The Impact of Viral Posts on Visibility and Behavior of Professionals: A Longitudinal Study of Scientists on Twitter

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Abstract

On social media, due to complex interactions between users' attention and recommendation algorithms, the visibility of users' posts can be unpredictable and vary wildly, sometimes creating unexpected viral events for 'ordinary' users. How do such events affect users' subsequent behaviors and long-term visibility on the platform? We investigate these questions following a matching-based framework using a dataset comprised of tweeting activities and follower graph changes of 17,157 scientists on Twitter. We identified scientists who experienced 'unusual' virality for the first time in their profile lifespan ('viral' group) and quantified how viral events influence tweeting behaviors and popularity (as measured through follower statistics). After virality, the viral group increased tweeting frequency, their tweets became more objective and focused on fewer topics, and expressed more positive sentiment relative to their pre-virality tweets. Also, their post-virality tweets were more aligned with their professional expertise and similar to the viral tweet compared to past tweets. Finally, the viral group gained more followers in both the short and long terms compared to a control group.

Introduction

Online platforms for professional networking (e.g., LinkedIn) grew tremendously over the last decade. Although such professional networking channels exist, general-purpose social platforms (e.g., Facebook and Twitter, where the boundary between professional and social communications is often blurred) are still being used as major channels for professional communication across science (Meishar-Tal and Pieterse 2017; Ke, Ahn, and Sugimoto 2017), business (Sivarajah et al. 2020), and politics (Buccoliero et al. 2020). Scientists, who serve multiple audiences, including their peers, their institutions' administration, the public, and others (Kozinets 2017), and face pressures to develop an online presence and digital personae (Duffy and Pooley 2017), may benefit from participating in an open network such as Twitter.

Online platforms facilitate interactions among vast numbers of people from diverse backgrounds, and occasionally 'viral' events stem from such complex interactions. Going 'viral,' where a tweet is "spread quickly and widely" (Jenders, Kasneci, and Naumann 2013), may have life-changing impacts on individuals, both favorable and adverse. For example, individuals have gained internet fame (Stampler 2014) and career opportunities (Arató 2019) after memes[1] featuring them went viral. Contrarily, people faced severe personal and social consequences after memes featuring them went viral (Amon et al. 2020; Hasan et al. 2021), and they lost their jobs and faced social embarrassment after their tweets were judged as inappropriate and caught the attention of the news media (Ronson 2015; Strehlke 2015). Although such massive viral events are rare for ordinary people, smaller-scale viral events that reach a 'much larger than average' audience for the person posting the tweet occur more frequently. We term such events as 'micro-viral events.' How does experiencing such micro-viral events for the first time affect social media users, particularly those who use the platform for professional purposes? Do the users alter their behaviors, e.g., by increasing platform engagement? Do such events help the users achieve higher levels of visibility in the long-term?

In this paper, we examine these questions using a longitudinal dataset of scientists on Twitter and a matching-based causal inference method (Stuart 2010). Specifically, we study how *anomalous*, micro-viral tweets—tweets with an unusually large number of retweets for the particular user but that would not necessarily be considered viral in the traditional sense—affect scientists' subsequent tweeting behaviors and their popularity on Twitter. Concretely, we examine how scientists reacted to such exposures and whether they used this *sudden* popularity to promote their professional self, such as by adopting specific strategies to create additional viral events. We further examine if these events help accumulating followers, the 'social capital' in the virtual world. We focus on Twitter because of its increasing popularity among scholars for professional purposes and its general-purpose nature; indeed, a majority of scholars use Twitter primarily to fulfill professional goals (Yu et al. 2019). Scholars use Twitter to attract potential employers (Radford et al. 2020), advertise academic positions (Guzman, Alkadhi, and Seyff 2016), build an 'expert' identity (Han 2020; Dauenhauer 2020), and connect with

[1]Merriam-Webster defines a 'meme' as "an idea, behavior, style, or usage that spreads from person to person within a culture." https://www. merriam-webster.com/dictionary/meme

peers and related associations to build a community (Mohammadi et al. 2018). Additionally, Twitter's public nature facilitates complex and unexpected interactions that breed viral events, thereby making Twitter an appropriate and attractive platform to study our research questions.

We study the following research questions:

RQ1 Do micro-viral events influence people's tweeting behaviors on Twitter (e.g., changing tweeting frequency, sentiment, objectivity, and topics of tweets, and posting tweets that are more similar to the viral tweets and relevant to the users' professional expertise)?

RQ2 Do micro-viral events influence short- and long-term visibility on Twitter (i.e., follower gain or loss)?

We study the impact of micro-viral events on the posters of a tweet using a matching-based inference framework on a longitudinal Twitter dataset. The dataset was collected over a period of more than two years and eight months. During that time span, we monitored 17,157 Twitter users, who were identified as scientists (Ke, Ahn, and Sugimoto 2017), and recorded their tweeting activities and changes in the follower graph using the Twitter API. From this data, those who experienced micro-viral events (the 'viral group'; for simplicity, in the rest of the paper we will omit the designation 'micro' unless we want to highlight the features of our definition; the formal definition of micro-viral events is provided below) *for the first time* since they started using Twitter were identified. Using a matching procedure, we identified a 'non-viral' control group of users who never experienced virality but had a similar profile and tweeting activities as the users in the viral group (until the viral event). By comparing these two groups, we quantified the impact of micro-viral events on viral users' behaviors and the short- and long-term visibility (follower gain or loss).

Our findings suggest that micro-viral events changed scholars' tweeting behaviors. After a viral event, viral scholars tweeted and retweeted more frequently compared to their matched non-viral counterparts. Compared with their pre-virality tweets, they also posted tweets i) with a higher positive sentiment, ii) containing more factual information, iii) focused on fewer topics, and iv) similar to their first viral tweet. Additionally, viral events facilitated short- and long-term follower gains, and expanded one's reach to the general public. These findings add to the understanding of the use of social media to promote professional reputation by scholars and people in other professions where reputation helps to advance their careers.

Background and Related Work

Scholars' Use of Twitter

Jordan and Weller identified four reasons for using social media platforms by academics: maintaining a personal learning network, promoting the professional self, promoting and seeking research publications, and advancing one's career (Jordan and Weller 2018). Maintaining presence on online platforms (including Twitter) was regarded as creating a 'digital self,' where academics promote themselves in a competitive environment (Shah and Cox 2017; Radford et al. 2020; Mohammadi et al. 2018; Lemon, McPherson, and Budge 2015). Twitter provides a unique opportunity for scholars to communicate science to the public (Côté and Darling 2018; Dudo and Besley 2016; Mohammadi et al. 2018) as Twitter is open to all and tweets are, by default, public. Scholars use Twitter to share research ideas (Dauenhauer 2020) and build collaborations (Mohammadi et al. 2018) that may directly benefit professional success. Twitter facilitates continued discussion and collaboration during academic conferences (Li and Greenhow 2015; Kimmons and Veletsianos 2016). In this paper, we go beyond understanding *why* and *how* scholars use twitter, and study how unexpected, but perhaps desired, events (such as viral tweets) help them achieve their identified goals, such as getting a community's attention, and if and how impacted scholars capitalize on such events by changing their behaviors on the platform.

Defining and Identifying Micro-viral Events

Previous research characterized 'viral' events from different perspectives. Jenders et al. indicated a tweet as viral when the number of retweets it had received exceeded some threshold (such as 50) (Jenders, Kasneci, and Naumann 2013). Subbian et al. considered a tweet as a viral tweet when it received a higher number of retweets compared to other tweets (e.g., 90th percentile) (Subbian, Prakash, and Adamic 2017). More complex measures of virality have also been proposed that consider the structural properties of the diffusion, such as the depth of the cascades (Dow, Adamic, and Friggeri 2013) and the average distance between all pairs of nodes in a diffusion tree (Goel et al. 2015). By contrast, we characterized a tweet as a micro-viral tweet if it had received a higher number of retweets compared to other tweets of the *same* user, as our goal is to measure the impact of viral events that are rare and unusual for the person who experienced them, even if they would be unremarkable for highly popular users, which is why we call them micro-viral events.

