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Information Propagation In Online Social Networks – A Simulation Case Study

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Abstract

Nowadays, social media platforms are the primary information exchange channel utilised by milliards of people worldwide. These platforms are characterised by quick communication, no effort, being payless and always available for users. These conditions make it easy to spread information from one user to another in close neighbourhoods and around the whole social network located in the given platform. The paper presents the simulation studies around the rumor spread process via the varied range of the networks topologies, information spread strategies and aspects taking part in this process to find relationships between them.

Keywords

online social network, information spread, diffusion, simulation

Introduction and Research Motivation

In modern times people are abandoning the traditional ways of communicating and getting information about the world like TV, newspapers, radio, phone calls, texts messages etc. Instead of the mentioned media, they utilise social platforms to share their status, personal events or obtain information about the current news. Moreover, it is reported that social media platforms are the primary source of information for most young people, which exposes them to very different types of information. Together with this trend come both advantages and threads. There are many examples of utilising social media platforms to help people, like raising money for good causes or warning them about upcoming dangerous events. Recently, it can be observed that the trend of utilising them maliciously is increasing and can affect different aspects of life, i.e. mental health, financial situation, and even impact election results or encourage people to riot. The information spread in both mentioned approaches is crucial as the author wants to notify as many people as possible in the shortest time to get help or mislead them(Borgatti, 2006; Frąszczak, 2021; Guille et al., 2013).

This paper aims to perform a simulation case study about the crucial aspects of taking part in the information spread over the network. The presented results highlight the relationships between assumed information propagation models and their propagated networks. Moreover, studies show the difference of the source nodes based on some of the centrality metrics. This type of study can be beneficial for many domains as it provides a way to understand better a variety of aspects taking part in this process.

This paper is divided into six main parts. The first one introduces the definition of online social networks, some facts about them and the mathematical representation. Moreover, it contains information about the online social network topologies used in the analysis. The second provides information about the models used to simulate information spread via the network. This

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paper utilises both epidemics, contact, and opinion dynamics approaches. The third section provides information about the techniques for the best nodes to spread information. Fourth introduces RP&SDT (Rumor Propagation & Source Detection Toolkit) simulation environment utilised to perform the case study analysis. Fifth introduces the performed examinations and presents the obtained results in the simulation environment. The last one concludes the paper, summarises the problems and introduces possible future development directions in that area.

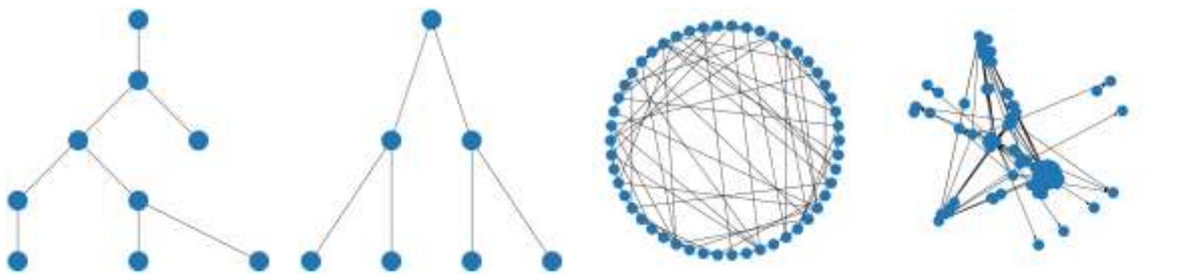
Online Social Networks and Information Propagation

Nowadays, social media platforms are the primary information exchange channel utilised by milliards of people worldwide. These platforms are characterised by quick communication, no effort, being payless and always available for users. The number of active users is still increasing. For Facebook, this number in the five years increased twice, giving in 2020 about 2,740 mln active users using that platform(*Digital News Report 2016*, n.d.). This trend provides new possibilities to contact other people worldwide and diffuse information about them. The propagated information can relate to different facts, like a personal status update, a diary, advertising some product or being propagated for educational purposes (Bello-Orgaz et al., 2016). Unfortunately, sometimes that information is sent maliciously to modify people's perception of the world. Many vicious incidents probably impact election results, stock changes, or people's lives (Higdon, 2020). The mentioned types of information, i.e. "positive" and "negative", similarly propagate over the network based on the people network communities and each person's impact in the community separately. This paper presents the most popular network topologies and information diffusion strategies to find some relationships between them to help future "positive" campaigns to select persons that can help to be successful and for a fight with "negatives" ones to stop rumor propagation over the network or how to optimise vaccination strategies.

Online social networks are represented with the graph theory, where the social structure is defined by the graph $G=(V,E)$ where V is a countably infinite set of nodes (persons, computers etc.) and E is a set of edges (connections between them) represented via an adjacency matrix where value 1 is set when nodes are connected otherwise 0 is used. Depending on the modelling context, the edges can represent the one-directional relationship between nodes representing an independent relationship, i.e. Twitter following relation between two users (Raj P.M. et al., 2018). This type of association is called "directed". In contrast, the two-directional relationship between nodes is called "undirected" and is used to model mutual relationships, i.e. Facebook friendship.

