Interplay between epidemic and information spreading

A Life Data Epidemiology project
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Overview

- context to the problem
- project objective
- model & hypothesis
- dynamics
- simulation
- evaluation techniques
- results
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- future prospects

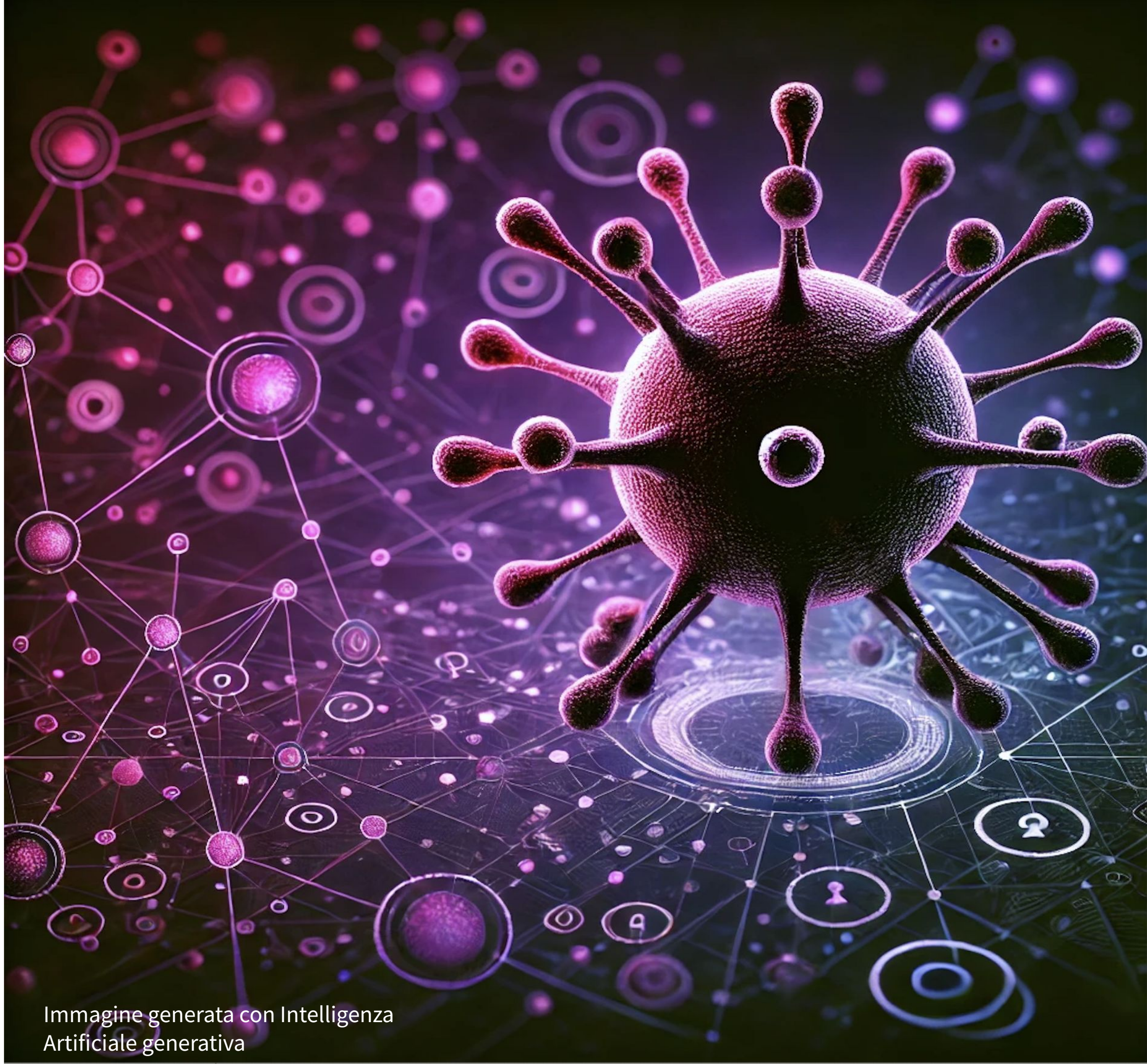


Immagine generata con Intelligenza Artificiale generativa

[Chou et al., 2020; Roozenbeek et al., 2020]

Understanding the problem

Epidemic spreading

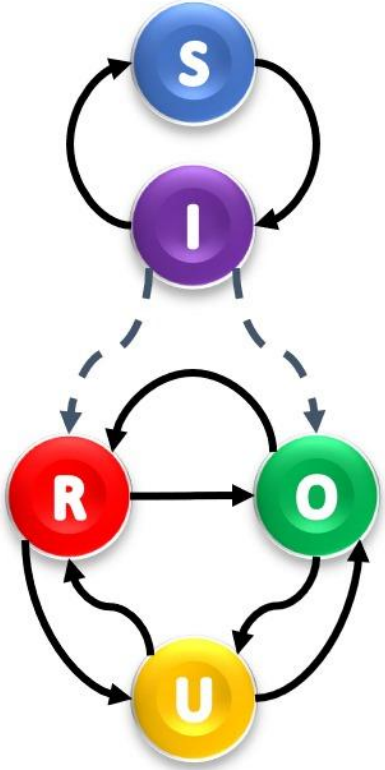
Disease spreading is based on biological and social mechanisms, and involves two states:

- susceptible S
- infected I

Information spreading

Information spreading depends on social interactions, and involves three states:

- official info O (by public institutions)
- rumors R (by unverified sources)
- uninformed U



