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AP Statistics, p7
May 9, 2016

Viral Social Media Movements

Abstract

In the past decade, social media has become a very powerful – at times almost indispensable – tool for organizations to use as a means of spreading ideas, but the nature of viral social media movements is not yet very well understood.

In our study, we examined the factors that may affect movements' abilities to go viral and/or sustain their virality. In particular, we focused on the virality and lifecycles on Twitter of two charitable social media movements: Black Lives Matter (BLM) and Bring Back Our Girls (BBOG). Using an open-source program found online (sc: Henrique), we searched for and collected data on all tweets – containing the relevant hashtags – since the movements' births to the present day. We analyzed the data on two levels: 1) how users engage with individual tweets and 2) how virality evolves over time.

On the level of individual tweets, we found that tweets containing photos tended to also receive high engagement, whereas tweets containing links had no statistically significant relationship with engagement. On the level of tweet trends over time, we found that the two movements' popularities evolved according to slightly different models. Both would start off with sudden peaks – prompted by high-profile news stories. Following the initial peak, BLM's popularity tended to evolve according to a reciprocal model, whereas BBOG's tended to evolve according to a logarithmic one. Regardless of the mathematical model, however, both movements saw steep declines immediately following the "sparking" high-profile news stories, suggesting that such movements are only sustainable as long as current events warrant the hashtags' continued use.

Introduction/Overview

With the rapid growth of many social networks within the past decade, the Internet has emerged as a powerful medium for mass and rapid publicity. There are countless videos, Twitter hashtags, and Facebook posts that have racked up millions – even billions – in views, comments, and shares. This new era represents an exciting time for social awareness and change movements. Before, these movements had to rely on slow, local word-of-mouth. However, with social media, they can now theoretically reach a global audience. The power of social media as a tool for spreading awareness is undisputed; what is more uncertain, at this point, is the nature of viral social media movements – its causes and effects. Understanding virality is especially important to charitable organizations, as they often do not have the capital to gain popularity through brute force – as a commercial or for-profit brand might have. Therefore, they need to carefully choose effective strategies for sharing their content to get the best return on investment.

We initially aimed to study eight different charitable social media movements. However, after some research into the limitations – often privacy-related – on the types of data that were available to collect, we decided to focus on just two:

- #BlackLivesMatter was started in July 2013 after the acquittal of George Zimmerman, who'd shot and killed Trayvon Martin. The movement – on Twitter and in demonstrations – has grown since then; since the hashtag still gets several thousand hits a day, the movement is generally considered successful, when evaluated in terms of popular social media.
- #BringBackOurGirls was sparked by the mid-April 2014 Chibok kidnapping, when 276 Nigerian female students were abducted by Boko Haram. The movement called for more aggressive and urgent action to prompt the girls' release. However, two years after the incident with 219 girls still missing, the hashtag has fallen out of usage and Bring Back Our Girls is widely considered to be a failed movement.

The movements have some clear similarities – both were sparked by violent high-profile news events; both were hosted on Twitter – and some clear differences, the most important of which is their varying levels of success. Studying these specific movements provided a good basis of comparison, which would be helpful for trying to understand what factors played into relative "successes" of different movements.

DEFINITION OF VIRALITY

Before we continue, we should agree on a formal definition of "virality." Virality, in its most general sense, refers "to the number of people who accessed [and engaged with] a given content in a given time interval" (sc: Guerini, et al, 2011). Past this definition, virality and "engagement" take on a variety of meanings for different movements. For some, like KONY 2012 – short video about Joseph Kony's military cult in Uganda –, commenting and high view counts (action on the existing content, or *narrowcasting*) suffice as measures of engagement. Other movements call for more public action, such as sharing with friend networks (*broadcasting*), replicating content – in the case of the ALS Ice Bucket Challenge –, and even engaging outside of the shared content by donating money or signing petitions – in the case of Red Equals Sign.

Through the following "Background" section, we tried to account for most of the possible virality definitions for proper context. In our analysis, however, our definition of virality was largely focused on amount of engagement with specific tweets and volume of hashtag usage per day.

Background

Even before the introduction of the Internet, psychologists, sociologists, and marketers have been exploring the nature of mass media. Their studies have shown that virality in those media cannot be attributed to one single factor, but instead a combination of the emotional responses evoked, audience background, reputability of the source, etc.

However, with the newfound and still evolving power of social media, many of the companies and organizations interested in researching virality do so without publishing their findings publicly. There is not much public literature so far on what causes virality or how movements progress once virality has been reached. This is what we learned from the few studies of virality we found.

EMOTIONAL RESPONSE – Valence, Arousal, and Dominance

One major theory on a factor in virality is based on the audience's emotional response. In the somewhat separate world of behavior research, emotion is classified based on the 3D model of the *Valence-Arousal-Dominance* circumplex or VAD. *Valence* is defined as the positivity of the article's content; *arousal* as how compelled the audience feels to mobilize and take action (anger and awe are high arousal emotions, while sadness and contentment are low arousal); and *dominance* as the amount of control the audience feels after reading the article (how empowered they feel to affect change on the topic).

Berger and Milkman in 2011 collected data on New York Times articles and found that in general, articles with high arousal were shared more than low-arousal articles, and positive-valence more than low-valence articles. These results were confirmed by a controlled experiment where Berger and Milkman invented articles on similar topics written with different emotional valence and arousal. The proposed partial reasoning was that shared content was a reflection of the sharer, who would prefer to be seen as a more positive person. However, this reasoning breaks down with some high arousal content, for example an article dominated that causes an anger-driven response.

Later in 2015, Guerini and Staiano attempted to consolidate many of the past 5 years' findings or theories into a single model. Using the emotional tags on articles from Rappler and Corriere.it (a popular Italian news source), they found that different types of virality evolve differently. *Narrowcasting* is sharing content to a narrow audience, while broadcasting is distributing to a mass audience. Guerini and Staiano used the number of comments on an article to measure its amount of narrowcasting – since only readers of the article would see the comments – and the number of links found in other social media sites as a measure of broadcasting. While high arousal articles had the greatest effect on narrowcasting, high dominance had the greatest effect on broadcasting.

With our limited resources – we were unable to collect data on tweets' emotional associations. However, looking at these studies helped set our context for analyzing social media movements at the level of engagement individual content. We also applied Guerini and Staiano's idea of narrowcasting and broadcasting – as they relate to news articles – to characteristics of tweets (see "Findings").

AUDIENCE AND CONTENT GENERATOR BACKGROUNDS

There have also been several studies looking at which demographics are swayed most by published media, taking the ideas of *reception* and *acceptance* into account. Reception is how likely an individual will see content. Acceptance is how likely the individual will change their opinion according to the content. Most research and theory in the 20th century said that people with medium level of education were affected most by media, since they had the right balance between reception and acceptance. For example, during a political campaign, someone who actively sought information about candidates (high reception) would most likely have already formed a strong opinion (low acceptance). However, in a 1998 study of recycling PSA's in Florida, Martinez and Scicchitano found that people of higher education were affected by the distribution of media more than any other group.

We weren't able to find more recent papers on how education level relates to viral campaigns on social media. It would be interesting to 1) connect this to what we know from studies on media and VAD and 2) create a more detailed map of which types of media can best compel different demographics to take action.

In addition to the background of the target audience, the background of a content generator also plays a role in the spread of the content. Often informally misnamed "influencers," these popular social media users have large numbers of followers/friends and good online reputations. However, a 2010 study by Romero, et al on Twitter "influencers" showed that "high popularity does not necessarily imply high influence and vice-versa." Romero observed that content propagation through social networks needs active engagement; even if influencers have many followers that can passively read their content, these followers won't necessarily spread the content. Since the number of followers is not a good predictor of influence, we were interested in identifying traits of social media users or their posts that are. We were unable to follow this line of reasoning due to time and data collection restraints. However, this analysis is important for future research, since understanding relative influence of social media posters can help an organization make their social media strategy more economical – for example, when deciding who to recruit to promote a cause.

NETWORKS AND THE SPREAD OF VIRAL CONTENT

Not very many studies have looked at how viral content evolves over long stretches of time. However, Haralabopoulos and Anagnostopoulos in 2014 were able to create a model of when and where content migrated, for a specific case study: Reddit. They found that content consistently migrated to Twitter within a few hours of the post's creation, then to Facebook after about 12 hours, when the post's popularity would start to decrease. In other words, Reddit posts tended to reach their peak popularity within hours of creation. Haralabopoulos and Anagnostopoulos made a further conjecture that virality is multi-layered, where the layers represent different social media sites where content can be shared.

