THE DYNAMICS OF INFORMATION DIFFUSION ON ON-LINE SOCIAL NETWORKS

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

Shaomei Wu

August 2012

THE DYNAMICS OF INFORMATION DIFFUSION ON ON-LINE SOCIAL NETWORKS

Shaomei Wu, Ph.D.

Cornell University 2012

Your abstract goes here. Make sure it sits inside the brackets. If not, your biosketch page may not be roman numeral iii, as required by the graduate school.

BIOGRAPHICAL SKETCH

Your biosketch goes here. Make sure it sits inside the brackets.

This document is dedicated to all Cornell graduate students.

ACKNOWLEDGEMENTS

Your acknowledgements go here. Make sure it sits inside the brackets.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Understanding how information spreads in the society has attracted a growing interest from both practitioners and scholars. It is an essential element for many interesting problems, such as the diffusion of innovation, formation of public opinion, product adoption, and viral marketing.

Historically, one of the biggest challenges in the study of information diffusion is data collection. Given the difficulty of observing and tracing the diffusion process over all possible channels, most empirical studies in this field have been conducted manually by sociologists and communication researchers, through in-person interviews or standardized surveys of population samples. Therefore, these studies are largely confined by the scale and the data accuracy. As a result, existing theoretical models in the literature have relied on many assumptions about the underlying diffusion mechanism instead of empirical evidence. Being widely applied, these models are, however, hard to be verified or rebutted empirically on a large scale.

In recent years, the abundance of digital records of online interactions has provided us both the explicit network structure and detailed dynamics, supporting global-scale, quantitative study of diffusion in the real world. Using these large scale datasets collected from social media sites (i.e. Twitter, Orkut), this thesis addresses the following three questions: “who influences whom?”, “how do different types of information spread?”, and “how does the network structure impact the diffusion process?”

1.1 The Influencer Problem

Can we estimate person influence and pick out the influencers? Think of influence in context:

1. general influence: mass media
2. domain influence: masspersonal (celebrities, bloggers, organizations)
3. personal influence: tie strength, content, language, timing (accidental influencers)

1.1.1 Life of information in Social Media

How long should we expect a piece of information to live in the social media space [**?**]? Who are involved in each stage (production, circulation, and consumption) of lifecycle of information?

1.1.2 Modeling personal influence

1.1.3 The intersection between content and people

1.2 The role of content in diffusion process

Section 2 text.

1.2.1 Subsection heading goes here

Subsection 1 text

Subsubsection 1 heading goes here

Subsubsection 1 text

Subsubsection 2 heading goes here

Subsubsection 2 text

1.3 Diffusion and network structure

Section 3 text. The dielectric constant at the air-metal interface determines the resonance shift as absorption or capture occurs.

$$k_1 = \frac{\omega}{c(1/\varepsilon_m + 1/\varepsilon_i)^{1/2}} = k_2 = \frac{\omega sin(\theta)\varepsilon_{air}^{1/2}}{c} \tag{1.1}$$

where ω is the frequency of the plasmon, c is the speed of light, ε_m is the dielectric constant of the metal, ε_i is the dielectric constant of neighboring insulator, and ε_{air} is the dielectric constant of air.

CHAPTER 2

BACKGROUND

A variety of methods have been applied by scholars to study the diffusion of information. From the theoretic perspective, sociologists and economists developed agent-based modeling (ABM) to explore the dynamics of diffusion in different networks and interactions [Centola and Macy 2007, Watts and Dodds 2007]. Computer scientists designed the algorithm to maximize the extent of diffusion by seeding the diffusion with specially-picked individuals [Liben-Nowell et al 2008].

On the other hand, modeling and predicting the propensity of real world diffusion going viral through WOM process is of central interest in recent empirical studies. Built on top of the cascade model, Gruhl et al [2004] tracked the diffusion of topics in blogspace to estimate the transmission probability with an expectation-maximization(EM)-like algorithm. Leskovec et al [2007] studied interpersonal recommendations on an e-commerce site to infer the adoption probability based on the category of products and invitation history. Cha et al [2008] studied the viral process of photos being marked as favorite on the Flickr social network. By applying the SIR model with infinite recovery time, they estimated the reproduction number with the mean degree of nodes at each step of contagion. Backstrom et al. [2006] modeled the probability of a user joining a community and the growth of communities on LiveJournal using decision trees with network structure features.

2.1 Social theories

2.2 Diffusion models

2.3 Temporal analysis

2.3.1 Temporal pattern detection

2.3.2 Trend detection

2.4 Lingusitic analysis

2.5 On-line social network as the lab for studying information diffusion

2.5.1 Twitter

In my work, I frequently study the diffusion of information in the context of Twitter. As a highly popular micro-blogging service, Twitter provides a natural environment for the study of diffusion process. Unlike other online social networks (e.g. Facebook), Twitter is expressly devoted to disseminating information in that users subscribe to the information broadcasted by other users; thus the network of potential adoption can be reconstructed by crawling the corresponding ”follower graph”. In addition, because of the need of users to share web content, with the restriction of maximal tweet length as 140 characters, URL shortening services (e.g., bit.ly, TinyURL, etc) are used widely, and effectively tag numerous pieces of information with unique and easily-identifiable tokens. Our study takes advantage of these features in following aspects:

(a) We are able to observe essentially everything that is spreading on Twitter. Thus although we have only one type of social media, we have a very high level of resolution and coverage regarding what is being diffused.

(b) Although it may be non-representative in some respects, Twitter is very representative in at least one respect–namely it includes essentially all actors of any consequence in the information diffusion process in the society: media outlets and formal organizations of all sizes, bloggers, and public figures like celebrities, as well as tens of millions of ordinary individuals. In this sense, it really is a complete sample of one (admittedly narrow) slice through the diffusion landscape.

(c) Because Twitter users themselves classify other users by including them on lists, Twitter effectively provides a ready-made, crowd-sourced classification scheme of users. Thus even though we do have content information for many of the Tweets we observe, we can reliably classify the source of the content being circulated over Twitter.

(d) For certain subsets of URL/Tweets (e.g. those originating from certain news sources) we can automatically classify content into topical domains (“international news”, “entertainment”, “business”, “science” etc.); and for other subsets (e.g. persistent URL’s - URL’s that are shared repeatedly by different users over a big timespan) we can identify certain content-related attributes (e.g. video, music, etc.). So for certain restricted domains we can make some statements about how content matters in the diffusion process.

(e) Even though our view of “effects” is limited (i.e., URL persistence and retweeting rate), we have very high resolution temporal information over the lifespan of any piece of information in diffusion.