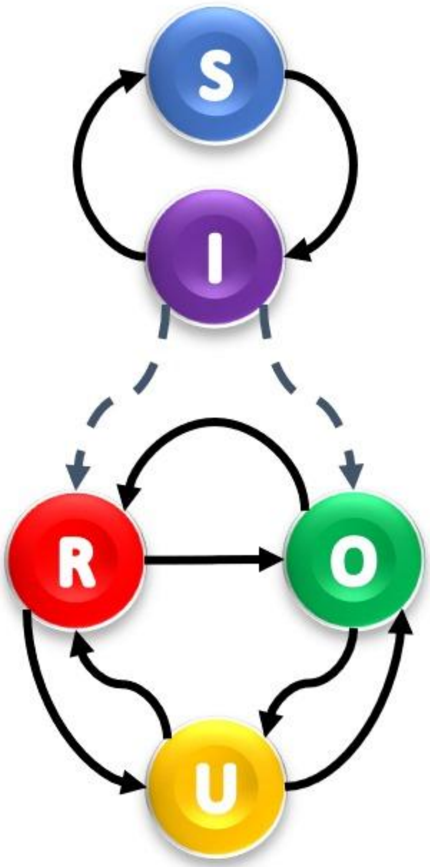
[Chou et al., 2020; Roozenbeek et al., 2020]

Understanding the problem

Effects of rumours	Effects of official info	Effects on the behaviors
Dangerous rumours and misinformation can lead to lead to mischaracterizing and/or undermining the severity of the epidemic	Official information can guide the public towards more effective epidemic prevention	Accurate information can improve public health behavior whereas misinformation can lead to risky behaviors.

Project Goal

If the individual's exposure to types of information influences their behaviour towards the epidemic, how is the size of the epidemic impacted?



Model

- Compartmental Model for both Information and Health states
- Scale-Free Network based on Barabasi-Albert model
- Multilayer Network describing both Epidemic Dynamics and Information Dynamics

[Chou et al., 2020; Roozenbeek et al., 2020]

Hypothesis

SIS Epidemic Dynamic	Susceptible (S) → Infected (I) → Susceptible (S)
Unaware-Aware-Unaware Communication Dynamic for both type of information	individuals are by default U and can become aware of information (O/R) but can also forget about it
$p(I\|O) < p(I\|U)$	O adopt behaviors that decrease the risk of infection
$p(I\|R) > p(I\|U)$	R adopt behaviors that increase the risk of infection

[Chou et al., 2020; Roozenbeek et al., 2020]

Simulation Dynamics

Disease Infection

- is a contagious process and depends on the number of infected neighbours and on the node information state

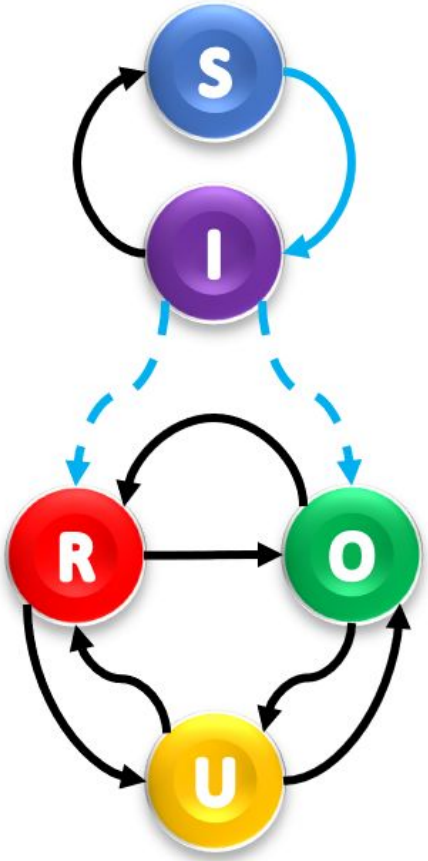
$$S + N_I \cdot I \xrightarrow{p_{S\to I}^{N_I}} I + N_I \cdot I$$

$$\text{where} \quad p_{S\to I}^{N_I} = 1 - (1 - p_{S\to I})^{N_I}$$

$$p_{S\to I} = \begin{cases} (1-\varepsilon)\cdot p_{\mathrm{i}} & \text{if } O \\ p_{\mathrm{i}} & \text{if } U \\ (1+\varepsilon)\cdot p_{\mathrm{i}} & \text{if } R \end{cases}$$

- forces the individuals to become aware of information (R or O) with the following re-normalized probabilities

$$p(U \to R|I) = \frac{p_{U\to R}}{p_{U\to R} + p_{U\to O}} \quad , \quad p(U \to O|I) = \frac{p_{U\to O}}{p_{U\to R} + p_{U\to O}}$$



Rumour Infection

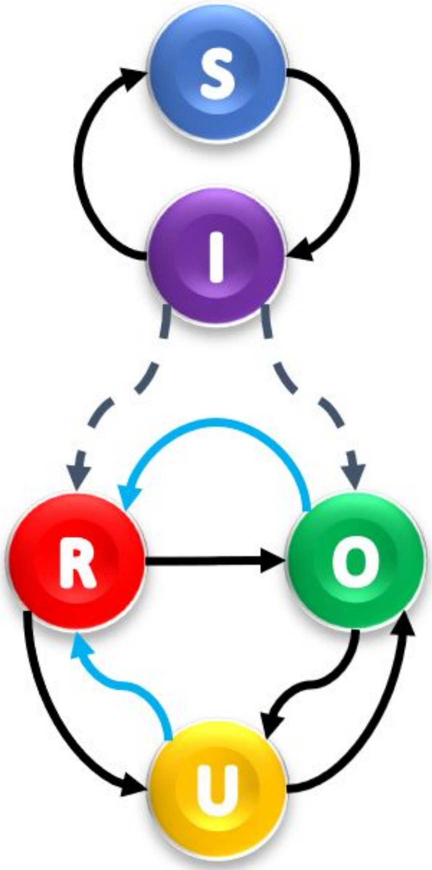
- is a contagious process and depends on the number of rumour informed neighbours of the node