Whereas Haralabopoulos and Anagnostopoulos studied lifecycles of movements across multiple social media platforms, we zoomed in on and analyzed the time period immediately following peak popularity in a single platform.

CONCURRENT NEWS COVERAGE

The lifecycles of both BLM and BBOG, as well as "It Gets Better" (LGBTQ youth solidarity), were closely intertwined with concurrent news coverage, both of the sparking events and the movement itself. One day after the "It Gets Better" first content was released, the suicide of Tyler Clementi, a gay college student, grabbed national headlines for weeks (especially as the criminal trial began) and propelled LGBTQ youth into the spotlight. TV news networks also picked up on the spreading “It Gets Better” videos and began including snippets in their nightly reports. Today, the It Gets Better Project is still generating new content five years after their first video.

In contrast, for the BBOG awareness campaign, American news coverage of the Nigerian girls’ kidnapping (the sparking event) was noticeably delayed – the first stories on major news networks began to air two weeks after the kidnapping. Even after the stories appeared, they were often eclipsed by other domestic news. Some online news articles even criticized the movement as useless “hashtag activism,” further harming its reputation. The movement has since died down one year after the kidnapping. The majority of the girls still have not been found.

Unlike BBOG which had a single sparking event, BLM’s lifecycle has revolved around a series of news stories throughout the last few years related to ongoing police brutality.

There does not appear to be substantial literature on the relationship between social media and traditional news sources. Though we did not collect data on news articles, we did observe and discuss a strong tie between news events and virality of the two hashtags (see Findings).

Methodology

ORIGINAL ANALYSIS PLAN

We originally planned to investigate the factors that cause “awareness” social media movements to go viral by sampling data from eight such movements. We picked these eight in particular because they covered a wide spectrum of:

- media types – videos, hashtags, text posts, images, profile pictures
- movement duration – from a few days (Red Equals Sign) to 12 years (Movember)
- success levels – despite their popularity, Bring Back Our Girls and KONY 2012 have been widely touted as failures for not achieving their original goals

	Media Platform			Movement	Content and Data
1			**Youtube** views, comments, likes/dislikes	Dove Beauty Campaign (2006)	single video
2	**Facebook** views, likes, comments			Ice Bucket/ALS (June-September 2014)	many videos by individuals, news coverage
3				Red Equals Sign (March-June, 2013)	profile picture changes, news coverage of Supreme Court ruling
4		**Twitter** hashtags, retweets, replies		Movember (2003-present)	many videos by individuals, hashtag (#movember)
5				Kony 2012	single video, hashtag (#kony2012, #stopkony), news coverage
6				It Gets Better (September 2010-present)	many videos by celebrities, hashtag, news coverage of suicides
7				Black Lives Matter (2013-present)	images of protest, hashtag, news coverage of events/protests
8				Bring Back Our Girls (April 2014-December 2015)	images, hashtag, news coverage of kidnapping

For each movement, we planned to measure the “popularity” of the respective content based on the following characteristics:

- The **view frequency** (i.e. view counts for Facebook and YouTube, unavailable on Twitter).
- The **response frequency**. We define a “response” to be any action that only involves the viewer and author (i.e. likes for Facebook, thumb-up/down for YouTube, and favorites for Twitter).

- The **sharing frequency**. “Sharing” includes any action that spreads content beyond the author and direct viewers (i.e. comments Facebook and YouTube and retweets for Twitter).

- The **duration of popularity**. Ways we can quantify:
    - Time it takes to reach some percentage of max popularity (eg. $T_{Max} – T_{50\% \text{ of } Max}$).
    - Number of peaks in popularity. Some hashtags we analyzed for our background paper had “comebacks” after their first peaks; each subsequent peak seemed to be less than the last.

OBSTACLES & REVISIONS: Data Collection

Data collection turned out to be much more of a challenge than we originally anticipated. After discussing the Facebook API with Piyush Mangalick (Facebook’s director of Developer Platform and Partnerships), we learned that privacy controls made it impossible to collect all posts on a certain topic. Only public posts were available for querying, and because of Facebook’s typical user experience, most users only posted content for their friends. Mr. Mangalick suggested we look into Instagram, but we found that Facebook had recently extended many of its privacy controls to the child company.

Our second platform, YouTube, also had some limitations. We could not find a way to collect data on the characteristics of the videos themselves, like video length, presence or absence of advertisements, and volume range. We also realized that, if such an analytical tool exists, the process of iterating through and analyzing every video for those characteristics would require too much run-time. Even if we wanted to collect data on peripheral characteristics of videos – like username, number of views, number of thumbs up, etc – each query to the API would return data on a maximum of only fifty videos.

Due to the limitations with Facebook, Instagram, and YouTube, we decided to narrow our focus, collecting data on two viral Twitter movements: Bring Back Our Girls and Black Lives Matter. We selected these two because Twitter was their primary platform, and because they were often assessed with very different success levels.

Twitter, however, had similar constraints to other social media sites. The Twitter search API did not return tweets that were more than a week old, which rendered it a less than ideal resource for the range of dates in which we were interested. After some research, we found an old tweets retrieval script written by Jefferson Henrique. His code completely bypassed the search API and instead queried the Twitter website as if it were a human user. It generated a custom HTTP request with parameters like keyword and desired date range, and then parsed through the JSON response (very similar to the HTML/CSS-rendered page that a human would see) to extract each tweet’s username, text, date, location, and number of retweets and favorites.

We were able to modify his code to filter tweets based on number of retweets/favorites and to write the tweet information to an output txt file. Unfortunately, we encountered problems with consistency – every other day for at least two weeks, the code would stop collecting data; we were unable to identify or fix the source of this inconsistency in the code. The code also crashed when it encountered nonstandard characters like accents or emojis in the tweet text. We were only able to fix the issue recently, which may have caused some inconsistency in our data.

We had also planned to investigate the relationship between traditional news coverage and social media activity running in parallel. Some of our original questions were:

- Did news coverage peak before or after social media?
- Were the peaks shorter or longer?

Unfortunately, the Google News Search API has been deprecated as of 2011, and we struggled to find a news search service with comparable breadth. The only alternatives we could find were APIs for specific news sources like the New York Times or Associated Press, which wouldn't be representative of total news coverage for our movements. Due to these limitations in data collection resources, as well as limitations in time, we decided to abandon data collection about the patterns in parallel news coverage.

OBSTACLES & REVISIONS: Analysis

The major changes to our data collection plan also meant major changes to our analysis strategy. We split our analysis tasks into two major goals: 1) investigating factors that make an individual tweet popular, and 2) investigating trends in the popularity of all tweets over time.

We added the following formula columns to our table to supplement the analysis process for the first goal:

- *reaction_sum*: Quantitative variable for the sum of # retweets and # favorites.
- *has_pic*: Ordinal categorical variable for whether a tweet contains a picture (delineated by "pic.twitter", 1 = has picture, 0 = doesn't have picture)
- *has_link*: Ordinal categorical variable for whether a tweet contains an outside link (delineated by "www.", 1 = has link, 0 = doesn't have link)

We tried as much as possible to produce graphs with the same variables and perform the same tests across both social media movements, so as to make them more comparable for our analysis. We were interested in seeing whether or not there were universal characteristics that could be attributed to movements that go viral.

Findings

INDIVIDUAL TWEET ENGAGEMENT

What makes an individual tweet popular?