The information simulation process via the network can be carried out utilising both real and synthetical topologies. While working on the real network structure researcher is obliged to gather all necessary data legally. Some public datasets come with data from platforms like Facebook, Twitter, Sina Weibo included in Stanford Large Network Dataset Collection ("Stanford Large Network Dataset Collection," n.d.). For the generated online social network topology approach, there are various options to utilise. The most popular are Erdös and Rényi random graphs, Small-World and Scale-free topologies (Frąszczak, 2021). Erdös and Rényi random graphs were the first topologies used to model online social networks. They assume nodes to connect with a fixed, constant probability. Currently, it is proved that that model has limited usage to model real online social networks.

Small-World networks were proposed based on the observation that online social network topologies are random and regular. The generation starts with creating the regular graph, and then some of the edges are randomly swapped between nodes. They are characterised by the small number of hops between any nodes. It means that they are combing multiple cliques and subnetworks, which allows a connection between any two random nodes. The average path length is low, while the clustering coefficient remains high. This property is also observed in real online social networks. There is a "Six degrees of separation" idea that all people need six or fewer connections away from each other (Guare, 1992). It can be observed with Facebook that currently, this number is being convergent with 3.5 what is a great result and confirms that idea (Rossetti et al., 2018). Scall-free topology was proposed based on two assumptions: constant growth and preferential attachment, leading to the power law's degree distribution. It means that most network nodes have a low degree, whereas just a few have a high value of these metrics. A new node is added to the existing nodes with a probability proportional to their connectivity. Another property of this topology is the literality of the words "scale-free". These networks are immeasurable, which means that they always look the same regardless of their scale, so the appropriate scale cannot be adjusted.



(a) random tree network (b) regular d-tree (d=2) (c) small-world network (d) scale-free network

Figure 1 : Different network topologies: (a) random tree, (b) regular d-tree, (c) small-world, (d) scale-free network.

The information propagation process can spread from both a single or set of nodes which are the information source $v \subseteq G$. Depending on the adopted propagation model, these nodes are called active/susceptible (Mei Li et al., 2017), and they are responsible for the initial information spread through the network. Each node tries to pass the information to its neighbours and encourage/infect them with information. This process aims not only to convince the neighbours but also to encourage them to pass the information further into the network. If the neighbour accepts and starts passing the information via the network, it automatically becomes active too, which causes the propagation of information in the network. As time passes and more nodes become infected, an infection (propagation/spread) graph $G_I = (V_I, E_I)$ is created. G_I is a G subgraph and consist of infected nodes V_I which have taken part in information propagation via edges E_I

Propagation Models

Information propagation in real online social networks can propagate in various ways. However, the aim of this process is always the same: to cover as many nodes of the networks as soon as possible. Based on the past events and data from propagations, the researchers have developed a wide range of models used to simulate different behaviours. In general, the information diffusion under the network can be modelled according to one of the following schemes: random walk, snowball spreading, contact process (Jiang et al., 2017) and opinion dynamics. In a random walk, the node delivers a message randomly to one of the neighbours. Snowball spreading corresponds to a broadcast scheme where the node delivers a message to all neighbours. In the contact process, the message is delivered to a selected group of its neighbours. The last technique is most important in online social networks analysis as it is likely to be real cases. Contact based diffusion models can be divided into three main categories: epidemic, predictive and opinion dynamics based. Nodes in those models can be in different states. However, in all of them, two states are always present: active/infected – node takes an active part in passing a message over the network and inactive/suspicious – node does not take part in information propagation. Opinion dynamics techniques have a lot in common with those seen in epidemics and spreading but with some differences. The node's state with opinion dynamics can oscillate freely between the possible values, simulating thus how opinions change in a reality where this change is irreversible for the many spreading and epidemics models. Moreover, opinion dynamics utilise the external information that can be treated as the effect of mass media (Rossetti et al., 2018)

Epidemic models come from an epidemic spread analysis in society. They are based on compartments, mutually exclusive groups based on their disease status. Each individual is located in one compartment at a given time but can move to another one depending on the model parameters. There are two main hypotheses around this approach: each node can be classified into a distinct state (compartment), and each individual has the same opportunity to meet an infected node. It is proven that information spread via online social networks can follow the same rules. The most significant disadvantage of this approach is that the online social network structure is not considered in the simulation, and nodes come into contact only with a restricted set of peers. Nowadays, many epidemics models differ in node states and transitions functions. A summary of the most popular ones is presented in the figure below (Cheng et al., 2013; Mei Li et al., 2017).

