The Effect of Awareness on the Spread of Disease in Different Network Topologies

Mozhgun Orujlu, Yakub Shahmari

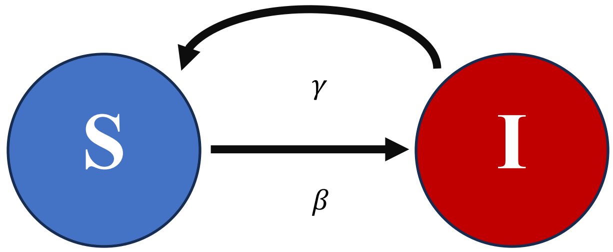
Sharif University of Technology, Physics Department

Abstract:

In this research paper, we delve into the dynamics of the SIS (Susceptible-Infectious-Susceptible) model within diverse static networks, emphasizing the impact of knowledge regarding outbreak conditions. Our model considers the pivotal role of community members' awareness in mitigating the severity of disease transmission by prompting a reduction in communication among individuals within the community. We extend our exploration across various network topologies, specifically focusing on three distinct structures: Erdos-Renyi network, periodic 2D grid network, and Barabasi-Albert network. Through our investigation, we aim to discern and analyze the tangible effects of awareness within these networks. The focal parameter for evaluating the influence of awareness in this study is the reproduction number. To effectively measure this, we employ the conversion of SIS dynamics into a simple SIS mean-field model. Our simulation endeavors to quantify the impact of awareness-induced social distancing on the probability of disease transmission. By employing these methodologies, our research sheds light on the nuanced interplay between knowledge, network structures, and disease spread, contributing valuable insights to the understanding of epidemic dynamics in diverse social contexts.

Introduction:

In the context of network-based epidemiological models, the Susceptible-Infectious-Susceptible (SIS) dynamic serves as a fundamental framework for comprehending the interplay between individuals and the spread of infectious diseases. In this model, individuals within a network transition between two states—susceptible to infection and actively infectious. The transmission of the disease occurs through interpersonal connections within the network. As susceptible individuals come into contact with infectious counterparts, transmission takes place, perpetuating the cycle. This dynamic is intricately linked to the network topology, where nodes represent individuals, and edges signify the connections facilitating disease transmission. The SIS model provides a foundational understanding of how infectious diseases propagate through interconnected populations, forming the basis for our exploration into the impact of awareness on disease spread in various network structures.



Within the SIS dynamic on a network, two crucial parameters govern the transition between susceptible and infectious states: the infection rate and the recovery rate. The infection rate encapsulates the probability of transmission (β) when a susceptible individual comes into contact with an infectious counterpart. It essentially quantifies the contagiousness of the disease within the network. On the other hand, the recovery rate characterizes the probability of an infectious individual recovering and transitioning back to a susceptible state per unit of time (γ). The reciprocal of the recovery rate represents the average duration an individual remains infectious. These parameters collectively determine the dynamics of disease spread in the network. A higher infection rate amplifies the likelihood of transmission, while a higher recovery rate, reduces average duration of recovery process. The balance between these parameters dictates the overall behavior of the SIS model on the network, influencing the prevalence and persistence of the infectious state. In our exploration, we will consider the implications of these parameters in conjunction with the awareness factor, shedding light on how knowledge of outbreak conditions influences the interplay between infectious diseases and network structures.

To incorporate the influence of awareness, we introduce a nuanced approach by considering the density of infectious individuals. Two distinct types of awareness, namely Local Awareness (λ) and Global Awareness (Γ), are defined to capture different facets of the epidemic landscape. Local Awareness quantifies the density of infectious neighbors surrounding an individual, offering a localized perception of the outbreak, while Global Awareness represents the overall density of infectious individuals across the entire network. These two awareness metrics are amalgamated into a unified scaling weight termed Awareness Effect (α), ranging from 0 to 1, which modulates the probability of disease transmission. To achieve this, we introduce three critical parameters: Local Awareness weight (ω_λ), Global Awareness weight (ω_Γ), and Total Awareness weight (ω_α). The calculation of the transmission probability involves a weighted combination of Local and Global Awareness, expressed as $\alpha = \omega_\lambda \cdot \lambda + \omega_\Gamma \cdot \Gamma$, and the adjusted transmission rate $\beta_\alpha = \beta \times (1 - \omega_\alpha \cdot \alpha)$. This holistic framework enables us to quantify the impact of awareness on disease transmission, accounting for both local and global contextual information.