Types of engagements (favorites versus retweets)

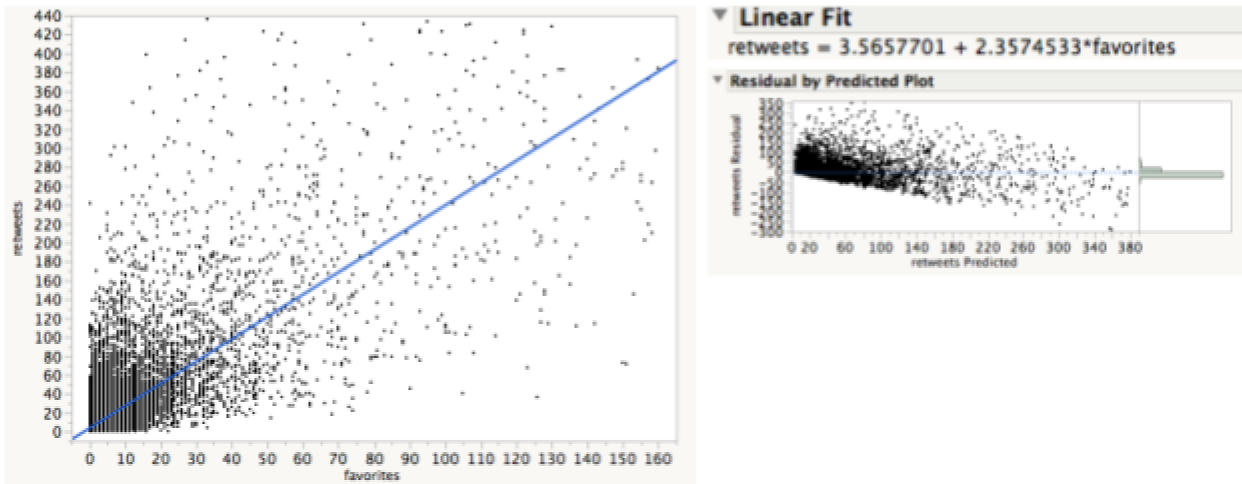


Figure 1.1: Bivariate analysis and linear regression on # favorites by # retweets (from BBOG)

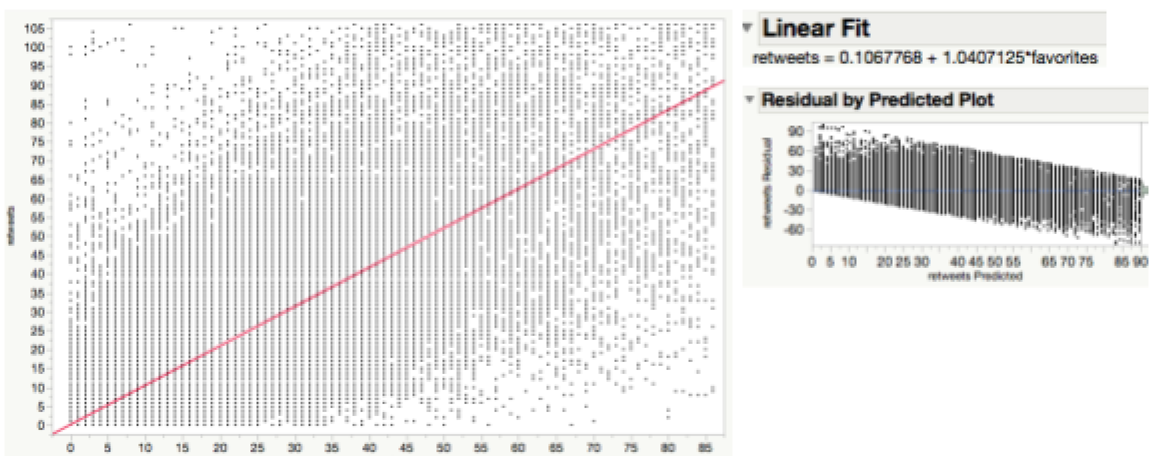


Figure 1.2: Bivariate analysis and linear regression on # favorites by # retweets (from BLM)

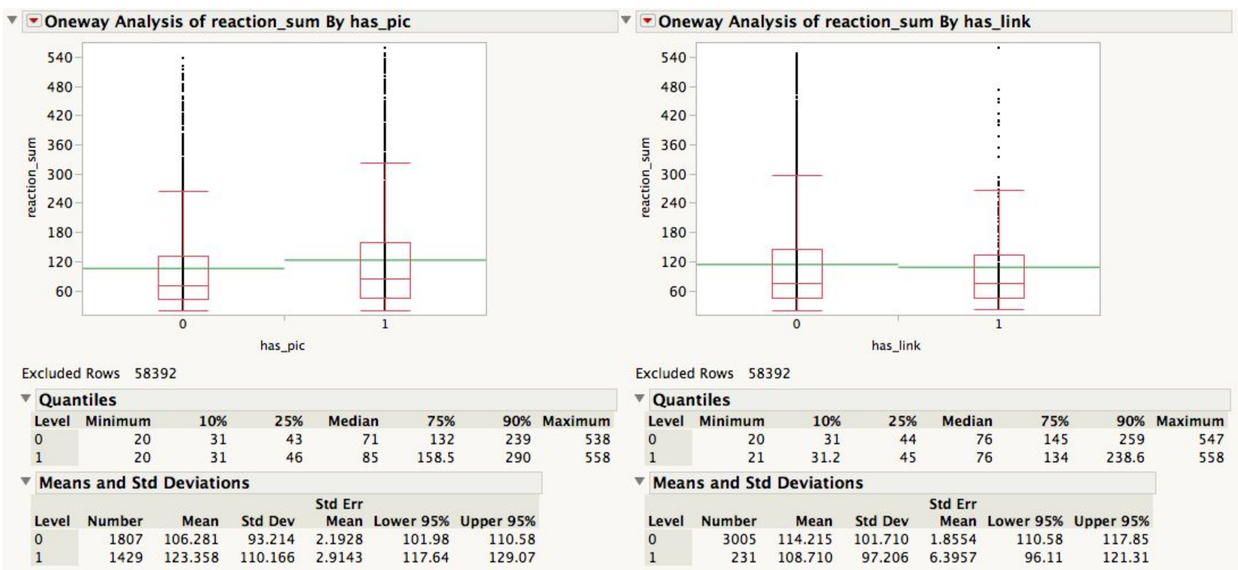
For Twitter, we classify “favoriting” a tweet as a narrowcasting, response action – one only between the author and direct viewers, and we classify “retweeting” as a broadcasting, sharing action – one that spreads the content beyond the direct viewer. As measures of engagement, one would consider retweets as more valued than favorites because they involve a broader potential audience (oneself versus one’s followers). We performed a bivariate analysis on # favorites by # tweets to see if there is a strong correlation between the two differently weighted engagement measures.

The distributions of # retweets and # favorites are both extremely skewed right; there are a handful of outlier tweets by very famous users like Hillary Clinton and Michelle Obama that attracted an unusual amount of engagement. See Figures B.2 and B.3 in Appendix B for summary statistics on these outliers. We excluded 392 tweets with the top 0.5% of retweets (> 436 retweets) or favorites (> 160 favorites) so that these outliers wouldn't skew the analysis.

The regressions for both movements show there is a medium-strength correlation (Bring Back Our Girls: r^2 = 0.59, Black Lives Matter: r^2 = .71) between favorites and retweets. The residual plots did show downward patterns, which suggests this linear model overestimates for lower # favorites and underestimates for higher # favorites. After trying various curve fit models like square root and natural logarithm, we were unable to find a model better than the linear fit.

A significance test of the regression coefficient (Bring Back Our Girls: 2.357, Black Lives Matter: 1.04) returns a p-value of essentially 0 (see Appendix A, test #1), confirming that the slopes are greater than 1.

Influence of pictures or external links on engagement



Oneway Analysis of reaction_sum By has_pic

Excluded Rows 58392

Quantiles

Level	Minimum	10%	25%	Median	75%	90%	Maximum
0	20	31	43	71	132	239	538
1	20	31	46	85	158.5	290	558

Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean	Lower 95%	Upper 95%
0	1807	106.281	93.214	2.1928	101.98	110.58
1	1429	123.358	110.166	2.9143	117.64	129.07

Oneway Analysis of reaction_sum By has_link

Excluded Rows 58392

Quantiles

Level	Minimum	10%	25%	Median	75%	90%	Maximum
0	20	31	44	76	145	259	547
1	21	31.2	45	76	134	238.6	558

Means and Std Deviations

Level	Number	Mean	Std Dev	Std Err Mean	Lower 95%	Upper 95%
0	3005	114.215	101.710	1.8554	110.58	117.85
1	231	108.710	97.206	6.3957	96.11	121.31

Figure 2: One-way analyses of has_pic, has_link by reaction_sum (from BBOG) red lines are the quantiles, green lines are the means

With the same upper outlier tweets still excluded, we wanted to investigate the influence of pictures and external links on engagement. However, the distributions of the reaction_sums were too far skewed right to be meaningful – all four distributions' interquartile ranges were limited to between 0 and 10 (or less) reaction_sum, while their maximums hovered around 550. Thus we decided to add a lower threshold to the tweets; after experimenting with various thresholds, we found that excluding tweets with less than 20 reaction_sum resulted in larger and more meaningful quantiles. This thresholding, combined with the exclusion of upper outliers, left 3,236 tweets to analyze.