$$O + N_R \cdot R \xrightarrow{p_{O\to R}^{N_R}} R + N_R \cdot R$$

$$\text{where} \quad p_{O\to R}^{N_R} = 1 - (1 - p_{O\to R})^{N_R}$$

$$U + N_R \cdot R \xrightarrow{p_{U\to R}^{N_R}} R + N_R \cdot R$$

$$\text{where} \quad p_{U\to R}^{N_R} = 1 - (1 - p_{U\to R})^{N_R}$$



Official Infection

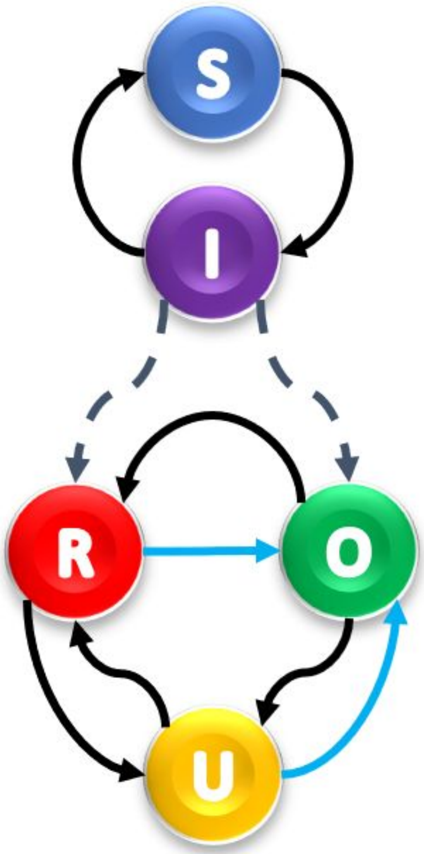
- is a contagious process and depends on the number of officially informed neighbours of the node

$$R + N_O \cdot O \xrightarrow{p_{R\to O}^{N_O}} O + N_O \cdot O$$

$$\text{where} \quad p_{R\to O}^{N_O} = 1 - (1 - p_{R\to O})^{N_O}$$

$$U + N_O \cdot O \xrightarrow{p_{U\to O}^{N_O}} O + N_O \cdot O$$

$$\text{where} \quad p_{U\to O}^{N_O} = 1 - (1 - p_{U\to O})^{N_O}$$



Recovery

- is a spontaneous process (does not depend on the nodes' neighbors)
- is independent of the information status

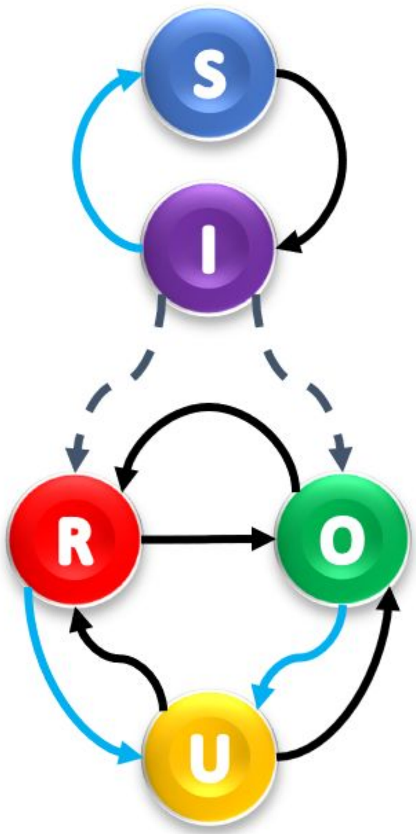
$$I \xrightarrow{p_{I \to S}} S$$

Forgetting

- is a spontaneous process
- cannot happen while the node is infected

$$O \xrightarrow{p_{O \to U}} U$$

$$R \xrightarrow{p_{R \to U}} U$$



Simulation

- was run on a large network of 2000 individuals
- consisted of evolving the simultaneous spreading of the epidemic and information over 200 days
- the number of individuals in each state (S, I, U, O, R) were saved at all times
- the (final) attack rates were computed
- the maximum number of newly infected was computed
- was run for different values of its parameters to analyze their role
- was run, for each combination of parameters, 100 times in order to evaluate a mean value and 95% confidence interval
- in each analysis, only one or two parameters are changed at once, and the remaining ones are initialized to realistic values

[Guess, A., Nagler, J., & Tucker, J. (2019). Misinformation and fake news exposure during the 2018 U.S. midterm elections. HKS Misinformation Review.]

Parameters

- **p_U_to_O = 0.55** describes how likely a person is influenced by official information: we suppose an efficient official information spreading campaign and set a higher value
- **p_U_to_R = 0.35** as a consequence of an efficient campaign, we set a lower value
- **p_R_to_O** is the probability of a person correcting themselves
- **p_R_to_U** is the probability of forgetting rumours
- **p_O_to_U** is the probability of forgetting official information so, in an efficient campaign, it should be low
- **p_O_to_R** is the probability of an officially informed believing rumours and is non-null
- **m:** number of edges to attach from a new node to existing nodes when building the network based on the Barabasi-Albert model
- **p_i** is the disease transmission probability
- **R_0 = 2.5** is the basic reproductive number of the Covid19 disease
- **p_I_to_S**: is the recovery probability and is computed based on the reproductive ratio number.
- symmetric correction **ε** codifies the change of behaviour and susceptibility of an individual based on their information status

