Luddism on Diffusion Networks

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Introduction

As E.M. Rogers put it: 'When new ideas are invented, diffused, and are adopted or rejected, leading to certain consequences, social change occurs" [1]. This project concerns itself with the way in which novel innovations may result in a dichotomy between innovation *adopters* and *luddites* (those who reject innovations.) Such a dichotomy is especially relevant in a time when extreme partisanship and anti-politics run rampant through society [2]. We introduce a novel model, the Terminal LISA (T-LISA) model, as a modification to the LISA model [3] such that the resulting stable state contains only *adopter* and *luddite* population proportions. Following the LISA model, our model includes *ignorant* and *susceptible* populations proportions as an intermediary between *adopter* and *luddite*. The T-LISA model is ultimately a generalization of Frank Bass's 1969 Bass model [4] for predicting the timeline of consumer good adoption. We explore the results of the T-LISA model in the mean-field theory, where it acts like a standard contagion model, and in stochastic simulation. We analyze the agreement between stochastic simulation and mean-field theory.

Mean-Field Model Description

- In the mean-field theory (MFT) we assume a well mixed system in which every agent has some effect on every other agent in the system. While this isn't the case for actual social networks, it gives us a good starting point to understand our model.

- We define the following coupled set of differential equations which govern our model in the mean field:

$$L' = \gamma r S I + \omega r A I$$
$$I' = -(S + A)I - \gamma r S I - \omega r A I$$
$$S' = (S + A)I - \gamma S$$
$$A' = \gamma S$$

- Parameter γ sets the rate at which *susceptibles* turn to *adopters*, making L' dependent on the rate of increase in *adopters*.
- Parameter ω represents the *ignorant* population's tendency to become anti-establishment, or to reject innovation when many others in the system adopt it.
- Parameter r establishes the prevalence of luddism for the particular innovation at hand.

