Information Diffusion in Social Networks

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Information Diffusion

- The process by which a piece of information is communicated through certain channels over time among the members of a social system

Why?

- Knowing what information is being produced and where,

along with

- where, how and why it is being transferred

will help in identifying the hidden functionalities, the anatomy and the intricacies of Social Networks and to false news detection.

So what?

- Critical or malicious information can spread uncontrollably over a network. The management and prediction of information diffusion in Social Networks is not possible until there is a model that can capture and analyse the hidden mechanism underlying diffusion.

- Researchers have in recent years developed a variety of techniques and models to capture Information Diffusion in Social Networks, analyse it, extract knowledge from it and predict it.

Linear Threshold & Independent Cascades

Graph-based models - nodes are users, edges are relations

Diffusion:

1. LT: Adjacent edges have a weight sum > threshold (receiver-centric)
2. IC: Probability p per edge (sender-centric)

Weights or probabilities - Maximum Likelihood problem

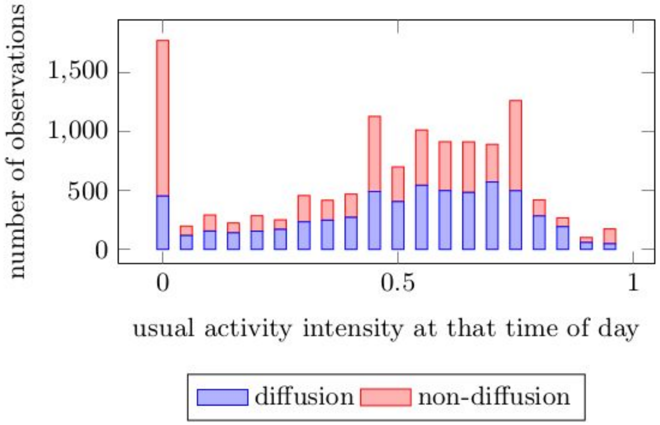
Discrete time-steps - not like in real world

Solve by using a time-delay δ

AsIC

Asynchronous Independent Cascades - use a time delay δ after which they retry activating adjacent nodes

Active user time plays an important role - use it in parameter estimation

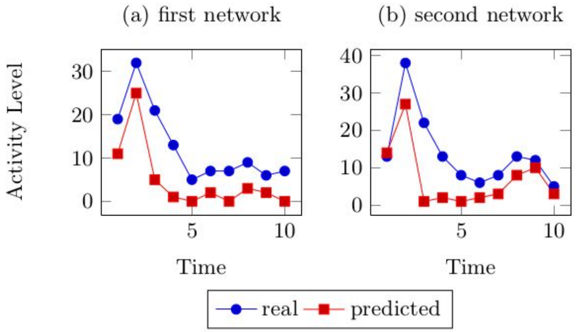


AsIC-Extended

Estimating parameters with Bayesian Logistic Regression

Given a feature vector V (social, semantic and temporal features), the goal is to estimate the probability P(Y|V), where Y={diffusion, non-diffusion}

Tested on a dataset of 467 million tweets from 20 million users



Topic: acquisition of a startup by Google

Epidemiological Models - SEIZ

Information spreading modelled as an epidemic

4 types of users:

1. Susceptible (S) - not yet received the piece of information under study
2. Exposed (E) - have received the information, but have not tweeted yet about it
3. Infected (I) - have tweeted this piece of information
4. Skeptic (Z) - have received the information but choose not to tweet about it

Epidemiological Models - SEIZ

Users can move around categories with the following rules:

- With rate b, susceptible users may become skeptic with probability l, or they may become exposed with probability (1-l)
- A susceptible user will automatically believe a news story or rumor with probability p, or he will be moved to the exposed category with probability (1-p)$
- Exposed users can turn into infected by i) coming in contact with another infected user, with contact rate ρ, ii) or by themselves, with rate ε.

Epidemiological Models - SEIZ

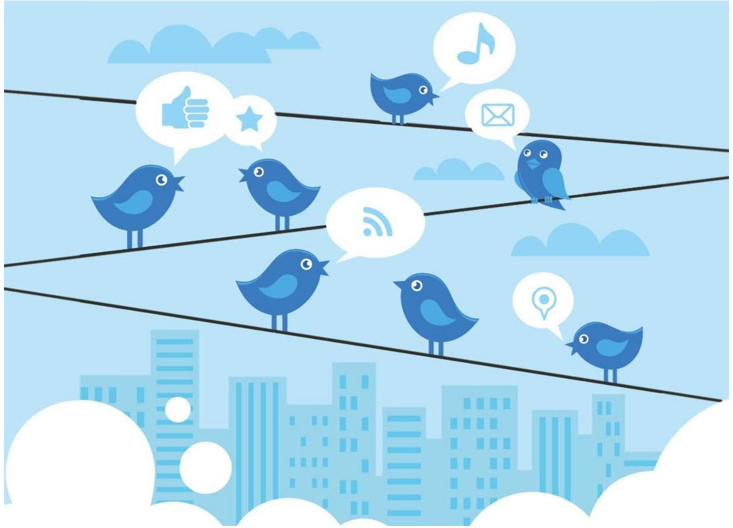
Parameter estimation by solving Ordinary Differential Equations

Tested on gathered tweets about specific topics, both news, like the Boston Marathon Bombings and rumors, like the Doomsday of December 21 2012

$$\frac{d[S]}{dt} = -\beta S \frac{I}{N} - bS\frac{Z}{N}$$
$$\frac{d[E]}{dt} = (1-p)\beta S\frac{I}{N} + (1-l)bS\frac{Z}{N} - \rho E\frac{I}{N} - \epsilon E$$
$$\frac{d[I]}{dt} = p\beta S\frac{I}{N} + \rho E\frac{I}{N} + \epsilon E$$
$$\frac{d[Z]}{dt} = lbS\frac{Z}{N}$$

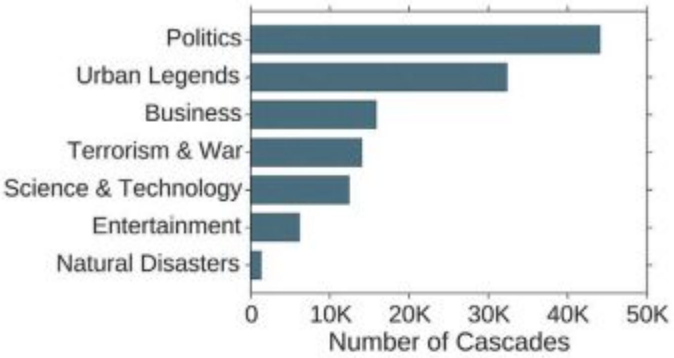
The spread of true and false news

- What is a rumor cascade?
    - If a rumor “A” is tweeted by 10 people separately, but not retweeted, it would have 10 cascades, each of size one. Conversely, if a second rumor “B” is independently tweeted by two people and each of those two tweets is retweeted 100 times, the rumor would consist of two cascades, each of size 100.

