Internet slang words can very quickly become ubiquitous because of social memes and viral online content. Weibo, a Twitter-like service in China, demonstrates that the adoption of popular Internet slang undergoes 2 distinct peaks in its temporal evolution, in which the former is relatively much lower than the latter. An in-depth comparison of the diffusion of these different peaks suggests that popular attention in the early stage of propagation results in large-scale coverage, while the participation of opinion leaders at the early stage only leads to minor popularity. Our empirical results question the conventional influential hypothesis and provide some insights for marketing practice and influence maximization in social networks.

Keywords: Internet Slang Words, Online Social Media, Opinion Leaders, The Crowd, Information Diffusion.

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Introduction

With the rapid growth of online social media, people are inundated every day with various types of information. Everyone is a social sensor detecting and experiencing news, and vast numbers of individuals across the globe continuously share news, statuses and sentiments through their online social networks. For instance, Twitter-like services make users instantly aware of real-world events and allow them to spontaneously voice their opinions. Online social interactions such as retweets, replies, comments, and
mentions further boost the propagation of information, spread different ideas and synchronize the collective attention of the masses and might ultimately result in online social media trends (Borner et al., 2004; Crane and Sornette, 2008). In other words, by replacing traditional news portals and providing convenient channels for information exchange, online social media have fundamentally changed the diffusion patterns of social networks and brought about significant challenges to existing understandings. Furthermore, aggregated data of behavioral records in online social media provide an unprecedented chance to thoroughly investigate the detailed dynamics of diffusion in social networks from diverse perspectives.

In previous research, much attention from multidisciplinary fields has been devoted to understanding the mechanisms underlying popularity trends. The main focus in recent decades in particular has been on the properties of collective attention and the principles underlying the diffusion of novel items. For example, hashtags on Twitter and its equivalents are frequently used to gain insight into the generation mechanism of social memes by comparing items that succeed or fail to gain social popularity (Lehmann et al., 2012; Chang, 2010; Paradowski and Jonak, 2012, 2011; Bao et al., 2013a). Lehmann et al. (2012) focus on the tracking of hashtags on Twitter and identify discrete classes of hashtags according to their popular evolution over time. The authors also find that exogenous factors are more important than epidemic spreading in establishing hashtag popularity. JafariAsbagh et al. (2014) propose a streaming framework for detecting and clustering memes in online social networks. Bao et al. (2013) investigate the cumulative effect of information diffusion on Weibo and argue that additional exposures do not improve the probability of retweets. Meanwhile, tracking popular topics or emergent events is also an effective way to study the dynamics of collective attention or collective response (Bagrow et al., 2011), which essentially drives the formation of trends or spikes (Asur et al., 2011; Bao et al., 2013b; Wu and Huberman, 2007; Gomez Rodriguez et al., 2010; Lin et al., 2011; Romero et al., 2011b; Bauckhage et al., 2014; Sasahara et al., 2013; Ferrara et al., 2013; Bagrow et al., 2011; Ferrara et al., 2014). Romero et al. (2011b) study the mechanics of information diffusion by comparing the spreading process across different topics on Twitter. Bauckhage et al. (2014) investigate the adoption patterns of 175 social media services and Web businesses using Google Trends data and argue that collective attention in almost all services experiences a phase of accelerated growth followed by saturation and prolonged decline. Ferrara et al. (2013) find that topics with global popularity emerge from the major air traffic hubs in the US. In addition to hashtags and topic tracking, the formation of neologisms is another opportunity to study intrinsic factors of collective attention (Swarup et al., 2011; Eisenstein et al., 2012; Bentley et al., 2012; Stroud et al., 2014). Swarup et al. (2011) focus on the linguistic innovation phase of lexical dynamics in social networks and find that the probability of the existence of a norm is inversely related to the probability of innovation. Eisenstein et al. (2012) conclude that the diffusion of neologisms is restricted to geographically compact areas and tends to spread from city to city. Stroud et al. (2014) indicate that a news organization can affect the deliberative behavior of commenters by tracking and cultivating deliberative norms via news organization involvement. While the above studies mainly concentrate on the temporal or spatial dynamics of trends in online social media, a discussion on the roles of different users in the formation of popularity is missing. This gap is the primary motivation of our study.

