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News Diffusion Through Online Social Network

By

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Abstract

Today, false news diffuses at an unprecedented speed through online social networks. Such news causes unnecessary chaos or panic and might even post a threat to our democracy. I collect the Tweets (including Retweets) containing both identified *true* and *false* news via Twitter APIs. I then analyze their diffusion patterns and study their relationship to the engaged users' characteristics. I find that false news diffuses significantly faster, deeper and broader than the true news. Moreover, regardless of its veracity, news spreads faster while being circulated by users who have less followers but more friends and post fewer Tweets but more likely to "like" other users' posts. Furthermore, I find that the Twitter community can recognize false news and correct it over time. Three distinct false-correction features are identified, namely *concurrent*, *gothic* and *camel*. Examining these features might help discover and curb false news.

Keywords: Online Social Network, False News, News Diffusion, Computing Science

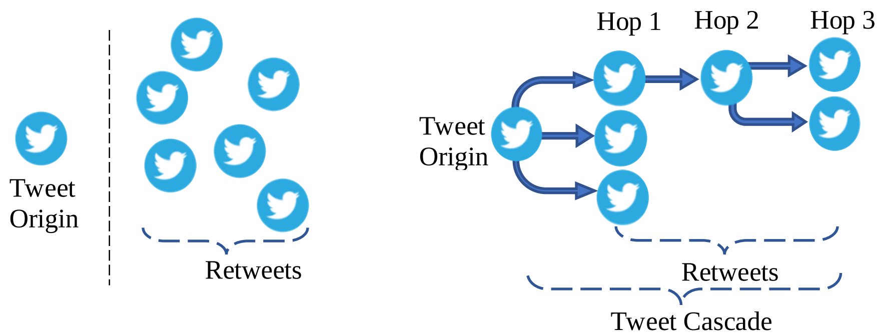
1 Introduction

Nowadays, online social networks play a critical role in people's daily lives. Apart from simply acting as a consumer, users are also able to share various pieces of news and information at unprecedented rates through online social networks. According to Pew Research Center, two-thirds of Americans report that social media is a source of news they read (Shearer, 2017). Facebook deals with more than 310,000 status updates and 54,000 shared links per minute (Osman, 2018). On YouTube, 5 billion videos are uploaded and viewed by over 30 million visitors per day (Donchev, 2018). Social networks facilitate the information diffusion and sharing. Meanwhile, more fake news is generated and circulated for malicious purposes. Its circulation can lead to chaos and panic, e.g. during the natural disasters such as Hurricane Sandy and Chile Earthquake (Gupta *et al.*, 2013; Mendoza *et al.*, 2010; Allcott, 2017). More seriously, false news diffusion could even harm our democracy. For instance, a study by Cunter *et al*. (2018) shows that fake news might have substantially depressed Hillary Clinton's support during the 2016 presidential election and, consequently impacted the election outcome (Richard Cunter, 2018; Nyhan, 2018). Hence, online social network not only accelerates information diffusion, but also propagates false news more widely and faster than ever before.

In this paper, I examine news diffusion through Twitter by comparing the diffusion patterns of false and true news. False news refers to unreliable information, and true news refers to authentic information. Figure 1 is the anatomy of a typical Tweet cascade displaying the diffusion pattern. A cascade starts with a tweet origin, and gets expended through the re-tweeting process. The main focus of this paper is to study how false and true news diffusion are different in terms of speed, size, breadth, and depth, corresponding to how fast the news diffuses, the number of Tweets, the number of Tweet origins, and the number of hops in each Tweet cascade, respectively. These four parameters characterize the cascade's structure. Whether users or bots are circulating the Tweets containing false news, some users would sooner or later recognize their falsity and correct them by posting correction Tweets. I have discovered three distinctive false-correction features: namely *concurrent*, *gothic* and *camel*. These features depict how the occurrence of false Tweets correlates with the correction Tweets. Since Twitter community autonomously filter out false news, examining these features helps discover and curb false news diffusion.

In general, I find that over 70% Tweets containing false news were posted by the middle of false news lifespan`. In contrast, the diffusion of Tweets containing true news has a longer lifespan and the Tweets were posted more evenly over time. False news diffuses faster, broader, and deeper than the true news. On the other hand, false news could be recognized and filtered out by the autonomous Twitter correction system. I believe my study provides an in depth understanding of news diffusion through online social network and sheds light on detecting false news propagation. These findings help the social media, such as Twitter and Facebook, learn more about the features of false news diffusion, and come up with better solutions to alleviate the negative effect of its propagation.

Figure 1: Tweet Cascade and Retweet Topology Construction



The rest of the paper is organized as follows: Section 2 discusses the literature review and the potential contribution of this paper. Section 3 presents the methodology, including news selection, data collection and data preprocessing. Section 4 discusses the important discoveries from the graphics of Tweet topology and the engaged user's characteristics. Section 5 testifies the statistical significance of these discoveries in a more rigorous way by running regressions. Conclusions is in Section 6.

2 Literature Review

Studying the information diffusion through online social network is based on the understanding of the network structure. Alan Mislove *et al.* (2007) compared four online social networks, namely Flickr, YouTube, LiveJournal and Orkut. They concluded that online social networks consist of highly connected clusters which connecting to each other via some high-degree nodes. Hence, the average path length is short, leading to the small world property of the network.

Besides studying the online social network structure, Cha *et al*. (2009) started to look at the information diffusion on Flickr which is a social media to post, like and search pictures. They find that only a handful of pictures gained wide attention and spread widely. However, most of the pictures on Flickr are diffused slowly and locally, regardless of a photo's popularity. Afterwards, Bakshy *et al*. (2011) studied the information propagation on Twitter and discovered that a Tweet tended to be spread wider if the source node had more significant past influence and a larger number of followers. Kitsak *et al.* (2011) find that the scale of the information diffusion correlates with the original user who posted the information at the very beginning. If the user is at the core of the network, the diffusion cascade tends to be larger-scaled. On the other hand, Bakshy *et al.* (2012) conducted a controlled experiment to study the information diffusion through Facebook. They rigorously proved that online social networks accelerate the information transmission.

Information is propagated much faster than even before. This makes the communication in society more efficient, but also leads to rampant false news or misinformation circulation. Gupta *et al.* (2013) studied the diffusion of fake *images* during the 2012 Hurricane Sandy. They concluded that during the hurricane, only a small portion of the Twitter users contributed to the majority of the fake images diffusion via retweeting. During the crisis, users' Retweets number was affected little by how many friends or followers they have. Instead, they tended to retweet the hourly-updated trending topics posted by Twitter. Vosoughi *et al.* (2018) is the most relevant study to my paper. They conducted a large-scaled study by analyzing how the identified true and false news distributed on Twitter from 2006 to 2017. They find that false news, especially the political false news, are propagated significantly faster, deeper and more broadly. Besides working on the news diffusion pattern after 2010 Chile earthquake, Mendoza *et al.* (2010) find that the "false" rumors are more likely to be questioned by the Twitter users. Hence, the Twitter Community could filter and correct the "false" rumors over time. Starbird *et al.* (2014) further studied such information correction by analyzing three rumors during the 2013 Boston Marathon Booming. They observed that the correction messages peaked at the same time of the misinformation.