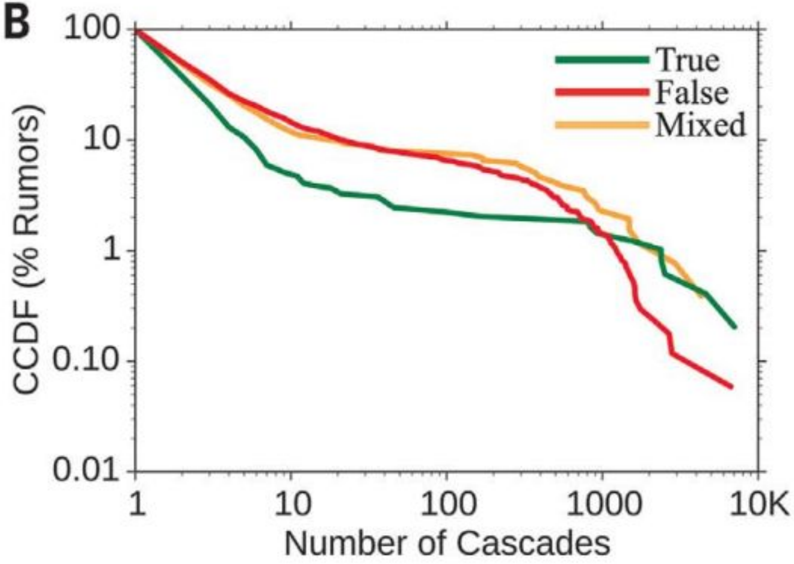


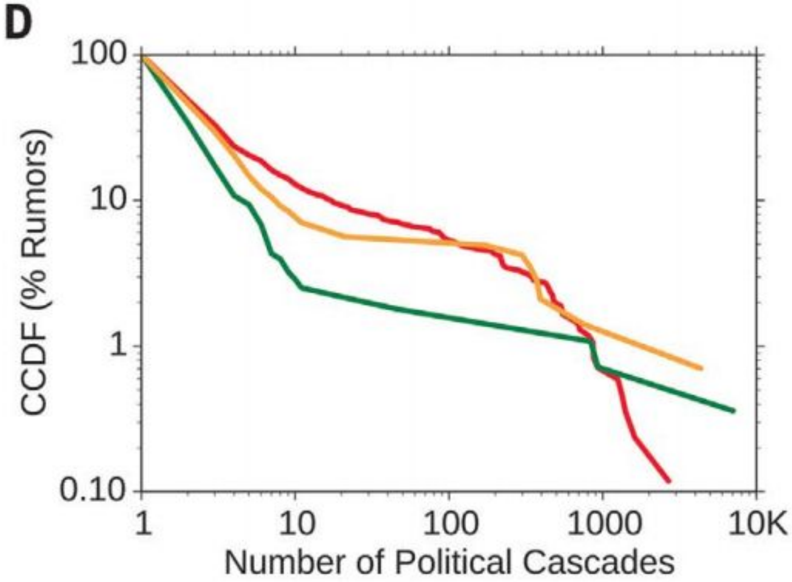
The spread of true and false news - Dataset

- Investigation of the differential diffusion of true & false news
- Tweets from 2006 - 2017
- ~126,000 rumor cascades
- Source: six - fact checking organization (snopes.com, politifact.com, factcheck.org, truthorfiction.com, hoax-slayer.com, urbanlegends. about.com)



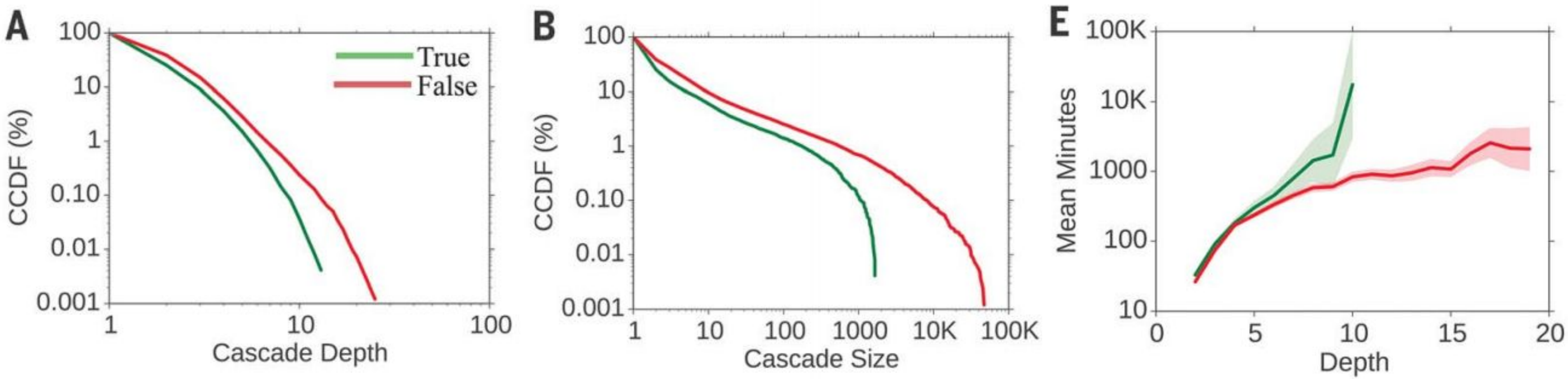
The spread of true and false news





The spread of real and false news

➔ False rumors diffused significantly farther, faster, deeper, and more broadly than the truth in all categories



Who spread falsity?

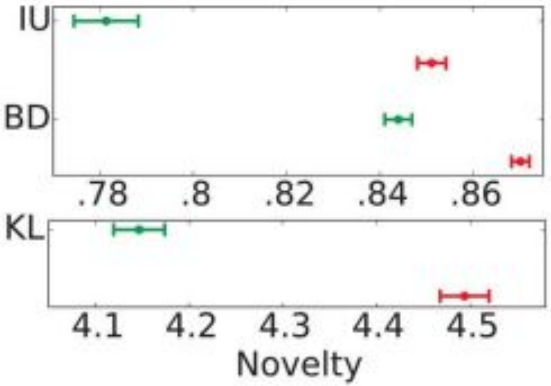
- Intuition: those who spread falsity “followed” more people, had more followers, tweeted more often, were more often “verified” users, or had been on Twitter longer?

➔ **Falsehood** diffused farther and faster than the truth **despite these differences**, not because of them.

	median		mean		mean (log)		stdv (log)		ks-test
	false—true		false—true		false—true		false—true		
followers	410	466	2234	5240	2.62	2.68	0.69	0.88	D=0.104, p~0.0
followees	383	509	1002	1707	2.59	2.72	0.85	0.96	D=0.136, p~0.0
verified	0	0	0.002	0.006	nd	nd	nd	nd	D=0.005, p<0.001
engagement	9.52	9.54	19.70	24.65	0.91	0.90	0.65	0.76	D=0.054, p~0.0
account age	982	1214	1072	1269	2.90	2.97	0.39	0.42	D=0.125, p~0.0

What affects people to spread falsity?

