Rumors Spread On A Facebook Forum

Introduction

Social networks are where large groups of people share a commonality where people can be connected and have conversations, share information, and create web content. People would use social media like Facebook, Twitter, WhatsApp etc. to communicate with other individuals. From the usage of social media, it is possible for individuals to encounter false information about current events, health issues, or political issues and spread it further by sharing or engaging with it. To give an example, the world became accustomed to the term "coronavirus" and "COVID-19" during the pandemic from an abundance of information online/social media. With the spread of information, falsified news is also spread and contributes to vaccine hesitancy and lengthen the pandemic (WHO, 2020). The spread of false information between users via social media resembles a network structure. Therefore, we chose to study how rumors are spread in Facebook as it ranked as the most popular social network site in the world (Statista, 2022). We studied how rumors are spread by observing the network's structure and statistics. Then proceeded to analyze the network characteristics that have the major influence on rumor spread and determine the parameter by examining the cluster density that can stop the spread of rumors.

Data Description

The Facebook Social Circle network data set was collected from the Stanford Network Analysis Project. This data set is a Network from a Facebook Forum, including node features, circles, and ego networks. Table 1 is the data statistics of the data.

Data Statistics	
Nodes	4039
Edges	88234
Diameter(longest shortest path)	17
Average path length	4.3377
is.connected	True
is.weighted	FALSE
Average Degree	39.15
Number of community(walktrap)	68

Table 1. Date Statistics for Facebook Social Circle network data

This is a primary community detection graph of our data plotted by python Networkx library. In Figure 1, we detect multiple communities in our network by distinguishing between the different colors. Besides, there are some local bridges with high edge betweenness between different communities.

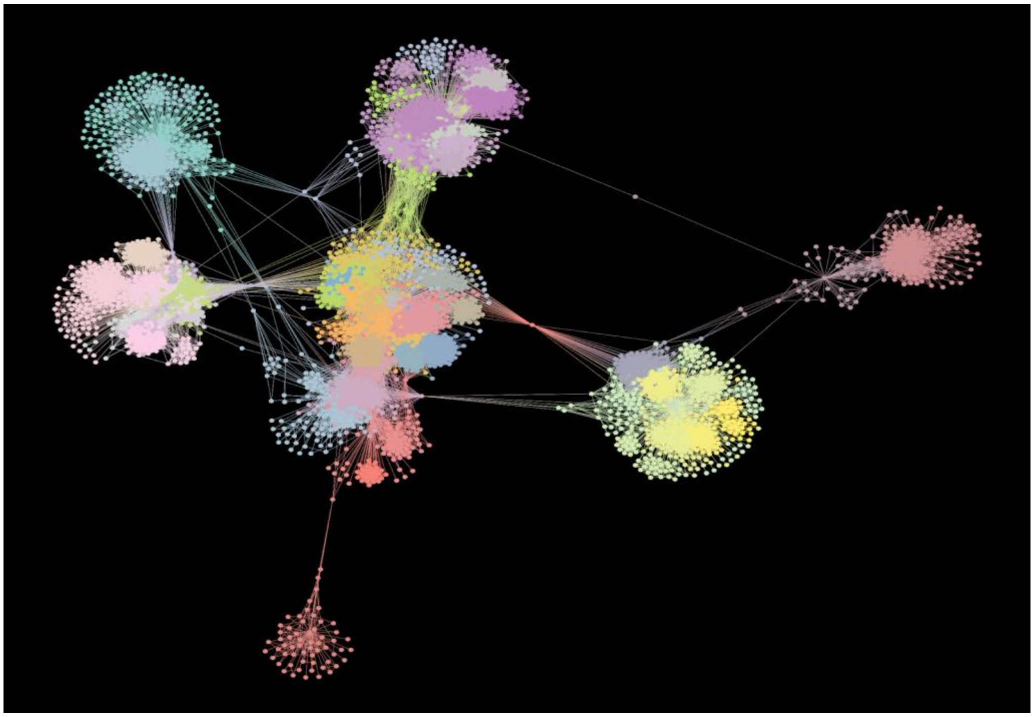

Figure 1. Community Detection Graph

Background research

Woo et al. (2011) proposed the violent topic diffusion model for a major international Jihadi forum and simulated the SIR (Susceptible, Infective, and Recovered) model in the propaganda phrase to analyzed the diffusion of the extreme opinion. They evaluated five parameters and analyzed the logistic growth of potential authors, the interaction between possible authors and current authors, and the decline of the influence of past authors. As a result, "the SIR model with variable population is a plausible model for the topic diffusion in the web forum" (Woo et al., 2011, 18) .

The research of Ozturk et al. (2015) tested how the counter rumor is efficient to reduce the rumor spread and simulated the spread using Amazon Mechanical Turk data. Finally, they found the counter rumor in social media was not effective unless the counter rumor appeared at the same time as rumor or before rumor came out. Therefore, researchers suggested social media to build their own self-correcting mechanism, where it allows users to search counter tweets and display them together with corresponding rumors to prevent the spread of rumors (Ozturk et al., 2015).