Nevertheless, we are aware that our analysis is limited in some important respects:

(a) It is limited to Twitter, which is not only just one diffusion channel among many, but may well be unlike other channels in a number of ways; (b) We can not observe the kind of offline ”effects” that viral marketers and social scientists are most interested in, such as, adoption of products, change in attitude;

(c) We have only limited information about the content that is being shared (although this constraint could be relaxed with some effort).

2.5.2 Other on-line social media

2.6 Web as a source for knowledge

2.7 MapReduce and parallel network algorithms

Introduction to MapReduce.

MapReduce is good with easy-parallelible tasks, hard for tasks that need certain global information (e.g., shortest path). However, many network problems are the second case.

Methods to convert a global problem to a series of mapreduce jobs [**?**].

CHAPTER 3

THE LIFE OF INFORMATION: THE INTERACTION BETWEEN PEOPLE AND CONTENT IN ONLINE NETWORKS

We study the lifespan of information, from production, flow, to consumption. We can also extend our findings to general diffusion process, the spread of behavior.

We have seen different temporal patterns in the life of information - very small amount got picked up, but substantial amount exist for a long time. (although note that exist does not necessarily means spread). Factors that lead to differnet temporal patterns: interactions between people and content.

Information diffusion like virus spread in the sense that it is produced by some people, consumed by some people, and can be further spread by the consumer. However, it is much more complex in the sense that people can be infected by multiple channels, including the environmental factors, but classic epedimic models can not fully describe (ZZZZZ: need more research to make this claim).

My contributions:

1. Study one-way, one-hop flow of information, which is although the majority but largely overlooked. We did it by showing the distribution of attention among different groups.
2. Study the temporal pattern of information, especially, the persistence. Most previous work focused on the spikes but not the persistence.
3. (ZZZZZ: possible remove) Diffusion as an organic process integrating people, content, and time.

3.1 The production and consumption of information: distribution of attention

Typical lifespan of a piece of information on social media is one-way, zero or one hop - depending how a hop is define: from production directly to (potentially) consumption, without any additional node in the chain.

Why is it interesting to study the direction production-consumption flow of information? 1. Majority of information; 2. Interesting social science problem; 3. very similar to mass communication - debates on the role of social media; 4. significant effect of environmental influence that will largely determine public opinion formation;

In this seciton, we focus on the production and consumption of information. Our study is led by classic communication theories: debate on two modes of communications. Different people play different roles, and which role they are playing is largely determined by two factors: (1) internally, their own goal, taste, and agenda; (2) externally, the amount of attention they enjoyed from the public.

Our contributions:

1. introduce a low-cost, crowd-sourcing method to classify users into categories that parallel to media/communication research;
2. investigate one-way, one-hop flow of information among these categories, present a high level picture of the distribution of attention;
3. show the interaction between people and content.

ZZZZZ Put two-step flow in next chapter?

3.1.1 Data And Methods

Twitter Follower Graph

In order to understand how information is flowing in the Twitter system, we need to know the channels by which it flows; that is, who is following whom on Twitter. To this end, we used the data shared[1] by Kwak et al. [**?**], which included 42M users and 1.5B edges. This data represents a crawl of the follower graph seeded with all users on Twitter as observed by July 31st, 2009.

Twitter Firehose

In addition, we were interested in the content that was being shared—particularly bit.ly URLs—so that we could trave the flow of information through the Twitter graph. We examined all tweets over a 223 day period from July 28, 2009 to March 8, 2010 using the data from the Twitter "firehose". From these 5B tweets we observed 260M bit.ly URLs.

Twitter Lists

Our method for classifying users exploits a relatively recent feature of Twitter: Twitter Lists. Since its launch on November 2, 2009, Twitter Lists have been welcomed by the community as a way to group people and organize one's incoming stream of tweets by specific sets of users. To create a Twitter List, a user needs to provide a name (required) and description (optional) for the list, and

[1] At the time of this study, the data was free to download from http://an.kaist.ac.kr/traces/WWW2010.html

decide whether the new list is public (anyone can view and subscribe to this list) or private (only the list creator can view or subscribe to this list). Once a list is created, the user can add/edit/delete people in the list. As the purpose of Twitter Lists is to help users organize people they follow, the name of the list can be considered a meaningful label for the listed users. List creation therefore effectively applies the "wisdom of crowds" to the task of classifying users, both in terms of their importance to the community (number of lists on which they appear), and also how they are perceived (e.g. news organization vs. celebrity, etc.).

There is not yet a standard way to classify users by lists, or even a central portal to obtain lists for all users. In order to capture the variety of users invloved in mass media, masspersonal, and interpersonal commmunication described in section **??** in a reasonably parsimonious manner, we restrict our attention to four classes of what we call "elite" users: media, celebrities, organizations (including both public and private), and bloggers. In addition to these elite users, we also study the much larger population of "ordinary" users, as well as the relationships between elite and ordinary users. [2].

Given the rate limits established by Twitter's API, moreover, crawling all lists for all Twitter users (reportedly over 100M, where some users are included on tens of thousands of lists) would be prohibitively time consuming. Thus we instead devised two different sampling schemes—a snowball sample and an activity sample—each with some advantages and disadvantages, discussed below.

[2] Some third-party sites such as Listorious (http://listorious.com/) now maintain categorized directories of Twitter Lists; however, their methodology is not sufficiently transparent for our purposes. We also found their data largely not-up-to-date.

Snowball sample of Twitter Lists

The first method for identifying elite users employed snowball sampling. For each category, we chose a number of seed users that were highly representative of the desired category and appeared on many category-related lists. For each of the four categories above, the following seeds were chosen:

- Celebrities: Barack Obama, Lady Gaga, Paris Hilton
- Media: CNN, New York Times
- Organizations: Amnesty International, World Wildlife Foundation, Yahoo! Inc., Whole Foods
- Blogs[3]: BoingBoing, FamousBloggers, problogger, mashable. Chrisbrogan, virtuosoblogger, Gizmodo, Ileane, dragonblogger, bbrian017, hishaman, copyblogger, engadget, danielscocco, BlazingMinds, bloggersblog, TycoonBlogger, shoemoney, wchingya, extremejohn, GrowMap, kikolani, smartbloggerz, Element321, brandonacox, remarkablogger, jsinkeywest, seosmarty, NotAProBlog, kbloemendaal, JimiJones, ditesco

After reviewing the lists associated with these seeds, the following keywords were hand-selected as representative of the desired categories:

- Celebrities: star, stars, hollywood, celebs, celebrity, celebrities-on-twitter, celebrity-tweets, celebrity-list, celebrities, celebsverified
- Media: news, media, news-media

