Modeling the Mere Exposure Effect in Temporal Information Diffusion

Computational Modeling of Social Systems 2025 Summer

Final Project Report

Group 35

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Abstract

In real-life social contexts, individuals tend to develop more positive attitudes or less negative attitudes when they are exposed to a stimulus repeatedly, which is known as the mere exposure effect. In this study, we extend the work of Karimi and Holme (2013) considering this psychological phenomenon. The research question is set as "does a higher number of contacts with information sources have a greater influence on individuals, leading to wider information spread? "The simulations were implemented by Python using given datasets. The result partially supports the research question, suggesting that repeating contacts do not always result in wider information spread.

1. Introduction

The social influence process has often been modeled using the threshold model. Karimi and Holme (2013) extend Watts's cascade model to a temporal network, showing that individuals are influenced by past contacts within a time window rather than only by current neighbours. Additionally, the dynamics of information spread and adoption process have been explored by several studies. Yanchenko, Murata, and Holme (2024) investigate influence maximization (IM) strategies on temporal networks focusing on nodes, who spread information. Pinheiro & Vasconcelos (2025) study how post-receiving behaviour, whether and when information spreads further, affects information cascades in networks. Also, the study by Huang, Zhang, Xu, and Fu (2016) focuses on the adoption process influenced by persuasion. However, it remains unclear whether individuals are more likely to adjust their behaviour based on the frequency of contact with informed neighbours, rather than simply their presence.

In real-life social contexts, individuals tend to adopt information after repeated contact with the same information source over time. This phenomenon is known as the mere exposure effect, where repeated exposure to a stimulus increases positive attitudes or reduces negative ones toward the stimulus. Considering this psychological phenomenon, this study extends the work of Karimi and Holme (2013) by examining the impact of the frequency of contact with informed others. Thus, the research question is defined as follows:

Does a higher number of contacts with information sources have a greater influence on individuals, leading to wider information spread?

To address this research question, we explore the dynamics of adoption considering the frequency of contact by developing and implementing a new model, a weighted-threshold model, based on the fractional-threshold model. The threshold rule is calculated as the ratio of contacts with adopted neighbours to total contacts, aggregated over a recent time window of θ steps. All simulations were implemented by Python using given data sets.

This study finds that more repeated contacts do not always result in more information widespread. Figure 1 and figure 2 show that while a higher number of repeated contacts with information sources can promote early adoption and result in larger cascades under certain conditions, they are also very sensitive to threshold values and memory parameters, potentially limiting the robustness of spread.

2. Methodology

2.1 Overview and schema

In this project, we explore the dynamics of adoption in a networked social system by developing and implementing what we call a weighted-threshold model. This approach extends classical threshold models by explicitly incorporating temporal exposure, where each individual's decision to adopt depends on the proportion of their contacts who have recently adopted.

A schematic representation of our model is shown in Figure 2 where each node aggregates exposure over a sliding time window before making an adoption decision. This captures the intuition that repeated or recent exposure to adopted peers has a stronger influence than isolated, past interactions.

2.2 Motivation for our choice of method

We selected this method to address scenarios where adoption is not driven by single contacts but by accumulated influence over time. Traditional threshold models typically evaluate adoption based on the current fraction of adopted neighbors at a single point in time. However, many real-world behaviors such as technology use, health practices, or opinion formation depend on sustained exposure to social signals. By integrating temporal windows, our weighted-threshold model provides a more realistic mechanism for how influence builds up and leads to adoption.

2.3 Model description and parameters

Our model operates on an undirected network where nodes represent individuals and edges denote social ties. At each discrete time step, nodes evaluate the recent adoption activity of their contacts.

Formally, for a node *i* at time *t*, the adoption rule is:

$$\frac{\text{Number of adopted contacts in } [t-\theta, t]}{\text{Total contacts in } [t-\theta, t]} > \phi$$

where:

- **θ (time_window)** controls the length of the temporal window (how many past time steps are considered).
- **φ (threshold)** is the critical proportion of adopted contacts required for adoption.