We performed two-sample t-tests to compare the differences in reaction_sum mean. For pictures, the significance test returned a p-value of 1.49e-6 (essentially 0) which indicates that the reaction_sum mean for tweets with pictures is significantly greater than the mean for tweets without. For external links, the significance test returned a p-value of 0.795, which indicates that the reaction_sum means for tweets with and without links were <u>not</u> significantly different.

POPULARITY OVER TIME

Trends immediately following a "spark" event

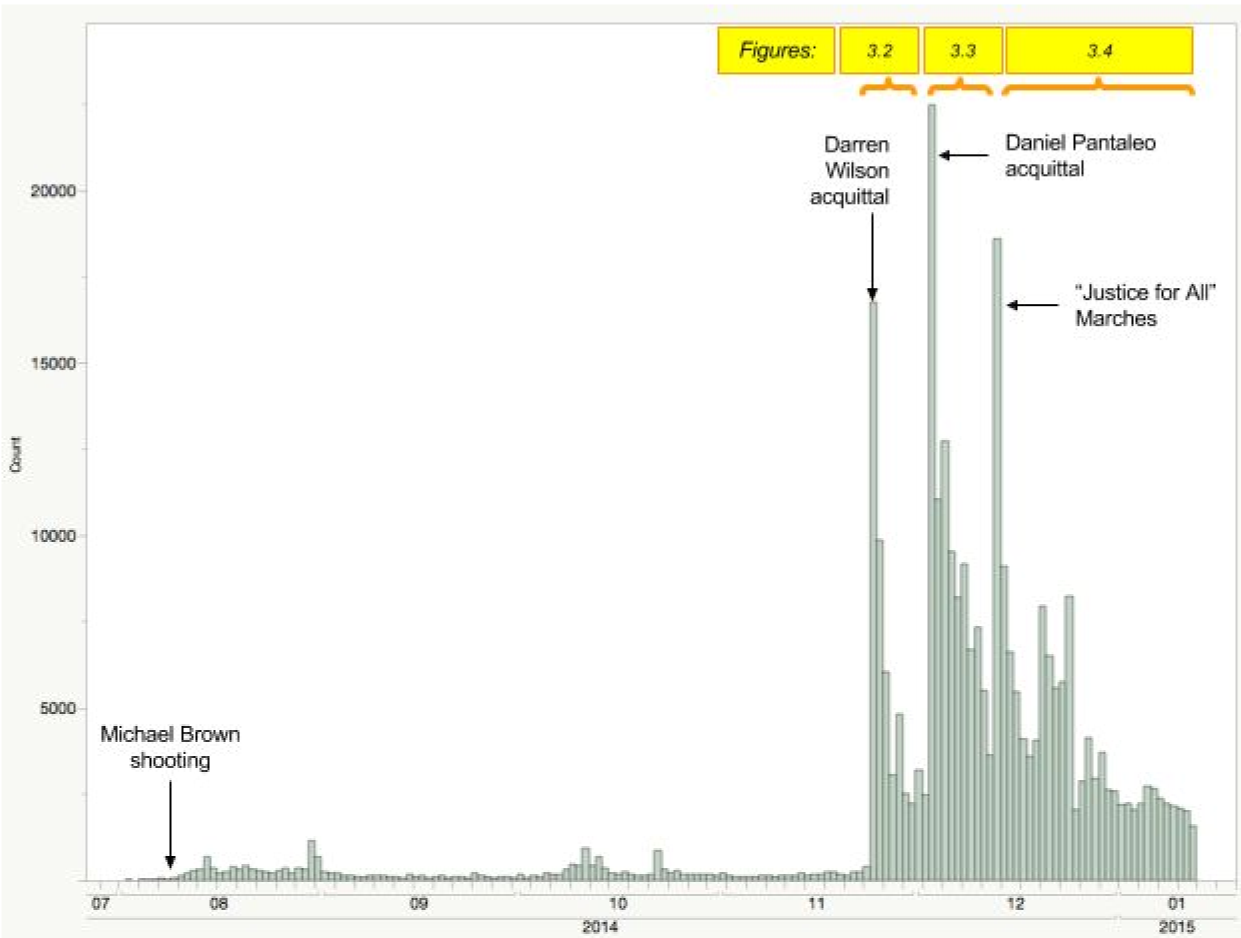


Figure 3.1: histogram of dates (serving as a time series) of tweets for the ~6 months following Michael Brown shooting, 8/9/2014

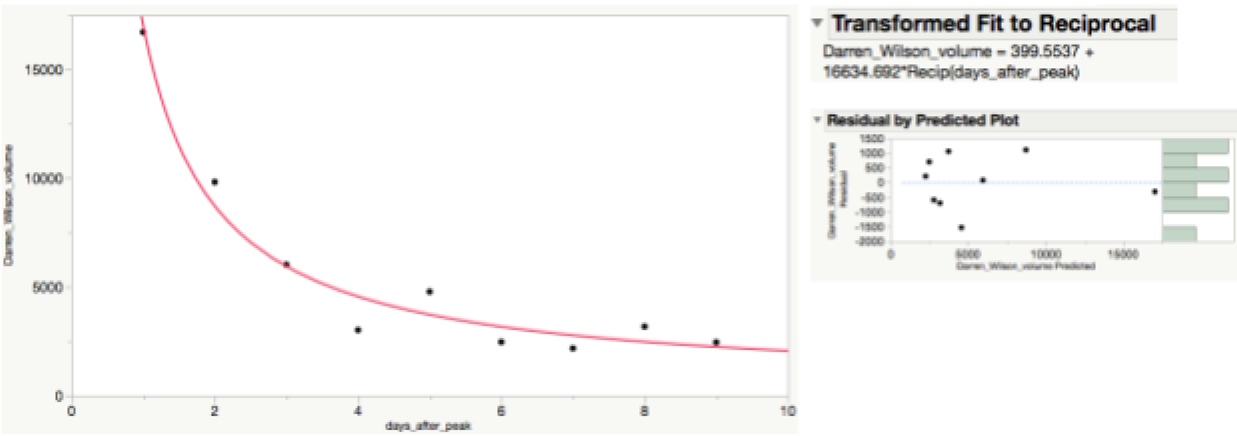


Figure 3.2: bivariate analysis of # days after Wilson acquittal by tweet volume

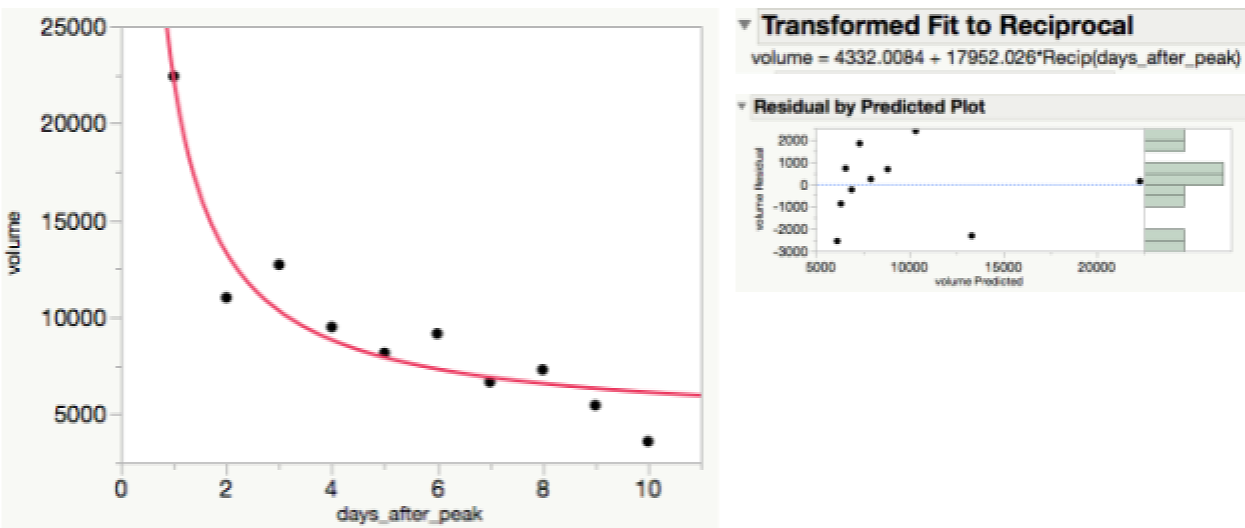


Figure 3.3: bivariate analysis of # days after Pantaleo acquittal by tweet volume