Impact of Viral Events and Strategic Behaviors

Prior research has shown that viral events help accumulate followers (Myers and Leskovec 2014). Such events may help scientists reach people outside of specific research fields or even scientific professions (Côté and Darling 2018). Such unusual but desired attention from peers may increase (or decrease) scientists' engagement to the platform and their tweeting behaviors (Adelani et al. 2020). In particular, we aim to detect if scientists' behavioral changes are directed to increase the odds of receiving more attention (e.g., subsequent viral tweets) and accumulate more followers. Prior research has shown that frequent tweeting promotes follower accumulation (Schnitzler et al. 2016). Regarding content, Berger and Milkman found that content expressing positive sentiment were more likely to go viral (Berger and Milkman 2012). Schnitzler et al. advocated scientists to maintain objectivity in tweet content (i.e., free from personal bias) and engage in professional conversations with fellow scientists (Schnitzler et al. 2016). In this work, we investigate whether scholars demonstrate more of these behaviors, and several others, after achieving virality, even if it is a small degree of virality.

Method

Establishing causal effects with observational data is challenging, as it is difficult to eliminate all non-causal explanations (Shalizi and Thomas 2011). Here, we employ a matching method with a longitudinal database of tweeting activities and follower accumulation to compare outcomes experienced by viral and non-viral users after viral events. To create this dataset, we followed 17,157 scholars on Twitter from July 1, 2017 to February 15, 2020 and collected their tweets, retweets, and changes in followers over time. Using this dataset, we identified users who experienced micro-viral events (we call them 'viral users') for the first time in their profile's lifespan. Although viral events may influence future interactions and follower gains/losses on Twitter, simply comparing tweeting behaviors and the number of followers of viral users before and after viral events would lack a counterfactual. Thus, to isolate the impact of viral events, each viral user was matched with a user with a similar number of followers and tweeting behaviors up to the point of the viral event but who never experienced virality. This matching procedure approximates controlled experiments (Ho et al. 2007) and allows for stronger inference from observational data. Although it is impossible to rule out possible influences of unobserved confounders (e.g., factors that affect both the ability to create engaging tweets that go viral and attracting large followings), by comparing how the tweeting behaviors and number of followers of viral vs. non-viral users diverge after a viral event, we provide a stronger argument for a causal relationship between the viral event and the observed changes than simply examining correlations.

Data collection procedure

Selecting the initial set of users. Our dataset builds on previous research on the use of Twitter by scientists (Ke, Ahn, and Sugimoto 2017). Their dataset comprised of 45,867 Twitter users, a majority being scientists or researchers. Since Twitter API has rate limitations (Twitter 2020), we selected a subset of the users for continuous data collection as follows. First, we identified the "novel tweets" (i.e., not a retweet, but can be a reply to another tweet) of each user in the initial dataset with the highest number of retweets to date (the 'peak tweet'). Then, the difference between the average number of retweets for tweets posted *before* and *after* the 'peak tweet' was calculated. After sorting users based on these values, the top 3,000 and bottom 3,000 users were selected for continuous monitoring. This set, therefore, contains users with the maximum 'ups' and 'downs' during their profile lifespan. We extended and diversified this set in two ways: A) users who had at least one tweet with 50 or more retweets were included, resulting in a set of 8,157 users and, B) a random sample of 9,000 users who never had a tweet with 50 or more retweets were included, totaling to 17,157 users. From July 1, 2017 to February 21, 2020, we continuously collected tweets posted by these users and changes in their follower graphs. This data collection procedure was approved by our institute's ethics board.

Selecting the final set of users. We monitored 17,157 users, but data from many of these users were discarded for various reasons that we describe in this section. We aimed to detect 'anomalous' viral events that were experienced by the users for the first time. The Twitter API provides a maximum of 3,200 past tweets of a user. Thus, we discarded 5,573 users who had posted more than 3,200 tweets before we started monitoring them. Next, users who either deleted their profiles or made them 'protected' (N=3,113), or did not post any tweets (N=762) during the data collection period, were removed. From the remaining users, 753 (9.7%) were identified as bots by the Botometer (Varol et al. 2017) (using a classification threshold of 0.49 as suggested by the authors of Botometer (Varol et al. 2017)). After this step, 6,956 users remained in the final set.

Defining and detecting micro-viral tweets

We consider a tweet as a *micro-viral tweet* only if it was both *popular* (in 'absolute' terms, although using a relatively low bar) and *unusual* (in 'relative' terms with respect to the user's past tweets). These criteria exclude some of the hugely popular tweets (e.g., by celebrities or politicians) because people with larger followings may regularly garner large numbers of retweets. Therefore, in our definition, we use both the absolute number of retweets and how anomalous it is for a given user, which is estimated by the z-score of the number of retweets. We chose 50 as the absolute threshold for retweets based on a previous study (Jenders, Kasneci, and Naumann 2013), which shows that retweets follow a Pareto distribution and only 4% of tweets get 50 or more retweets.[2] Thus, at first, we identified all tweets of a user with at least 50 retweets and included them in the set of 'potential viral tweets', T, for that user. Then, for each tweet $t \in T$, the z-score was calculated using the mean and standard deviation of retweets for tweets posted within the 10 weeks before t. If the z-score of a tweet was above eight, it was classified as a 'viral tweet.' Below, we explain how the 10-week time window and z-score threshold of eight were determined.

We chose 10 weeks as the window for calculating the z-score based on the auto-correlation of the users' weekly tweeting frequency as follows. First, for the duration of our data collection period, each user's weekly tweeting frequency was represented as a time series. Then, the auto-correlation coefficients of that time series was calculated for lags ranging from 1-to-20 weeks. For each time lag, we computed the mean, standard deviation, and 95% confidence intervals of the auto-correlation coefficients across all users (Figure 1). We selected 10 weeks because this is the longest time duration with mean correlation coefficient greater than

[2]We experimented with other threshold values: 75, 100, and 150. But using higher values simply resulted in a smaller set of viral users, without any qualitative change. For example, using 100 as the threshold returned a *proper* subset of the set of viral users who were identified using 50 as the threshold. This was true for other higher thresholds as well.

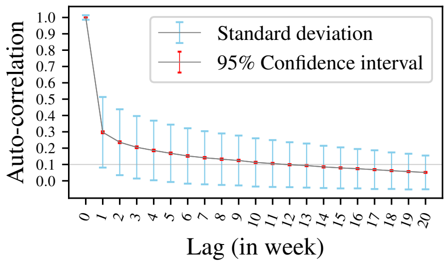

Figure 1: Auto-correlation of tweeting frequency per week.

0.1, indicating that the users' tweeting behavior had some consistency over this time interval.

The threshold for z-score was selected with the goal of maximizing the number of users who had only one viral event. This selection criterion would maximize the extraordinary aspect of the event for an user and minimize the number of users with subsequent viral events so that the effect of the first viral event on the outcomes could be isolated. To do that, we computed the percentage of users with a single viral event for different thresholds of z-score (ranging from two to 30) and chose eight since this maximized the number of such users.

Using these thresholds, we identified 1,610 tweets from 758 users as 'viral' events. Of them, 409 (54%) users had only one viral event and 68 (8.9%) users had 5 or more viral events.