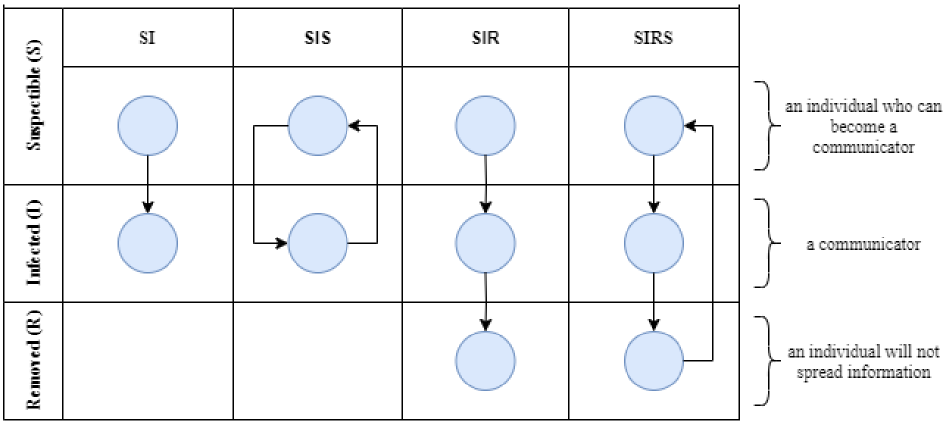


Figure 2 Epidemic models in information spread context.

Predictive models are based on certain sociological factors to predict the information propagation process in online social networks (Jiang et al., 2017; Mei Li et al., 2017). The most popular of them are Independent Cascade (IC) and Threshold-based.

The Independent Cascade model goes through a network via cascades from initially defined source nodes. The diffusion process works according to the following steps:

- When a node becomes active in step t, it has a single opportunity to activate each inactive neighbour with a given probability p.
- If a node has multiple recently activated neighbours, their infection attempts are performed randomly.
- If a node infects its neighbour, it becomes active in the next step. Otherwise, the infector cannot try to infect that neighbour in the future.
- The procedure runs until there are no more possibilities to activate nodes.

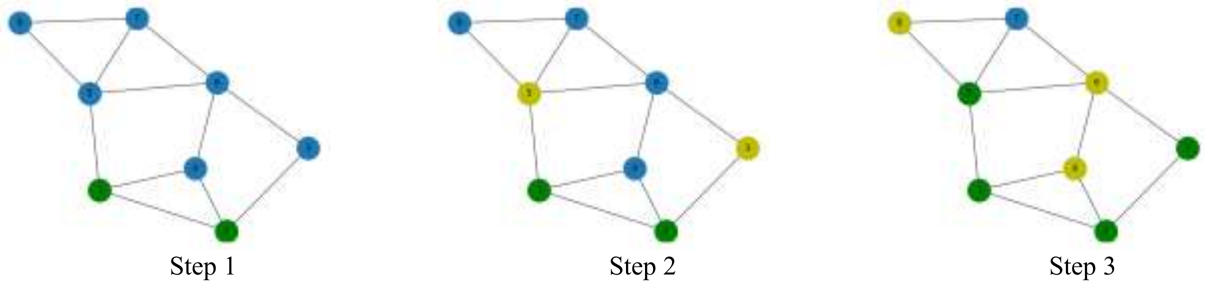


Figure 3 Independent cascade model

The threshold-based approach utilises the group influence on the node at a time t . It is a widespread technique to model population behaviour in a riot as an individual has two distinct and exclusive behavioural alternatives, e.g. participate or not participate in a strike. Node decision depends on some ratio of its neighbours that made the same decision, thus fulfilling the threshold. The diffusion process for Linear Threshold models that is the most straightforward works according to the following steps:

- Each node has its threshold and status (infected or susceptible).
- If the number of the infected neighbours is greater than its threshold at each step node, it becomes infected too.

The voter is one of the simplest opinion dynamics models and assumes a discrete variable to model an individual opinion. The information propagation under the network takes place according to the following procedure. A node is randomly selected at each step and then copied its state to the random neighbour. The process takes place until the consensus on one of the two options is set.

The majority role is another opinion dynamics model utilised to describe public debates. Nodes are presented via a discrete state in a Voter technique, but they interact with all nodes. The voting procedure is very similar to a Voter one.

Sznajd model is a spin model and utilises the theory of social impact. It takes into account a phenomenon called social validation that means that a community of individuals with the same opinion can influence their neighbours more than one single node. Each opinion is also represented as a discrete state. In each step, a pair of neighbouring nodes is selected and if their opinion consents, all their neighbours accept that opinion.

