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CX 4230 Computer Simulation

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Mini Project 2: Product Adoption Models

Part A: ODE Model vs. Agent Based Model

Introduction

Product adoption is defined as the probability of an individual to buy or adopt some product. Generally, the product adoption process is defined as the chain of events all prospective consumers undergo before purchasing or rejecting a product. The typical product adoption process involves the following five steps: 1) Product Awareness 2) Product Interest 3) Product Evaluation 4) Product Trial 5) Product Adoption (Chandra 2014). The following is an example of a successful production adoption workflow: when a person is first introduced to a product, he might be interested in the product's features, compare the product to existing solutions, try it out, and then finally purchase it.

To accurately measure how well a product will perform over time, models are created to simulate real life product adoption processes. For our simulation, we intend to explore how an ordinary differential equations (ODE) based model and an agent based model influence product adoption. In the following sections, we will compare these two product adoption models, explore network effects on product popularity, and analyze product adoption on a real social network.

ODE Model vs Agent Based Model

The ODE model solves a differential equation to provide a theoretical product adoption curve. This differential equation measures the rate at which people adopt the product. In the agent based model, the fraction of neighbors who have adopted the product determines each agent's perceived value for that product. The more people who adopt the good, the higher the chance that another agent will also adopt. In this case, each person sees every other person in the network and the perceived value of a good depends on the global popularity of the product.

A simulation was developed allowing one to visually see the differences in these models. These differences are best seen when the number of agents and the number of trials are varied. Trends were developed by setting the number of agents to either 100, 1000, or 10000 agents and by setting the number of trials to either 1, 10, 100, or 1000 trials.

Below we've provided a qualitative description of our observations ordered by the number of trials. Each passage describes the behavior of agents for that number of trials. In general, as the number of trials increases, the median value becomes closer to the theoretical value and the standard deviation increases away from the mean. The mean curve generated by the agents model often looks quite different from the theoretical sigmoid created by the ODE model. This is because the mean is subject to fluctuation by outliers in the data. As the number of trials increases, the mean becomes more stabilized; however, it generally does not maintain a sigmoid shape. In contrast, the median is a better estimate for the theoretical value. It obtains the expected sigmoid shape since outliers do not fluctuate the median. This makes sense because as the number of trials increases, the effect of outliers will be minimized and the overall behavior will emerge.

Effects of Agents

Trial 1

Across all the agents, the mean and median curves are generally in the form of a sigmoid. Since there is only one trial, the mean and median are the same. Because there is only one trial, there seems to be no apparent pattern in this subset of the data. Every time a trial is run (for any number of agents) we produce a different sigmoid curve. At one trial there isn't much credibility to the data since any fluctuation or outlier will not be normalized and will be shown as the total output. Additionally, note that for the smaller number of agents, we see an initial fluctuation in the fraction of adopters. As the number of agents increases, this initial fluctuation smoothens out. We can see this property in **Figure 1** below.

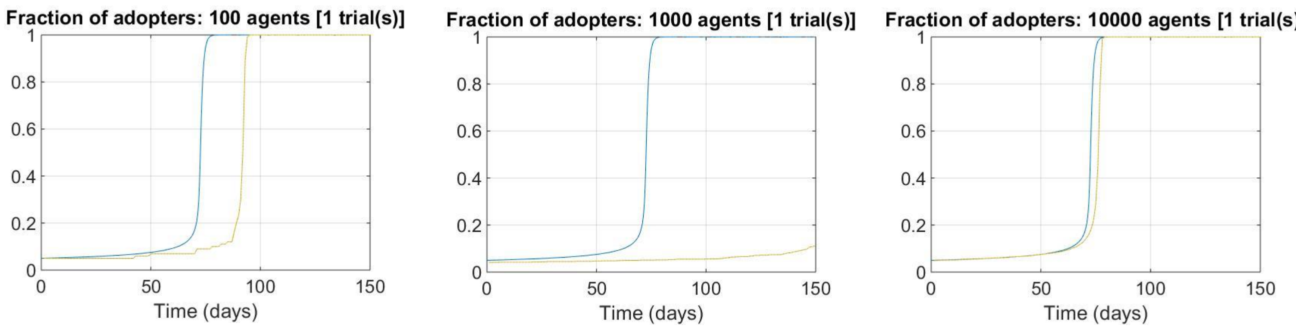

Figure 1: Effect of Increasing Agents for Trials = 1

10 Trials

As the amount of agents increases, the mean and median curves shift closer to the theoretical curve. The mean is very originally very erratic because of the variations in the sigmoid curves. Similar to what we observed at the single trial level, since each single trial for a specific number of agents provides a different curve, it makes sense that the mean of these curves would look like a staircase. Additionally, note that as we increase the number of agents, the curves for mean-stddev and mean+stddev curves shift inward. This might occur because we have more agents to determine our overall product adoption rate and so the ratio of outliers to normal adopters decreases. **Figure 2** on the right shows an example of change from 1000 agents to 10000 agents at 10 trials.

