Quantifying Information Overload in Social Media and Its Impact on Social Contagions

Manuel Gomez-Rodriguez
MPI for Intelligent Systems
manuelgr@tue.mpg.de

Krishna P. Gummadi
MPI for Software Systems
gummadi@mpi-sws.org

Bernhard Schölkopf
MPI for Intelligent Systems
bs@tue.mpg.de

Abstract

Information overload has become an ubiquitous problem in modern society. Social media users and microbloggers receive an endless flow of information, often at a rate far higher than their cognitive abilities to process the information. In this paper, we conduct a large scale quantitative study of information overload and evaluate its impact on information dissemination in the Twitter social media site. We model social media users as information processing systems that queue incoming information according to some policies, process information from the queue at some *unknown* rates and decide to forward some of the incoming information to other users. We show how timestamped data about tweets received and forwarded by users can be used to uncover key properties of their queueing policies and estimate their information processing rates and limits. Such an understanding of users' information processing behaviors allows us to infer whether and to what extent users suffer from information overload.

Our analysis provides empirical evidence of information processing limits for social media users and the prevalence of information overloading. The most active and popular social media users are often the ones that are overloaded. Moreover, we find that the rate at which users receive information impacts their processing behavior, including how they prioritize information from different sources, how much information they process, and how quickly they process information. Finally, the susceptibility of a social media user to social contagions depends crucially on the rate at which she receives information. An exposure to a piece of information, be it an idea, a convention or a product, is much less effective for users that receive information at higher rates, meaning they need more exposures to adopt a particular contagion.

Introduction

Since Alvin Toffler popularized the term "Information overload" in his bestselling 1970 book Future Shock (Toffler 1984), it has become a major problem in modern society. Information overload occurs when the amount of input to a system exceeds its processing capacity. Humans have limited cognitive processing capacities, and consequently, when they are overloaded with information, their quality of decision making suffers (Gross 1964).

The advent of social media and online social networking has led to a dramatic increase in the amount of information a user is exposed to, greatly increasing the chances of the user experiencing an information overload. In particular, microbloggers complain of information overload to the greatest extent. Surveys show that two thirds of Twitter users have felt that they receive too many posts, and over half of Twitter users have felt the need for a tool to filter out the irrelevant posts (Bontcheva, Gorrell, and Wessels 2013). Prior studies show that information overload has a major impact on users in a broad range of domains: work productivity (Dean and Webb 2011), recommendation systems (Borchers et al. 1998), or information systems (Bawden and Robinson 2009). However, all these prior works have typically relied on qualitative analysis, surveys or small-scale experiments.

In this paper, we perform a large-scale quantitative study of information overload experienced by users in the Twitter social media site. The key insight that enables our study is that users' information processing behaviors can be reverse engineered through a careful analysis of the times when they receive a piece of information and when they choose to forward it to other users. Abstractly, we think of a Twitter user as an information processing system that queues the incoming flow of information (or in-flow) according to a last-in first-out (LIFO) policy, processes the information from the queue at some *unknown* rate, and decides to forward some of the processed information. By uncovering key properties of the queueing policies and processing rates of users with different in-flow rates, we attempt to (i) understand how users' information processing behaviors vary with the in-flow rate, (ii) estimate information processing limits of users, and (iii) ultimately infer the level of information overload on users.

To this end, we use data gathered from Twitter, which comprises of all public tweets published during a three months period, from July 2009 to September 2009. In Twitter, a user's information queue corresponds to her Twitter timeline (or feed), the incoming flow of information corresponds to the stream of tweets published by the users she follows, and the queuing policy corresponds to the way the user reads and forwards (retweets) tweets from her feed. We show how we can reverse engineer different characteristics of the users' processing behaviors using only the timestamps of the tweets sent / received and the social graph between the users.

Our analysis yields several insights that not only reveal the extent to which users in social media are overloaded with information, but also help us in understanding how information overload influences users' decisions to forward and disseminate information to other users:

1. We find empirical evidence of a limit on the amount of information a user produces per day. We observed that very few Twitter users produce more than $\sim$40 tweets/day.
2. In contrast to the tight limits on information produced, we find no limits on the information received by Twitter users. The information received scales linearly with the number of users followed and many Twitter users follow several hundreds to thousands of other users.
3. We observed a threshold rate of incoming information ($\sim$30 tweets/hour), below which the probability that a user forwards any received tweet holds nearly constant, but above which the probability that a user forwards any received tweet begins to drop substantially. We argue that the threshold rate roughly approximates the limit on information processing capacity of users and it allows us to identify users that are overloaded.
4. When users are not overloaded, we observe that they tend to process and forward information faster as the rate at which they receive information increases. However, when users are overloaded, we find that the higher the rate at which they receive information, the longer the time they take to process and forward a piece of information.
5. When users are overloaded, they appear to prioritize tweets from a selected subset of sources. We observe that even as overloaded users follow more users, the set of users whose tweets they forward remains fairly constant and increases very slowly.

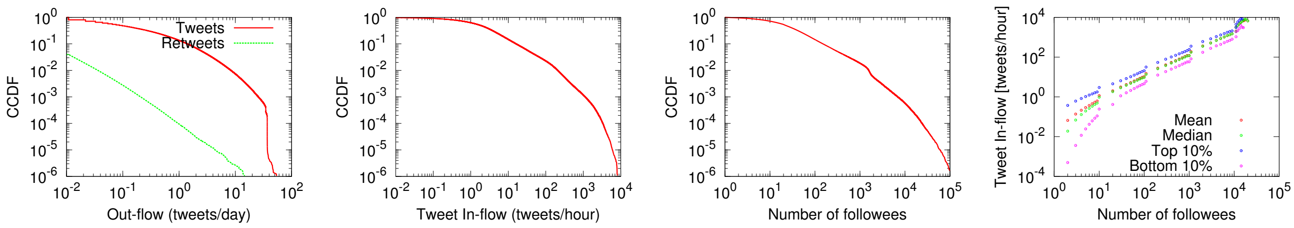
Our findings about the information processing and forwarding behaviors of overloaded users have important implications for propagation of information via *social contagions*. While a large number of previous studies have focused on social contagions in on-line media (Du et al. 2013; Goel, Watts, and Goldstein 2012; Gomez-Rodriguez, Leskovec, and Krause 2010; Leskovec, Backstrom, and Kleinberg 2009), most ignore the impact of information overload on users' forwarding behavior. They consider the spread of a single piece of information through an underlying network, ignoring the effect of lots of other background information simultaneously spreading through the network. Here, we investigate the impact of such background traffic on the spread of social contagions. In particular, we study the propagation of hashtags (Romero, Meeder, and Kleinberg 2011), retweet conventions (Kooti et al. 2012), and URL shortening service usage (Antoniades et al. 2011) through the Twitter network. One of our main findings is that the rate at which users receive information, i.e., the extent to which they are overloaded, has a strong impact on the number of exposures a user needs to adopt a contagion.

