is to improve the integrity of social media research. In this paper we will prove that the sampling mechanism of Twitter's Sample API is highly vulnerable to manipulation and is prone to creating sampling artifacts that can jeopardize representativeness of accessible data. Therefore, the samples from the Sample API cannot be regarded as random. They have the potential to damage the validity of scientific research.

Contributions and Findings. In the following we will demonstrate how a flaw in the sampling mechanism underpinning Twitter's Sample API can be used to skew the analysis creating bias by design and making the sampling vulnerable to attacks. The findings of our research challenge the credibility of using Twitter's Sample API for both academic and non-academic purposes. The main contributions of this article are the following:

1. We showcase that it is very easy to tamper with the data in Twitter's 1% and 10% Sample API.
2. We illustrate how this tampering can be used to manipulate the extent and content/sentiment of a topic in the Sample API data.
3. We show that groups of users are already over-represented in the Sample API.
4. We discuss the implications of our findings on sampling challenges and provide arguments why open/shared data needs open algorithms in order to give researchers and practitioners a fair chance to know and assess the data.

The remainder of this article is structured as follows: after reporting on related work in Sect. 2, we proceed to describe our experimental setup in Sect. 3. Section 4 covers the experimental results and discusses the potential scale of such attacks. The goal of Sect. 5 is to derive expected behavior that we would observe in a random system and to develop thresholds for outlier detection. These metrics are then used in Sect. 6 to identify groups of over-represented accounts in Twitter's Sample API, so that in Sect. 7 we can propose potential solutions for the demonstrated issues. Section 8 concludes the paper with a discussion of our findings and aligns them with pressing issues of social media research.

2 Related work

Attention to Twitter from researchers is continuously increasing [23–25] and Twitter's APIs are widely used to collect data from the platform. The impact and relevance of Twitter as source for news and information in particular for younger users is widely documented [26–28] and journalists and editors use Twitter as radar [29] to identify news and as information source when writing their articles [30], even to re-negotiate their professional norms [31]. Companies use Twitter to monitor or promote their brands and campaigns [32]. Twitter's Sample API is utilized when researchers want to avoid filtering Tweets by keywords or accounts as well as when large amounts of historic Tweets should be accessed or new trends are detected in real-time. For instance, sentiment extracted from the 10% Sample API has been linked to public opinion time series [33] and the same source has helped to early detect promoted campaigns [32]. Among many other works, the 1% Sample was used to find how gender and social rank relate to people's propensity to curse and the choice of curse words [34]. Recently, misinformation networks were studied using the 1% Sample data [35].

As researchers, journalists, but also companies and policy consultants use Twitter in their daily work, we are interested in biases because they jeopardize data quality and hence reliability and validity of these analyses. We can build on a broad body of literature elaborating the challenges and biases of social media data—for an overview see [10, 11, 36]. By and large, social media biases can be arranged into two groups, *bias by design* and *bias by purpose*.

Bias by design results from built-in characteristics of the platform [11]. Some platforms are more attractive to specific sociodemographic groups than others [37] and specific services of platforms can appeal differently to certain groups, e.g. geo-referencing [38]. The neglect of cultural differences driving the way users interact with a site distort results [39]. Bias that results from the architecture of the technical infrastructure is harder to diagnose. Platform effects, e.g. changes in the graphical user interface, can heavily influence user behavior [40]. Lazer et al. [41] revealed that Google does not store the search term typed by the user but the search term selected based on suggestions, which has tremendous implications for the analysis of human behavior based on those data. Our work focuses on issues resulting from sampling [42, 43] of Twitter data. Since Twitter does not reveal how data sampling is performed, the use of Twitter data is generally regarded as highly problematic, especially in the social sciences [42, 44–46]. Several studies discuss working, compositions and possible biases of data [47, 48] and a "reverse-engineered" model has been developed for the Sample API, which indicates that the sampling is based on a millisecond time window and that the timestamp at which the Tweet arrived at Twitter's servers is coded into the Tweet's ID [42, 43]. Although it has been shown that Twitter creates non-representative samples with non-transparent and highly fluctuating sample rates of the overall Twitter activity [49], this has had no effect on its popularity amongst researchers [50]. It was suggested in the past that Sample API data can be used to estimate the quality of Streaming API data [51]. Social scientists have elaborated on sampling techniques and theories for ages, while the discussion of sampling and, in particular, of representativeness in the context of big data has remained marginal until now [36, 41, 52–54].

Bias by purpose includes all forms of approaches to manipulate data on a platform or the analysis that is based on data from a platform. We face a variety of biases in social media data, such as targeted user collaboration to skew contents of a site [55], changing statistics on site like trends and follower counts in an attempt to skew the perception of real users on the site [56]. The most studied phenomenon in this category are bots [57–59]. Detection of bots can use content of Tweets [60] or profile information, e.g. usernames [61]. Chu et al. [62] try to classify users as bots, humans, or cyborgs based upon the user's behavioral patterns. In [63], the authors use a network of 60 honeypots to tempt bots to follow them. Each of these honeypots focuses on gaining attraction by tweeting trending topics and links as well as regular tweets and tweets mentioning other honeypots. They then engineered several features to detect these accounts.

Our work contributes to these lines of research on data quality as it focuses on both purposeful and accidental attacks on built-in functionalities. We are introducing another big issue with Twitter's data sampling: the observation and experimental evidence of intentional and unintentional tampering with the allegedly random samples that Twitter is providing. We will show how the sample data can be manipulated, so that samples cannot be regarded as random anymore.

3 Experiments

We apply a two-fold approach to provide evidence for Twitter's tampered samples. First, as described in this and the next section, we test the blackboxed sampling procedure of the Twitter Sample API by inducing tweets into the feed in that way that they appear later in the sample with high certainty. Second, by finding ways to identify over-representation in the sample, we describe typical account groups that might inhibit the integrity of the sampling procedure in Sects. 5 and 6. With this two-fold approach we can exemplify the potential exploitation of the system architecture, which can lead to a biased interpretation.

In the following, we reveal details about the sampling procedure which is used by Twitter to provide data via the Sample API. The approach of Twitter to decide whether a Tweet is in the Sample API or not is solely based on timestamps. This mechanism was shown to be a potential weakness [43]. Building on this insight, we show that by timing the sending of a Tweet accordingly, it is possible to influence with high accuracy what goes into the sample and, hence, manipulate Twitter's Sample API samples. Here, we demonstrate that the millisecond sample criteria is vulnerable as the Tweet processing time delay can be learned so that (for the 1% Sample API) the 10 millisecond selection time window can be hit with 80 times higher chance than random. We use this approach to showcase manipulation of the composition of the sample and present the results of short-term experiments that manipulated global dynamics of the 2016 US Presidential Election related hashtags.

