Virality Prediction and Community Structure in Social Networks

Yong-Yeol "YY" Ahn @yy



INDIANA UNIVERSITY

Bloomington



Most populated countries









1,200,000,000+

300,000,000+



Most populated countries

1,300,000,000+

Social media can **amplify** messages.

"Casually pepper spraying everything cop" meme











Is Oprah's Network Too White?
The Mammogram Hustle

Newsweek.

Rage Goes Viral

From Tunisia to Egypt to Yemen, a youthquake is rocking the Arab world. Get ready for the aftershocks.

Will Business Buy What Obama's Selling?

The Dirty Secret of Apple's Design

America's Happiest Unconventional Family

Companies are desperately trying to leverage **social media**

to make their products and ads viral.



Original, useful ideas - hard

"viral marketing"

VOTE FOR ME.!

'Astroturfing' may change election results.

"1/3 of online reviews may be fake." - Bing Liu (UIC)



KEEP CALM AND GANGNAM STYLE

How can we understand *virality*?

Can we **predict** viral memes?



Clue #1: Complex contagion

Memes

Infectious diseases?

Germs spread through the "social" network



Memes, ideas and behaviors also **spread** through **social network**.

Memes

Infectious diseases?

Maybe not.



"Large" world "Small" world

D. Centola, Science 2010

Which network is better at spreading information quickly?



"Large" world "Small" world

D. Centola, Science 2010









Multiple exposures are crucial.

Social reinforcement



Complex Contagion





three








Complex Contagion needs multiple exposures.



Social contagion seems to be complex contagions.

Clustering should be important.



Highly clustered structure?

Communities!



Newman, 2006

Communities should enhance the spread of complex contagion.

Clue #2: Homophily

"Birds of a feather flock together."





Eric Fischer, Race and ethnicity



Adamic & Glance, 2005

You are likely to share similar interests with your friends.

You are more likely to adopt something from your social circles.

Again, **communities** become important.

A community ~ a common characteristic or shared interests



Adamic & Glance, 2005



Language and Country

Trivial example:



Retweet Network



Follower Network

Both clues indicate that

Communities should play a crucial role in complex contagion.

Communities weakly trap simple contagions.

Communities **strongly trap complex** contagions.



Communities: traps for random walkers

Rosvall, Bergstrom, Lambiotte, ...



Affects **both** simple and complex contagions.



Affects complex contagions.



Affects complex contagions.

Simple contagion



Complex contagion



Communities weakly trap simple contagions.

Communities **strongly trap complex** contagions.





If our idea is correct, then we will see **strong concentration.**

In complex contagion, The edges in the communities should transmit more information.

What about simple contagion?

Traversing probability of an edge from many events of simple contagion

~ that from many random walks
P: transition matrix

P: transition matrix

 $P^T\pi = \pi$

P: transition matrix $P^T \pi = \pi$

$$w^{\mathrm{rw}}(u,v) = \pi_{u} p_{u \to v} + \pi_{v} p_{v \to u}$$

= $\frac{k(u)}{\sum_{m} k(m)} \frac{1}{k(u)} + \frac{k(v)}{\sum_{m} k(m)} \frac{1}{k(v)}$
= $\frac{2}{\sum_{m} k(m)} \sim \text{const.}$

For simple contagion, we expect to see no difference between edges inside communities vs. ones between communities. In complex contagion, The edges in the communities should transmit more information.

Then, why don't we measure the concentration of memes and edge activities regarding communities?



Provides data of both social networks and meme diffusion.

A multiplex, timedependent network.

Following, RT, mention



If A **follows** B, B's tweets and retweets will appear in A's timeline



If B **retweets** a tweet, this tweets show up in the timelines of B's followers.



If A mentions B (with @B), B gets a notification about the tweet.

As an initial analysis, we constructed **three networks separately**.

120 million tweets (Mar 24 – Apr 25, 2012)

600k users, only reciprocal edges.

Hashtag ~ Meme

#hashtags

874

search

What's happening right now on twitter

Paris Hilton's here. #3turnoffwords less than a minute ago #3turnoffwords 1.428

#3hotwords Wish. Is. Here, less than a minute ago #3hotwords 1.003

#simpleplan #simpleplan #simpleplan #simpleplan #simpleplan

#simpleplan #simpleplan #simpleplan #simpleplan

#simpleplan #simpleplan #simpleplan ;2 about a minute ago



Past 6 hours

Past 6 hours

Past 6 hours

From 10 million hashtags, we pick only the '**new**' hashtags (fewer than 20 tweets in the previous month).