Moreover, Akbarpour and Jackson (2017) argued that the efficiency of the information diffusion relies not only on the network structure but also the agents. They proved that, in contrast to a network with homogenous agents, one with various types of agents diffuses information more efficiently. They proposed two main types of agents – the agents active on Twitter at random time throughout the day, and the agents alternatively active and inactive. Vicario *et al.* (2015) compared the dissemination of scientific and conspiracy theories via Facebook posts but did not find any major differences. Instead, they discovered the critical role of homogeneity in diffusing the contents. Homogeneity serves as a primary driver of information diffusion. Bakshy *et al*. (2015) studied the correlation between the social network structure and the media exposure to ideologically diverse news. Their work suggested that people are still very willing to listen to the opposing party's opinions. They also find that the Liberals tend to make more friends with the opposing viewpoints.

The contribution of this paper is to give a complete understanding of the news diffusion through online social network. The paper configures the true and false news diffusion topology and compare them in terms of speed, size, breadth and depth. It studies how false news is corrected autonomously by the Twitter community and discovers three distinct correction features. It explores the Twitter users engaged in news diffusion and how their characteristics affect the true and false news diffusion pattern.

3 Methodology

In this section, I discuss my research methodologies in detail. I will describe false and true news studied in this paper, the data collection process, and the data preprocessing.

3.1 News Selection

I selected 6 false news and 2 true news for analysis. The false news come from the fact-checking website *Snopes.com*. This website investigates whether a piece of information is *True*, *False* or *Mixed* and provides analysis correcting the rumors or misinformation circulated on social media such as Twitter and Facebook. All 6 false news have been identified and labeled as "False" by Snopes.com. These 6 false news are selected because they recently happened so that the Tweets containing the false news could be retrieved via *Twarc* API which only accesses all Tweets within the recent 7 days. Moreover, I tried to select the false news which are most widely circulated so that the number of retrieved Tweets and Retweets is large. These false news have various topics, including media, food & safety, politics etc. Two true news are the current events reported by several reputed newspapers. Table 1 provides the content of the 8 news. To diversify the types of the news, I select the topics of food & health, media, politics, and human rights.

Table 1: Summary of News

News Id	Veracity	News Id and Content	# Tweets	# Users Engaged	Tweets Time Span*
News 1	False	HIV-infected blood was injected into Pepsi or Frooti plant.	6,113	5,440	2011-07-12 13:35:37~ 2018-03-21 05:49:48
News 2	False	Type “BFF” on Facebook. If it turns green, then the account is secure.	964	911	2018-03-19 10:28:48~ 2018-03-25 09:52:52
News 3	False	Coors Light beer was contaminated with cocaine.	578	568	2018-02-18 11:01:49~ 2018-03-30 11:37:00
News 4	False	Coca-Cola recalled Dasani because a clear parasite was found in bottles across the United States.	1558	1515	2018-02-10 12:15:54~ 2018-04-07 17:54:13
News 5	False	Emma González, a Parkland mass shooting survivor, admitted to bullying a former student who later killed seventeen people.	9007	8441	2018-03-19 10:27:17~ 2018-04-05 06:53:07
News 6	False	George Soros paid $300 to ‘March for Our Lives’ Protesters.	807	762	2018-03-24 21:03:44~ 2018-04-05 00:39:16
News 7	True	Facebook categorizes users by political preferences	1,383	1,358	2018-01-23 09:44:53~ 2018-04-07 14:54:27
News 8	True	50 million Facebook profiles data leaked out.	24,771	20,919	2018-03-27 17:26:49~ 2018-04-04 20:47:06

* The dates of the first and last collected Tweets

3.2 Data Collection

3.2.1 Retrieve Tweets via API

The data is crawled by means of various available Twitter Application Programming Interface (API). First, I used Twitter’s *Twarc* API. This API retrieves the tweets posted in the last 7 days based on certain query parameters such as *keywords*, *language*, *user name*, etc. I collected Tweets via *Twarc* API by querying the keywords of the false news. Notice that querying the API for the keywords returns the Tweets containing the keywords and the hashtags made of the keywords. To double-check the coverage of the *Twarc* results as well as access old Tweets, I also used the *OldTweet* API. It retrieves all the historical tweets based on certain querying parameters. One of the biggest advantages of the *OldTweet* API is that it bypasses some limitations of the *Twarc* API. For instance, *Twarc* API only returns the Tweets posted within the last 7 days. *OldTweet* API is able to retrieve some of the deepest and oldest tweets. In short, I used both APIs to retrieve the Tweets of the identified false and true news.

3.2.2 Request for Additional Information

One Tweet may or may not be retweeted. I took only the Tweets which have been retweeted. For each of these Tweets, I used *Tweepy* API to retrieve the information of all its Retweets and the engaged users. Information includes the id of the Retweets, the time by which the Retweets were posted, the id of the users posting the Retweets, the users' friend list and follower list. All the information is used to construct the Retweets propagation topology as shown in Figure 1. Moreover, I collected the users' activity patterns by retrieving 270 posts (i.e. tweet, retweet, or quotes) from the user's timeline, 135 before and after the user post the true or false news. Doing so could best reflect the user's activity pattern at the time of engaging in the information diffusion.

3.3 Data Preprocessing

3.3.1 Retweet Topology

I manually labeled the Tweets as "true", "false", "correction", or "irrelevant". "True" represents the Tweets transferring the true information. "False" represents the Tweets propagating false news or misinformation. "Correction" denotes the Tweets trying to correct the false news or misinformation. "Irrelevant" refers to the useless Tweets which were removed from the dataset. In the end, I keep three types of Tweets, namely *true* Tweets, *false* Tweets, and *correction* Tweets. Only the first type associates with the *true* news. The rest of the two are the Tweets dealing with the *false* news. In addition, I convert the post time (i.e. year-month-day-hour-min-sec) of each Tweet into the *elapsed time*. It is the time difference between the first Tweets of the same news and this Tweet.

Next, I recovered the news diffusion process, i.e. the Retweets topology as shown in Figure 1. With all the collected Tweets, I first put aside those which have never been retweeted.

Subsequently, the remaining Tweets are either the tweet origins or a piece of Retweet. Denote only those tweet origins as T_i. The topology is constructed based on the two assumptions proposed by Wu and Shen (2015).

1. A user retweets a news at the first time she reads a tweet containing that news.
2. A user only reads the tweets posted by the accounts that he follows, i.e. his friends.

Let RT_{ij} represent the *j*th Retweet of T_i. T_user_i is the user who posted T_i. Similarly, RT_user_{ij} posted RT_{ij}. $Friends_{ij}$ is the set of friends of RT_user_{ij}. $Earlier_{ij}$ denotes the set of users who also retweeted T_i but at an earlier time than RT_user_{ij}. Clearly, T_i is the parent of $RT_{ij}, \forall j$. Among all the RT_{ij}, the parent-child relationship is configured by the following algorithm.