To quantify the impact of awareness, a comprehensive analysis of the reproduction ratio (R_0) is recommended. Calculating the reproduction ratio involves mapping our stochastic dynamics to a deterministic framework, specifically the simple mean-field SIS model. The ordinary differential equation (ODE) governing this deterministic model is expressed as follows:

$$\frac{dS}{dt} = -\beta SI + \gamma I, \qquad \frac{dI}{dt} = \beta SI - \gamma I$$

To bridge the gap between stochastic and deterministic dynamics, we propose defining a cost function that captures the time-series evolution of infectious density. This function is then used to compare the observed data with the solutions derived from our ODE. The optimization process involves minimizing the cost function to obtain the parameters of our mean-field model, specifically the infection rate (β) and recovery rate (γ). Subsequently, the reproduction number is computed as $R_0 = \beta/\gamma$. This method allows for a robust evaluation of the awareness-induced effects on disease transmission, providing a quantitative measure through the reproduction ratio.

Results:

The results across various systems consistently revolve around specific R_0 values. Within our simulations, a set of parameters is utilized, consisting of both fixed constants and selectively varied parameters exploring specified ranges. The following parameters serve as the foundation for our analyses, ensuring a standardized approach to evaluating the impact of awareness on disease spread.

Parameter	Size of Network	Initial Infectious Density	Transmission Probability	Recovery Probability
Symbol	N	I_0	β	γ
Value (Constant)	10000	0.1	0.1	0.15
Parameter	Local Awareness Weight	Global Awareness Weight	Awareness Effect Weight	Average degree
Symbol	ω_λ	ω_Γ	ω_α	$\langle k \rangle$
Value (Default)	½	½	½	4

Table.1: Constant and default parameters of our simulations.

In the SIS model, the primary character shaping the system's dynamics is the time-series of infectious density. To visually depict our model and offer a tangible representation, we present a historical plot showcasing the fluctuations in infectious density over time. This graphical representation serves as a key insight into the dynamic nature of our SIS model and facilitates a clearer understanding of the temporal evolution of infectious states within the system.

