REPORT

**A-Study-of-Resiliency-of-Large-Networks-to-Worm-Propagation**

The purpose of this program is to study the propagation of worms on the three different types of networks through simulation when no cure (that is, worm defense) is applied. In other words, the worm will continue to spread until no uninfected node remains.

This project simulates the propagation of a worm through various network types and evaluates the effectiveness of defense mechanisms in mitigating the spread. The simulation covers two main programs:

1. **Worm Propagation**: Models the spread of a worm in a network without any defense mechanisms.

2. **Worm Propagation with Defense**: Extends the first program by incorporating defense mechanisms that either inoculate uninfected nodes or cure infected nodes.

**Features**

- Simulation of worm spread in networks based on the Erdös-Rényi, Barabási-Albert, and Watts-Strogatz models.

- Implementation of defense mechanisms to combat worm propagation.

- Analysis of the spread dynamics through cumulative and per-time-step visualizations.

- Comparison of the impact of different network topologies on the spread and defense effectiveness.

**Setup**

Ensure you have Python installed on your system along with the necessary libraries: **networkx** for network manipulation and **matplotlib** for plotting, **csv** for csv file generation, and **os** and **numpy**

**Usage**

**Prepare Network Files:**

Generate or obtain CSV files representing the network graphs. Each file should list the edges in the network, with one edge per line, formatted as node1, node2.

**Running Simulations:**

For basic worm propagation, use the simulate\_infection function.

For simulations with defense mechanisms, use the simultaneous\_infection\_with\_defense function.

**Input Parameters:**

Enter the filename of the network graph CSV.

Specify the probability of worm infection.

List initial infected nodes.

(For defense simulations) Specify the probability of node inoculation or curing and the initial cured node.

**Visualizing Results:**

The plot\_result\_1 and plot\_results\_2 functions plot the cumulative number of infections over time, the number of new infections per time step, and, for defense simulations, the cumulative number of cures respectively.

**Example**

# Example of running a basic simulation

filename = '{name\_of\_the\_file}\_{num\_nodes}.csv'

p\_infect = 0.1

initial\_infected = 23,45,78,90 # comma separated, no spaces when prompted

simulate\_infection(graph, p\_infect, initial\_infected)

# Example of running a simulation with defense

p\_defense = 0.05

initial\_cured = 45,67,89,1

simultaneous\_infection\_with\_defense(graph, p\_infect, p\_defense, initial\_infected, initial\_cured)

Also, additional input called `choice` was included to give the user the option between executing `Program1` or `Program2` or `both`

Please wait until all the inputs are entered, the reason being when moving up the number of nodes, the program takes extra time to ask for `choice` input.

Tested the code on 100 to 10\_000 nodes for both simulations.

Including an example file for convenience.

**Deliverable (a)**

1. Erdos-Reyni Network showed uniform spread to their random nature.

2. Barabasi-Albert Network with free-scale properties, exhibited faster initial spread due to the presence of highly connected nodes.

3. Watts-Strogatz Network demonstrated a mix of behaviours due to their small-world properties, with rapid spread within local clusters(rings) but slower spread between them

The rate depends on the type of network for sure.

I have run manual testing with different values of p\_infect and p\_defense, changing the number of nodes in infection and cure. Some observations for the erdos reyni network are that the rounds (time units) though differed in simulation, the average time taken to infect, and cure are the same over the different numbers of nodes.

The barabasi\_albert network showed a difference in the average time taken for both simulations.

Watt Strogatz was where the average time taken showed higher differences.

The plot at the end, describes the infection and cures simulation much better.

**Deliverable (b):**

I believe drawing analogies between the observations from the worm propagation simulation and the current pandemic involves understanding how the dynamics of infectious disease spread in populations and how interventions (like vaccines or treatments) can impact this spread.

**1. Initial Spread and R0**

The basic reproduction number R0 in epidemiology indicates the average number of people (here nodes) to whom a single infected person will transmit the virus(infection) in a fully susceptible population. Similarly, in worm propagation simulation, the probability *pinfect* of infecting an uninfected node reflects the ease of spread. Networks with higher connection (e.g., Watts-Strogatz Network) probabilities can see faster and wider spread, mirroring how a higher R0 can lead to more rapid pandemic escalation.

**2. Some Effects of Network Structure**

**Erdös - Rényi networks** can be likened to randomly mixing populations where everyone has a roughly equal probability of interacting with any other individual. This structure is idealized and not often found in real populations.

**Barabási - Albert networks** reflect scale-free networks with few highly connected nodes (hubs) and many nodes with fewer connections. This can be analogous to super-spreader events where certain individuals or locations contribute disproportionately to the spread of a disease.

**Watts - Strogatz networks** demonstrate small-world properties with high clustering and short path lengths, akin to real-world social networks where tight-knit communities (clusters) have occasional bridges connecting them to other communities. Diseases can spread rapidly within clusters but may spread more slowly between them without those bridges.

**3. Impact of Interventions**

Identifying defense mechanisms can drastically slow down or even halt the spread, mirroring the effects of public health interventions like vaccination, lockdowns, and contact tracing in real-world pandemics. For example, the delay was observed in one of the above observations in the **Barabasi-Albert network** the infection w/o cure took 6.73 sec while w/ cure took 17.6 sec.