Related Work

The work most closely related ours (Backstrom et al. 2011; Hodas and Lerman 2012; Miritello et al. 2013) investigates the impact that the amount of social ties of a social media user has on the way she interacts or exchanges information with her friends, followees or contacts. Backstrom et al. measure the way in which an individual divides his or her attention across contacts by analyzing Facebook data. Their analysis suggests that some people focus most of their attention on a small circle of close friends, while others disperse their attention more broadly over a large set. Hodas et al. quantify how a user's limited attention is divided among information sources (or followees) by tracking URLs as markers of information in Twitter. They provide empirical evidence that highly connected individuals are less likely to propagate an arbitrary tweet. Miritello et al. analyze mobile phone call data and note that individuals exhibit a finite communication capacity, which limits the number of ties they can maintain active. The common theme is to investigate whether there is a limit on the amount of ties (*e.g.*, friends, followees or phone contacts) people can maintain, and how people distribute attention across them.

However, partly due to a lack of complete temporal data, there are several fundamental differences between the above mentioned studies and our work. First, we find a sharp threshold or phase transition that roughly approximates the limit on the amount of information social media users can process (read and possibly forward) (Fig. 2(b)). This allows us to identify users that are overloaded. Instead, no sharp threshold exists on the number of ties a user can distribute attention across (Hodas and Lerman 2012, Fig. 3). Second, we uncover key properties of the users' reading and forwarding policies and find dramatic qualitative and quantitative differences between non overloaded and overloaded users. These differences have important implications for the large and growing number of studies on information propagation and social contagion. In contrast, previous studies could not unveil most of these differences. Third, our work explores to which extent the probability of adoption of an idea, social convention, or product, or more generally, a contagion, depends on the social media user's in-flow and finds striking differences on the susceptibility for social contagion of users with different in-flows. Instead, Backstrom et al. and Miritello et al. do not investigate social contagion; Hodas et al. only pays attention to one type of contagion, urls, and analyzes to which extent the probability of forwarding a url depends on the number of ties a user distribution attention across. Finally, our work naturally extends existing models of information and influence propagation to support background traffic. The extended models are able to capture two important features for information cascades: cascade sizes are limited and a few cascades have prolonged lifetimes. In contrast, previous work does not provide any roadmap or ideas on how to incorporate their findings in terms of number of ties to well-known information and influence propagation models.

Last, very recently, there have been attempts to analyze and model information propagation assuming competition and cooperation between contagions (Goyal and Kearns



(a) Out-flow rate (b) In-flow rate (c) Followees (d) In-flow rate vs. followees

Figure 1: Distributions of tweet out-flow rates, tweet in-flow rates and followees.

2012; Myers and Leskovec 2012; Weng et al. 2012). However, this line of work considers only interactions between pairs of contagions (Myers and Leskovec 2012) or present theoretical models without experimental validation (Goyal and Kearns 2012). In contrast, our work investigates the effect that observing a great number of contagions simultaneously propagating, not necessarily informative or interesting, has on the ability of a person to process and forward information. We believe this is a key point for understanding information propagation in the age of information overload.

Methodology

In this section, we describe our methodology for estimating information processing limits and behaviors of users in social media sites from observational data. One of the key challenges we faced is that we could not directly observe (i.e., gather data about) how users read, process and forward information. Instead, we only had access to observational data about the times when users receive each piece of information and the times when they forward a particular piece of information. However, we do not know which pieces of information each user actually reads or when the users read the pieces of information. To overcome this limitation, our methodology assumes each user applies some policy to read, process and forward information.

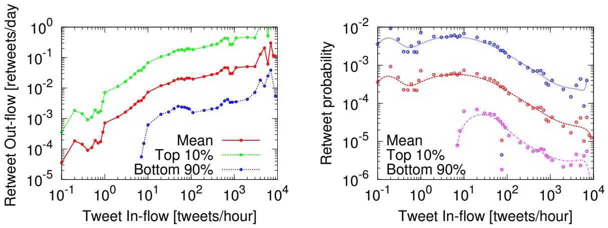
We think abstractly of a social media user as an information processing system that receives an incoming flow of information (or in-flow) on an information queue. The in-flow is composed of information generated by other information processing systems (users), which the system decides to subscribe to. Then, we assume the system applies a last-in first-out (LIFO) queueing policy to process and sometimes forward particular pieces of information from the in-flow. The rationale behind our LIFO queuing policy choice is twofold. First, in most social media platforms, each user has a feed (be it in the form a Facebook user's wall, a Twitter user's timeline or an Instagram user's feed) which she periodically checks out, where the information generated by other users she subscribes to is accumulated. Second, a user browses the feed from top to bottom because, even if the user skips some of the content, she still has to scroll from the top to the bottom of the feed. Therefore, it seems natural to consider the feed as a LIFO queue. In Twitter, the information queue is persistent and corresponds to a user's Twitter timeline, the incoming flow of information (or in-flow) corresponds to the stream of tweets published by the user's followees[1], and the queuing policy corresponds to the way a user reads and possibly retweets tweets from her feed. Importantly, at the time when we gathered our data (in the year 2009), Twitter sorted each user's feed in inverse chronological order and thus, it is possible to reconstruct a user's queue at any given time.

In this framework, we use the times in which information was generated and forwarded to estimate properties of the queueing such as the queues sizes (i.e., the position in the queue beyond which users do not process information), the queues processing delays (i.e., the time spent by information in the queue waiting to be processed), or the priority given to information received from each followee on the users' queues, among others. It may seem surprising that we are able to estimate such properties without observing additional behavioral data such as which information each user actually reads or when the user reads each piece of information. Our key insight is that retweets (forwarded tweets) provide a sample of the underlying queueing policies. More specifically, we assume that a user retweets soon (almost instantaneously) after reading a tweet for the first time. Under this assumption, we observe that (i) retweet delays are independent samples of the reading delays, and, (ii) queue positions of retweeted tweets at the time of retweets are lower bounds of the queues sizes. In subsequent sections, we show how the above observations make it possible to estimate information processing limits and behaviors of users from our limited observational data consisting only of the times when users receive and forward tweets.