For this article we focus on the freely available 1% Sample API. However, our findings are transferable to the 10% academic Sample data as both APIs are based on the same sampling logic and have overlapping sampling windows.

3.1 Twitter's data samples

To collect Twitter data, researchers typically use the freely available API endpoints for public data. There are three different APIs to collect Twitter data. The Representational State Transfer (REST) API provides information about individual user accounts or popular topics and allows for sending or liking Tweets as well as following accounts. The Streaming APIs are used for real-time collection of Tweets and come in two flavors. First, the Filter API extracts Tweets based upon a user's query containing keywords, user accounts, or geographic areas. The Filter API is used for studying Twitter content based on a predefined set of topics, user accounts, or locations. In contrary, the Sample API delivers a purportedly random 1% sample of all publicly sent Tweets, currently about 3.5 to 4 million Tweets per day. When interested in trends or emerging topics, the Sample API is used. By archiving Sample API Tweets, non-predictable events (e.g. natural disasters, terrorist attacks) can be analyzed in retrospect because this sample cuts across all topics on the site.

Access to a 10% academic version of the Sample API (a.k.a. Decahose or Gardenhose in the literature), which offers the ten-fold amount of Tweets, was granted from the early days to selected research collaborators of Twitter for free and access to a 10% enterprise sample can be purchased for tens of thousands of dollars per month by everybody else. The Firehose, which includes 100% of public Tweets, is currently not generally available to

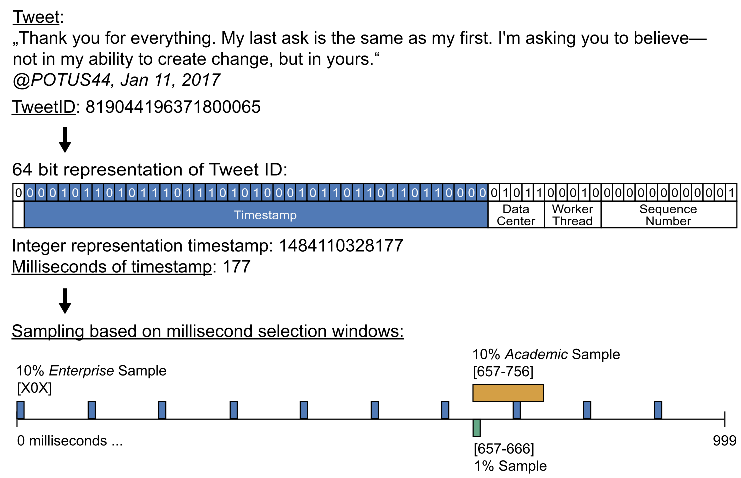


Figure 1 Twitter Sample API data sampling. Every Tweet gets a Tweet ID assigned by Twitter. Tweet IDs include the millisecond timestamp of when the Tweet arrives at a Twitter server. Whether a Tweet is in one of the Sample APIs is solely based on this millisecond timestamp. Three different samples based on their milliseconds coverage have been identified, namely 1%, 10% academic, 10% enterprise

researchers and practitioners. In a nutshell, the Filter API *filters* data based on parameters and the Sample API *samples* data based on rate limits.

For the purpose of this study, we examine the sampling procedures of three types of Twitter's Sample API, the public and free 1% Sample API, the 10% academic sample, and the fee-based 10% enterprise sample. First, the public Sample API is an endpoint that is provided for free by Twitter to anyone who wishes to obtain a 1% sample of Twitter data. The API users have no ability to specify a particular query to this endpoint; they are only able to connect to it and receive a fixed set of Tweets from Twitter. Every user who connects to this endpoint will receive the same set of Tweets [47].

Since Twitter does not reveal the technical details about the sampling mechanism of the Sample API, researchers have reverse engineered that process [42]. The way this sample is created is purely based on the millisecond timestamp that the tweet arrived at Twitter's servers. When a Tweet arrives at one of Twitter's servers, it gets assigned an ID (see Fig. 1). Part of this ID is the millisecond timestamp of when the Tweet arrived at the server. This timestamp is crucial for Twitter's sampling. Any tweet that arrives at one of Twitter's servers between milliseconds 657–666 will be available in the 1% Sample API, as indicated in Fig. 1.

The other two samples follow a similar policy, but widened to yield 10% of all Tweets. One is the academic 10% sample, which is sampled from a fixed block of 100 milliseconds. This endpoint was granted to a small number of researchers nominated by Twitter, and selects the 100-millisecond window of 657–756 of every second, as demonstrated by [42]. The other type of sample—the enterprise 10% sample—is offered to customers willing to pay for elevated access to Tweets. This selects any Tweet whose millisecond pattern matches "X0X," which is also 100 milliseconds. While both of these samples are from 100-millisecond time ranges, the windows, where the tweets are sampled are different, and will result in a different sample of Tweets. Figure 1 shows the milliseconds based selection windows of the three known Sample APIs.

3.2 Experimental setup

Morstatter et al. [43] showed that it is possible to learn the millisecond time difference from sending a Tweet until the Tweet gets assigned the Tweet ID. Looking only at the millisecond portion of the timestamp, we state that the arrival milliseconds t_a equals the sending milliseconds t_s plus a milliseconds time offset t_δ that comes from the time it takes for the Tweet to pass from sending to getting processed as well as the clock differences between the local computer and the respective Twitter server: $t_a = t_s + t_\delta$. From this equation we know t_s from our local computer and t_a from the Tweet ID, so that we can calculate t_δ.

We used this technique to adjust the timing of the send events so that the Tweets we sent were more likely to arrive at the server within the 1% Sample API's selection time window. In other words, we maximized the proportion of Tweets that gets handled by the Twitter servers within the specific 10 millisecond time window of every second. Crucial for determining the time difference between sending a Tweet and the arrival of the same Tweet at one of Twitter's servers is that Twitter provides the assigned ID as return information when sending the Tweet with the REST API. To demonstrate this vulnerability, we chose two major hashtags for short-term manipulation. At the time of our experiments, in late October and early November 2016, right before the US presidential election, prominent hashtags were: #imwithher (used by supporters of Hillary R. Clinton) and #trump (used by supporters and critics of Donald J. Trump).

