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Measuring User Influence in Twitter: The Million Follower Fallacy

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Abstract

Directed links in social media could represent anything from intimate friendships to common interests, or even a passion for breaking news or celebrity gossip. Such directed links determine the flow of information and hence indicate a user's *influence* on others—a concept that is crucial in sociology and viral marketing. In this paper, using a large amount of data collected from Twitter, we present an in-depth comparison of three measures of influence: indegree, retweets, and mentions. Based on these measures, we investigate the dynamics of user influence across topics and time. We make several interesting observations. First, popular users who have high indegree are not necessarily influential in terms of spawning retweets or mentions. Second, most influential users can hold significant influence over a variety of topics. Third, influence is not gained spontaneously or accidentally, but through concerted effort such as limiting tweets to a single topic. We believe that these findings provide new insights for viral marketing and suggest that topological measures such as indegree alone reveals very little about the influence of a user.

Introduction

Influence has long been studied in the fields of sociology, communication, marketing, and political science (Rogers 1962; Katz and Lazarsfeld 1955). The notion of influence plays a vital role in how businesses operate and how a society functions—for instance, see observations on how fashion spreads (Gladwell 2002) and how people vote (Berry and Keller 2003). Studying influence patterns can help us better understand why certain trends or innovations are adopted faster than others and how we could help advertisers and marketers design more effective campaigns. Studying influence patterns, however, has been difficult. This is because such a study does not lend itself to readily available quantification, and essential components like human choices and the ways our societies function cannot be reproduced within the confines of the lab.

Nevertheless, there have been important theoretical studies on the diffusion of influence, albeit with radically different results. Traditional communication theory states that a minority of users, called *influentials*, excel in persuading others (Rogers 1962). This theory predicts that by targeting these influentials in the network, one may achieve a large-scale chain-reaction of influence driven by word-of-mouth, with a very small marketing cost (Katz and Lazarsfeld 1955). A more modern view, in contrast, de-emphasizes the role of influentials. Instead, it posits that the key factors determining influence are (*i*) the interpersonal relationship among ordinary users and (*ii*) the readiness of a society to adopt an innovation (Watts and Dodds 2007; Domingos and Richardson 2001). This modern view of influence leads to marketing strategies such as collaborative filtering. These theories, however, are still just theories, because there has been a lack of empirical data that could be used to validate either of them. The recent advent of social networking sites and the data within such sites now allow researchers to empirically validate these theories.

Moving from theory into practice, we find that there are many other unanswered questions about how influence diffuses through a population and whether it varies across topics and time. People have different levels of expertise on various subjects. When it comes to marketing, however, this fact is generally ignored. Marketing services actively search for potential influencers to promote various items. These influencers range from "cool" teenagers, local opinion leaders, all the way to popular public figures. However, the advertised items are often far outside the domain of expertise of these hired individuals. So how effective are these marketing strategies? Can a person's influence in one area be transferred to other areas?

In this paper, we present an empirical analysis of influence patterns in a popular social medium. Using a large amount of data gathered from Twitter, we compare three different measures of influence: indegree, retweets, and mentions.[1] Focusing on different topics, we examine how the three types of influential users performed in spreading popular news topics. We also investigate the dynamics of an individual's influence by topic and over time. Finally, we characterize the precise behaviors that make ordinary individuals gain high influence over a short period of time.

[1] Indegree is the number of people who follow a user; retweets mean the number of times others "forward" a user's tweet; and mentions mean the number of times others mention a user's name.

The Twitter dataset used in this paper consists of 2 billion follow links among 54 million users who produced a total of 1.7 billion tweets. We refer readers to our project webpage *http://twitter.mpi-sws.org/* for a detailed description of the dataset and our data sharing plan.

Our study provides several findings that have direct implications in the design of social media and viral marketing:

1) Analysis of the three influence measures provides a better understanding of the different roles users play in social media. Indegree represents popularity of a user; retweets represent the content value of one's tweets; and mentions represent the name value of a user. Hence, the top users based on the three measures have little overlap.
2) Our finding on how influence varies across topics could serve as a useful test for answering how effective advertisement in Twitter would be if one is to employ influential users. Our analysis shows that most influential users hold significant influence over a variety of topics.
3) Ordinary users can gain influence by focusing on a single topic and posting creative and insightful tweets that are perceived as valuable by others, as opposed to simply conversing with others.