[3]The blogger category required many more seeds because bloggers are in general lower profile than the seeds for the other categories

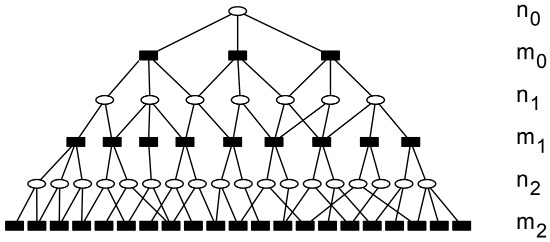


Figure 3.1: Schematic of the Snowball Sampling Method

- Organizations: company, companies, organization, organisation, organizations, organisations, corporation, brands, products, charity, charities, causes, cause, ngo
- Blogs: blog, blogs, blogger, bloggers

Having selected the seeds and the keywords for each category, we then did a snowball sample of the bipartite graph of users and lists (see Figure 3.1). For each seed, we crawled all lists on which that seed appeared. The resulting "list of lists" was then pruned to contain only lists whose names matched at least one of the chosen keywords for that category. We then crawled all users appearing in the pruned "list of lists". We then repeated these last two steps.

Table 3.1 shows how many (a) users and (b) lists were obtained at each level of the snowball sample. In total, $495,000$ users were obtained, who appeared on $7,000,000$ lists. Because users can be listed in multiple categories (e.g., Oprah Winfrey is frequently included in lists of "celebrity" and "media"), we next compute a user u's membership score in category c:

$$w_{uc} = \frac{n_{uc}}{N_c}, \tag{3.1}$$

where n_{uc} is the number of lists in category c that contain user u and N_c is the total number of lists in category c. We then assign each user to the category in

Table 3.1: Snowball Sample

Level	celeb	media	org	blog
u_0	3	2	4	32
l_0	2342	11403	1170	1347
u_1	3607	5025	20122	16317
l_1	30490	71605	4970	9546
u_2	108836	309056	115034	140251
l_2	91873	171912	22518	19946

which he or she has the highest membership score. Users that appear in the follower graph but not in the snowball sample are assigned to the "ordinary" category.

Activity Sample of Twitter Lists

Although the snowball sampling method is convenient and is easily interpretable with respect to our theoretical motivation, it is also potentially biased by our particular choice of seeds. To address this concern, we also generate a sample of users based on their activity. Specifically, we crawl all lists associated with all users who tweet at least once every week for the entire observation period.

This "activity-based" sampling method, which yields $750,000$ users and $5,000,000$ lists (see Table 3.2 for comparison to the snowball method), is also clearly biased towards users who are consistently active. Importantly, however, the bias is likely to be quite different from any introduced by the snowball sample; thus obtaining similar results from the two samples should give us confidence that our findings are not artifacts of the sampling procedure.

	Snowball Sample		Activity Sample	
category	# of users	# of lists	# of users	# of lists
celeb	108,836	91,873	22,803	68,810
media	309,056	171,912	66,300	145,176
org	115,034	22,518	19,726	16,532
blog	140,251	19,946	49,987	17,259

Table 3.2: Statistics of crawled lists. The number of users refers only to people who appear in at least one list of the specific category.

3.1.2 Distribution of attention

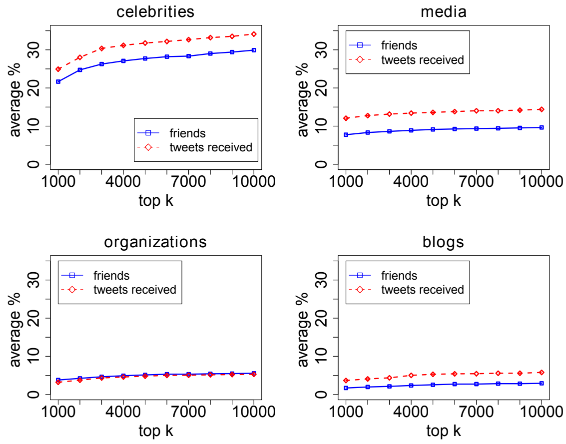
After categorizing people into categories, we can calculate the amount of attention sent and received by each category, at a global level. The way we do it is to show the reach of the "elite" categories. It can be considered as the influence of each category, as well as an estimate of the impact of the information introducted by each category. In other words, it is the maximal reach of the information produced by each category.

Concentration of attention

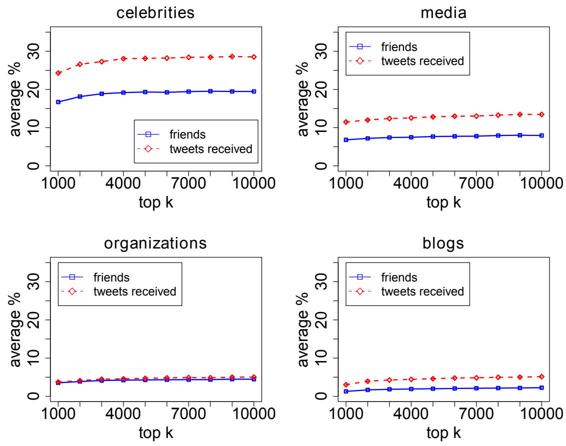
With either sampling method, the initial categorization of users is quite coarse and noisy as a result of the arbitrary labeling allowed in Twitter Lists. To filter categories to the most representative users, we further rank the users in each of the 4 elite categories by how frequently they are listed in each category, and take only the top k users in each category, relabeling the remainder as "ordinary" users. To determine the appropriate k, we measure the flow of information from the four elite categories to an average "ordinary" user in two ways: the proportion of people the user follows in each category, and the proportion of tweets the user received from everyone the user follows in each category. We sampled 100K random "ordinary" users and calculated the average information flow from the "elite" users using these two measures.

Figure 3.2(a) shows that each category accounts for a significant share of both the following links and also the tweets received by an average user, where celebrities outrank all other categories, followed by the media, organizations, and bloggers. Also of note is that the bulk of the attention is accounted for by a relatively small number of users within each category, as evidenced by the relatively flat slope of the attention curves in Figure 3.2(a). In order to define which users should be classified as "elites", we seek a tradeoff between (a) keeping each category relatively small, so as not to include users who are not distinguishable from ordinary users, while (b) maximizing the volume of attention that is accounted for by each category. In addition, it is also desirable to make the four categories the same size, so as to facilitate comparisons. Balancing these requirements, we therefore choose 5K as a cut-off for the elite categories.