Twitter Dataset

We use data gathered from Twitter as reported in previous work (Cha et al. 2010), which comprises the following three types of information: profiles of 52 million users, 1.9 billion directed follow links among these users, and 1.7 billion public tweets posted by the collected users. The follow link information is based on a snapshot taken at the time of data collection, in September 2009. In our work, we limit ourselves to tweets published from July 2009 to September 2009 and filter out users that did not tweet before June 2009, in order to be able to consider the social graph to be *approximately* static. After the preprocessing steps, we have 5,704,427 active users, 563,880,341 directed edges,

[1] Followees of a Twitter user are the users she follows on Twitter.



(a) Retweet rate vs in-flow rate (b) Retweet prob. vs in-flow rate

Figure 2: Retweets vs in-flow. Panel (a) shows retweet rate and panel (b) shows probability of retweet.

318,341,537 tweets and 1,807,748 retweets.

For every user, we build her in-flow and out-flow by collecting all tweets published by the people she follows, the tweets she published and the retweets she generated. Since back in 2009, Twitter did not have a retweet button, and instead, users were explicitly identifying retweets using several conventions, we identify retweets by searching the most common conventions, following previous work (Kooti et al. 2012). Another important characteristic of Twitter in 2009 is that it did not have features such us "Lists" and "Personalized Suggestions" and so the primary way users received and processed information was through their feed, for which we have complete data. However, this comes at the cost of observing a smaller number of users and information flows.

Information Processing Limits

In this section, we investigate the information processing capacity of social media users. More specifically, we attempt to answer the following three questions in the context of the Twitter social medium:

1. What, if any, are the limits on the amount of information users generate and forward to their friends?
2. Do users try to limit the amount of information they receive from other users?
3. Is there evidence of users suffering from information overload? If yes, does information overload impact users decisions to forward and disseminate information?

Limits on information generation & forwarding

We begin by focusing on the rate at which users produce information in Twitter. Specifically, we compute the number of tweets they generate per day, considering original tweets and retweets of the tweets they receive from other users separately. Figure 1(a) shows the distributions of tweet *out-flow rates*, i.e., the number of total tweets and retweets individual Twitter users post per day. We find several interesting patterns in the plots which we briefly discuss next.

First, we observe a sharp fall-off on the total number of tweets a user produces per day, located at ∼40 tweets/day. This provides empirical evidence that there exists a limit on the amount of tweets, or more generally, information, most Twitter users produce every day. There are several plausible reasons that may explain the existence of such limit. For example, posting tweets is a manual task and therefore, intuitively, one would expect to find some limit on the number of tweets posted by a user. Moreover, users may choose to limit their posts for fear of overloading (or spamming) their followers with information (Comarela et al. 2012).

Second, the distribution of the number of retweets a user produces per day follows a power-law, in contrast with the distribution of the total number of tweets a user produces per day, which decays much slower up to a sharp fall-off. This suggests that the underlying policies users follow to process and forward incoming tweets, or more generally, information, are essentially different to the policies they follow to publish their own tweets.

Origins of information overload

We now shift our attention to the amount of information Twitter users receive per time unit. Figure 1(b) shows the distribution of tweet *in-flow rates*, i.e., the number of tweets individual Twitter users receive per hour. While 50% of users receive fewer than 50 tweets per day, 10% of users receive more than 500 tweets per day. Many of these tweets contain URLs (pointers to web pages) (Mislove et al. 2007). Surprisingly, unlike in the case of tweet out-flows, users do not appear to be limiting their tweet in-flows (potentially, by following fewer users). The relatively high in-flow rates of tweets and information for some of the users suggests the potential for users to be overwhelmed with information.

Next we investigate whether users receiving more (less) information are systematically following higher (smaller) number of users. Figure 1(d) shows the average, median, and top / bottom 10% in-flow rates against number of followees for Twitter users. The plot shows that the tweet in-flow rates of individual users are strongly and linearly correlated with the number of users they follow. As one might expect, the higher the number of followees a user follows the greater the number of tweets she receives. Figure 1(c) shows the distribution of number of followees for Twitter users. Similar to what has been observed in prior work (Kwak et al. 2010), we find that roughly 30% of the users follow more than 50 people, but only around 0.15% of the users follow more than 5,000 people.

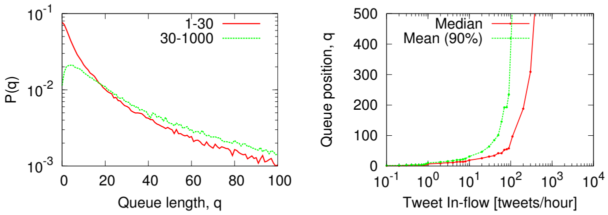
Our findings suggest that the origins of information overload in social media lie in the tendency of Twitter users to oversubscribe, i.e., follow a lot more users than those whose tweets they can process (as we show in the next section). *Why do users choose to receive a lot more information than they can process?* One explanation proposed by prior work is that users are choosing to follow users but not necessarily all their tweets, i.e., users' following behavior is driven by their desire to follow people they find interesting, but they are not necessarily interested in all the tweets posted by the users they follow (Hodas, Kooti, and Lerman 2013). Thus, information overload in social media today arises out of users' tendency to socialize (exchange information) with many other users.

Evidence of information overload

Our above observations about unbounded information inflow rates and bounded information out-flow rates for users suggest that the chances of a user forwarding an incoming piece of information may depend on the in-flow rate itself, i.e., the extent to which the user is overloaded. Here, we elucidate this question by investigating the relationship between the tweet in-flow rate and the retweet out-flow rate.

