Investigating the Role of Network Structure on the Diffusion Dynamics of a New Prescription Drug Using an Agent-Based Model

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Introduction

In this paper, we develop a framework using the methodology of agent-based modeling to investigate the role of network structure on the diffusion dynamics of a new prescription drug. Our investigation is centered on modeling the role of social influence on the adoption of a new prescription drug. Since social influence is mediated through social networks it appears to be crucial to understand the role of network structure on the emergent dynamics of diffusion of a new product. Agent-based models provide a natural platform to investigate network effects on process dynamics similar to product diffusion.

Model

Setup

Suppose that the market for prescription drugs for a particular health condition consists of M products. The drugs on the market are represented by $D_i \ \forall(i = 1, ..., m)$. When the drugs are introduced, they are evaluated based on a set of n attributes, represented by $A_j \ \forall(j = 1, ..., n)$. It is reasonable to assume that expert evaluations of the drugs are available publicly. Let the expert's evaluation ratings on the products be represented as matrix $\mathbf{E} = (r_{ij})_{m\times n}$

$$\mathbf{E} = \begin{pmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,n} \\ r_{2,1} & r_{2,2} & \cdots & r_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m,1} & r_{m,2} & \cdots & r_{m,n} \end{pmatrix}$$

In the matrix, the rating r_{ij} of drug D_i with respect to attribute A_j is represented using a real number in the interval $[0, a]$ where $a > 0$. We assume that consumers access the product information $\mathbf{E}$ through mass media.

Individuals generally have varying sensitivities to different attributes of a given product, including prescription drugs. Let $\mathbf{W_k} = (w_{k1}, ..., w_{kn})$ be a weight vector for attributes $A_j \ \forall(j = 1, ..., n)$ assigned by consumer-agent, k. Assume that these weights are on some interval $[0, b]$ where $b > 0$. Such an information can be obtained by well-designed surveys. We assume here that such survey information is available.

Using the expert evaluation information of the prescription drugs, ($\mathbf{E}$), and the individual weights for different attributes, we formulate the perceived worth of different drugs in the following way. Let

$$\mathbf{Q_k} = \begin{pmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,n} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m,1} & x_{m,2} & \cdots & x_{m,n} \end{pmatrix}$$

Where $x_{kij} = w_{kj} \times r_{ij}$. $\mathbf{Q_k}$ represents a personalized product valuation matrix. The matrix, $\mathbf{Q_k}$, is further normalized to $\bar{\mathbf{Q}}_\mathbf{k} = (\bar{x}_{kij})_{m \times n}$ using:

$$\bar{x}_{kij} = \frac{x_{kij}}{\sqrt{\sum_{i=1}^{m} (x_{kij})^2}}$$

In our model, $\bar{x}_{kij}$ is taken to be only the partial worth of the drug D_i for attribute A_i for individual k. We assume that social influence also plays a role in individual, k's valuation of each attribute, A_i, for each drug, D_i. We account for social influence using parameter $\alpha \in [0, 1]$. For simplicity, we assume that α is constant for the entire population. With this parameter, the overall attractiveness of drug D_i with respect to the attribute A_i is computed as:

$$\bar{x}_{kij} = (1 - \alpha)\bar{x}_{kij} + \alpha \sum_{l \in L_k} \frac{\bar{x}_{lij}}{|L_k|}$$

Where, L_k is the set of individuals in individual k's neighborhood who have adopted product i. The sum $\sum_{j=1}^{n} \bar{x}_{kij}$ is then interpreted as the perceived worth V_{ki} of drug D_i for individual k.

Following the literature of discrete choice models, we assume that an individual k chooses drug i based on the total perceived worth of drug i according to the logit probability:

$$p_{ki} = \frac{e^{V_{ki}}}{\sum_{l=1}^{m} e^{V_{kl}}}$$

Using the above formulation, we study a market where individuals purchase one of the drugs for a given health condition every month. Thus, in our model, each time step corresponds to one month. In each time step, individuals make their purchase decision based on the probabilistic choice model outlined above.