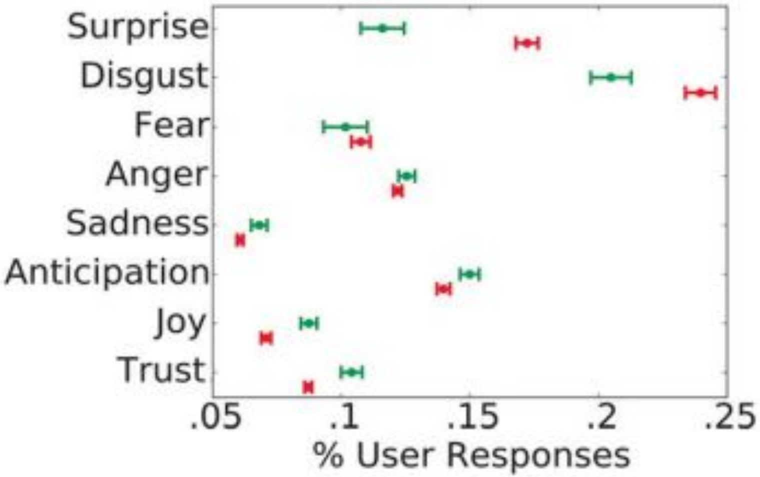
- **Novelty** (contributes to productive decision-making, and encourages information sharing because novelty updates our understanding of the world)
- comparing the topic distributions of the rumor tweets with the topic distributions of the tweets to which users were exposed in the 60 days before their retweet



What about the emotional content?

- ~140,000 English words and their associations with eight emotions based on Plutchik's work on basic emotion

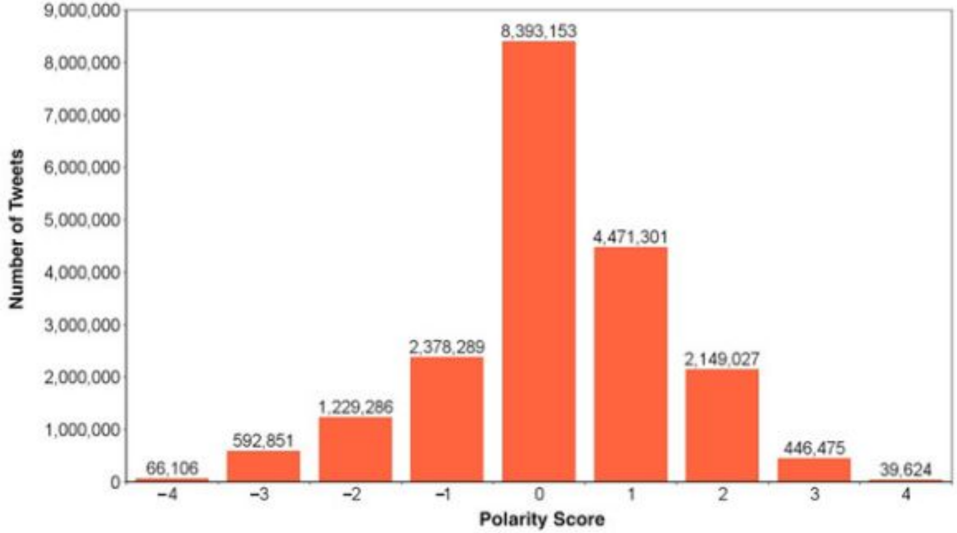
Falsity:
Surprise
Disgust



Truth:
Sadness
Anticipation
Trust

Quantifying the effect of sentiment - Sentiment analysis

- Dataset: 19,766,112 tweets & 8,130,481 distinct user (September 2014)
- SentiStrength algorithm
- Polarity score: S(t) range: -4 to 4



Positive score (1-5)

Negative score (1-5)

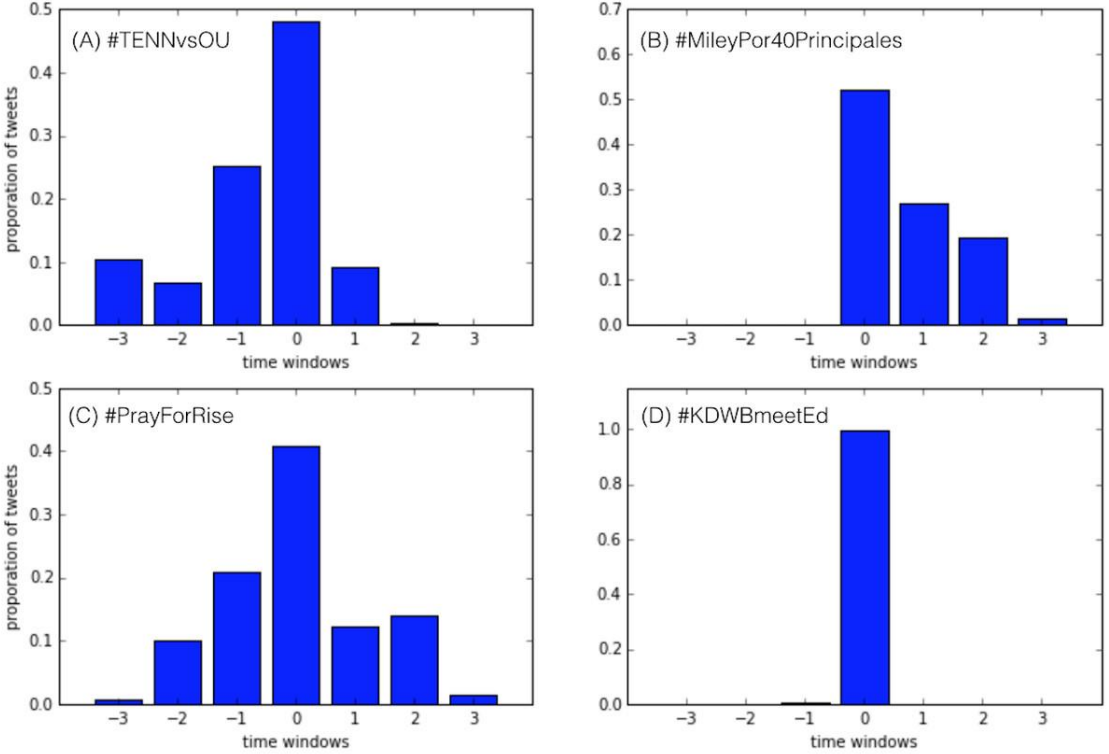
$S(t)=S^{+}(t)-S^{-}(t)$

S=0 (42,46%)
S>=1 (35,95%)
S<=1 (21,59%)

