# Sentiment Analysis of Twitter Audiences: Measuring the Positive or Negative Influence of Popular Twitterers

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**Twitter is a popular microblogging service that is used to read and write millions of short messages on any topic within a 140-character limit. Popular or influential users tweet their status and are retweeted, mentioned, or replied to by their audience. Sentiment analysis of the tweets by popular users and their audience reveals whether the audience is favorable to popular users. We analyzed over 3,000,000 tweets mentioning or replying to the 13 most influential users to determine audience sentiment. Twitter messages reflect the landscape of sentiment toward its most popular users. We used the sentiment analysis technique as a valid popularity indicator or measure. First, we distinguished between the positive and negative audiences of popular users. Second, we found that the sentiments expressed in the tweets by popular users influenced the sentiment of their audience. Third, from the above two findings we developed a positive-negative measure for this influence. Finally, using a Granger causality analysis, we found that the time-series-based positive-negative sentiment change of the audience was related to the real-world sentiment landscape of popular users. We believe that the positive-negative influence measure between popular users and their audience provides new insights into the influence of a user and is related to the real world.**

## Introduction

As the term suggests, microblogging is the blogging of small statements such as “I am having lunch” and is considered a passive form of blogging. Microblogging services provide a simple, easy form of communication that enables users to broadcast and share information about their day-to-day activities, opinions, news stories, current status, and other interests. Commercial or purposive microblogs also exist and are used to promote websites, services, products, or individuals by using microblogging on popular platforms such as Twitter, Facebook, etc., as marketing and public relations services.

Since its launch in October 2006, Twitter[1] has become a ubiquitous real-time information network powered by people all around the world that lets users share and discover what is happening now. Twitter is a social medium for people to communicate and stay connected through the exchange of quick, frequent messages. People write short updates, often called “tweets,” limited to 140 characters, about various topics such as their day-to-day activities. They share information, news, and opinions with followers, and seek knowledge and expertise through public tweets.

Twitter employs a social-networking model called “following,” in which Twitter users can follow any other user without permission, i.e., the relationship of following requires no reciprocation. To follow someone on Twitter means to subscribe to their tweets or updates on the site almost in real time. A “follower” is another Twitter user who has followed you. Other common features in Twitter are as follows. A “reply” is a tweet posted in reply to another user’s message; it begins with “@username,” where the “@” sign is used to call out usernames in tweets. “RT,” which stands for “retweet,” is the act of forwarding another user’s tweet to all of your followers. Users can respond to another person’s tweet, which is called “mention.” A “mention” is any Twitter update that contains “@username” in the tweet content.

Currently, Twitter is a social medium that produces and propagates information, rather than a social networking site. Previous research (Kwak, Lee, Park, & Moon, 2010) has shown that the top users, as measured by the number of

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[1]http://twitter.com

followers on Twitter, are mostly celebrities and those who attract the keen interest of the mass media. An electronic platform for word-of-mouth influence in marketing (Jansen, Zhang, Sobel, & Chowdury, 2009), Twitter also serves as a political sentiment analysis predictor of elections (Diakopoulos & Shamma, 2010; O'Connor, Balasubramanyan, Routledge, & Smith, 2010; Tumasjan, Sprenger, Sandner, & Welpe, 2010) and as a stock market movement predictor (Bollen, Mao, & Zeng, 2011; Bollen, Pepe, & Mao, 2009; Gilbert & Karahalios, 2010; Zhang, Fuehres, & Gloor, 2010). This has widened its appeal to politicians and other pundits. It can be used to quickly share information with people, promote new products, and communicate with fans or political supporters. People respond to popular users by retweeting, mentioning, or replying positively or negatively. This new and important phenomenon motivated our study of the nature of the interactions between popular Twitter users and other twitterers, i.e., audiences.

It is important for popular users such as celebrities, politicians, or corporations to understand their audiences, and to measure their influence toward audiences on Twitter. The goal of this study is to develop a measure of positive-negative influence for popular users on Twitter and reveal how this measure of influence is related to real-world phenomena. We collected the tweets of certain popular users, together with the tweets of other users that contained the @username of the popular users. Then, we performed an empirical analysis of user sentiment on Twitter based on an analysis of negative and positive words. We developed a measure of the positive-negative influence between popular users and their audience and then investigated whether the positive-negative influence changes over time. Our results indicate that the time series of positive-negative influence changes are related to real-world sentiments, such as Obama's job approval ratings on Gallup Daily and artists' movements on the Billboard weekly chart. The primary contribution of this work is that this measure of influence on Twitter can be used as an indicator to identify real-world audience sentiments, providing new insights into influence and a better understanding of popular users. Moreover, this can be applied to predict elections, evaluate the effect of product marketing, and evaluate customer responses for celebrities, politicians, companies, etc.

## Related Work and Background

Recently, there have been several investigations into the role of Twitter in social media. Some researchers focused on understanding microblogging usage and community structures (Honeycutt & Herring, 2009; Huberman, Romero, & Wu, 2008; Java, Song, Finin, & Tseng, 2007). Kwak et al. (2010) showed that the top users of Twitter (those who have the most followers) are mostly celebrities and mass media organizations, many of whom do not follow their followers back. That is, Twitter shows a low level of reciprocity: 77.9% of links connected one-way, with only 22.1% having reciprocal relationships. Thus, social links on Twitter represent an influence relationship, rather than homophily (Cha, Haddadi, Benevenuto, & Gummadi, 2010; Kwak et al., 2010). Cha et al. (2010) considered three measures of influence: indegree (the number of followers), retweets, and mentions. They found that indegree represents a user's popularity, but does not necessarily correspond to a user's influence; therefore, retweets and mentions should be considered as other important measures of influence. Honeycutt and Herring (2009) showed that Twitter is not only used for one-way communication, but is often used for conversational interaction and collaboration between users by mentioning or replying using an "@" sign.

Jansen et al. (2009) showed that microblogging can be used as an online tool for customer word-of-mouth communication, such as the sharing of customer opinions concerning brands or overall marketing strategy for corporations. They analyzed more than 150,000 microblog postings containing branding comments, sentiments, and opinions. Their research findings showed that 19% of microblogs mentioned a brand, and that 20% of the branding microblogs displayed a sentiment toward a brand, i.e., over 50% were positive and 33% were negative with respect to a company or product.

More recently, some researchers have focused on research involving the prediction of political elections (Diakopoulos & Shamma, 2010; O'Connor et al., 2010; Tumasjan et al., 2010; Yu, Kaufmann, & Diermeier, 2008), stock market indicators (Bollen et al., 2011; Bollen et al., 2009; Gilbert & Karahalios, 2010; Zhang et al., 2010), and box-office revenues for movies (Asur & Huberman, 2010) through Twitter.

Tumasjan et al. (2010) investigated whether Twitter reflected offline political sentiment in the German federal election by conducting a content analysis of over 100,000 messages containing a political party or politician using LIWC (Linguistic Inquiry and Word Count) text analysis software. They showed that Twitter is used extensively for political deliberation and is a valid indicator of political sentiment. O'Connor et al. (2010) analyzed several surveys of consumer confidence and political opinion over the 2008–2009 period, and they found that there is a strong correlation between measures of public opinion measured from polls and sentiment word frequencies in contemporaneous Twitter messages over time. Diakopoulos and Shamma (2010) demonstrated that the sentiment of Twitter messages around a televised political debate in the 2008 U.S. presidential election was negative, and found that tweeters tended to be more favorable to Obama than to John McCain. They also showed that interesting events and controversial topics can be detected by anomalies in the pulse of the sentiment signal and correlated sentiment responses.

Zhang et al. (2010) showed that it was possible to predict stock market indicators such as Dow Jones, NASDAQ, and S&P 500 by analyzing Twitter posts for six months. They analyzed the correlation between measures of hope or fear on each day and the stock market indices, and found that there was a significant negative correlation between the emotional tweet percentage and the stock market. They showed that simply checking Twitter for emotional outbursts of any kind can help to gauge the following day's stock market movement. Gilbert and Karahalios (2010) showed that estimating emotions from weblogs can be used to predict stock market movement. They estimated anxiety, worry, and fear from over 20 million posts on the LiveJournal site, and found that an increase in anxious expressions could predict downward pressure on the S&P 500 index. Bollen et al. (2009) showed that social, political, cultural, and economic events are correlated with changes in Twitter mood levels, even though there are delayed fluctuations between the events and the public mood. More recently, they (Bollen et al., 2011) investigated whether measurements of public mood obtained from over 9 million Twitter feeds were correlated with the value of the Dow Jones Industrial Average (DJIA) over time. They found that the accuracy of DJIA predictions can be significantly improved by the inclusion of specific public mood dimensions, e.g., the Google-Profile of Mood States (GPOMS), which measures six mood dimensions (Calm, Alert, Sure, Vital, Kind, and Happy). Moreover, they found that "Calm" had the highest correlation with changes in the DJIA over time.