Khurana et al. (2018) applied an epidemic analytical modeling approach to estimate the spread of Fake news on Whatsapp. The study introduces a framework to compare misinformation dynamics on Whatsapp based on the topical age group as well as a framework for the prediction of topic occurrence. They distinguished authors in the age group 19-24 who are highly active for posting the fake information and authors in the age group 40-60 who are inactive to spread the fake information (Khurana et al., 2018). Compared to the older group, the younger group increased the transmission of misinformation rapidly every year.

In Pierri et al. (2020) article, the research was done in different ways to analyze the diffusion of misleading information. The authors built linear regression, KNN models and SVM using different data ranges, and compared the performance of the models. They mentioned that ‘communities of users sharing misleading news tend to be more connected and clustered, with stronger interaction between users’(Pierri et al., 2020, 1372). This idea was novel for explaining why people tried to spread misinformation. Therefore, according to their model results, they concluded, misleading information transmitted more widely and deeper than mainstream.

Zhao et al.(2013) cited the rumor spreading model which divided people into three groups: ignorants(I), spreaders(S), and stiflers(R). Then they simulated the transmission process of rumor by using the epidemic analysis model. Tuning parameters respectively, they compared the density of spreaders in the legacy media and new media and concluded that the ignorants would not change their mind even after they contacted with spreaders and stiflers.

Methodology

Our model is based on a modified SIR rumor-spread model introduced by Zhao et al.(2013). In this model, we have a population of size N. With respect to the rumor, there are three distinct groups: ignorant, spreaders, and stiflers.

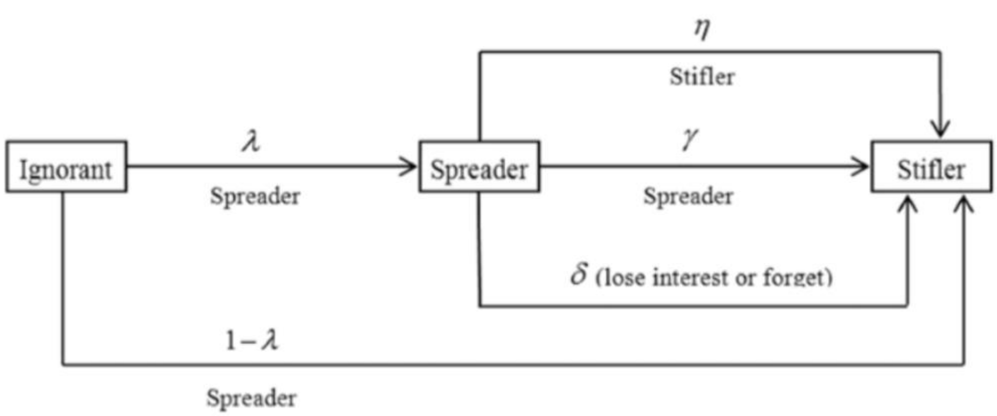

Figure 2. Structure of the SIR model for the rumor spreading process (Zhao et al.,2013,996)

Zhao et al.(2013) explained the distinct groups according to their status in spreading rumors. Each group influences each other and has a specific probability to be a rumor spreader or a stifler. The details are in the table below.

Three Distinct Groups Respect To The Rumor Spreading	**Explanation**
Ignorants	When a spreader contacts an ignorant, the ignorant accepts the rumor with probability λ and becomes a spreader. Otherwise, they become a stifler.
Spreaders	A spreader can spontaneously lose interest or forget about the rumor with probability δ. This also captures situations where a user doesn't share the post due to inactivity.
Stiflers	If a spreader contacts a stifler, they become a stifler with probability η. This captures the stifler's influence on their peers to stop spreading a rumor. If a spreader contacts another spreader, the initial spreader becomes a stifler with probability γ. This models the possibility that the spreader sees another spreader take on the rumor that differs from theirs (say, a different article/source/conclusion) and doubts the credibility of it. $\eta < \gamma$. That is, it is more likely that a spreader will be convinced by a stifler to stop spreading a rumor versus another spreader (since spreaders may create an "echo-chamber effect" amongst themselves).

Table 2. The description of three groups in the rumor spreading (Zhao et al.,2013)

To estimate the contact rate κ, the network's average node degree was used, which was 39.15. It is important to note that this is an ego network. In figure 3, the node degree distribution is highly left-skewed and the network's mean node degree is much higher than the median.