Mean-Field Model Results

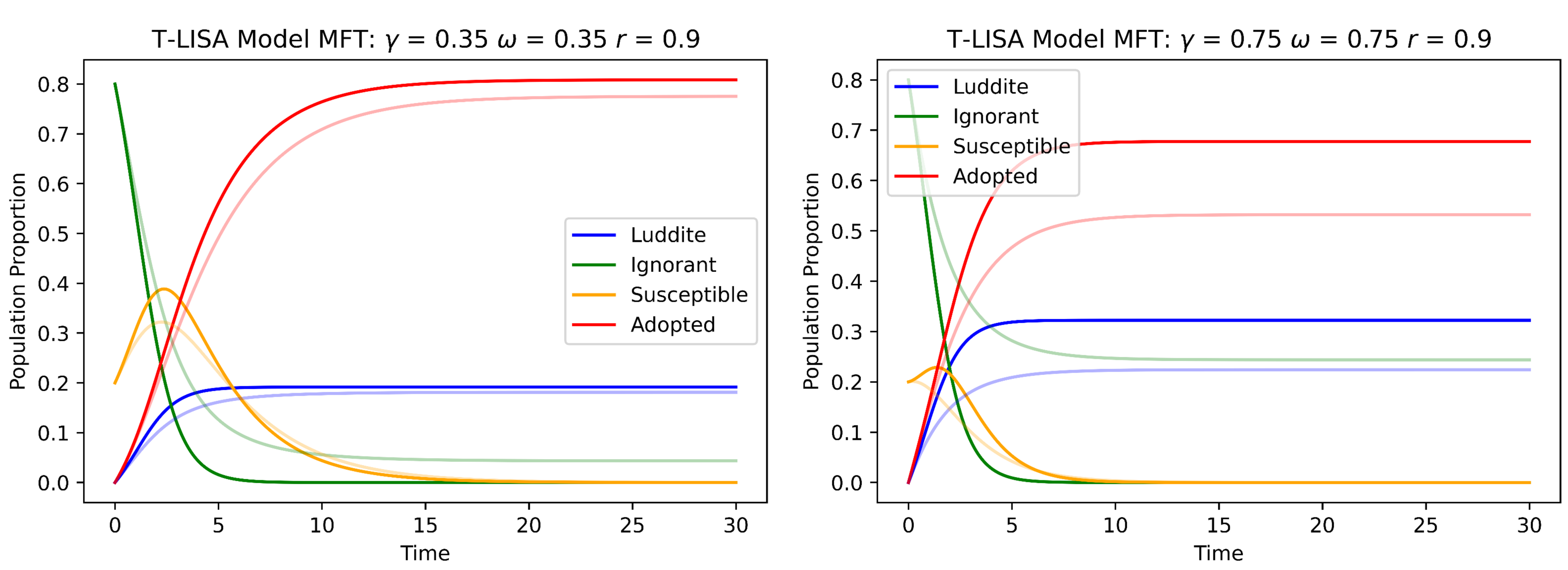


Figure 1. MFT plots of T-LISA model with $\omega = \gamma, r = 0.9$, and $S_0 = 0.2$. LISA model [3] results based on the listed γ and r values are overlayed on each graph with less opacity.

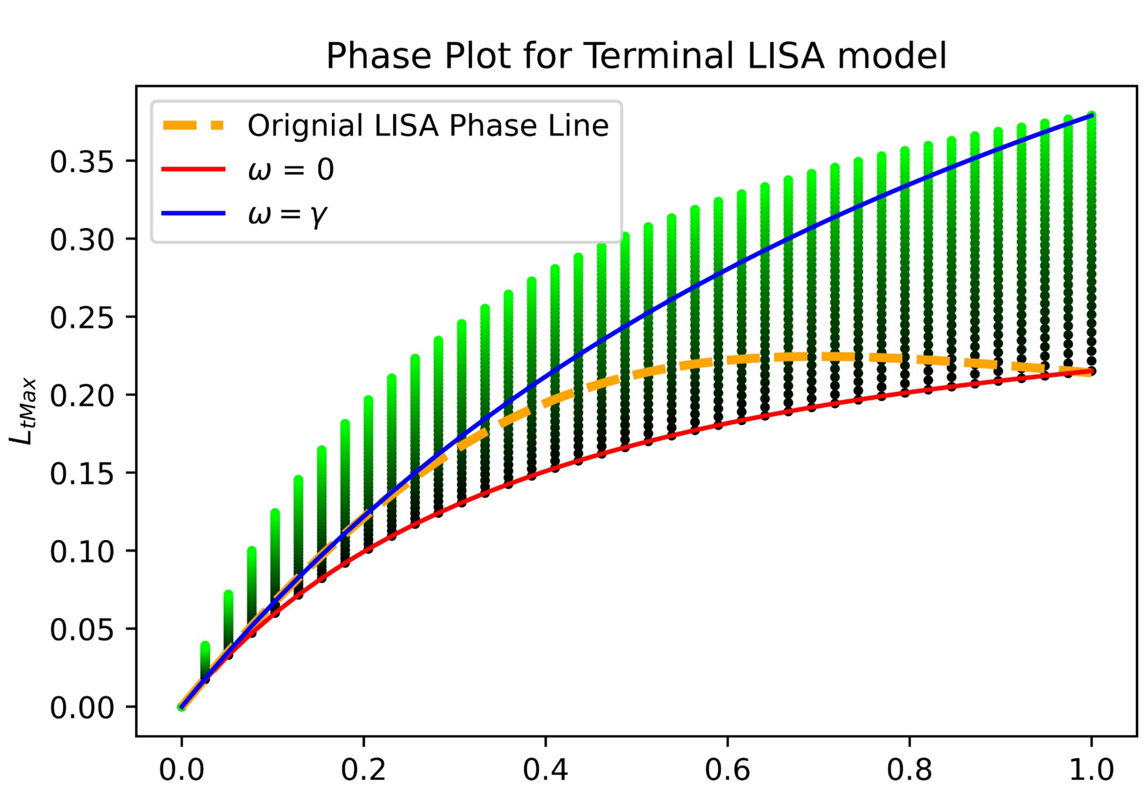


Figure 2. Phase diagram for the T-LISA model with $r = 0.9$, and $S_0 = 0.2$. The range of black and green dots coming off the $\omega = 0$ line represent the possible results for L_{tMax} when introducing an anti-establishment pressure parameter ranging from 0 to 1.