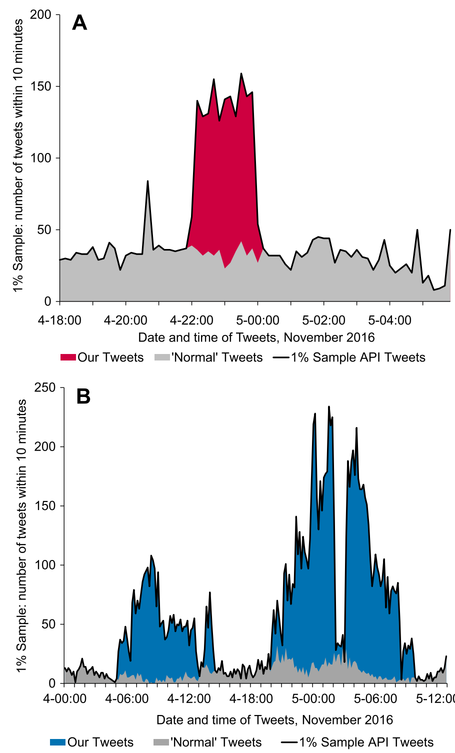
We created 100 Twitter accounts for the purpose of this study and sent about 21,000 Tweets in a series of short-term experiments in late October and early November 2016. User IDs of our bot accounts and Tweet IDs of all 15,207 Tweets that made it into the 1% Sample API can be found at http://www.pfeffer.at/data/tampering, so that other researchers and practitioners analyzing the affected time period can remove them easily. The accounts were used in rotation to send Tweets. At the same time, we collected data from Twitter's 1% Sample API and the 10% academic Sample API for the analysis of this article. To identify other user accounts that are over-represented in Twitter's Sample APIs, we analyzed 220 million Tweets of the 1% Sample API and 2.2 billion Tweets of the 10% academic Sample API (10/1-11/30 2016). Tweets were published with Twitter's REST API. We used Twitter's Filter API to collect all Tweets that we have sent with our accounts to ensure that the data we sent was accepted by Twitter and to confirm the timestamps that Twitter's servers assigned to our Tweets. Twitter APIs were accessed with Python's Twython package. The times of day shown in the analyses are Coordinated Universal Time (UTC).

3.3 Sentiment analysis

Another very popular method for analyzing Tweets is sentiment analysis [33, 64–66], attaching a score or scores to Tweets representing emotions in the message. In the context of elections, O'Connor et al. [33] used data from the academic 10% Sample API to study the 2008 US Presidental Elections and Wang et al. [67] presented a system for real-time Twitter analysis of the 2012 US Presidential Elections.

To measure sentiment, we employ the Linguistic Inquiry and Word Count (LIWC) [68]. The reason we chose LIWC for sentiment analysis is because it is a keyword-based approach to sentiment analysis. It is an approach which underpins many state-of-the-art approaches like VADER [69], and thus gives us an understanding of how a wide variety of keyword-based sentiment analysis approaches can be tainted by this methodology.

Figure 2 Manipulation experiments—volume. The grey areas represent Tweets in Twitter's 1% Sample API from all 328 million users, excluding Tweets that were sent from our 100 automated accounts, which were designed to hit the sample time window with high probability. The thick lines are what researchers and analysts see when they study the respective hashtags through the lens of the Sample API. Data shows Tweets per 10 minutes in the 1% Sample API, so that 50 Tweets would be perceived as 5000 on all of Twitter. (**A**) #trump Sample API manipulation experiment. (**B**) #imwithher Tweets per 10 minutes in 1% Sample



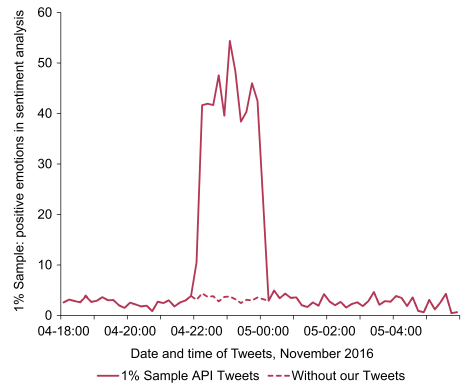
4 Experimental results

Figure 2 shows the results of our interventions related to the #trump as well as the #imwithher hashtags. The gray areas in these two figures represent Tweets in Twitter's 1% Sample API in 10 minutes time intervals. This figure is provided to give the reader a baseline of the activity. Consequently, we excluded Tweets that were sent from our 100 automated accounts, which were designed to hit the sample time window with high probability. It is important at this point to emphasize two aspects. First, the Tweets in the gray area represent the activity of 328 million monthly active users on Twitter. Second, these Tweets present 1% of the overall activity on Twitter. In other words, 50 Tweets stand for approximately 5000 Tweets within a 10 minute time period.

The red area in Fig. 2A represents the 1222 of our 2000 sent Tweets for the #trump experiment that were selected by the Sample API. This rather small number of Tweets was sufficient to quadruple the global activity of a high-frequency hashtag in the Sample API. To picture the potential extent of this manipulation, one needs to consider that, for people analyzing the US Elections by utilizing the Sample API, these 1220 Tweets of the #trump experiment create the wrong impression of being a random 1% sample of about 120,000 Tweets related to this hashtag.

For the #trump experiments, we turned all of our 100 accounts on and off at the same time, which created the steep slopes visible in Fig. 2A. Figure 2B demonstrates controlled experiments to approximate a pre-defined more *normal looking*, i.e. smoother, global time series for the #imwithher hashtag in the 1% Sample API [70]. The result shows that it is possible—aside from short service interruptions in this case[a]—to create a specific over-time distribution for a globally trending topic.

Figure 3 Manipulation experiment—sentiment. Sentiment analysis experiment. Analyzing the sentiment of texts is based on counting words from word lists describing different emotional categories. The chart shows the Linguistic Inquiry and Word Count [68] scores of positive emotions in #trump Tweets from Fig. 2A with and without our Tweets



Since sentiment analysis generally relies upon analyzing the frequency of words with emotional cues [71], our experimental intervention injected Tweets containing these kinds of words into Twitter's Sample API. The 2016 US Presidential Election campaign was bitterly hard-fought, and observers witnessed new and radical styles of social media campaigning [72]. To maximize the demonstrated impact of our manipulations, we therefore decided to inject Tweets containing words with encoded positive emotions together with the above-mentioned hashtags. Figure 3 visualizes a sentiment analysis of positive emotions in the Tweets in the 1% Sample API with the #trump hashtag that were also used for the analysis of Fig. 2A. The level of positive emotions without our Tweets is unsurprisingly low. Injecting 1222 Tweets with positive words into the Sample API created a ten-fold increase in the LIWC score [68] for positive emotions, making it outperform all other categories in the Sample API, and changing this analysis substantially.