User influence or social capital in social networks can be a convincing proxy to understand the successful diffusion of innovative ideas, neologisms, and new products (Johnston et al., 2014). Conventional diffusion theory states that a minority of people, called influentials, are generally considered to be the most critical factors affecting information cascades (Rogers, 2003); this theory is also known as the influentials hypothesis (Watts, 2007). With the help of influentials, large-scale popularity might be achieved at an extremely low cost (Katz, 1957; Gladwell, 2002; Flynn et al., 1996; Dholakia et al., 2004; Iyengar et al., 2011; Cha et al., 2010; Wu et al., 2014; Kempe et al., 2005; Trusov et al., 2010). As a result, many
previous studies have focused on how to target influential in social networks. Cha et al. (2010) investigate the dynamics of user influence on topics over time based on three measures of indegree, retweets, and mentions. They find that most influential can have a significant influence on a variety of topics. Kempe et al. (2005) propose an influence propagation model to study the problem of targeting initial influential nodes. Luarn et al. (2014) find that people with more connections might exert a greater influence on information dissemination. However, whether the traditional two-step flow theory (Katz, 1957) is applicable to online social networks is still unknown. Moreover, the role of influential might be exaggerated. Weng et al. (2012) argue that there is no need to include influential users to explain the emergence of trending conversations and popular content. In trending conversations, exogenous events and the behavior of influential individuals can affect the irregular dynamics of emerging trends (Conover et al. 2013, Varol et al. 2014). Romero et al. (2011a) propose an algorithm that can determine users’ influence and passivity based on their information-forwarding activities, and the authors demonstrate that more popularity does not always result in great influence. Domingos and Richardson (2001) insist that the key factors in determining influence are the relationship among ordinary users and the readiness of the social network to accept a novel item. More directly, Watts (2007) and Watts and Dodds (2007) challenge the influential hypothesis and note that social epidemics tend to be driven by a critical mass of easily influenced individuals. Harrigan et al. (2012) also find that it is the community structure rather than hubs that can substantially increase social contagion on Twitter. Weng et al. (2011a) propose an algorithm that can determine users’ influence and passivity based on their information-forwarding activities, and the authors demonstrate that more popularity does not always result in great influence. Domingos and Richardson (2001) insist that the key factors in determining influence are the relationship among ordinary users and the readiness of the social network to accept a novel item. More directly, Watts (2007) and Watts and Dodds (2007) challenge the influential hypothesis and note that social epidemics tend to be driven by a critical mass of easily influenced individuals. Harrigan et al. (2012) also find that it is the community structure rather than hubs that can substantially increase social contagion on Twitter. Weng et al. (2013) argue that the role of network structure is more likely to be a powerful driver for the emergence of trends on Twitter. However, empirical data to carefully validate these controversial arguments against the influential hypothesis are still missing, which is the second motivation for our study.

Trends in online social media can be reflected by the popularity of hashtags, topics or even neologisms such as Internet slang. The collective attention underlying popularity peaks indicate the participation of a massive number of individuals during the diffusion of the relevant information. As shown above, the previous literature neglects long-term analyses of popularity and mainly concentrates on the highest peaks. Moreover, studies of the temporal dynamics of popularity are isolated from discussions about the role that different individuals play in diffusion. To fill these crucial gaps, we argue that studying how different individuals function in the propagation of information should be embedded in the context of the lifecycle dynamics of popularity. Along this line, taking Weibo, the Chinese variant of Twitter, as an example, we selected 92 popular Internet slang words from 2013 to observe how their popularity varies over time. The popularity of a word can be quantified in a straightforward manner by the frequency of its occurrence in daily tweets on Weibo. Surprisingly, we find that up to half of these trendy neologisms undergo two obvious peaks in the timeline of their emergence, and the first peak is much lower than the second. It is important to note that low peaks might occur before the largest peak, but most of these peaks are trivial and only indicate tiny cascades. Therefore, it is reasonable to omit them in the following analysis. Three examples are shown in Figure 1. This unexpected phenomenon has not drawn attention in previous studies. In fact, the two peaks indicate that in the lifecycle of each slang word, there are two opportunities to receive collective attention and become a trend, and the first opportunity fails, but the second one succeeds. In addition, because the average interval between the two peaks is approximately 103 days and the minimum is greater than four weeks, it can be assumed that the two peaks occur independently of each other. The comparison of the diffusion represented by these two peaks offers us a good opportunity to understand how trends form in online social media. Specifically, the difference between the second peak and the first peak is exactly the reason why a word manages to obtain collective attention and become a trend. Inspired by this finding, we try to uncover who actually creates trends in online social media. Is it the crowd made up of ordinary users, or is it opinion leaders who have significant influence and great social capital?
Materials and Methods