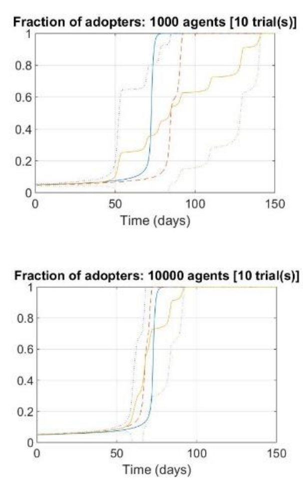

Figure 2: Comparison of [1000 Agents, 10 Trials] to [10000 Agents, 10 Trials]

100 Trials

For 100 trials and an increasing number of agents, we can see that the mean shapes more to a sigmoid curve and is more stable. There is also a considerable decrease in the amount of standard deviation. As with 10 trials, the number of agents increases the closer the results get to the theoretical value. **Figure 3** below shows the change in the results for agents at 100 trials.

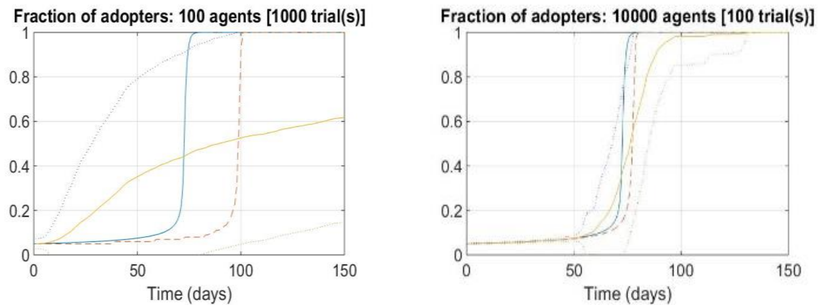

Figure 3: Comparison of [100 Agents, 1000 Trials] to [10000 Agents, 100 Trials]

1000 Trials

Similar to the 100 trials, as agents increase, the mean becomes more sigmoid shaped and the standard deviation is decreases. The median is now the closest it has been to the theoretical value. **Figure 4** to the right shows the change in the results for agents at 1000 trials.

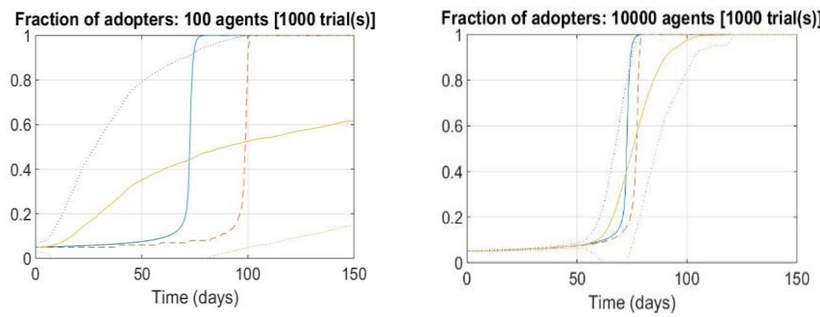

Figure 4: Comparison of [100 Agents, 1000 Trials] to [10000 Agents, 1000 Trials]

Effects of Trials

As we saw previously, increasing the *number of agents* provided more accurate results that neared the theoretical curve over time. Here, increasing the *number of trials* will provide more accurate results since more sample data can be factored into the model. **Figure 5** on the following page shows the differences generated by increasing the number of trials for a set number of agents. We ran this simulation multiple times by setting the number of agents fixed (10, 100, and 1000) and by increasing the number of trials from 1, 10, 100, to 1000 trials. Overall, as the number of trials increased the median moved closer to the theoretical value and the standard deviation decreased. Standard deviation decreased because increasing the number of trials, increased the ratio of influential points to outliers. So, this provided a better estimate of the behavior of the system.