1. If $Friends_{ij} \cap Earlier_{ij} = \emptyset$, then RT_{ij} is retweeted from T_i.
2. Otherwise, I consider the users are in $Friends_{ij} \cap Earlier_{ij}$. Let RT_user_{ij*}be the user in this set that retweeted T_i latest. His post RT_{ij*} is assumed to be the parent of RT_{ij}.

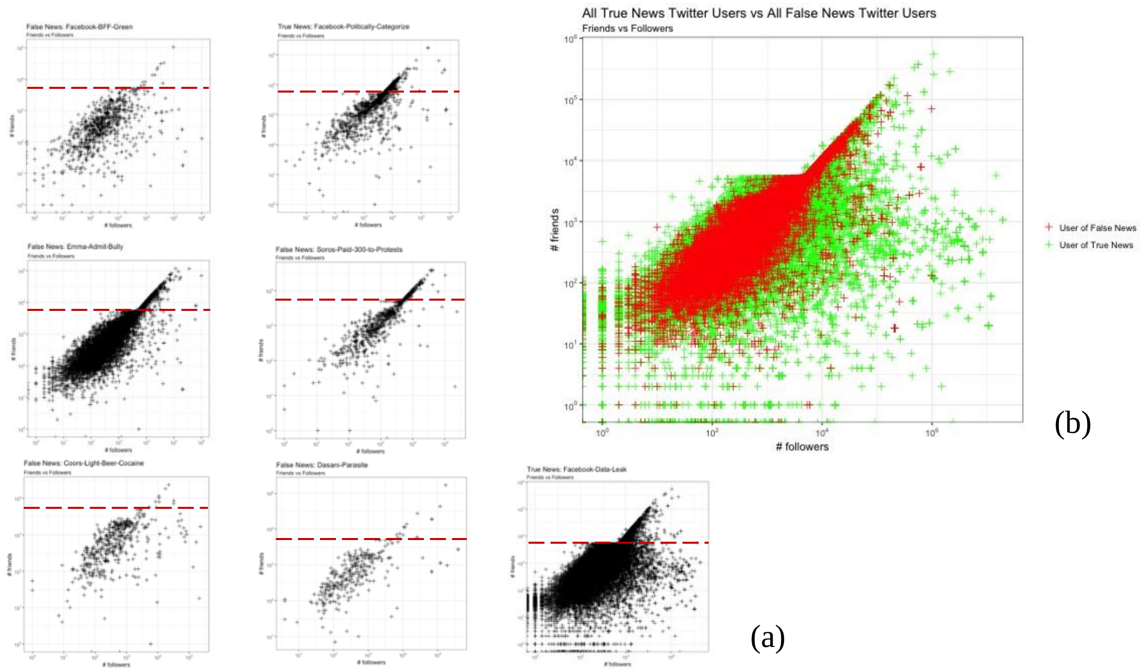
4 Statistical and Graphical Analysis

I will present the engaged users' characteristics first by describing the number of their friends, followers, Tweet posts and the relationships among these characteristics. Then I will discuss the diffusion of the *false* Tweets and *correction* Tweets (if any) over time by identifying three distinctive false-correction features. Finally, I provide the visualization of how the Retweets topology evolved over time and some interesting findings.

4.1 The Engaged Users' Characteristics

I pooled all the user data together and separated them based on the true or false news they engaged in. There are 25,790 users engaged in the true news, and 12,249 users engaged in the false news. Figure 2 shows the log-log plot of the number of friends and the number of followers that the engaged users may have. There exists a clear plateau at 5,000 friends level. It reflects the following limit set by Twitter. Specifically, each Twitter user could follow at most 5,000 accounts. Once the limit is reached, the user has to wait for more people to follow him, until he could continue to have more friends. Therefore, in Figure 2, when the Twitter users have less than 5,000 followers, they could only have maximum 5,000 friends. For those accounts with more than 5,000 followers, this limit is removed, and hence it is possible to get more friends than 5,000.

Figure 2: # friends vs # followers.



Panel (a) is for the individual news. Panel (b) aggregates all the false (red) and true (green) news.

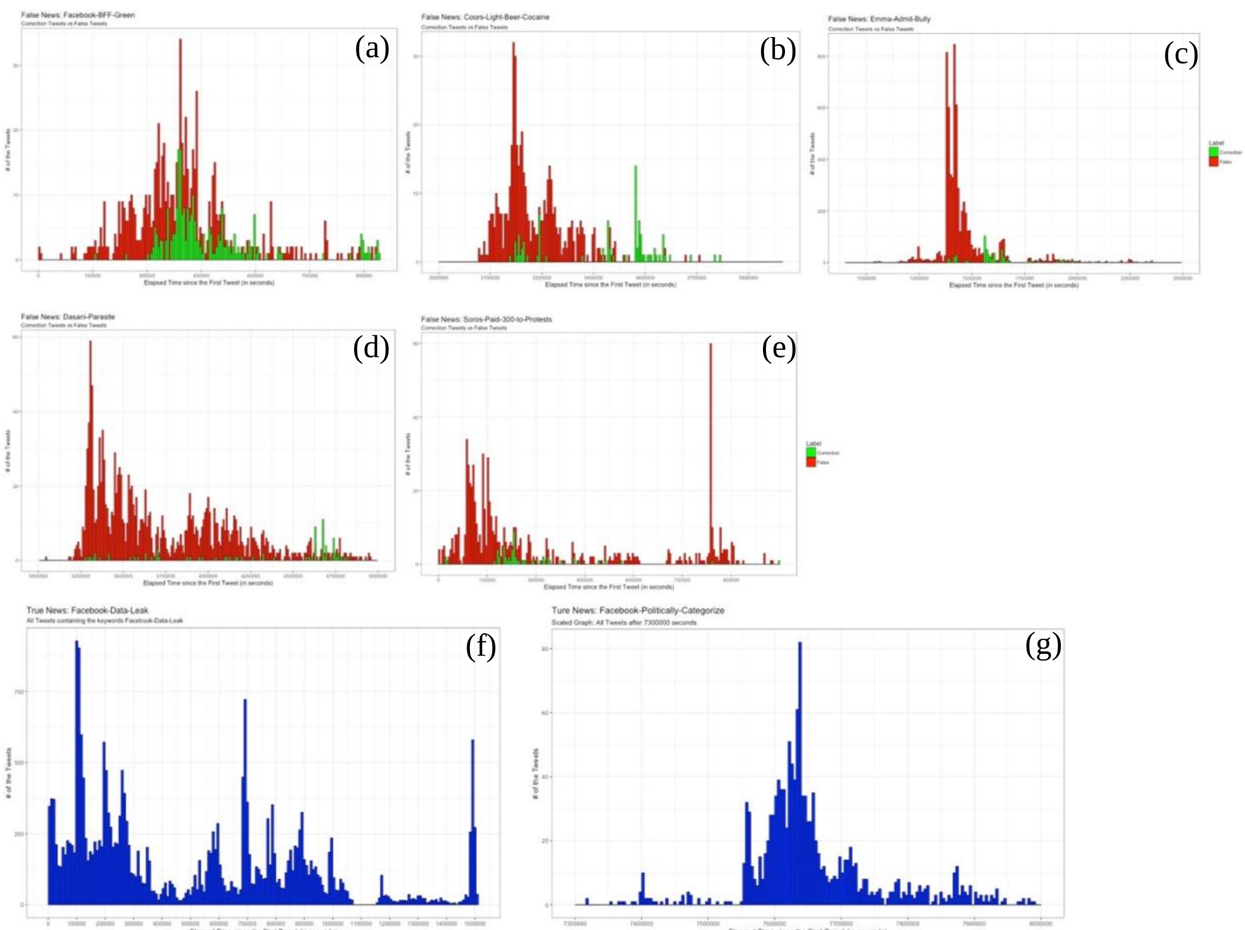
The friend-follower pair of the false news users highly concentrates in Figure 2 (red area). In contrast, the friend-follower pair of the true news users takes a broader space (green area). Hence, given the same number of friends, the false news users have less followers; and given the same number of followers, they usually have more than 10 friends. It tells the opposite story to the conventional expectation which assumes that the false news spreaders should have a large number of followers so that they expose to a larger population and get the false news diffuse easier.