Example Scenario

In this section, we present the details of an agent-based model that we have implemented to estimate the model in the previous section. To keep things simple, we start with a market of one prescription drug for a particular health condition and at time $t = 1$ the new prescription drug is introduced in the market. The population must then choose between the new drug or the older drug on the market. Our interest is in predicting the diffusion pattern of the new drug given the expert rating information and the heterogeneity in the population. We model the two drugs with four attributes. For this example, we explore the diffusion of Prescription Drug A that is introduced into the market at time $t = 1$. Drug B is the existing competitor for drug A on the market. We consider the following expert evaluation of the two drugs. The ratings are given on the interval of $[1, 10]$. Here, we consider the following expert rating information:

	A_1	A_2	A_3	A_4
Drug A	1	3	8	10
Drug B	4	4	2	4

Only on the first two attributes is Drug B rated as slightly or moderately better than drug A. On the third and fourth attributes, Drug A is rated much higher than Drug B. Therefore, on average, drug A should be adopted at a higher proportion than drug B since the total of the ratings of Drug A is larger than that of Drug B. The individual weights for attributes are assumed to be distributed on the interval [0, 10]. For this example, we assume that $A_1 \sim N(4, 1)$, $A_2 \sim N(8, 1)$, $A_3 \sim N(9, 1)$, $A_4 \sim N(1, 1)$ are estimated from the data. These distributions are truncated on both sides at 0 and 10. For the initialization, we assume that 20% of the population, which we select randomly, tries the new drug A in the first month. With this setup, we will explore the role of social influence and the structure of the network on the adoption of drug A.

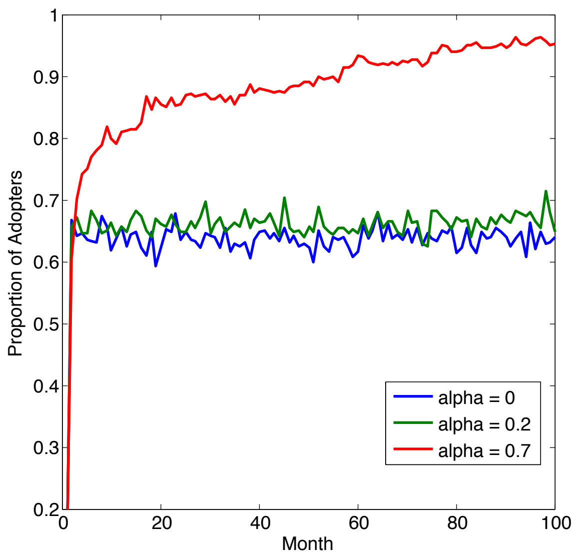
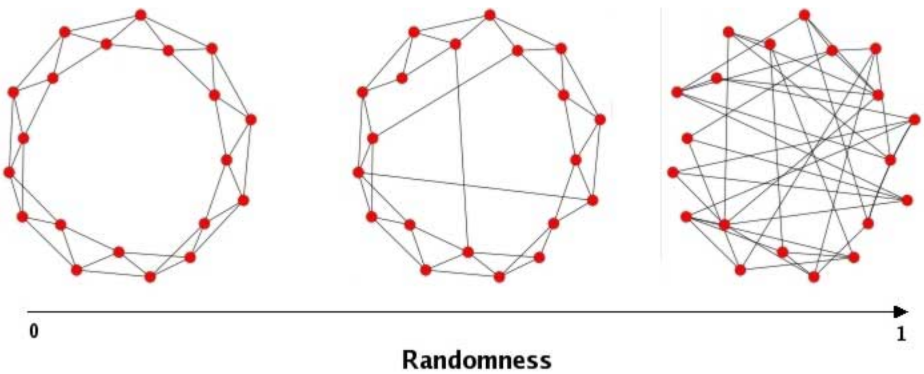


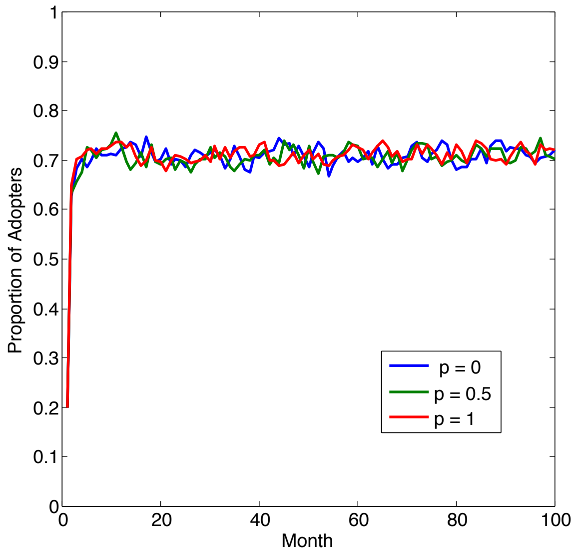
Figure 1: Role of social influence on the diffusion of drug A

Investigating the Role of Social Influence

First, we explore if social influence makes any difference in the given scenario. For this exercise, we use a simple regular graph of size N = 1000, where each individual has



(a)



(b)

Figure 2: a. Small-world property and rewiring probability (p). When $p = 0$ the graph is regular and when $p = 1$ graph is random. b. Drug diffusion over two scale-free networks with different densities.

the same degree $d = 4$. We consider three values for the social influence parameter $\alpha \in \{0, 0.2, 0.7\}$.