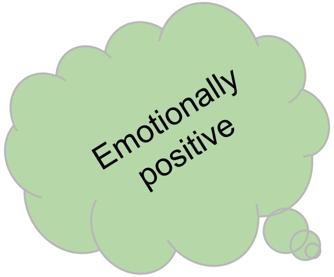
Quantifying the effect of sentiment - Results (2)

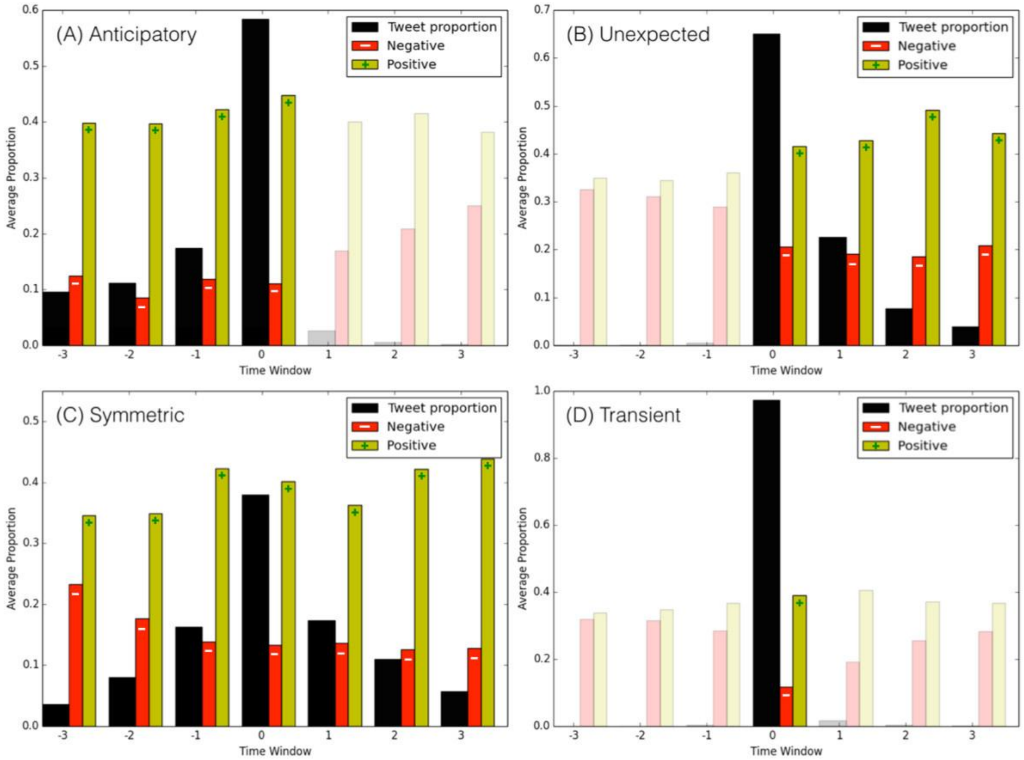
Four classes of conversations:

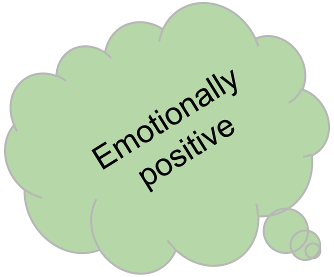
1. *anticipatory discussions*
2. *unexpected events*
3. *symmetric discussions*
4. *ransient events*



Quantifying the effect of sentiment - Results (3)







Fake Images Diffusion on Twitter

- People tend to share also media in Twitter and a common way of misinformation is using images or videos.
- One of the papers we studied have collected images from tweets about the Sandy Hurricane.

Dataset

- Collecting tweets for about 20 months, and filter them to contain the keywords 'sandy' and 'hurricane' resulted in:
  - 1,782,526 tweets
  - 1,174,266 unique users
  - 622,860 tweets with URL

Dataset

- They manually tagged each photo to be real or fake based on online sources.
  - Tweets with fake images: 10,350
  - Users with fake images: 10,215
  - Tweets with real images: 5,767
  - Users with real images: 5,678

Methodology

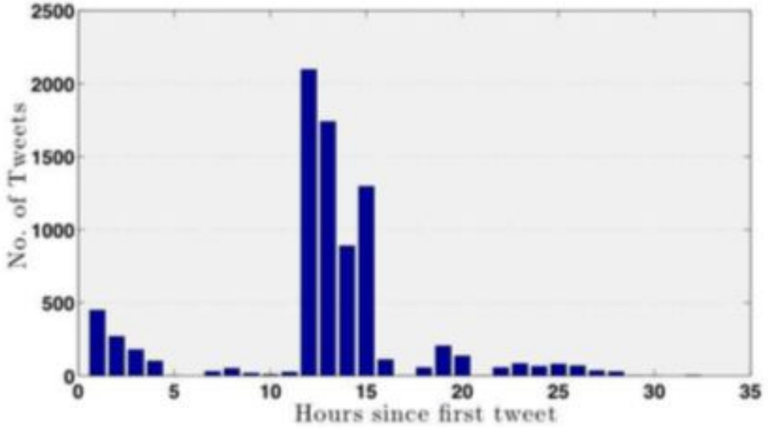
- They analyzed how many such tweets were shared per hour on Twitter. Also analyzed the sudden peaks from hour to hour in the graph to find out what changes in the network topology lead to the viral spread of these images.

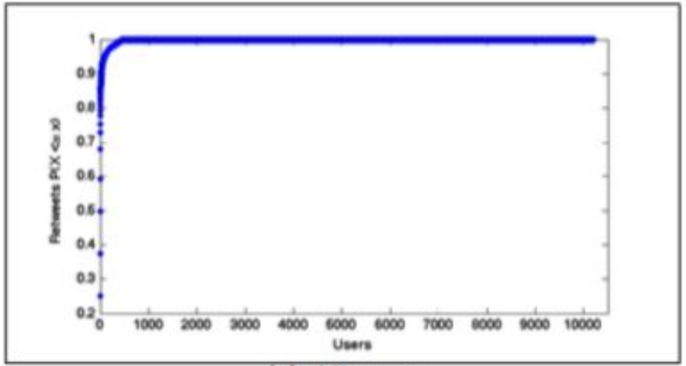
- They studied what role the social network graph of a user on Twitter plays in propagation of fake URLs by analyzing what percentage of information diffusion takes place via this follower network graph of a user.