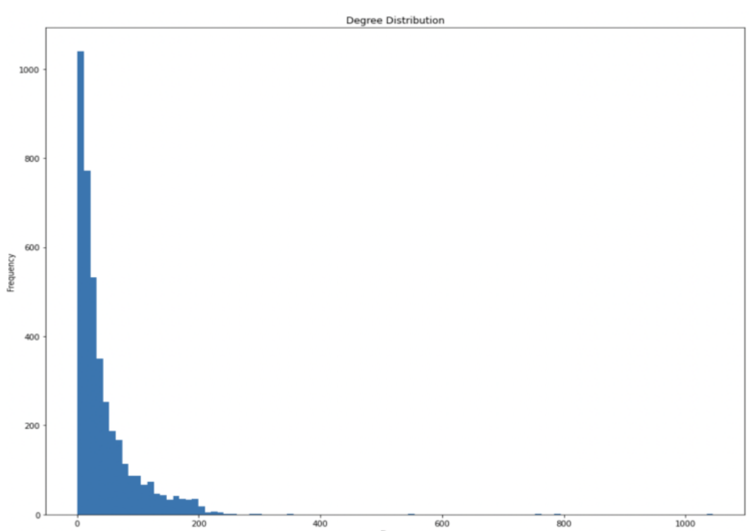

Figure 3. Degree Distribution

The rumor acceptance probability λ was estimated using findings from surveys conducted on the spread of unverified information by Greenhill and Oppenheim(Greenhill et al., 2017). Here, we took the average probability of belief in a rumor which was 0.2. The spreader-stifler stifle probability η was estimated by informally surveying friends on Facebook. Approximately 10% of them would stop spreading a rumor if one of their peers were trying to stop them. The spreader-spreader stifle probability was estimated by dividing by two. The reasons here is that a widely distributed rumor would cause two spreaders to communicate and rely on verification bias rather than relying on each other to stop spreading a rumor.

Parameter	Meaning	Estimated Value
N	Population size	4039
K	Avg contacts per timestep	39.15
λ	Rumor acceptance probability	0.2
γ	Spreader-spreader stifle probability	0.05
η	Spreader-stifler stifle probability	0.10
δ	Forget probability	0.5

Table 3. Parameters used in our model

Simulation based on SIR model

We visualized the network using graph-tool, an efficient Python library for network analysis. The figures below, we plotted the network and color nodes based on each node's closeness, centrality and local cluster coefficient, and calculated it using their implementations in graph-tool. The closeness centrality of a node was calculated as the reciprocal of the sum of the length of the shortest paths between the node and all other nodes in the graph. Intuitively, the local cluster coefficient describes the embeddedness of a single node. The nodes with a green color are "ignorants", the nodes with red color are the "spreaders" and the nodes with blue colors are the "stiflers". Below we can see the simulation results by time.