Matching Procedure to Create the Control Group

To isolate viral events' influence on users' behaviors and follower gain, we created a control group to compare with the viral group. For a 'fair' comparison, users in the control group should have similar follower networks and tweeting behaviors as those who experienced virality (Stuart 2010) until the viral event (after which the groups might diverge). Thus, each user in the *viral group* was paired with the most 'similar' user from the 'non-viral group', and these matched non-viral users formed the control group.

Selecting covariates for measuring 'similarity' between a viral and a non-viral user. The similarity was measured based on the following variables: number of followers, number of *novel* tweets (i.e., not a retweet, reply, or quoted tweet) and average number of retweets, URLs, and hashtags. These covariates were selected based on relevant literature. Prior research has shown that tweeting frequency, number of followers, and including URLs and hashtags in tweets were associated with obtaining large retweets (Suh et al. 2010; Schnitzler et al. 2016). We included *average number of retweets* to pair users whose tweets usually received similar attention. Although account age may influence retweets (Suh et al. 2010), we omitted it since many Twitter users remain inactive after creating their profiles (Ruhela et al. 2016). We also omitted sentiment and emotion of tweets as many viral and non-viral users had posted only a few tweets and thus estimations of affective properties may be unreliable. Including these variables would also increase the large number of covariates and may result in a poor similarity measure in the Euclidean space (Stuart 2010).

	Viral users		Non-viral users	
	Before	**After**	**Before**	**After**
Tweets	34.36 (51.68)	38.94 (115.58)	27.97 (47.22)	24.32 (38.30)
Retweets	5.14 (7.70)	9.93 (21.68)	4.20 (6.29)	3.94 (12.63)
URLs	0.75 (0.25)	0.81 (0.24)	0.76 (0.25)	0.78 (0.30)
Hashtags	0.37 (0.47)	0.33 (0.44)	0.38 (0.52)	0.39 (0.52)

Table 1: Mean (SD) number of tweets and retweets, URLs, and hashtags per tweet in 10 weeks before and after viral events.

Estimating covariates. The identified covariates were estimated as follows. For viral users, the number of followers was equal to how many followers they had immediately prior to their respective first viral event. Covariates whose value depended on tweets (e.g., the average number of URLs) were computed using tweets posted by viral users within 10 weeks prior to their respective first viral event. For non-viral users, the covariates were computed based on the viral users with whom they are being compared to measure similarity. Thus, while computing the similarity between a *non-viral* user and a *viral* user, tweets posted by the *non-viral* user within 10 weeks before the first viral event of the *viral* user were used to calculate the covariates, and the number of followers was equal to how many followers the non-viral user had immediately before the same viral event. Measuring similarity based on covariates computed prior to the viral events ensures that no covariate was affected by the treatment (the viral events in our case) (Stuart 2010). The 10 week period was selected by observing the consistency of users' behavior within this interval. Table 1 shows covariate estimates for the two groups before and after the first viral events (the number of followers is not shown as they were computed just before the viral events).

Matching with the Nearest Neighbor in an Euclidean space. All users were embedded in a Euclidean space defined by the covariates as axes. The z-scores of the covariates defined the position of the users in that space. Then, each viral user was paired with the closest non-viral user as identified by the *k-nearest neighbor (KNN)* algorithm (with $k = 1$). We used z-scores of covariates instead of raw values in the matching procedure since the covariates feature widely different ranges. For example, number of followers varies in the order of thousands, while the average number of hashtags per tweet has a range of zero to one. Thus, if these raw values were used, covariates with smaller ranges of values would have been ignored while computing the distance between two users in the Euclidean space. Note that using z-scores does not disregard the correlations among covariates while computing the distance since it only normalizes with variance and not co-variance.

Our goal was to find unique matches; one way to achieve this was to match without replacement: once a non-viral user had been matched with a viral user, we discarded the non-viral user from the pool of potential matches for subsequent viral users. But the result from this procedure would depend on the order in which non-viral users were considered for matching and may not result in the best possible matched pairs. We avoided this shortcoming by considering all non-viral users as potential matches for all viral users, pairing two users when they had the smallest distance among all potential pairs. This resulted in duplicate matches, which we resolved with an iterative procedure outlined in Algorithm 1 and explained in the following section.

At first, this algorithm finds N non-viral users who are nearest to a viral user (N was set experimentally, see below). Then, it matches the closest (non-viral) neighbor with the viral user. But that non-viral user may be nearest to more than one viral user, creating duplicate matches. It then finds and removes duplicate matches iteratively. In each iteration, it identifies a non-viral user who was matched with multiple viral users. Then, the match with the lowest distance was retained and the non-viral user was removed from all other matched pairs. The viral users in those pairs were re-matched with the next nearest neighbor (from the initial set of N neighbors that were matched with each of them). This process continues until there are no duplicate matches anymore, or it is not possible to find a unique match for every viral user. The latter can happen when N is too small and it becomes impossible to re-match a viral user after detecting a duplicate match. We experimented with different values of N and found that setting $N = 10$, i.e. initially identifying 10 nearest neighbors for each viral user, was sufficient to obtain unique matches. This procedure identifies the best possible unique matched pairs regardless of the order of matching.

Data: Set of 'viral users' and set of 'non-viral users'
Result: Returns subset of users from 'non-viral user' group each of who was matched against one of the users in 'viral group'
N=10
foreach $u_1 \in$ *'viral group'* **do**
    find the set V of the closest N users of u_1 from 'non-viral users' in terms of the co-variates using nearest neighbor search;
    Sort these N neighbors in V according to their distance from u_1 in the ascending order and match u_1 with its closest neighbor v;
    set $V = V - \{v\}$;
end
while *not all users in 'viral group' have unique match* **do**
    foreach $u_2 \in$ *'non-viral group' who were matched with more than one users in the 'viral group'* **do**
        let U is the set of users who were matched with u_2;
        find the user $u \in U$ who has the minimum distance with u_2;
        foreach $u_1 \in U - \{u\}$ **do**
            remove u_2 from the neighbors of u_1, (i.e. set $V = V - \{u_2\}$)
            if V *is empty* **then**
                Error('Failed to find unique match for all users in viral group');
                Exit();
            end
            else
                match $v \in V$ with u_1 where v has the minimum distance with u_1;
            end
        end
    end
end

Algorithm 1: Procedure for finding unique matched pairs.

We further enhanced the comparability between matched pairs by removing pairs that had distances larger than one standard deviation, resulting in 670 matched pairs.

Evaluating the quality of the matching procedure. To assess the balance in the *observed* covariates in the matched sample, we compared the standardized mean differences (SMD) of the covariates for the matched pairs using our algorithm with SMDs for randomly matched pairs (Zhang et al. 2019). We conducted 100 trials of the random matching, computed the mean SMDs of the covariates across these trails, and compared them with the SMDs for the pairs matched by our algorithm. As Fig. 2 shows, all covariates except the number of followers had much smaller differences when matching was performed using our algorithm compared to random matching. We followed up this analysis with significance tests to examine whether differences in means are negligible for the matched pairs (see Table 2). The significant differences between covariates disappeared after matching, indicating that the paired viral and non-viral users had comparable follower networks and tweeting behaviors before viral events.

To assess the balance in the *unobserved* covariates, we conducted sensitivity analysis for three outcomes: change in followers after 10 weeks, change in followers at the end of data collection period, and change in the proportion of 'scientist' followers (see below for details on outcome variables). Note that the remaining outcome variables (e.g., tweeting frequency) cannot be used for sensitivity analysis since they were not compared between the viral and non-viral group; rather, they were compared within the viral group at two time points (i.e., before and after viral events). Figure 3) shows the results from sensitivity analysis using Rosenbaum bounds (Rosenbaum 2014), where the grey horizontal line indicates $p = 0.05$.