Consistent with this view, we find that the population of users identified by the activity sample is somewhat different from the snowball sample: the intersection of the two populations is only 20% (100,000 accounts). However, the intersection of the top k users in each population increases as k decreases: for the top $5,000$ users in each category, the intersection is 41%, and for the top $1,000$ users it is 51%. Thus, although the population of consistently active users is somewhat different from those reached with the snowball sample, the most frequently listed users in both populations tend to be similar. In addition, Figure 3.2(b) shows that the attention paid to the top k users in the four categories is essentially the same as for the snowball sample. Thus in the rest of this paper, when we talk about "celebrity", "media", "organization", "blog", we mean the top 5K users listed as "celebrity", "media", "organization", "blog", respectively,



(a) Snowball sample



(b) Activity sample

Figure 3.2: Average fraction of # following (blue line) and # tweets (red line) for a random user that are accounted for by the top K elites users crawled

drawn from the snowball sample. Table 3.3 shows the top 5 users in each of the four categories.

ZZZZZ: Move the paragraph and tables below to content part.

To confirm the validity of these categories, we now consider the number of URLs introduced by various categories. As Table 3.4 (left column) shows, the vast majority of URLs are initiated by ordinary users, not by any of the elite

Table 3.3: Top 5 users in each category

Celebrity	*Media*	*Org*	*Blog*
aplusk	cnnbrk	google	mashable
ladygaga	nytimes	Starbucks	problogger
TheEllenShow	asahi	twitter	kibeloco
taylorswift13	BreakingNews	joinred	naosalvo
Oprah	TIME	ollehkt	dooce

Table 3.4: # of URLs initiated by category

category	# of URLs	per-capita # of URLs
celeb	139,058	27.81
media	5,119,739	1023.94
org	523,698	104.74
blog	1,360,131	272.03
other	244,228,364	6.10

categories. This result, however, is deceptive: as we have just determined, our elite categories number only $20K$ users in total, whereas we classify over $40M$ users in the "ordinary" category. A more calibrated view is presented in the right hand column of Table 3.4, which shows the per-capita number of URLs originating from various categories. Here it is clear that users classified as "media" far outproduce all other categories, followed by bloggers, organizations, and celebrities. In contrast to the previous result, ordinary users originate on average only about 6 URLs each—far fewer than any category of elite users.

Conceivably, our classification scheme above has omitted an important category; that is, within the current "other" category may be hidden additional categories of opinions. As Figure 3.1.2 shows, however, even the top 10,000 most

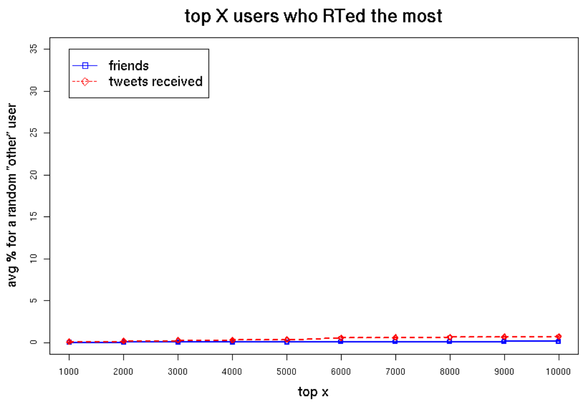


Figure 3.3: Average fraction of # following (blue line) and # tweets (red line) for a random user that are accounted for by the top K most retweeted users in the "Other" category

followed of these users accounts for a negligible fraction of attention among the remaining population.

Homophily of attention

As indicated above, the top $20K$ elite users account for almost 50% of all attention within Twitter; yet this population of users comprises less than 0.05% of the population. In other words, although Twitter clearly reflects the conventional wisdom that audiences have become increasingly fragmented, it nevertheless shows remarkable concentration of information production and received attention among a relatively small number of actors. Even if the media has lost attention relative to other elites, information flows have not become egalitarian by any means.

The prominence of elite users raises the question of how these different categories listen to each other. To address this issue, we compute the percentage of following links and received tweets among elite categories. Specifically, Table

Table 3.5: Information flow among the elite categories

% of friends	in celeb	in media	in org	in blog
celeb	**30.56**	3.63	1.99	1.64
media	3.59	**16.67**	2.07	2.15
org	3.62	3.33	**7.38**	2.65
blog	4.41	2.27	2.03	**10.25**
% of tweets	from celeb	from media	from org	from blog
celeb	**38.27**	6.23	1.55	3.98
media	3.91	**26.22**	1.66	5.69
org	4.64	6.41	8.05	**8.70**
blog	4.94	3.89	1.58	**22.55**

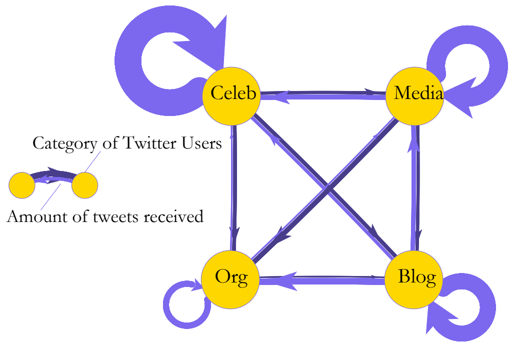


Figure 3.4: Share of attention among elite categories

3.5 shows the average percentage of friends/tweets category i get from category j. Table 3.5 shows striking homophily with respect to attention: celebrities overwhelmingly pay attention to other celebrities, media actors pay attention to other media actors, and so on. The one slight exception to this rule is that organizations pay more attention to bloggers than to themselves. In general, in fact, attention paid by organizations is more evenly distributed across categories than for any other category.

3.2 ZZZZZ: Transmissive probability

ZZZZZ: should we combine this section with previous or next section?

For information that do spread, most previous works study the factors that contribute to the spread at each hop, independently. (ZZZZZ related work).

The categorization of actors, as introduced previously, also helped shed some light on the one-hop diffusion probability, depending on the type of users in the diffusion edge, and people's interest at different types of content.

My contribution:

1. Show homophily at diffusion;
2. Show difference in attention and influence (as measured by RTs)
3. Show people's interest at different content.

People

The origin of information will influence how it will be RTed.

Before proceeding, it is helpful to differentiate between two mechanisms by which information can diffuse in Twitter. The first is via retweeting, when a user, having received a tweet, subsequently rebroadcasts it to his or her own followers. In some instances, users retweet each other using the official retweet function provided by Twitter, but in other cases they credit the retweet with an informal convention, most commonly either "RT @user" or "via @user." The

Table 3.6: RTs among categories

	by celeb	by media	by org	by blog	by other	TOTAL
celeb	4,334	1,489	1,543	5,039	1,070,318	1,082,723
media	4,624	40,263	7,628	32,027	5,204,719	5,289,261
org	1,570	2,539	18,937	11,175	1,479,017	1,513,238
blog	3,710	6,382	5,762	99,818	3,457,631	3,573,303
other	34,455	93,934	86,630	318,537	34,814,456	35,348,012

second mechanism is what we label reintroduction, where a user independently tweets a URL that has previously been introduced by another user.