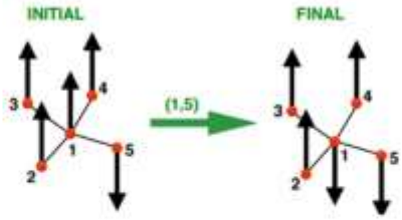


Figure 4 Voter model

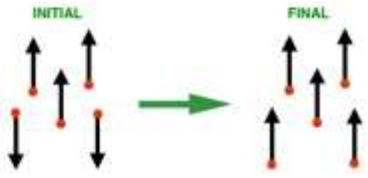


Figure 5 Majority rule model

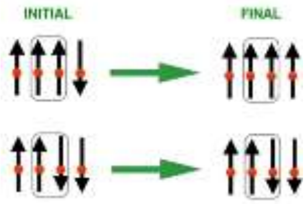


Figure 6 Sznajd model

Simulation Environment

The presented simulation experiments were conducted with RP&SDT (Rumor Propagation & Source Detection Toolkit). It is an open-source application available with an MIT licence that the author of this paper is developing. It utilises a range of well-known computing libraries in Python to provide a highly configurable, easily reusable and designed in user-friendly way GUI based application that allows the user to prepare a propagation experiment under any kind of network topology, utilising the well-known literature diffusion models to simulate the propagation in the network and based on the information spread graph identify potential sources of the diffusion. Moreover, RP&SDT provides a set of additional tools to perform sophisticated network analyses like selecting propagation sources based on well-known techniques, performing a simulation study about the network coverage under given network topology and sources. It is helpful to find an optimal configuration to model, for example, an advertising campaign and understand how the propagation looks with different models, parameters, and network topologies. The software can also simulate the propagation and source detection for other domains like epidemics or virus detection. This propagation can be simulated with available models in the toolkit and the source identification process with available methods. It is worth mentioning that the GUI layer is designed according to the multiple window approach that allows the researchers to analyse different cases simultaneously in a graph way. Moreover, it provides functionality to perform both diffusion and source detection simulation and automatically assess the results of the conducted process utilising the well-known metrics and helps to select the best one under a given set of conditions. RP&SDT is a self-described software that directly leads a user with each step to prepare a simulation experiment.

This paper utilises the mentioned functionalities of the RP&SDT, and to sum up what and how was used to perform the case study, a sample experiment is presented. The simulation is performed for the following requirements:

- A Watts-Strogatz synthetical network topology simulates a real online social network.
- The initial structure is analysed with different metrics and techniques.
- The information spreaders are selected based on the betweenness centrality metric.
- The rumor propagation process is simulated by an SIS model with 10 iterations.
- The propagation graph is analysed under different aspects and metrics.

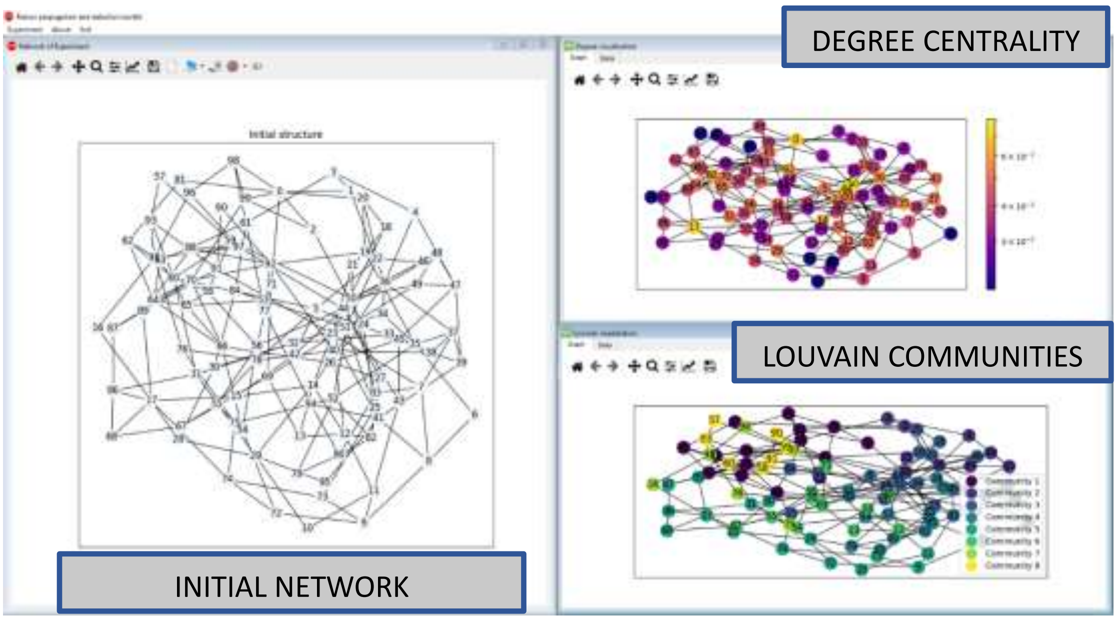


Figure 7: Network initial structure and performed analysis

As the first step user is obligated to configure an initial network structure. It can be a real graph provided in an acceptable format or generated according to the selected algorithm. In general, the next step performed by the researchers is to analyse the initial structure of the network to identify the crucial nodes. RP&SDT comes with a set of tools that helps alleviate that problem. The results of the mentioned actions are presented in the figure below. It is worth noticing that all analyses can be visible at the same what is helpful while conducting the analysis and comparing different views.