Agent-Based Model Description

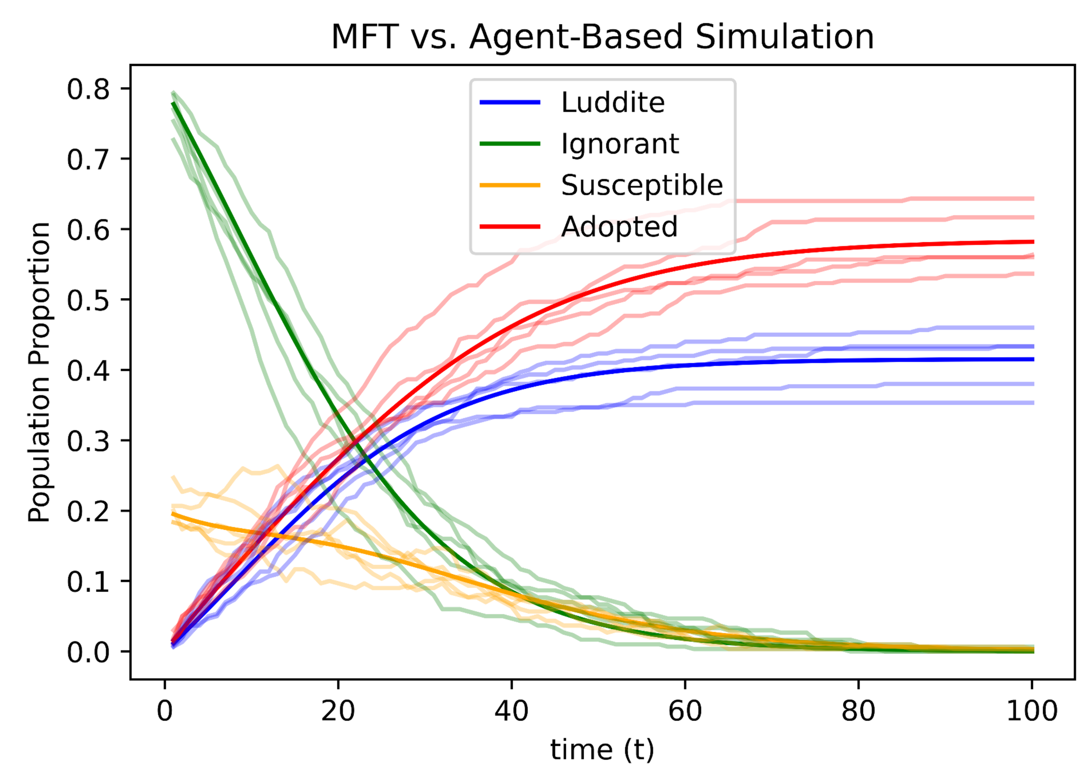
- For agent-based simulation, we define Erdos-Renyi (ER) random graph $G(N, k)$ where N is the total number of nodes in G, and k is the average degree of a node within G.
- The following propensities for node i to change state based on s_i (node i's *susceptible* neighbors) a_i (node i's *adopted* neighbors) and k_i (node i's total neighbors.)

$$I \rightarrow S : \frac{s_i + a_i}{N}$$
$$I \rightarrow L : r(\gamma \frac{s_i}{k_i} + \omega \frac{a_i}{k_i})$$
$$S \rightarrow A : \gamma$$

- Using Monte-Carlo methods, we iterate over the entirety of G and update node states based on the above propensities.

Comparing MFT and Agent-Based Results

- To rescale MFT to fit our ER graph simulation, we must multiply the two-body contagion processes I' and S' by a factor of k/N.
- We calculate error by subtracting MFT results from Monte-Carlo results at every integer step of time. We average these lists to find average error for L, I, S, and A. We average the absolute value of average error in L, I, S, and A to calculate total average error.