We ran several experiments to inject Tweets into the 10 millisecond selection time window of the 1% Sample API. During these experiments, 60–90%[b] of the Tweets we sent appeared in the data distributed by the 1% Sample API.

Our manipulation experiments focused on the 1% sample. However, our experiments also influenced the 10% academic sample, as the 1% selection time window is part of this 10% selection window (Fig. 1).

5 Identifying over-represented accounts

After demonstrating that Twitter's Sample API can be manipulated, we are interested in whether there are already accounts that employ this or other approaches to be over-represented in the Sample API data. In this section, we will show how we approach the identification of over-represented accounts. In the next section, we will derive three groups of accounts that are potentially over-represented in this data stream. The underlying idea of our approach is to estimate what we would see in a *random* system and to compare this with our observations. Most of the analysis focuses on the top 1000 accounts with the most Tweets. By doing so, we lose some power in generalization to all of Twitter activity. Nevertheless, we have decided to focus significant parts of the analysis for this article on a smaller set of accounts. This allows an analytical *deep dive* including manual inspection of accounts, which is necessary to assess content and possible purpose of accounts, and consequently allows us to hypothesize about potential groups of over-represented accounts. When analyzing black boxes we are confronted with many unknown parameters.

Our approach offers different perspectives on data and can help us to better illuminate concealed systems.

In order to identify patterns of user accounts that are over-represented in Twitter's 1% Sample API, we collected all data from the 1% Sample API (220 million Tweets from 41 million user accounts) and, to increase the validity of the statistics (see later in this section), from the 10% academic Sample (10-fold number of Tweets from 90 million accounts) in the time period 10/1/2016-11/30/2016. To better understand and explain Twitter's sampling dynamics, we focused the analysis for this article on the 1000 accounts with the most Tweets in the 1% Sample from that time period.

5.1 Suspicious number of days with ≥ 48 tweets each day

We applied two heuristics to detect over-represented accounts. The first is volume based. Twitter allows a user account to send up to 2400 Tweets per day. Looking for accounts having significantly more than 24 Tweets per day in the 1% Sample is a straightforward approach to identify users potentially tampering with the sampling mechanism. The challenge is to determine *significant* anomalous behavior. In a system with hundreds of millions of active users, some accounts having more than 24 Tweets in the 1% Sample is within statistical expectation. First, we model the sampling events for Tweets as Bernoulli processes and utilize the binomial distribution to estimate the proportion of Tweets per account that we should find in a random 1% Sample. The curves in Fig. 4A visualizes the expected proportion of users having exactly n% of Tweets (in 0.1% steps) in the 1% Sample API as well as the accumulated probabilities. For an account sending the maximum possible number of Tweets without millisecond tampering, the probability of getting ≥ 48 Tweets ($\geq 2\%$) into the 1% Sample is 0.3%. 249 of the top 1000 accounts have at least 1 day in the two months' time period with ≥ 48 Tweets.

Again, out of 328 million monthly active user accounts, a 0.3% chance of having $\geq 2\%$ Tweets in the 1% Sample still includes about 1 million accounts. That is why we employ a second expectation distribution for determining whether an account is over-represented by chance or as the result of some form of manipulation. We know from the binomial distribution in Fig. 4A that the chance is about 3:1000 to have $\geq 2\%$ coverage. The second question now is whether an account is multiple times in the ≥ 48 Tweets/day list within our 61 day observation period and how many days would be *significant* from random expectation.

We created the expected probability chart for having x days with ≥ 48 Tweets by using the probability of having $\geq 2\%$ coverage with another binomial distribution. As you can see in Fig. 4B, multiple days with ≥ 48 Tweets/day within a 61-day period is statistically highly likely for a small number of accounts out of hundreds of millions of accounts. The dashed cross in this figure marks $1/N$ with $N = 328$ million—the number of monthly active users on Twitter. Accordingly, if all Twitter accounts would send the maximum allowed number of Tweets per day over a time period of 61 days, we would statistically expect just a single account in all of Twitter being represented in a 1% Sample with ≥ 48 Tweets/day on seven or more days. In our data, we found many more (see Sect. 6). It is important to realize that a small number of accounts actually sends the maximum number of Tweets per day on a regular basis. Hence, our analysis can be seen as a lower bound on the suspicious users.

5.2 Entropy scores and suspicious entropy scores

The second statistic comes from observation of our own bot accounts. Regular Twitter users tweeting at random time intervals create uniform millisecond distributions. In other words, there is equal chance for any millisecond [0–999] to be assigned to a Tweet. Non-random tweeting times skew this distribution. Consequently, for identifying potential user accounts that already use our approach, we take a closer look at the distribution of milliseconds. Uneven distributions can be identified with Shannon's entropy measure [73] $H(X) = -\sum_{i=1}^{n} P(x_i) \log_2 P(x_i)$ where $P(x_i)$ is the probability of the tweet being posted at timestamp i, and n is the set of timestamps under consideration. Random tweeting time points will result in normalized entropy values $\eta(X) = H(X)/\log_2 10$ very close to 1.0; lower values signal suspicious accounts. Shannon's entropy [73] was used to identify non-random tweeting behavior because it is an efficient metric for outlier detection [74]. For our data, the values for *normal behavior* (based on random timestamps) are in a very narrow range (see next paragraph). Consequently, spotting suspicious (outlier) behavior is easy. However, the challenge is again to define statistically *significant* anomalous behavior.

For our analysis, we calculated entropy scores with the 10% academic Sample API data. For the 10% academic Sample API, Tweets in the millisecond range [657–756] are collected. First, milliseconds for all Tweets in this sample per user were extracted and grouped into 10 bins based on milliseconds, i.e. 657–666, 667–676, etc. Here, the first bin equals the 1% Sample API. With the frequencies of Tweets in these 10 bins the entropy scores were calculated for every day of the 61 days observation period.

To identify *significantly* deviating entropy scores, we applied the following procedure. As we have hundreds of Tweets in the above mentioned 10 bins, the chance of a non-uniform distribution of milliseconds is very low, i.e. the entropy scores resulting from random sending times will be very close to the maximum possible score of 1.0. To estimate the range of expected entropy values we took all 10% Sample API Tweets of the top accounts and created random timestamps. Based on these random timestamps we calculated the entropy scores. Applying this procedure ten times created the density plot in Fig. 4C that shows the expected entropy score distribution for random timestamps. It turns out that expected values can be found in the interval [0.985–1.000] and values lower than that can be treated as suspicious. For the analysis in the next section, we used the average entropy score per day of all days with ≥ 48 Tweets for every account. Therefore, a low average score requires an account to have multiple days with significantly low entropy scores.