We hypothesized that viral events would positively impact follower-change. Thus, for the two outcomes related to follower-change, we plotted the upper bound of p-values (Rosenbaum 2014). As the plot shows, virality affects both outcomes in the expected direction, and the effects become insignificant (i.e., $p >= 0.05$) only after bias due to unobserved confounders (i.e., γ) exceeds 4.5 and 3.5, respectively. Thus, our findings are robust against strong bias from unobserved confounders (Rosenbaum 2014). For example, our analysis and conclusion regarding follower change after 10 weeks are valid even if the odds of treatment (i.e., experiencing virality) increase by 350% due to confounding bias.

For the third outcome (i.e., change in the proportion of 'scientist' followers) we plotted the lower bound of p-values, as we hypothesized that experiencing viral events would expand one's reach outside of the scientist community, leaving the proportion of 'scientist' followers lower than before.[3] According to Fig. 3, the expected effect of viral-

[3]Findings matched our expectation (page 9)

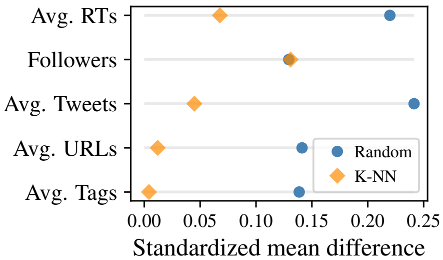

Figure 2: Standard mean differences of covariates for matching randomly and using our algorithm.

	Before matching		After matching	
Covariate	***t-statistic***	***p***	***t-statistic***	***p***
Average hashtags	-1.1	0.27	0.41	0.68
Average URLs	3.1	0.002	-0.4	0.7
Number of tweets	2.5	0.01	1.2	0.23
Followers	2.8	0.006	0.83	0.41
Retweet per tweet	4.6	0.0001	1.44	0.15

Table 2: Results of significance tests to assess the differences in means among covariates before and after matching.

ity on this outcome only diminishes when γ reaches to around 1.7, indicating moderate sensitivity to unobserved confounders (Rosenbaum 2014).

Pre-processing tweets

Computations involving tweet content (e.g., sentiment) were preceded by a pre-processing step using the TweetTokenize library.[4] This step removed white-spaces and punctuation, and replaced usernames, URLs, phone numbers, and time with *USER*, *URL*, *PHONE*, and *TIME* tokens, respectively. Only English tweets were used for these analyses.

Evaluating the Effects of Viral Events on Outcome Variables

Below, we list the outcome variables (related to scholars' behaviors and follower gains) we examined, detail the procedures for estimating them, and explain how the effects of viral events on them were computed and compared. Although we report findings involving all the users who had (one or more) viral events, these computations were repeated for users with only one viral event and yielded comparable results.

Behavioral Changes

We studied virality's impact(s) on behavioral changes. We focused on behaviors related to building scholarly reputation as identified by prior research: tweeting frequency, sentiment, objectivity, and engaging *professionally* with other scholars (i.e., posting tweets that are aligned with the posters area of expertise) (Mueller and Stumme 2017; Schnitzler et al. 2016). We also examined if viral users, after the first

[4]https://github.com/jaredks/tweetokenize/

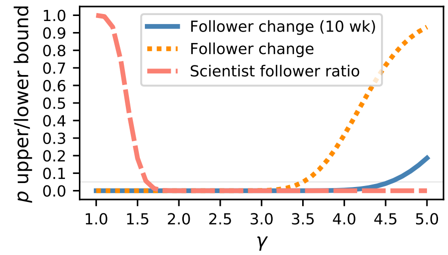

Figure 3: Results from sensitivity analysis. The horizontal axis shows odds of being treated (i.e., bias due to unobserved variables) and the vertical axis shows the upper/lower bounds of the probability of significant outcomes. The points where the curves cross the horizontal line (representing $p = 0.05$) indicate when the outcome becomes non-significant from significant (and vice versa). The large values of γ at these points indicates that there has to be large amount of bias for that switch to occur, demonstrating robustness of our findings against unobserved confounders (Rosenbaum 2014).

virality, posted tweets that were more similar to the viral tweet, presumably, as a way to re-create the cascading phenomenon, and if they tweeted on more (or less) diverse topics after the viral events, than before. Similar computations were performed for the non-viral group. All computations were performed on tweets posted in a 20-week time period (within 10 weeks before or after the first viral event). Below, we describe the behavioral measures we examined and how they were computed using these tweets.

Change in tweeting frequency. The average number of tweets per day for 10 weeks ($\approx$ 75 days) *before* the first viral event was computed that indicates the *baseline* tweeting frequency of each user. Then, the average number of tweets per day within 7, 15, 30, 60, and 75 periods *after* the same event was computed and compared to the baseline frequency to detect any changes over time.

Change in tweet sentiment. The sentiment score of a pre-processed tweet was estimated as follows. First, the sentiment scores of individual English words in the tweet were taken from the NRC Word-Emotion Association Lexicon (Mohammad and Turney 2010) dataset and then summed. Next, the emoticon sentiment lexicon dataset (Hogenboom et al. 2013) and the emoji lexicon dataset (Kralj Novak et al. 2015) were used to obtain sentiment scores for emoticons and emojis, respectively. The final sentiment score of a tweet is just the average of the previous three scores. The average sentiment scores of the tweets that were posted within 75 days before viral events represent the 'baseline' score. As before, the average sentiment scores across the tweets posted within different time intervals after viral events were computed and compared with the baseline to detect changes in tweet sentiment.

Objectivity of tweets. Following the pre-processing step, a tweet's objectivity score was estimated using the Senti-

WordNet dataset (Baccianella, Esuli, and Sebastiani 2010). Each lexicon in this dataset has both positive (P) and negative (N) *subjectivity* ratings. The objectivity of a lexicon was calculated using the equation: $objectivity = 1 - (P + N)$ (Baccianella, Esuli, and Sebastiani 2010). The average objectivity score across all tokens in a tweet represents to what extent the tweet was free from positive/negative subjectivity of the author. Change in objectivity was compared in a similar way as the sentiment estimates.

Similarity of tweets with users' professional expertise. We examined if post-virality tweets were more (or less) related to their authors' professional expertise compared to pre-virality tweets. To do that, first, we estimated users' area(s) of professional expertise using list membership (Ghosh et al. 2012). Using TF-IDF, the top five keywords were identified from the titles and descriptions of all lists that a user created or subscribed to. The keywords were then embedded in a vector space using Gensim (Rehurek and Sojka 2010) library and a FastText (Bojanowski et al. 2016) model for vector embedding that was trained with 400 million tweets (Godin 2019). Next, we computed the *World Mover's Distance* (WMD) (Kusner et al. 2015) between the keywords and a tweet (after embedding it in the same vector space). WMD between two text sequences is the sum of the distances from each word of one sequence to the nearest word (in a vector space) of the other sequence. WMD allows one to compute a 'meaningful distance' between two text documents even when they share no common words and has been shown to outperform other state-of-the-art methods (Kusner et al. 2015).We treat WMD as the similarity measure of a tweet with the tweeter's professional expertise where smaller WMDs indicate more similarity.

Similarity of tweets with the viral tweet. We examined if users, after experiencing the first viral event, posted tweets that were more (or less) similar to the viral tweet than before. To do that, first, for each viral user, we computed average similarity of the first viral tweet with the tweets posted within 75 days *before* that tweet. This score represents 'baseline' similarity. Next, the average similarity of the viral tweet with the tweets posted within different intervals (7, 15, 30, 60, and 75 days) *after* the viral event was computed and compared to the baseline similarity. Similar computation was repeated for tweets posted within those intervals *before* the first viral event to verify whether any observed change in similarity was due to the experienced virality or simply a function of time (e.g., people may post similar tweets for a specific amount of time regardless of the tweets' popularity). The similarity between two tweets was indicated by the Word Movers' Distance (WMD) between them after they were embedded in a vector space; lower WMD indicates higher similarity between two tweets.