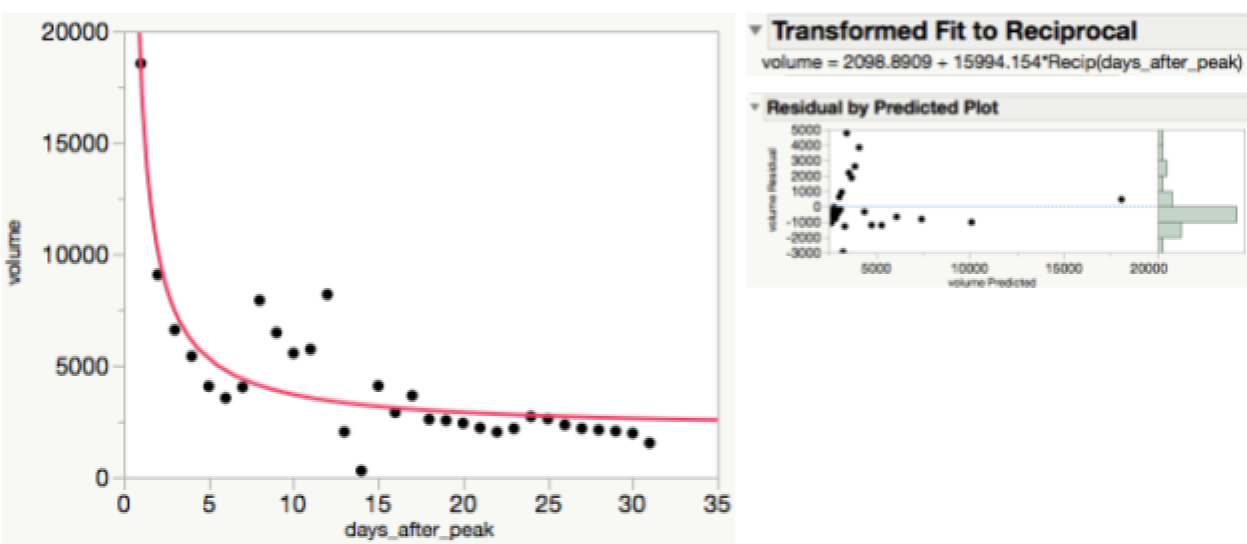


Figure 3.4: bivariate analysis of # days after "Justice for All" Marches by tweet volume

Both Bring Back Our Girls and Black Lives Matter were prompted to go viral by one or many high-profile news events (we will refer to these as "spark" events). As can be seen in figure 3. – in which a few sparks are indicated – there seemed to be a strong relationship between spark events and a movement's short-term popularity, especially for Black Lives Matter.

We selected three chunks of time – within the ~6-month period shown in figure 3.1– which were sandwiched by successive sparks, and we performed a bivariate analyses on volume (# tweets per day) by # days after the spark event (figures 3.2, 3.3, 3.4). For each time period, the volume seemed to decline over time according to a reciprocal model (*y = 1/x*); each reciprocal regression had a medium-strong to very strong correlation (Wilson acquittal: r^2 = .966, Pantaleo acquittal: r^2 = .907, "Justice for All": r^2 = .79). The residual plots show no pattern other than a fanning out towards lower values, since the model may be less precise for lower-volume data. The slopes of the transformed regressions (Wilson acquittal: b = 16634, Pantaleo acquittal: b = 17952, "Justice for All": b = 15994) are also very large, suggesting that hashtag popularity consistently underwent a sharp drop immediately following the spark event. Significance tests on the slopes of the regressions all yielded p-values less than .0001, allowing us to conclude that the slopes were statistically significantly greater than 0 (see Appendix A, test #4).

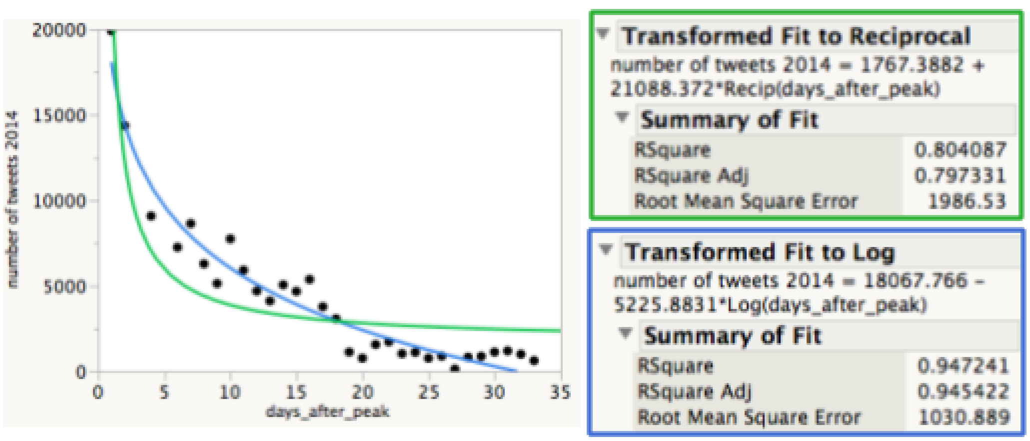


Figure 4.1: bivariate analysis of # days after BBOG 2014 kidnapping (5/13/2014-6/14/2014) peak by tweet volume

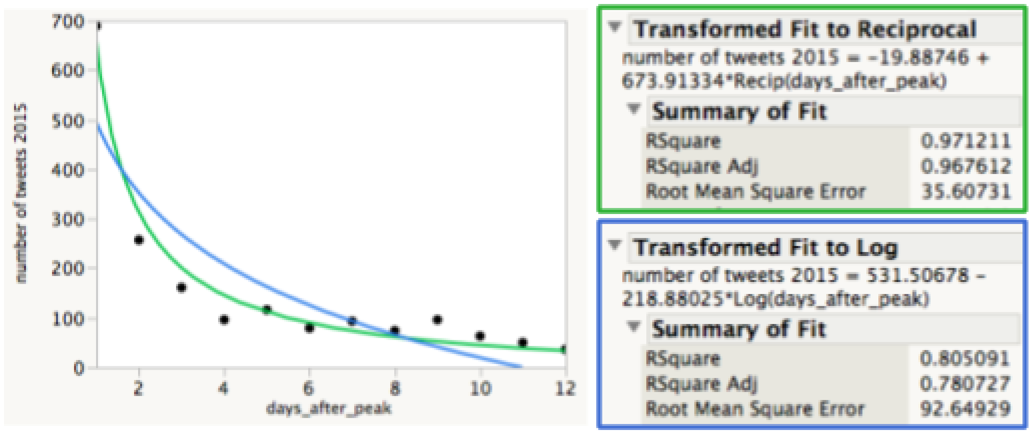


Figure 4.2: bivariate analysis of # days after BBOG 2015 anniversary (4/28/2015-5/9/2015) peak by tweet volume

The Bring Back Our Girls movement had two major peaks: one a few weeks after the April 2014 kidnapping, and one during the 2015 anniversary of the kidnapping. We performed the same bivariate analysis on these two peaks to compare tweet volume decline models.

On the 2014 peak (Figure 4.1), we tried both a reciprocal and logarithmic fit and found the logarithmic model had a higher r^2 value (0.8 for reciprocal versus 0.95 for logarithmic) that was more comparable to the r^2 values of the BLM reciprocal fits. On the 2015 peak (Figure 4.2), however, the reciprocal fit had a higher r^2 value, comparable to the three BLM peaks that were analyzed above.

Discussion and Conclusion

INTERPRETING FINDINGS

Engaging with individual tweets

We had known going into our analysis that BBOG, especially, was well known for being propagated by the use of photos; users would post photos of themselves holding up signs on which the hashtag was written. Our analysis confirmed that the inclusion of photos in a tweet was strongly correlated with the amount of engagement – measured in retweets and likes. Other characteristics of tweets like link inclusion, however, seemed to have little effect on the popularity of an individual tweet.

(Due to technical difficulties in data collection, we were unable to perform a similar analysis on individual tweet characteristics for BLM.)

Trends in popularity decline

After performing analysis on a few time periods immediately following spark events, we found that, in every instance we studied, the BLM hashtag declined in popularity approximately according to a reciprocal model. Our significance tests on the regression coefficients showed that the relationship between # days following a spark and volume per day was statistically significant.

On the other hand, BBOG's decline in hashtag popularity following its spark event seemed to be better modeled by a logarithmic curve. Hashtag popularity decline following BBOG's first anniversary, however, followed more of a reciprocal curve. For all sparks in both movements, however, popularity decline immediately following the spark was very steep, suggesting the unsustainability of single-spark-prompted movements.