Asur and Huberman (2010) demonstrated that public sentiment extracted from Twitter can be used to predict real-world outcomes, such as box-office revenue for movies, and can improve the forecasting power of social media. Thelwall et al. (2011) analyzed whether peaks of interest in online topics were associated with changes in sentiment. They found that the top 30 popular events are normally associated with increases in negative sentiment strength and that peaks of interest in events have a stronger positive sentiment than they did before the peak.

Previous studies have shown that Twitter is widely used for reflecting the landscape of the offline world such as in product marketing or the prediction of elections, stock markets, etc. There have been many sentiment-based analyses of Twitter to predict real-world phenomena. However, there has been no research into the use of positive-negative sentiment between popular twitterers and their audience as a new measure of influence.

## Research Questions

There are many interactions between popular users and their audiences on Twitter. In addition to favorable users, the audience of a popular user contains users that are unfavorable to the popular user, even though they are followers. It is important for popular users like celebrities, politicians, or corporations to identify and handle these negative users opportunely or to predict the future sentiment change of their audience. In the opposite direction, the sentiment of popular users can influence the sentiments of their audiences. For instance, if the very famous actor Ashton Kutcher tweets negatively, how will his audience respond to him? Therefore, if we could measure the sentiment of their audiences, we would be able to estimate the positive or negative influence of popular Twitter users. Finally, we want to determine whether time-series-based positive-negative influence changes are related to the real-world sentiment landscapes of popular users. For instance, when the sentiment changes over time for the audience of Barack Obama on Twitter, how does this relate to Obama's job-approval survey data from Gallup Daily? Is there a correlation between the sentiment changes of famous singers such as Lady Gaga or Britney Spears on Twitter and their ranks on the Billboard chart? Therefore, the goal of our research was to address the following research questions:

- Who are the positive or negative audiences of popular users?
- Do popular users influence the sentiment changes of their audiences positively or negatively?
- How can we measure a positive-negative influence?
- How is the time-series-based positive-negative influence change related to the real-world sentiment landscape of popular users?

## Data Set and Methodology

### *Data Set*

Before we collected a data set for our study, we first selected several popular users in various societal areas, such as celebrities, politicians, bloggers, media, and religious leaders known to most people. We chose 13 popular users (Barack Obama, Donald J. Trump, Bill Gates, Oprah Winfrey, Larry King, Lady Gaga, Ashton Kutcher, Britney Spears, the Dalai Lama, TechCrunch, Mashable, CNN Breaking News, BBC Breaking News) based on the criteria that they had more than 1 million followers (except for Donald J. Trump, who has less than 1 million followers) and were ranked in the top 50 of online social influence services such as Klout,[2] Twitalyzer,[3] and PeerIndex[4] during May 2011.

### *Tweet*

Followers retweet the tweets of those they are following to disseminate information to other people, or people respond to popular users by "replying" or "mentioning." Therefore, we collected the tweets of popular users and their audiences. Twitter provides a search application program interface (API) for extracting tweets containing particular search keywords. To obtain the data set for our study, we queried the Twitter search API at 30-min intervals over 57 days from May 13, 2011, to July 8, 2011, for all tweets containing the "@" sign with the names of the specified popular users, along with all of the tweets from the specified popular users. We collected 3,321,387 tweets and identified

[2]http://www.klout.com
[3]http://www.twitalyzer.com
[4]http://www.peerindex.com


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each tweet as replying to, retweeting about, or mentioning one of the specific 13 popular users, or as a tweet posted by one of the 13 popular users.

### *User Graph*

At the same time, we made the directed graph data set of users. A vertex (V) represents a user, and an edge (E) represents the relationship between a source and a target user for the replying, retweeting, or mentioning: (1) if a source user retweets a target user; (2) if a source user replies to a target user; (3) if a source user mentions a target user. This enabled us to build 1,227,864 graph data of users. A directed user graph with vertices and edges and the audience of a popular user can be defined as follows:

$$Directed\ User\ Graph = G\left(V, E_{\{reply \cup mention \cup retweet\}}\right), \quad (1)$$

$$\begin{aligned} Audience(i) &= \{V \mid (v_i, v_j) \in E\}. \\ v_j &\rightarrow v_i \in E_{\{reply \cup mention \cup retweet\}} \end{aligned} \quad (2)$$

As seen in definition (2), we define the audience of popular user *i* as users who reply to, mention, or retweet about the popular user. This means that we only consider active users who respond to the popular user, not mere followers.

### *Methodology*

To detect which of a popular user's followers are generally positive or negative toward the popular user, i.e., to classify the sentiment of tweets posted by users, we used a sentiment analysis method. We then applied statistical analysis methods to find the correlation between the popular users and their audiences, or between changes in sentiment on Twitter and in the real world.

*Sentiment analysis.* Sentiment analysis is also known as opinion mining and/or subjectivity analysis. It is used to extract opinions, sentiments, and subjectivity in unstructured text, that is, to identify whether the expressions indicate positive (favorable) or negative (unfavorable) opinions toward the subject (Pang & Lee, 2008). Sentiment analysis normally deals with detecting polarity, i.e., only positive or negative sentiment, rather than discrete emotions (e.g., happiness, sadness).

We used a lexicon-based sentiment analysis technique, which is a term-based matching technique based on a list of words that are precoded for polarity (Taboada, Brooke, Tofiloski, Voll, & Stede, 2011). This lexicon-based approach has been used in many previous studies to identify sentiment, especially in Twitter, because it does not require training and testing and enables the sentiment analysis of a very short length of text data (Bollen et al., 2011; Bollen et al., 2009; Gilbert & Karahalios, 2010; Kim, Gilbert, Edwards, & Graeff, 2009; Thelwall et al., 2011; Thelwall et al., 2010; Tumasjan et al., 2010). There are many precoded dictionaries for sentiment, such as ANEW (Affective Norms for English Words), POMS (the Profile of Mood States), LIWC (Linguistic Inquiry and Word Count), etc. ANEW (Bradley & Lang, 1999) provides a set of normative emotional ratings for a large number of words in the English language along three dimensions (pleasure, arousal, dominance). It was used in a sentiment analysis of the death of Michael Jackson (Kim et al., 2009) and for large-scale measurements of the happiness associated with written songs, blogs, and U.S. presidential speeches (Dodds & Danforth, 2010). The extended version of POMS (Bollen et al., 2009) provides six dimensions of mood (tension, depression, anger, vigor, fatigue, confusion). LIWC (Pennebaker, Chung, Ireland, Gonzales, & Booth, 2007; Pennebaker, Francis, & Boot, 2001) provides several dimensions of mood for positive emotions, negative emotions (anxiety, anger, sadness), etc.

To extract the sentiment of tweets, we used the LIWC dictionary because it enables a lexicon-based sentiment analysis by measuring positive and negative emotions. LIWC has been widely used in psychology and linguistics to find important psychological cues for thought processes, emotional states, intentions, and motivations (Tausczik & Pennebaker, 2010). For instance, Tumasjan et al. (2010) and Yu et al. (2008) used LIWC to measure sentiment levels on Twitter. The LIWC dictionary is composed of almost 4,500 words and word stems in 70 categories, including overall emotion and positive and negative feelings. The LIWC dictionary consists of four main categories (linguistic, psychological, personal concern, and spoken) to reflect emotional state, social relationships, thinking styles, individual differences, etc. In particular, the psychological category has subcategories such as affect, cognition, and biological processes. The dimension of affective processes is composed of subcategories: positive emotion, negative emotion, and three specific emotions of anxiety, anger, and sadness. LIWC uses simple word counting, measuring the frequency of words related to each LIWC psychological dimension in a text. For example, if the words "love," "nice," "sweet," and "hate" occur in a given text sample, the words "love," "nice," and "sweet" are counted as "positive emotion," and the word "hate" is counted as "negative emotion."

In our study, before conducting a sentiment analysis, we preprocessed the tweet data set by removing URLs and words in the form "@username," because these do not assist our sentiment analysis. We focused on the LIWC positive emotion, negative emotion, anxiety, anger, and sadness dimensions. The LIWC dictionary provides for word truncation (e.g., "laugh*" matches any word starting with "laugh"). In addition to the original LIWC emotional dimensions, we also considered emoticons to have positive and negative emotional dimensions (positive: ":)," ":-)," etc. and negative: ":(," ":-(," etc.), because these emoticons are widely used online to express emotion (Pak & Paroubek, 2010; Thelwall et al., 2010). The words in a given tweet are


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counted as positive if they match with a positive emotion, whereas the words in a given tweet are counted as negative if they match with a negative emotion, anxiety, anger, or sadness. We then calculated the sentiment score of each tweet, i.e., the positive-negative ratio of each tweet, which is defined as the number of positive words divided by the number of negative words occurring in the text of a tweet. The polarity of a given tweet is classified as positive if the positive-negative ratio is larger than 1; otherwise, it is classified as negative. Detailed definitions of the measures for sentiment analysis are described in definitions (3) to (8) in the next section.