Figure 2(a) shows how the retweet out-flow rate λ_r varies against the tweet in-flow rate λ. Interestingly, as the in-flow rate increases, the retweeting rate increases, but at a declining rate. In other words, the retweet rate seems to follow a law of diminishing returns with respect to the in-flow rate; mathematically, $\lambda_r(\lambda_1 + \Delta\lambda) - \lambda_r(\lambda_1) \leq \lambda_r(\lambda_2 + \Delta\lambda) - \lambda_r(\lambda_2)$ for $\lambda_1 \geq \lambda_2$. Figure 2(b) shows how the probability of retweeting an incoming tweet β_r varies against the in-flow rate λ. Interestingly, we find two different in-flow rate regimes: below ~30 tweets/hour, the retweeting probability β_r is relatively constant, however, over ~30 tweets/hour, it falls sharply against the inflow rate, specifically, we observe a power law $\beta_r \propto \lambda^{-0.65}$, where we found the power-law coefficient using maximum likelihood estimation (MLE). The second regime represents the scenario in which a user is overloaded. In this scenario, the more tweets a user receives, the lower the probability of any received tweet to be retweeted by the user, indicating a greater information overload on the user. Note that this phenomena cannot be simply explained by the existence of a limit on the users' out-flow rates – even if the retweet probability would remain constant, the retweet rate would still be far away from the limit on information generation we have observed previously. For example, consider there exists a user with an incoming rate $\lambda = 10^3$ tweets/hour and a retweet probability $\beta_r = 10^{-3}$, then her retweet rate would be $1 \ll 40$ retweets/hour. Therefore, we argue it provides empirical evidence of information overloading. Perhaps surprisingly 10% of the active users in our dataset have an in-flow rate in the second regime and thus are likely suffering from information overload. Who are those overloaded users? They are typically very popular users, with a significant amount of followers, who tweet more frequently than the *average* user. For example, while 95% of the overloaded users have more than 200 followers, 86% of the non overloaded users have less than 100 followers. Strikingly, the set of overloaded users are responsible for 45% of all retweets. Our results provide strong empirical evidence for (a) the existence of an information processing limit for social media users and (b) the prevalence of information overloading, i.e., breaching of the information processing limits, in social media today.

Our above finding has important implications for the large and growing number of studies on information cascades and social contagion in social media (Du et al. 2013; Goel, Watts, and Goldstein 2012; Gomez-Rodriguez, Leskovec, and Krause 2010; Leskovec, Backstrom, and Kleinberg 2009). In particular, many studies today focus on the dissemination of a single piece of information, completely ignoring the presence of background traffic. On the contrary, our finding here suggests that excessive background traffic can have a strong negative impact on information dissemination and it provides supporting empirical evidence for the few prior studies that have postulated that information overloading might explain why most information cascades in social media fail to reach epidemic proportions (Hodas and Lerman 2012; Ver Steeg, Ghosh, and Lerman 2011). Later, we will investigate further how information cascades and social contagion depend on the background traffic.



(a) Queue position distribution (b) Average queue position

Figure 3: Queue position. Panel (a) shows the empirical distribution and panel (b) shows average/median position of a tweet on the user's queue (feed) at the time when it got retweeted for different in-flow rates, where $q = 0$ means the tweet was at the top of the user's queue at retweeting time.

User Processing Behaviors

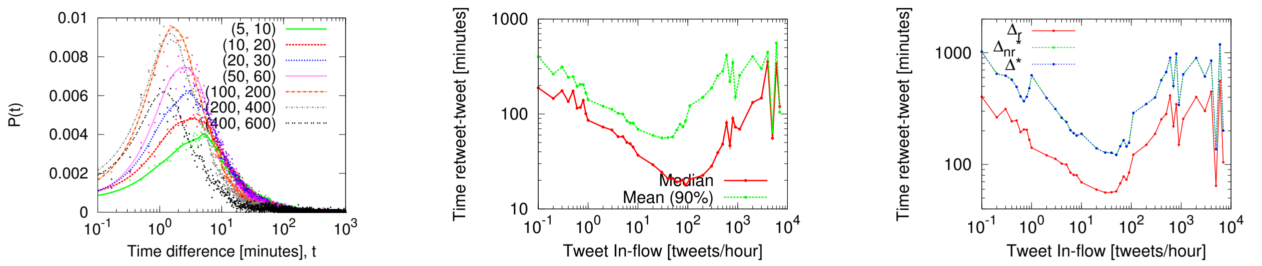
In the previous section, we showed evidence of information overload amongst Twitter users, but lacked a detailed understanding of the underlying ways in which users process the information they receive. As discussed earlier, information received by a user can be thought of as being added to her LIFO information queue and processed asynchronously whenever the user logs into the system. In this section, we present a detailed analysis of how users process information in their queues. Specifically, we attempt to characterize three aspects of their information processing behaviors:

1. How does the probability of processing a piece of information vary with its position in the queue? Can we estimate the queue sizes beyond which users effectively ignore information?
2. How large are typical queueing (processing) delays for information? How does it vary with the rate of incoming information?
3. When users are overloaded, do they tend to separate information into priority queues? Do they tend to prioritize and process information from certain users over others?

Queue position vs. processing probability

Intuitively, we may expect that when Twitter users login and begin processing tweets in their queues (feeds), they are much more likely to process tweets closer to the head of the queue than the tweets further down. Here, we estimate the likelihood that users process information further down in the queue by estimating the position of the tweets that are retweeted at the time of their retweet.

Figure 3(a) shows the empirical distribution of the position of a tweet on the user's queue (feed) at the time when it got retweeted for two different in-flow rate intervals, where queue position $q = 0$ means the tweet was at the top of the user's queue at retweeting time. For low in-flow rates ($1-30$ tweets/hour), the user is not overwhelmed with information



(a) Delay (forwarded information)

(b) Delay vs in-flow (forwarded information)

(c) Delay (non forwarded information)

Figure 4: Queueing delay. Panel (a) shows the empirical queuing delay distribution for forwarded information. Panel (b) shows the average and median time delay between a user's retweet and the original tweet against in-flow rate. Panel (c) shows three average time delays for non forwarded information: Δ_r is the average time users take to read and decide to retweet, Δ_{nr}^* is a lower bound on the average time users take to read and decide not to retweet, and $\Delta^* = \Delta_r + \Delta_{nr}^*$.

and is likely processing new tweets as soon as they arrive. That means the tweet is most likely at the head of the user's queue at the time of retweet. However, for larger in-flow rates ($30 - 1000$ tweets/hour), the user is increasingly overloaded and would likely have to process information that is accumulating in the queues faster than she can process. As a result, we observe a shift in the most likely positions of retweets down the queue. There is a clear difference between the plots for low and high in-flow rates in Figure 3(a). Nevertheless, in both cases, the probability of retweeting a tweet positioned beyond the first 100 slots in the queue is more than an order of magnitude lower than the probability of retweeting a tweet positioned in the first 10 slots in the queue. The low probability values for forwarding information located lower down the queue suggest that, for the purposes of information processing, queues are bounded, i.e., once information slides out of the top few positions in the queue, the chance of it being processed drops precipitously. When users are overloaded, their high tweet in-flow rates quickly push the tweets lower down the queue and beyond the processing limits on queue sizes.