RECOMMENDED ACTION

For organizations aiming to go viral

Both Bring Back Our Girls and Black Lives Matter intended to raise awareness about an event and spur action to stop it. For an individual or nonprofit who would like to quickly raise awareness about an event for a few weeks, we recommend highlighting that event and starting with a small but dedicated user base. As BBOG proved (where the hashtag's creator Obiageli

Ezekwesili started the movement by asking a room of people to tweet #bringbackourgirls), starting a social media movement by word of mouth and without any costly intentional marketing tactics is very possible. The individual or nonprofit may also consider including photos as an integral part of their movement's posting experience, as photos improve visibility and engagement with individual tweets.

However, if the individual or nonprofit would like their movement to be sustainable – for example to spur actionable change in government or other slower-moving organizations – they cannot rely solely on the techniques above. Pure user activity can only maintain a movement's popularity levels for a few weeks. For longer term engagement, as BLM showed, there must be repeated "sparking" events or another aspect of the movement's message that changes periodically to keep users on their toes. Social media is not the best medium to promote a single unchanging message for more than a few weeks.

For social media companies

One of the topics we were most interested in originally was the relationship between a post's evoked emotion and its popularity. However, as mentioned in "Methodology," it was nearly impossible to study this relationship, as we would need to run textual or visual sentiment analysis on every single piece of content we collected (1,500,000+ tweets). Since we're guessing that emotion plays a big role in content popularity, it would be beneficial for there to exist a more easier way to collect data on emotion.

It would be unrealistic to ask a company to run sentiment analysis on every single piece of content that has been published so far. Therefore, our request to social media companies – especially the ones that host public content like Youtube or Twitter – is that they run sentiment analysis log emotion-related data on posts *as they are being posted*. This way, emotion-related data can be retrieved much more easily for future studies.

FURTHER QUESTIONS AND STUDY

Since our analysis on BBOG identified photos as having a strong relationship with tweet engagement, we would like to apply the same analysis to other photo-heavy movements (like #ILookLikeAnEngineer) to confirm this correlation. We would also like to examine if different types of photos spur the same amount and type of engagement. The BBOG photos heavily featured the users themselves; would the engagement have been different if they featured inanimate objects or scenes unrelated to the user? We would also like to examine the effect of multimedia other than photos. Especially with the recent integration of Vine and Twitter, users are able to post brief videos. For similar tweets (similar authors, similar post dates, and similar topics), do Vine videos create more engagement than photos?

One of our findings that was most unexpected was the consistency with which popularity decline follows certain models – reciprocal for BLM and BOGG's first anniversary, logarithmic for BBOG. It would be interesting to study other news-event-prompted movements to see if the trends we found were not accidental.

The observed difference in models – between BOGG's first spark and every other spark we analyzed – could potentially be explained by differing prominence in public consciousness. Perhaps because the Chibok Schoolgirls Kidnapping was a both unusual and surprising spark event, Twitter users were willing to stay on the BBOG topic for longer – hence the logarithmic model, which is less steep than the reciprocal. On the other hand, the unfortunate frequency and familiarity of police brutality might explain why use of the BLM hashtag died down more quickly. Similarly, BBOG's first anniversary might have declined in popularity more sharply, because the topic had already been discussed the previous year. We would like to perform more research to further investigate our ideas or find more thorough explanations for why the reciprocal or logarithmic models might be appropriate.

Due to our data collection limitations, we weren't able to address many of the topics in our background research. With further studies, we hope to explore:

- author background (query the Twitter API for information about the tweet authors)
- author retention (how long and often does each author post on the same topic?)
- emotional content of tweet (sentiment analysis on text, color composition and sentiment analysis of image; how do these factors contribute to the viewer's engagement?)
    - If Facebook loosens its privacy controls, we could expand our definition of viewer engagement from just view counts to actual emotional response with Facebook reactions.

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Appendices

APPENDIX A (technical)

Test #1 (favorites vs. retweets):

State: significance test of regression coefficient, # favorites vs. # retweets

H_0: slope of regression = 1

H_A: slope of regression > 1

Plan: check conditions:

1. linear – yes, we believe the true relationship between favorites and retweets is linear
2. independent observations – almost all the tweets were independent (a few may have been written in direct and immediate response to others)
3. normal – yes, the residuals are approximately normally distributed around 0
4. equal variance – yes, see residual plot
5. random – not applicable, as we are essentially looking at the entire "population" of tweets and not just a random sample

Do (Bring Back Our Girls): slope of regression = 2.357; standard error of slope = 0.00777, alpha level = 0.05

after calculator t-test: t-statistic = 174.65, p-value is basically 0

Do (Black Lives Matter): slope of regression = 1.04; standard error of slope = 0.0005, alpha level = 0.05

after calculator t-test: t-statistic = 80, p-value is basically 0

Conclude: With a p-value of basically 0, we reject the null hypothesis and conclude that the slope of this regression line is significantly greater than 0.

Test #2 (has_pic) and #3 (has_link):

We are combining the procedures for two tests because they are so similar.

State: two sample t-test on difference of means, has_pic vs. reaction_sum and has_link vs. reaction_sum

H_0: μ without picture/link = μ with picture/link

H_A: μ without picture/link ≠ μ with picture/link

(where μ = population mean reaction_sum)

Plan: check conditions:

1. random – not applicable
2. normal – sample size = 3,236 tweets, by CLT we can approximate their distribution as normal
3. independent – almost all the tweets were independent from each other; 3,236 tweets is less than 10% of the total number of tweets ever sent

Do:

alpha level = 0.05

for has_pic

without picture: $\bar{x}$ = 106.281, S_x = 93.214, n = 1807

with picture: $\bar{x}$ = 123.358, S_x = 110.166, n = 1429 p-value = 1.49e-6 (essentially 0)

for has_link

without link: $\bar{x}$ = 114.215, S_x = 101.71, n = 3005

with link: $\bar{x}$ = 108.71, S_x = 97.206, n = 231

p-value = 0.795

Conclude: For has_pic, we can reject the null and conclude that the mean with pictures is significantly different from that without. For has_link, we do not have enough evidence to reject the null and conclude that the means with and without links are not significantly different.

Test #4 (Black Lives Matter: days after spark vs. volume):

State: significance test of regression coefficient (for data with reciprocal transformation), # days after spark vs. tweet volume

H_0: slope of regression = 0

H_A: slope of regression > 0

Plan: check conditions:

6. linear – yes, we believe the true relationship between 1/(days after spark) and volume is linear; no other model yielded as high a correlation coefficient
7. independent observations – almost all the tweets were independent (a few may have been written in direct and immediate response to others)
8. normal – yes, the residuals are approximately normally distributed around 0
9. equal variance – yes, see residual plots
10. random – not applicable

Do (Wilson acquittal): slope of regression = 16634.692; standard error of slope = 1167.4, alpha level = 0.05

after calculator t-test: t-statistic = 14.25, p-value is basically 0

Do (Pantaleo acquittal): slope of regression = 17952.026; standard error of slope = 2021.574, alpha level = 0.05

after calculator t-test: t-statistic = 8.88, p-value is basically 0

Do (“Justice For All”): slope of regression = 15994.154; standard error of slope = 1530.461, alpha level = 0.05

after calculator t-test: t-statistic = 10.45, p-value is basically 0

Conclude: With a p-value of basically 0, we reject the null hypothesis and conclude that the slope of this regression line is significantly greater than 0.