*Correlation analysis.* We used three correlation methods: a Pearson correlation analysis, Spearman rank correlation analysis, and Granger causality analysis. Correlation analysis is widely used to measure the strength of dependence, i.e., any statistical relationship between two variables. The closer the correlation coefficient is to +1, the stronger the positive correlation. The closer the correlation coefficient is to −1, the stronger the negative correlation. If the correlation coefficient is zero, the two variables are independent, i.e., they are uncorrelated.

First, a Pearson correlation analysis was used to determine whether the popular users influenced the sentiment change in their audience positively or negatively. The Pearson correlation coefficient between two variables is defined as the covariance of the two variables divided by the product of their standard deviations:

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y}$$

We calculated a Pearson correlation coefficient between each sentiment change of a popular user and his/her audience on a daily basis. One variable denoted the sentiment score of a popular user on a daily basis. The other variable was set to four types of sentiment scores for the popular user's audience on a daily basis, according to the four tweet types, i.e., "reply," "mention," "retweet," and "all" (reply + mention + retweet), because we wanted to find which types of tweet are highly correlated to the sentiment of popular users when their audience responds to them.

Second, we applied a Spearman rank correlation to determine whether Billboard's weekly chart ranks were associated with an audience sentiment change toward Lady Gaga and Britney Spears. We were able to obtain weekly chart data for 8 weeks, from May 21 to July 9, 2011, for Lady Gaga and Britney Spears, provided by Billboard.com.[5] The Spearman rank correlation coefficient is a nonparametric measure of statistical dependence between two variables using a monotonic function. It is useful when the sample size is small and makes the coefficient less sensitive to nonnormality in distributions using only ranks of the variables' values. The Spearman rank correlation coefficient is defined as follows:

$$\rho = 1 - \frac{6\sum (x_i - y_i)^2}{n(n^2-1)},$$

where $x_i$ is the rank of the song on Billboard's weekly chart and $y_i$ is the rank of the audience's sentiment score on a weekly basis for an $n$ week data set. The variable $y_i$ was set to the following three types: the total audience number, the number of positive users, and the number of negative users.

Third, we applied the econometric technique of a Granger causality analysis to determine whether the time-series-based sentiment change of the audience on Twitter was associated with the real-world sentiment landscape of the popular users. Granger (1969) suggested a causal modeling technique that is now in widespread use in economics and business. For instance, political scientists have used Granger causality analyses to assess the causal character or direction of political relationships over time (Freeman, 1983). More recently, a Granger causality analysis has been used to find the correlation between public mood changes on blogs and the stock market and to predict a stock market index (Bollen et al., 2011; Gilbert & Karahalios, 2010). The Granger causality analysis[6] is a statistical hypothesis test for determining whether one time series is useful in forecasting another based on linear regression modeling of stochastic processes. According to Granger causality, if a variable $X$ "Granger-causes" a variable $Y$, then past values of $X$ should contain information that helps predict $Y$. A Granger causality bivariate linear regression model of two variables $X$ and $Y$ is defined as follows:

$$Y_t = \alpha + \sum_{i=1}^{n} \beta_{1t-i} Y_{t-i} + \sum_{i=1}^{n} \beta_{2t-i} Y_{t-i} + \varepsilon_t$$

$$X_t = \alpha + \sum_{i=1}^{n} \beta_{3t-i} X_{t-i} + \sum_{i=1}^{n} \beta_{4t-i} Y_{t-i} + \varepsilon_t$$

where $n$ is the maximum number of lagged observations included in the model, the matrix $\beta$ contains the coefficients of the model (i.e., the contributions of each lagged observation to the predicted values of $X_t$ and $Y_t$ ), and $\varepsilon_t$ is the residual (prediction error) for each time series. In our research, we defined the maximum number of lagged observations as 7 days. We focused on finding the causal correlation between Obama's job approval from Gallup Daily[7] and sentiment changes in Obama's audience on Twitter from May 13 to July 7, 2011. We were able to obtain the opinion poll results for Barack Obama provided by Gallup Daily,

[5]Billboard.com (http://www.billboard.com)

[6]http://en.wikipedia.org/wiki/Granger_causality

[7]Gallup tracks the daily percentage of Americans who approve or disapprove of the job Barack Obama is doing as president. The results are based on telephone interviews with approximately 1,500 adults in the nation; the margin of error is 3%. (SOURCE: http://www.gallup.com/poll/113980/Gallup-Daily-Obama-Job-Approval.aspx)


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TABLE 1. Positive and negative audience of popular users.

| Popular user | Total Tweets | Total Audience | Positive emotion Tweets | Positive emotion Users (%) | Negative emotion Tweets | Negative emotion Users (%) | PN User Ratio |
|---|---|---|---|---|---|---|---|
| ladygaga | 1,434,605 | 381,863 | 561,487 | 180,666 (47%) | 142,078 | 42,782 (11%) | 4.22 |
| mashable | 412,141 | 148,868 | 125,411 | 61,627 (41%) | 29,130 | 14,631 (10%) | 4.21 |
| Techcrunch | 169,896 | 79,706 | 48,018 | 29,422 (37%) | 11,676 | 6,994 (9%) | 4.21 |
| BillGates | 20,165 | 15,224 | 6,564 | 5,553 (36%) | 1,662 | 1,365 (9%) | 4.07 |
| Kingsthings | 5,084 | 3,898 | 2,001 | 1,703 (44%) | 611 | 499 (13%) | 3.41 |
| britneyspears | 497,720 | 135,234 | 168,273 | 57,412 (42%) | 47,008 | 16,967 (13%) | 3.38 |
| DalaiLama | 51,641 | 35,457 | 25,262 | 18,468 (52%) | 7,791 | 5,748 (16%) | 3.21 |
| aplusk | 149,851 | 98,882 | 46,065 | 34,523 (35%) | 15,553 | 11,657 (12%) | 2.96 |
| Oprah | 140,844 | 87,779 | 57,761 | 39,380 (45%) | 21,315 | 13,928 (16%) | 2.83 |
| BarackObama | 317,068 | 167,460 | 101,360 | 64,312 (38%) | 50,816 | 25,957 (16%) | 2.48 |
| realDonaldTrump | 15,525 | 10,723 | 5,134 | 3,974 (37%) | 2,757 | 2,080 (19%) | 1.91 |
| BBCBreaking | 16,615 | 11,816 | 3,455 | 2,917 (25%) | 3,532 | 2,907 (25%) | 1.00 |
| cnnbrk | 90,232 | 50,435 | 14,329 | 9,743 (19%) | 23,668 | 17,071 (34%) | 0.57 |

which tracks the daily percentage of Americans who approve or disapprove of the job he is doing as president. Each result is based on a 3-day moving average. Therefore, we converted the daily positive and negative tweet count data of Twitter into 3-day moving average data. We conducted a Granger causality analysis according to the four scenarios and set the variables at time *t* as follows:

- Scenario 1: Positive tweet rate (= number of positive tweets / total number of tweets) $\rightarrow$ Gallup approval rate
- Scenario 2: Negative tweet rate (= number of negative tweets / total number of tweets) $\rightarrow$ Gallup disapproval rate
- Scenario 3: Gap between positive and negative tweets (= positive tweet rate—negative tweet rate) $\rightarrow$ Gap between Gallup approval and disapproval (= approval rate—disapproval rate)
- Scenario 4: Ratio of positive to negative tweets (= number of positive tweets / number of negative tweets) $\rightarrow$ Ratio of Gallup approval to disapproval (= approval rate / disapproval rate)

## Findings and Results

### *Who Are the Positive or Negative Audiences of Popular Users?*

We define the sentiment score and polarity of each tweet and user in order to detect the positive or negative audience of a popular user. We then define the positive-negative ratio of a popular user. We define the sentiment score for each popular user, *i*, audience user, *j*, and tweet, *k*, as the ratio of the positive word count versus negative word count. If a sentiment score is greater than 1, we can classify the polarity as positive; otherwise, it is negative. The positive-negative ratio (PN ratio) for a popular user is defined as the number of positive tweets or users from the audience divided by the number of negative tweets or users from the audience. These are defined as follows:

$$tweet\ sentiment\ score(i, j, k) = \frac{count_{i,j,k}(pos.\ word)}{count_{i,j,k}(neg.\ word)} \tag{3}$$

$$user\ sentiment\ score(i, j) = \frac{count_{i,j}(pos.\ word)}{count_{i,j}(neg.\ word)} \tag{4}$$

$$tweet\ polarity(i, j, k) = \begin{cases} positive, & if\ tweet\ sentiment\ score(i, j, k) > 1 \\ negative, & if\ tweet\ sentiment\ score(i, j, k) \le 1 \end{cases} \tag{5}$$

$$user\ polarity(i, j) = \begin{cases} positive, & if\ user\ sentiment\ score(i, j) > 1 \\ negative, & if\ user\ sentiment\ score(i, j) \le 1 \end{cases} \tag{6}$$

$$PN\ tweet\ ratio(i) = \frac{count_i(pos.\ tweets\ of\ audience\ for\ popular\ user\ i)}{count_i(neg.\ tweets\ of\ audience\ for\ popular\ user\ i)} \tag{7}$$

$$PN\ user\ ratio(i) = \frac{count_i(pos.\ users\ of\ audience\ of\ popular\ user\ i)}{count_i(neg.\ users\ of\ audience\ of\ popular\ user\ i)}. \tag{8}$$