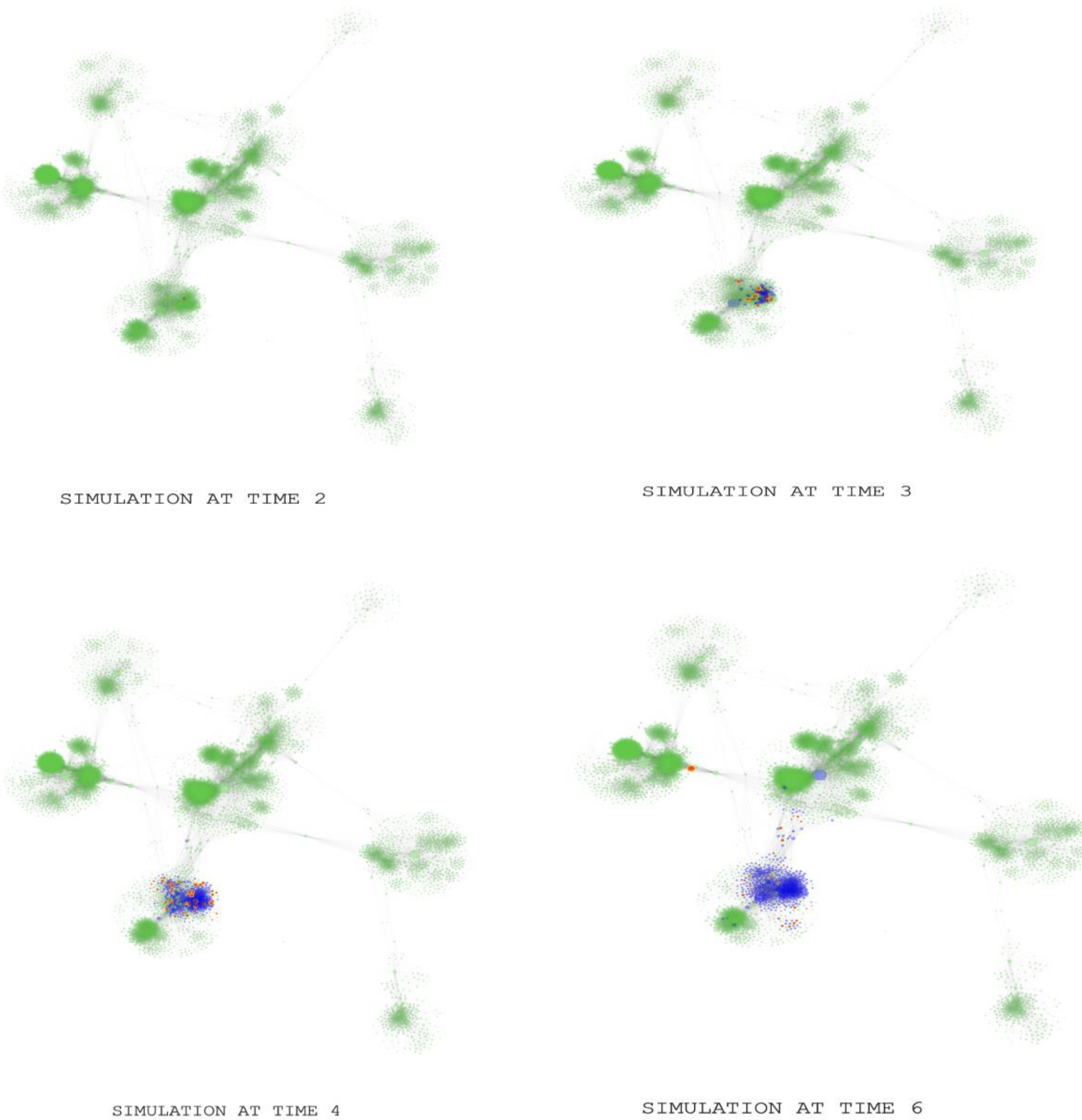

Figure 4. Simulation at time 2, 3, 4 and 6

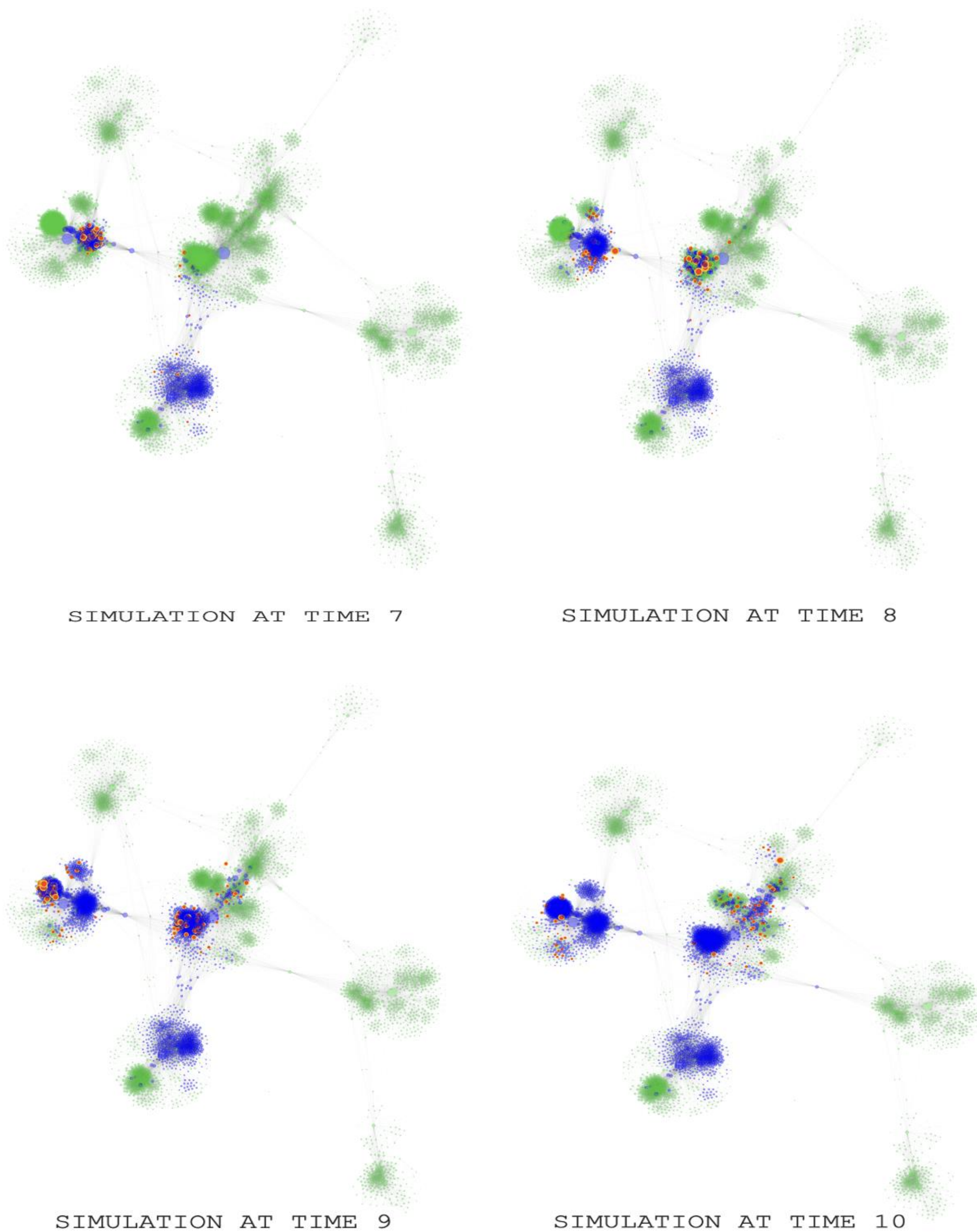

Figure 5. Simulation at time 7, 8, 9 and 10

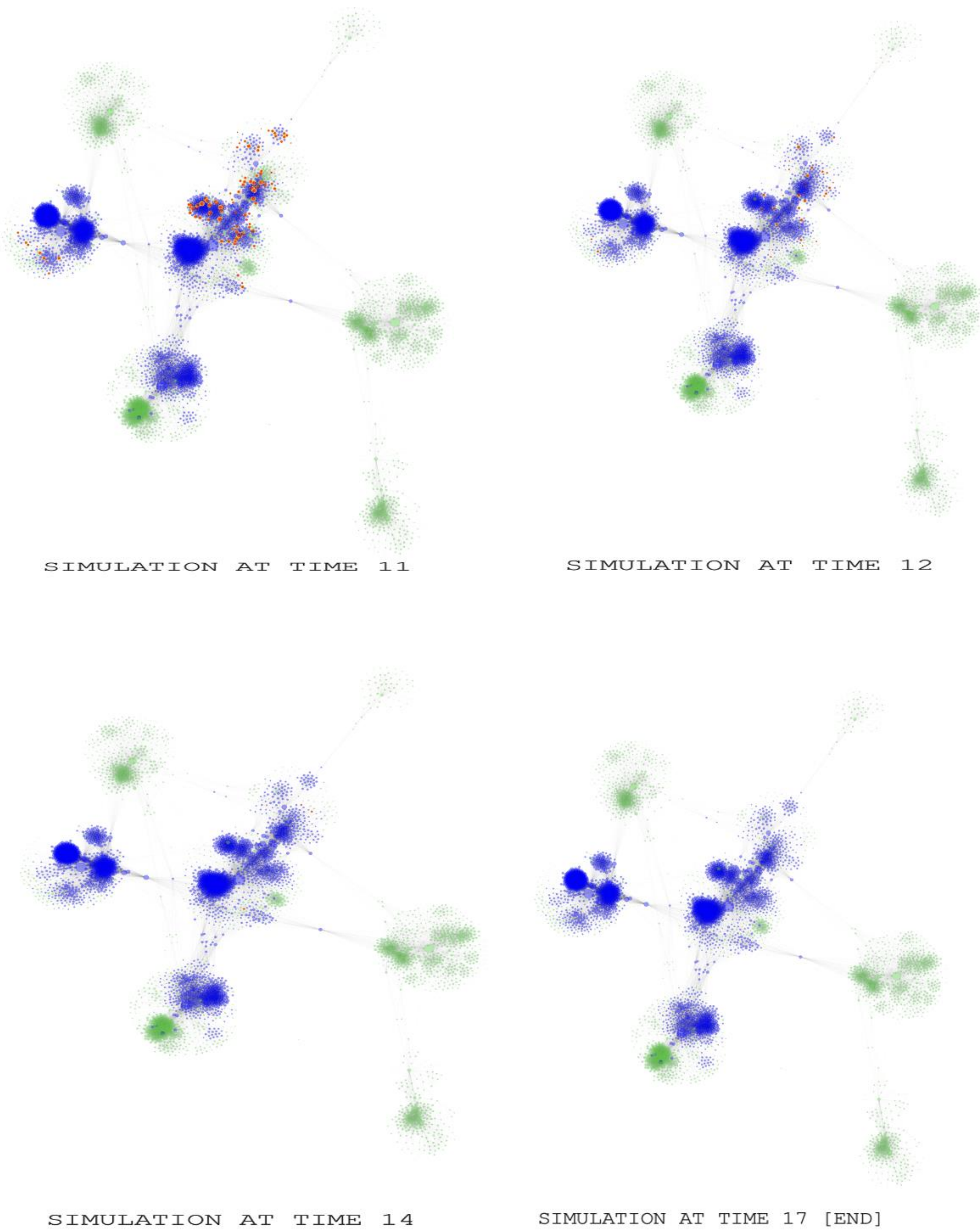

Figure 6. Simulation at time 11, 12, 14 and 17

In figure 4 at stimulation at time 2, a red node indicates as a "spreader" and by observing the red nodes, then we can see the start of rumor spread and some of its neighbors accept the rumor and turn to be a "spreader" in stimulation at time 3, some ignorants and spreaders turn to be stifler on stimulation at time 3 as well. When we observe the simulations at different times closely, we can see there are more red nodes and more blue nodes, which means there is an increase of "spreaders" and "stifler." Overtime, the rumors are penetrated into other communities by local bridges (weak ties) as the rumor continues to spread into other communities.

As in Figure 6, stimulation at time 11 to 12 the rumors spread starts to slow down and many nodes turn to stiflers and the number of spreaders start to decrease. This trend continues until the stimulation at time 14 where the stiflers(blue dots) are completely dominant and we can see four spreaders (red dots) in the whole network. By the stimulation at time 17, we do not have any spreader in the network. In the final graph, we only see blue nodes which represent the "stiflers" and some green nodes that are "ignorants" who never accept the rumors. So, we plotted a line graph to show the rumor size during time. As you can see in figure 7, when all the spreaders disappeared from the network and simulations stopped, the percentage of the network infected by the rumor is just around 50%.