APPENDIX B (interesting or helpful graphs)

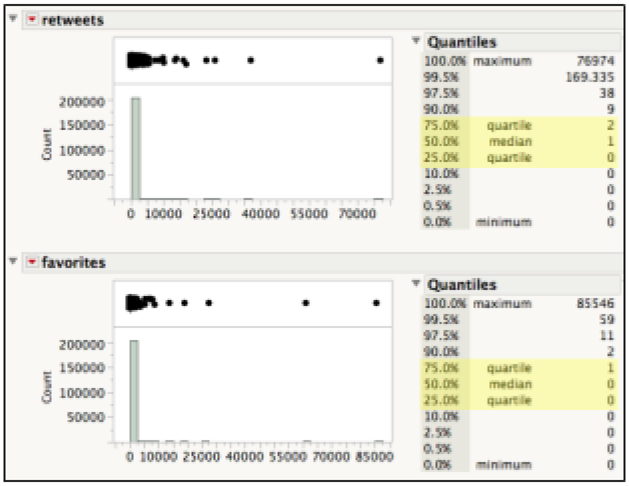


Figure B.1 distribution of retweets and favorites for all BBOG tweets

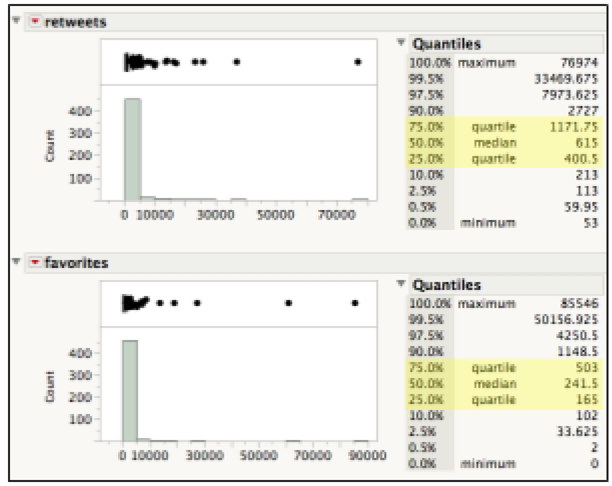


Figure B.2 distribution of retweets and favorites for top 0.5% of BBOG tweets

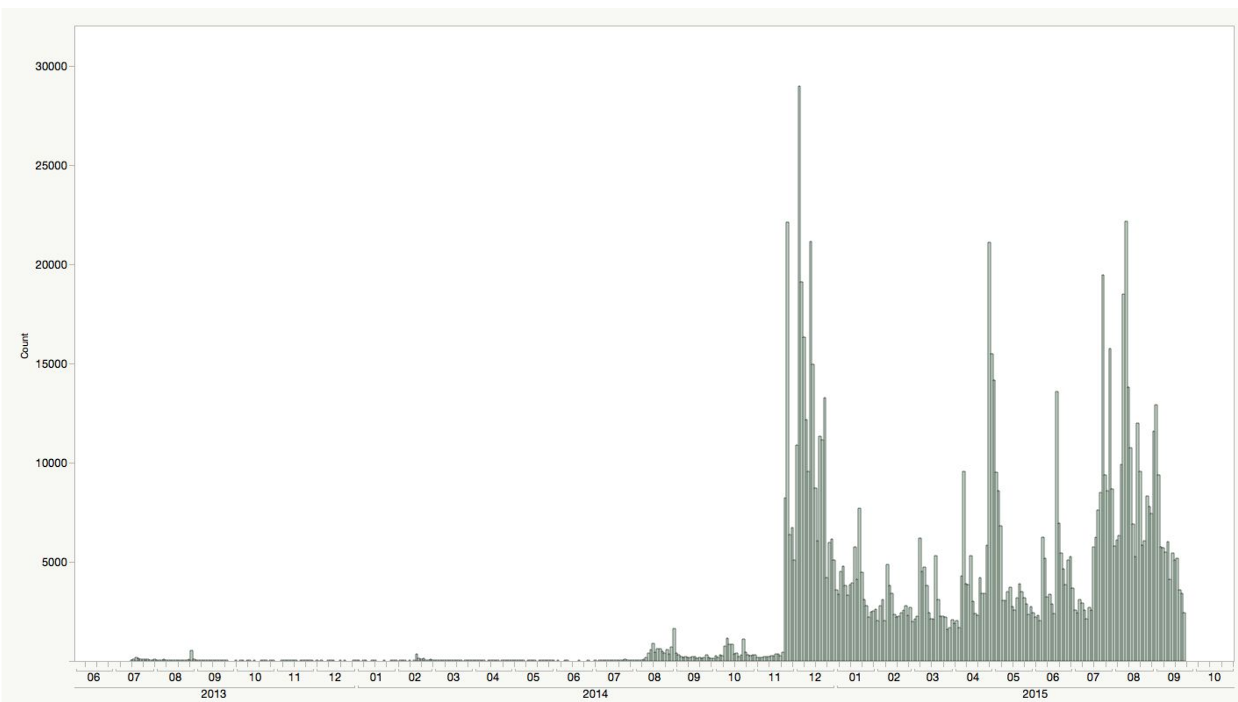
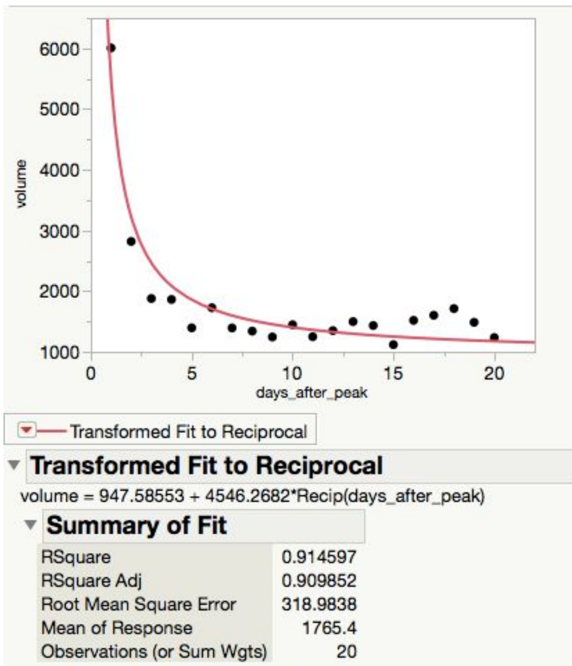


Figure B.3 Histogram of #BlackLivesMatter tweets' dates serving as a time series, data collected since hashtag nascence July 2013 till September 2015

Figures B.4 - B.10: curved regressions on BLM volume vs days_after_peak for time periods after Ferguson (Note: We tried both reciprocal and log fits on all peaks. When one fit was clearly more suitable than the other – much higher R^2 –, we only included the better fit in the appendix. When the R^2 were relatively close to each other, we included both fits.)



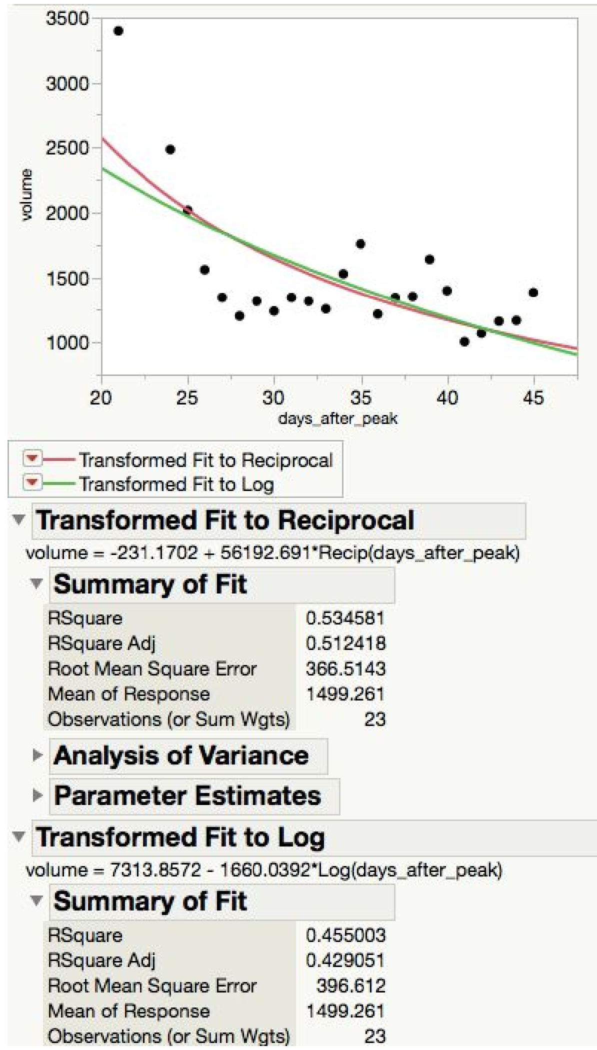
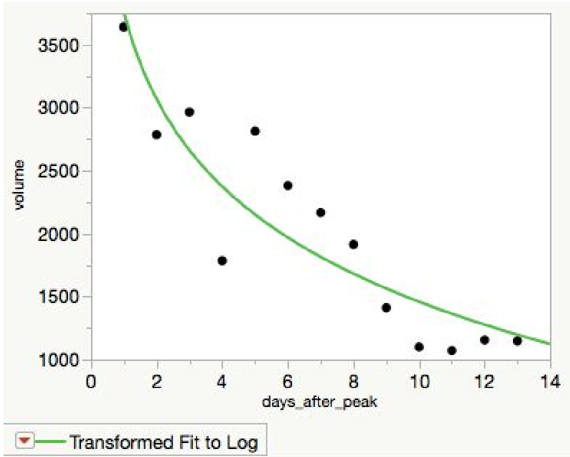