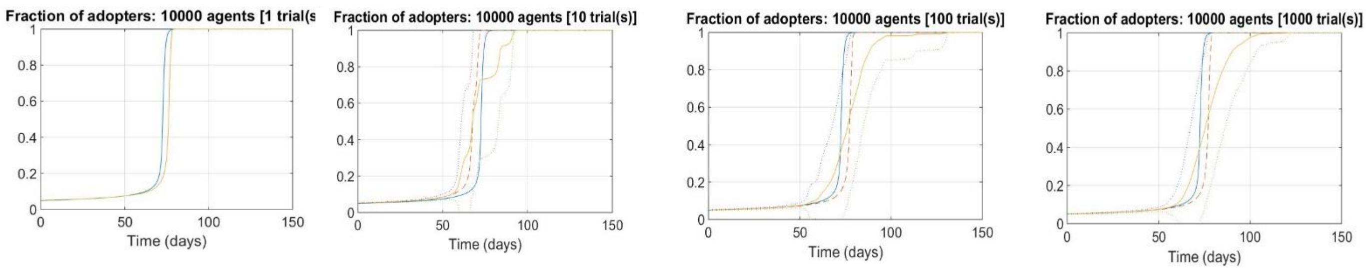

Figure 5: Effect of Increasing Trials for Agents = 10000

Part B: Modeling Network Effects

Random Network Effects

The previous models had assumed that every person could perceive the global popularity of a product in the same way. In reality, product adoption relies on the popularity of a product in one's familial/close social network to influence individuals. To emulate this property, agents are set to perceive the *localized* popularity of a product instead of its global popularity. We test this property by running the agent-based simulator with 1000 agents for 100 trials on a random network in which each agent has an average of *k* neighbors. *k* was changed on different iterations of the simulation, setting it first to 10, then 30, and finally 100.

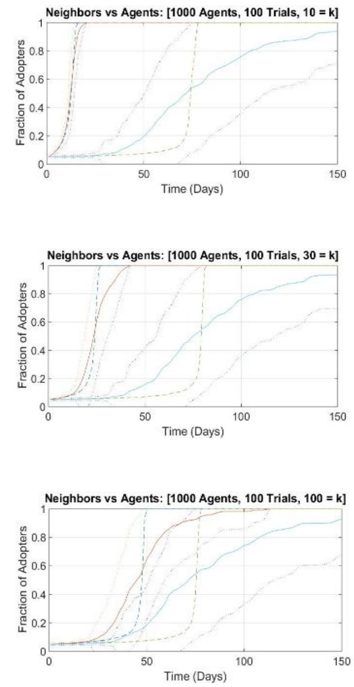

Figure 6: Comparison of Increasing Number of Neighbors [10, 30, 100] to Agent Based Model

As expected, when the number of neighbors increased, the median and mean curves approached the fully connected curve. This is because as the number of neighbors increases, we approach a fully connected network in which every person can see every other person. Thus, if *k* increased up to the 1000, for 1000 agents at 100 trials, we would obtain the same graph as the one obtained by the fully connected model. When *k* is small, the time to reach max rate of fraction of adopters decreases. This is because a smaller neighborhood might more easily influence someone to adopt a good since a higher portion of them have been adopted. So, if it's easier to influence a smaller community to adopt a product than the entire population, if an individual only considers the people in his community who have adopted this product then he'd have a higher chance of wanting to adopt this product. Comparatively, if one looks at the popularity of a product as a whole, it would take much longer for an individual to convert since not many people initially are converted. So the ratio of unconverted to converted people is much higher in a fully connected network than in a neighbor based network. Thus, it takes longer for number of adopters to increase. **Figure 6** above depicts the fraction of those adopted in a local network with an average of *k* neighbors. The red line represent the mean of the *k* neighbors. The blue line represents the mean of the fully connected network. **Figure 7** below shows the progression of how an increasing *k* compares with the ODE model and **Table 1** below displays the observations obtained by varying *k* relative to the ODE model.

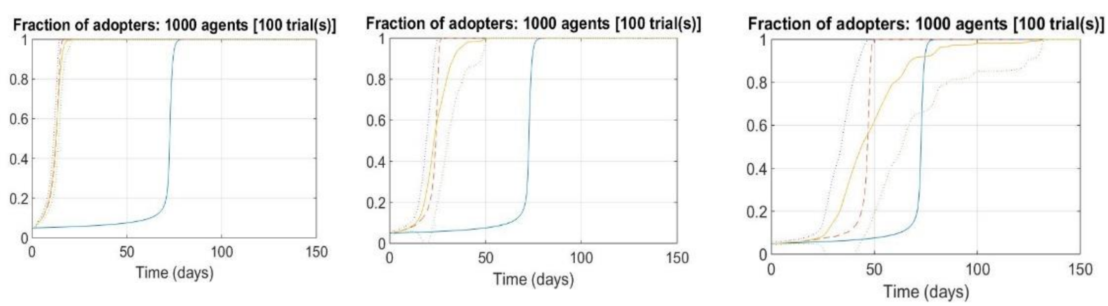

Figure 7: Comparison of Increasing Number of Neighbors [10, 30, 100] to ODE Model