2.4 Implementation details

Our weighted-threshold model was implemented in Python using Jupyter notebooks. The workflow involved:

Data preparation:

- Temporal contact networks were constructed directly from the given empirical datasets. These were processed into edge lists with explicit timestamps, then reorganized into contact dictionaries mapping each node to their historical contacts.
- **Simulation:**
  At each time step, nodes aggregated exposure over a sliding window (θ) and adopted if the fraction of recently adopted contacts exceeded a threshold (ϕ).
- **Exploration:**
  We varied θ (100, 500, 1000) and ϕ (0.1 to 1.0) to analyze different adoption dynamics. Simulations are run for 100 time steps.
- **Libraries:**
  Used pandas for data handling, numpy for computations, and matplotlib for visualization.

2.5 Materials, data, and code

This study is based on empirical temporal contact networks, allowing us to simulate realistic patterns of interaction over time.

All code was implemented in Python in a Jupyter notebook environment. To promote transparency and reproducibility, the full implementation including pre-processing scripts, simulation code, and figure generation routines is available in our GitHub repository.

3. Results

In this study, we compare the outcomes of our weighted-threshold model with those of the fractional-threshold model to observe how incorporating the individuals' contact counts influences the cascade dynamics.

3.1 Effect of threshold value φ and time window size θ on cascade size Ω

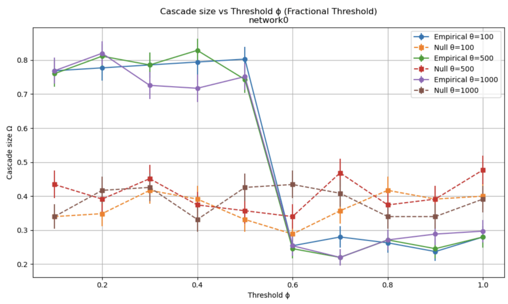
Following Karimi and Holme (2013), we examine how the threshold value φ affects the cascade size Ω under various time window size θ. Additionally, we apply the null model as well to compare with the empirical model as it is used in the study of Karimi and Holme (2013) to exclude the effect of network and temporal structure. Figure 2 shows mainly three insights.

First, in the weighted-threshold model, we observe that the cascade size Ω decreases sharply when the threshold φ exceeds a certain value (mostly φ=0.6), after which the cascade size Ω plateaus. This reflects the fact that in the weighted-threshold model, repeated interactions with the same individual (information source) contribute significantly to adoption, making the model highly sensitive to contact patterns dominated by strong ties. On the other hand, in the fractional-threshold model, the cascade size Ω tends to be comparatively larger in high thresholds than in the weighted-threshold model. This occurs because the fractional-threshold model takes into account the proportion of recent contacts in state-1, not their frequency, making it easier to exceed the threshold φ even with sparse but diverse interactions. Overall, we can say the weighted-threshold model has the disadvantage of spreading information compared to the fractional-threshold model when the threshold φ is high.

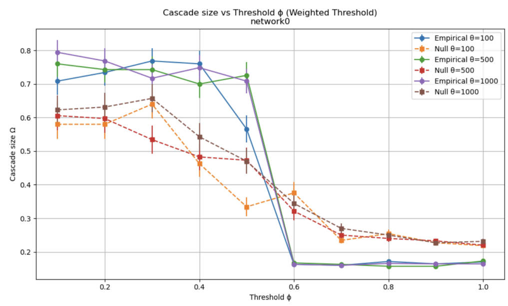
Secondly, in the fractional-threshold model, the cascade size of the null model remains relatively constant across threshold values while the empirical model shows different trends. In contrast, the weighted-threshold model has similar trends between null model and empirical model. This indicates that the cascade dynamics in the weighted-threshold model are less sensitive to temporal ordering of interactions, as the model aggregates contact counts over the time window rather than their sequence.

Thirdly, we observed that the weighted-threshold model has relatively a larger cascade size than the fractional-threshold model until it drops sharply at the certain threshold., indicating that strong ties tend to be more effective for widespread adoption.