We can also extend definition (7) to the time-series-based PN ratio on day *t* as follows:

$$PN\ tweet\ ratio(i, t) = \frac{count_i(pos.\ tweets\ of\ audience\ for\ popular\ user\ i, day\ t)}{count_i(neg.\ tweets\ of\ audience\ for\ popular\ user\ i, day\ t)}$$

The audience responds to popular users by replying, mentioning, or retweeting them with a positive or negative sentiment. Table 1 and Figure 1 summarize our results, which show the total volume and PN ratio of the tweets and the audience who are replying, mentioning, or retweeting each popular user. Lady Gaga, Mashable, and TechCrunch are the top 3 with the highest PN user ratios; that is, they have the most positive audiences. Donald Trump, BBC Breaking


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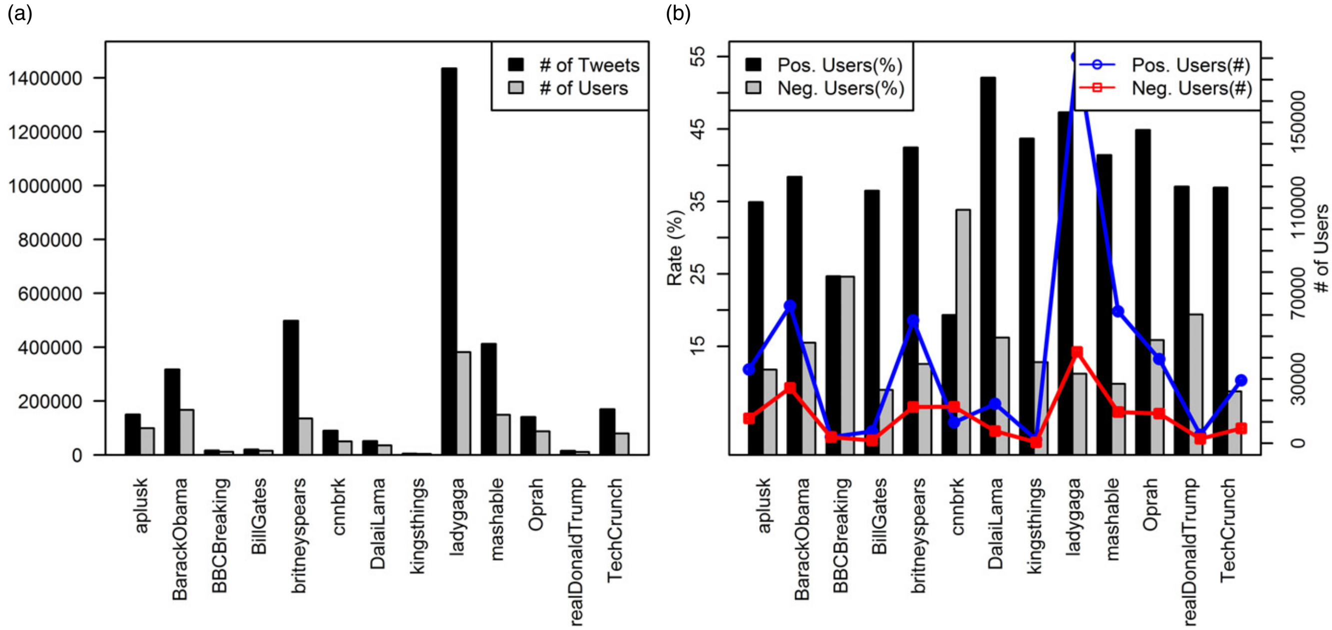


FIG. 1. Volume of audience and positive/negative audience of popular users. (a) Number of tweets and users. (b) Absolute and relative positive/negative users. (Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.)

News, and CNN Breaking News are the bottom 3 with the most negative audiences. Lady Gaga is the most tweeted by her audience, with a total tweet count of 1,434,605. Her audience count is 381,863, and 47% of her audience is positive, while 11% is negative. The Dalai Lama has a much larger positive audience percentage (52%) than Lady Gaga. However, the PN user ratio is higher for Lady Gaga because the Dalai Lama's negative audience percentage is also larger (16%) than Lady Gaga's (11%). Most of the popular users such as celebrities have larger positive audiences than negative, while news media such as CNN Breaking News and BBC Breaking News have larger negative audiences. This could arguably be because Western news agencies primarily report the downside of human nature rather than upbeat and hopeful happenings, whereas social media like Mashable and TechCrunch have audiences that are more positive because they publish useful information and news. Barack Obama and Donald J. Trump are political competitors who might be the next U.S. presidential candidates. Obama has an audience that is about 16 times larger, with larger positive and smaller negative audience percentages than Trump. User polarity makes possible the identification of the favorable and unfavorable parts of the audience of a popular user. Unfavorable users could exist among the followers of a popular user, which indicates that users' followers are not always favorable to them.

### *Do Popular Users Influence the Sentiment Changes of Their Audiences Positively or Negatively?*

How do the sentiment changes of popular users influence the sentiments of their audiences? For instance, if the very famous actor *Ashton Kutcher* writes negative tweets, how will his audience respond to these? In order to find the correlation, we computed Pearson correlation coefficients. Table 2 shows Pearson correlation coefficients between the sentiment changes of popular users and their audiences on a daily basis.

For example, Figure 2 shows, on daily scale, how their audience responds when Ashton Kutcher or the Dalai Lama writes positive or negative tweets. In (a) and (b), the top two charts are the sentiment changes of the popular users, while the bottom two charts are the sentiment changes of their audiences. The charts on the left side just show the number of tweets based on a time series. To enable the comparison of tweet counts on a common scale, we normalized tweet counts to *z*-scores. The charts on the right side show the *z*-scores, that is, normalized values for the numbers of tweets.

We did find that a correlation exists between the sentiment changes of popular users and their audiences. Most of the popular users, except Oprah Winfrey, have a correlation with their audience. Popular users influence their audiences in positive or negative ways. Therefore, if we could measure the sentiment of their audiences, we might be able to measure the positive or negative influence of popular users.

Furthermore, we found that people respond to the sentiment changes of popular users positively or negatively, that is, they respond to "positive tweets of a popular user" with "positive tweeting" and respond to "negative tweets of a popular user" with "negative tweeting." In addition, we wanted to determine which types of tweets (retweet, mention, and reply) were the most highly correlated to the sentiments of popular users when their audiences respond to them. We were able to determine that, in general, an audience responds to "positive tweets of a popular user" with


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TABLE 2. Pearson correlation coefficients between sentiment changes of popular users and their audiences on a daily basis: Do the sentiment changes of popular users influence the sentiments of their audiences?