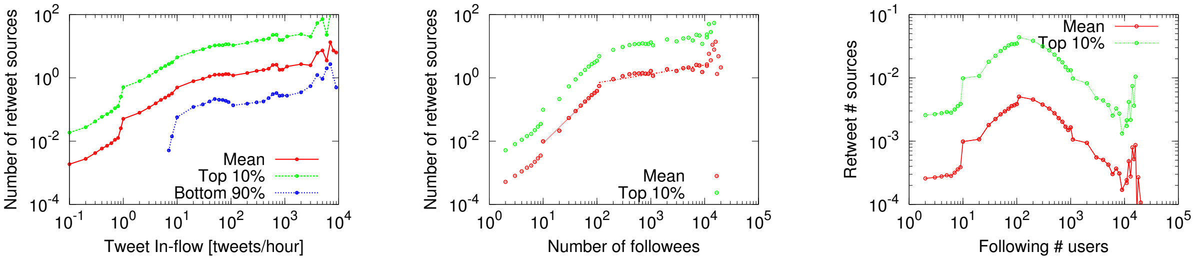
The average (median) position of a tweet on the user's queue at the time of retweet keeps increasing with larger in-flows, as shown in Figure 3(b). Interestingly, we find that the precipitous rise in average queue position occurs at an in-flow rate of ~30 tweets/hour, matching the value of the threshold in-flow rate at which users begin to suffer from information overload, found previously. This finding suggests that when users are overloaded, their retweets are no longer drawn from their queues but instead users find the information they retweet through some other mechanisms. We investigate one such plausible mechanism later in this Section.

Quantifying queuing delays

The temporal dynamics of information propagation, and in particular, the speed at which information propagates depends crucially on the time users take to process the information they receive and determine if they would like to forward it to other users (Gomez-Rodriguez, Balduzzi, and Schölkopf 2011). Here, we investigate the queueing delays, i.e., the time delays between the time when a tweet was received by a user and the time when the user retweeted it. We are particularly interested in understanding the impact of information overload on queueing delays.

Queueing delays for forwarded information Figure 4(a) shows the empirical queueing delay distribution for different in-flow rates. There are several interesting patterns. First, queueing delay distributions for different in-flow rates seem to belong to the same distribution family, in particular, the convolution of two lognormal distributions, one modeling the observation time, and another one modeling the reaction time, provides a good fit, in agreement with previous work (Doerr, Blenn, and Van Mieghem 2013). Importantly, the mean, variance, and peak value depend on the in-flow rate. In other words, the amount of information overload of a user influences the time she takes to read and retweet a tweet. The larger the tweet in-flow, the smaller time delay the peak value is located at, as shown in Fig. 4(a). For example, the queueing delay distribution for users receiving in average 5 to 10 tweets/hour peaks at 5 minutes, in contrast, the distribution for users receiving in average 100 to 200 tweets per hour reaches its maximum at less 2 minutes. This indicates that users with higher tweet in-flow rates are more engaged into the service and observe and retweet tweets quicker. However, although the peak value keeps shifting to smaller time values for larger in-flows, it becomes less likely and the variance increases. What about the median and average time delay? Figure 4(b) shows the median and (bottom 90%) average of the empirical queueing delay against in-flow rate. Perhaps surprisingly, the median and average keep decreasing until some in-flow rate threshold value, and afterwards increase. Importantly, the threshold value for the average queueing delay seems to be coherent with our previous results, since it roughly coincides with value of the threshold in-flow rate at which users begin to suffer from information overload, found previously. This suggests that overloaded users cannot keep up with the amount of incoming information and either look for tweets directly in other user's profiles or use tools to sort their incoming tweets.

Queueing delays for nonforwarded information So far we have focused our attention on the amount of time users take to read and retweet a tweet and its position on the user's



(a) # sources vs in-flow rate (b) # sources vs # followees (c) Source probability vs # followees

Figure 5: Number of different sources vs. in-flow rate and number of followees.

queue when it got retweeted. However, can we tell something about the time users take to read a tweet and decide not to retweet it? We can use Little's Theorem (Kleinrock 1975) from queue theory to answer this question. In our context, the theorem states that the long-term average number of unread tweets N_u is equal to the long-term in-flow rate, λ, multiplied by the average time a user takes to read (and possibly retweet) a tweet or average queueing delay, Δ; mathematically, $N_u = \lambda\Delta$. Here, we assume that a non retweeted tweet *exists* the queue once it exceeds a position. We can split Δ in $(\lambda_r \Delta_r + \lambda_{nr}\Delta_{nr})/\lambda$, where λ_r (λ_{nr}) is the in-flow rate due to tweets that (do not) get retweeted, and Δ_r (Δ_{nr}) is the average time users take to read and decide (not) to retweet a tweet. We can measure λ, λ_r, λ_{nr}, and Δ_r, and bound N_u below by the average position of a tweet in the feed at the time it was retweeted, $N_r \leq N_u$. Therefore, we can compute a lower bound on the average time users take to read and decide not to retweet a tweet, $\Delta_{nr} \geq (N_u - \lambda_r\Delta_r)/\lambda_{nr} = \Delta^*_{nr}$, and thus on the average queueing delay, $\Delta \geq (\lambda_r\Delta_r + \lambda_{nr}\Delta^*_{nr})/\lambda = \Delta^*$. Figure 4(c) compares Δ_r, Δ^*_{nr} and Δ^* against in-flow rate λ. Since the lower bounds Δ^*_{nr} and Δ^* are always larger than Δ_r, then $\Delta_{nr} \geq \Delta \geq \Delta_r$; in other words, tweets that get retweeted are actually the ones that users happen to read and decide to retweet the *earlier*.

It has proven difficult to know what makes an idea, a piece of information, a behavior, or, more generally, a contagion to spread quicker or slower. Our above observations suggest that a particular social medium itself may heavily bias how quickly users process and forward information. In particular, it highlights the key role that a user's in-flow rate in the social medium has on the user's queueing delay for particular contagions on the social medium, independently on the contagion content. Later, we will investigate further the impact of a user's in-flow rate on social contagion.