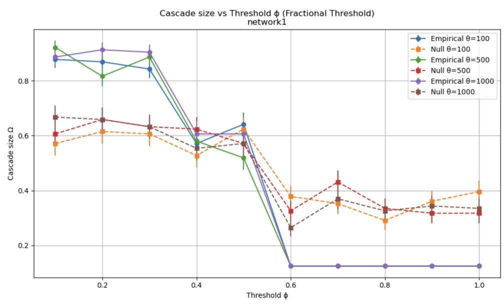
(a) - 1 Network0 (Fractional-threshold)



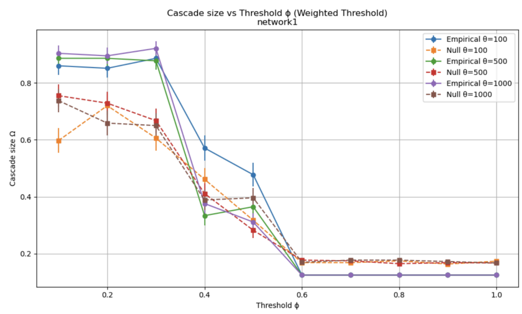
(a) - 2 Network0 (Weighted-threshold)



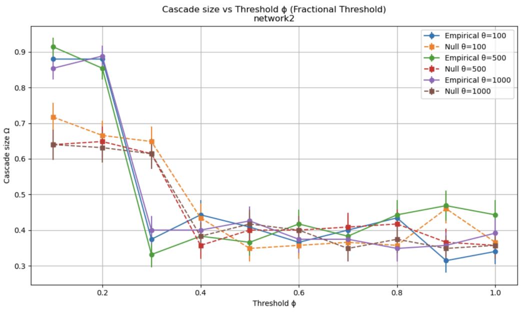
(b) - 2 Network1 (Fractional-threshold)



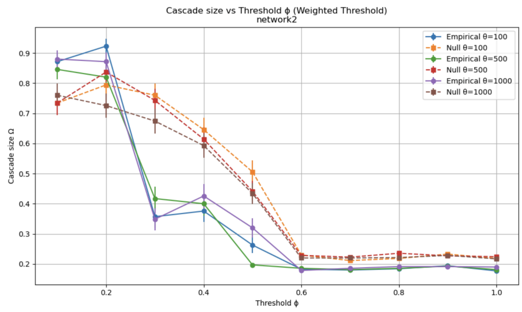
(b) - 2 Network1 (Weighted-threshold)



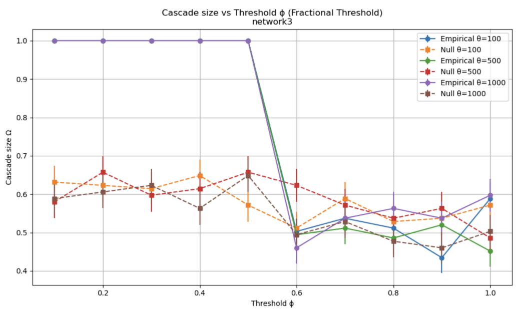
(c) - 1 Network2 (Fractional-threshold)



(c) - 2 Network2 (Weighted-threshold)



(d) - 1 Network3 (Fractional-threshold)



(d) - 2 Network3 (Weighted-threshold)

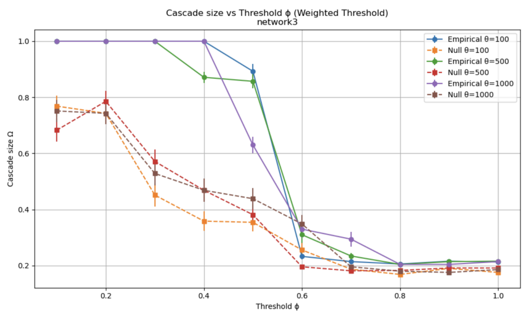


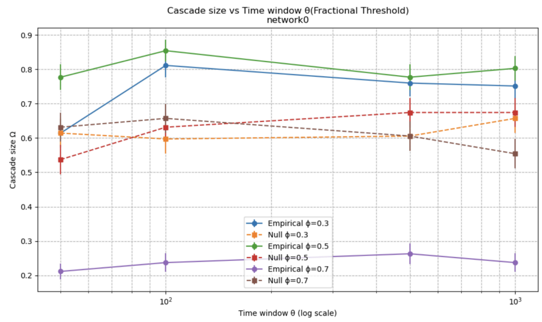
Fig1. Cascade size Ω versus threshold value φ from 0.1 to 1.0 for various time window size θ. The error bar indicates the standard error from 100 independent simulation runs.