Evaluation techniques

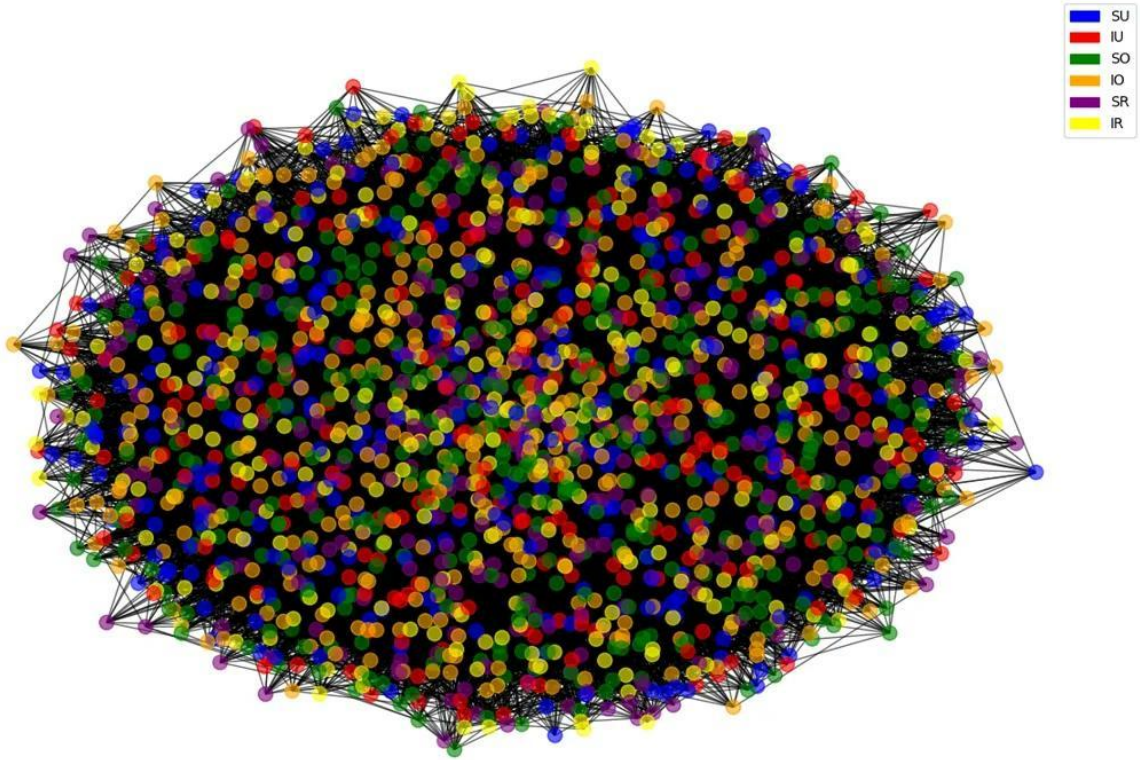
Evolution of the Epidemic

- shows the evolution of the simulation over time
- shows the results of the simulations for different values a one parameter
- the epidemic behaviour is quantified by computing the total number of infected at each time

Heat Maps

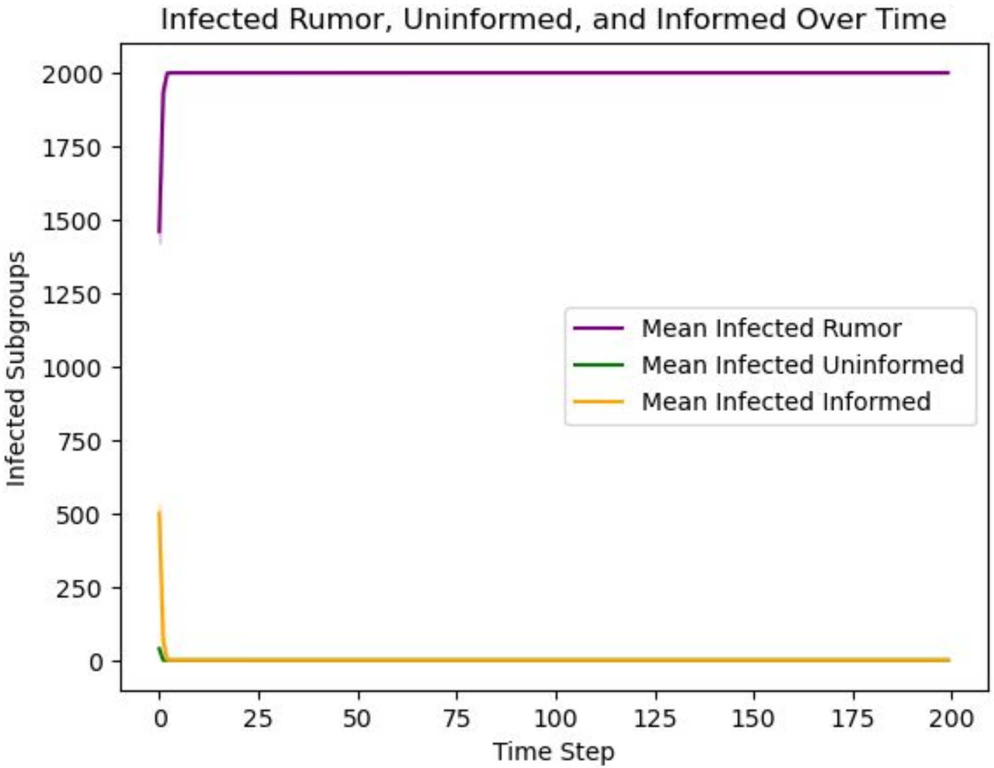
- are used to explore the relationship between two parameters of the network, by varying their values
- are useful to observe the impact of the information layer on the epidemic
- the maximum number of newly infected in a day was chosen over the final attack rate as it showed more contrast