4.2 The False-Correction Tweets Interaction

Previous studies have found that the online social community is able to autonomously correct false news overtime (Mendoza *et al.*, 2010; Starbird *et al.*, 2014). To study how false news are corrected, I have manually labeled each Tweets as “true”, “false”, “correction” or “irrelevant”. A *false* Tweet propagates the false news. A *correction* Tweet claims the falsity of the false news and usually attaches a valid URL link directing to more cohesive evidence, such as fact-checking website Snopes.com etc. Figure 3 displays the diffusion of false and correction Tweets over time. Among five of the false news, I discovered three different false-correction features. Note that the time span of Panel (b) (c) (e) does not start from 0, because only a handful Tweets appeared at the very beginning and skewed the graph. So, I removed these Tweets.

Panel (a) gives the *concurrent* feature. The distribution of correction Tweets is the same as that of the false Tweets, but just starting later and to a smaller extent. The peaks of both distributions were reached at very close time points. Panel (b) and (c) shows the *gothic* feature. Specifically, the distribution of false Tweets looks thin and high like the Gothic architecture. There are only a few correction Tweets which emerged rather late, imposing little effect on the diffusion of the false Tweets. This may be due to the outbreak of the false news which started to be spread suddenly and cooled down shortly. Thus, the diffusion peak was reached too fast to allow people recognized the falsity, composed correction Tweets and propagated them. By the time of the correction Tweets starting to be circulated, the false news no longer caught much public attention, and hence the correction Tweets dwindled soon as well. Panel (d) shows the *camel* feature.

Figure 3: False-Correction Tweets



Panel (a) depicts the *concurrent* feature. Panel (b) and (c) depict the *gothic* feature. Panel (d) and (e) depict the *camel* feature. Panel (f) and (g) are true news.

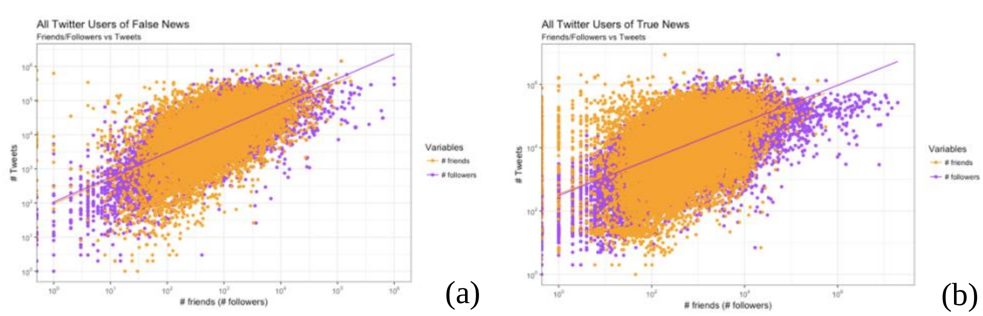
The false Tweets were circulated in more than one rounds, where the distribution looks like the humps of the camel. In panel (d), the first peak was reached quickly, then followed by a downslope, and then a second peak. There are little corrections happening during this period. More correction Tweets emerged at the end of the second “hump” and tended to outweigh the false news seeking for a third but dwarf peak. Similarly, in panel (e), more corrections appeared at the end of the first “hump”, after which the false news got curbed. By the time the corrections attenuated, the false tweets seized a second of propagation and peaked within 38 hours. Table 2 displays the summary statistics of *false* and *correction* Tweets. Therefore, false news could propagate and get corrected in different patterns. They could display *concurrent*, *gothic*, or *camel* features. Examine these features might be helpful to better curb the false news diffusion. In addition, Figure 3 also shows the diffusion of two true news over time. Panel (f) depicts the diffusion of the news about Facebook data leak. Panel (g) is about “Facebook categories users based on their political leaning”.

Table 2: False News and the Corresponding Tweets

News Id	# Unique Tweets	Peak (hours)	# False Tweets	# Correction Tweets
News 2	964	104.17	718 (74.48%)	246 (25.52%)
News 3	578	31.25	496 (85.81%)	82 (14.19%)
News 4	1558	{52.08, 243.06}	1479 (94.93%)	79 (5.07%)
News 5	7056	69.44	6450 (91.41%)	606 (8.59%)
News 6	807	{25, 231.25}	748 (92.69%)	59 (7.31)

Figure 4 shows the relationships between the number of Tweets the users post and the number of friends or followers the users have, respectively, for the false news users and true news users. The two panels (a) and (b) look similar, which displays a positive relationship between the number of Tweets and the number of friends or followers.

Figure 4: # Tweets vs # friends / # followers.



(a) (b)

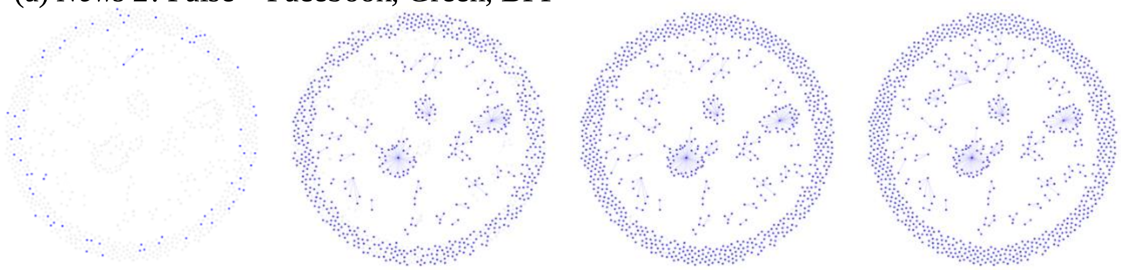
Panel (a) aggregates all the false news. Panel (b) aggregates all the true news.