| Sentiment of popular user | | Correlation with the tweets of audience | | | |
|---|---|---|---|---|---|
| | | Reply | Mention | Retweet | All |
| aplusk | positive | $\mathbf{0.359}^{**}$ | $\mathbf{0.262}^{*}$ | $\mathbf{0.513}^{***}$ | $\mathbf{0.321}^{**}$ |
| | negative | –0.179 | $\mathbf{0.528}^{***}$ | 0.062 | $\mathbf{0.414}^{**}$ |
| BarackObama | positive | $\mathbf{0.425}^{***}$ | –0.121 | 0.272 | –0.007 |
| | negative | –0.113 | 0.204 | NA | 0.211 |
| BBCBreaking | positive | $\mathbf{0.590}^{***}$ | $\mathbf{0.547}^{***}$ | $\mathbf{0.621}^{***}$ | $\mathbf{0.607}^{***}$ |
| | negative | $\mathbf{0.374}^{***}$ | $\mathbf{0.284}^{*}$ | 0.020 | $\mathbf{0.606}^{***}$ |
| BillGates | positive | 0.398 | 0.080 | $\mathbf{0.727}^{**}$ | 0.392 |
| | negative | –0.228 | 0.481 | NA | 0.471 |
| britneyspears | positive | $\mathbf{0.587}^{***}$ | 0.009 | $\mathbf{0.579}^{***}$ | 0.200 |
| | negative | –0.116 | $\mathbf{0.405}^{***}$ | NA | $\mathbf{0.417}^{***}$ |
| cnnbrk | positive | $\mathbf{0.230}^{*}$ | $\mathbf{0.288}^{**}$ | $\mathbf{0.707}^{***}$ | $\mathbf{0.421}^{***}$ |
| | negative | –0.170 | $\mathbf{0.348}^{**}$ | $\mathbf{0.313}^{**}$ | $\mathbf{0.507}^{**}$ |
| DalaiLama | positive | 0.095 | $\mathbf{0.467}^{***}$ | $\mathbf{0.746}^{***}$ | $\mathbf{0.623}^{***}$ |
| | negative | $\mathbf{0.347}^{**}$ | $\mathbf{0.334}^{**}$ | $\mathbf{0.588}^{***}$ | $\mathbf{0.852}^{***}$ |
| kingsthings | positive | 0.043 | $\mathbf{0.369}^{**}$ | $\mathbf{0.452}^{**}$ | $\mathbf{0.332}^{*}$ |
| | negative | $\mathbf{-0.319}^{*}$ | $\mathbf{0.757}^{***}$ | NA | $\mathbf{0.597}^{***}$ |
| ladygaga | positive | $\mathbf{0.409}^{***}$ | $\mathbf{0.350}^{**}$ | 0.039 | $\mathbf{0.415}^{***}$ |
| | negative | 0.036 | 0.063 | NA | 0.217 |
| mashable | positive | $\mathbf{0.703}^{***}$ | $\mathbf{0.771}^{***}$ | $\mathbf{0.730}^{***}$ | $\mathbf{0.780}^{***}$ |
| | negative | NA | $\mathbf{0.442}^{***}$ | 0.216 | $\mathbf{0.666}^{***}$ |
| Oprah | positive | 0.148 | –0.176 | 0.101 | –0.099 |
| | negative | 0.050 | –0.108 | NA | –0.094 |
| realDonaldTrump | positive | 0.277 | 0.212 | $\mathbf{0.449}^{**}$ | 0.256 |
| | negative | 0.156 | –0.024 | NA | 0.009 |
| TechCrunch | positive | $\mathbf{0.794}^{***}$ | $\mathbf{0.821}^{***}$ | $\mathbf{0.774}^{***}$ | $\mathbf{0.830}^{***}$ |
| | negative | $\mathbf{0.262}^{**}$ | $\mathbf{0.408}^{***}$ | 0.000 | $\mathbf{0.548}^{***}$ |

*: $p < 0.1$
**: $p < 0.05$
***: $p < 0.01$

"positive retweeting" and responds to "negative tweets of a popular user" with "negative mentioning or retweeting," as can be seen in Table 2.

### *How Can We Measure a Positive-Negative Influence?*

There have been earlier studies that focused on social influence and propagation (Cha et al., 2010; Romero, Galuba, Asur, & Huberman, 2011; Weng, Lim, Jiang, & He, 2010). Cha et al. (2010) performed a comparison of three measures of influence: indegree, retweets, and user mentions. They discovered that indegree represents a user's popularity but is not related to other important notions of influence such as engaging the audience, i.e., retweets and mentions. On the other hand, Romero et al. (2011) proposed an influence-passivity algorithm that determines the influence and passivity of users based on their information-forwarding activity. The passivity of a user is a measure of how difficult it is for other users to influence him, i.e., a user's passivity score depends on how much she rejects the influence of another user as compared to the aggregated influence of everyone else. However, there has been no research on measuring the sentiment influence to determine the influence of a popular user.

*Positive-negative influence measure.* In our study, we developed another new user influence measure on Twitter, which could also be used for other social media. We call this the "positive-negative influence (PN influence)." The value of the PN influence could be viewed as an influence rate factor that describes how the audience of an influential user is affected positively or negatively. The PN influence is defined as follows:

$$\begin{aligned} &\mathit{Positive{-}Negative\ Influence}\left(PN_{i,d}\right) \\ &= O_{i,d} \times \mathit{PN\ User\ Ratio}\left(i, d\right) \\ &= O_{i,d} \times \frac{count_{i,d}\left(pos.\ users\ of\ audience\ of\ popular\ user\ i\right)}{count_{i,d}\left(neg.\ users\ of\ audience\ of\ popular\ user\ i\right)}, \end{aligned} \tag{9}$$

where $O_{i,d}$ is the user count of the audience for popular user $i$, and duration $d$ is the period of time from the start to end date. Hence, audience size $O_{i,d}$ is the number of users who retweet, reply, or mention the popular user during the specific period of time. This implicitly implies that $O_{i,d}$ has other important influence measures, such as retweet, reply, and mention, to some degree. Therefore, the positive-negative influence that we suggest is defined as the audience size multiplied by the PN user ratio. Although we did not delve deeply into the overall user influence in this research, the overall influence of a Twitter user could be defined as follows:

$$\begin{aligned} \mathit{User\ Influence} \leftarrow \{&\mathit{PN\ Influence}, \mathit{Retweets}, \\ &\mathit{Mentions}, \mathit{Indegree}, \mathit{etc.}\} \end{aligned}$$

The drawback of analysis of the three influence measures suggested by Cha et al. (2010) is that positive or negative influence is not considered. The larger the number of indegree, retweets, and mentions, the more influential a user is although most retweets or mentions contain negative intention. For instance, suppose that there are two presidential candidates and we want to predict who will be elected. The measures of indegree, retweets, mentions, and PN influence are as shown in Table 3. If we consider only three measures (indegree, retweets, and mentions), candidate B is more influential than candidate A; that is, candidate B is the likely winner. However, if we compute a measure of PN influence, candidate A has a greater likelihood of winning because the many voters who support candidate A retweeted or mentioned candidate B with unfavorable intention. Therefore, the importance of PN influence is that it provides new insights into influence and a better understanding of popular users.

Table 4 shows the ranks of the popular users calculated using the PN influence definition. The number of followers shows the number on October 9, 2011, while the number of audience members is the number who retweeted, mentioned, or replied to popular users from May 13 to July 8, 2011. Lady Gaga is ranked number 1, with the most followers, largest audience, and highest PN user ratio. After her, Mashable, Britney Spears, and Barack Obama are


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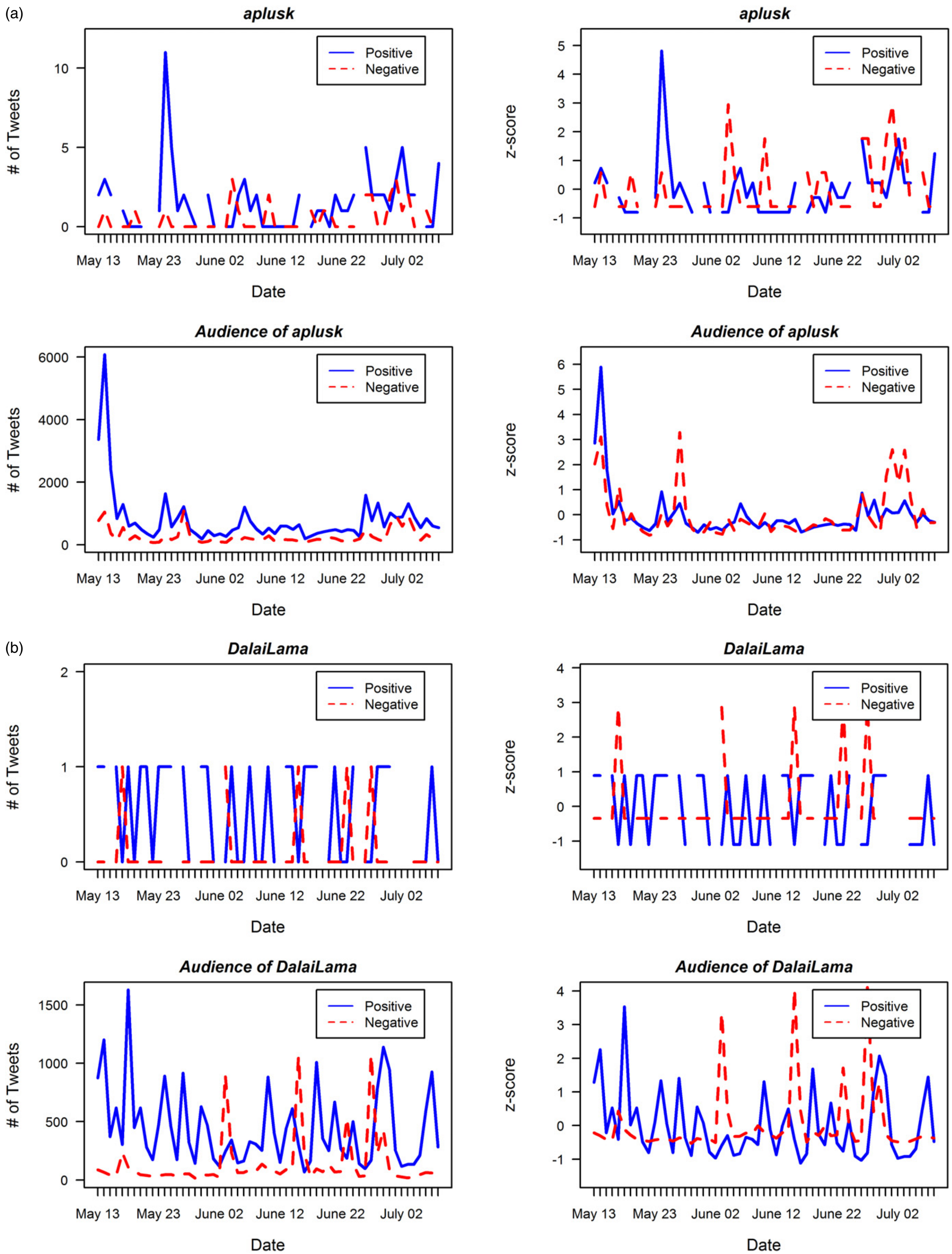