In addition to attention, Table 3.6 shows how much information originating from each category is retweeted by other categories, while Table 3.7 shows how much is subsequently reintroduced. As with attention, both retweeting and reintroduction activities are strongly homophilous among elite categories; however, bloggers are disproportionately responsible for retweeting and reintroducing URLs originated by all categories. This result reflects the characterization of bloggers as recyclers and filters of information; however, Table 3.6 and 3.7 also show that the total number of URLs either RT'd or reintroduced by bloggers is vastly outweighed by the number retweeted or reintroduced by ordinary users. Even though on a per-capita basis, therefore, bloggers disproportionately occupy the role of information recyclers, their actual impact is relatively minimal (see Figure 3.4).

Table 3.7: Re-introductions among categories

	by celeb	by media	by org	by blog	by other	TOTAL
celeb	2,868	1,239	522	1,664	488,229	494,522
media	1,678	205,165	2,439	9,681	2,006,888	2,225,851
org	816	1,511	8,628	3,711	610,373	625,039
blog	1,415	5,644	1,416	52,909	1,148,137	1,209,521
other	45,547	793,741	69,441	335,690	86,853,224	88,097,643

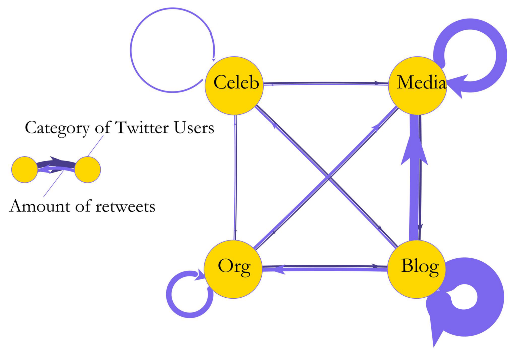


Figure 3.5: RT behavior among elite categories

3.2.1 Content

People have different interest at different content. So the type of content can also determine what a person will RT.

Given the large size of the URL population in our observation period (260M), and the large number of ways in which one can classify content (video vs. text, news vs. entertainment, political news vs. sports news, etc.), classifying even a small fraction of URLs according to content is an onerous task. Bakshy et al [?], for example, used Amazon's Mechanical Turk to classify a stratified sample of

1,000 URLs along a variety of dimensions; however, this method does not scale well to larger sample sizes.

Instead, we restrict attention to URLs originated by the New York Times which, with over 2.5M followers, is the second-most followed news organization on Twitter after CNN Breaking News. NY Times, however, is roughly ten times as active as CNN Breaking News, so is a better source of data. To classify NY Times content, we exploit a convenient feature of their format—namely that all NY Times URLs are classified in a consistent way by the section in which they appear (e.g. US, World, Sports, Science, Arts, etc) [4]. Of the 6398 New York Times bit.ly URLs observed, 6370 could be successfully unshortened and assigned to one of 21 categories. Of these, however, only 9 categories had more than 100 URLs over the observation period, one of which—"NY region"—was highly specific to the New York metropolitan area; thus we focused our attention on the remaining 8 topical categories. Figure 3.6 shows the overall RT and reintroduction rates by category. World news is the most popular category, followed by US news, business, and sports, where increasingly niche categories like Health, Arts, Science, and Technology are less popular still. In general, the overall pattern is replicated for all categories of users, but there are some minor deviations: In particular, organizations show disproportionately little interest in business and arts-related stories, and disproportionately high interest in science, technology, and possibly world news. Celebrities, by contrast, show greater interest in sports and less interest in health, while the media shows somewhat greater interest in US news stories.

In addition, we also consider the accumulated RT/Reintroduction behavior

[4]http://www.nytimes.com/year/month/day/category/title.html?ref=category

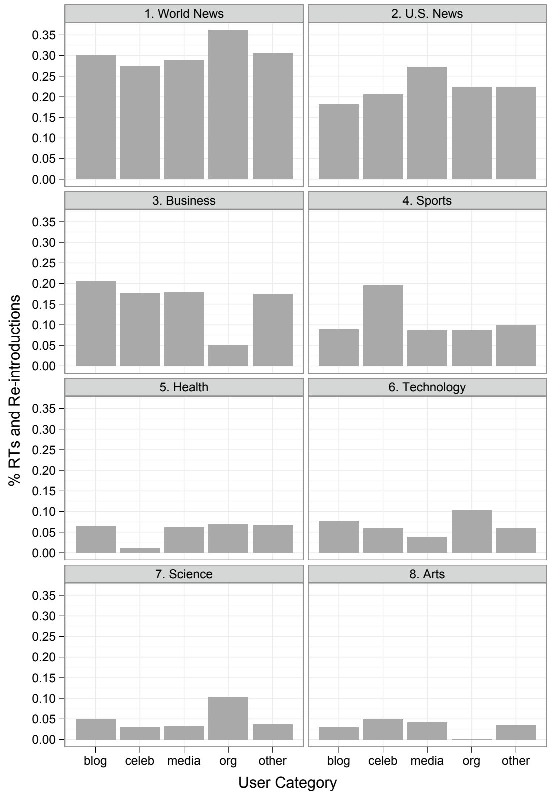


Figure 3.6: Number of RT's and Reintroductions of New York Times stories by content category

for a small selection of the most popular URLs. As Figure 3.7 shows, the link to the official White House blog, which expressed the administration's initial response to the Haiti earthquake, was rebroadcast in largely the same manner by all categories of users, as was the announcement of President Obama winning the Nobel Peace Prize. By contrast, the news story announcing the unexpected death of the actress Brittany Murphy was rebroadcast largely by bloggers, while the breaking news about Tiger Woods' accident and affair was picked up mostly by the news media and other celebrities. Finally, Figure 3.7 shows two examples of URLs that exhibit very different patterns from news stories. First, the URL for DealPlus, a website for "finding, discussing, and sharing thousands of deals and coupons for all types of stores," was popular among ordinary users, but al-