Data sets
The tweets employed in this study were collected through the open API (Application Program Interface) under Weibo’s license. We randomly sampled approximately 700,000 tweets from the Weibo stream every day in 2013. Each tweet contains the following attributes: ID number, timestamp, (textual) content, retweet status, author with number of followers (#Followers), the number of followees (#Followees), the number of tweets (#Tweets), address and verified state. In total, we collected 173,548,881 tweets (with the slang words introduced later) and captured 9,021,435 users after filtering for spam. Specifically, we manually labeled approximately 3,000 tweets as being spam or not and then used an SVM classifier to implement the filtering process. The classification accuracy level reached 85%. By filtering for spam, we managed to diminish the interference produced by social bots and particularly online advertisements because such accounts often try to use trendy slang words to promote their tweets’ popularity without considering the meaning of the words.

We collected 92 popular Internet slang words from several different websites, but most were found on “baike.com.” It should be noted that similar to Wikipedia and Urban Dictionary (urbandictionary.com), “baike.com” provides a crowdsourcing platform for a large number of Internet users in China to manually select and vote for the most popular and influential slang words each year. Consequently, these words are interesting material for our study. Furthermore, we inspect the dynamics of these slang words’ temporal popularity, which can be quantified by their frequency of occurrence in daily tweets on Weibo. By using the peak detection algorithm, which will be introduced in the next section, 42 Internet slang words are selected. The data set is publicly available to the research community and it can be downloaded freely through http://goo.gl/WHXDjB.

Identifying peaks
As shown in Figure 2, we assume that the day with the highest popularity is when the second peak, $p_2$, takes place, and its popularity is denoted by $P_2$. Similarly, the highest peak among the smaller peaks before $p_2$ is the day when the first peak ($p_1$) takes place, and its popularity is denoted by $P_1$. By searching for the highest popularity during the year, we can easily locate $p_2$. Subsequently, we find the first peak. As seen in Figure 2, $p_1$ is our target peak, but there might be other noisy peaks existing, such as $p_n$ and $p_c$. Among these noisy peaks, $p_n$ is located very close to $p_2$, and it may even represent the same event.
as $p_2$. However, $p_c$ is too small compared with $p_1$’s popularity and only indicates a tiny and trivial cascade. Based on this analysis, we present a peak detection method to determine $p_1$. The method contains two thresholds, i.e., $R$ and $T$. $R$ represents the popularity threshold and is defined as $\delta \ast P_2$ ($\delta \in [0, 1]$). $T$ denotes the time interval threshold between $p_1$ and $p_2$. Intuitively, if $\delta$ is too large, $p_n$ might be selected with high probability. Inversely, if $\delta$ is too small, trivial peaks such as $p_c$ will be selected. Similarly, an excessively small $T$ cannot guarantee independence between the two peaks, while an excessively large $T$ may hide the actual target peak ($p_1$). We randomly selected 10 words with two peaks; the average ratio between $p_1$ and $p_2$ is approximately 0.09, and the average time interval is approximately 102 days (more than 3 months). Based on these observations, we performed a series of experiments with different thresholds and found that when $\delta$ is set to 0.01 and $T$ is set to 28 (4 weeks), noisy peaks can be successfully eliminated. Finally, using this approach, we obtained 42 Internet slang words and successfully located their two peaks.