Diversity in tweet topics. We examined if tweeters diversify the tweet topics after experiencing virality compared to the non-viral group. We trained an LDA (Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan 2003)) model using all tweets posted by users in both viral and non-viral groups. To improve model accuracy, we identified and extracted unigrams, bi-grams, and tri-grams in tweets using Gensim's 'Phraser' module (Rehurek and Sojka 2010) and used them to train several LDA models. The number of topics was set as a hyper parameter, which varied from 50 to 500 with a step size of 50. The models were evaluated based on the coherence score, which is a widely used metric to evaluate topic models (Röder, Both, and Hinneburg 2015). We picked the model with 100 topics as it had the highest coherence value. Then, tweets posted within 75 days before the viral events were combined and the top five topics (based on probability) were identified using the trained LDA model. Next, for each topic, the top five words/phrases were extracted from the model and pairwise similarities among these 25 phrases were computed and summed that indicated how similar the tweets' topics were. The difference in similarity score for tweets posted after viral events and tweets posted before viral events was computed; a positive value indicates less diversity in tweet topics after virality than before. Similar computations were done for non-viral users. The differences in similarity scores were then compared to assess whether viral events impacted the topic distributions of tweets.

Changes in the Number and Composition of Followers

Change in the number of followers. To measure viral events' influence in follower gain, the changes in followers of viral and non-viral groups after 10 weeks of the respective first viral events were compared. To assess the long-term impact, the same comparison was made at the end of the data collection period.

Change in the proportion of 'scientist' followers. For both viral and non-viral groups, their followers who are also scientists were identified using scientist titles compiled by Ke, Ahn, and Sugimoto (2017): if at least one title was found in the profile description of the followers, they were considered as scientists. The change in the proportions of scientist followers between two time points—immediately before the first viral event and at the end of data collection period—were compared for both viral and non-viral groups.

Findings

Descriptive Statistics

We identified 1,426 viral tweets posted by 670 users. Most of these tweets received less than three hundred retweets: $mean = 515$, $sd = 2721$, $min = 50$, $Q1 = 72$, $Q2 = 113$, $Q3 = 243$, and $max = 63695$. There were 147 (10.3%) non-English tweets from 69 users. The number of viral events per user ranged from 1 to 18: a majority of the viral users (54%, $N = 366$) had only one viral event, 132 (20%) and 65 (9%) had two and three viral events, respectively, and 63 (9.4%) had five or more viral events. During the 20-week period covering the viral events (10 weeks before and after the viral events), the viral users posted 239,459 novel tweets (i.e., those with some original content, and not simply retweets) where 214,330 (89.5%) of them were in English. Within the same time period, non-viral users posted 150,796 novel tweets; 121,445 (80.5%) of them were in English.

Influence of Viral Events on Tweeting Behaviors

Tweet frequency. Fig. 4a shows the number of tweets per day for different time intervals before and after viral events. Immediately after experiencing virality, users increased tweeting activities, which then dropped off after some time. Viral users posted significantly more tweets within 7, 15, and 30 days after the viral event compared to their baseline frequency ($t = 4, 2.92, 2.3$, $d = 0.17, 0.13, 0.10$ and $p < .001$, $p = .004$, and $p = .021$). Differences for more than the 30 day interval were not significant. In contrast, non-viral users reduced tweeting activities over time; they posted significantly lower number of tweets in all intervals compared to their baseline frequency ($t = -3.13, -2.57, -3.10, -3.06, -3.12$, $d = 0.10, 0.10, 0.10, 0.11, 0.11$ and $p = .002, .01,$ and $.002$).

Change in tweet-sentiment. Fig. 4b shows the changes in the sentiment of tweets posted within different time intervals after the first viral event compared to the mean sentiment scores of tweets posted within 75 days before that event. Tweets posted by viral users within 7 and 15 days of experiencing viral events had a higher (positive) sentiment ($t = 2.66, 2.87$, $d = 0.15, 0.14$, and $p = .012, .007$) than their baseline; but after this interval sentiment scores reverted to the baseline levels. No significant difference in tweet sentiment was found for the non-viral group.

Change in objectivity. Viral users posted tweets that were more factual and contained less subjective opinions compared to the non-viral users (Fig. 4c). The objectivity scores of their tweets went even higher after the viral events: for all intervals, the tweets had higher objectivity scores compared to the tweets they posted over 75 days before the viral events ($t = 2, 2.51, 3.42, 3.91, 4.28$, $d = 0.9, 0.9, 0.10, 0.11, 0.12$ and $p = .042, .016, .001$ for 7, 15, and 30 days and $p < .001$ for 60, and 75 days intervals, respectively). No difference in the objectivity score was found for the non-viral group.

Similarity of tweets with users' professional expertise. The mean World Mover's Distance (WMD) between professional expertise and tweets posted within 75 days before viral events was 7.65 and 7.68 for the viral and non-viral groups, respectively. Thus, both groups behaved similarly in posting tweets aligned with their professional expertise. This behavior remained unchanged after viral events (mean WMD 7.68 and 7.67 for viral and non-viral groups, respectively).

Similarity of tweets with viral tweet. Tweets that were posted during the surrounding days of viral events were more similar to the viral tweets (i.e., lower WMD) where the most similar tweets were posted immediately following the viral events (Fig. 4d). The tweets posted within 7, 15, 30, 60, and 75 days *after* the viral event were more similar to the viral tweet compared to the baseline similarity (i.e., average similarity of tweets posted within 75 days before viral event with the viral tweet, indicated by the dotted line in the plot) ($t = -3.33, -4.17, -3.89, -3.56, -3.18$, $d = 0.22, 0.26, 0.23, 0.21, 0.19$, and $p < .001$ in all cases). The similarity between tweets posted within the same intervals *before* the viral tweet did not differ from the baseline

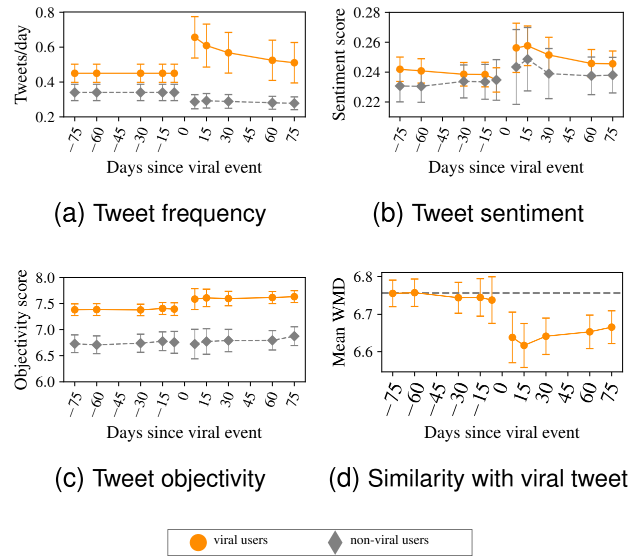

Figure 4: Tweeting frequency, sentiment and objectivity of the tweets, and similarity of tweets with the viral tweet; they were measured using tweets posted within 7, 15, 30, 60, and 75 days intervals before and after the viral events. The similarity of tweets with the viral tweet was measured only for viral users, as shown in Fig. 4d where the dotted line represents the 'baseline similarity' score. Note that, in Fig. 4b and 4c, measurements (sentiment and objectivity) before the viral event (the 'baseline' measurements) are not parallel to the x-axis. This is because the comparisons were pairwise, i.e., measurements for a specific time interval after viral events for each user were compared to the baseline measurements of the same user. But not all users tweeted within a given interval (e.g., seven days) after the viral event, and they were not considered when the means of sentiment and objectivity were computed. Thus, these baseline measurements varied across the time intervals.

similarity ($p = .58, .71, .66, .96, .98$). These results suggest that the similarity among tweets posted by the same user may not vary as a function of time; instead, the users may have deliberately posted tweets that were more similar to the tweet that went viral.