5.3 Using 10% data to increase statistical validity

Even though the focus of our analysis is on the 1% Sample API, we added the 10% academic Sample API for the study of potentially over-represented accounts to increase the validity of the statistics as follows. The average number of Tweets in the 1% sample of the top 1000 accounts is 24.3 Tweets. This is a small number for calculating entropy based on 10 1-milliseconds bins. Because of the large number of accounts on Twitter, it is highly likely that even the most skewed distribution can be created by chance. By using the 10% sample (and ten-fold number of Tweets) and creating 10 10-millisecond bins for the entropy calculations we reduce the chance for randomly skewed distributions. Contrasting the expected 10% Sample API entropy density of the top accounts (black line in Fig. 4D) with what we would expect from the 1% Sample API, it is clear that identifying outliers will be easier with the 10% data.

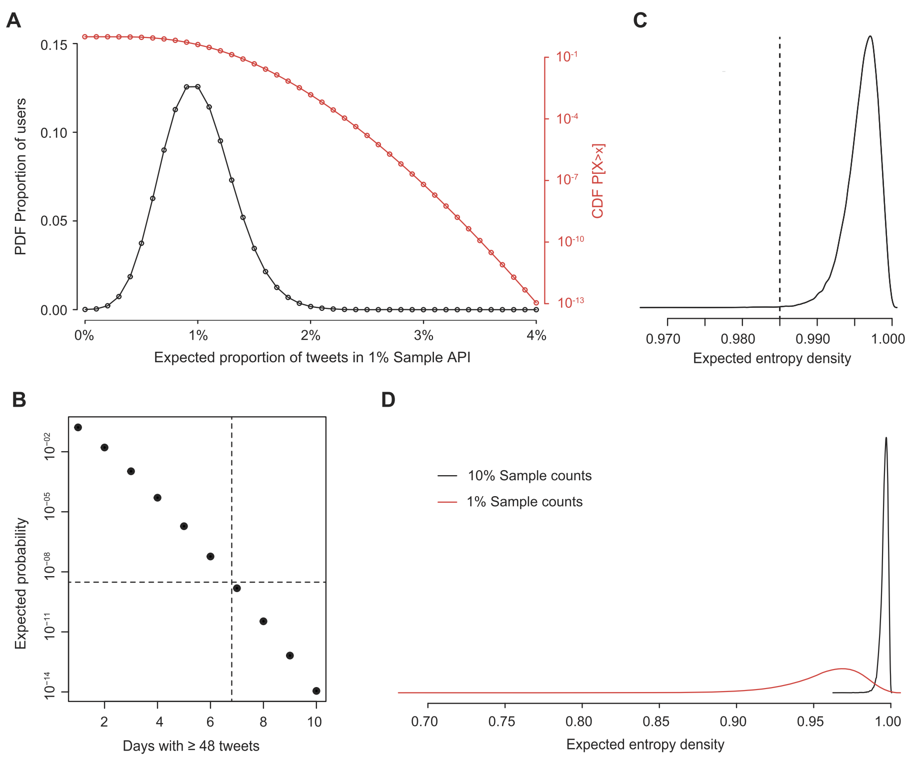


Figure 4 Estimating suspicious values. (**A**) Binomial distribution ($n = 1000$, $p = 0.01$) to estimate the expected exact proportion of Tweets per user in the 1% Sample API with *n*% Tweets in 1% Sample API (PDF, black line) as well as accumulated probabilities (CDF, red line), e.g. 3 out of 1000 users reach at least 2% coverage. (**B**) Expected probability that an account has ≥ 2% coverage on *x* days. The suspicious threshold *p* (dashed lines) is set to $1/N$, where $N = 328M$, the overall number of active Twitter accounts. (**C**) Expected entropy scores for millisecond distribution of accounts in 10% Sample. Values below 0.985 can be considered as very rare events, i.e. suspicious. (**D**) Expected entropy density for the 1% Sample and 10% Sample to illustrate that identifying suspicious entropy scores (i.e. outliers) is easier in the 10% Sample

6 Groups of over-represented accounts

In this section we will provide empirical evidence to show that some user accounts are already over-represented in Twitter's Sample API. While our findings indicate that there seems to be no intentional large-scale tampering happening during the time-period of our analysis, we are able to prove that there are in fact groups of user accounts that get over-sampled *accidentally* by Twitter's sampling approach. Combining the above mentioned two statistics, namely entropy and number of days with ≥ 48 Tweets, we identified three types of accounts in the top 1000 accounts in the time period 10/1/2016-11/30/2017 that distort the quality of Twitter's Sample API as well as additional interesting artifacts: Sample Cheaters, Corporate Spammers, and In-Syncs.

Figure 5 summarizes the findings. The horizontal dashed line represents the significance level for suspicious behavior (described in the previous section) of 7 days with ≥ 48 Tweets per day; the vertical dashed line at 0.985 maps the lower boundary for expected entropy scores. We use the resulting quadrants to define the interesting groups of accounts that are discussed in the following. The accounts in the lower right quadrant can be seen as being lucky, i.e. they are with ≥ 48 Tweets in the 1% Sample on one or a few days but the timestamp distribution does not create suspicious entropy scores. The three suspicious groups of accounts are:

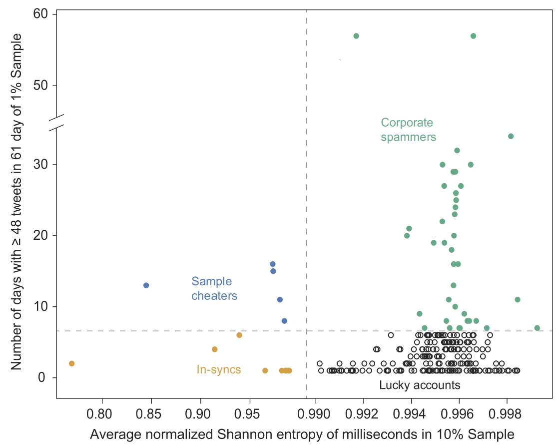


Figure 5 Types of over-represented accounts. 249 of the 1000 accounts with the most Tweets in the 1% Sample. Blue: Sample cheaters. Accounts with low entropy score and many days with ≥ 48 Tweets/day are defined as likely cheaters. Green: Corporate spammers. Accounts over-represented on many days but without suspicious entropy scores; all of these accounts can be linked to commercial activity. Yellow: In-syncs. Frequency bots that are temporarily synced with the sampling mechanism. Black: Lucky accounts that are randomly over-represented but show no suspicious characteristics

a. *Sample cheaters*. We expect cheaters that game the sampling mechanism to have a larger number of days with ≥ 48 Tweets in the sample and show non-uniform millisecond distributions. In the analyzed time period, we found 5 likely cheaters. By also analyzing other time periods, we could identify one dozen likely cheaters. All of the identified likely cheaters link thousands of times to websites, indicating that these are accounts from click-bait websites. Although this is a small number, it gives clear evidence that some users have been already exploiting this avenue to manipulate Twitter's sample data.