**4. S-Shaped or Bell-Shaped Curves**

As explained previously, the shape is affected by the **type of** network and the **number of nodes** in the network. The shape of the bell curve of new infections per time (rounds) mirrors the daily cases in a pandemic, peaking when the spread is most rapid and tapering as interventions take effect or susceptible individuals become less common.

**5. Herd Immunity and Inoculation**

Reaching a point where a sufficient portion of the network is inoculated can lead to herd immunity, significantly slowing the spread of the worm (infection) to nodes that are not immune yet. The simulation's defense mechanisms can be seen as analogous to vaccination efforts and the concepts of herd immunity in controlling the spread of infectious diseases.

**Deliverable (c):**

The application of a cure (either through inoculating uninfected nodes or curing infected ones) significantly slows down the rate of worm spread. In the context of the simulation:

* **Immediate Impact**: As soon as the cure starts to be applied, the growth rate of newly infected nodes per round decreases. This is because cured or inoculated nodes either block the path of infection or reduce the pool of infectable nodes.
* **Cumulative Effect**: Over time, the cumulative number of infections grows more slowly, potentially reaching a plateau if the cure is applied efficiently enough to outpace the infection rate. This can lead to scenarios where the network never reaches full infection because the cure effectively controls the spread.

**Deliverable (d):**

**Without Cure**: The type of network significantly affects the spread rate due to differences in network topology.

* **Erdös-Rényi (ER)** networks tend to have a uniform random spread, with the average time to full infection depending on the probability of edge creation. The spread might be moderate due to the lack of highly connected hubs.

A screenshot of a graph

Description automatically generated

Figure 1. Cumulative Number of New Infections (only infection simulation) 500 nodes

A comparison of a graph

Description automatically generated with medium confidence

Figure 2. Cumulative, Infections and Cures (both infection and defense simulation) 500 nodes

A graph of a line and a line

Description automatically generated with medium confidence

Figure 3. Cumulative Number of New Infections (only infection simulation) 5000 nodes

A graph of a graph and a graph of a graph

Description automatically generated with medium confidence

Figure 4. Cumulative, Infections and Cures (both infection and defense simulation) 5000 nodes

Note: The figures 1,2,3 and 4 are for the **Erdos-Reyni (ER)** Network

* **Barabási-Albert (BA)** networks, with their scale-free nature, can see faster spread due to the presence of highly connected nodes that act as super-spreaders.

A graph and a diagram

Description automatically generated with medium confidence

Figure 5. Cumulative Number of New Infections (only infection simulation) 500 nodes

A graph of diseased cures

Description automatically generated

Figure 6. Cumulative, Infections and Cures (both infection and defense simulation) 500 nodes

A graph and a diagram

Description automatically generated with medium confidence

Figure 7. Cumulative Number and New Infections (only infection simulation) 5000 nodes

A graph and chart of diseased cures

Description automatically generated with medium confidence

Figure 8. Cumulative, Infections and Cures (both infection and defense simulation) 5000 nodes

Note: Figures 5,6,7 and 8 are for the **Barabasi-Albert (BA)** Network

* **Watts-Strogatz (WS)** networks demonstrate clustering and short path lengths, which can lead to rapid spread within clusters but potentially slower spread between them, depending on the rewiring probability.

A graph and diagram of a graph

Description automatically generated with medium confidence

Figure 9. Cumulative Number and New Infections (only infection simulation) 500 nodes

A graph and chart of disease

Description automatically generated with medium confidence

Figure 10. Cumulative, Infections and Cures (both infection and defense simulation) 500 nodes

A graph and chart of a graph

Description automatically generated with medium confidence

Figure 11. Cumulative Number and New Infections (only infection simulation) 5000 nodes

A graph of diseased diseases

Description automatically generated with medium confidence

Figure 12. Cumulative, Infections and Cures (both infection and defense simulation) 5000 nodes

Note: Figures 9,10,11 and 12 are for the **Watts-Strogatz (WS)** Network

**With Cure**: The effectiveness of the cure varies by network type.

**ER** networks have seen a more evenly distributed effect of the cure due to their uniformity.

**BA** networks benefited significantly from targeting cures at highly connected nodes, slowing the spread more effectively due to the role of hubs.

**WS** networks require strategic placement of cures in both highly connected nodes and bridge nodes between clusters to effectively manage spread.

**Deliverable (e):**

Given the impact of network topology on the spread and the effectiveness of cures, strategies to enhance network resilience should focus on network structure and strategic application of defenses:

* **Targeted Inoculation/Curing**: Prioritize nodes based on their connectivity and role in the network. For **BA** networks, targeting hubs (nodes with high degrees) for curing or inoculation dramatically reduces the spread rate. In **WS** networks, targeting bridge nodes between clusters proved to be effective.
* **Enhancing Network Robustness**: Modify the network structure to reduce the likelihood of rapid spread. This could involve adding redundant connections to dilute the impact of hubs or increasing the clustering coefficient to localize potential outbreaks.
* **Adaptive Strategies**: Implement dynamic strategies that adjust based on real-time data on the spread, such as increasing the cure rate in regions (or nodes) experiencing rapid spread or preemptively inoculating nodes in the path of the spread.