3.2 Effect of time window on cascade stability

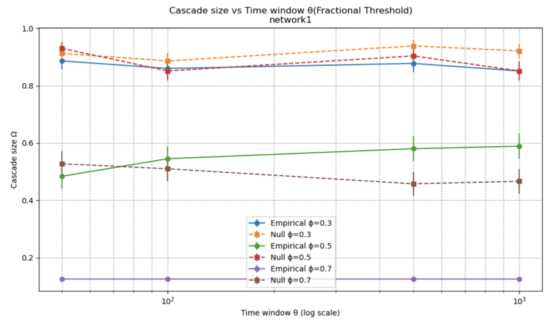
Now, we examine how the time window size θ affects the cascade size Ω under various threshold values φ. Again, we use the null model to exclude the effect of network and temporal structure. This analysis is expected to reveal how temporal memory, how far back individuals look into their contact history, shapes diffusion dynamics (fig 2).

Compared to the fractional-threshold model, the weighted-threshold model exhibits greater variability in cascade size Ω across different threshold values φ, not only in empirical models but also in null models. This instability arises from the model's sensitivity to the frequency and timing repeated interactions: small changes in the observation time window can significantly after the weighted influence ratio, as both the numerator (i.e., repeated contacts with adopters) and the denominator (i.e., total contacts) are affected. In contrast, the fractional-threshold model, which relies solely on the proportion of influenced neighbours, remains more stable over the various threshold values φ.

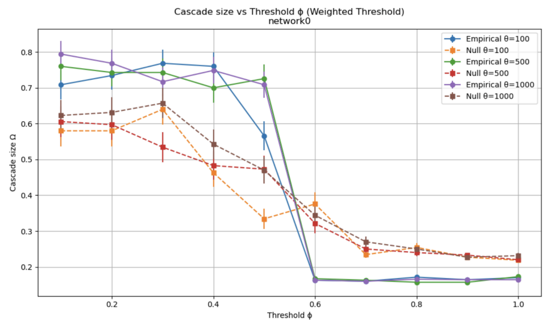
(a) - 1 Network0 (Fractional-threshold)



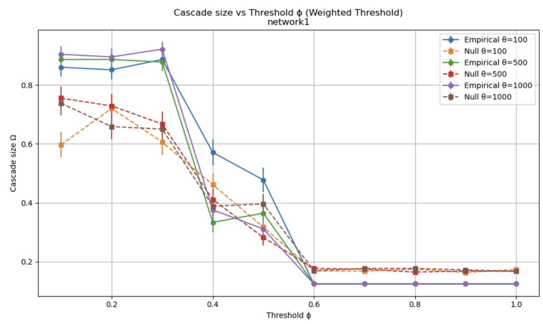
(a) - 2 Network0 (Weighted-threshold)



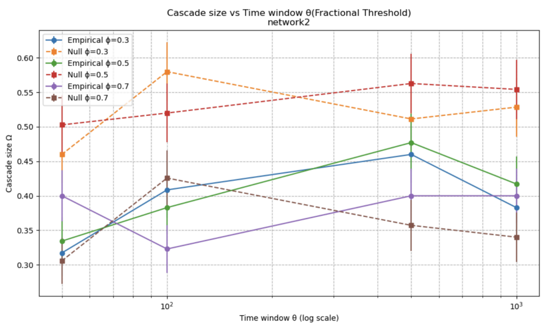
(b) - 1 Network1 (Fractional-threshold)



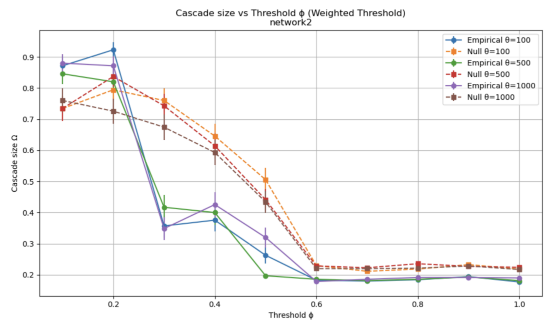
(b) - 2 Network1 (Weighted-threshold)



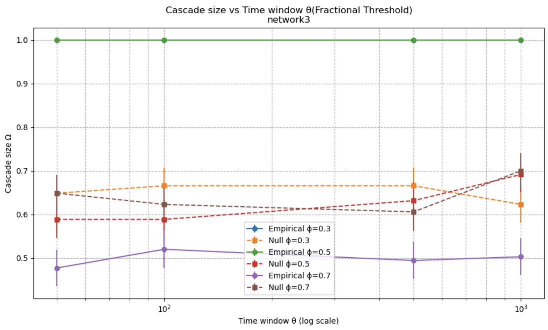
(c) - 1 Network2 (Fractional-threshold)