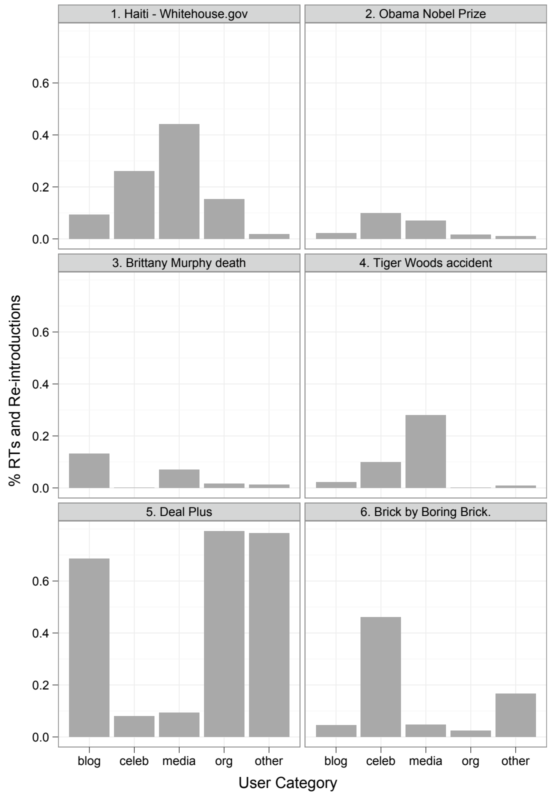


Figure 3.7: Number of RT's and Reintroductions of most popular URLs originating from media and other

most completely ignored by all categories of elite users. And second, the video for the song "Brick by Boring Brick," by the band Paramore, was again reposted mostly by ordinary users, but in this case celebrities also reposted it. Although this analysis is far from systematic, it suggests that different categories of users respond to different sorts of content in ways that are consistent with our classification scheme.

3.3 Persistence of information

In our work, we noticed that although a small amount of information spread and travels, among them, a substantial portion has a very long lifespan. We think this is very interesting phenomenon that has not been well investigated yet.

3.3.1 Lifespan by the category of originator

ZZZZZ: Content produced by different people have different persistence. Blogger's role of information filter.

By lifetime, we mean the time lag between the first and last appearance of a given URL on Twitter. Naively, measuring lifetime seems a trivial matter; however, it is complicated by the finite observation window, which results in "censoring" of our data. In other words, a URL that is last observed towards the end of the observation period may be retweeted or reintroduced after the period ends, while correspondingly, a URL that is first observed toward the beginning of the observation window may in fact have been introduced before the window began. What we observe as the lifetime of a URL, in other words, is in reality a lower bound on the lifetime. Although this limitation does not create much of a problem for short-lived URLs—which account for the vast majority of our observations—it does create large biases for long lived URLs. In particular, URLs that appear towards the end of our observation period will be systematically classified as shorter-lived than URLs that appear towards the beginning.

To address the censoring problem, we seek to determine a buffer δ at both

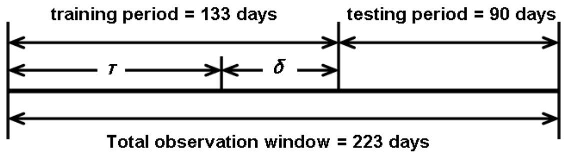


Figure 3.8: Schematic of window estimation procedure

the beginning and the end of our 223 day period, and only count URLs as having a lifetime of τ if (a) they do not appear in the first δ days, (b) they first appear in the interval between the buffers, and (c) they do not appear in the last δ days. As Figure **??** shows, to determine δ we first split the 223 day period into two segments - the first 133 day training segment and the last 90 day testing segment, and then ask: if we (a) observe a URL first appear in the first $163-\delta$ days and (b) do not see it in the δ days prior to the splitting point, how likely are we see it in the last 90 days? Clearly this depends on the actual lifetime of the URL, where initially we know for each URL that it persists for at least τ days. As the longer a URL lives, the more likely it will re-appear in the future, Figure **??** shows the upper-bound on lifetime for which we can determine the actual lifetime with 95% accuracy as a function of δ. Finally, because we require a beginning and ending buffer, and because we can only classify a URL as having lifetime τ if it appears at least τ days before the end of our window, we need to pick τ and δ such that $\tau + 2\delta < 223$. From Figure **??**, we determined that $\tau = 60$ and $\delta = 48$ sufficiently satisfy our constraints.

ZZZZZ: some of the numbers here should be move above!!!

Figure **??** is the histogram of the lifespan of URLs, grouped by the category of users who introduced the URLs[5]. URLs initiated by the elite categories ex-

[5]This figure only shows URLs that appeared in our dataset more than once. The majority of the URLs (220M) appeared only once, which is 10 times as many URLs as had a lifespan of only

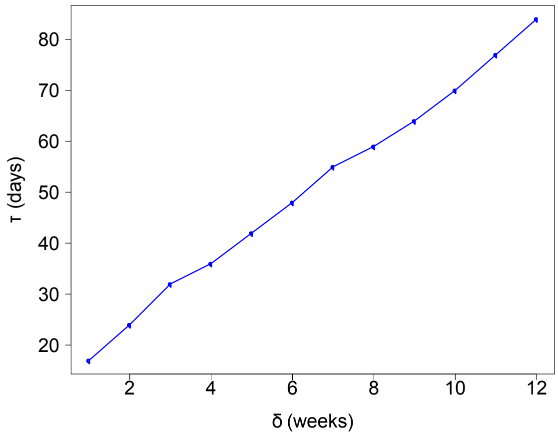


Figure 3.9: Upperbound of τ with confidence level ¿ 0.95, as a function of δ.

hibit a similar distribution over lifespan to those initiated by ordinary users. As Figure **??** shows, however, when looking at the percentage of URLs of different lifespans initiated by each category, we see two additional results: first, URLs originated by media actors generate a large portion of short-lived URLs (especially URLs with lifespan 0, which are URLs that only appeared once); and second, URLs originated by bloggers are overrepresented among the longer-lived content. Both these results can be accounted for by the type of content that originates from different sources: whereas news stories tend to be replaced by updates on a daily or more frequent basis, the sorts of stories that are picked up by bloggers are of more persistent interest, and so are more likely to be RT'd or reintroduced months or even years after their initial introduction.

A second related point, is illustrated by Figure **??**, which shows the average RT rate = (# of retweets) / (total # of occurrences) of URLs with different lifespan, grouped by categories[6]. Unsurprisingly, URLs introduced by elite users

a day.

[6]Note here that URLs with lifespan = 0 are those URLs that only appeared once in our dataset, thus the RT rate is zero.