Based on the performed analysis, the researcher should select information sources that start spreading messages under the network in the next step. The user can do this step manually or automatically with the available algorithms. Afterwards, the user chooses and configures the diffusion model used to simulate information spread under the network. It provides a set of well-known diffusion models consisting of epidemics and dynamic opinion ones. When the diffusion configuration is ready, the propagation process can start. It can be performed in three modes: step, batch and the whole network infection. At each step, the user can see how many nodes are infected and how the network's diffusion trend and prevalence look. The results of the mentioned actions are presented in the below figures.

Simulation

This paper presents the simulation case study result to highlight the relationships between different network topologies, propagation methods, their parameters, and source nodes. This analysis is essential for modelling the advertisements campaigns, optimising vaccination strategies or preventing fake news from spreading over the network. The presented analysis has been performed with most popular network topologies like Erdös and Rényi random networks, scale-free and small-world ones with the following assumptions:

- Different topologies were used with the constant number of nodes: 500.
  - Erdös and Rényi – probability of node connection: 0.1, 0.25, 0.5.
  - Small-world – each node is joined with its 5 neighbours in a ring topology, with the probability of rewiring each edge: 0, 0.25, 0.5
  - Scale-free - number of edges to attach from a new node to existing nodes: 5, 10, 20.
- Source nodes were selected based on different strategies: random, betweenness centrality, closeness centrality, degree centrality, page rank centrality. For the epidemics models, there were always 5 of them. For opinion dynamics ones 200.
- There were 10 experiments of 200 iterations of the following models with constant, presented parameters for all of the experiments:
  - SI – infection probability = 0.1.
  - SIS - infection probability = 0.1, recovery probability = 0.05.
  - SIR – infection probability = 0.1, immunization rate = 0.005.
  - SEIR - infection probability = 0.1, immunization rate = 0.005, latent period = 20 iterations.
  - Voter.
  - Q-Voter - number of neighbours = 5.
  - Majority rule - number of neighbours = 5.
  - Sznajd.

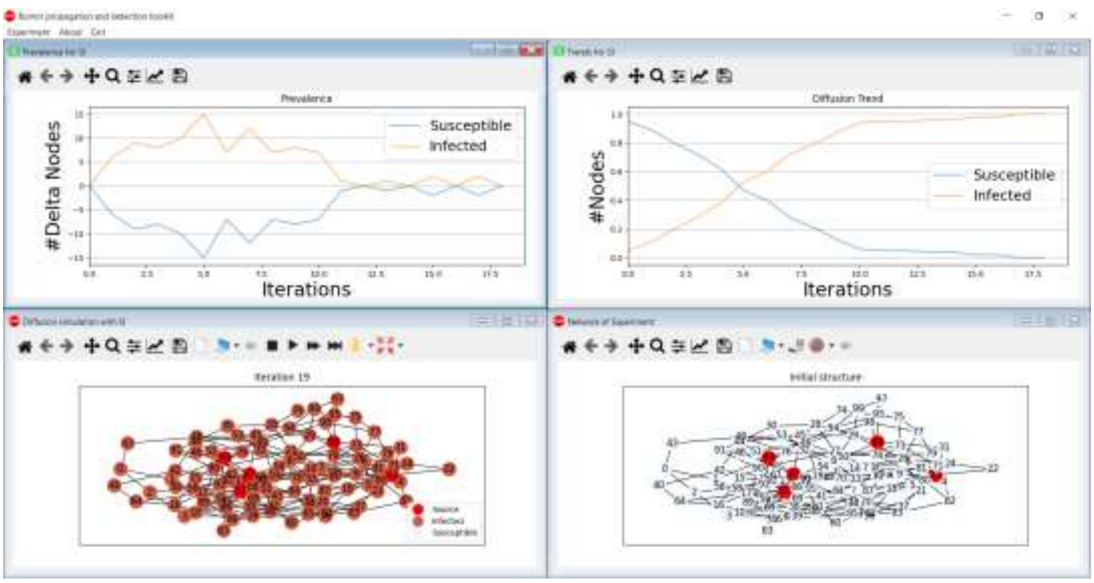


Figure 8 Information propagation simulation with trend and prevalence analysis

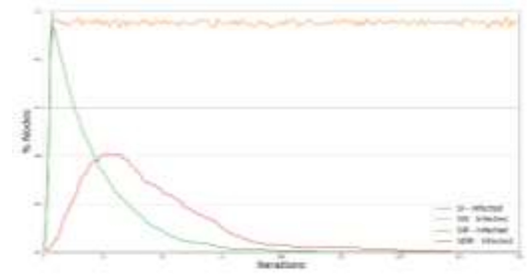
Simulation results are presented in **Error! Reference source not found.** where: NT – network type, NC – network config, SS – source selection, R – random selection, D – degree centrality based selection, B – betweenness centrality based selection, C – closeness centrality based selection, PR – page rank centrality based selection. Moreover, each cell contains the average number of iterations in four different coverages ratios, according to the following scheme: *25%/50%/75%/100%.* "1" value in that column means that that ratio has not been reached.