FIG. 2. Comparison of sentiment changes between popular users and their audiences. (a) Ashton Kutcher and his audience. (b) Dalai Lama and his audience. (Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.)


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TABLE 3. Comparison of three measures (indegree, retweet, mention) and positive-negative influence measure.

| User | Indegree | Retweet | Mention | Positive-negative influence |
|---|---|---|---|---|
| A | 100 | 2,000 | 1,500 | 80 |
| B | 100 | 3,000 | 3,500 | 75 |

ranked numbers 2, 3, and 4. These top-ranked users are the most influential users. They influence their audiences more positively and have larger audiences on Twitter. Meanwhile, users such as CNN Breaking News, Donald J. Trump, Larry King, and BBC Breaking News are in the lower ranks, with lower PN user ratios, with the exception of Larry King, who has a relatively high PN user ratio (3.41) but is ranked low because his audience number (5,084) is too small.

*How Is the Time-Series-Based Positive-Negative Influence Change Related to the Real-World Sentiment Landscape of Popular Users?*

There are time series that describe the changes in sentiment over time with respect to sentiments about online topics. Such time series have been analyzed, and these analyses have shown that they do predict offline sentiments (Jansen et al., 2009; Thelwall et al., 2011; Tumasjan et al., 2010; Zhang et al., 2010).

*Time-series analysis of sentiment changes.* We performed a time-series-based analysis to determine how the change in positive or negative influence over time is related to the real-world sentiment landscape of popular users by plotting comparison charts between changes in Twitter sentiment and the real-world landscape over time, and by conducting a Granger causality analysis. In order to answer this question, we focused on Barack Obama. We obtained offline opinion poll results based on a three-day moving average for Barack Obama from Gallup Daily. Before we compared Gallup with Twitter, we converted the daily positive and negative tweet count data from Twitter into three-day moving average data to correspond with the Gallup survey results. To enable the comparison of Gallup and Twitter time series, we normalized them to *z*-scores on the basis of a mean and standard deviation. This *z*-score normalization provided a common scale for comparisons of the Gallup and Twitter data and allowed the time series to fluctuate around a zero mean and one standard deviation. The *z*-score of time series *t* is defined as follows:

$$z\text{-}score(t) = \frac{x_t - \mu}{\sigma}$$

where $x_t$ is the observed value during period *t*, and $\mu$ and $\sigma$ are the mean and standard deviation.

The results for the time-series sentiment changes for *Barack Obama* are shown in Figure 3. Figure 3(a) shows comparisons of the Gallup approve and Twitter positive tweet counts, and the Gallup disapprove and Twitter negative tweet counts. Figure 3(b) shows comparisons of the Gallup approve count minus disapprove and the Twitter positive tweet count minus negative tweet count, i.e., the gap, along with the Gallup approve divided by disapprove count and the Twitter positive tweet count divided by the negative tweet count, i.e., the ratio. As shown in Figure 3, the Gallup and Twitter time series frequently point in the same direction, that is, the favorable and unfavorable changes for both Gallup and Twitter fluctuate very similarly.

We used a Granger causality analysis to find the statistically significant causal correlation between Twitter and Gallup. We found that the time series sentiment changes on Twitter cause the changes in the Gallup poll.

Table 5 shows that positive changes on Twitter have a Granger causality relation with the job approval changes on Gallup for lags of 2, 4, and 5 days ($p$-values $< 0.1$). Negative changes on Twitter cause job disapproval changes on Gallup for lags ranging from 1 to 7 days (especially for 2, 4, 5, and 6 days; $p$-values $< 0.01$). Furthermore, the gap (positive—negative) on Twitter has a high Granger causality relation with the gap (approve—disapprove) on Gallup for lags from 1 to 7 days (for 2, 3, 4, and 5 days; $p$-values $< 0.01$). The ratio (positive/negative) on Twitter also has a high Granger causality relation with the ratio (approve/disapprove) on Gallup for lags from 1 to 6 days (for 2, 3, and 4 days; $p$-values $< 0.01$). As shown in Table 5, based on the results of our Granger causality analysis, we can reject the null hypothesis that the time-series-based sentiment changes in Obama's audience on Twitter do not relate to or predict his job approval counts from Gallup Daily. This means that there is a strong causality correlation between Twitter and Gallup, and Twitter may be used as a predictor of the real-world landscape. We find that the Twitter negative variable has a much higher causality relation with the Gallup disapprove than the positive variable. This implies that the negative sentiment changes on Twitter influence the sentiment changes of the real world more significantly than the positive sentiment changes. The positive mood on Twitter is expressed in the real world less than the negative mood, and vice versa.

In addition, we focused on other celebrities such as famous singers (Lady Gaga and Britney Spears) to determine whether the time-series-based sentiment changes in their audiences are related to the real-world landscape, such as their song's position on the Billboard chart. Billboard.com provides a weekly chart of top artists. We obtained weekly chart data from May 21 to July 9, 2011, for Lady Gaga and Britney Spears. We could find four songs ("Born This Way," "Judas," "The Edge of Glory," "The Fame") from Lady Gaga and two songs ("Till the World Ends," "Femme Fatale") from Britney Spears from May 21 to July 9, 2011. To compare the Billboard chart ranks with Twitter, we first summarized the Twitter data on the basis of the weekly time


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TABLE 4. Positive-negative influence of popular users.

| Popular user | # of followers* | # of audience (A)** | Retweet + Mention + Reply | PN user ratio (B) | PN influence (= A * B) | Rank |
|---|---|---|---|---|---|---|
| ladygaga | 14,309,198 | 381,863 | 1,434,605 | 4.22 | 1612586.15 | 1 |
| mashable | 2,525,348 | 148,868 | 412,141 | 4.21 | 627044.51 | 2 |
| britneyspears | 10,043,488 | 135,234 | 497,720 | 3.38 | 457597.36 | 3 |
| BarackObama | 10,447,956 | 167,460 | 317,068 | 2.48 | 414904.94 | 4 |
| TechCrunch | 1,843,463 | 79,706 | 169,896 | 4.21 | 335303.11 | 5 |
| aplusk | 7,885,791 | 98,882 | 149,851 | 2.96 | 292845.78 | 6 |
| Oprah | 7,665,958 | 87,779 | 140,844 | 2.83 | 248186.17 | 7 |
| DalaiLama | 2,564,392 | 35,457 | 51,641 | 3.21 | 113921.34 | 8 |
| BillGates | 3,779,455 | 15,224 | 20,165 | 4.07 | 61933.24 | 9 |
| cnnbrk | 5,236,770 | 50,435 | 90,232 | 0.57 | 28784.97 | 10 |
| realDonaldTrump | 791,249 | 10,723 | 15,525 | 1.91 | 20487.12 | 11 |
| kingsthings | 1,951,348 | 3,898 | 5,084 | 3.41 | 13303.19 | 12 |
| BBCBreaking | 1,962,576 | 11,816 | 16,615 | 1.00 | 11856.65 | 13 |

**: # of followers is based on period of October 9, 2011.*
***: # of audience reflects those that Retweet + Mention + Reply to popular users from May 13 to July 8, 2011.*

series. We then normalized the Billboard and Twitter data to *z*-scores. The *z*-scores of the Billboard chart ranks decreased as they moved closer to the top. Therefore, we multiplied the *z*-scores of the Billboard chart ranks by negative one so that they would increase as they moved closer to the top. Figure 4 shows the comparisons of the weekly rank changes for songs on the Billboard chart and sentiment changes on Twitter for Lady Gaga and Britney Spears. The changes in the total tweeting audience and positive audience of Lady Gaga have trends similar to the Billboard chart rank changes for most of her songs, as seen in Figure 4(a). For Britney Spears, we can see that the Billboard chart rank of the song "Femme Fatale" (second dashed green line in Figure 4(b)) has a trend similar to the changes in her total tweeting audience.