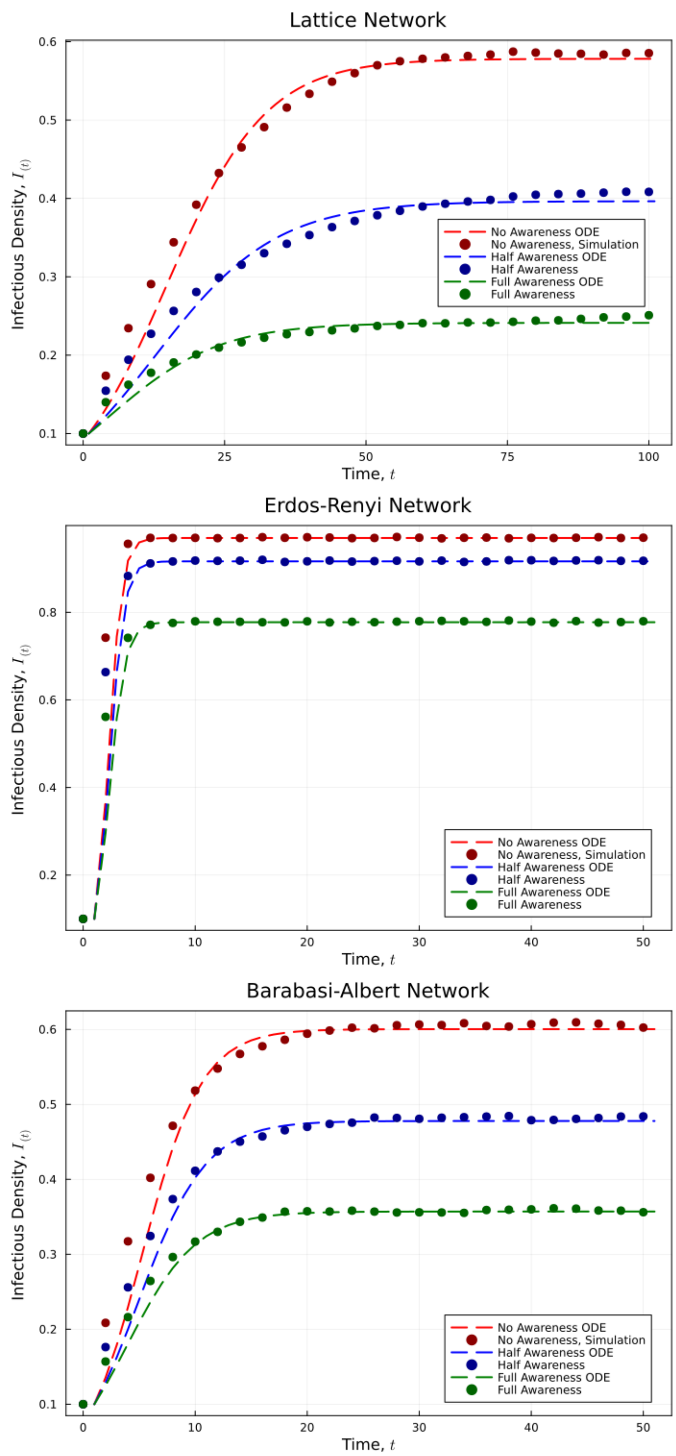


Fig.1: Time-series plot illustrating the SIS dynamics with awareness on Lattice, Erdos-Renyi, and Barabasi-Albert networks, alongside the solutions derived from the corresponding mean-field models. The parameters align with those specified in Table 1.

Here we change the default value of awareness weights to analysis its effect on R_0 (Which represents how strong the spread is) for different networks.

Lattice:

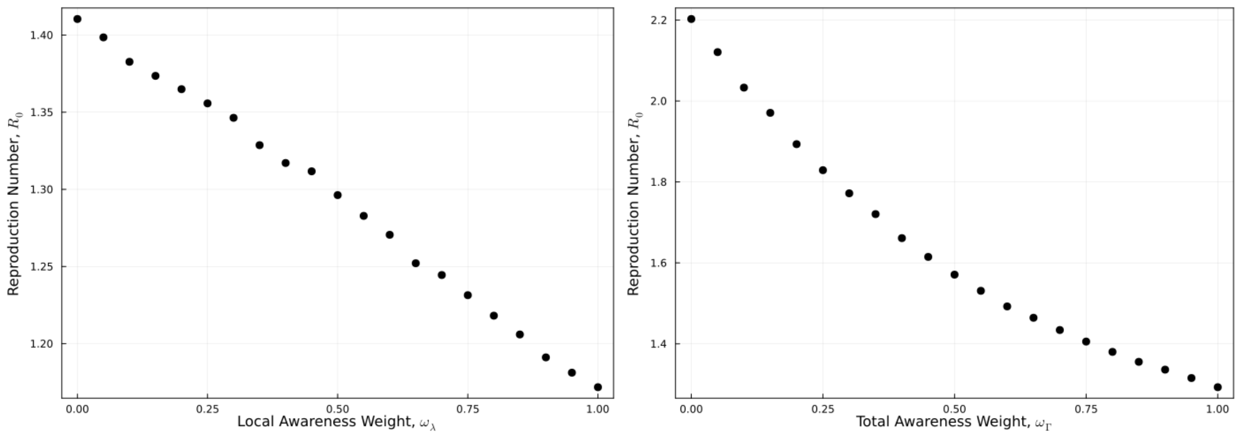


Fig.2: Reproduction ratio over awareness weights for Lattice network.