Results

The various roles of individuals in diffusion can be divided into five groups based on their propensity to adopt a given innovation, namely, innovators, early adopters, early majorities, late majorities and laggards. Among these five groups, early adopters are considered to be more important than the others (Rogers, 2003). Thus, we can compare the diffusions represented by the two peaks of popularity in terms of user composition and ascertain the degree of early adopters in each because all tweets are randomly sampled from the stream.

For each slang word, as mentioned, we define the first popularity peak as $p_1$ and the second peak as $p_2$. These two peaks represent two different diffusions: $p_1$ represents the diffusion with small-scale coverage, while $p_2$ represents the diffusion with large-scale coverage. Assuming the popularity value of a peak is $P$, we determine the interval between $\alpha P$ and $\beta P$ ($0 < |\alpha| < 1$ and $0 < |\beta| < 1$) of the peak as $(\alpha, \beta)$, which is the specific stage of the diffusion that the peak represents. If $\alpha < 0$ and $\beta < 0$, the interval is defined in the left half section of the peak, which is the early stage of the diffusion. The laggard stage of the diffusion can be found in the right half section of the peak, where $\alpha > 0$ and $\beta > 0$. With regard to user influence in online social networks, several measures can be employed to reflect a user’s significance in relation to others in the network. González-Bailón et al. (2013) and Varol et al. (2014) argue that users’ influence is determined by their social connectivity and their online interactions. The influence of a given user is a function of #Followees, #Followers, the number of retweets produced by the user and
the number of times that other users repost the user’s tweets. Among these four factors, #Followers is generally the most convincing indicator because the #Followers a user has directly determines how many potential listeners there might be in the first stage when a user posts a tweet in which a new word is adopted. Supposing each individual participates in adoption with the same probability, having many followers suggests more chances for dissemination in the second stage. Cha et al. (2010) find that users with large #Followers are the most retweeted users on Twitter. Moreover, Wu et al. (2014) evaluate five dimensions of user influence and argue that the #Followers and their authority significantly affect the spread of information in first-stage communication. Consequently, here we use #Followers to define a user’s influence. Opinion leaders tend to possess a substantial #Followers, while most people only have a few followers. Following González-Bailón et al. (2013), we also strive to demonstrate the rationality of using #Followers to define user influence. Because our data contains no retweet information, we use #Tweets instead of retweet information to describe users’ online social activity.

Number of Followers
We first compare the proportion of different users with different #Followers in the early stage of the two peaks; accordingly, we consider these users to be early adopters. We use proportion(i) to denote the proportion of different users with \( i \) followers to all users during a particular period, where \( S \) is the set of users’ #Followers during this period. The proportion(i) can be computed by

\[
\text{proportion} (i) = \frac{\#(i)}{\sum_{i \in S} \#(i)}
\]

where #\((i)\) denotes the number of users with \( i \) followers. As shown in Figure 3, for the period of peaks ((-0.1, 0.1)), there is no distinction between \( p_1 \) and \( p_2 \), which indicates that the distribution of #Followers for different participants during these peaks is irrelevant to the peaks’ height. In the early stages of diffusion ((-0.1, -0.3) and (-0.1, -0.5)), the proportion of users with a small #Followers (<200), i.e., the crowd, is significantly higher than that of users with a large #Followers, i.e., the opinion leaders, which in \( p_2 \) results in successful diffusion. Similarly, in all of the stages shown in Figure 3, we can observe an increase in the proportion of users with a large #Followers by approximately \( 10^5 \) in \( p_1 \), which indicates a failed diffusion. The above observations are consistent and strongly suggest that the crowd includes a higher proportion of early adopters in \( p_2 \) than in \( p_1 \), which indicates that the crowd’s participation in the early stage of propagation can result in a massive diffusion. Indeed, the participation of opinion leaders at the early stage does not guarantee successful diffusion; in such a case, the peak only achieves small coverage, represented by \( p_1 \) in Figure 1.