Neighbors	***Observations***
10	The median is very far away from the theoretical value. The standard deviation is very small as well. These statistics are reasonable because we only consider 10 neighbors, meaning that the time for individuals to adopt a product will be much less.
30	The median gets closer to the theoretical value than it was for 10 neighbors. The mean increases slower than it did at 10 trials because there is an increased number of those who do not adopt the product. This same reason explains the increase in standard deviation.
100	Now that we have increased the number of neighbors 10 fold from the original value of *k*, we know that in general as we increase the number of neighbors, both the median and mean curves begin flattening out and that the standard deviation continues to increase.

Table 1: Effects of Increasing Neighbors Compared to ODE Model – [1000 Agents, 100 Trials]

Epinions Network Simulation

Finally, we tested the agent based simulator on the Epinions network hosted by Stanford University's SNAP (Stanford SNAP 2003). The Epinions dataset is based on the realistic online social network, Epinions.com, and contains 75888 agents. We ran the simulation over 100 trials and compared the results with the uniform random model from before. The trial ran with an average number of neighbors *e*, in which *e* is chosen to match the average number of neighbors per agent in the Epinions network. For this network, *e* was calculated to be ~6.7 neighbors.

Figure 8 below provides a comparison of the product adoption curves for the Epinions network [75888 agents, 100 trials, *e* = 6.7] and for the uniform random model [75888 agents, 100 trials, *k* = 6.7]. As we can see for the Epinions network, the mean and median curves level off at approximately .75. Comparatively, the uniform random model is *normalized* and levels off at approximately 1. This normalization is not performed on the Epinions network and therefore we see the mean and median level off to a much lower fraction of adopters for this network.

Note how the uniform random model for a small number of neighbors starts increasing rapidly within 5-15 days of introduction of the product. On the other hand, we see that Epinions network starts off more slowly and then gains traction around 17-30 days. This latency might occur because products are introduced initially to only some individuals (beta-testers). This implies most of the population does not even know about the product during the first few days. As these groups adopt the product, they may spread information about it and begin raising its popularity. These groups would be central to the popularity of the product (similar to a celebrity/group of celebrities endorsing a product). As more individuals learn of the product, there is a drastic increase for an interval of time. After 40 days, the fraction of adopters levels off. In the uniform random model, we hypothesize that instead of a small group of individuals mainly expanding the popularity of the product, all small groups are introduced to the product at the same time. This would mean more neighbors per individual are adopting the product, even if the number of neighbors per individual is small (in this case ~6.7).

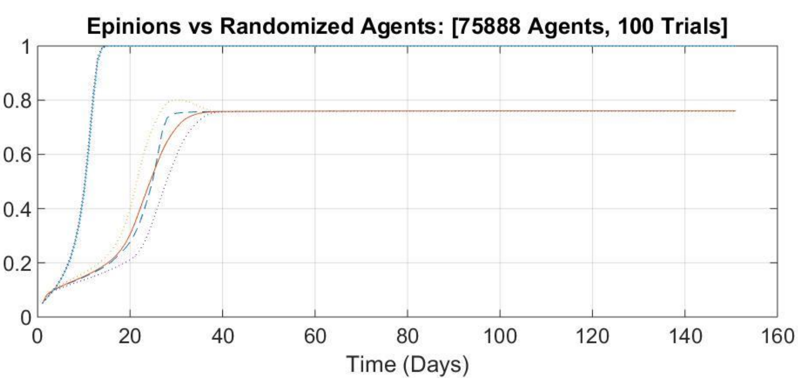

Figure 8: Comparison of Epinions Network to Uniform Random Network

Works Cited

Chandra, N. "5 Stages to the Consumer Adoption Process." *LinkedIn Pulse*. 24 Oct. 2014. Web. 3 Feb. 2015. <https://www.linkedin.com/pulse/20141024185121-17707777-5-stages-to-the-consumer-adoption-process>.

Stanford SNAP. "Epinions Social Network." *SNAP: Network Datasets*:. Web. 3 Feb. 2015. <http://snap.stanford.edu/data/soc-Epinions1.html>.