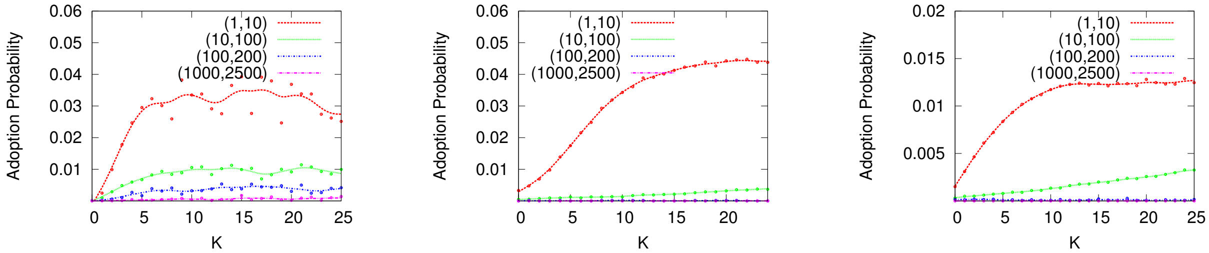
Priority queueing to select sources

In the previous sections, we observed that when users are overloaded with information, their choice of tweets to forward becomes independent of the queue positions and queueing delays of the tweets. Users are likely selecting these tweets through some other mechanisms which differs from the LIFO information queue. One potential hypothesis that we investigate now is that overloaded users focus only on tweets from a small subset of all the users they follow. These small subset of users may be considered as influential for the overloaded users. Then, the processing behavior of such overloaded users can be modeled using multiple priority queues (Kleinrock 1975), where tweets from important sources are placed in a queue with higher priority and the rest of the tweets are placed in a lower priority queue.

To test whether overloaded users indeed limit the choice of Twitter users whose tweets they forward, we compute the average retweet source set size ${S_r}^2$ against in-flow rate and show the results in Figure 5(a). We observe that similarly to the retweet rate, as the in-flow rate increases, the source set size increases at a declining rate. In other words, the source set size follows a law of diminishing returns with respect to the in-flow rate: $S_r(\lambda_1 + \Delta\lambda) - S_r(\lambda_1) \leq S_r(\lambda_2 + \Delta\lambda) - S_r(\lambda_2)$ for $\lambda_1 \geq \lambda_2$. This sub-linear increase suggests that the larger the in-flow rate of a user, the more difficult is for a followee to become a source. Next, we investigate whether users tend to prioritize information from some followees over others as their number of followees increases. Figures 5(b-c) allow us to answer this question by showing the average retweet source set size and the probability of a followee to be a source against number of followees F. Interestingly, these plots exhibit two clear regimes: below $\sim$100 followees, the number of average retweet sources increases as $S_r \propto F^{1.68}$, while over $\sim$100 followees, the number of retweet sources flattens dramatically, increasing slowly as $S_r \propto F^{0.28}$. Importantly, $\sim$100 followees roughly corresponds to an in-flow rate of $\sim$30 tweets/hour, which coincides with the threshold in-flow rate at which users begin to suffer from information overload, found previously. This indicates that as users follow more people and are overloaded with more information, they prioritize information produced by a smaller subset of influential followees, whose aggregate out-flow rate is below the users' processing limits.

Our results support a previous study which analyzed mobile phone data and found that individuals exhibit a finite communication capacity, which limits the number of ties they can maintain actively at any given time (Miritello et al. 2013). Our results also offer a different perspective on the role of influentials and the nature of their influence – when users suffer from information overload, they tend to priori-

[2] A user's retweet source set is the set of different users from whom she retweets from



(a) Hashtags

(b) “RT” retweet conventions

(c) bit.ly url shortening service

Figure 6: Exposure curves vs in-flow rate for information units (hashtags), social conventions (retweet conventions) and product adoptions (url shortening services). We group users by their in-flow rate in four different ranges: $(1, 10)$, $(10, 100)$, $(100, 200)$ and $(1000, 2500)$ tweets/hour.

tize or selectively process information from influential users at the expense of the remaining users.

Impact on Social Contagions

Our study so far has demonstrated that *background traffic* plays an important role in users' decisions to forward any piece of information they receive. Now, we investigate the impact of the background traffic and the resulting information overload on social *contagions* or *cascades*, i.e., the viral propagation of information across a social network.

Contagions need more exposures to spread

In recent years, there has been an increasing interest in understanding social contagion, where a recurrent theme has been studying the number of exposures to a contagion a user needs to adopt it. In sociology, the “complex contagion” principle posits that repeated exposures to an idea are particularly crucial when the idea is in some way controversial or contentious (Centola 2010; Centola and Macy 2007). Recently, this hypothesis has been validated in a large scale quantitative (Romero, Meeder, and Kleinberg 2011), and, even more recently, it has been argued that the number of social ties a user has is crucial to assess how effective an exposure may be (Hodas and Lerman 2012). Here, we provide further and stronger empirical evidence that the background traffic received by a user plays an essential role on the number of required exposures to adopt a contagion.

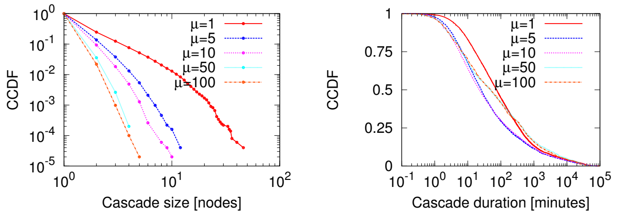
We use *exposure curves* (Cosley et al. 2010) to measure the impact that exposure to others' behavior has in an individual's choice to adopt a new behavior. We say that a user is k-exposed to a contagion c if she has not *adopted* (mentioned, used) c, but follows k other users who have adopted c in the past. Given a user u that is k-exposed to c we would like to estimate the probability that u will adopt c in the future. Two different approaches to estimate such probability have been proposed: ordinal time estimate or snapshot estimate, the former requiring more detailed data (Cosley et al. 2010). Here, we compute ordinal time estimates since our data is detailed enough, following the same procedure as Romero, Meeder, and Kleinberg: assume that user u is k-exposed to some contagion c. We estimate the probability that u will adopt c before becoming $(k + 1)$-exposed. Let $E(k)$ be the number of users who were k-exposed to c at some time, and let $I(k)$ be the number of users that were k-exposed and adopted c before becoming $(k + 1)$-exposed. Then, the probability of adopting c while being k-exposed to c is $P(k) = I(k)/E(k)$.