Results (1)

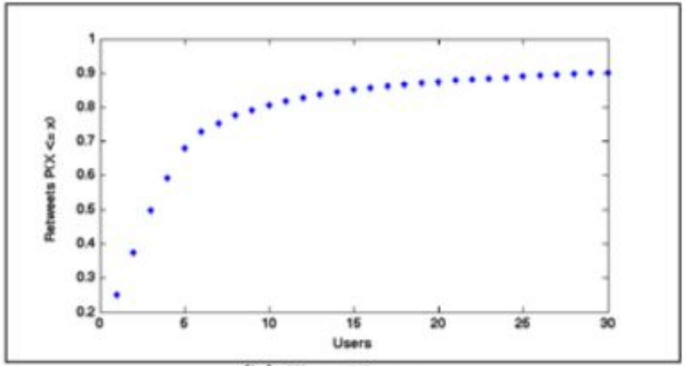
- 86% of the tweets containing fake URLs were retweets.
- Only 14% of people originally tweeted fake content.
- The fake URLs were present in the Twitter network for almost 12 hours before they became viral.
- The sudden spike in their propagation via retweets happened only because of a few users.

Results (2)



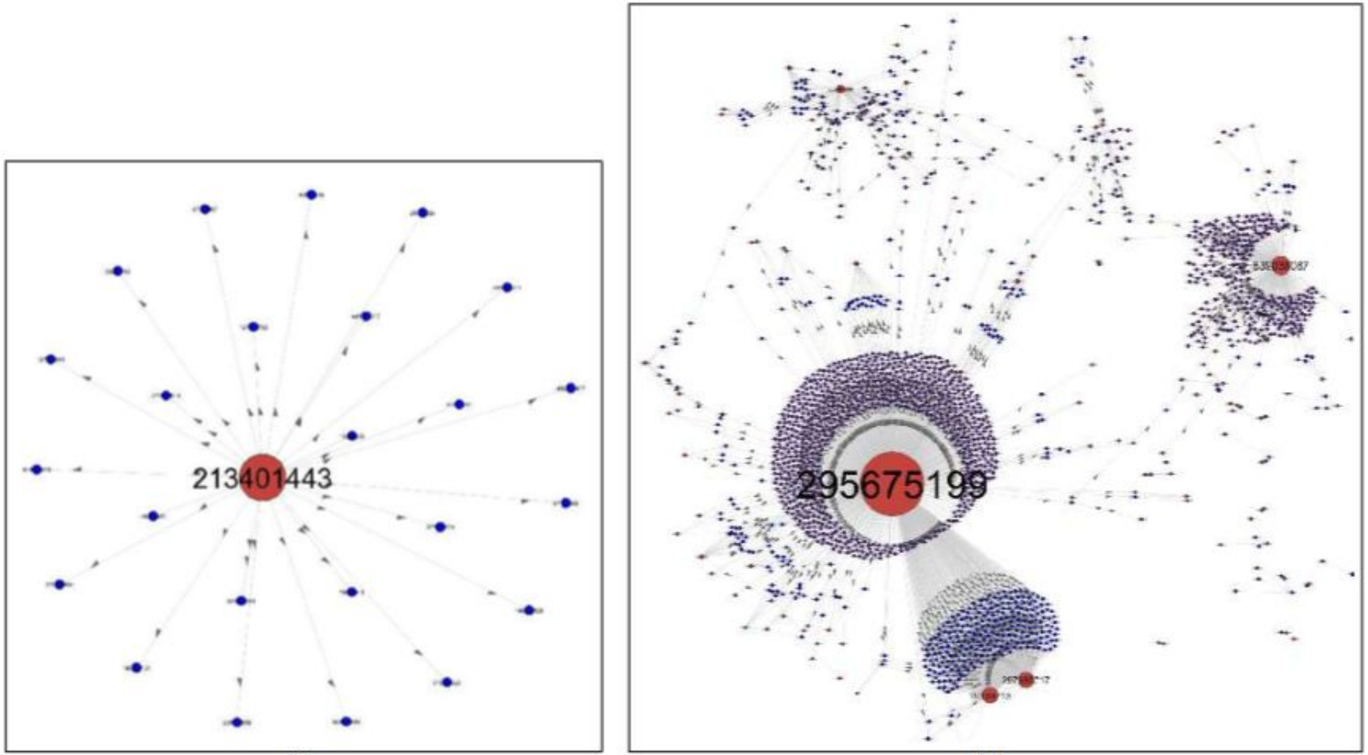


(a) All users



(b) Top 30 users

Results (3)



(a) (b)

Results (4)

- They ran an algorithm named ‘Compute overlap.
- They found the number of overlapping edges as 1.215, which leads to a percentage overlap of 11% between the retweet and follower graphs.

In cases of crisis, people often retweet and propagate tweets that they find in Twitter search or trending topics, irrespective of whether they follow the user or not.

Information Diffusion in Implicit Networks

- **Implicit Network:** graph whose nodes or edges are not represented as explicit objects in a computer's memory, but are determined algorithmically from some input.

They can only observe when nodes got “infected” but not *who* infected them.

➔ **LIM model:** focuses on the global influence a node has on the rate of diffusion through the (implicit) network.

LIM - Linear Influence Model (1)

- The number of newly infected nodes depends on which other nodes got infected in the past
- Each node has an *influence function $Iu(t)$* associated with it
- $Iu(t)$ represents the number of follow-up mentions, t time units after node u mentioned the information

LIM - Linear Influence Model (2)

- Nodes become “infected” when they mention the information
- They define the *volume* $V(t)$ as the number of nodes that mention the information at time t

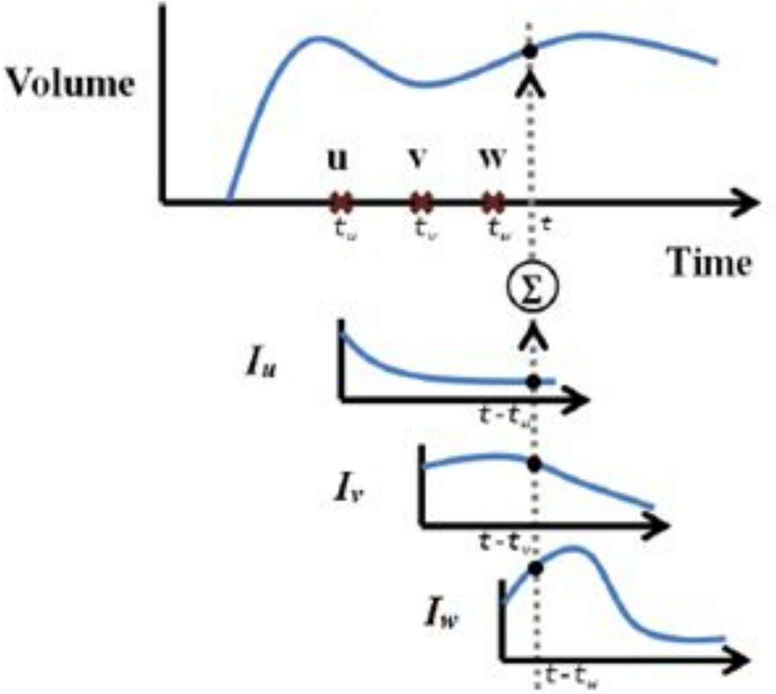
➔ **Aim**: relation between the volume $V(t)$, and the influence functions *Iu(t)* of nodes u that mention the information at times *tu (tu* < *t)*