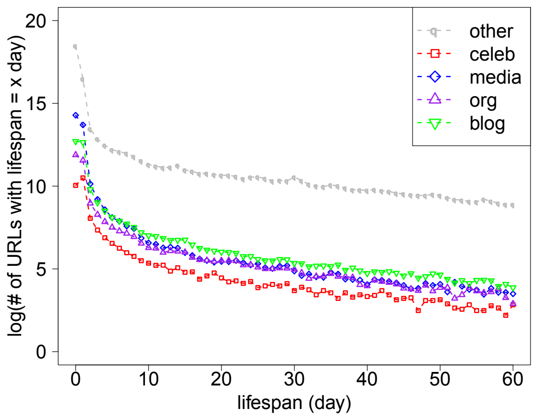


Figure 3.10: Histogram of lifespan of URLs originating from different categories

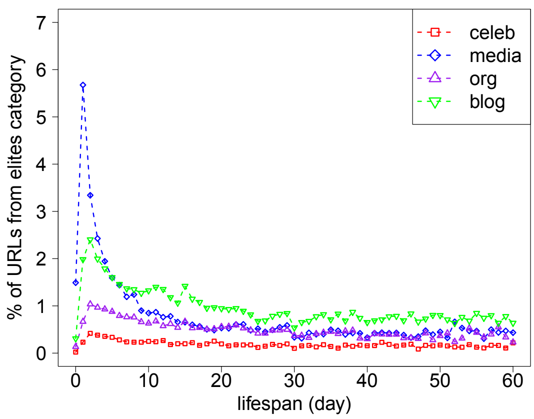


Figure 3.11: Percentage of URL initiated by 5 categories, with different lifespan

are much more likely than those introduced by ordinary users to be RT'd—a result that is likely driven by the higher-than-average number of followers for elite users. Somewhat less expected, however, is that for all categories the majority of appearances of URLs after their initial introduction derives not from rebroadcasting, hence diffusion within Twitter, but rather from reintroduction. As large and diverse as Twitter is, in other words, it is nevertheless a subset of a

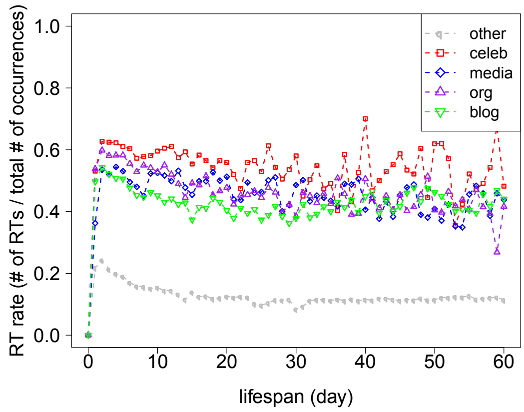


Figure 3.12: Lifetime avg RT rate, by categories

much larger media ecosystem; that is, content "lives" outside of Twitter, where users can rediscover it repeatedly. Some of this content—such as daily news stories—has a relatively short period of relevance, after which a given story is unlikely to be reintroduced or rebroadcast. At the other extreme, classic music videos, movie clips, and long-format magazine articles have lifespans that are effectively unbounded, and can be rediscovered and reintroduced by Twitter users indefinitely without losing relevance.

To shed more light on the nature of long-lived content on Twitter, we used the bit.ly API service to unshorten 35K of the most long-lived URLs (URLs that lived at least 200 days), and mapped them into 21034 web domains. As Figure **??** shows, the population of long-lived URLs is dominated by videos, music, and books, consistent with our interpretation above that certain types of online content retain their relevance indefinitely, and their persistence on Twitter is driven mostly by users rediscovering content outside of the Twitter ecosystem.

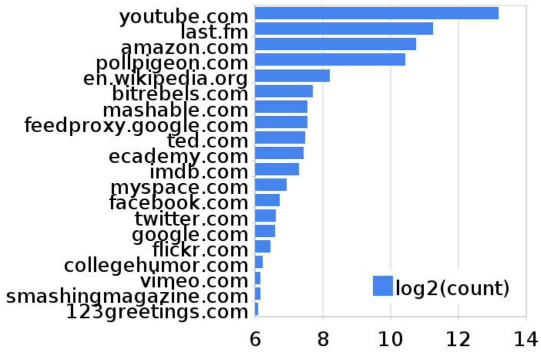


Figure 3.13: Top 20 domains for URLs that lived more than 200 days

3.3.2 Content

Informatoin filtering does not mean high interpersonal influence. The persistence of long-last content can not be fully contributed to contagion process - the role of content.

Evidence: RT rate for information with different lifespan.

Role of content? Domain breakdown.

Data

To study content in more details, we introduce a smaller Twitter dataset with richer HTML content.

Relationship between content and persistence

Strong collrection between content and the persistence of information.

3.3.3 Negative influence

Data

Orkut: social network with detailed structure, spread of behavior.

CHAPTER 4

ANSWER SOCIAL SCIENCE QUESTIONS WITH SOCIAL MEDIA DATA

4.1 Lasswell's Maxim

4.2 Two-step flow

4.3 Social movement

CHAPTER 5

THE INTERACTION BETWEEN PEOPLE AND INFORMATION

In [**?**], we studied the production, flow, and consumption of information in Twitter. As suggested in previous research in public communications, we classified users into 5 categories (celebrities, bloggers, mass media, organizations, and others) and found a striking concentration of attention on a small number of “elite” users on Twitter, as well as a significant homophily within categories. We also applied the classical “two-step flow” theory of communications in the context of social media sites such as Twitter. Our results confirmed that there are a large number of intermediary users who actively filter and disseminate information from media to the masses, and the composition of intermediaries is highly diverse. We also examined the lifespan and content of URLs broadcasted by different categories of users. We found that although content picked up by bloggers tends to stimulate a more persistent interest, the longevity of information is determined not by diffusion process, but by many different users independently rediscovering the same content.

CHAPTER 6

THE ROLE OF CONTENT

Following up our previous work, in [**?**], we studied the relationship between content and the temporal dynamics of information on Twitter, focusing on the persistence of information. Our results demonstrated a strong association between the content and the temporal dynamics of information. For example, rapidly-fading information contains significantly more words related to negative emotion, actions, and more complicated cognitive processes, whereas persistent information contains more words related to positive emotion, leisure, and lifestyle.

CHAPTER 7

NETWORK EFFECT AND BEHAVIORAL CONTAGION

CHAPTER 8

DIFFUSION WITHOUT ACTIVE DISSEMINATION

Arrival and Departure Dynamics in Online Social Networks (submitted to the International Conference on Web Wide Web, 2012).

In this paper, we compared the dynamics of user arrival and departure in online social networks. We showed although user disengagement has been considered less viral than engagement, there is a substantial network effect of the departure of friends on a user's tendency to leave a network. Taking into account such network effect, we are able to build machine learning models to predict the departure of users based on their local network properties.

