Math 574 Midterm Proposal: Internet Social Contagion: Fear, Entertainment, & Disease Spread

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October 25, 2024

1 Background & Literature Review

Of the many complex and often irrational phenomena observed in human behavior, one of the most important and interesting remains the problem of *social contagion*. As Barash (2011) [1] and Hill et al. (2010) [2] point out, this phenomenon is driven by social networks; in particular, as people interact with and observe the beliefs and behaviors of other individuals within their social network, their own behavior is also influenced accordingly [2]. In fact, even general socially-held norms around certain behaviors have a significant effect on their popularity; for instance, Hill et al. (2010) theorize that the destigmatization of obesity in society may be responsible for its widespread propagation [2].

The processes of social contagion often mimic those of a biological epidemic, as beliefs, rumours, trends, products, and even religious movements can spread from person to person within a social network to the extent that minority views can eventually become very popular [1, 3]. For this reason, a large variety of epidemiological models have been proposed to describe these complex social phenomena. For instance, Barash (2011) introduced and discussed the properties and advantages of a variety of epidemiological models, including the classic SIR model, the SIS model, and the SI model [1]. Meanwhile, Hill et al. (2010) proposed an SIS (Susceptible-Infected-Susceptible) model that incorporated 'spontaneous' infection (arising without contact with an infected individual) to model public health impacts of social contagion phenomena (with special focus on obesity) [2]. Furthermore, Afilipoaei and Carrero (2023) proposed an differential equation (epidemiological) model to describe the spread of optimism and pessimism in an asset market over the course of an asset bubble's lifetime, along with the attendant changes in asset price [4]. Finally, Sprague and House (2017) used epidemiological models to fit to a variety of internet trends from 2016, as measured by Google Trends data [5].

Although social contagion models such as the one proposed by Dodds and Watts (2005) assume that behaviors spread through person-to-person contact (and hence direct transmission) [3], with the potential for some spontaneous infection augmenting the spread [2], the invention and increasingly central role of social media and internet communication in recent years has shifted the underlying dynamics of social contagion. As the Pew Research Center observes, social media and internet communication is overwhelmingly viewed as helping increase public access to information regarding current events, although it has played a major role in fomenting political division and vulnerability to manipulation and misinformation [6]. In particular, social media has led to the appearance of algorithm-based transmission processes that both bypass and enhance person-to-person transmission, and has also brought an increase in the impact of media, celebrities, and influencers on the public consciousness.

2 Study Questions and Model Proposal

In this study, we are primarily interested in examining how the spread of internet activity and behavior can be modeled and depicted using an epidemiological approach. In particular, we are interested in how risk-aversion plays a role in observed internet activity among individuals, given its importance in general human behavior [7]. For this purpose, we will examine several different internet topics, which can be classified in the general categories of "fear" and "entertainment". Behavioral risk aversion among humans [7] leads us to predict that topics that elicit fear will create both a stronger and longer-lasting reaction than trivial topics such as entertainment, and we hope to investigate this difference in our study. As such, the primary study question to be addressed in this project is *how does individual reaction and residence time differ in internet trends between topics inducing "fear" and those that are merely meant for "entertainment"?*