- *A(t): the set of already active nodes*

$$V(t+1) = \sum_{u2A(t)} Iu(t - tu)$$

LIM - Linear Influence Model (3)

- First curve: volume over time
- Nodes u, v, w got infected at times tu, tv, tw
- Sum of Iu, Iv, Iw at time unit t-tu gives the overall V(t) at that time



Extensions

- **Time:** nodes are more likely to mention recent information while ignoring old
  - *a*(*t*) factor models how much more/less influential a node is at the time when it mentions the information

$$V(t+1) = a(t) \sum_{u2A(t)} Iu(t{-}tu)$$

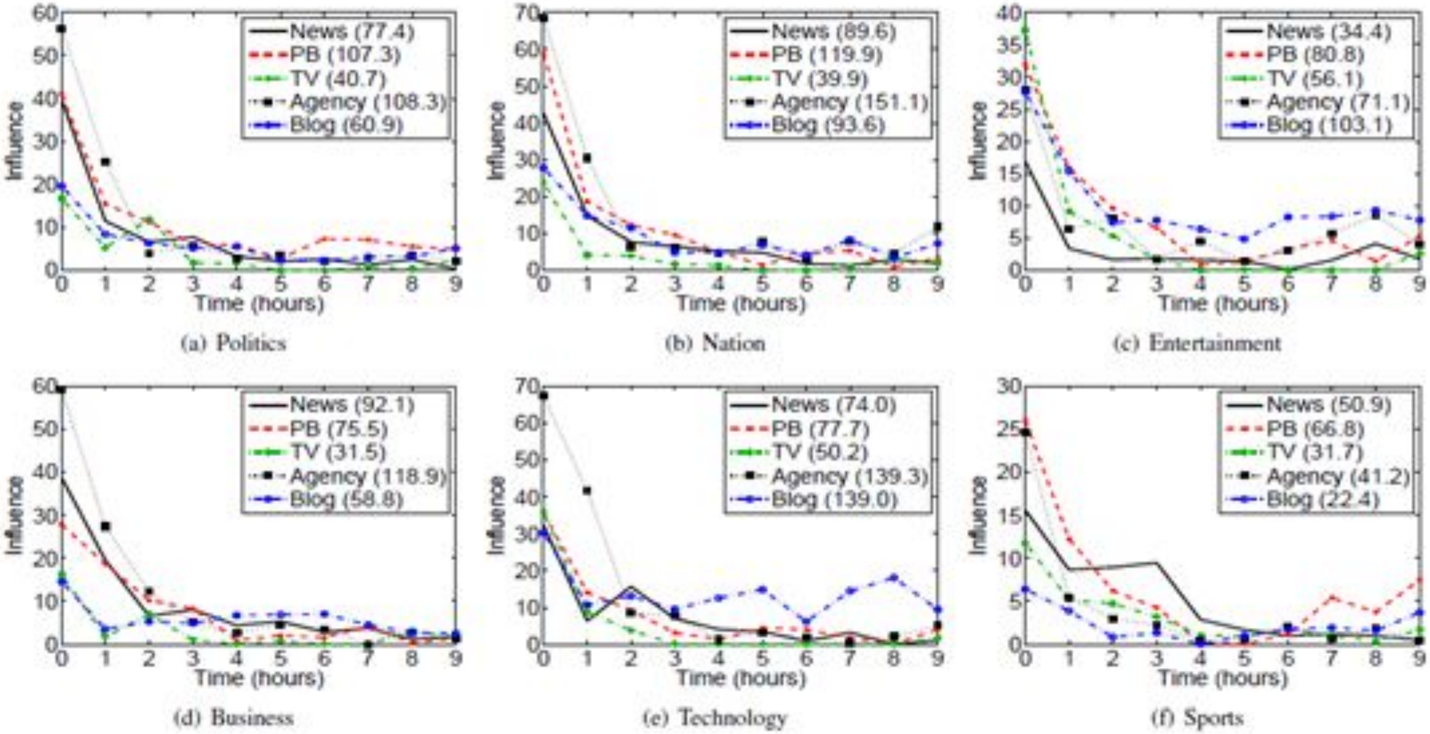
- **Imitation:** some nodes imitate one another because the information is popular and everyone talks about it
  - Factor *b(t)*

$$V(t+1) = b(t) + \sum_{u2A(t)} Iu(t{-}tu)$$

Memetracker Dataset

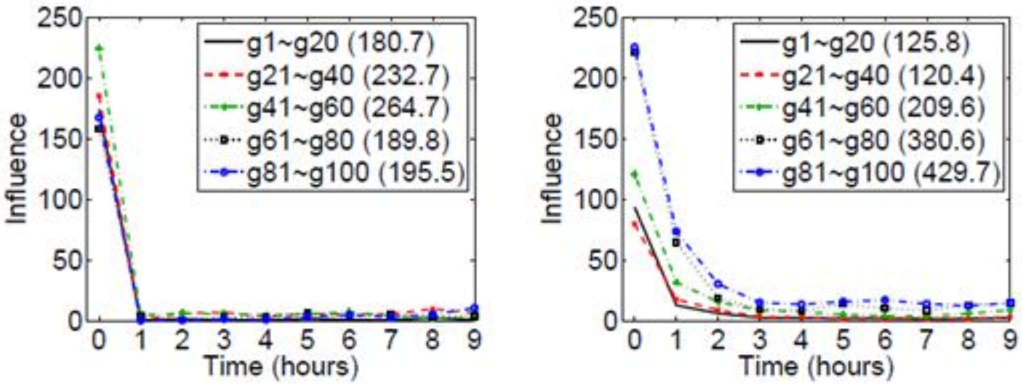
- Tracks quotes and phrases that appear most frequently over time across this entire online news spectrum
- 343 million short textual phrases from a set of 172 million news articles and blog posts
- **5 types of media**: Newspapers, Professional blogs, TV stations, News agencies and (persoal) Blogs
- **6 topics**: Politics, Nation, Entertainment, Business, Technology, Sports

Results


News (77.4)
PB (107.3)
TV (40.7)
Agency (108.3)
Blog (60.9)
Influence
Time (hours)
(a) Politics
News (89.6)
PB (119.9)
TV (39.9)
Agency (151.1)
Blog (93.6)
Influence
Time (hours)
(b) Nation
News (34.4)
PB (80.8)
TV (56.1)
Agency (71.1)
Blog (103.1)
Influence
Time (hours)
(c) Entertainment
News (92.1)
PB (75.5)
TV (31.5)
Agency (118.9)
Blog (58.8)
Influence
Time (hours)
(d) Business
News (74.0)
PB (77.7)
TV (50.2)
Agency (139.3)
Blog (139.0)
Influence
Time (hours)
(e) Technology
News (50.9)
PB (66.8)
TV (31.7)
Agency (41.2)
Blog (22.4)
Influence
Time (hours)
(f) Sports