To test for a statistically significant correlation between Twitter and the Billboard chart, we used the Spearman rank correlation coefficient as a measure of the strength of the association between the Billboard chart and sentiment changes on Twitter. Table 6 shows the Spearman rank correlation coefficients between Billboard's weekly charts and Twitter for Lady Gaga and Britney Spears. The negative values of the Spearman rank correlation coefficients in Table 6 indicate that a greater number of tweets is related to a higher rank. Lady Gaga has strong correlations between her Billboard weekly chart ranks and the total number of tweeting audience changes for the two songs "Born This Way" and "The Fame." The three songs "Born This Way," "Judas," and "The Fame" show strong correlations between their Billboard weekly chart ranks and the positive audience changes on Twitter. However, the negative audience changes on Twitter have no significant correlation with the Billboard weekly chart. Britney Spears has a strong correlation between the Billboard weekly chart ranks and the total number of tweeting audience changes for only one song, "Femme Fatale," and there is no significant correlation between the Billboard weekly chart and her positive/negative audience changes. In this example of Lady Gaga and Britney Spears, we can see that changes in the total tweeting audience and positive audience on Twitter have significant correlations with the Billboard weekly chart ranks, although in the example of Britney Spears, there is only a correlation for the total number of tweeting audience changes.

By performing a time-series-based analysis to determine how a time-series-based PN influence change in an audience is related to the real-world sentiment about popular users such as Barack Obama, Lady Gaga, and Britney Spears, we found that a time-series-based positive-negative influence change in an audience is related to the real-world sentiments reflected in the Gallup Daily and the Billboard weekly chart.

## Discussion

In response to the four research questions, first, we investigated who are the positive and negative audiences of popular users. We measured the sizes of positive and negative audiences of popular users and measured the positive-negative ratio to identify the favorable and unfavorable parts of the audience of a popular user. This investigation is meaningful because unfavorable users could exist among even the followers of a popular user, which indicates that a user's followers are not always favorable to them.

Second, we identified how the sentiment changes of popular users influence the sentiments of their audiences. Popular users influence their audiences in positive or negative ways. In general, an audience responds to "positive tweets of a popular user" with "positive tweeting" and responds to "negative tweets of a popular user" with "negative tweeting"; more specifically, an audience tends to respond to "positive tweets of a popular user" with "positive retweeting" and respond to "negative tweets of a popular user" with "negative mentioning or retweeting." This


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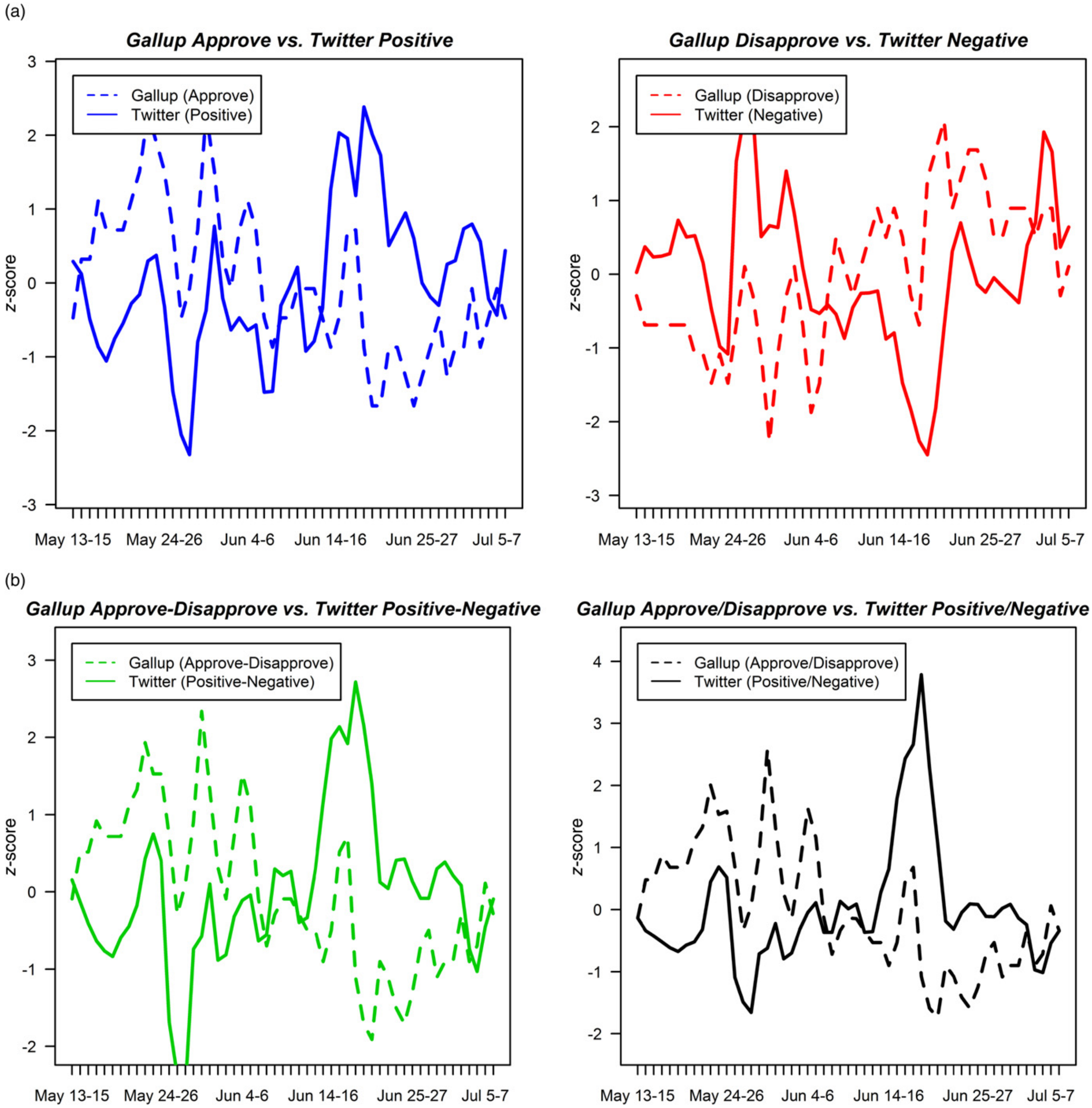


FIG. 3. Obama's job approval on Gallup and sentiment changes on Twitter between May 13 and July 7, 2011. All of the values on the y axis are normalized to $z$-scores: (a) Approve versus positive and disapprove versus negative. (b) Gap and ratio comparisons of Gallup and Twitter. (Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.)

behavior on Twitter implies that people tend to share positive sentiments with their followers by retweeting a popular user's positive tweets, and tend to respond by mentioning or retweeting a popular user's negative tweets. There are limitations to how this finding can be generalized, because we investigated the audiences of only 13 popular users.

Third, we suggested the PN influence measure, which provides new insights into influence and a better understanding of popular Twitter users. Simple influence measures, such as the number of followers (indegree), retweets, and mentions cannot represent the hidden sentiment of an audience that may have positive and negative emotions toward popular users. As shown in Table 3, if we consider only three measures (indegree, retweets, and mentions), candidate B is more influential than candidate A. However, if we compute a measure of PN influence, candidate A is more influential than candidate B. Furthermore, the influence at a specific period is important because the influence of a popular user


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TABLE 5. Statistical significance (*p*-values) of Granger causality correlation analysis between Barack Obama job approval counts from Gallup Daily and sentiment changes for Obama on Twitter.

| Lag | Positive → Approve | Negative → Disapprove | Positive-Negative → Approve-Disapprove | Positive/Negative → Approve/Disapprove |
|---|---|---|---|---|
| 1 Day | 0.275 | **0.055*** | **0.077*** | **0.043**** |
| 2 Days | **0.061*** | **0.002***** | **0.002***** | **0.010***** |
| 3 Days | 0.127 | **0.007**** | **0.005***** | **0.009***** |
| 4 Days | **0.050*** | **0.001***** | **0.003***** | **0.008***** |
| 5 Days | **0.100*** | **0.002***** | **0.009***** | **0.016**** |
| 6 Days | 0.161 | **0.006***** | **0.020**** | **0.037**** |
| 7 Days | 0.261 | **0.024**** | **0.071*** | 0.116 |