CHAPTER 9

SOCIAL MEDIA IN ARAB SPRING MOVEMENT

Joining social media data with real world events, we are able to study one of the most interesting (and also the most difficult) parts in media communication research (Lasswell's maxim): the effect of information. One of my ongoing projects is to study the role of social media in social movements, in order to understand how the propagation of information is leading or reflecting societal changes. We have collected a large number of tweets and twitter networks related to big social movements (i.e., Middle East Revolution, Occupy Wall-Street Movement). Using effective algorithms for community detection, hub detection, trend detection, and opinion mining, we will be able to identify the informal structure of massive communication networks for social movements and study the diffusion of ideology and behaviors within and across organizational/geographical boundaries.

9.1 Data

To collect a substantial set of users and their tweets from the Middle East area in the period of the recent social movements, we first identified a set of countries of interest, including Tunisia, Egypt, Libya, Bahrain, Iran, Iraq, Israel, Algeria, Morocco, Saudi Arabia, Kuwait, Yemen, United Arab Emirates, Palenstine, Quatar, Oman, Jordan, Cyprus, Syria, and Lebanon. For each country, we used Yahoo Maps APIs to get the list of cities and towns in that country, together with the geographical centroid point for each city/town, in the form of (latitude, longitude).

After we had the centroid points of cities/towns within a country, we used Twitter search APIs to retrieve all the recent tweets generated within 100 miles from every centroid point in that country. We then parsed these tweets and extracted the authors of these tweets.

Using these authors as "seeds", we crawled one degree out from the seeds, and retrieved the profiles of all the seeds, and all the neighbors (friends/followers) of the seeds. The size of graph grows rapidly in one-degree distance. In fact, the network induced by the seeds and their one-degree neighbors already cover over 3 millions distinct Twitter users.

We crawled the profiles of these 3M users, and tried to identify their country of origin in three ways:

1. look for the country name in their self-reported location in their profile;
2. if the time-zone city is specified in their profile, map the city to the corresponding country;
3. if the location-tracking service is turned on, get the tracked location in Twitter meta data.

After parsing the profiles for all 5M users, we were able to identify the country of origin for 260K of them.

In the end, we crawled the maximal available history of tweets generated by these $260K$ users, which is, up to 3200 tweets per user. In the end we collected in total $96,350,865$ tweets in this way. Among them, 36,857,387 were generated between Dec 1st, 2010 and March 31st, 2011, by 112,661 users from the countries listed above.

Here is a breakdown of the amount of data we collected from each country.

To compare the diffusion of protest and non-protest content on Twitter, we first identify protest-related tweets. We say a tweet is related to protest if it contains at least one protest hashtag . Protest hashtags are hand-picked by political scientists. However, as there are hundreds of thousands of hashtags in our dataset, it is not feasible for political scientists to manually label all the hashtags. To effectively identify protest-related hashtags while maintaining a high recall, we narrow the pool of hashtags to be examined based on two metrics: (1) the volume of tweets containing the hashtag; and (2) the bursty-ness (as defined by Kleinberg 2004 KDD) of the hashtag occurrence. In this way, we narrow the scope down to only the top 1000 most frequently used hashtags and the top 1000 most bursty hashtags. We then have the experts to only go through those 2000 hashtags, and are able to identify about 500 protest-related hashtags among them.

9.2 Method and Results

As shown in the previous section, there had been a substantial amount of protest content introduced by Egyptian users on Twitter, even before Jan 25, 2011, when the first big protests took place in Tahrir Square, Cairo. Who were V those foresighted users? Were they planning and organizing the protests? Were they qualitatively different than other users on Twitter? In this section, we will investigate these questions, focusing on the relationship between the status of users and their earliness at participating in the protest activities on Twitter.

To start, we first represent the earliness of a user by his mobilization day.

A user u's mobilization day d(u), is defined as the day when u first used any protest hashtag. We then quantify the status of user u on day t, by the number of Twitter followers u has on day t. In order to show the aggregated status of users who started to participate in the protest at different times, we group users by their mobilization day d, and calculate f(d), the median value of user status, for each group. In Figure 4, we plot f(d) for d between December 10, 2010 and January 25, 2011. Here we can see a clear trend of decreasing status as the mobilization day gets closer to the actual protest day.

9.3 Conclusion

By analyzing Twitter activity in Middle East area during the Arab Spring movement, we have shown that social media were used to both activate and reflect the on-goings of Middle East social movement. The relative weights of these two roles differed across countries. In particular, Egyptian users actively used Twitter to plan protests and call for a critical mass, and the users from Saudi Arabia or UAE mostly used Twitter to support or comment on on-going events. We also found that protest content travelled directionally from the central to the peripheral of the Twitter network: most protest memes were initiated by hub users and later picked up by the masses. At the individual level, we found that the adoption of protest content can be modeled by the complex contagion process - while the overall adoption rate of protest content is relatively low, people become significantly more likely to start tweeting about the protest when more than 2 friends already doing so.

Although our work is to our best knowledge the largest study of the role of social media in social movements, we have to acknowledge that our dataset is rather disproportionate: 80% of the tweets we studied came from only 5 Middle East countries. Due to technical issues, we were not able to collect an equally large number of tweets from countries such as Libya, Tunisia, and Algeria, when dramatic societal changes were taking places in these countries.

For the future work, we want to extend our study to the diffusion of protest content among countries and communities through social media. Another interesting direction is to understand how mass media (newspaper, TV, radio) and social media interact and influence each other in social movements.

This work presents one of the largest studies on the role of social media in the Arab Spring movement. Using over 2 million tweets generated by 110 thousand users in 11 Middle East countries during early 2011, we depict the landscape of aggregated Twitter usage in those countries as the revolution unfolded. Our results suggest that social media has been used to both lead and reflect real world protest activities. Compared to non-protest-related content on Twitter, we find that protest-related content travels directionally from central users to peripheral users, and the adoption of protest-related content can be modeled by a complex contagion process.

CHAPTER 10

CONCLUSION

In summary, I am deeply intrigued by the developing characteristics of information diffusion in online social media. Thanks to the Internet and social media technologies, I believe that we are heading towards a more democratic era where revolutions can be started by ordinary people and the power to change is in the hands of the masses. As part of this process, social media sites such as Facebook and Twitter have also evolved from friendship networks to a much broader platform for organizing social/political changes and communicating with various communities. I hope my work can help understand this movement and foster the effective flow of information in the society.

APPENDIX A

CHAPTER 1 OF APPENDIX

Appendix chapter 1 text goes here