Twitter Dataset

- 10,000 Twitter users
- Aggregate them into 100 groups of 100 users
- 2 different types of grouping:
    - Amount of activity (e.g. hashtag volume)
    - Followers count



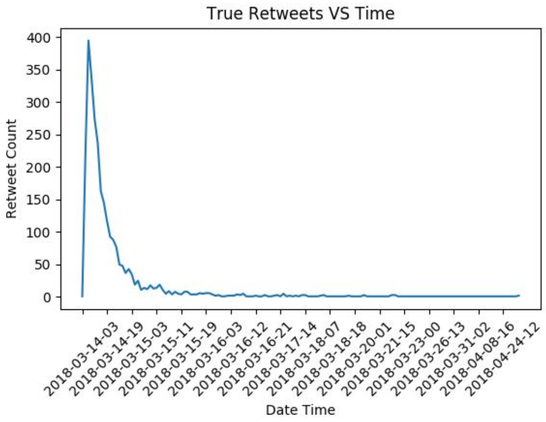
(a) Average influence functions of each group based on volumes

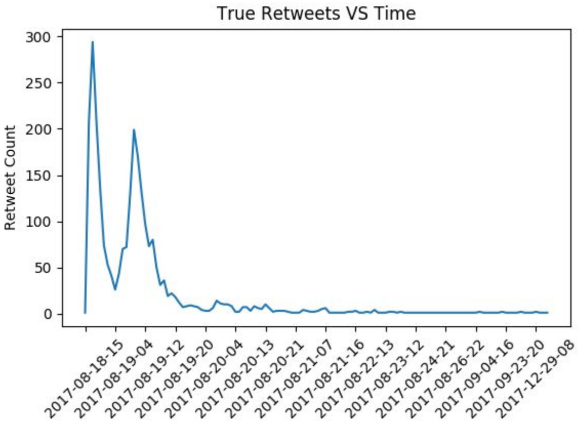
(b) Average influence functions of each group based on follower counts

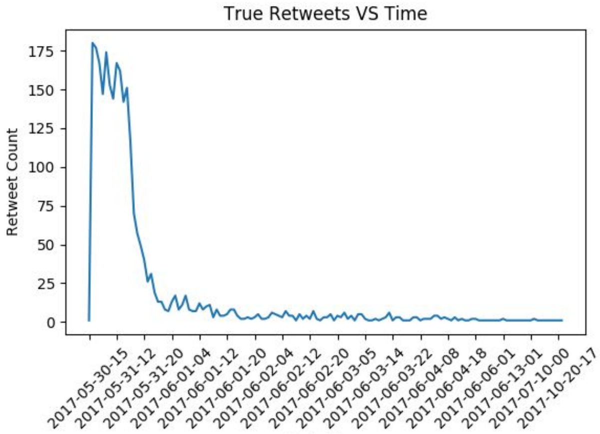
Our project on Twitter Dataset

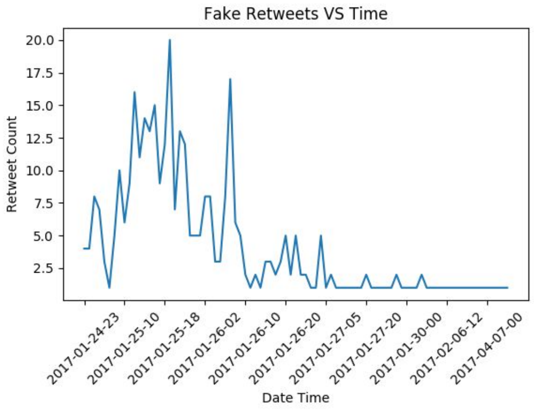
- Real news account: BBCBreaking
- Fake news account: BurrardStreetJ

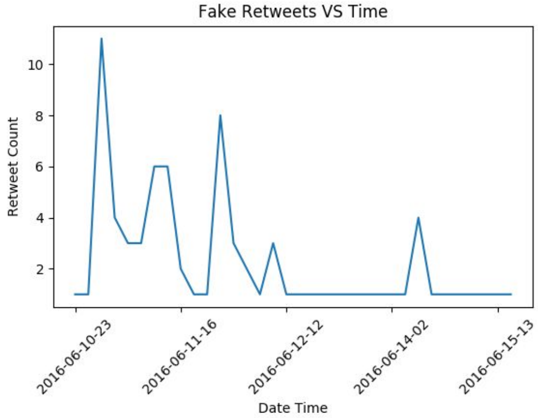
Our Results - Real vs Fake (Retweets)

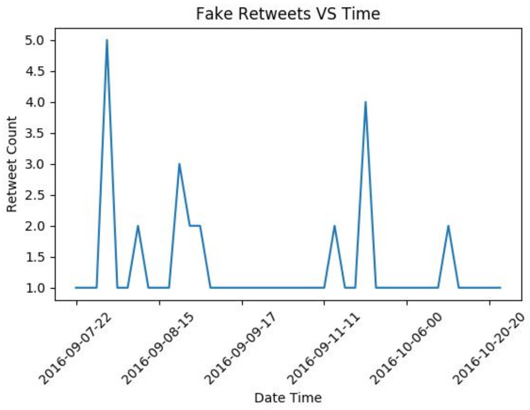










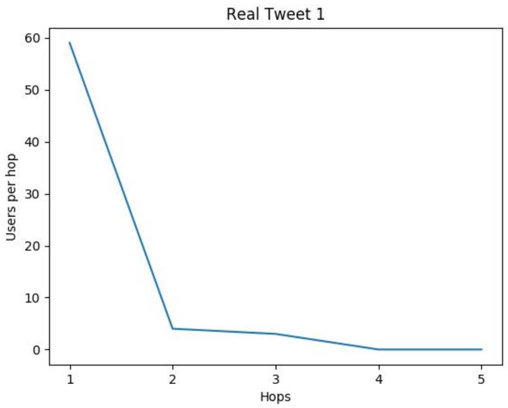


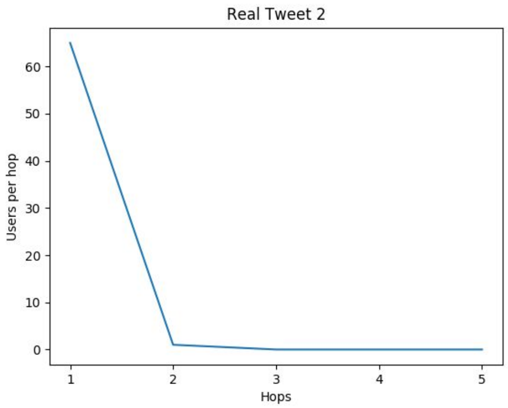
Our Results - Real vs Fake (Retweets)