Two community detection methods



Infomap (Rosvall & Bergstrom, 2008)



Link clustering (Ahn, Bagrow, Lehmann, 2010)

Didn't use edge weights when detecting communities.

		Network types		
		Retweet	Mention	Follower
Number of nodes		300,197	374,829	595,460
Number of edges		598,487	1,048,818	14,273,311
	Avg. clustering coefficient	0.0902	0.1284	0.1972
InfoMap	Number of communities	14,144	14,222	6,360
	Node coverage	99.86%	99.72%	99.72%
LinkComm	Number of communities	57,317	97,198	321,774
	Node coverage	48.42%	67.23%	47.62%

Are memes complex contagions?

If it's complex contagion, The edges inside communities should transmit more information.

Two types of edges in the **following graph**.

Intra-edges: E_{\bigcirc} Inter-edges: E_{\frown}

 $\langle w_{\circlearrowright} \rangle_c = \frac{1}{|E_{\circlearrowright}^c|} \sum_{(u,v) \in E_{\curvearrowleft}^c} w(u,v)$

$$\langle w_{\frown} \rangle_c = \frac{1}{|E_{\frown}^c|} \sum_{(u,v) \in E_{\frown}^c} w(u,v)$$

For each type of edges, we measure the **# of retweets and mentions through** the edges.





Fraction of interactions for each person

$$f_{\circlearrowright}(u) = \frac{\frac{1}{k_{\circlearrowright}(u)} \sum_{(u,v) \in E_{\circlearrowright}} w(u,v)}{\frac{1}{k(u)} \sum_{(u,v) \in E} w(u,v)}$$
$$f_{\curvearrowleft}(u) = \frac{\frac{1}{k_{\curvearrowleft}(u)} \sum_{(u,v) \in E_{\curvearrowleft}} w(u,v)}{\frac{1}{k(u)} \sum_{(u,v) \in E} w(u,v)}$$

 $k_{\circlearrowright}(u) = |\{v \mid (u, v) \in E_{\circlearrowright}\}|$ $k_{\curvearrowleft}(u) = |\{v \mid (u, v) \in E_{\curvearrowleft}\}|$ $k(u) = k_{\circlearrowright}(u) + k_{\curvearrowleft}(u).$





Indeed, we see more activities within communities.

How do we measure "concentration"?

We need models to compare

	Network effect	Social reinforcement	Homophily	
MI				Random sampling
M2	0			Simple cascade
M3	Ο	Ο		Social reinforcement
M4	Ο		0	Homophily

r(h)

the proportion of **tweets** produced in the dominant community



r(h) the proportion of **tweets** produced in the dominant community

g(h) the proportion of **users** adopted in the dominant community

 $H^t(h)$ Tweet entropy in terms of communities

r(h) the proportion of **tweets** produced in the dominant community

g(h) the proportion of **users** adopted in the dominant community

 $H^t(h)$ Tweet entropy in terms of communities

 $H^u(h)$ User entropy in terms of communities

Normalize every one with M1

$r(h)/r_{M_1}(h) \qquad H^t(h)/H^t_{M_1}(h)$

And use only the first 50 tweets.














0└_ 10⁰

$$10^{1}$$
 10^{2} 10^{3} 10^{4} 10^{5}
U (Final # of adopters)











All memes are not equal.

Unsuccessful memes behave like complex contagions

Viral memes behave like simple contagions

Viral memes are literally *viral*.

Simple contagion



Complex contagion



Viral memes



Complex contagion



Viral memes



Non-viral memes



Another perspective

Each community

~ interest group

Concentrated in one community

The meme only appeals to the population

Distributed throughout many communities

The meme appeals to the general population

"We did not make the corrections suggested by reviewer 1 because we think reviewer 1 is a f***ing idiot" #OverlyHonestMethods



Viral memes are literally like viruses.

Viral memes are attractive to everyone.

Then, can we use this information to predict viral memes?

Task: Given the network structure and early tweets, predict the final popularity.





With random forest classifier





Summary

- Communities give us invaluable information about spreading patterns of memes.
- We can predict viral memes by looking at communities
- Non-viral memes seems to be strongly affected by social reinforcement and homophily while viral memes are not.
- Viral memes spread (literally) virally.





Lilian Weng

Fil Menczer

Virality Prediction and Community Structure in Social Networks [arxiv.org:1306.0158]