We study the effects of background traffic on the exposure curves for the following three types of contagions over the Twitter network:

1. Ideas: Hashtags. Hashtags are words or phrases inside a tweet which are prefixed with the symbol # (Romero, Meeder, and Kleinberg 2011). They provide a way for a user to generate searchable metadata, keywords or tags, in order to *describe* her tweet, associate the tweet to a (trending) topic, or express an idea. Hashtags have become ubiquitous and are an integral aspect of the social Web nowadays. Here, we consider hashtags as information units and study the impact of background traffic on their spread. In particular, we track every mention of 2,413 hashtags used by more than 500 users during the three months under study. We then estimate the exposure curve of each hashtag for all users who did not use the hashtags before July 2009.

2. Conventions: Retweets. In order to study the impact of background traffic on the propagation of a social convention, we focus on the way Twitter users indicated back in 2009 that a tweet was being retweeted. Different variations of this convention emerged organically during the first few years of Twitter and until November 2009, when Twitter rolled out an official, built-in retweet button. Here, we track every use of the most popular retweeting convention, “RT”, during the three months under study, using a similar procedure to Kooti et al., and estimate exposure curves using all users who did not use “RT” before July 2009.

3. Product innovations: url shortening services. We investigate the impact of background traffic on the propagation of a technological product by tracking user's adoption of url shortening services in Twitter (Antoniades et al. 2011). These services existed before Twitter, however, by constraining the number of characters per message, Twitter increased their proliferation. Here, we track every use of the most popular url shortening service, bit.ly, during the three months under study, and estimate exposure curves using all



(a) Cascade size distribution (b) Cascade duration distribution

Figure 7: Cascade size and cascade duration distributions for different average in-flow rate. We used a core-periphery Kronecker network with 1,024 nodes and 20,000 edges and simulated 50,000 cascades per average out-flow rate μ.

users who did not use bit.ly before July 2009.

We analyze the influence of the background traffic on the probability of adoption of hashtags, social conventions and url shortening services by grouping users according to their in-flow rates and estimating an exposure curve for each group. Figure 6(a) shows the average exposure curve across hashtags for users with different in-flows. We draw several interesting observations. First, exposures for users with smaller in-flows results in a much larger increase in probability of adoption of a hashtag. Second, if we compare the maximum value of the probability of adoption of users with small in-flows and users with large in-flows, they differ in one order of magnitude. In other words, an exposure to a hashtag is dramatically much less *effective* for users that suffer from information overload. Figure 6(b) shows exposure curves for users with different in-flows for the retweet convention "RT". Remarkably, we find similar patterns to the ones we found previously for hashtags adoption an exposure to a social convention is also much less *effective* for overloaded users. Finally, Figure 6(c) shows exposure curves for users with different in-flows for the url shortening service bit.ly. Our findings are again consistent with previous findings in hashtags and social conventions adoption.

Cascades sizes are limited

To the best of our knowledge, existing models of information and influence propagation do not account for the background traffic. However, we have given empirical evidence that the background traffic has a dramatic impact on the users' adoption probability in social media. Here, we extend the well-known independent cascade model (Kempe, Kleinberg, and Tardos 2003) to support background traffic and show that, for given a network, there are striking differences in terms of cascade size depending on the amount of background traffic flowing through the network. The larger the background traffic, the shorter the cascades become.

To this aim, we first generate a network $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ using a well-known mathematical model of social networks: the Kronecker model (Leskovec et al. 2010), and set the out-flow rate of each node in the network by drawing samples from $\lambda_i \sim N(\mu, \sigma)$, where μ is the average out-flow rate. By this procedure, the in-flow rate for each node j in the network is $\sum_{i:(i,j)\in\mathcal{E}} \lambda_i$. We then set the adoption probability β_r of the independent cascade model using Fig. 2(b), incorporating in that way the background traffic in the model. Figure 7(a) shows the cascade size distribution under different average out-flow rate values for a core-periphery Kronecker network (parameter matrix $[0.9, 0.5; 0.5, 0.3]$) with 1,024 nodes and 20,000 edges. We simulated 50,000 cascades per average out-flow rate. The background traffic has a dramatic impact on the cascade size distribution, and the larger the amount of background *traffic*, the more rare large cascades become. For example, while for $\mu = 1$, there are more than 12% cascades with at least 3 nodes, for $\mu = 100$, there are only 0.1%. Our simulated results provides an explanation to why most information cascades in social media fail to reach epidemic proportions (Ver Steeg, Ghosh, and Lerman 2011).

A few cascades have prolonged lifetimes

We have shown that the background traffic has a dramatic impact on the users' queueing delays, *i.e.*, the time users take to process information they receive. However, discrete time propagation models such us the independent cascade model used previously do not allow us to model queueing delays. In contrast, continuous time propagation models allow us to do so. Here, we extend the continuous time propagation model recently introduced by Gomez-Rodriguez, Leskovec, and Krause to support background traffic and show that, given a fixed network structure, there are striking differences in terms of cascade temporal duration depending on the amount of background traffic flowing through the network. In particular, we show that while most simulated cascades have shorter lifetime as the background traffic increases, as one could expect due to smaller cascade sizes, larger background traffic also leads to the emergence of more cascades with very prolonged lifetimes, which may be surprising at first. However, this is a consequence of our findings in previous sections, users that suffer from information overload sometimes look for tweets directly in other user's profiles or use tools to sort their incoming tweets and then prolong the lifetime of contagions that otherwise would die out earlier.

We proceed similarly as in previous section: we generate a synthetic network $\mathcal{G}$ using the Kronecker model, and set the out-flow rate of each node in the network by drawing samples from $\lambda_i \sim N(\mu, \sigma)$. Then, given the in-flow rate of a node j, we incorporate the background traffic into the continuous time model by setting the node's retweet delay distribution $f(\Delta_r)$ using Fig. 4(a) and its adoption probability β_r using Fig. 2(b). Then, we simulate and record sets of propagating cascades for different μ values. Figure 7(b) shows the cascade duration distribution for cascades with 2 or more nodes on a core-periphery Kronecker network with 1,024 nodes and 20,000 edges under different average out-flow rate values. We simulated $50,000$ cascades per average out-flow rate. Cascades that die out quicker are more frequent the larger the average out-flow rate is. However, for sufficiently large average out-flow rate ($\mu > 10$), longer cascades emerge and the tail of the CCDF decreases slower. This is a consequence of our previous results: people suffering from large information overload cannot keep up with the amount of incoming information and either look for tweets directly in other user's profiles or use tools to sort their incoming tweets, delaying information diffusion.