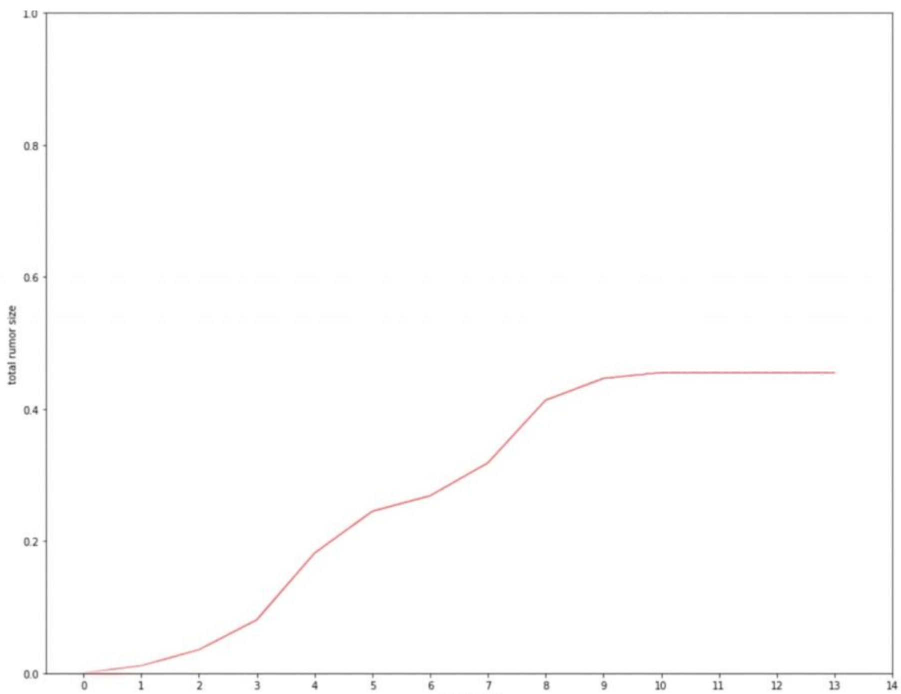

Figure 7. Rumor size Over Time (with λ =0.2, k=39)

Then we decided to increase the λ (Rumor acceptance probability) to examine the rumor size. As you can see in Figure 8, the rumor size is completely related to the λ and once we increase it the rumor final size increases.

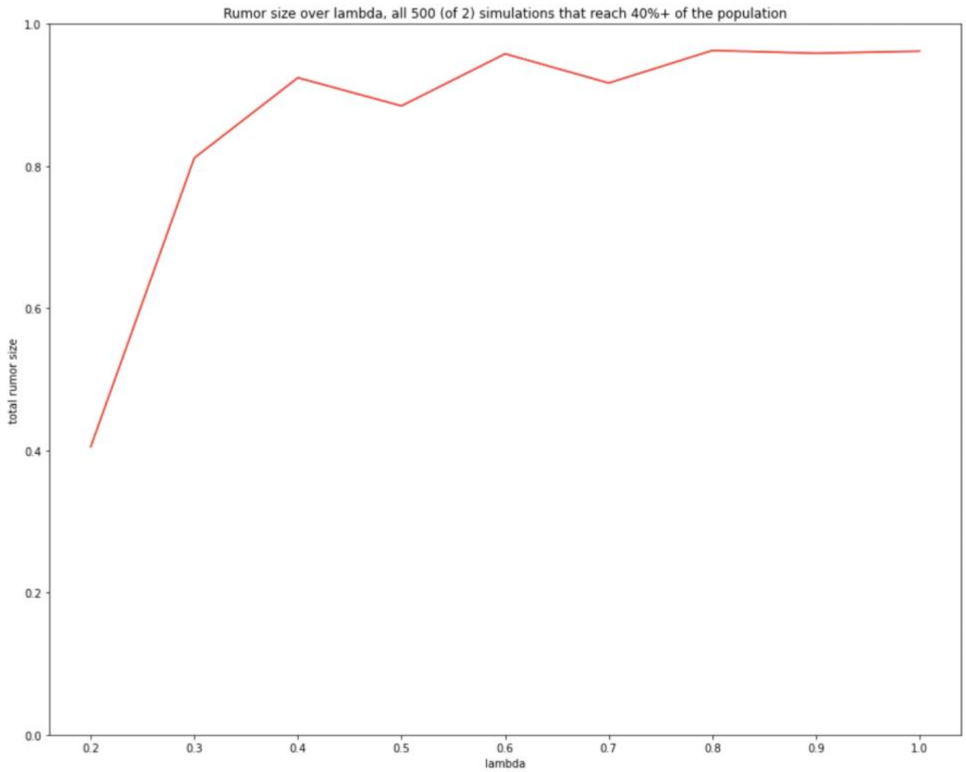

Figure 8. Rumor size over λ

As we set λ=0.2, only two of our main clusters resist rumor spreading. In our experimental simulation, the result in the last stage proves our findings based on this calculation. In Figure 9, there are just two main clusters that rumor cannot penetrate into them and we weren't able to detect the communities in the network. From our stimulation, we know that clustering the network is based on our parameters, and the number of main clusters differ based on our algorithm for the same network. Therefore, we look for an alternative way to detect the community.