These findings provide new insights for viral marketing. The first finding in particular indicates that indegree alone reveals little about the influence of a user. This has been coined *the million follower fallacy* by Avnit (Avnit 2009), who pointed to anecdotal evidence that some users follow others simply for etiquette—it's polite to follow someone who's following you—and many do not read all the broadcast tweets. We have empirically demonstrated that having a million followers does not always mean much in the Twitter world. Instead, we claim that it is more influential to have an active audience who retweets or mentions the user.

Defining influence on Twitter

We start by reviewing studies of diffusion of influence and related work on influence propagation on Twitter.

Background

There are a number of conflicting ideas and theories about how trends and innovations get adopted and spread.

The traditional view assumes that a minority of members in a society possess qualities that make them exceptionally persuasive in spreading ideas to others. These exceptional individuals drive trends on behalf of the majority of ordinary people. They are loosely described as being informed, respected, and well-connected; they are called the opinion leaders in the two-step flow theory (Katz and Lazarsfeld 1955), innovators in the diffusion of innovations theory (Rogers 1962), and hubs, connectors, or mavens in other work (Gladwell 2002). The theory of influentials is intuitive and compelling. By identifying and convincing a small number of influential individuals, a viral campaign can reach a wide audience at a small cost. The theory spread well beyond academia and has been adopted in many marketing businesses, e.g., RoperASW and Tremor (Gladwell 2002; Berry and Keller 2003).

In contrast, a more modern view of information flow emphasizes the importance of prevailing culture more than the role of influentials. Some researchers have reasoned that people in the new information age make choices based on the opinions of their peers and friends, rather than by influentials (Domingos and Richardson 2001). These researchers argued that direct marketing through influentials would not be as profitable as using "network"-based advertising such as collaborative filtering.

The traditional influentials theory has also been criticized because its information flow process does not take into account the role of ordinary users. In order to compare the role of influentials and ordinary users, researchers have developed a series of simulations, in which information flows freely between users, and a user adopts an innovation when he is influenced by more than a threshold of the sample population (Watts and Dodds 2007). Influentials were defined as those in the top 10% of influence distribution. The simulation showed that influentials initiated more frequent and larger cascades than average users, but they were neither necessary nor sufficient for all diffusions, as suggested in the traditional theory. Moreover, in homogeneous networks, influentials were no more successful in running long cascades than ordinary users. This means that a trend's success depends not on the person who starts it, but on how susceptible the society is overall to the trend (Watts 2007). In fact, a trend can be initiated by any one, and if the environment is right, it will spread. Therefore, Watts dubbed early adopters or opinion leaders "accidental" influentials.

The above competing ideas have remained as hypotheses for several reasons. First is the lack of data that could be used to empirically test them. Although there exist a handful of empirical studies on word-of-mouth influence (Leskovec, Adamic, and Huberman 2007; Cha, Mislove, and Gummadi 2009), no work has been conducted on the relative order of influence among individuals. A second issue is the variety of ways that influence has been defined (Watts 2007; Goyal, Bonchi, and Lakshmanan 2010). It has been unclear what exactly influence means. Finally, decades have passed since the influentials theory appeared. Even if the theory was reasonably accurate when it was proposed, things have changed and now we have much more variability in the flow of influence. In particular, online communities have become a significant way we receive new information and influence in such communities needs to be explored. In this paper, we investigate the notion of influence using a large amount of data collected from a popular social medium, Twitter.

Measuring influence on Twitter

The Merriam-Webster dictionary defines influence as "the power or capacity of causing an effect in indirect or intangible ways." Despite the large number of theories of influence in sociology, there is no tangible way to measure such a force nor is there a concrete definition of what influence means, for instance, in the spread of news.

In this paper, we analyze the Twitter network as a news spreading medium and study the types and degrees of influence within the network. Focusing on an individual's potential to lead others to engage in a certain act, we highlight three "interpersonal" activities on Twitter. First, users interact by *following* updates of people who post interesting tweets. Second, users can pass along interesting pieces of information to their followers. This act is popularly known as *retweeting* and can typically be identified by the use of `RT @username` or `via @username` in tweets. Finally, users can respond to (or comment on) other people's tweets, which we call *mentioning*. Mentioning is identified by searching for `@username` in the tweet content, after excluding retweets. A tweet that starts with `@username` is not broadcast to all followers, but only to the replied user. A tweet containing `@username` in the middle of its text gets broadcast to all followers. These three activities represent the different types of influence of a person:

1. **Indegree influence**, the number of followers of a user, directly indicates the size of the audience for that user.
2. **Retweet influence**, which we measure through the number of retweets containing one's name, indicates the ability of that user to generate content with pass-along value.
3. **Mention influence**, which we measure through the number of mentions containing one's name, indicates the ability of that user to engage others in a conversation.