Total Average Error: 0.0204
L Average Error: -0.0032
I Average Error: -.0.0001
S Average Error: -0.0016
A Average Error: 0.0050

Figure 3. MFT vs. agent-based results for $N = 300, r = 0.9, \gamma = 0.08$, $\omega = 0.08, k = 20$. Monte-Carlo simulated results are overlayed with low opacity.

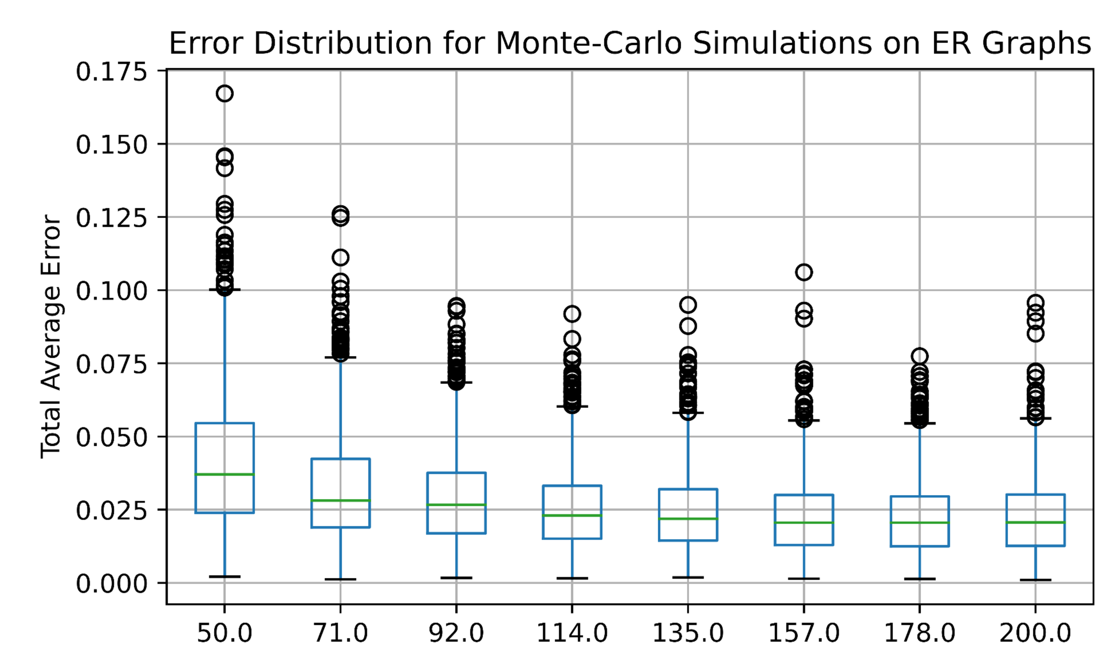


Figure 4. Distribution of total average error across 9000 Monte-Carlo simulations, grouped by N. Error is especially high for low values of N.

Conclusions and Open Questions

We have demonstrated a match in our agent-based Monte-Carlo simulation on ER graphs and deterministic mean-field simulation. The match is particularly good for ER graphs with a large N. We plan to address the following questions:

- Does Luddism spread in network clusters?
- How does network position (centrality, in-betweenness, and degree) impact a node's likelihood to become a *luddite* or *adopter?*
- How do varying initial conditions effect Monte-Carlo simulations?
- How does our model perform on real-life social network data? What insights can we draw from this?

References

- [1] Everett M. Rogers. Diffusion of Innovations, 5th Ed. New York: The Free Press, 2003.
- [2] Alan I. Abramowitz and Steven Webster. The rise of Negative Partisanship and the Nationalization of U.S. elections in the 21st Century. Electoral Studies, 41:12–22, 2016.
- [3] Andrew Mellor, Mauro Mobilia, S. Redner, Alastair M. Rucklidge, and Jonathan A. Ward. Influence of Luddism on Innovation Diffusion. Phys. Rev. E, 92:012806, Jul 2015.
- [4] Frank M. Bass. A New Product Growth for Model Consumer Durables. Management Science, 15(5): 215–227, 1969.