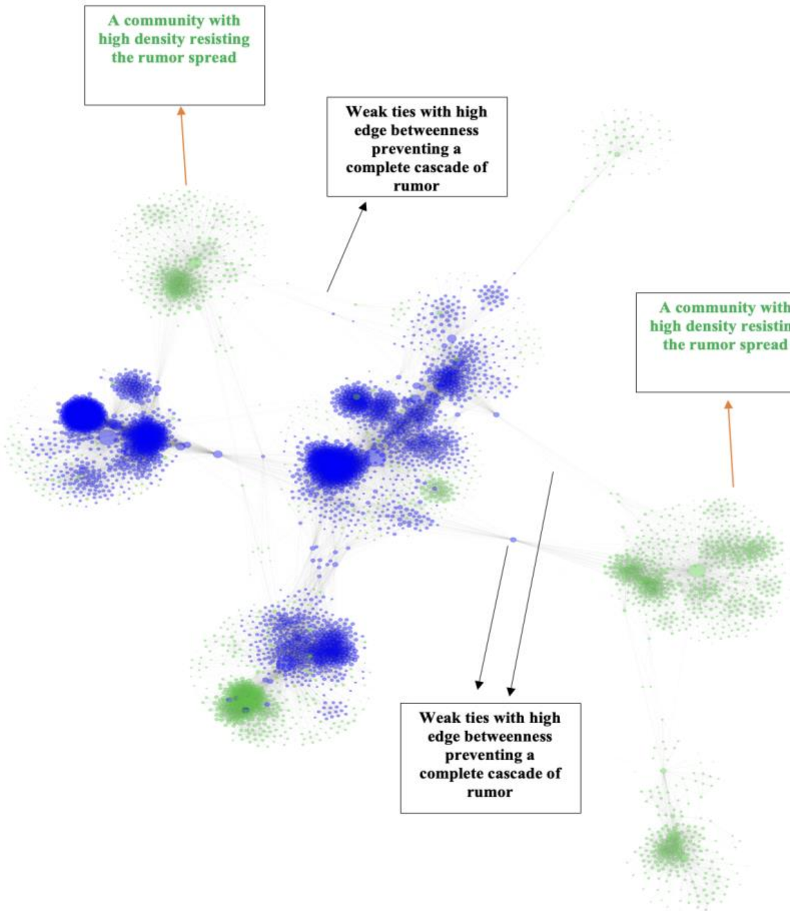

Figure 9. The Final stage of rumor spread - the two communities never penetrated by rumor

Another surprising observation from the simulation plots is that the rumor could not penetrate into some communities or clusters until the end of the simulation. Therefore, we referred to class materials and there were some slides about what elements can stop a complete cascade.

What makes cascade stops?

Tightly Knit Communities Sometimes Cannot be penetrated. A cluster of density p is a set of nodes such that each node in the set has at least a p fraction of its neighbors in the set.
Set of initial adopters of A (S), threshold q:

1. If the remaining network contains a cluster of density greater than 1-q then set S will not cause a complete cascade.

2. Whenever set S does not cause a complete cascade with threshold q the remaining network must contain cluster of density greater than 1-q.

The figure below indicates that new behavior cannot penetrate into the two clusters because the clusters density is higher than the 1-q (1-initial adopters threshold).

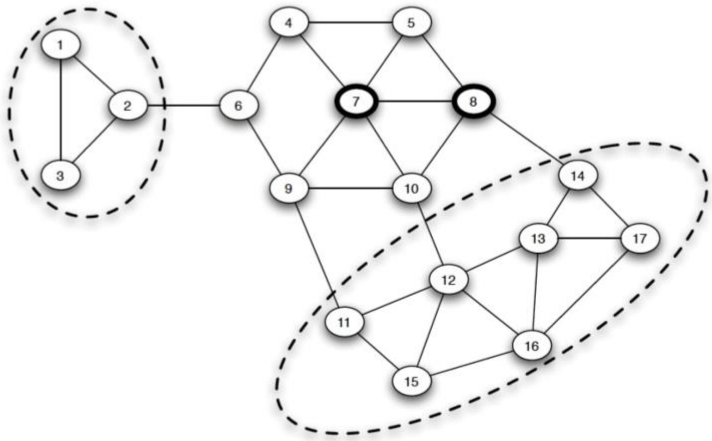

Figure 19.7: Two clusters of density 2/3 in the network from Figure 19.4.

12

Figure 10. Figure 19.7 from the EK book (p.574)

Since we found out that the rumor did not penetrate into some of our communities due to their high density, we decided to detect main clusters in our network and calculate their densities. The table below, indicates the lowest cluster density is around 0.03 and the highset is 0.93. We sort the clusters based on their density value.