4.3 The Retweet Topology Evolution

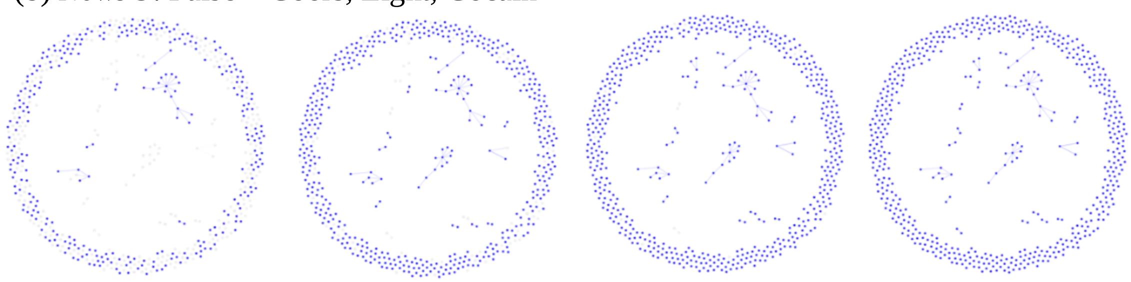
The topology has been constructed from Section 3.3.1. Figure 5 visualizes the evolution of the topology for each news. Each node represents a Tweet. The edge directs from the Tweet to its Retweet. I have split the life span of the news diffusion into 4 equal periods. Each graph displays the Tweets (blue nodes) and the diffusion topology by the end of the corresponding period. The white nodes represent those Tweets appeared in later periods. Panels (a) and (b) show the topology evolution of the false news. A fairly large number of Tweets were already posted in the first period.

Figure 5: Retweet Topology Evolution.

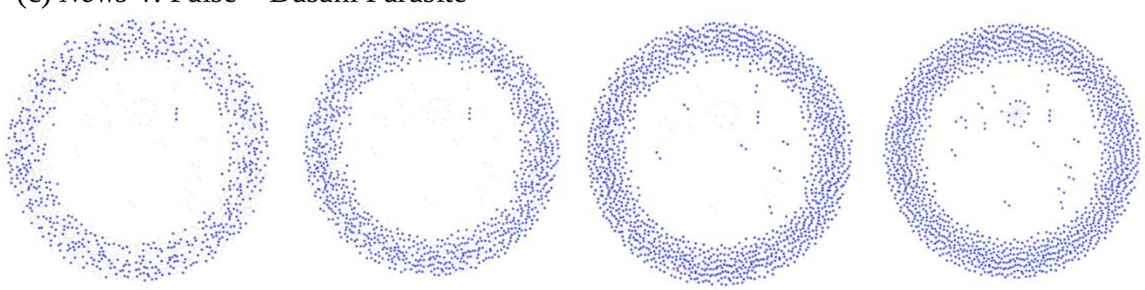
(a) *News 2*: False – Facebook, Green, BFF



(b) *News 3*: False – Coors, Light, Cocain



(c) *News 4*: False – Dasani Parasite



(d) *News 7:* False – March Our Lives, Soros, 300

(e) *News 7:* True – Facebook Users, Political Category, Preference

A majority of them (over 70%) were posted by the second period. In periods 3 and 4, some more Tweets were generated or retweeted. More detailed statistics are recorded in Table 3 In contrast, the evolution of true news, as shown in panel (c), spread slower and took longer time. This will be further testified in Section 5.

Table 3: Percentage of nodes by each period

News Id	Veracity	By period 1	By period 2	By period 3	By period 4	By period 5
News 2	False	7.94%	73.34%	94.93%	100%	--
News 3	False	54.24%	86.22%	97.53%	100%	--
News 4	False	46.25%	74.3%	92.57%	100%	--
News 6	False	59.78%	74.38%	82.61%	100%	--
News 7	True	19.84%	28.31%	49.74%	85.19%	100%

5 Econometrics Analysis

In the previous statistics section, three main discoveries are (1) the false Tweets diffusion could correlate with the appearance of the correction Tweets: the false Tweets intervened by few or late correction Tweets seem to either rocket to the peak quickly or sustain longer with several “humps”; (2) the twitter users’ characteristics, such as the number of followers and friends, might affect the diffusion patterns of the true and false news; (3) the false and true news may spread at different rates and have different life spans. To testify these discoveries in a more vigorous way, I conduct linear regressions and logistic regression and observe the statistical significance of these discoveries. To be clear, I am exploring how different factors affect the diffusion pattern of the false and true news. The diffusion pattern is featured by *speed* (the disseminating rate of tweets), *size* (the total number of Tweets generated), *breadth* (the total number of tweet origins), and *depth* (the number of retweet hops from the Retweet to the tweet origin).

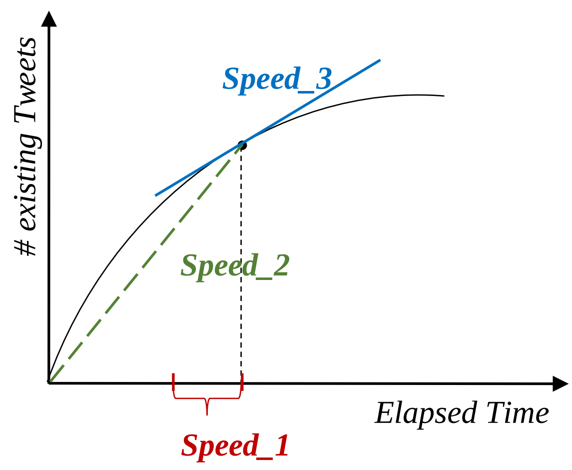
5.1 Regression Model

To identify the correlations between the news diffusion patterns and various factors, such as the veracity of the news and user's characteristics, I study the specification model:

$$Pattern_i = \beta_0 + \beta_1 Veracity_i + \beta_2 ElapTime_i + \beta_3 X_i + \beta_4 U_i + \varepsilon_i \qquad (1)$$

All the variables and their meanings are summarized in Table 4. $Pattern_i$ includes four dependent variables, namely $Speed_i$, $Size_i$, $Breadth_i$ and $Depth_i$. $Size_i$ represents the number of Tweets by the time Tweet *i* was generated. $Breadth_i$ measures how broadly the news diffused. Hence, it is the number of the tweet origins by the time Tweet *i* was generated. $Speed_i$ measures the disseminating rate of the Tweet. I use three ways to define the speed of news diffusion. $Speed\_1_i$ is the time difference between Tweet *i* and its predecessor. $Speed\_1_i = 0$ if Tweet *i* is a tweet origin. $Speed\_2_i$ models the *average speed* of the news diffusion, i.e. $Speed\_2_i = \frac{\#Tweets\ by\ ElapsedTime_i}{ElapsedTime_i}$. $Speed\_3_i$ models the *marginal speed* of the news diffusion. $Speed\_3_i = \frac{1}{\partial ElapsedTime_i}$, where $\partial ElapsedTime_i$ is calculated by subtracting the latest elapsed time from the Tweet *i*'s elapsed time. It measures the number of new Tweets generated by taking 1 more unit of time. $Speed\_1_i$, $Speed\_2_i$, $Speed\_3_i$ are visualized in Figure 6. $Depth_i$ is the hop position of Tweet *i*. If Tweet *i* is a tweet origin, $Hop_i = 0$; if Tweet *i* is at hop level 2, then $Hop_i = 2$.