Related work on Twitter

Several recent efforts have been made to track influence on Twitter. The Web Ecology Project tracked 12 popular Twitter users for a 10-day period and grouped a user's influence into two types: conversation-based and content-based (Leavitt et al. 2009). This work concluded that news media are better at spreading content, while celebrities are better at simply making conversation. Our work extends their notion of influence and uses extensive data to further examine the spatial and temporal dynamics of influence.

More recently, a PageRank-like measure has been proposed to quantify influence on Twitter (Weng et al. 2010). The authors found high link reciprocity (72%) from a non-random sample of 6,748 Singapore-based users, and argued that high reciprocity is indicative of homophily. They then exploited this fact in computing a user' influence rank. Our study, however, contradicts the observation about high reciprocity; near-complete data of Twitter shows low reciprocity (10%). Thus, we predict that social links on Twitter represent an influence relationship, rather than homophily. Accordingly, we ask what are the different activities on Twitter that represent influence of a user and to what extent a person's influence varies across tweet topic and time.

Characteristics of the top influentials

We describe how we collected the Twitter data and present the characteristics of the top users based on three influence measures: indegree, retweets, and mentions.

Dataset

We asked Twitter administrators to allow us to gather data from their site at scale. They graciously white-listed the IP address range containing 58 of our servers, which allowed us to gather large amounts of data. We used the Twitter API to gather information about a user's social links and tweets.

We launched our crawler in August 2009 for all user IDs ranging from 0 to 80 million. We did not look beyond 80 million, because no single user in the collected data had a link to a user whose ID was greater than that value. Out of 80 million possible IDs, we found 54,981,152 in-use accounts, which were connected to each other by 1,963,263,821 social links. We gathered information about a user's follow links and all tweets ever posted by each user since the early days of the service. In total, there were 1,755,925,520 tweets. Nearly 8% of all user accounts were set private, so that only their friends could view their tweets. We ignore these users in our analysis. The social link information is based on the final snapshot of the network topology at the time of crawling and we do not know when the links were formed.

The network of Twitter users comprises a single disproportionately large connected component (containing 94.8% of users), singletons (5%), and smaller components (0.2%). The largest component contains 99% of all links and tweets. Our goal is to explore influence of users, hence we focus on the largest component of the network, which is conceptually a single interaction domain for users.

Because it is hard to determine influence of users who have few tweets, we borrowed the concept of "active users" from the traditional media research (Levy and Windhal 1985) and focused on those users with some minimum level of activity. We ignored users who had posted fewer than 10 tweets during their entire lifetime. We also ignored users for whom we did not have a valid screen name, because this information is crucial in identifying the number of times a user was mentioned or retweeted by others. After filtering, there were 6,189,636 users, whom we focus on in the remainder of this paper. To measure the influence of these 6 million users, however, we looked into how the entire set of 52 million users interacted with these active users.

Methodology for comparing user influence

For each of the 6 million users, we computed the value of each influence measure and compared them. Rather than comparing the values directly, we used the relative order of users' ranks as a measure of difference. In order to do this, we sorted users by each measure, so that the rank of 1 indicates the most influential user and increasing rank indicates a less influential user. Users with the same influence value receive the average of the rank amongst them (Buck 1980). Once every user is assigned a rank for each influence measure, we are ready to quantify how a user's rank varies across different measures and examine what kinds of users are ranked high for a given measure.

We used Spearman's rank correlation coefficient

$$\rho = 1 - \frac{6 \sum (x_i - y_i)^2}{N^3 - N} \qquad (1)$$

as a measure of the strength of the association between two rank sets, where x_i and y_i are the ranks of users based on two different influence measures in a dataset of N users. Spearman's rank correlation coefficient calculation is a non-parametric test; the coefficient assesses how well an arbitrary monotonic function could describe the relationship between two variables, without making any other assumptions about the particular nature of the relationship between the variables. Our inclusive and complete dataset guarantees reliability of the correlation estimates. The closer ρ is to $+1$ or -1, the stronger the likely correlation. A perfect positive correlation is $+1$ and a perfect negative correlation is -1.

Comparing three measures of user influence

To see what kinds of users are the most influential, we visited the Twitter pages of the top-20 users based on each measure.