	density	transitivity	members
2	0.035736	0.258982	857, 862, 865, 868, 1085, 3437, 3438, 3439, 34...
1	0.040557	0.393780	107, 348, 349, 350, 352, 353, 354, 355, 356, 3...
4	0.042446	0.283949	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, ...
0	0.052717	0.478861	1061, 1239, 1271, 3313, 1285, 1290, 3326, 1301...
3	0.093474	0.533165	2048, 2049, 2050, 2051, 2052, 2053, 2054, 2057...
7	0.093914	0.406612	686, 687, 688, 689, 690, 691, 692, 693, 694, 6...
8	0.117475	0.304834	3980, 3981, 3982, 3983, 3984, 3985, 3986, 3987...
5	0.228897	0.517108	3073, 3078, 3080, 3084, 3085, 3090, 3092, 3095...
6	0.713164	0.806337	2560, 2561, 2563, 2564, 2055, 2056, 2059, 2060...
9	0.738739	0.821811	901, 1798, 903, 1802, 1548, 1424, 1568, 1186, ...
11	0.790850	0.873134	3008, 2699, 2703, 2767, 2959, 2834, 3283, 2972...
10	0.866667	0.898976	576, 640, 577, 578, 643, 582, 583, 647, 650, 6...
12	0.933333	0.923077	2817, 3074, 2774, 3127, 3147, 3055

Table 4. The list of clusters ordered by density

The graph below shows there are five main clusters showing high density. Among them, **two clusters** have a density of more than 0.80.

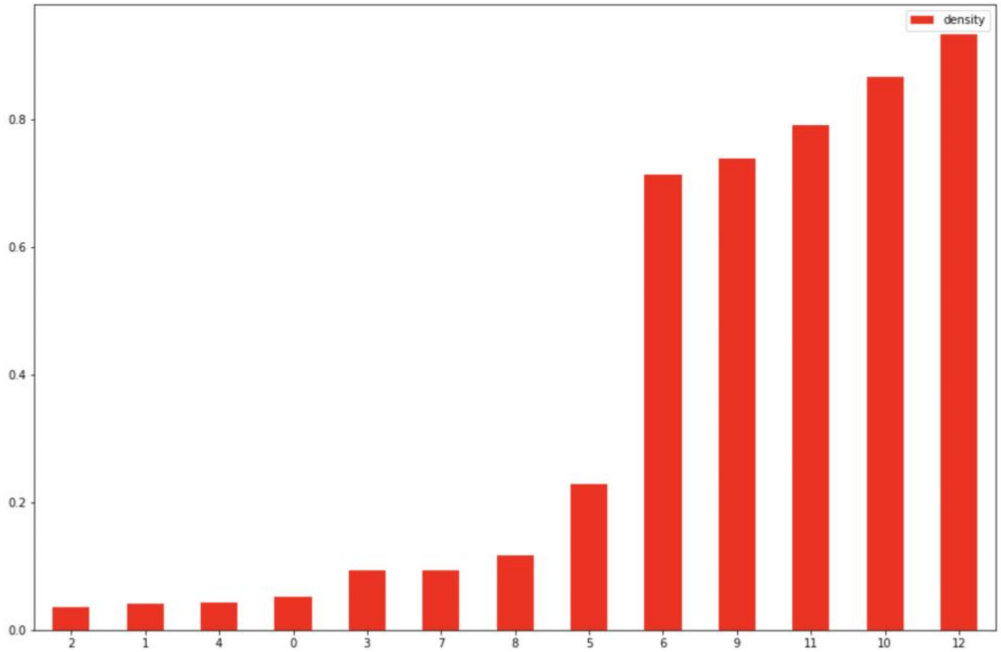

Figure 11. The bar chart of clusters by density

Our hypothesis is that these two main clusters' with high density are those clusters that were not penetrated in our simulation and their density is higher than the (1-initial adopters acceptance threshold). Besides, while weak ties are very powerful in spreading new information, weak ties are weak at transmitting behaviors that are somehow risky and costly to adopt.

Cluster index	**P (density)**	**p>1-q ?**	**rumor spread through that cluster**
2	0.03	No	No
1	0.04	No	No
4	0.04	No	No
0	0.05	No	No
3	0.09	No	No

7`	0.09	No	No
8	0.11	No	No
5	0.22	No	No
6	0.71	No	NO
9	0.73	No	NO
11	0.79	No	NO
10	**0.86**	**Yes**	**Yes**
12	**0.93**	**Yes**	**Yes**

Table 5. Comparison between p and 1-q to determine if the cluster is penetrated by rumors

Conclusion

We simulated a rumor spread through a Facebook forum based on the SIR model. We defined some parameters such as k, λ, γ, η, δ to define our model. Each of these parameters will determine how a rumor spreads in a network. Next, we found each of these parameters can affect the rumor spread speed and dynamic. Besides, the network structure and the clustors densities and initial adopters are playing an important role in rumor spread.

The most important factors that can affect the rumor spread through a social network
The clusters densities
The network structure
The probability of accepting rumor by people
The average contacts between nodes per timestep

Table 6. The most important elements for rumor spreading

We have also noticed that from the 9 days, the proportion of rumors began to increase very slowly, almost no change at all. Why does this phenomenon appear? We are guessing that rumor spreaders hardly spread misinformation when the population of stiflers is large enough to be counter rumors.

Therefore, we can boldly say that if social media makes rumors and all truth about rumors showing together, stiflers could be involved in the network from the earlier phase of the rumor transmitting, and the population of stiflers would be increased sooner than our network. It is an efficient way to decrease the time of rumor spreading and stop rumors. Finally, we detected these elements as the most important factors that affect the rumor spread through a social network.

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