(c) - 2 Network2 (Weighted-threshold)



(d) - 1 Network3 (Fractional-threshold)



(d) - 2 Network3 (Weighted-threshold)

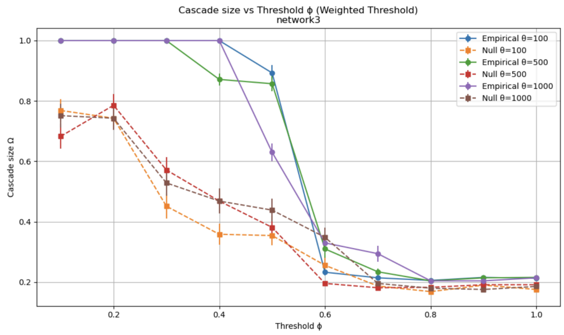


Fig2. Cascade size Ω versus time window size θ for various threshold values φ. The error bar indicates the standard error from 100 independent simulation runs.

These findings suggest that while a higher number of repeated contacts can enhance early adoption and result in larger cascades under certain conditions, they also introduce greater sensitivity to threshold values φ and memory parameters, potentially limiting the robustness of spread. This highlights that more contact does not always guarantee wider spread of information.

4. Discussion

The main takeaway from this study is that how often people come into contact has a mixed impact on how information spreads. On one hand, repeated contact can help people adopt something early on. But it also makes the spread more sensitive to threshold values, for example, when the threshold goes above 0.6, the spread drops sharply in the weighted-threshold model. This shows that having more contact does not always mean the information will spread more widely. The study looked at two different spreading models: the weighted model, which depends on strong and repeated ties (good for quick, powerful spread but not very stable), and the fractional model, which focuses on a wider range of contacts and stays more stable across different situations. Basically, there is a trade-off between intensity and diversity of influence. The weighted model tends to start with bigger cascades but becomes unstable as threshold or time settings change. In practical terms, repeated contact works better when people need only a little push to adopt (low thresholds), while a wider mix of contacts is more helpful when people need more convincing (high thresholds). So, it is important to think about the context. Theoretically, this study adds to our understanding by including how often people connect and showing that the "mere exposure effect" has its limits when applied to whole networks. The weighted model, in particular, reveals hidden weaknesses that help explain how influence works over time in social networks.

5. Limitations

This study comes with a few important limitations. One major issue is that the results are highly sensitive to the chosen threshold values φ, meaning small changes can significantly impact how information spreads. The model also does not take into account differences between individual nodes; everyone is treated the same, which is not very realistic. While the main focus is on comparing two threshold models, the deeper psychological processes behind repeated exposure are not directly explored, even though they are central to the mere exposure effect. Additionally, the scope of the network itself is limited, and factors such as network size and density might have influenced the results in ways not fully captured. Another limitation is the way thresholds were handled, the model assumes that people adopt something just based on how many of their neighbors already have, without considering things like how credible or trustworthy the source is, or whether the information feels personally relevant. It also does not account for individual differences in how easily someone is influenced. On top of that, the model does not distinguish one-time contact from repeated contact with the same person, and it does not factor in the psychological impact of that exposure. Technically, the study only tested a narrow range of parameters, and while it ran 100 simulations, that might not be enough to capture all possible variations. Lastly, all social connections were treated equally, even though in real life, some ties are stronger or more meaningful than others.

6. Conclusion

This study examined whether a higher number of contacts with information sources leads to wider information spread, based on the mere exposure effect. By implementing a weighted-threshold model, we incorporated contact frequency into the adoption process and compared it with the traditional fractional-threshold model.

Our results show that repeated contacts can encourage early adoption and larger cascades in low-threshold settings. However, they also introduce sensitivity to threshold values and time windows, making the spread less stable. In contrast, the fractional-threshold model, based on diverse contacts, showed more consistent results.

Overall, while repeated exposure can enhance influence under certain conditions, it does not always result in broader information spread. Thus, the research question is only partially supported. The findings highlight a trade-off between contact intensity and diversity, suggesting that the effectiveness of influence depends strongly on the network context and parameter settings.

7. **References**

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