Results of the simulations

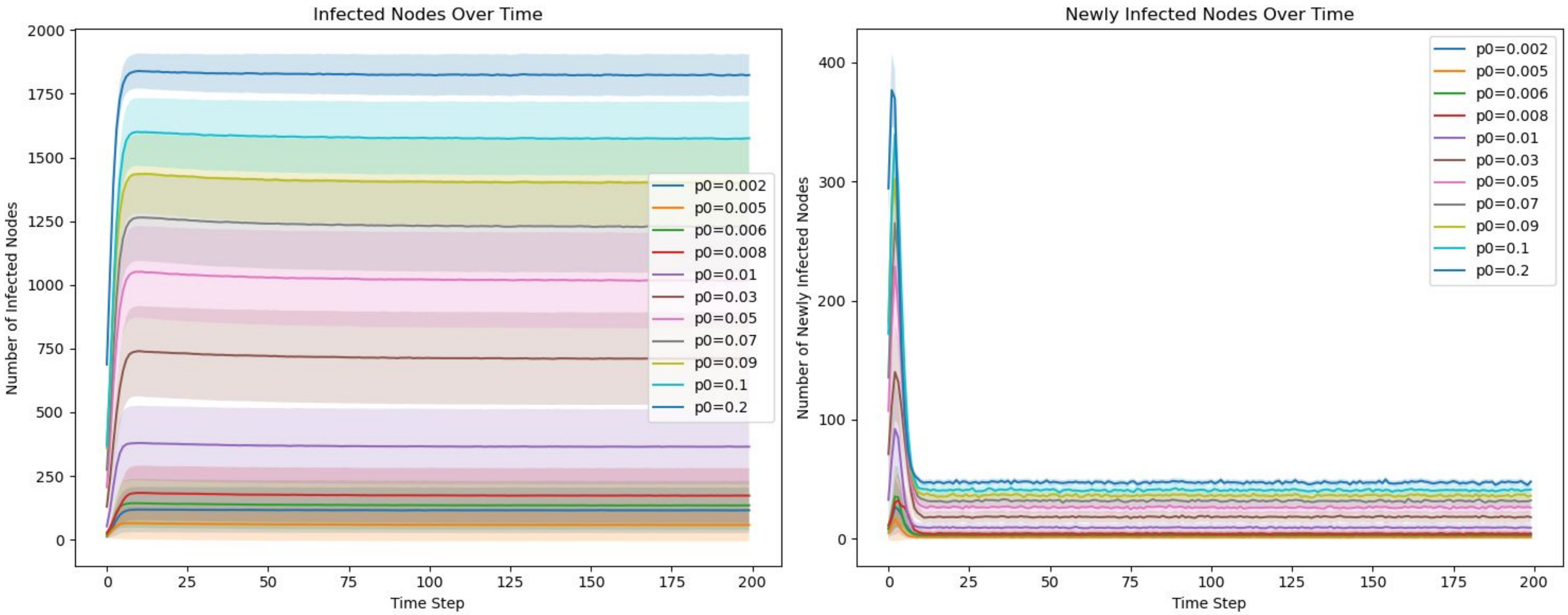


Recording: Example of nodes states evolving in time during the simulation.