We can see the intuitive result that social influence increases the diffusion of drug A. Individuals who have a low preference for adopting drug A are influenced by early adopters in the neighborhood and eventually adopt drug A.

Impact of Network Structure on the Diffusion Dynamics

In this section, we investigate if the network structure makes a difference in the diffusion of the new drug. To this end, we consider the Watts-Strogatz small world network model. We chose this model since by varying the rewiring probability (p) we can obtain regular graphs, small world networks, and random networks with the same algorithm. We have

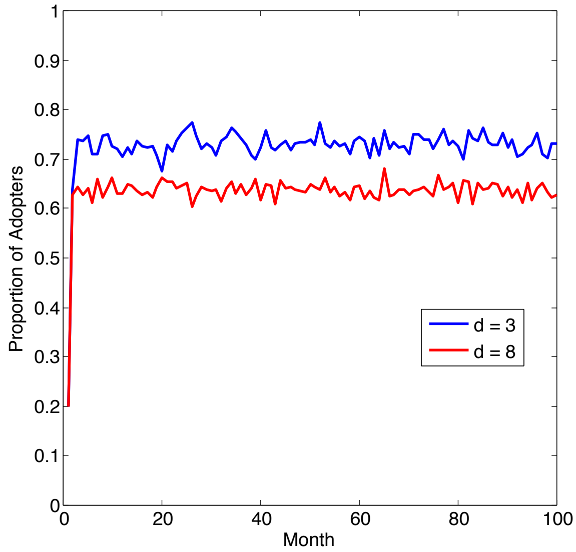


Figure 3: Diffusion on two scale-free networks.

conducted one experiment with each of the three networks by considering p=0, p = 0.5, and p =1. In all cases, we have set $\alpha = 0.5$ for all individuals and the network size at 1000. Figure 2 shows the proportion of agents who adopt drug A for each network. The graph shows averages over 30 simulations.

It appears from these simulations that structure of the network in this context does not really matter. There are no statistically significant differences. This is mainly because in all three networks, we have considered that the density of the network is the same.

Since adoption seems to depend mainly on density, we have further explored the role of density on the rate of adoption by considering a scale-free network. The main parameter in a scale-free network is the number of new edges introduced in each step of the preferential attachment algorithm. We have considered d = 3 and d = 8 for our experiments. We kept all other parameters of the simulation constant from the small world experiment. Figure 3 shows the averages over 30 simulations for the two cases.

The results are counter-intuitive. These results imply that as the density increases, the adoption of drug A decreases. However, this has more to do with the heterogeneity in the degree distribution of a scale free network. In our model, we start with 20% of individuals trying Drug A at $t = 1$. The remaining 80% of agents, who use Drug B, occupy the high degree nodes in the network with a high probability. The social influence of these agents is larger because they are connected to a larger number of other agents than those who adopt drug A.

Conclusion

In this paper, we have presented an agent-based model that we used to study diffusion dynamics of a new prescription drug. First, we showed that social influence significantly alters the diffusion of the new product. We have also shown that when social influence is taken into account, some network structures lead to faster diffusion than others.

Future Extensions

- In this paper, we have limited our attention to only a few special instances of networks due to time constraints. However, it would be desirable to thoroughly explore the space of specific network topologies by varying input parameters such as the rewiring probability in the small-world network context.
- In this paper we have assumed that social influence affects all individuals equally. However, a more reasonable approach would be to model heterogeneity in the social influence parameter (α) using a distribution.
- The two product setup can be easily extended to M product general case.
- In this model, we have used synchronous activation. Future extensions of the model could consider asynchronous activation.

Possible Applications of Our Model

- We have applied this model to a drug market, but this type of model is applicable in a broad range of product markets. This type of model would be useful for marketing departments of companies who are interested in releasing a new product.
- This type of model can also be used to model a wide range of diffusion more generally. Such applications would include the diffusion of public policies across states, religions across people and regions, and ideas more broadly.