The top influentials The most followed users span a wide variety of public figures and news sources. They were news sources (CNN, New York Times), politicians (Barack Obama), athletes (Shaquille O'Neal), as well as celebrities like actors, writers, musicians, and models (Ashton Kutcher, Britney Spears). As the list suggests, indegree measure is useful when we want to identify users who get lots of attention from their audience through one-on-one interactions, i.e., the audience is directly connected to influentials.

The most retweeted users were content aggregation services (Mashable, TwitterTips, TweetMeme), businessmen (Guy Kawasaki), and news sites (The New York Times, The Onion). They are trackers of trending topic and knowledgeable people in different fields, whom other users decide to retweet. Unlike indegree, retweets represent influence of a user beyond one's one-to-one interaction domain; popular tweets could propagate multiple hops away from the source before they are retweeted throughout the network. Furthermore, because of the tight connection between users as suggested in the triadic closure (Granovetter 1973), retweeting in a social network can serve as a powerful tool to reinforce a message—for instance, the probability of adopting an innovation increases when not one but a group of users repeat the same message (Watts and Dodds 2007).

The most mentioned users were mostly celebrities. Ordinary users showed a great passion for celebrities, regularly posting messages to them or mentioning them, without necessarily retweeting their posts. This indicates that celebrities are often in the center of public attention and celebrity gossip is a popular activity among Twitter users.

If retweets represent a citation of another user's content, mentions represent a public response to another user's tweet—the focus of a tweet is on content for retweets, while the focus is on the replied user for mentions. This can be confirmed from the usage of conventions in tweets: 92% of tweets that had a `RT` or `via` marker contained a URL and 97% of them also contained the `@username` field. This means that retweets are about the content (indicated by the embedded URL) and that people typically cite the authentic source when they retweet. However, fewer than 30% of tweets that were classified as mentions contained any URL, indicating that a mention is more identity-driven.

Across all three measures, the top influentials were generally recognizable public figures and websites. Interestingly, we saw marginal overlap in these three top lists. These top-20 lists only had 2 users in common: Ashton Kutcher and Puff Daddy. The top-100 lists also showed marginal overlap, as shown in Figure 1, indicating that the three measures capture different types of influence.

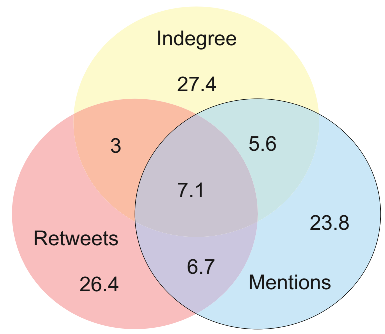


Figure 1: Venn diagram of the top-100 influentials across measures: The chart is normalized so that the total is 100%.

Relative influence ranks In order to investigate how the three measures correlate, we compared the relative influence ranks of all 6 million users (Table 1). We see a moderately high correlation (above 0.5) across all pairs. However, the high correlation appears to be an artifact of the tied ranks among the least influential users, e.g., many of the least connected users also received zero retweet and mention. To avoid this bias, we focused on the set of relatively popular users. We considered users in the top 10th and 1st percentiles based on indegree, in the hope that users who get retweeted or mentioned must have some followers.

Table 1: Spearman's rank correlation coefficients

Correlation	All	Top 10%	Top 1%
Indegree vs retweets	0.549	0.122	0.109
Indegree vs mentions	0.638	0.286	0.309
Retweets vs mentions	0.580	0.638	0.605

After this filtering step, the top users showed a strong correlation in their retweet influence and mention influence. Sampling the top users based on retweets or mentions leads to similar results. This means that, in general, users who get mentioned often also get retweeted often, and vice versa. Indegree, however, *was not* related to the other measures. We conclude that the most connected users are not necessarily the most influential when it comes to engaging one's audience in conversations and having one's messages spread.

Discussion of methodology Normalizing retweets and mentions by total tweets would yield a different measure of influence, which might have led to very different results. When we tried normalizing the data, we identified local opinion leaders as the most influential. However, normalization failed to rank users with the highest sheer number of retweets as influential. Therefore, in this paper, we use the sheer number of retweets and mentions without normalizing these values by the total tweets of a user.

Other measures such as the number of tweets and outdegree (i.e., the number of people a user follows) were not found to be useful, because they identified robots and spammers as the most influential, respectively. Therefore, we do not use these measures.