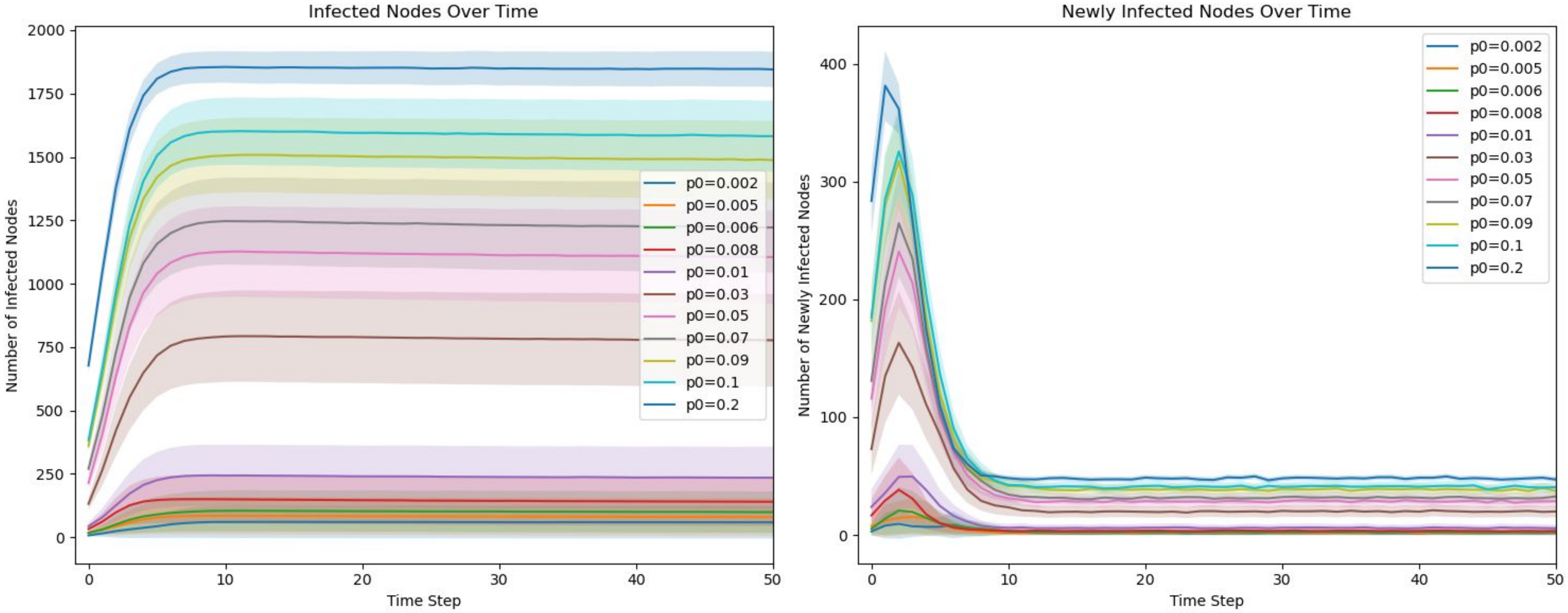
Informed density population evolution



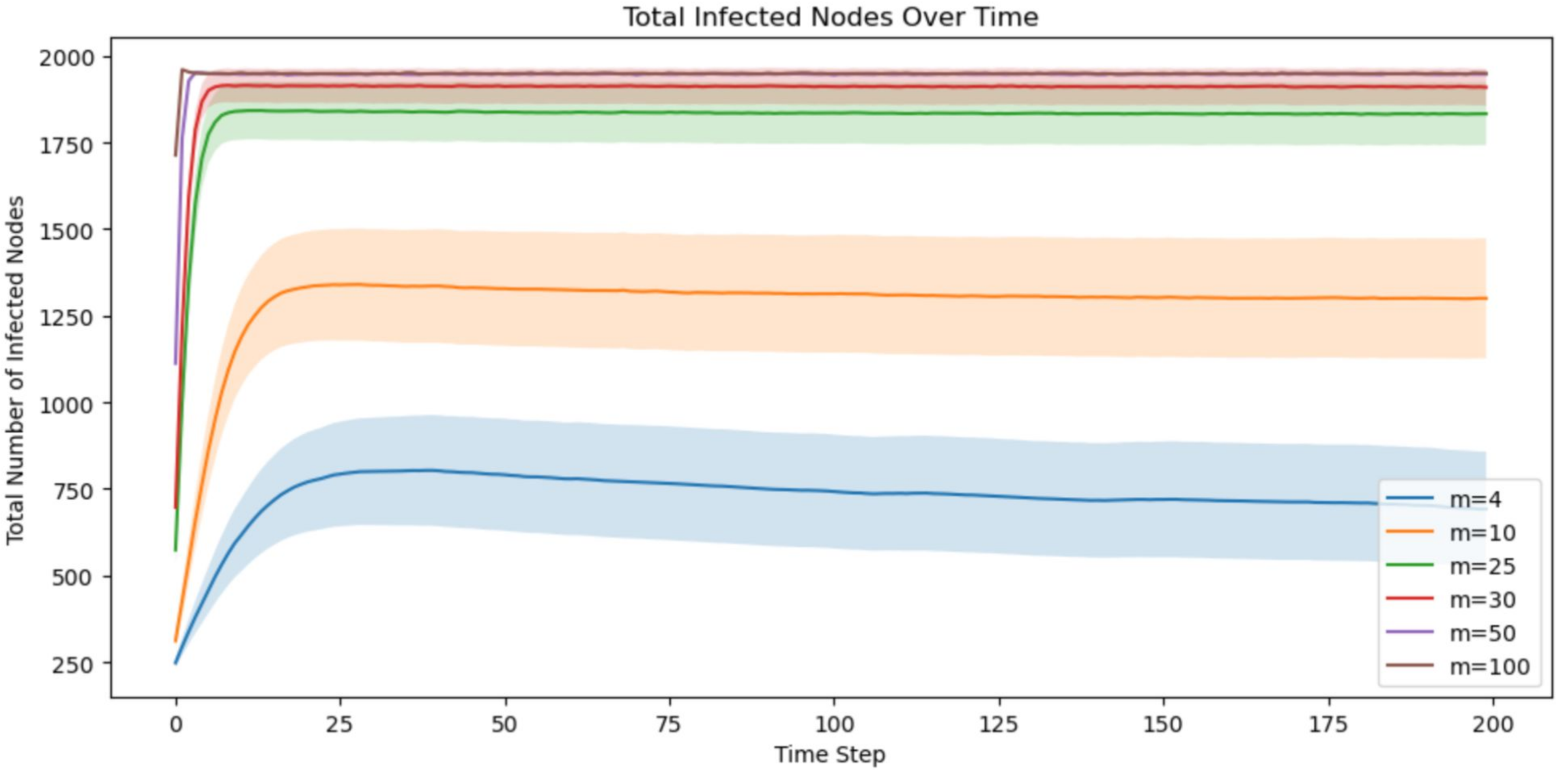
Minimum density of infected individuals to start the epidemic



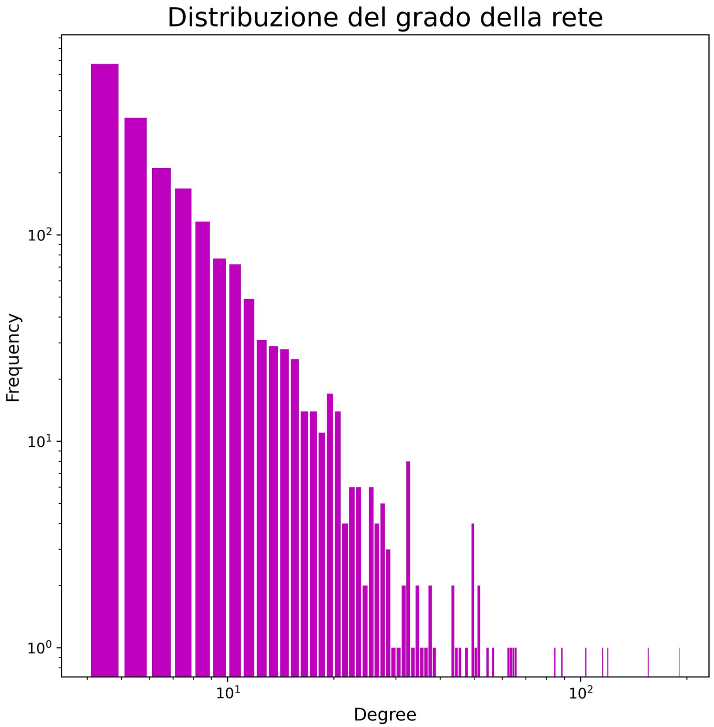
Minimum density of infected individuals to start the epidemic (zoom)