Figure B.4: MLK Day, (1/19/2015 - 2/7/2015); Figure B.5: Black History Month (guessed), (2/8/2015 - 3/4/2015)

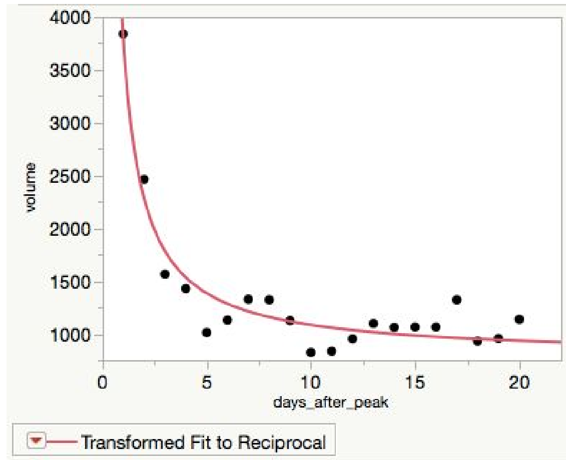


Transformed Fit to Log

volume = 3756.6514 - 998.41719*Log(days_after_peak)

Summary of Fit

RSquare	0.816536
RSquare Adj	0.799857
Root Mean Square Error	378.3602
Mean of Response	2024.615
Observations (or Sum Wgts)	13



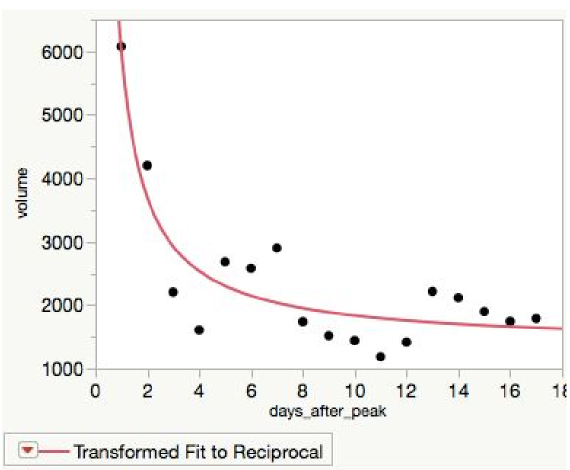
Transformed Fit to Reciprocal

volume = 785.76698 + 2984.5574*Recip(days_after_peak)

Summary of Fit

RSquare	0.931884
RSquare Adj	0.9281
Root Mean Square Error	185.274
Mean of Response	1322.65
Observations (or Sum Wgts)	20

Figure B.6: Ferguson Report Released, (3/5/2015 - 3/17/2015); Figure B.7: Martese Johnson Violence/#RaceTogether Initiative, (3/18/2015 - 4/6/2015)

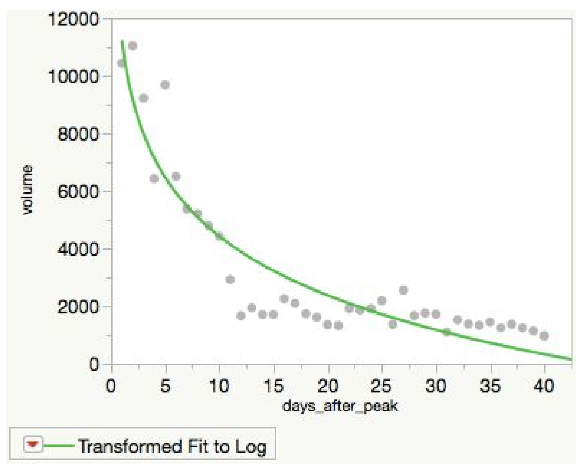


Transformed Fit to Reciprocal

volume = 1368.6718 + 4662.9841*Recip(days_after_peak)

Summary of Fit

RSquare	0.828316
RSquare Adj	0.816871
Root Mean Square Error	517.6558
Mean of Response	2312.118
Observations (or Sum Wgts)	17



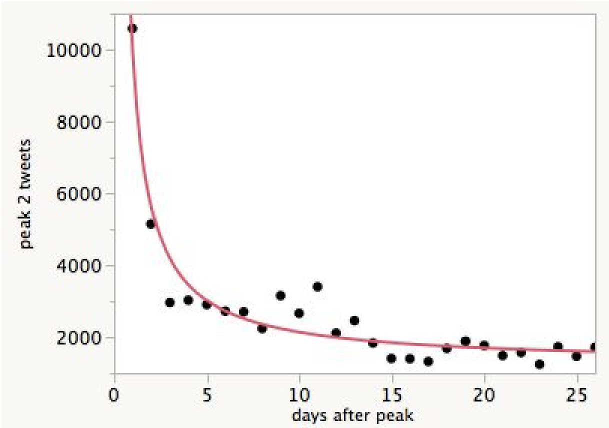
Transformed Fit to Log

volume = 11224.395 - 2953.7339*Log(days_after_peak)

Summary of Fit

RSquare	0.860182
RSquare Adj	0.856503
Root Mean Square Error	1053.676
Mean of Response	3077.95
Observations (or Sum Wgts)	40

Figure B.6: Walter Scott, (4/8/2015 - 4/24/2015); Figure B.7: Baltimore Protest, (4/27/2015 - 6/5/2015)



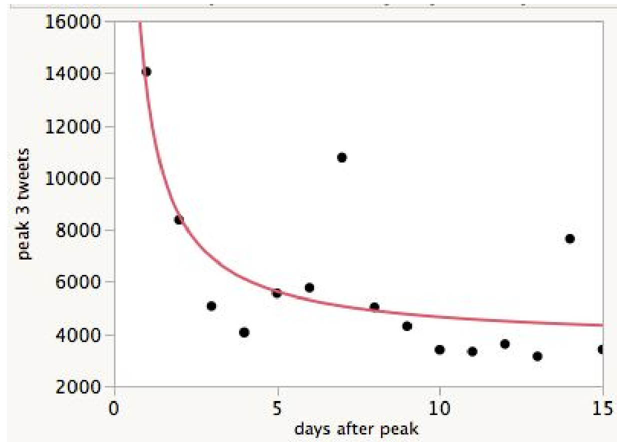
Transformed Fit to Reciprocal

Transformed Fit to Reciprocal

peak 2 tweets = 1258.1503 + 8770.2158*Recip(days after peak)

Summary of Fit

RSquare	0.926133
RSquare Adj	0.923056
Root Mean Square Error	514.5516
Mean of Response	2558.308
Observations (or Sum Wgts)	26



Transformed Fit to Reciprocal

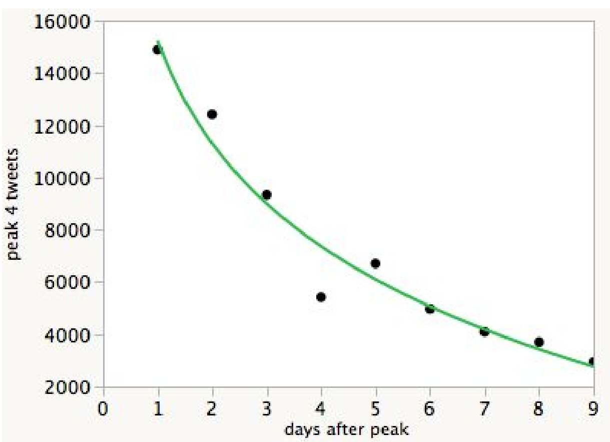
Transformed Fit to Reciprocal

peak 3 tweets = 3668.9551 + 9759.6259*Recip(days after peak)

Summary of Fit

RSquare	0.581271
RSquare Adj	0.549061
Root Mean Square Error	2113.615
Mean of Response	5827.933
Observations (or Sum Wgts)	15

Figure B.8: Charleston Church Shooting, (6/18/15-7/13/15); Figure B.9: Sandra Bland, (7/23/15-8/7/15)



Transformed Fit to Log

Transformed Fit to Log

peak 4 tweets = 15242.061 - 5682.2004*Log(days after peak)

Summary of Fit

RSquare	0.958627
RSquare Adj	0.952716
Root Mean Square Error	907.6844
Mean of Response	7159.556
Observations (or Sum Wgts)	9

Figure B.10: Michael Brown Anniversary, (8/9/15-8/17/15)