Table 2: Summary information of the three major topics events studied

Topic	Period	Keywords	Users	Tweets	Audience
Iran	Jun 11—Aug 10	#iranelection, names of politicians	302,130	1,482,038	22,177,836
Swine	May 3—July 2	Mexico flu, H1N1, swine	239,329	495,825	20,977,793
Jackson	Jun 25—Aug 24	Michael Jackson, #mj	610,213	1,418,356	23,550,211

Finally, we calculated indegree based on the snapshot of the network at the time of crawling in 2009, because we do not know the time when each follow link was formed. For the calculation of retweets and mentions, however, we used longitudinal data (i.e., since the beginning of the Twitter service in 2006). This difference could have resulted in a weaker correlation between indegree and the other influence measures (Table 1). Nevertheless, nearly three quarters of Twitter users joined in 2009, suggesting that the effect on the correlation would have been minimal.

Does influence hold across different topics?

Having defined three different measures of influence on Twitter, we now investigate whether a user's influence varies by topic genres. In order to investigate this, we first need to find users who tweeted about a diverse set of topics.

Methodology for identifying target topics

To find as many users to monitor as possible, we picked three of the most popular topics in 2009 that were considered engaging and revolutionary in Twitter[2]: the Iranian presidential election, the outbreak of the H1N1 influenza, and the death of Michael Jackson. While all three topics were popular, they span political, health, and social genres. To extract tweets relevant to these events, we first identified the set of keywords describing the topics by consulting news websites and informed individuals. Using the selected keywords, we then identified relevant tweets by searching for the keywords in the tweet dataset.

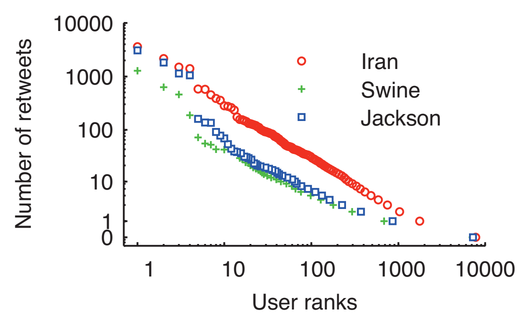
Table 2 displays the keywords and the total number of users and tweets for each topic. We focused on a period of 60 days starting from one day prior to the start of each event. We limited the study duration because popular keywords were typically hijacked by spammers after certain time. The table also shows the total number of users who received any tweet on the topic (termed *audience*). Each topic reached an audience of over 20 million, indicating that over 40% of users in Twitter were aware of at least one of the three topics.

Among the users who tweeted about any of these topics, fewer than 2% discussed all three topics. Although 2% is a small fraction, this set contains 13,219 users, which is a large enough sample size for statistical analysis. These users were generally well connected; they had on average 2,037 followers, and together reached an audience of 16 million. Furthermore, none of these users were dedicated to these three topics; no user had dedicated more than 60% of their tweets to these topics. This means that the set of 13,219 users is enthusiastic about sharing thoughts on popular news topics from diverse genres. These properties make this group ideal for studying how a user's influence varies across vastly different topic genres.

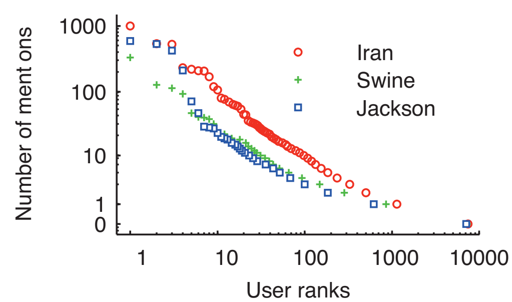
Distribution of the influence ranks

To get a measure of influence *for a given topic*, we count only the retweets and mentions a user spawned on the given topic. Because indegree is invariant across topics, we do not use the measure in this analysis.

Before investigating the dynamics of influence across topics, we first need to understand the high-level characteristics of user influence, such as the degree to which users' influence can differ. Figure 2 displays the influence ranks of users based on retweets and mentions across the Iran, Swine, and Jackson topics. The influence ranks are calculated for each topic and a user's rank may differ for different topics. The plots show a straight line on a log-log plot, a property that is referred to as the power-law characteristic. The power-law pattern is indicative of the fact that users' degree of influence can differ by orders of magnitude: the top influentials were retweeted or mentioned disproportionately more times than the majority of users. This suggests that utilizing top influentials has a great potential payoff in marketing strategy.



(a) Retweet influence ranks



(b) Mention influence ranks

Figure 2: Distribution of user ranks for a given topic

[2]The top Twitter trends identified by the Twitter Research team are listed at *http://tinyurl.com/yb4965e*.