Figure 6: Three definitions of speed



$Veracity_i$ is a categorical variable with levels "True" (Tweets of true news), "False" (Tweets propagating the false news), "Correction" (Tweets correcting the false news). $ElapTime_i$ is the time difference between Tweet *i* and the first Tweet of the same news.

X_i contains more control variables relative to Tweet *i*, namely *Tweet_ID*, *Tweet_Origin*, and *News_Tag*. Each Tweet has a unique *Tweet_ID*. *Tweet_Origin* is a binary variable. It is 1 if the Tweet is a tweet origin, and otherwise 0. *News_Tag* is categorical variable with levels representing each piece of news, such as DP for Dasani-Parasite news and FBG for Facebook-BFF_Green news and so on.

U_i contains the user information, including *User_Favorite* (total number of posts the user ever liked), *User_Friend* (total number of user's friends), *User_Follower* (total number of user's followers), and *User_Tweet_Post* (total number of Tweets (including Re-tweets) issued by user).

Table 4: Regression Variables, Measurement and Meaning

Variable	Measurement & Meaning
$ElapTime_i$	Elapsed time of Tweet *i*. It is the time difference between the first Tweet of the same news and Tweet *i*.
$Size_i$	Total number of Tweets of the same news by the time Tweet *i* was generated
$Breadth_i$	Total number of the tweet origins by the time Tweet *i* was generated
$Depth_i$	Hop position of Tweet *i*
$Speed\_1_i$	Number of hours between Tweet *i* and its predecessor,
$Speed\_2_i$	$Speed\_2_i = \frac{\#Tweets\ by\ ElapsedTime_i}{ElapsedTime_i/3600}$
$Speed\_3_i$	$Speed\_3_i = \frac{1}{\partial ElapsedTime_i/3600}$
$Veracity_i$	Categorical variable. Whether the Tweet is *true*, *false* or *correction* Tweet.
Tweet_ID	Unique Tweet ID
Tweet_Origin	Binary variable. Whether the Tweet is a tweet origin or not. 0 if it is tweet origin. 1 otherwise
News_Tag	Categorical variable to tag Tweet by its corresponding news
User_Favorite	Total number of posts the user ever liked
User_Friend	Total number of user's friends
User_Followe	Total number of user's followers
User_Tweet_Post	Total number of Tweets (including Re-tweets) issued by user

5.2 Regression on Diffusion Pattern: Speed

Table 5 displays the regression results on Speed_2. The base model only includes the veracity of the news. The numerical value is less important, while the sign and the significance level are more informative. Column (1) shows that the correction Tweets diffused slower than the true Tweets; and there is no significant difference between the speeds of the false Tweets and the true ones. However, this result is spurious, because the R^2 is close to zero, indicating a rather weak explanatory power of the base model.

Table 5: Regression on Speed_2

	Dependent variable:					
	Speed_2				Speed_1	Speed_3
	Base (1)	Add Tweet Info (2)	Add User Info (3)	Full (4)	Full (5)	Full (6)
“Correction” Tweets	-0.84** (0.393)	6.30*** (0.536)	-0.72* (0.392)	6.37*** (0.541)	3,260,967 (3,262,826)	-36.15 (41.436)
“False” Tweets	0.13 (0.319)	6.17*** (0.471)	0.242 (0.319)	6.33*** (0.481)	3,004,586 (2,898,465)	-59.657 (36.809)
Time elapse		-0.026*** (0.001)		-0.03*** (0.001)	1,063 (6,153)	-0.18*** (0.078)
Depth		-0.142 (0.125)		-0.16 (0.125)	5,735,000*** (751,947)	17.843* (9.549)
Size		0.01*** (0.001)		-0.01*** (0.001)	-333 (3,550)	-0.048 (0.045)
Breadth		-0.02*** (0.001)		-0.02*** (0.001)	-8,285 (6,402)	0.08 (0.081)
Tweet origin		-0.962*** (0.270)		-1.00*** (0.274)	-202,448 (1,649,371)	-9.22 (20.946)
User_Favorite			0.00001* (0.000)	-0.00 (0.000)	-34.770** (17.291)	-0.0001 (0.000)
User_Friend			0.0001*** (0.000)	0.00004** (0.000)	30.377 (99.587)	0.0004 (0.001)
User_Follower			-0.00** (0.000)	0.00 (0.000)	1.245 (11.427)	-0.0001 (0.000)
User_Tweet_Post			0.00*** (0.000)	0.00*** (0.000)	0.380 (7.604)	0.00003 (0.0001)
Constant	4.79*** (0.296)	2.47*** (0.518)	4.37*** (0.305)	2.15*** (0.526)	-855,974 (3,167,728)	147.57*** (40.229)
Observations	2,331	2,331	2,331	2,331	2,331	2,331
R2	0.005	0.32	0.026	0.33	0.050	0.008

Note: *p<0.1; **p<0.05; ***p<0.01

Hence, I add more variables relevant to the Tweets in column (2) which yields a much higher $R^2 = 0.32$. The result shows that both the false Tweets and correction Tweets diffuse faster than the Tweets of the true news. The correlations are statistically significant. Moreover, the significantly negative coefficient of the *time elapsed* tells that the news diffusion gets slower over time. This is intuitive as the news attained less attention as time goes by. Hence, less people would continue to circulate the news and also at a lower speed. The difference between the effects of *Size* and *Breadth* is interesting. On the one hand, a larger size (i.e. more existing Tweets) correlates with a higher speed, which is due to the definition of Speed_2. On the other hand, a faster diffusion correlates with less breadth (i.e. the existing tweet origins). It indicates that, when there are less tweet origins, the diffusion gets faster.

Column (3) adds more user's information onto the base model. It does not provide significant findings, nor the explanatory power of this model is strong ($R^2 = 0.026$). The full model specification is displayed in column (4). All the findings in column (2) are enhanced. Especially, the false news diffuses faster than the true news. Moreover, keeping other variables fixed, the number of friends positively correlates with the diffusion speed of the Tweet posted by the corresponding user. Friends are those whom the user follows. Most of the time, a user gets the information from his friends, because the friends' activities would be displayed on the user's time line. Therefore, having more friends increase the probability for a user to expose to news and retweet it, which facilitates the news diffusion. However, this is not the case for the user's followers. One rarely sees his friends' posts through his own timeline. Hence, there is not much effect of the number of followers on the diffusion rate. Although the coefficient of the number followers number is positive, it is not statistically significant. Last but not least, a user with more historical posts tends to diffuse the news much faster. This might be explained by the user's activity habit, such as how frequent he is active on Twitter.

I also regressed on *Speed_1* and *Speed_3*. The results are displayed in columns (5) and (6). Both performed worse than *Speed_2*, hence I will only consider about *Speed_2* in the future analysis.