The observed data (Fig.2) indicates that Local awareness exhibits a more effective mitigation of the disease spread compared to Global awareness. Specifically, Local awareness leads to a linear reduction in the reproduction ratio, with a slope of -0.24. As anticipated, the incorporation of total awareness demonstrates a notable reduction in the spread of the disease, aligning with our expectations.

The exponential decline in R_0 aligns seamlessly with the assertion made in the main article, emphasizing that while awareness has the capacity to mitigate the impact of the disease, it doesn't alter the threshold of phase transmission. This observation underscores the nuanced influence of awareness on disease dynamics, showcasing its effectiveness in curbing spread without fundamentally reshaping the critical transmission threshold.

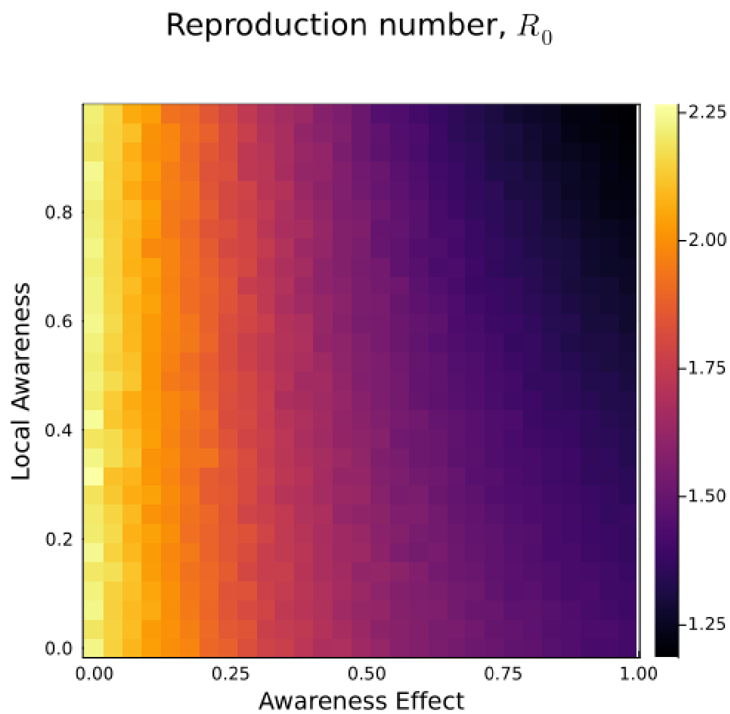


Fig.3: Heatmap of reproduction ratio over awareness weights.

Erdos-Renyi:

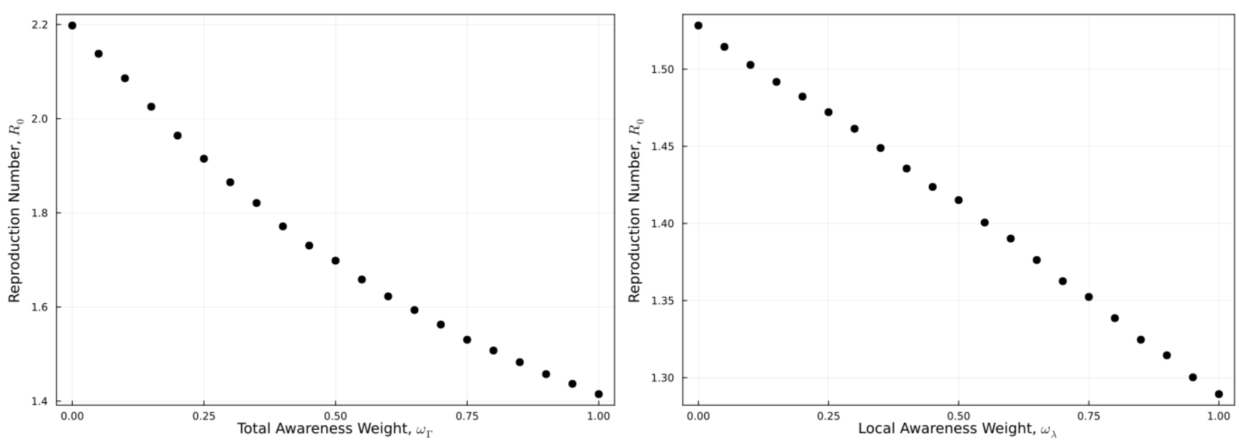


Fig.4: Reproduction ratio over awareness weights for Erdos-Renyi network.

While one might reasonably anticipate significant distinctions between the outcomes of a non-random network, such as Lattice, and a random network, like Erdos-Renyi, our findings reveal notable similarities between the two. Surprisingly, the slope of the line depicting the linear reduction in the reproduction ratio remains consistent at -0.24 for both networks. This unexpected parallelism suggests that, despite their structural differences, the influence of awareness on disease spread manifests in a remarkably similar manner across diverse network topologies.

Barabasi-Albert:

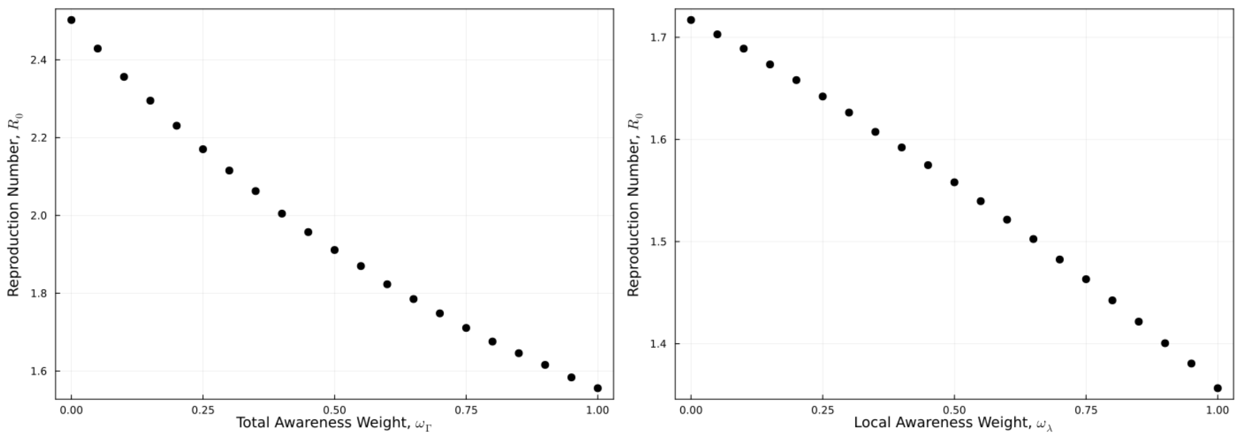


Fig.5: Reproduction ratio over awareness weights for Barabasi-Albert network.

Significant disparities emerge in the current results compared to previous findings. Notably, the impact of Local awareness is considerably more pronounced, evident in the smaller slope of the line, which now equals -0.36. This variation could be attributed to the higher clustering coefficient inherent in the Barabasi-Albert network. The intricate network structure appears to amplify the efficacy of Local awareness, highlighting the network-specific nuances in the dynamics of disease spread influenced by awareness.

Reference:

Paarporn, Keith & Eksin, Ceyhun & Weitz, Joshua & Shamma, Jeff. (2016). Networked SIS Epidemics with Awareness. IEEE Transactions on Computational Social Systems. PP. 10.1109/TCSS.2017.2719585.