Diversity in tweet topics. For viral users, the tweets posted before the viral events had an average similarity score (as measured from similarities between pairs of keywords) of 144.37 (SD= 27.30), while the score for the tweets posted after the viral events was 140.53 (SD=36.04). For non-viral users, the average similarity scores in tweet topics before and after the analogous time points were 137.41 (SD=38.38) and 117.90 (SD=59.19), respectively. Thus, both groups had diversified tweets over time, although non-viral users did so at a significantly larger scale ($t = 6.1$, $d = 0.32$, and $p < .001$). In other words, experiencing virality resulted in more focused tweeting in terms of topic distribution.

Impact of Viral Events on Gaining Followers

Gaining followers. Ten weeks after the first viral event, the viral group gained followers: mean = 322.9, SD = 1196, median = 133. The matched non-viral group also gained followers within this time period: mean = 66.8, SD = 162.5, median = 34. The changes in followers had log-normal distributions, as verified by conducting Kolmogorov-Smirnov tests of goodness of fit (ks = .041, .046 for viral and non-viral groups, respectively, $p > .2$ in both cases). The difference between the two groups were compared using a *Mann-Whitney U* test: $u = 70339.0$, $p < 0.001$, with a 'large' effect-size (r=0.62) (Cohen 1988), indicating that virality indeed resulted in large gains in followers.

At the end of our data collection period, the average follower gain was 2,793.7 (SD = 9356.4, median = 998) for the viral group and 652.14 (SD = 2515.9, median = 283) for the non-viral group. By comparing the log-normal distributions of follower gains (ks = .036 and .035, $p > .4$ in both cases), we detected a 'medium' to 'large' effect (r=0.49) of virality in increasing followers ($u = 113686$, $p < 0.0001$) in the long-term.

Change in the proportion of 'scientist' followers. Before the first viral event, on average, 11.2% followers of the viral users were scientists, and at the end of the data collection period, this proportion became 10.9%. The difference between these proportions was negative and significant ($t = -2.84$, $d = 0.04$, $p < 0.001$). For non-viral users, the proportions were 9.2% and 9.3% during the same time points, but the difference was not significant ($p > 0.05$). Thus, virality facilitates a slightly greater reach to the general public.

Robustness of the findings

To demonstrate that our findings represent true differences between the viral and non-viral groups, we conducted random-split analyses. Specifically, we randomly assigned treatment and control conditions to users and again compared the three outcomes (change in followers after 10 weeks, change in followers at the end of data collection period, and change in the proportion of scientist followers) between these two groups using the Mann-Whitney U test. In all cases, the effect size was negligible (0.00008, 0.01, and 0.03), and not significant (all $p > 0.1$). These results further corroborate our findings.

Discussion

Developing an online-presence is becoming increasingly important for scientists and researchers. Atlhough many studies have documented why and how celebrities use social media and behave online, scientists' goals for using these platforms differ than those populations. Celebrities engage with social media to seek publicity for their already famous public personae, and, thus, their actions are oriented toward projecting an intimate and relatable image while maintaining fans' expectations (Marwick and boyd 2011). The goal of scholars are probably closer to micro-celebrities. The term micro-celebrity was coined by Senft (2008) to refer to people that aim to develop a following by leveraging digital media technologies. They use social media to develop a self-brand, and they personally engage with their followers (Abidin 2018; Senft 2008). However, big differences exist in the goals of micro-celebrities and scholars, e.g., scientists serve multiple audiences, and their professional success is tied to scientific contributions and recognition within the community (Kozinets 2017). Thus, it is important to document scientists' behaviors on social platforms and how they change behaviors after receiving attention from their peers.

In this paper, we examined how scientists adjust their Twitter behavior after their first surges in visibility, which we called micro-viral events. We employed a longitudinal dataset of scientists on Twitter that captured both tweeting activities and their follower network structure over a span of two years and eight months. Different from prior studies, our definition of virality included both absolute and relative measures, as we seek to identify the impact of events that are 'exceptional' relative to the users' usual experiences on Twitter, and investigated how such events influenced the users' subsequent engagement with and their popularity on the platform.

Our results suggest that scientists modify their behaviors after experiencing micro-virality. We observed increased engagement with the platform: both tweeting and re-tweeting frequency surged immediately after viral events. For a short period after the viral event, we also observed that tweets expressed more positive sentiments but reverted to normal after a few weeks.

Our results also suggest that viral users consistently posted tweets with more objective content compared to the non-viral group, which was further enhanced after experiencing a viral event. Moreover, following the event, users posted tweets that were more similar to viral tweets and focused on fewer topics. None of these behavioral changes were observed for the non-viral users who had similar profiles and tweeting patterns as the viral users until the later group experienced viral events. Since we analyzed our data using a matching-based causal inference framework, these group differences may be attributable to the viral events.

These behavioral changes agree with the previously identified behaviors that are beneficial for building online reputation (Suh et al. 2010; Schnitzler et al. 2016). However, our data did not allow us to examine whether the users strategically changed their behaviors to get additional viral events and/or followers, which is an interesting direction for future research.

Finally, our analysis shows that scholars on Twitter accrued significantly more followers in the long term after experiencing micro-viral events relative to comparable non-viral scholars. While prior work has established correlations between large-scale viral events and follower-gain (Myers and Leskovec 2014), we define virality relative to the users' past experiences, and we established causal relationships between micro-virality and the observed outcomes.

Limitations

Although we collect a novel longitudinal dataset that allows us to study the evolution of users' followers and tweeting behaviors, our data is limited to a small subset of Twitter users (scientists). Personal reputation and broad impact of one's work is particularly important for career outcomes in the academia. Thus, it might have been easier to observe behaviors related to advancing one's reputation, visibility, and diffusion of work in this group of users. People in other professions, however, may behave differently, and our results may be less relevant to other populations.

One of our key motivations for engaging in this research was to understand how Twitter users may leverage the platform to enhance their professional reputation. In practice, we analyzed the impact of viral events on follower gain and users' tweeting behaviors. Although the number of followers indicates 'popularity' on Twitter, and being followed and discussed by fellow scholars may result in increased scholarly reputation, more research with other metrics and proxies is needed to further triangulate the effects of virality on *professional reputation*.

We approximated virality as random exogenous events; but they could be the result of a deliberate strategy to increase visibility on the platform or confounded by unobserved characteristics of the users that may lead to large follower accumulations. Although we attempted to reduce confounding bias through matching and demonstrated the robustness of our findings against *unobserved* confounders through sensitivity analyses, causal effect can rarely be established with certainty from observational data.

Finally, our analysis was limited to Twitter. Other external, unobserved factors might have influenced virality and changes in behaviors and followers (e.g., popularity on other platforms or research findings being discussed in the news).

Conclusions

When people's posts on social media go viral, it can have a major impact on their lives, both positive and negative. Such viral events can also cause significant changes in people's posting behaviors, particularly if virality is experienced for the first time.

We monitored a population of scientists (N=17,157), who are known to leverage Twitter to increase professional reputation, for nearly three years. We identified 670 scientists who experienced 'micro-viral' events—viral events that may be insignificant for popular users but an 'extraordinary' experience for a large fraction of Twitter users—for the first time in their profile's lifespan. We then examined how micro-viral events influenced the subsequent behaviors of viral users on Twitter, and the long-term effect on the total number of their followers as well as the composition of the followers.