*: $p < 0.1$
**: $p < 0.05$
***: $p < 0.01$

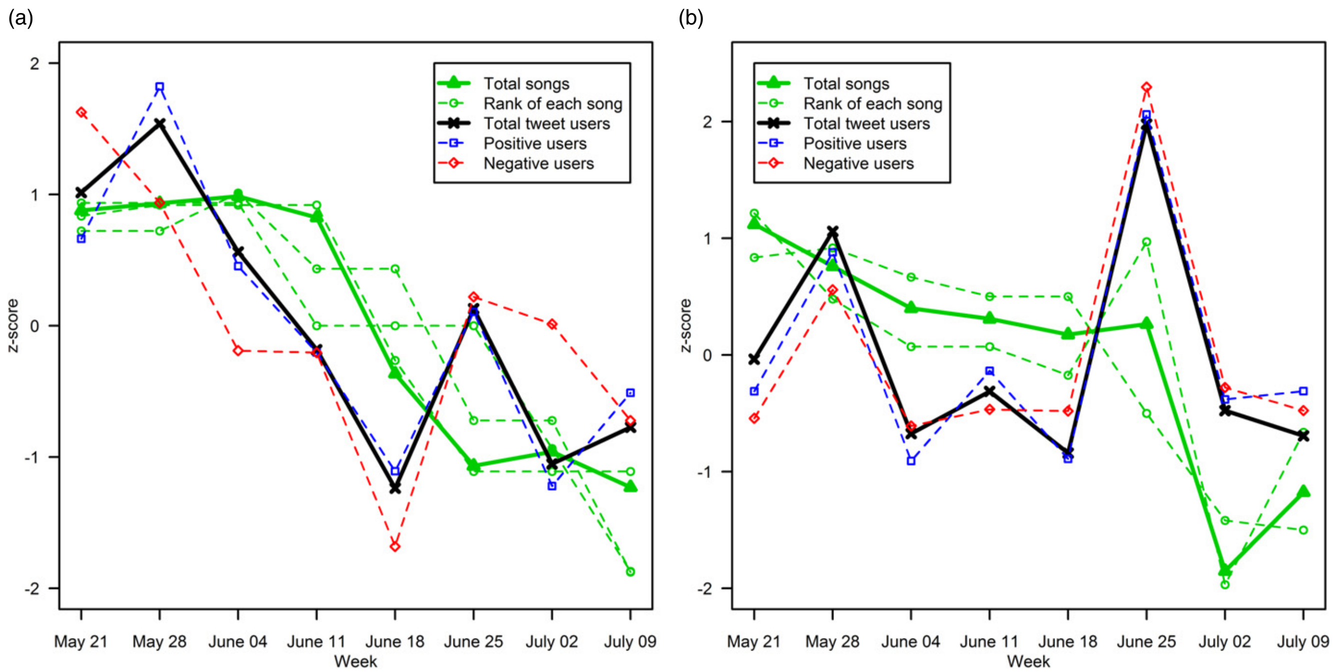


FIG. 4. Comparisons of weekly rank changes for songs on Billboard chart and sentiment changes on Twitter for Lady Gaga and Britney Spears. (a) Lady Gaga. (b) Britney Spears. (Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.)

changes as time goes by. The PN influence measure that we suggest can cover these variables. It incorporates the audience size of a popular user (the audience size implies measures such as retweet, reply, and mention) for the specified time period and the PN user ratio for the specific duration, as shown in definition (9) of the Findings and Results section.

Finally, we investigated how the PN influence of popular users is related to the real-world landscape. The time-series-based sentiment changes in Barack Obama's audience on Twitter relate to his job approval ratings on Gallup Daily, based on the results of our Granger causality analysis. There is a strong causality correlation between Twitter and Gallup, and Twitter may be used as a predictor of the real-world landscape. As shown in Table 5, positive changes on Twitter have a Granger causality relation with the job approval changes on Gallup for lags of 2, 4, and 5 days ($p$-values $< 0.1$), and negative changes on Twitter cause job disapproval changes on Gallup for lags ranging from 1 to 7 days (especially for 2, 4, 5, and 6 days; $p$-values $< 0.01$). In our study of politician Barack Obama, there was a much higher causal correlation between the negative tweet rate and the Gallup disapproval rate than the correlation between the positive tweet rate and the Gallup approval rate, i.e., the negative sentiment changes of an audience on Twitter influenced the sentiment changes of the real world more significantly than the positive sentiment changes. On the other hand, in our study of singers Lady Gaga and Britney Spears, the negative sentiment changes of the audiences of Lady Gaga and Britney Spears had no significant correlation with the Billboard weekly chart, whereas the positive audience


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TABLE 6. Spearman rank correlation coefficients between Billboard weekly charts and Twitter for Lady Gaga and Britney Spears.

| Singer | Title of song | # of total tweet users | # of positive users | # of negative users |
|---|---|---|---|---|
| Lady Gaga | "Born This Way" | **–0.643*** | **–0.691*** | –0.364 |
| | "Judas" | –0.576 | **–0.626*** | –0.150 |
| | "The Edge of Glory" | –0.316 | 0.211 | –0.316 |
| | "The Fame" | **–0.801**** | **–0.851***** | –0.576 |
| | For total of 4 songs | –0.643* | –0.667* | –0.357 |
| Britney Spears | "Till the World Ends" | –0.359 | 0.024 | 0.240 |
| | "Femme Fatale" | **–0.743**** | –0.443 | –0.048 |
| | For total of 2 songs | –0.500 | –0.143 | 0.262 |

*: $p < 0.1$
**: $p < 0.05$
***: $p < 0.01$

and the total tweeting audience did have a strong correlation with the Billboard weekly chart. Although we investigated only three popular users (Barack Obama, Lady Gaga, and Britney Spears) for about two months, this result shows that the type of sentiment change (positive or negative) associated with the real-world landscape depends on the user's domain, such as societal areas, politics, entertainment, etc. For instance, in previous research, Bollen et al. (2011) showed that the "calm" dimension (rather than alert, sure, vital, kind, or happy) had the highest correlation with changes in the DJIA over time. In our future research, we need to break the dimensions of sentiment down and find those that are highly correlated with the specific real-world landscape of various fields.

## Conclusions

In this paper, we investigated popular users and their audiences on Twitter to understand popular users' influence on audiences with respect to PN influence, and to reveal how this measure of influence is related to real-world phenomena. We analyzed over 3 million Twitter messages that mentioned thirteen popular users from May 13, 2011 to July 8, 2011. Before we derived a PN influence, we first found the positive and negative audiences of these popular users, after which we determined how these popular users influence sentiment changes in their audiences, positively or negatively. We then developed a measure of PN influence for popular users on Twitter and revealed how this measure of influence is related to real-world phenomena over time. Previous studies did not consider PN influence measure, therefore, the larger the number of indegree, retweets and mentions, the more influential a user is although most of retweets or mentions contain negative intention. Hence, an implication of this study, based on the proposed PN influence measure, is that it provides new insights into influence and a better understanding of popular users. This could be used as another new influence measure, along with influence measures such as retweets and mentions, and is applicable to Twitter or other microblogging services. Finally we found that the time-series PN influence changes for the audiences of the popular users Barack Obama, Lady Gaga, and Britney Spears on Twitter are related to real-world sentiment changes or offline measures such as Obama's job approval data from Gallup Daily and the Billboard weekly chart over time. It reflects the offline landscape of popular users such as their degree of popularity, approval rating, and so on. An implication of the results of this investigation is that time-series-based PN influence changes on Twitter can be used, to predict real-world phenomena or can be associated with real-world phenomena. We believe that the PN influence can be used as an indicator to measure a user's influence, predict elections, evaluate the effect of product marketing, or evaluate customer response for popular users in various societal areas, such as celebrities, politicians, companies, media, and religious leaders.

This study has the following limitations. First, the period used for the time series analysis, approximately 2 months, is too short to find long-term trends or correlations between Twitter and the real world. Moreover, comparative analyses with various offline data are needed to demonstrate that Twitter has strong correlations with a variety of additional offline phenomena. Second, from our time-series analysis of how sentiment changes are related to real-world phenomena, we could construct various prediction regression models to forecast future sentiments such as the presidential job approval rate, Billboard chart ranks of artists, and so on. However, we have not provided these prediction models in this research. Moreover, we have not shown how the PN influence could be applied to an overall influence algorithm in order to find influential users, and how this algorithm is more effective than other Twitter influence measures or real services providing measures of online social influence such as Klout, Twitalyzer, and PeerIndex. Nevertheless, no previous studies or social influence services have dealt with PN influence as an influence measure.

Therefore, in our future research, we should obtain much-longer-term data sets and much more popular users from Twitter and various kinds of real-world data from Gallup, Billboard, etc. in order to investigate the correlation between Twitter and various kinds of real-world phenomena. Furthermore, we will develop various prediction models to forecast future sentiments from Twitter, as mentioned above. We should also develop a positive-negative influence algorithm and perform comparisons with other influence measures.

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