Table 1: Epidemic models simulation results over different topologies and source selection methods

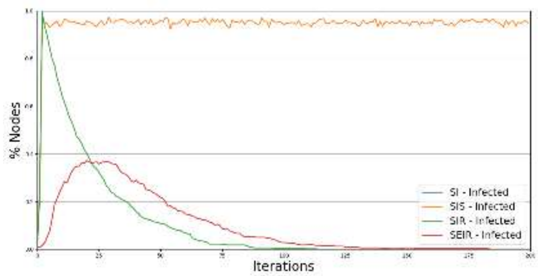
NT	NC	SS	SI	SIS	SIR	SEIR
Erdös and Rényi	0.1	R	4.7/7.2/10.1/29.6	4.9/7.6/11.2/-1	5/7.7/8.8/-1	26.2/-1/-1/-1
		D	4.7/7.1/10.1/30.7	4.7/7.6/10.9/-1	4.6/7.3/8.7/-1	25.7/-1/-1/-1
		B	4.7/7.2/10.3/27.8	4.7/7.2/11.1/-1	4.7/7.5/10.4/-1	26.2/-1/-1/-1
		C	4.4/7/9.9/30.7	4.8/7.5/11.2/-1	4.8/7.6/10.3/-1	27/-1/-1/-1
		PR	7.7/10.2/13.1/30.8	8.3/11/14.5/-1	8.9/11.9/8.7/-1	40.8/-1/-1/-1
	0.25	R	3.1/4.2/6.1/15.5	3.1/4.7/6.5/-1	3.1/4.7/6.5/-1	18.4/19.1/-1/-1
		D	3/4.5/6/15.2	3.1/4.3/6.1/-1	3.2/4.8/6.6/-1	19.9/19.6/-1/-1
		B	3.3/4.5/6.2/15	3.2/4.6/6.3/-1	3.2/4.5/6.4/-1	18.2/25.1/-1/-1
		C	3.1/4.6/6.1/14.7	3/4.8/6.3/-1	3.2/4.7/6.4/-1	18.9/18.2/-1/-1
		PR	5.2/6.4/8/17.9	5.1/6.6/8.2/-1	5.1/6.8/8.7/-1	28.7/19.4/-1/-1
	0.5	R	2.4/3/4/8.7	2.3/3.1/4/-1	2.1/3/4/-1	15.5/26/-1/-1
		D	2.4/3/4/9.3	2.1/3/4/-1	2.2/3/4/-1	16/24.8/-1/-1
		B	2.2/3/4/9.3	2.6/3/4.1/-1	2.1/3/4/-1	15.7/18.8/-1/-1
		C	2.4/3.1/4/9.2	2.4/3.1/4.1/-1	2.3/3/4/-1	15.3/28.6/-1/-1
		PR	3.3/4.3/5.1/9.6	3.3/4.2/5/-1	3.5/4.3/5.3/-1	20.7/11.1/-1/-1
Scale-free	5	R	3/3.8/4.1/6.9	3/4/4.4/-1	3/3.9/4.2/-1	17.5/25.4/-1/-1
		D	3/3.8/4.2/6.9	3/4/4.4/-1	3/3.9/4.4/-1	17/28.7/-1/-1
		B	3/3.7/4.3/7.2	3/4/4.3/-1	3/4/4.4/-1	17.5/22.7/-1/-1
		C	3/3.8/4.2/6.7	3/4/4.3/-1	3/4/4.1/-1	17.7/19.9/-1/-1
		PR	3.1/4/4.9/7.5	3/4/4.8/-1	3.4/4/4.8/-1	18.8/28.8/-1/-1
	10	R	2/3/3/4.1	2/2.9/3/-1	2/3/3/-1	12.8/22.5/-1/-1
		D	2/2.9/3/4	2/2.8/3/-1	2/2.9/3/-1	12.7/23.7/-1/-1
		B	2/2.8/3/4	2/2.7/3/-1	2/2.7/3/-1	12.7/18.8/-1/-1
		C	2/2.7/3/4	2/2.9/3/-1	2/2.9/3/-1	13.3/21.4/-1/-1
		PR	2/3/3/4.1	2/3/3/-1	2/3/3/-1	13.8/16.9/-1/-1
	20	R	2/2/2/3	2/2/2/-1	2/2/2/-1	11.1/26.8/-1/-1
		D	2/2/2/3	2/2/2/-1	2/2/2/-1	10.8/20.5/-1/-1
		B	2/2/2/3	2/2/2/-1	2/2/2/-1	10.9/25.3/-1/-1
		C	2/2/2/3	2/2/2/-1	2/2/2/-1	10.8/28.2/-1/-1
		PR	2/2/2/3	2/2/2/-1	2/2/2/-1	11.4/27.9/-1/-1
Small-world	0	R	157.9/-1/-1/-1	18.5/-1/-1/-1	-1/-1/-1/-1	-1/-1/-1/-1
		D	-1/-1/-1/-1	-1/-1/-1/-1	-1/-1/-1/-1	-1/-1/-1/-1
		B	-1/-1/-1/-1	-1/-1/-1/-1	-1/-1/-1/-1	-1/-1/-1/-1
		C	-1/-1/-1/-1	-1/-1/-1/-1	-1/-1/-1/-1	-1/-1/-1/-1
		PR	86.4/54.7/37.2/-1	137.3/-1/-1/-1	-1/-1/-1/-1	-1/-1/-1/-1
	0.25	R	25.4/36.5/48/91.7	32.2/47.3/65/-1	35.2/-1/-1/-1	50.9/-1/-1/-1
		D	28.7/40.3/51.1/99.9	34.3/49/67.6/-1	42.5/-1/-1/-1	101.4/-1/-1/-1
		B	27/39.3/49.9/92.9	31.5/46/64.1/-1	38.1/5.1/-1/-1	83.6/-1/-1/-1
		C	27.8/38.8/49.4/101.9	32.1/46.3/63/-1	41.8/-1/-1/-1	80.8/-1/-1/-1
		PR	33.6/45.3/56.7/103.5	39.1/54.8/72.5/-1	51.8/-1/-1/-1	106.8/-1/-1/-1
	0.5	R	24/33.2/42.3/87	27.1/39.8/54.3/-1	28.4/12.6/-1/-1	17.7/-1/-1/-1
		D	23/32/41.3/82.8	29.2/41.7/58.5/-1	35.1/21.5/-1/-1	45.7/-1/-1/-1
		B	21.5/30.8/40/82.6	26.6/39/53.3/-1	32.6/14.4/-1/-1	-1/-1/-1/-1
		C	23.3/32.7/41.7/91.2	27.8/39.6/54.3/-1	31.2/19.1/-1/-1	17.7/-1/-1/-1
		PR	25.6/35.5/44.5/87.3	35/47.4/62.8/-1	36.5/15.7/-1/-1	16/-1/-1/-1