We found that after experiencing virality, users increased tweeting and retweeting frequency, posted tweets that were more objective and similar to their viral tweets, expressed a higher positive sentiment, and focused on fewer topics. Additionally, viral users gained and retained followers at a higher rate than non-viral users, and virality helped scientists to reach Twitter users outside of the scientific community. Although our strategy is not without limitations, these findings may advance our understanding of how 'everyday' Twitter users react to 'unusual' visibility at a scale they had never experienced before. Additionally, our methodology may be leveraged by platform developers to detect viral events and increase the associated users' engagement with the platform and motivate them to improve the quality of user-generated content.

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References

Abidin, C. 2018. *Internet celebrity: Understanding fame online*. Emerald Group Publishing.

Adelani, D. I.; Kobayashi, R.; Weber, I.; and Grabowicz, P. A. 2020. Estimating community feedback effect on topic choice in social media with predictive modeling. *EPJ Data Science* 9(1): 25.

Amon, M. J.; Hasan, R.; Hugenberg, K.; Bertenthal, B. I.; and Kapadia, A. 2020. Influencing Photo Sharing Decisions on Social Media: A Case of Paradoxical Findings. In *the Proceedings of the IEEE Symposium on Security & Privacy (SP '20)*. IEEE Computer Society. doi:10.1109/SP.2020.00006. URL https://doi.ieeecomputersociety.org/10.1109/SP.2020.00006.

Arató, A. 2019. Experience: my face became a meme. URL https://www.theguardian.com/lifeandstyle/2019/nov/08/experience-hide-the-pain-harold-face-became-meme-turned-it-into-career.

Baccianella, S.; Esuli, A.; and Sebastiani, F. 2010. SentiWordNet 3.0 : An Enhanced Lexical Resource for Sentiment Analysis and Opinion Mining SentiWordNet. *Analysis* 10(2010): 1–12. ISSN 09255273. doi:10.1.1.61.7217. URL http://nmis.isti.cnr.it/sebastiani/Publications/LREC10.pdf.

Berger, J.; and Milkman, K. L. 2012. What Makes Online Content Viral? *Journal of Marketing Research* 49(2): 192–205. doi:10.1509/jmr.10.0353. URL https://doi.org/10.1509/jmr.10.0353.

Blei, D.; Ng, A.; and Jordan, M. 2003. Latent Dirichlet allocation. *Journal of machine Learning Research* 3(Figure 1): 993–1022. ISSN 1532-4435. doi:10.1162/jmlr.2003.3.4-5.993.

Bojanowski, P.; Grave, E.; Joulin, A.; and Mikolov, T. 2016. Enriching Word Vectors with Subword Information. *arXiv preprint arXiv:1607.04606* .

Buccoliero, L.; Bellio, E.; Crestini, G.; and Arkoudas, A. 2020. Twitter and politics: Evidence from the US presidential elections 2016. *Journal of Marketing Communications* 26(1): 88–114. doi:10.1080/13527266.2018.1504228. URL https://doi.org/10.1080/13527266.2018.1504228.

Cohen, J. 1988. *Statistical power analysis for the social sciences*. Hillsdale, NJ: Erlbaum.

Côté, I. M.; and Darling, E. S. 2018. Scientists on Twitter: Preaching to the choir or singing from the rooftops? *FACETS*

3(1): 682–694. doi:10.1139/facets-2018-0002. URL https://doi.org/10.1139/facets-2018-0002.

Dauenhauer, P. J. 2020. Expand Your Academic Impact with Social Media Best Practices. *Matter* 2(4): 789–793. ISSN 2590-2385. doi:https://doi.org/10.1016/j.matt.2020.02.017. URL http://www.sciencedirect.com/science/article/pii/S2590238520300795.

Dow, P. A.; Adamic, L. A.; and Friggeri, A. 2013. The Anatomy of Large Facebook Cascades. *ICWSM* 1(2): 12.

Dudo, A.; and Besley, J. C. 2016. Scientists' Prioritization of Communication Objectives for Public Engagement. *PLOS ONE* 11(2): 1–18. doi:10.1371/journal.pone.0148867. URL https://doi.org/10.1371/journal.pone.0148867.

Duffy, B. E.; and Pooley, J. D. 2017. "Facebook for academics": the convergence of self-branding and social media logic on Academia. edu. *Social media+ society* 3(1): 2056305117696523.

Ghosh, S.; Sharma, N.; Benevenuto, F.; Ganguly, N.; and Gummadi, K. 2012. Cognos: crowdsourcing search for topic experts in microblogs. In *Proceedings of the 35th international ACM SIGIR conference on Research and development in information retrieval*, 575–590. ACM.

Godin, F. 2019. *Improving and Interpreting Neural Networks for Word-Level Prediction Tasks in Natural Language Processing*. Ph.D. thesis, Ghent University, Belgium.

Goel, S.; Anderson, A.; Hofman, J.; and Watts, D. J. 2015. The structural virality of online diffusion. *Management Science* 62(1): 180–196.

Guzman, E.; Alkadhi, R.; and Seyff, N. 2016. A needle in a haystack: What do twitter users say about software? In *Requirements Engineering Conference (RE), 2016 IEEE 24th International*, 96–105. IEEE.

Han, J. J. 2020. To Tweet or not to Tweet: no longer the question. *The Annals of Thoracic Surgery* ISSN 0003-4975. doi:https://doi.org/10.1016/j.athoracsur.2020.04.070. URL http://www.sciencedirect.com/science/article/pii/S0003497520308663.

Hasan, R.; Bertenthal, B. I.; Hugenberg, K.; and Kapadia, A. 2021. Your Photo is so Funny that I don't Mind Violating Your Privacy by Sharing it: Effects of Individual Humor Styles on Online Photo-sharing Behaviors. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, CHI'21. ACM. doi:10.1145/3411764.3445258. URL http://doi.acm.org/10.1145/3411764.3445258.

Ho, D. E.; Imai, K.; King, G.; and Stuart, E. A. 2007. Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference. *Political Analysis* 15(3): 199–236. doi:10.1093/pan/mpl013.

Hogenboom, A.; Bal, D.; Frasincar, F.; Bal, M.; de Jong, F.; and Kaymak, U. 2013. Exploiting emoticons in sentiment analysis. In *Proceedings of the 28th annual ACM symposium on applied computing*, 703–710. ACM.

Jenders, M.; Kasneci, G.; and Naumann, F. 2013. Analyzing and Predicting Viral Tweets. In *Proceedings of the 22Nd International Conference on World Wide Web*, WWW '13 Companion, 657–664. New York, NY, USA: ACM. ISBN 978-1-4503-2038-2. doi:10.1145/2487788.2488017. URL http://doi.acm.org/10.1145/2487788.2488017.

Jordan, K.; and Weller, M. 2018. Communication, collaboration and identity: factor analysis of academics' perceptions of online networking. *Research in Learning Technology* 26.

Ke, Q.; Ahn, Y.-Y.; and Sugimoto, C. R. 2017. A systematic identification and analysis of scientists on Twitter. *PloS one* 12(4): e0175368.

Kimmons, R.; and Veletsianos, G. 2016. Education scholars' evolving uses of twitter as a conference backchannel and social commentary platform. *British Journal of Educational Technology* 47(3): 445–464. doi:10.1111/bjet.12428. URL https://bera-journals.onlinelibrary.wiley.com/doi/abs/10.1111/bjet.12428.

Kozinets, R. V. 2017. Flow my bits, the professor screened: Netnography, academic micro-celebrity, and personal branding. In *Digital tools for academic branding and self-promotion*, 52–65. IGI Global.