To answer this question, we propose a new model to describe the spread of internet activity and interest that incorporates the three primary drivers of social contagion in the medium: (1) a direct (person-to-person) transmission component as described by Barash (2011) and Hill et al. (2010) [1, 2]; (2) the influence of large-scale media and social media 'influencers' on a general audience; and (3) the role of algorithm-based social media contagion. For the role of media and influencers in social contagion outbreaks, we take inspiration from the vector-borne Ross–MacDonald model for Malaria as outlined by Li (2018) [8], while for the algorithm-based transmission component, we take inspiration from the indirect-transmission model for Cholera proposed by Joh et al. (2009) [9]. For this purpose, we take 'infection' to denote those people who are interested in a particular topic and currently searching for it on the internet. A transfer diagram of the model to be used is given in Figure 1 below. In this case, we take U and U_M to denote the *uninterested* or *uninformed* population of internet users and media, respectively; I and I_M to denote the *interested* population of users and media, respectively; and B and B_M to denote the *bored* population of users and media, respectively. It should be noted that this designated *boredom* is treated like immunity to a disease upon recovery, whereby the individuals are not liable to regain their interest in a topic unless a significant event occurs to restart the cycle. The transmission factor $\lambda_1(I)$ denotes both direct transmission between users and algorithm-enhanced transmission (which may be either direct or indirect). Meanwhile, we assume that the media and influencer component is subject to direct transmission between its members, so we take the transmission parameter λ_2 to denote direct transmission in that component. Meanwhile, we take a vector-borne transmission parameter λ_3 to denote transmission from interested media to uninterested users; this relates to our model assumption that media and influencers can affect ordinary users through standard vector-borne contact processes. However, we assume that internet users can influence the media through an indirect threshold transmission process $\lambda_4(I)$, whereby sufficiently high numbers of interested users I can provoke a response from the media.

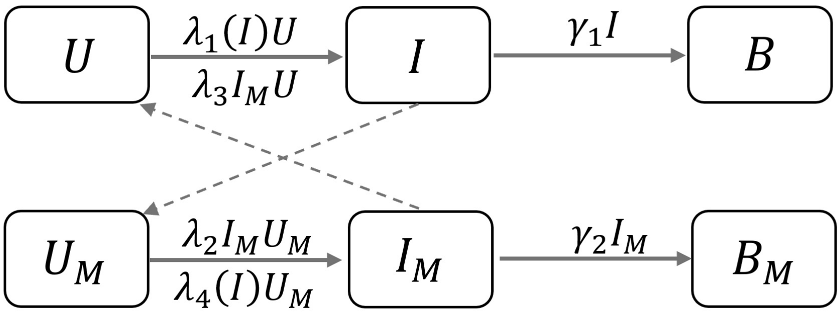

Figure 1: U and U_M denote the *uninterested* population of users and media; I and I_M denote the *interested* populations; and B and B_M denote the *bored* populations. The model includes direct transmission, algorithm enhancement, and vector-borne transmission.

To verify the validity of this model, we first conduct a mathematical analysis of the model to identify the equilibrium and final population points and their corresponding stability. Following this, we will fit the model to several major internet trends as measured by the internet search activity data recorded by Google Trends (similarly to the work by Sprague and House (2017) [5]). To answer the question posited at the beginning of this section, we define it in mathematical terms: namely, to determine whether there is a stronger reaction to "Fear" topics than "Entertainment" topics among individuals, we ask the mathematical question *how do the parameter estimates for $\lambda_1(I)$ and γ_1 compare between "Fear" and "Entertainment" trends?* This gives us insight into the question posed previously because $\lambda_1(I)$ denotes the 'infectiousness' of an internet trend between internet users and γ_1 denotes the inverse of the mean residence time in the *interested* compartment. We expect the parameter values for $\lambda_1(I)$ to be greater and γ_1 to be lower for "Fear" topics than for "Entertainment" topics.

In this project, we will also analyze the impacts of government control and censorship on the spread of internet trends, with particular emphasis on how this impact differs between trusting and cynical societies. In particular, a second study question to be addressed in this project is *how do social contagion processes influence the effectiveness of control measures in reducing the spread of a disease, with special emphasis on the difference in effectiveness between trusting and cynical societies?* To address this, we construct a model (inspired by the work by Joh et al. (2009) [9]) to depict the spread of cholera in a population, using both direct and indirect transmission processes, and use it to fit to cholera case count data recorded by the Africa Centres for Disease Control and Prevention [10]. We will then model the compliance to several common control measures using a social contagion model that differentiates between *believers* and *cynics*, and examine how the ebb and flow of information and case numbers influence the overall effectiveness of control measures.

Overall, the results of this project will help us gain a more accurate understanding of human behavior in both fear-inducing and trivial scenarios; this can help governments, media agencies, and individuals to better understand and adapt their strategies in regards to public disclosure of information in topics such as economics, epidemiology, and communication.

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