In Figure 3, we also find that during the early adoption phase, if the proportion of ordinary users with less than 200 followers meets a critical level, diffusion will be more likely to attract the collective attention of the crowd. As a result, we choose the early stage (-0.1, -0.5) to further explore the importance of the critical number of followers and the difference in user composition for different diffusions. To find this critical number of followers, we use the cumulative distribution function (CDF) of #Followers in the early stages of different diffusions. As shown in Figure 4, the CDF curve of \( p_2 \) exceeds the curve of \( p_1 \) for a small #Followers. This result again demonstrates that ordinary users play a more important role than opinion leaders for \( p_2 \). The point of greatest difference between these two CDF curves is the crucial number. We define this number as the threshold, and when users fall below this threshold of followers, their proportions of #Followers in the two peaks shows the most significant deviation. The thresholds of the 42 slang words are plotted in Figure 5: the median of the critical number of followers is 232, and the corresponding largest deviation of CDF is 0.17. This result indicates that during successful diffusion in \( p_2 \), ordinary users with less than 232 followers occupy a 0.17 higher proportion than those in the failed
diffusion represented by $p_1$. Note that the threshold we find here is close to Dunbar’s number (Dunbar, 1998), which is derived from the constraints of human cognition and still exists in online social networks (Zhao et al., 2014). Our findings are in agreement with the existing hypothesis that a global trend emerges from many small-scale trends, and the population of an efficient group launching small-scale trends must be less than Dunbar’s number (Gladwell, 2002). Our findings also empirically support the conjecture that the relationships among ordinary users are key factors in determining influence (Domingos and Richardson, 2001; Watts, 2007). Although opinion leaders are important in starting a diffusion, without enough participation from the crowd, diffusions will probably fail to create popular trends in online social media.

To verify the effectiveness of using #Followers to describe user influence, we analyze the user composition between $p_1$ and $p_2$ by determining user influence based on #Followers, #Followees and #Tweets. Figure 6 shows the relationships between #Tweets and the ratio of #Followers and #Followees for users in two diffusions. We draw a vertical line to distinguish between influential users on the right and ordinary users on the left. Users with a large amount of tweets can be considered broadcasters. Users with fewer followers and tweets, found on the bottom left of Figure 6, can be considered the crowd, while users with more followers and tweets can be considered as influential users. By comparing user composition

**Figure 3** The proportion of users with different #Followers in all the users during the two diffusions separately. Three different diffusion stages are selected. All the results are averaged over the entire set of slang words we collect.

**Figure 4** CDF of #Followers for three slang words.
between the two peaks, we can see that the crowd occupies a higher proportion of users in $p_2$ than in $p_1$, which is consistent with the analysis of #Followers.

**Verified status**

Weibo officially verifies opinion leaders with a large #Followers as VIPs, which is different from Twitter. *Figure 7* plots #Tweets as a function of the ratio between #Followers and #Followees. As shown in the figure, most verified users have more followers than followees, and their #Tweets are usually no less than several hundred. In other words, the majority of verified users can be considered influencers. In contrast,
most non-verified users have fewer followees than followers, and their #Tweets are less than several hundred. Thus, the crowd occupies a significant proportion of the non-verified users. Then, we compare users’ verified status distribution during the two peaks. Figure 8 shows that in both early stages of (-0.1, -0.3) and (-0.1, -0.5), the proportion of verified participants during the diffusion represented by $p_1$ is higher than that during the diffusion represented by $p_2$. Specifically, the ratio between verified users and non-verified users is approximately 3:7 for the small-scale diffusion $p_1$, while the ratio decreases to less than 2:8 for the successful diffusion $p_2$. This result suggests that in the process of a neologism becoming popular, non-verified users, which are largely ordinary users, play a decisive role in determining whether a phrase captures the collective attention.
Proportions of users with different retweet times in early stages of different diffusions. Here we mainly focus on times of 1 and 2, which take the majority of the retweets.