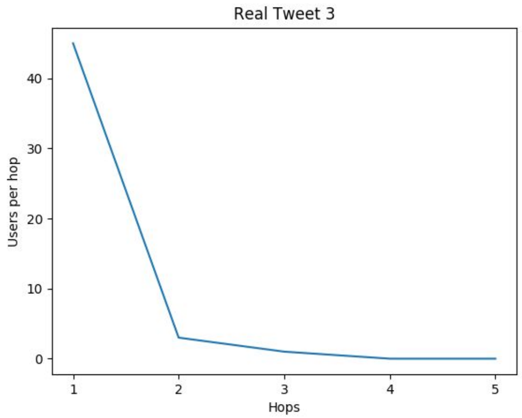
- **First row:** real retweets count VS time
    - One main big burst in the beginning
    - Same distribution in all 3

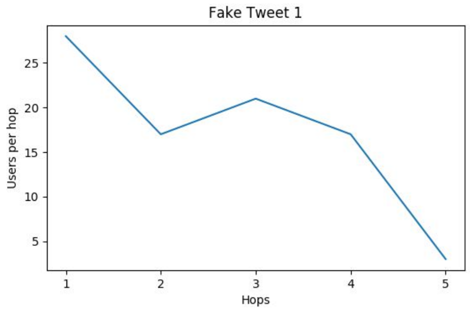
- **Second row:** fake retweets count VS time
    - Many bursts over time
    - Quite big all of them
    - Different, uneven distribution

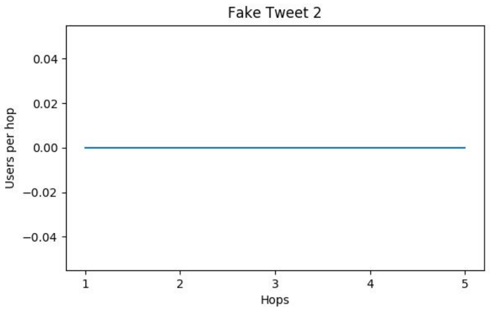
Our Results - Real vs Fake (Hops)

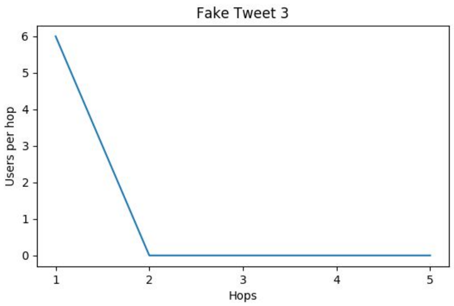




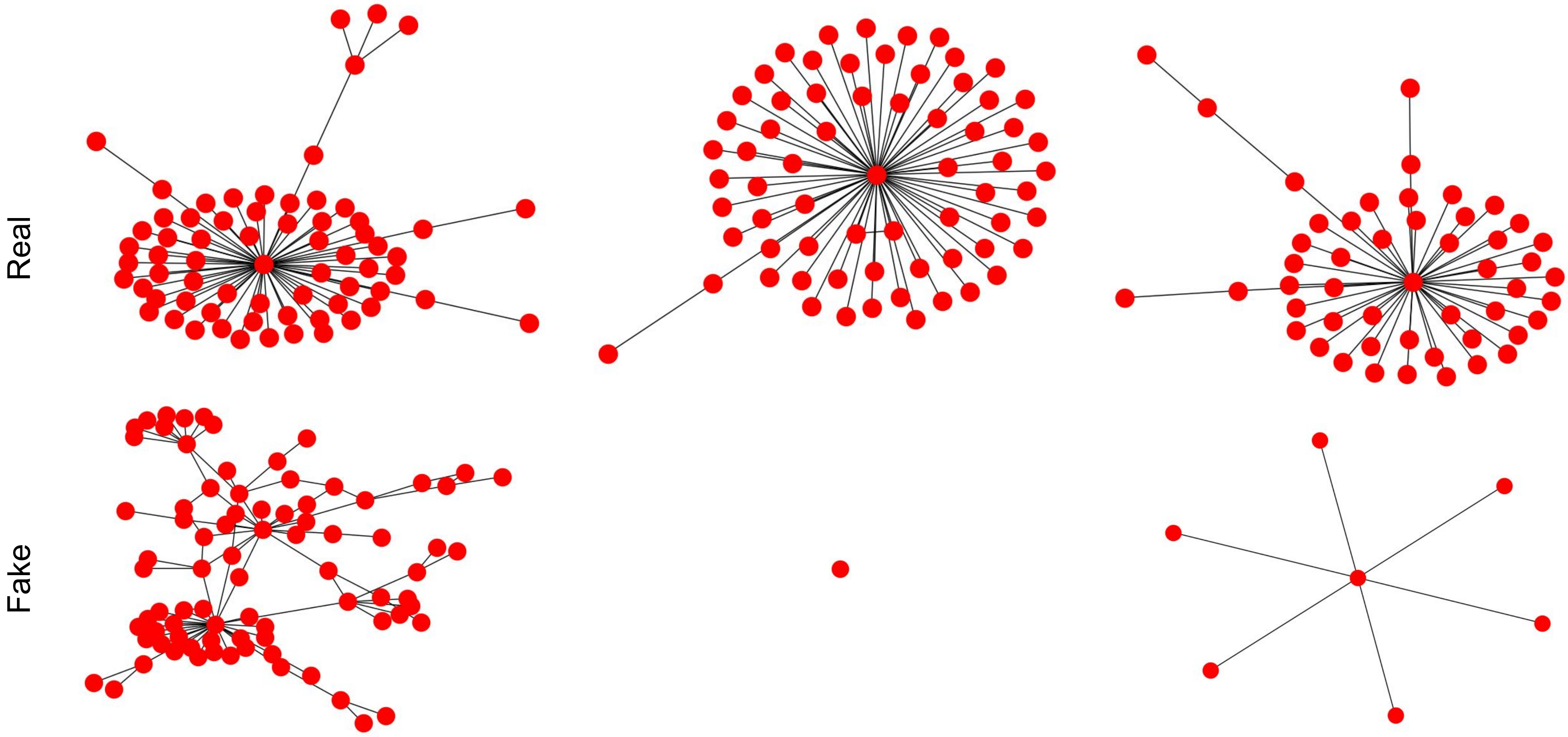








Our Results - Real vs Fake (Hops)



Our Results - Real vs Fake (Hops)

- **First row:** users in real retweets VS hops
    - Less users as hops increase (tend to 0)
    - Same distribution in all 3

- **Second row:** users in fake retweets VS hops
    - More than 0 users as hops increase
    - Different distribution in each

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Thank you!