b. *Corporate spammers*. We identified another 39 accounts in our account sample that had ≥ 48 Tweets per day in the Sample API on ≥ 7 days. Studying these accounts more closely, e.g. by collecting all of their Tweets with the Filter API for several days, we did not find any timestamp irregularities, but many more Tweets than the daily limit would allow. Through manual inspection we found that all of these accounts are related to companies or products and it seems that Twitter allows them to exceed the rate limits. For instance, a verified Twitter account of a major credit card company sent $\geq 10{,}000$ Tweets on multiple days—more than four times the rate limit of ordinary users. It is unclear at that point whether this service comes with a price tag. Recently, Twitter has started to offer that developers can request *elevated POST access*.[c] To potentially get that elevated access, Twitter describes a process that requires a "short description of your use case". We do not know at this point whether *regular* spammers will be granted elevated access, but the process suggests that this service is geared towards business accounts.

c. *In-syncs*. We found another group of accounts that is over-represented in the Sample API but that does not show characteristics of the first two groups. When inspecting these accounts in detail, it turned out that Twitter's Sample API sampling approach is very prone to being unintentionally tampered with by frequency bots, i.e. automated accounts that tweet, for example, the temperature of a weather station exactly every 10 minutes. When Tweets are sent time-triggered, the millisecond timestamps of the sending is constant. Consequently, the arrival time on a Twitter server and the ID assignment will also fall roughly into a constant time range. Each one of these time-triggered accounts has a 1% chance this arrival range is within the sampling time window, i.e. the account accidentally hitting the 1% sampling time window. Any of the successful automated accounts that are accidentally synchronized with Twitter's sampling time window for a certain amount of time will hit that time window on a regular basis resulting in over-representation of the account in the sample. Conversely, the many that miss this millisecond window will be invisible through the lens of the Sample API. We found 11 (4.5%) frequency bots in our dataset and found similar numbers in other observations. Current research estimates that 9–15% of all accounts on Twitter are bots [58]. Consequently, with 328 million monthly active users, we estimate that about 1.3–2.2 million frequency bots are currently accidentally polluting Twitter's Sample API.

Tweet scheduling tools. By looking at the lower ranked accounts in addition to the top 1000 accounts, we identified another potential source of misrepresentation in Twitter's 1% Sample API that can be seen as *human in-syncs*. An unknown number of regular human user accounts that employ Tweet scheduling tools might have similar millisecond signatures as frequency bots, since time-triggered sending events can have the potential to sync users with Twitter's servers. However, since human users on average tweet considerably less, the overall impact on sample quality will be negligible in this case.

6.1 In-syncs and the flipped sample

Here, we want to hypothesize the effect that the above mentioned in-syncs can have on Twitter's sampling procedure. This also shows how decisions related to a system's design and inner workings can pollute the integrity of a sample. We created a time-triggered frequency bot that sent 4512 Tweets, one Tweet exactly every 42 seconds. As the sending events have non-random milliseconds timestamps, the Tweet-IDs also show non-random milliseconds values. Figure 6 displays the distribution of milliseconds extracted from the Tweet IDs of theses Tweets. 58% of all Tweests are in the 10 milliseconds time interval [778–787] while no single Tweet out of 4500 is in the 1% Sample API selection window. Consequently, Tweets from this account are completely muted from the 1% Sample API. [d] It is important to realize at this point, that these results are a random artifact of the sending time—no purposeful manipulation was applied for this experiment. However, based on the previously described binomials, the chance for having 4512 consecutive Tweets outside of the 1% Sample API selection window is $1:2x10^{-20}$. This examples also shows that the time delay from sending a Tweet till the Tweet is assigned a Tweet ID is fairly stable.

While seemingly innocuous, this can have interesting effects on the resulting sample data. While in terms of the overall numbers, Twitter's 1% sample might still be close to 1%, the above-described dynamics have change sample composition, which can be called a *flipped sample*. For any given data collection period, we might get an extensive sample of Tweets sent from about 1% of these time-triggered accounts, namely, those that are temporarily synchronized with Twitter's sampling time window. At the same time, however, the clear majority of these accounts, which are out-of-sync with the Sample API, will be under-represented to the point of being almost invisible (cf. Figure 6B). This demonstrates that not only is it subject to spammers, but possibly to regularly-tweeting bots that are fortunate to always have their tweets selected, or unfortunate enough to never have their tweets selected. In this way, this selection mechanism inadvertently censors, or

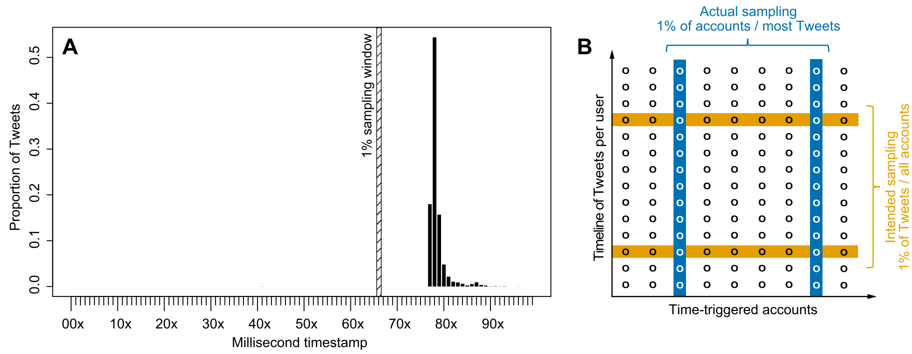


Figure 6 Twitter's tampered samples. (**A**) Sampling artifact created by a time-triggered frequency bot. For several hours, we sent a Tweet exactly every 42 seconds. The bar-graph shows the distribution of milliseconds of the Tweets's ID. Most Tweets are in a very narrow range, none is in the 1% Sample API time window. (**B**) Schematic representation of Tweet selection process for time-triggered accounts (x-axis). Accounts send Tweets (circles) over time (y-axis). Statistically sound sampling would give every Tweet from every account the same chance of being in the sample. Instead, Twitter's sampling mechanism selects a large amount of Tweets from about 1% of time-triggered frequency accounts for any time period

over-samples accounts based on a feature that has nothing to do with the composition of the Tweet.