Variation of a user's influence across topics

Next, in order to examine how volatile a user's rank is across different topics, we compare the relative order of influence ranks across topics in Table 3. For the same reason we previously discussed in Table 1, we ignore the least popular users who have tied ranks and focus on the set of relatively popular users, as measured by indegree. The top 10th and 1st percentiles included 1,322 and 132 users, respectively.

Table 3: Spearman's rank correlation coefficients over topics

	Retweet		Mentions	
Topics	Top 10%	1%	Top 10%	1%
Iran vs. Swine	0.54	0.62	0.59	0.68
Iran vs. Jackson	0.48	0.54	0.59	0.63
Swine vs. Jackson	0.55	0.50	0.80	0.68

The rank correlation is generally high (above 0.5) and gets stronger for the top 1% of users. Mentions show an even stronger correlation across topics than retweets. This means that a popular user who is good at spawning mentions from others can do so over a wide range of topics, more easily than when she is retweeted over diverse topics. Among topic pairs, Swine and Jackson showed the highest correlation for the top 10% of well-connected users for both the retweet and mention influence. This is perhaps due to the more social nature of these two events, which differs from the Iran topic where special interest groups like politicians and bloggers played a major role.

Given that the rank correlation gets stronger for users with high indegree, we investigated how widely the ranks of the top listed users change by topic. Figure 3 shows the retweet ranks of the top users in the Iran topic against the relative retweet ranks of the same users in the Swine and Jackson topics. It is clear from the figure that the top 5 users in the Iran topic retained their relative ranks in the other two topics. These users were *Mashable*, *CnnBrk*, *TweetMeme*, *Time*, and *BreakingNews*, who were all in the category of authoritative news sources and content trackers. The mention influence also showed a similar trend (not shown here); most influentials ranked consistently high amongst different topics. And we have observed this trend not only for the hyper-influentials: moderate influentials like opinion leaders and evangelists also had consistent influence ranks over diverse topics, as shown in Table 3.

Our findings about the highly skewed ability of users to influence others (Figure 2) and the strong correlation in a user's influence rank across different topics (Table 3) together lead to two interesting conclusions. First, most influential users hold significant influence over a variety of topics. This means that local opinion leaders and highly popular figures could indeed be used to spread information outside their area of expertise. In fact, new advertisement campaigns have recently been launched that insert advertisement links into a popular person's tweet (Fiorillo 2009). Second, the power-law trend in the difference among influence of individuals indicates that it is substantially more effective to target the top influentials than to employ a massive number of non-popular users in order to kick start a viral campaign.

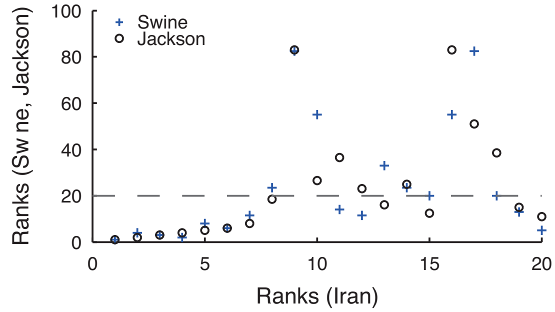


Figure 3: Users' retweet influence ranks over topics

The rise and fall of influentials over time

Many factors—social, political, and economical—affect popularity and influence of individuals and organizations. In online social media, such dynamics is facilitated by easy entry of competition. It only costs 140 characters to generate a tweet for any user. Likewise, it will be challenging for influentials to maintain their status when many emerging local opinion leaders and evangelists enter the arena.

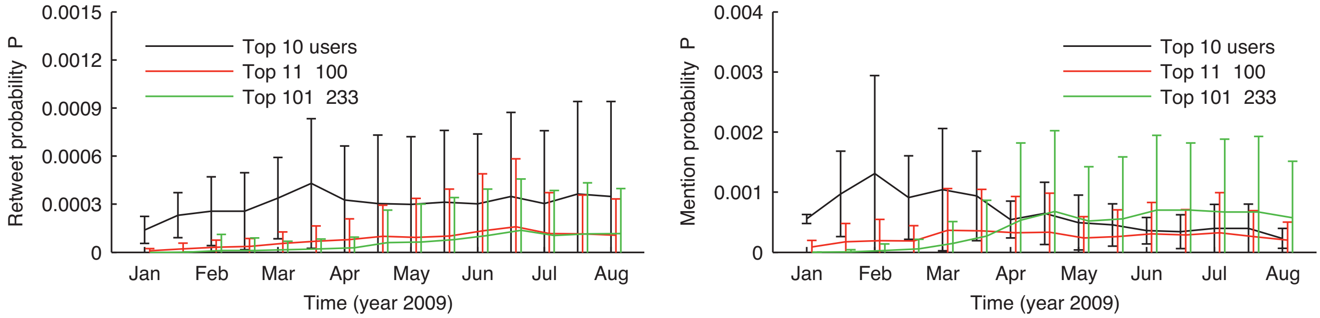
Here we analyze the dynamics of individual's influence over time in two ways. First, we track the popularity of top influentials over a long term period and check how well they maintain their ranks. Second, we focus on users who increased their influence in a specific topic over a short time period, in order to understand what behaviors make ordinary individuals influential.