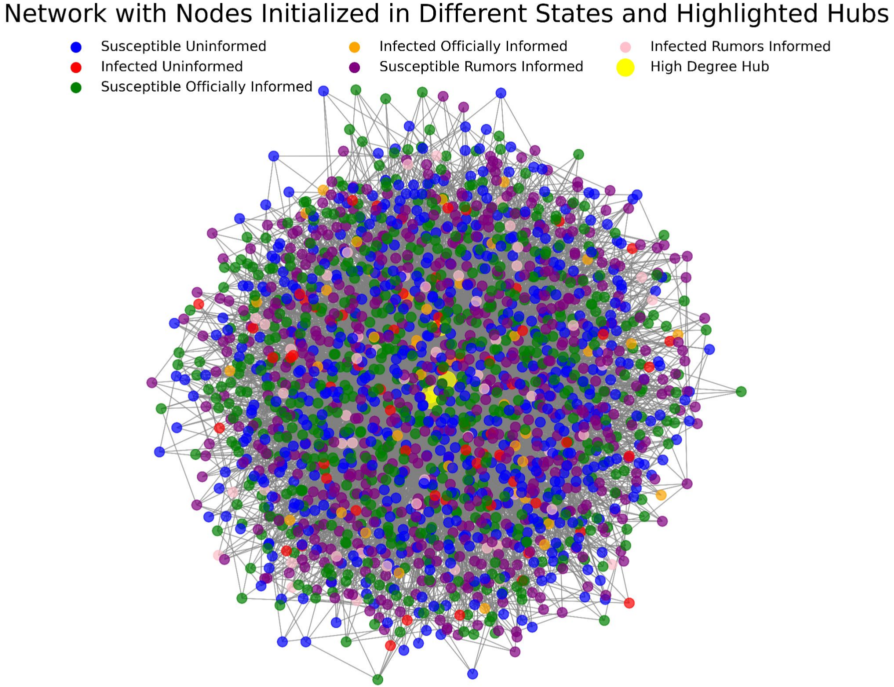


Connectivity: how it influences the spreading



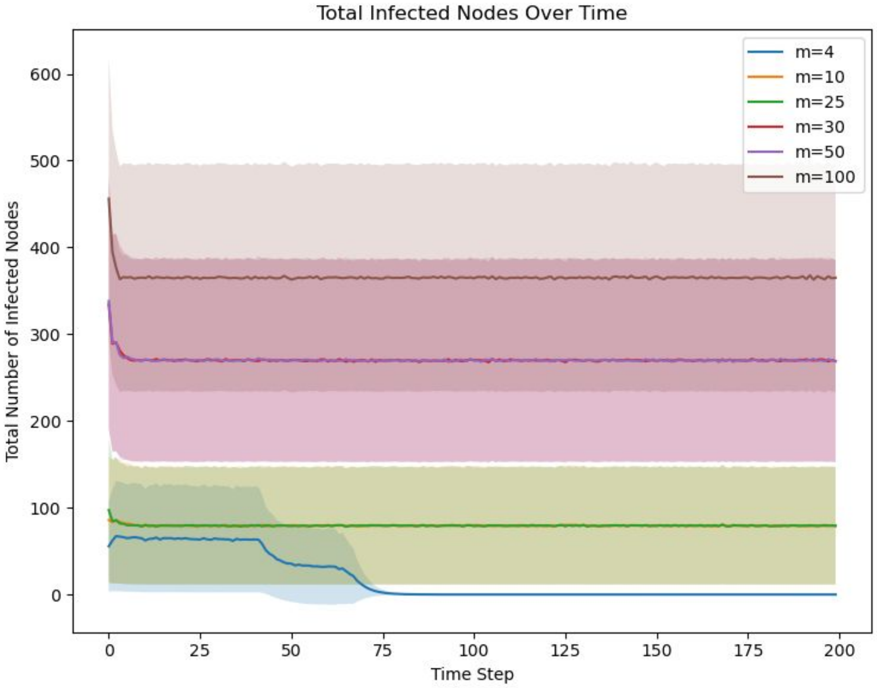
Targeted Infection of hubs as IR

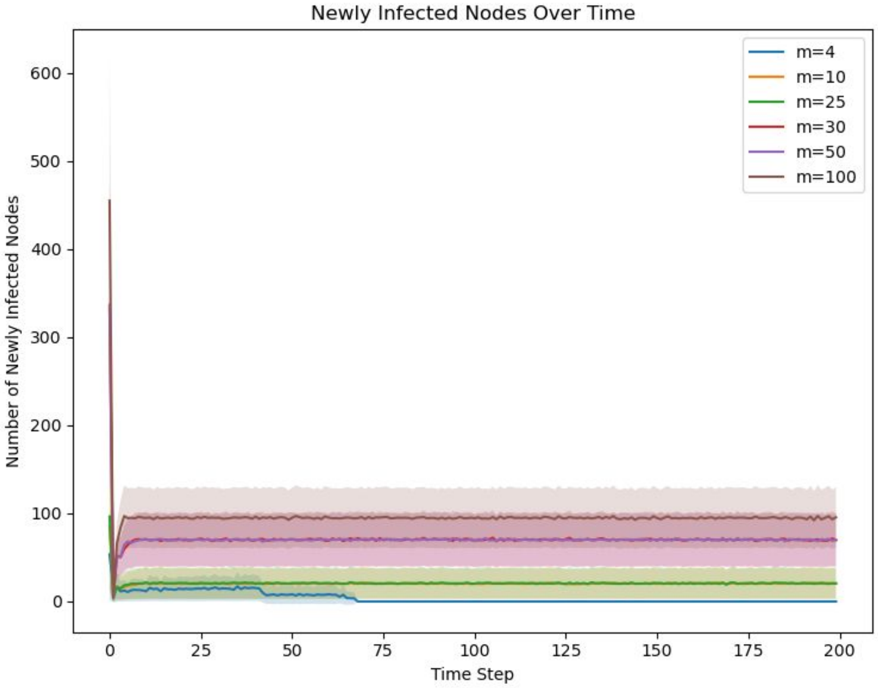




Target Infection: Only hubs get infected and rumor informed

Is this enough to start an epidemic?

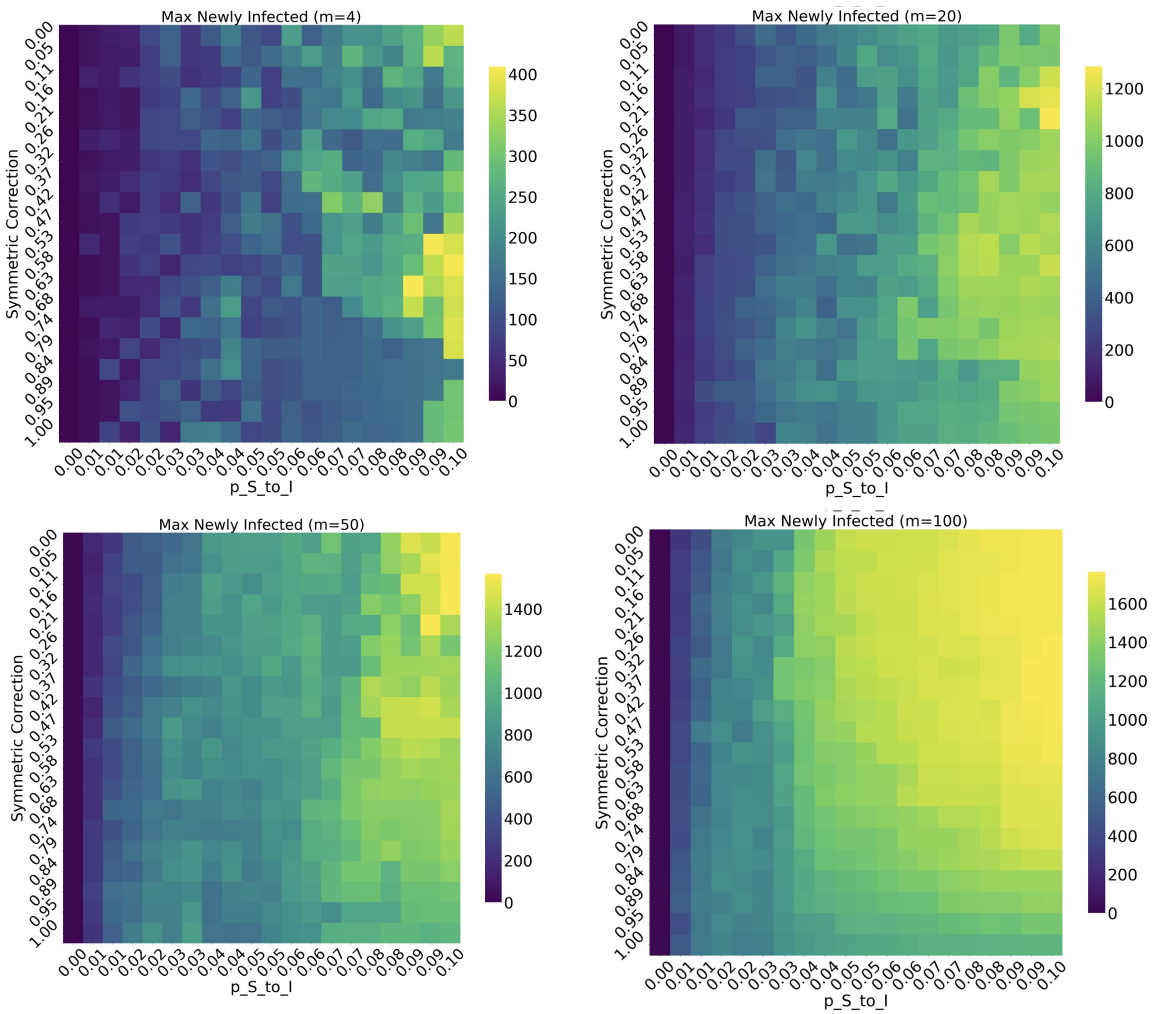




symmetric correction vs transmissibility

for many connectivities

- symmetric correction contrasts the increase in trasmissibility, slowing down the spreading
- the symmetric correction effect is



Conclusions

Observation 1

The symmetric correction, which means the capacity of information to influence people behavior, is a good instrument to contain the pandemic.

Observation 2

The connectivity of the network is a clear indication that reduce the contact between people is method to extinguish the epidemic.

Observation 3

Target infection for only hubs individual is not enough to start a pandemic, but we still believe that this are the individual that are more responsible of epidemic diffusion.

Future Prospect

Online Info Spreading

Create a more realistic network by including online interactions, which can lead only to information contagion.

Level of Education

Make susceptibility to information (R/O) dependent on the level of education of the individual

Age & Degree

Create a more realistic network by making the number of connections that a person/node has dependent on their age