7 Proposals for a solution

In this paper we have demonstrated a flaw in the sampling mechanism underpinning Twitter's Sample API. We have demonstrated that this can be used to skew the analysis done from this API. While sampling can be a feature in the sense that it would allow us an scientifically sound view into a large swath of data, this is precluded by Twitter's biased sampling methodology, which is hampered both by bias by design and purposeful manipulation.

The problem stems from Twitter using information in the Tweet itself to decide whether or not a Tweet is selected. An approach that does this will be vulnerable to the same or a similar attack. Fortunately, it is relatively straightforward to design approaches that do not depend on any information in a Tweet. A straightforward approach would be to draw a random number from a binomial distribution with $p = 0.01$ when a tweet arrives at Twitter's servers.

However, we do recognize that there might be reasons for Twitter to make the sampling decision *repeatable*. For instance, if a single Tweet is stored in multiple locations and the Sample decisions need to be made decentralized in order to create the same samples in all locations. In this case, the sampling feature needs to depend on information in the Tweet. A minimum change from the current system would be a random set of unconnected milliseconds. Hitting a single millisecond is harder, but still possible—we found accounts in our data that had 90+% of all Tweets in a single millisecond. In addition, this set of milliseconds could change periodically and the set is calculated from non-Tweet information, e.g. an internal signal.

Another option to create *repeatable* sampling decisions can be accomplished with hash functions on the text of the Tweet (or even metadata). Reverse engineering of a specific hash function would be hard. On the flip side, any sampling decision based on Tweet content or metadata could accidentally bias against Tweets with certain keywords, written in certain languages, or being sent from certain locations.

According to our observations, there are indeed *corporate spammers* flooding Twitter and its data samples with Twitter's permission. This does not just impact the Sample API but also the Filter API in case researchers or practitioners are collecting Tweets including keywords used by these accounts. The problem of corporate spamming could be tackled if Twitter marked accounts that are allowed to exceed rate limits. Analysts could then consider those, improving data quality of both the Sample API and the Filter API.

From researchers' perspective, the metrics presented in this article offer methods to identify and remove this kind of over-sampled accounts from Twitter's Sample API and can serve as features for bot detection.

8 Discussion and conclusion

Twitter has become the *de facto* core dataset for computational social science, and a large share of literature analyzing social media relies on samples drawn from its platform. Despite being one of the most open social media companies in terms of sharing data, even Twitter does not reveal details about its data handling and sampling strategies. Statistical validity and sampling techniques are at the heart of every empirical research design and are crucial for correct analysis and valid results. Whereas the randomness of random samples allows researchers to interpret their results in reference to the full dataset, the observed sampling technique based on the Sample API does not give all data points an equal chance of being selected.

Our insights into the flaws in Twitter's supplied sampling mechanism confirm and even amplify a broad concern: Twitter cannot provide scientifically sound random samples via its Sample API.[e] Moreover, by making Tweets appear up to 84 times more likely in the sample than expected, it is possible to deliberately influence the extent and content of any topic in the Sample API. The data are also tampered by automated accounts or bots through the unintentional side effects of platform logic and system architecture. Consequently, any account can be used to manipulate the analyses of researchers, journalists, and policymakers trusting that data source.

Our experiments followed careful considerations in order to limit the extent and time of our intervention (see Appendix 1: Research Ethics Statement). Our experiments were performed with 100 Twitter accounts that we had manually created for the purpose of these experiments. All experiments were conducted on a single office computer. Even though the resources needed for these experiments were very small, the impact on major topics was clearly visible; all of this was done just a few days before the very contested 2016 US Presidential Election. Based on state-of-the-art bot research [58], we would expect 30–50 million bot accounts on Twitter. There is evidence in the scientific literature for bot farms that harness hundreds or even thousands of times the number of accounts used in our experiments [75]. Every single one of these bot farms has greater potential to manipulate Twitter's Sample API at any given point and for longer periods of time.

The intentional or unintentional tampering that we have described in this article does not distinguish between the publicly available 1% Sample API and the 10% academic Sample API only available to a small number of researchers. Since the sampling mechanism of the 10% enterprise Sample API is also based on millisecond time windows, we will expect the same vulnerability for the costly data sample, unless Twitter has additional mechanisms that protect the integrity of this sample. From all we know, paying thousands of Dollars a month for elevated access does most likely not prevent potentially tampered data.

While the biases and potential tampering illustrated in this article are not inherent to big data as a methodology for the social sciences, the results of our analyses illustrate critical issues that come from doing research with proprietary data and undisclosed details about data handling. This problem points to a characteristic misconception of current expectations of big social data: most of the time we cannot work with full datasets due to constraints in methodological, infrastructural, and financial resources, so we rely on sampling.

Social media analytics are still met with high expectations, despite the nebulous understanding of big data and the challenges of their handling and analysis. Evidence-based policy making and data-driven modes of governance however need to take into account that they are at the mercy of data quality and sampling/filtering techniques. In daily research routines of social media analytics and big social data, we do not work on entire populations. Predictive methods and profiling approaches too often rely on access to samples of social media data and need to trust black box interfaces. Therefore, the need for sampling is not "an artifact of a period of information scarcity" [76]; in fact, it is even more of a necessity in times of information abundance.

Our study points to some of the pitfalls of regarding Twitter research as an end in itself and calls for responsible handling of Twitter data. To make Twitter a reliable data source for future research, especially in the social sciences, we must find ways to create scientifically sound samples from these data streams. The sharing of data should always be accompanied by open methods and transparent algorithms to give researchers and practitioners a fair chance to better know and assess the data at hand. Increasing the transparency of data collection and the integrity of research design and analysis should be in the interest of both the social media industry and the research community and would also enhance public trust in the methods and findings of computational social science.