Based on the presented result, it can be observed that depending on the epidemics model and available states, some of the experiments were not able to cover the whole network in the given simulation period as nodes can transit from being infected to other states, and for others, they stay as infected to the end. For most experiments, only the SI model allowed the fully covered network with infection.

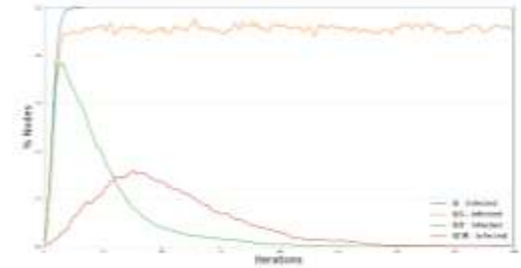
For random graphs, it can be observed that with the increased value of the probability of node connection, the number of required iterations to cover the whole network decreased because there are more neighbours able to pass information further. For scale-free networks, it was impossible to find a relationship between the number of the initial nodes and the speed of information propagation. For small-world, the relationship between the probability of rewiring edges and the speed of information diffusion can be observed. Based on the above results, the information propagation differs the fastest for the random graphs as there are connections between distant nodes in the network. The slowest was scale-free as most of the nodes are connected with a just of neighbours. These theses are confirmed with diffusion trends presented in Figure 9. Analysing the coverages ratio of the networks, it can be observed that for random networks, there