Number of retweets
Information diffuses in online social media, especially on Twitter and its variants, mainly through retweets, which forward the information from one user to another user in the social network. Opinion leaders on Weibo who have a large #Followers receive many more first-step retweets than members of the crowd, who have fewer followers. However, first-step retweets alone do not propagate information further in the network: Second-step retweets play a relevant role in spreading information further. We compare the proportions of users with different retweet steps in early stages of the diffusion, and as shown in Figure 9, users with second-step retweets are well represented in the early stage of $p_2$, which signifies the successful diffusion, while the domination of first-step retweets in $p_1$ does not make the diffusion reach a high level of popularity. Although forwarding by influentials might promote information to more followers in the first step, the repeat participation by a large number of ordinary users effectively facilitates the formation of trends.

Geographic coverage
In addition to temporal dynamics, information also diffuses in social networks along geographic lines. For example, Eisenstein et al. (2012) argue that neologisms tend to spread from city to city. Thus, we also investigate the difference in the geographic distribution of slang words’ adopters in different stages of different diffusions. Figure 10 shows the temporal-spatial diffusion of three typical Internet slang words during the two peaks. For the diffusion of (-0.1, 0.1), we define the first day as the date when the diffusion is at 10% of its highest popularity (in the early stage), and the peak day is the date with the highest popularity. We separately compare the geographic distributions on the first day and the peak day of both peaks. The figure shows that Internet slang words tend to spread from one or several places to other places around the country. For example, on the first day of $p_1$, “being headlines” appears only in Shanghai (SH). After a few days, the word can be seen in several major cities and provinces. By comparing the first day of both peaks, we find that Internet slang words appear and are distributed more uniformly at the early stage of diffusion during $p_2$. An interactive demonstration of geographical diffusion for all slang words is publicly available at http://ipv6.nlsde.buaa.edu.cn/zhaojichang/slang/index.html. Then, we compare the aggregated geographic distribution between the two peaks. As shown in Figure 11, for the early adoption
Figure 10  The temporal-spatial diffusion process of three Internet slang words on the first and peak day of two peaks. (A) "long hair to waist." (B) "being headlines." (C) "rich rednecks."

Figure 11  Difference between geographical distributions of adopters at different stages of different diffusions.

stage of (-0.1, -0.5), active regions such as Beijing (BJ), Guangdong (GD) and Shanghai (SH) have more users during the small-scale diffusion represented by p1 than in the large-scale diffusion represented by p2. Specifically, the information entropy in the geographic distribution of early adopters is 4.26 for p1, but it is 4.46 for p2, which implies that early participants in the successful diffusion in p2 are distributed more uniformly across the country. This result indicates that for the diffusion of p1, slang words are only locally popular phrases, and the opinion leaders from active regions only marginally aid diffusion. We can also see from Figure 11 that even during the period of peaks (-0.1, 0.1), the large-scale diffusion represented by p2 possesses greater information entropy (4.10) than that of p1 (3.72), which indicates a more uniform and broader adoption.
In summary, solid evidence from the in-depth comparison of two diffusions in the adoption of slang words suggests an unexpected role for the crowd in the creation of trends. Contrary to the previous focus on the role of influentials in social networks, we find that the participation of ordinary users at the early stage of the diffusion process can help the formation of trends in online social media.

Discussion and conclusion

The rapid growth of social media in recent decades has made online social networks the dominant channel of information exchange. For instance, Weibo in China has accumulated more than 500 million users in less than 5 years, and it generates approximately 100 million tweets every day. These tweets relay sophisticated messages about the real world, including personal statuses, public news, various opinions, and diverse sentiments. Meanwhile, new items such as events or neologisms might attract the collective attention of the masses and form trends in an extremely short time, which is subsequently reflected by their peaks in popularity.