Appendix 1: Research ethics statement

Our research was not subject to the Ethics Commission at Technical University of Munich (TUM), where the experiments were conducted. The focus of our work was on volume, not content or sender. Only public Twitter data were used. We were not interested in Personal Identifiable Information (PII). No analysis of PII was performed and no PII will be released. We consider our experiment as being *"not human-subjects research"* in line with the National Academy report (2014) and the definitions of the Office for Human Research Protections https://www.hhs.gov/ohrp/regulations-and-policy/regulations/45-cfr-46/index.html#46.102. The US National Academy report declares: "New forms of large-scale data should be included as not human-subjects research if all information is publicly available to anyone (including for purchase), if persons providing or producing the information have no reasonable belief that their private behaviors or interactions are revealed by the data, and if investigators have no interaction or intervention with individuals. Investigators must observe the ethical standards for handling such information that guide research in their fields and in the particular research context." *(National Academies Press, 2014: 4)*.

A.1 Minimizing risk and intervention

However, we are aware that just because data is publicly available does not mean that rules for research ethics do not apply. Our realistic experiment was carefully designed for minimal risk and intervention. It was necessary to further reverse-engineer the sampling process to get authentic insights into the architecture and logic of the platform.

Our study design does not focus on interaction or intervention with individual Twitter users. On the contrary, we created Twitter accounts for the purpose of our study that did not aim at establishing individual interactions on the social media platform. Our experiment aims at making visible how user interactions with the service and its technical architecture work. Our research has nevertheless an interventional dimension directed to the data and not to the users, which is necessary to test and document the possible ways of manipulation of data sampling on the Twitter platform. By doing so, we did violate Twitter's *Automation rules*, in particular the "Do not abuse the Twitter API or attempt to circumvent rate limits" rule. This was necessary since Twitter does not reveal its sampling method in detail, which would be essential for research integrity of studies using these data. However, we took the following measures to make these interventions as subtle as possible:

(A) User IDs of our bot accounts can be found in Appendix 2 of this article. Tweet IDs of all our 15,207 Tweets that made it into the 1% Sample API can be found at http://www.pfeffer.at/data/tampering, so that other researchers and practitioners analyzing the affected time-period can remove them easily.

(B) We have deleted all our Tweets after the experiments. When Tweets are deleted, a delete-message is sent via the Streaming APIs. According to Twitter's terms of use, people who collect data with these APIs are requested to delete all Tweets for which delete-messages are sent. Deleting a Tweet also covers Retweets, as all Retweets of a deleted Tweet also get deleted from Twitter, and consequently, delete-messages for the Retweets are sent via the Streaming APIs.

(C) We did not try to hide our Tweets and our Tweets did not deliver any specific message. In contrary, the content of our Tweets was random, except for the two hashtags #imwithher and #trump. The Tweets were either created by randomly selecting text from other people's Tweets or, in case of the sentiment experiments by randomly selecting words marked as "positive emotions" in the LIWC [68] dictionary. Here are some examples of random Tweets for the #trump sentiment analysis experiment:

- #trump plays shares casual luck loves
- #trump goodness careful sunniest appreciate helps
- #trump true value truly yay free
- #trump truer kind awesome hopefully heartfelt
- #trump casually graced beauty save pleasing

Appendix 2: Accounts used in our experiments

In order to send the Tweets for our experiments, we created these 100 Twitter accounts:

beatriz_kittle	JuergenTest	MclemoreDonny	rolandbass5611
BiancaBerends	juniorfritz5321	MercedezLohse	RubyePuls
brendapenn1741	kacie_mccart	MinnaBruning	RuggHeide
broderick_komar	kalis_mikel	ModeArletha	sanjuanacolung1
bromley_arvilla	karri_sin	NakayamaAilene	SantoHedrick
charlettebeauv2	kelly_stoneking	nannettemarkow2	SchoemakerFay
costin_neal	KinzerJerold	NellieGoodlett	SchurgDorian
danelleschroet2	KoskiCatheryn	nicolasabanner2	SellnerDinah
delpino_derek	KymberlyCamburn	NidiaDabney	SerinaLasker
delvalle_lavada	LaphamElois	NinjaGilbertjef	SobelSheron
Diesel_Lenard	LockeClint	NorbergBerenice	StaceyMuszynski
EmikoBeckwith	lorainepreside2	ObduliaBurgoon	stefaniaheinze1
EnriqueBorman	lorene_wilhite	OrickJacque	SteffanieKoger
fredrickairahet	luigiweatherbe1	packard_rosana	taraconnor3741
GemaDwight	LumsdenAlmeda	ProwellMaragret	TemikaPlatt
GeralynGaulke	LunaGarman	PuleoJung	TheaParmelee
GordilloSalvad	lyda_trinity	purkey_rickey	TillieKoziol
GreggBourgeois	MarciaBeaudette	PushardAlysia	TokarLatesha
HaworthAsia	marcotte_shon	PyburnEmmett	tracisolis9531
HiebertJanyce	margoriemcnaug2	quincymarc192	TwistedPainelis
hy_junita	MargrettJoachim	RebekahLacoste	VanishHans
jalisakirkwood1	MaroisChristene	RexAlvardo	VicentaDebow
JesusaAxley	marquettachron2	riley_bently	VickisabatSabat
JinkinsDanielle	MarrowCaryn	RisaCaraballo	YokoyamaBreanna
JohnieBreneman	MatzLucretia	RohdeEulah	ZiemannLarry

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List of Abbreviations
API, Application Programming Interfaces; REST API, Representational State Transfer; UTC, Coordinated Universal Time; LIWC, Linguistic Inquiry and Word Count.

Availability of data and materials
A discussion of ethical considerations is presented in Appendix 1. Accounts used for experiments are listed in Appendix 2. IDs of all our Tweets in the 1% Sample API can be found at www.pfeffer.at/data/tampering. Source code of Python scripts is available in Github repository: https://github.com/fredzilla/sample-api-timings.

Competing interests
The authors are neither affiliated with nor in collaborative agreements with Twitter or any competing social networking platform.

Authors' contributions
All authors contributed equally to all parts of the article. All authors read and approved the final manuscript.

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Endnotes

[a] Looking at Fig. 2B, between the first and last Tweet from our accounts (the blue area) several time periods with none or very little of our Tweets are in the data. While the lack of Tweets on Nov. 4, 3pm–8pm is on purpose, the negative spikes on Nov. 4, 1pm and Nov. 5, 2am are the result of our sending script being interrupted.

[b] Success rate depends on Internet connection speed and stability of web traffic to a Twitter server.

[c] Rate limit enforcement update posted on October 22, 2018. Source: https://twittercommunity.com/t/new-post-endpoint-rate-limit-enforcement-begins-today/115355

[d] This experiment was conducted in early December 2017.

[e] All biases and potential tampering found in this article only affect the Sample API, not the REST and Filter APIs.

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