Maintaining engagement of the top influentials

Out of all 6 million active users in the Twitter network, we picked the top 100 users based on each of the three measures: indegree, retweets, and mentions. We used all the tweets ever posted on Twitter in identifying these influentials. Due to the overlap we discussed in Figure 1, there were 233 distinct users, whom we call *all-time* influentials. In order to see how the influence of these all-time influentials varied over time, we tracked their influence scores over an 8 month period from January to August 2009.

To get a time-varying measure of influence, we counted the number of retweets and mentions the all-time influentials spawned in every 15 days over the 8 month period. Because we only know the indegree information based on the final snapshot of the Twitter network, we do not use this measure. For each user, we computed a single explanatory variable $\mathcal{P}$: the probability that a random tweet posted on Twitter during a 15 day period is a retweet (or a mention) of that user. Normalizing by the total number of tweets posted on Twitter is essential to cancel out any variable effect on the data and allows the underlying characteristics of the data sets to be compared. For instance, because the Twitter network quadrupled over time in terms of the registered users, the total volume of tweets merely increased over time. Hence, if we didn't normalize the results, the trend wouldn't be interesting. Google similarly normalizes the data when analyzing their search trends (Ginsberg et al. 2009).

Figure 4 displays the time evolution of the normalized retweets and mentions of the 233 all-time influential users.



(a) Retweet influence

(b) Mention influence

Figure 4: The temporal evolution of retweets and mentions for the all-time influential users. For each data point, the error bars are centered on the average retweet (or mention) probability, and they extend up and down by two standard deviations.

Although the values of $\mathcal{P}$ appear small, they account for a large volume of retweets and mentions: a single most popular influential user spawned up to 20,000 retweets and 50,000 mentions over a random 15 day period. In order to capture the trend in more detail, we classified the influentials into three groups based on indegree: the top 10 users, who were mostly the mainstream news sources; the next 90 users, who were mainly celebrities; and the rest, who were a mixed group of public figures and opinion leaders that competed with the traditional mass media.

The evolution of the retweet probability in Figure 4(a) shows that all three groups mildly increased their influence over time. Large error ranges for the top 10 users indicate a much wider variability in the popularity of this group. The growth, however, is marginal for all three groups. We conjecture that the marginal increase is due to the limited number of tweets users post a day. Broadcasting too many tweets puts even popular users at a risk of being classified as spammers. Hence, Twitter users should moderate the number of broadcast tweets in order to avoid crossing their followers' information processing limit.

The evolution of the mention probability in Figure 4(b) shows distinct patterns for the three groups. The top 10 users fell in popularity over time; the next group had consistent influence scores over time; and the last group (the least connected among the three) increased their popularity over time. Users in the last group, surprisingly, spawned on average more mentions than the top 100 users. While this trend is counter-intuitive at first, the differences between mentions and retweets can explain the trend.

The mainstream news organizations in the first group are retweeted the most, but they are not mentioned the most. This is because their names come up mostly when their content get retweeted; it is hard for media sources to engage users with their identities alone. The second group, comprised of celebrities, is more often mentioned than retweeted because of their name value. Their tweets also get retweeted, when influence is transferred across topics (Table 3). Evangelists in the last group successfully increased their influence. While many factors could explain this phenomenon, our manual inspection revealed that these users put significant efforts in conversing with others (e.g., replying to their audience). In a sense, they need self-advertisement the most, because mass media and celebrities have many other on- and off-line channels of to promote themselves.