Kralj Novak, P.; Smailović, J.; Sluban, B.; and Mozetič, I. 2015. Sentiment of emojis. *PLoS ONE* 10(12): e0144296. URL http://dx.doi.org/10.1371/journal.pone.0144296.

Kusner, M.; Sun, Y.; Kolkin, N.; and Weinberger, K. 2015. From word embeddings to document distances. In *International conference on machine learning*, 957–966.

Lemon, N.; McPherson, M.; and Budge, K. 2015. Academics Doing it Differently: Wooing, Hooking up and Spinning Stories. *Journal of Perspectives in Applied Academic Practice* 3(2).

Li, J.; and Greenhow, C. 2015. Scholars and social media: tweeting in the conference backchannel for professional learning. *Educational Media International* 52(1): 1–14. doi:10.1080/09523987.2015.1005426. URL https://doi.org/10.1080/09523987.2015.1005426.

Marwick, A.; and boyd, d. 2011. To see and be seen: Celebrity practice on Twitter. *Convergence* 17(2): 139–158.

Meishar-Tal, H.; and Pieterse, E. 2017. Why Do Academics Use Academic Social Networking Sites? *The International Review of Research in Open and Distributed Learning* 18(1). ISSN 1492-3831. URL http://www.irrodl.org/index.php/irrodl/article/view/2643.

Mohammad, S. M.; and Turney, P. D. 2010. Emotions Evoked by Common Words and Phrases: Using Mechanical Turk to Create an Emotion Lexicon. In *Proceedings of the NAACL HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text*, CAAGET '10, 26–34. Stroudsburg, PA, USA: Association for Computational Linguistics. URL http://dl.acm.org/citation.cfm?id=1860631.1860635.

Mohammadi, E.; Thelwall, M.; Kwasny, M.; and Holmes, K. L. 2018. Academic information on Twitter: A user survey. *PLOS ONE* 13(5): 1–18. doi:10.1371/journal.pone.0197265. URL https://doi.org/10.1371/journal.pone.0197265.

Mueller, J.; and Stumme, G. 2017. Predicting rising follower counts on Twitter using profile information. In *Proceedings of the 2017 ACM on Web Science Conference*, 121–130.

Myers, S. A.; and Leskovec, J. 2014. The Bursty Dynamics of the Twitter Information Network. In *Proceedings of the 23rd International Conference on World Wide Web*, WWW '14, 913–924. New York, NY, USA: Association for Computing Machinery. ISBN 9781450327442. doi: 10.1145/2566486.2568043. URL https://doi.org/10.1145/2566486.2568043.

Radford, M. L.; Kitzie, V.; Mikitish, S.; Floegel, D.; Radford, G. P.; and Silipigni Connaway, L. 2020. "People Are Reading Your Work,": Scholarly Identity and Social Networking Sites. *Journal of Documentation* .

Rehurek, R.; and Sojka, P. 2010. Software Framework for Topic Modelling with Large Corpora. In *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks*, 45–50. Valletta, Malta: ELRA.

Röder, M.; Both, A.; and Hinneburg, A. 2015. Exploring the Space of Topic Coherence Measures. In *Proceedings of the Eighth ACM International Conference on Web Search and Data Mining*, WSDM '15, 399–408. New York, NY, USA: Association for Computing Machinery. ISBN 9781450333177. doi:10.1145/2684822.2685324. URL https://doi.org/10.1145/2684822.2685324.

Ronson, J. 2015. How One Stupid Tweet Blew Up Justine Sacco's Life. URL https://www.nytimes.com/2015/02/15/magazine/how-one-stupid-tweet-ruined-justine-saccos-life.html.

Rosenbaum, P. R. 2014. Sensitivity Analysis in Observational Studies. In *Wiley StatsRef: Statistics Reference Online*. American Cancer Society. ISBN 9781118445112. doi:https://doi.org/10.1002/9781118445112.stat06358. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/9781118445112.stat06358.

Ruhela, A.; Bagchi, A.; Mahanti, A.; and Seth, A. 2016. The rich and middle classes on Twitter: Are popular users indeed different from regular users? *Computer Communications* 73: 219–228. ISSN 0140-3664. doi:https://doi.org/10.1016/j.comcom.2015.07.024. URL http://www.sciencedirect.com/science/article/pii/S0140366415002625.

Schnitzler, K.; Davies, N.; Ross, F.; and Harris, R. 2016. Using Twitter™ to drive research impact: A discussion of strategies, opportunities and challenges. *International Journal of Nursing Studies* 59: 15–26. ISSN 0020-7489. doi:https://doi.org/10.1016/j.ijnurstu.2016.02.004. URL http://www.sciencedirect.com/science/article/pii/S0020748916000729.

Senft, T. M. 2008. *Camgirls: Celebrity and community in the age of social networks*, volume 4. Peter Lang.

Shah, N. A. K.; and Cox, A. M. 2017. Uncovering the scholarly use of Twitter in the academia: Experiences in a British University. *Malaysian Journal of Library & Information Science* 22(3): 93–108.

Shalizi, C. R.; and Thomas, A. C. 2011. Homophily and contagion are generically confounded in observational social network studies. *Sociological Methods and Research* 40(2). ISSN 00491241. doi:10.1177/0049124111404820.

Sivarajah, U.; Irani, Z.; Gupta, S.; and Mahroof, K. 2020. Role of big data and social media analytics for business to business sustainability: A participatory web context. *Industrial Marketing Management* 86: 163–179. ISSN 0019-8501. doi:https://doi.org/10.1016/j.indmarman.2019.04.005. URL http://www.sciencedirect.com/science/article/pii/S0019850118305236.

Stampler, L. 2014. Who Is 'Alex From Target' and Why did the Internet Make Him Famous? URL https://time.com/3554572/alex-from-target/.

Strehlke, S. 2015. This Arizona State Student Was Fired from Her Internship After Her Racist Tweet Went Viral. URL https://www.teenvogue.com/story/intern-fired-racist-n-word-tweet.

Stuart, E. A. 2010. Matching Methods for Causal Inference: A Review and a Look Forward. *Statist. Sci.* 25(1): 1–21. doi:10.1214/09-STS313. URL https://doi.org/10.1214/09-STS313.

Subbian, K.; Prakash, B. A.; and Adamic, L. 2017. Detecting Large Reshare Cascades in Social Networks. In *Proceedings of the 26th International Conference on World Wide Web*, WWW '17, 597–605. Republic and Canton of Geneva, Switzerland: International World Wide Web Conferences Steering Committee. ISBN 978-1-4503-4913-0. doi:10.1145/3038912.3052718. URL https://doi.org/10.1145/3038912.3052718.

Suh, B.; Hong, L.; Pirolli, P.; and Chi, E. H. 2010. Want to be Retweeted? Large Scale Analytics on Factors Impacting Retweet in Twitter Network. In *2010 IEEE Second International Conference on Social Computing*, 177–184.

Twitter. 2020. Rate limits. URL https://developer.twitter.com/en/docs/twitter-api/v1/rate-limits.

Varol, O.; Ferrara, E.; Davis, C. A.; Menczer, F.; and Flammini, A. 2017. Online human-bot interactions: Detection, estimation, and characterization. *arXiv preprint arXiv:1703.03107* .

Yu, H.; Xiao, T.; Xu, S.; and Wang, Y. 2019. Who posts scientific tweets? An investigation into the productivity, locations, and identities of scientific tweeters. *Journal of Informetrics* 13(3): 841–855. ISSN 1751-1577. doi:https://doi.org/10.1016/j.joi.2019.08.001. URL http://www.sciencedirect.com/science/article/pii/S1751157718303079.

Zhang, Z.; Kim, H. J.; Lonjon, G.; and Zhu, Y. 2019. Balance diagnostics after propensity score matching. doi:10.21037/atm.2018.12.10.