5.3 Regression on Diffusion Pattern: Size

Table 6 displays the regression results on *Size* (the total number of Tweets). Similar to the case of Speed_2, column (1) is the base model only including the veracity of the news. Columns

(2) and (3) add more news diffusion characteristics and user's information. The full result is shown in column (4) which explains around 80% of the variations in the *Size* of news diffusion, and the effects are significant. Firstly, false news diffusion has smaller size compared with the true ones. This is inconclusive, because the false news studied in the paper are systematically small-scaled.

Table 6: Regression on Size

	Dependent variable: Size			
	Base (1)	Add Tweet Info (2)	Add User Info (3)	Full (4)
"Correction" Tweets	-370.23*** (18.991)	-370.23*** (18.991)	-367.28*** (18.939)	-671.60*** (12.128)
"False" Tweets	-503.69*** (15.412)	-641.68*** (9.622)	-507.35*** (15.406)	-650.68*** (9.529)
Time elapse		0.446*** (0.038)		0.433*** (0.037)
Depth		29.60*** (4.167)		28.67*** (4.096)
Speed_2		11.51*** (0.655)		11.23*** (0.648)
Breadth		1.38*** (0.023)		1.39*** (0.023)
Tweet origin		-11.31 (9.115)		-0.30 (9.102)
User_Favorite			0.001*** (0.0002)	0.0004*** (0.0001)
User_Friend			0.001 (0.001)	0.002*** (0.001)
User_Follower			-0.001*** (0.0001)	-0.0005*** (0.0001)
User_Tweet_Post			-0.0001 (0.0001)	-0.0001*** (0.00004)
Constant	801.69*** (14.283)	557.13*** (13.143)	799.16*** (14.716)	558.18*** (13.102)
Observations	2,331	2,331	2,331	2,331
R2	0.32	0.78	0.33	0.78

Note: *p<0.1; **p<0.05; ***p<0.01

For the news diffusion involving users who have liked more other users' tweets but himself posting less Tweets and make more friends but with less followers, it usually has a larger diffusion size. Interestingly, the number of user's followers and the historical posts negatively affect the news diffusion size. One potential explanation could be: a user usually reads Tweets via his time line. If a user has more friends, he will read their posts and the probability of on Tweet being retweeted by him gets higher. So the size of the news diffusion is larger.

5.4 Regression on Diffusion Pattern: Breadth

The regression on breadth (the total number of tweet origins) is in Table 7. Notice that most effects in columns (1) ~ (3) coincide with the result of column (4). First of all, the false news is generally more popular and hence being circulated broader. However, such popularity seems to be depressed by the news diffusion speed, (a statistically significant negative coefficient -19,351.960). This negative correlation is consistent with the result in Table 5.

As for the effect of the engaged users, I observe the opposite effects of user's friend number, follower number, total Tweets number and the number of Tweets he ever liked in Table 6 column (4). Specifically, For the news diffusion involving users who have liked less other users' tweets but himself posting many Tweets and make less friends but with more followers, it usually has a larger diffusion *breadth*.

5.4 Only False News

Next, I hope to study how the diffusion of false news is affected by the Tweet characteristics and the engaged users. Three specifications have been modeled as shown in Table 8. Column (1) shows that among the Tweets propagating false news, the later generated Tweets (a larger *Time_Elapse* value) spread slower. This is intuitive and consistent with the observations from Figure 1 panels (b) and (d). However, the opposite signs of the coefficients of *Size* (the total Table 7: Regression on Breadth number of Tweets) and *Breadth* (total number of tweet origins) are interesting. It tells that when there are more existing Tweets (larger *Size*), the diffusion speed at the same time is faster. This may be merely due to the fundamental definition of *Speed_2* (i.e. $\frac{\#Tweets\ by\ ElapsedTime_i}{ElapsedTime_i}$). However, when there are more existing tweet origins (lager *Breadth*), the diffusion speed is reduced, and the result is robust by replacing *Speed_1* by *Speed_2*. This is because the more tweet origins appeared, the closer to the end of the news life span, and intuitively the speed slowed down. Column (2) summarizes the results of the regression on *Size*. The positive coefficients of *Time_Elapse*, *Hop_Position* and *Speed_2* depict the simple story that as time goes by, for a Tweet located at a deeper hop and diffuses faster, the *Size* of the diffusion gets larger.

Table 7: Regression on Breadth

	Dependent variable: Breadth			
	Base (1)	Add Tweet Info (2)	Add User Info (3)	Full (4)
"Correction" Tweets	232.02*** (10.364)	386.60*** (6.648)	231.28*** (10.453)	388.99*** (6.606)
"False" Tweets	115.27*** (8.411)	334.85*** (6.072)	115.29*** (8.503)	341.52*** (6.070)
Time_Elapse		-0.005 (0.022)		-0.008 (0.022)
Depth		-15.76*** (2.343)		-15.38*** (2.315)
Speed_2		-5.45*** (0.375)		-5.38*** (0.372)
Size		0.44*** (0.007)		0.44*** (0.007)
Tweet_Origin		-7.72 (5.119)		-12.54** (5.132)
User_Favorite			0.00 (0.000)	-0.0002*** (0.0001)
User_Friend			-0.001* (0.001)	-0.001*** (0.0003)
User_Follower			0.00 (0.000)	0.0002*** (0.00004)
User_Tweet_Post			0.00 (0.000)	0.0001*** (0.00002)
Constant	80.66*** (7.795)	-228.70*** (8.611)	81.13*** (8.122)	-233.08*** (8.610)
Observations	2,331	2,331	2,331	2,331
R^2	0.18	0.71	0.18	0.72

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8: False News Diffusion

	Dependent variable: Speed_2/ Sixe/ Breadth		
	Speed_2 (1)	Size (2)	Breadth (3)
Time_Elapse	-0.03*** (0.001)	0.12*** (0.027)	0.02 (0.018)
Depth	-0.27* (0.152)	27.34*** (2.698)	-18.05*** (1.797)
Size	0.01*** (0.001)		0.60*** (0.007)
Speed_2		4.12*** (0.435)	-2.80*** (0.289)
Breadth	-0.02*** (0.002)	1.35*** (0.016)	
Tweet_Origin	-1.34*** (0.374)	-19.27*** (6.854)	3.23 (4.572)
User_Favorite	-0.00001* (0.000)	0.0002*** (0.000)	-0.0002*** (0.00005)
User_Friend	0.0001*** (0.000)	0.002*** (0.001)	-0.002*** (0.0004)
User_Follower	-0.00 (0.000)	0.00 (0.000)	0.00 (0.000)
User_Tweet_Post	0.00001*** (0.000)	-0.00 (0.000)	0.00005** (0.00002)
Constant	8.92*** (0.405)	-2.073 (8.403)	37.68*** (5.518)
Observations	1,691	1,691	1,691
R2	0.32	0.84	0.83

Note: *p<0.1; **p<0.05; ***p<0.01. The dataset is the one only containing *false* Tweets. The *true* and *correction* Tweets have been filtered out in this regression.