Conclusions

We have performed a large scale quantitative study of information overload by evaluating its impact on information dissemination in social media. To the best of our knowledge, our work is the first of its kind, it reveals many interesting insights and has important implications for the large and growing number of studies on information dissemination and social contagion. In particular, our work characterizes several aspects of social media users' information processing behaviors, for example, how frequently, from how many sources, and how quickly people forward information. It also estimates the limits of information processing of social media users and shows that the users' susceptibility to social contagion depends dramatically on the rate at which they receives information, *i.e.*, their degree of information overload.

Our work also opens many interesting venues for future work. For example, we have shown that social media users' information processing behavior depends on the rate at which they receive information. An open question is however whether it is possible to improve their own user experience by prioritizing pieces of information from some of their followees and particular topics over others. Further, we have assumed information flow rates to be stationary and the social graph to be static. However, on one hand, unexpected real world events may trigger sudden changes in the rates of information flows and, on the other hand, social media users' may start following new users over time. Therefore, a natural follow-up would be extending our analysis to dynamic information flows and time-varying networks, and investigate whether social media users modify their information processing behavior over time. Finally, our results rely on data gathered exclusively from Twitter. It would be interesting to study information overload in other microblogging services (Weibo) and social networking sites (Facebook, G+).

References

Antoniades, D.; Polakis, I.; Kontaxis, G.; Athanasopoulos, E.; Ioannidis, S.; Markatos, E. P.; and Karagiannis, T. 2011. we. b: The web of short urls. *WWW*.

Backstrom, L.; Bakshy, E.; Kleinberg, J. M.; Lento, T. M.; and Rosenn, I. 2011. Center of attention: How facebook users allocate attention across friends. *ICWSM*.

Bawden, D., and Robinson, L. 2009. The dark side of information: overload, anxiety and other paradoxes and pathologies. *Journal of information science* 35(2):180–191.

Bontcheva, K.; Gorrell, G.; and Wessels, B. 2013. Social Media and Information Overload: Survey Results. *Arxiv preprint arXiv:1306.0813*.

Borchers, A.; Herlocker, J.; Konstan, J.; and Reidl, J. 1998. Ganging up on information overload. *Computer* 31.

Centola, D., and Macy, M. 2007. Complex contagions and the weakness of long ties. *American Journal of Sociology* 113(3):702–734.

Centola, D. 2010. The spread of behavior in an online social network experiment. *Science* 329(5996):1194–1197.

Cha, M.; Haddadi, H.; Benevenuto, F.; and Gummadi, P. K. 2010. Measuring User Influence in Twitter: The Million Follower Fallacy. *ICWSM*.

Comarela, G.; Crovella, M.; Almeida, V.; and Benevenuto, F. 2012. Understanding factors that affect response rates in twitter. *HT*.

Cosley, D.; Huttenlocher, D. P.; Kleinberg, J. M.; Lan, X.; and Suri, S. 2010. Sequential influence models in social networks. *ICWSM*.

Dean, D., and Webb, C. 2011. Recovering from information overload. *McKinsey Quarterly*.

Doerr, C.; Blenn, N.; and Van Mieghem, P. 2013. Lognormal infection times of online information spread. *PloS one* 8(5):e64349.

Du, N.; Song, L.; Gomez-Rodriguez, M.; and Zha, H. 2013. Scalable influence estimation in continuous-time diffusion networks. *NIPS*.

Goel, S.; Watts, D. J.; and Goldstein, D. G. 2012. The structure of online diffusion networks. *EC*.

Gomez-Rodriguez, M.; Balduzzi, D.; and Schölkopf, B. 2011. Uncovering the Temporal Dynamics of Diffusion Networks. *ICML*.

Gomez-Rodriguez, M.; Leskovec, J.; and Krause, A. 2010. Inferring Networks of Diffusion and Influence. *KDD*.

Goyal, S., and Kearns, M. 2012. Competitive contagion in networks. *STOC*.

Gross, B. M. 1964. *The managing of organizations: The administrative struggle*. Free Press of Glencoe New York.

Hodas, N., and Lerman, K. 2012. How visibility and divided attention constrain social contagion. *SocialCom*.

Hodas, N.; Kooti, F.; and Lerman, K. 2013. Friendship paradox redux: your friends are more interesting than you. *ICWSM*.

Kempe, D.; Kleinberg, J. M.; and Tardos, E. 2003. Maximizing the spread of influence through a social network. *KDD*.

Kleinrock, L. 1975. *Theory, volume 1, Queueing systems*. Wiley-interscience.

Kooti, F.; Yang, H.; Cha, M.; Gummadi, P. K.; and Mason, W. A. 2012. The emergence of conventions in online social networks. *ICWSM*.

Kwak, H.; Lee, C.; Park, H.; and Moon, S. 2010. What is twitter, a social network or a news media? *WWW*.

Leskovec, J.; Backstrom, L.; and Kleinberg, J. 2009. Meme-tracking and the dynamics of the news cycle. *KDD*.

Leskovec, J.; Chakrabarti, D.; Kleinberg, J.; Faloutsos, C.; and Ghahramani, Z. 2010. Kronecker graphs: An approach to modeling networks. *JMLR*.

Miritello, G.; Lara, R.; Cebrian, M.; and Moro, E. 2013. Limited communication capacity unveils strategies for human interaction. *Scientific reports* 3.

Mislove, A.; Marcon, M.; Gummadi, K. P.; Druschel, P.; and Bhattacharjee, B. 2007. Measurement and analysis of online social networks. *SIGCOMM*.

Myers, S., and Leskovec, J. 2012. Clash of the contagions: Cooperation and competition in information diffusion.

Romero, D. M.; Meeder, B.; and Kleinberg, J. 2011. Differences in the mechanics of information diffusion across topics: idioms, political hashtags, and complex contagion on twitter. *WWW*.

Toffler, A. 1984. *Future shock*. Random House.

Ver Steeg, G.; Ghosh, R.; and Lerman, K. 2011. What stops social epidemics? *ICWSM*.

Weng, L.; Flammini, A.; Vespignani, A.; and Menczer, F. 2012. Competition among memes in a world with limited attention. *Scientific Reports* 2.