In contrast to existing studies, in this paper, we focus on a long-term analysis of popularity variation and find that there were two peaks in the lifecycle of Internet slang words in 2013. Specifically, the first peak is lower than the second, and these independent peaks represent different diffusions of the same word; the former only reaches a small audience, while the latter spreads widely across the network. Consequently, a comparison of these two different diffusions provides a good opportunity to investigate who creates trends. Is it the crowd, constituted by ordinary people, or is it opinion leaders who exert substantial influence? Counterintuitively, our results suggest that in online social media, the crowd plays a decisive role at the early stage of trend creation, while the participation of opinion leaders as dominant early adopters only results in small-scale coverage. Contrary to the influentials hypothesis, opinion leaders can start a diffusion locally, but only the participation of ordinary users can create broad coverage and, finally, form a trend. Our findings shed further light into classical issues such as viral marketing (Leskovec et al., 2007; Iyengar et al., 2011) and influence maximization (Kempe et al., 2003; Chen et al., 2010) in social networks. The typical solution to these questions provided in the previous literature is to examine the role of influentials in seeding the diffusion process. Our results suggest that more attention should be paid to the role of ordinary users with fewer than 232 followers during the early stage of the diffusion process. Given the definition of Dunbar’s number, ordinary users in online social media usually are individuals who are capable of normal social interactions within the limits of human cognitive ability. That is, online interactions between ordinary users and their subsequent behaviors are more reliable and diffusive than that of opinion leaders, who are always overwhelmed by a multitude of social ties and therefore act as inefficient information hubs (Harrigan et al., 2012). As a result, focusing on influential users only provides a limited perspective because it is the attraction of the crowd that generates a massive diffusion with global coverage.

Meanwhile, we also track the relative frequency of these Internet slang words around different peaks, for example, in the range from 2 weeks before to 2 weeks after $p_1$ and $p_2$. As shown in Figure 12, the relative popularity (which is normalized by dividing the popularity at the corresponding peak) of $p_1$ increases somewhat faster but decreases slower than that of $p_2$. With the fittings of these plots, as shown in Eq. 2 (for $p_1$) and Eq. 3 (for $p_2$), we can further corroborate the above observation. This result suggests that the influence of opinion leaders on information dissemination occurs faster at the early stage than the crowd’s influence (i.e., as $\tau < 0$, the exponential coefficient is 1.41 for $p_1$ but 1.01 for $p_2$ and greater positive value represents faster increment), and their influence might last somewhat longer (i.e., as $\tau > 0$, the exponential coefficient is -0.66 for $p_1$ but -0.86 for $p_2$ and smaller negative value represents faster decay), although global coverage remains limited. Therefore, when collective attention suddenly
The relative popularity around different peaks. The blue solid line and the red dashed line denote the best fitting for $p_1$ and $p_2$, respectively.

Figure 12

becomes focused, and small-scale coverage does not matter significantly, turning to influentials is still a wise choice. If the ultimate target of a marketing strategy is global trends in online social media, more attention should be paid to the crowd.

$$f_{p_1}(\tau) \sim \begin{cases} \exp^{1.41\tau} & \tau < 0 \\ \exp^{-0.66\tau} & \tau > 0 \end{cases} \tag{2}$$

$$f_{p_2}(\tau) \sim \begin{cases} \exp^{1.01\tau} & \tau < 0 \\ \exp^{-0.86\tau} & \tau > 0 \end{cases} \tag{3}$$

This study has inevitable limitations. First, data from other social networking platforms like Twitter should be considered for testifying and generalizing the results. It would be an interesting direction in the future work. Second, in comparing the different diffusions represented by different peaks, we mainly focus on the proportions of the crowd and opinion leaders. However, the intrinsic factors that drive the crowd to participate in the adoption of slang words are not fully understood. For example, they might be related to the slang word itself, pushed by exogenous events or influenced by the social environment (approximately one-third of the first peaks occurred during the May Day holiday, which indicates that people are more likely to take part in diffusion while enjoying leisure time). In fact, Sasahara et al. (2013) even suggest that strong collective attention is accompanied by a cascade of retweets and may be related to the mood of users at the group level. Hence, filtering out the essential factors underlying the participation of the crowd deserves further exploration in the future, which would help the design of appropriate strategies to increase the participation of the crowd at the early stage.

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