Moreover, the negative coefficient of *Tweet_Origin* tells that by the time a tweet origin was posted, the *Size* of the diffusion patter was still small. This indicates that Tweets were generated at early period when the *Size* of the news diffusion is still growing. This could be reflected from Figure 4.

The *Breadth* specification model is in column (3). The most interesting findings are the two significantly negative coefficients of the user’s friend number and liked posts number. For a user with more friends, by the time he posted the Tweet containing false news, the *Breadth* is still small. This indicates that user with more friends tends to act earlier in the news diffusion, which is intuitive if more friends provide more information sources for him.

Table 9: Logistic Regression

	Dependent variable: Veracity					
	Base (1)	Logit Base (2)	User (3)	Logit User (4)	Full (5)	Logit Full (6)
Tweet Origin	0.19*** (0.023)	2.17*** (0.291)			0.19*** (0.023)	2.22*** (0.297)
Depth	0.04*** (0.010)	0.57*** (0.182)			0.04*** (0.010)	0.63*** (0.186)
Speed_2	0.01*** (0.001)	227.2*** (49.545)			0.006*** (0.001)	246.1*** (50.344)
Breadth	0.001*** (0.0001)	0.014*** (0.001)			0.001*** (0.0001)	0.014*** (0.001)
User_ Favorite			-0.00* (0.000)	-0.00* (0.000)	0.00 (0.000)	-0.00 (0.000)
User_ Friend			-0.00 (0.000)	-0.00 (0.000)	-0.00 (0.000)	-0.00 (0.000)
User_ Follower			-0.00*** (0.000)	-0.00*** (0.000)	-0.00*** (0.000)	-0.00*** (0.000)
User_Tweet_ Post			-0.00 (0.000)	-0.00 (0.000)	-0.00** (0.000)	-0.00** (0.000)
Constant	0.53*** (0.026)	-1.93*** (0.315)	0.88*** (0.009)	1.944*** (0.073)	0.545*** (0.026)	-1.87*** (0.320)
Observations	1,969	1,969	1,969	1,969	1,969	1,969

Note: *p<0.1; **p<0.05; ***p<0.01. The dependent variable is *Veracity*. The dataset is the one only containing *true* and *false* Tweets. The correction Tweets have been filtered out in this regression.

5.5 Logistic Regression

Table 9 displays the result of the logistic regression on the news veracity, i.e. true or false news. The base is the true news. Columns (1) and (2) only includes the features of the diffusion pattern. It tells that the false news diffuses faster, deeper, and broader than the true news, which is consistent with the previous findings in Tables 5~8. Column (2) only considers about the characteristics of the engaged users. It tells that a false news is more likely to be circulated among users who has less followers and more likely to like other users' posts. Column (3) provides the full specification. Although the numerical values of the effect change slightly, most of the significance levels are retained. False news diffuses faster, deeper, and broader compared with the true news; and it is more likely to be diffused among users who have less followers and post less Tweets previously.

Table 10: Robustness Checking Logistic Regression

	Dependent variable: Random_Veracity					
	Base (1)	Logit Base (2)	User (3)	Logit User (4)	Full (5)	Logit Full (6)
Tweet Origin	-0.002 (0.035)	-0.003 (0.144)			0.01 (0.036)	0.03 (0.148)
Depth	0.023 (0.015)	0.096 (0.065)			0.02 (0.015)	0.09 (0.065)
Speed_2	-0.001 (0.002)	-0.005 (0.009)			-0.001 (0.0001)	-0.01 (0.009)
Breadth	0.0001 (0.0001)	-0.0005 (0.000)			0.00 (0.000)	-0.00 (0.000)
User_ Favorite			0.00 (0.000)	0.00 (0.000)	0.00 (0.000)	0.00 (0.000)
User_ Friend			0.00 (0.000)	0.00 (0.000)	0.00 (0.000)	0.00 (0.000)
User_ Follower			-0.00 (0.000)	-0.00 (0.000)	-0.00 (0.000)	-0.00 (0.000)
User_Tweet_ Post			-0.00 (0.000)	-0.00 (0.000)	-0.00 (0.000)	-0.00 (0.000)
Constant	0.52*** (0.040)	0.06 (0.161)	0.49*** (0.009)	-0.04 (0.051)	0.505*** (0.040)	0.01 (0.165)
Observations	1,969	1,969	1,969	1,969	1,969	1,969

Note: *p<0.1; **p<0.05; ***p<0.01. The dependent variable is the randomly labeled Randome_*Veracity*. The dataset is the one only containing *true* and *false* Tweets. The correction Tweets have been filtered out in this regression.

5.6 Robustness Checking

To check the robustness of the results. I randomly labeled the Tweets either *true* or *false*. The logistic regression is rerun as shown in Table 10. Compare tables 9 and 10. All the effects of variables on the veracity have disappeared when the veracity was randomly labeled. This distinct discrepancy in the regression results substantiate that the results in Table 9 are meaningful.

6 Conclusion

Online social networks facilitate the information propagation, but also nurtures more false news or misinformation. Its circulation through the social networks makes unnecessary chaos and panic of the online community, causes people's misconceptions of the events, and even possibility affects the democracy of the society. Hence, having deeper understanding about false news diffusion is critical to solve or at least alleviate the problem.

In this paper, I study how false news diffuses over time, how its diffusion pattern different from the true counterparty, and how the difference correlates with the Tweet and the engaged user's characteristics. I find that, false news diffuses quickly. A majority of the Tweets (over 70%) containing this false news were posted by the middle of the false news life span. In contrast, the Tweets containing the true news appear more evenly throughout the life of the news. Moreover, false news diffuses faster, broader, and deeper than the true news. More specifically, both Tweets of false news and Tweets correcting the false news are propagated faster than the true news. I also studied the correction mechanism of the Twitter community and identify three distinctive false-correction features, namely the *concurrent*, *gothic*, and *camel* features. Examine these features might be helpful to curb or control false news diffusion.

Surprisingly, the users engaged in transmitting false news have less followers. This is beyond the conventional assumption that users spreading false news should have a larger number of followers so that their Tweet of false news could reach more people and easier diffuses. This divergence from the expectation could be explained by the purpose of propagating false news. Admittedly, if the user is transmitting the false news on purpose, he might try to "solicit" more followers first so that to make the false news diffuse faster and broader. However, if the user transmitted the false news merely due to it is interesting, funny or surprising, then there should not be obvious correlation between posting false Tweet and having more followers. Henceforth, we could further study on this topic as it might be helpful to classify the "intentional" users posting false news.

There are several aspects could be improved. Firstly, the *true* and *false* news are of different topics. Although the variable *News_Tag* induces the fixed effect of each news, *true* and *false* news diffusions are more comparable if the news are of the same topic. For instance, *News 2* and *New 7* are both about Facebook. Secondly, among the engaged users in this study, some may be bots which might act differently from human beings and hence distort the results. Last but not least, the sample size is relatively small. It might be subject to selection bias, and the findings are hard to be generalized. In short, integrating more same-topic news pairs (i.e. one *true*, one *false*) and accounting for the bots issue is the focus of my future research.

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