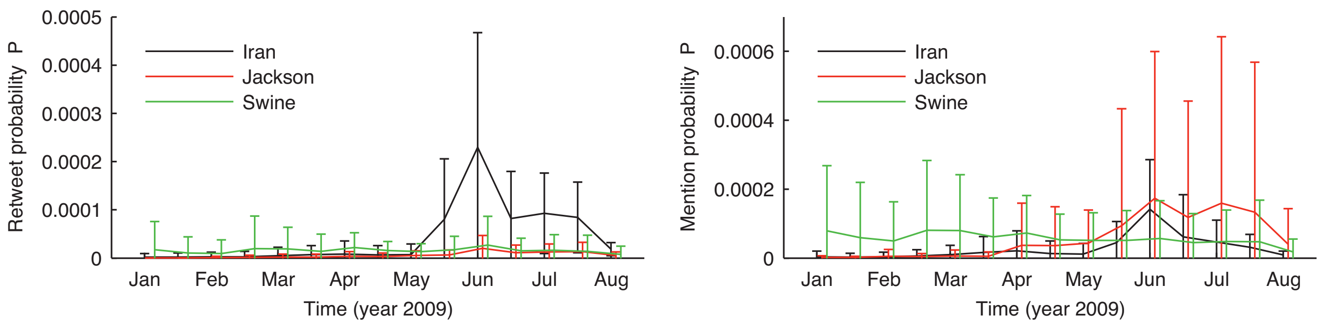
While our findings provide an interesting view of how different groups of people maintain their popularity, we should also emphasize that our analysis is in retrospect but not causal. These findings are based on the set of users who ultimately became popular. We also mention that all influentials put efforts in posting creative and interesting tweets, as shown from the high correlation in their retweet ranks.

Rising influence of the ordinary users

Finally we examined the users who increased their influence over a short time period to understand what behaviors make ordinary users influential. We focused on the set of users who talked about only one news topic, out of the three news topics in Table 2, and picked the top 20 users for each news topic based on indegree. We call these users *topical* influentials. The topical influentials included dedicated accounts like *iranbaan*, *oxfordgirl*, and *TM_Outbreak* who suddenly became popular over the course of the event. These users were literally unheard-of at the beginning of the news events and didn't receive any retweets or mentions prior to the relevant news event. The list also included users like *kevinrose* (the founder of digg.com) and *106andpark* (BET.com's music video site) who were already popular on a specific topic, and used the news events to extend their popularity.

We tracked the influence scores of the 60 topical influentials over the 8 month in 2009. Again, we computed the variable $\mathcal{P}$ as the probability that a random tweet posted in a 15 day period is a retweet (or a mention) to that user. Figure 5 displays the temporal evolution of influence for the topical influentials. Overall, the influence scores are much lower than that of the global influentials in Figure 4. This is expected since topical influentials had 3 to 180 times fewer followers than the global influentials.

Influentials on Swine flu experienced relatively stable influence scores for both retweets and mentions. This is because no single day involved a catastrophic event due to Swine flu. Influentials on the Iran election increased their



(a) Retweet influence

(b) Mention influence

Figure 5: The temporal evolution of retweets and mentions for the topical influential users

retweet influence substantially during the peak of the election in June and July, but they did not spawn many mentions. Our data shows that these influentials actively spread information about protests and controversial news. Influentials on Michael Jackson experienced a mild increase in their retweet influence in June, whereas their mention influence surged during the same time period. Our manual inspection revealed that users who limit their tweets to a single topic showed the largest increase in their influence scores.

Conclusions

This paper analyzed the influence of Twitter users by employing three measures that capture different perspectives: indegree, retweets, and mentions. We found that indegree represents a user's popularity, but is not related to other important notions of influence such as engaging audience, i.e., retweets and mentions. Retweets are driven by the content value of a tweet, while mentions are driven by the name value of the user. Such subtle differences lead to dissimilar groups of the top Twitter users; users who have high indegree do not necessarily spawn many retweets or mentions. This finding suggests that indegree alone reveals very little about the influence of a user.

Focusing on retweets and mentions, we studied the dynamics of influence across topics and time. Our spatial analysis showed that most influential users can hold significant influence over a variety of topics. The top Twitter users had a disproportionate amount of influence, which was indicated by a power-law distribution. Our temporal analysis identified how different types of influentials interact with their audience. Mainstream news organizations consistently spawned a high level of retweets over diverse topics. In contrast, celebrities were better at inducing mentions from their audience. This is because the name value of the mention influentials helped them get responses from others, rather than any inherent value in the content they posted.

Finally, we found that influence is not gained spontaneously or accidentally, but through concerted effort. In order to gain and maintain influence, users need to keep great personal involvement. This could mean that influential users are more predictable than suggested by theory (Watts 2007), shedding light on how to identify emerging influential users.

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