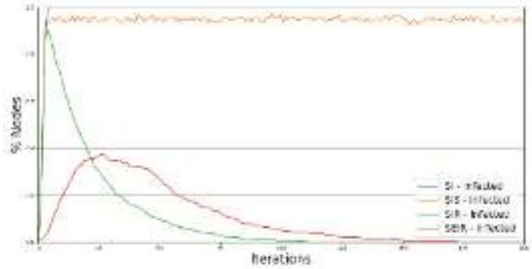
a) Erdös and Rényi, NC = 0.1



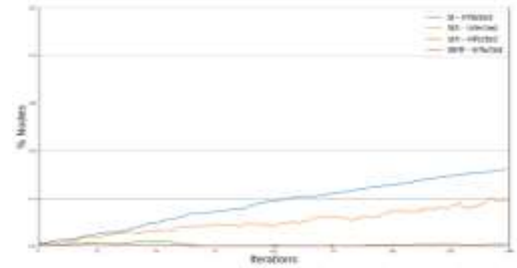
b) Erdös and Rényi, NC = 0.5



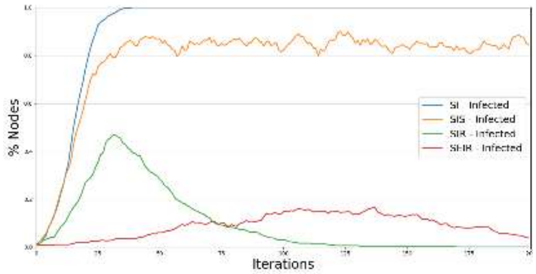
c). Scale-free, NC = 5



d). Scale-free, NC = 20



e) Small-world, NC = 0

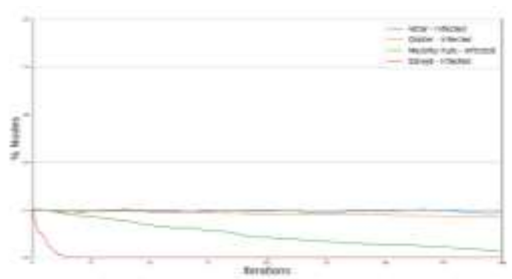


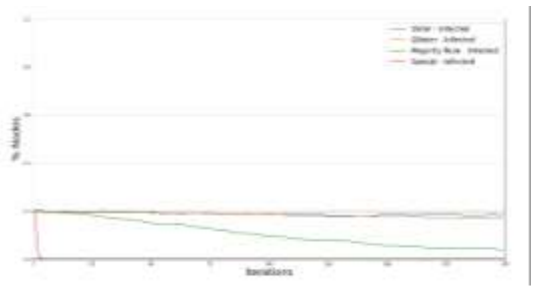
f) Small-world, NC = 0.5

Figure 9 Infected nodes trend for each topology with different configurations with epidemics models

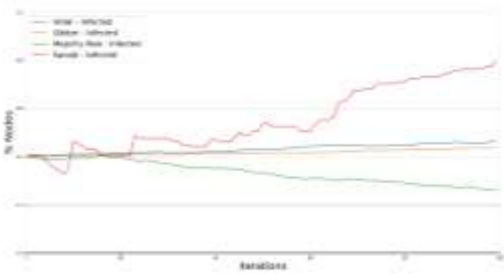
is a high growth of the number of infected nodes as there is a possibility to pass information between distant nodes. The start of the propagation process is very similar for scale-free but gets slowed down. The information is quickly propagated by hubs but slowly for single, distant nodes. Regular graphs – small world cases with the probability of rewiring each edge equal to 0 – allow diffusing information the slowest.

The network coverage for random graphs was the slowest for the PageRank selection. For others, the ratio was very similar. For scale-free networks, the diffusion speed is very similar for each source selection algorithm.

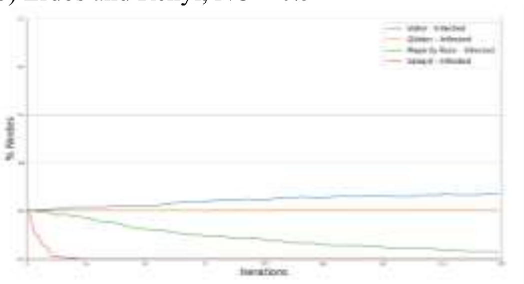




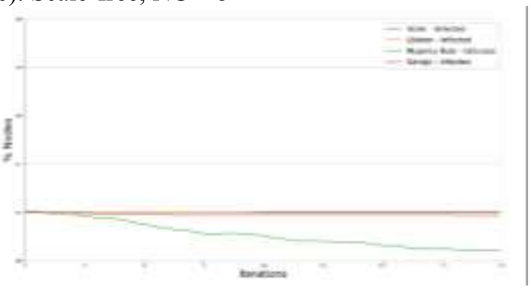
a) Erdös and Rényi, NC = 0.1



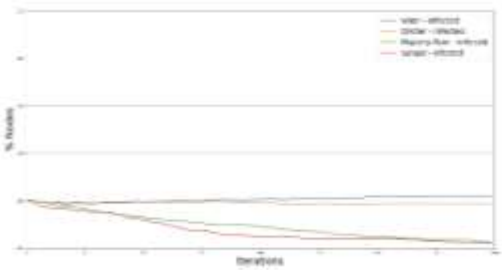
b) Erdös and Rényi, NC = 0.5



c). Scale-free, NC = 5



d). Scale-free, NC = 20



e) Small-world, NC = 0

f) Small-world, NC = 0.5

Figure 10 Infected nodes trend for each topology with different configurations with opinion dynamics models

For opinion dynamics, it can be observed that both Majority rule and Sznajd models are convergent to one of the opinions in the society. For others, the nodes could not find a consensus. The most significant impact on the speed of network coverage can be seen in scale-free networks. For other topologies, this impact is minor.

Conclusions

The paper presents the simulation studies around the rumor spread process via the varied range of the networks topologies, information spread strategies and aspects taking part in this process to find Relationships between them. The presented results highlight the relationships between assumed information propagation models and their propagated networks. The obtained results can be utilised in many domain-specific networks like virus or epidemic spread in online social networks, trojan propagation in a computer network, fake news diffusion in online social networks, advertisement campaigns etc. It is essential to know how different aspects affect the speed of the rumor spread in the network and how they can be treated to reduce their malicious intent.

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