Spatial Model of Innovation Diffusion

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Abstract

In recent years, the effect of innovation diffusion in the development of cities, regions, and the global economy is getting increasingly remarkable. On one hand, the literature in innovation geography, urban economics, and regional science points out that geographical proximity and social networks have significant effects on knowledge spillover and innovation diffusion. On the other hand, some scholars believe the effect of proximity is diminishing in this internet era. This paper studies the stylized theory of the S-shaped curve in innovation diffusion, and the effects of distance in generating the S-shaped curve. In previous literatures, three types of models have been developed to explain the emergence of the S-shaped curve in innovation diffusion, namely the Epidemic Models, Probit Models, and Strategic Models. However, none of them has taken the effects of spatial elements and social networks into consideration. I develop an agent-based spatial model that generates the asymmetric S-shaped curve in innovation diffusion, as described in many empirical studies. A reference model is developed to prove that distance is indeed making an impact in generating the S-shaped curve. The results imply that distance and social networks may play an important role in generating the S-shaped curve in innovation diffusion.

Keywords: Innovation diffusion; S-shaped Curve; Geographical Proximity; Social Networks; Agent-based Modeling.

Biographical Sketch

Yang Zhou is currently in her second year of study in Regional Science at Cornell University. In 2013, Ms. Zhou graduated from South China University of Technology with a BA in Civil Engineering. In August 2015, she will graduate from Cornell University with a Master's degree in Regional Science, with a focus in urban economics. Ms. Zhou has been interested in studying the emergence and diffusion of innovation in cities and regions. Her diploma research was done using agent-based modeling. She has presented her research in the Association of American Geographers Annual Meeting in 2015. Ms. Zhou plans to continue her research and pursue a doctoral degree at George Mason University.

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1. Introduction

Recent years have witnessed the rise of high-tech cities and regions, which refer to cities and regions that accumulate a lot of high-tech firms and entrepreneurial activities, such as Silicon Valley. Economists admit that innovations and technological progress is the driving force of economic growth of cities and regions. When talking about technological progress, more attention should be paid to the diffusion of innovations, because only when an innovation is sufficiently diffused, can it contribute to economic growth at its best. According to Stoneman (1985), innovation diffusion is the process by which innovations (be they new products, new processes or new management methods) spread within and across economies. As an urban economist and regional scientist, I am most concerned about a question: what is the relationship between innovation diffusion and geographical distance?

Some studies investigate the spatial diffusion of innovation and technology based on technological spillovers. There are three theories of knowledge spillovers. First is the Marshall-Arrow-Romer (MAR) spillovers, which is a combination of theories from Marshall (1890), Arrow (1962) and Romer (1986). In MAR spillover, knowledge is a public good, and agglomeration of a specialized industry is beneficial for knowledge spillover. The second type of spillover is the Jacobs spillover (1969). Jacobs observed the interactions among different industries empirically and claimed that innovations emerge when individuals experience different knowledge sources and meet with others with different backgrounds and experiences. Therefore, geographical proximity of diversified industries promotes innovation and economic growth. The third type is a Porter spillover (1990). Industrial agglomeration enhances the competitiveness of companies in it by providing access to experienced workers, industrial information, services from suppliers; as a result, companies reduce the costs to produce. Further, it is easier for companies in a cluster to cooperate and learn from each other through informal communication. Porter emphasizes the role of competition and believes competition among companies in a specialized industry promotes innovation. Glaeser (1992) developed a model and used empirical data to test which of the three theories of spillovers is better supported by the empirical evidence. His results show that the agglomeration of diversified industries is conductive to regional growth which is most consistent with Jacobs spillovers. Glaeser (2000) also points out that cities are centers of idea creation and transmission. In the past, companies agglomerated to reduce transportation cost of materials; nowadays, they do so to reduce the cost of exchanging information. These theories show that the impact of geographical proximity has to do with knowledge spillovers.

Hagerstrand (1966, 1968) was the first scholar who analyzed patterns and internal mechanisms of innovation diffusion. He summarized two patterns in the spatial diffusion of innovation—Neighborhood Effect and Hierarchy Effect. A neighborhood Effect points out the fact that the probability of adoption is higher for regions closer to the innovator. Hagerstrand agrees with the popular theory that private communication is more powerful than public communication in innovation diffusion, which explains why spatial components matter. Comin (2012) uses pattern citation data to demonstrate that technology diffuses more slowly to locations that are farther away from adoption leaders. Literatures on spatial innovation diffusion usually use human interaction to explain the impact of distance; it is based on the concept that human interaction is necessary for technology adoption. However, Rogers (2003) argues in his renowned book Diffusion of Innovations that the internet has changed the very nature of diffusion by decreasing the impact of distance. Since then, the relationship between geographical distance and innovation diffusion has been controversial.

An interesting finding about innovation diffusion is the emergence of the S-shaped curve. An S-shaped curve describes the rate of imitation, or in other words, how rapidly firms come to use a new technique. Rogers (1962) has defined the S-shaped curve as: when the number of individuals adopting a new idea is plotted on a cumulative frequency basis over time, the resulting distribution is an S-shaped curve. Very intuitively, the curve is an “S” shape, implying that the rate of adoption is increasing in the early phase, reaches maximum in medium phase, and then decreases to zero at the end. There are mainly three types of models trying to explain the emergence of S-curve, namely the Epidemic Model, Probit Model, and Strategic Model. However, none of these models has taken distance into consideration. Since geographical distance may play a role in innovation diffusion, can we build a spatial model of innovation diffusion to generate an S-shaped curve as well?

In this paper, I develop a spatial model that emphasizes distance between high-tech firms and find out that an asymmetric S-shaped curve emerges in this model. This finding shows that distance does play a role in innovation diffusion. In section 2, I review evidence of the S-curve in innovation and innovation diffusion, existing models that try to generate S-shaped curves, and other literature on innovation diffusion in general. In section 3, I introduce an agent-based model and reasons to use it as well as the spatial model I build. As a reference object, I also build a model without spatial elements that should not generate S-shaped curve. In section 4, I present the results of my spatial model and the reference object. In section 5, I try to explain the emergence of the S-shaped curve in my spatial model based on observations. In section 6, I pointed out the limitations of my model and further steps to take.

2. Literature Review

2.1 The S-shaped curve

The study of innovation diffusion started in the 19th century, when the S-shaped curve of knowledge diffusion was first observed by Gabriel Tarde in 1890, and he called it "the laws of imitation". Based on that, Rogers (1962) has developed the Innovation Diffusion Theory, or Innovation Adoption Curve (Figure 1). As shown in the figure, the Y-axis shows the cumulative proportion of states (or population in general) having adopted, and the X-axis shows Time. In other words, as time goes by, the number of people who have adopted the innovation is increasing; the increasing speed is slow at first, but gets faster in the middle, and then decreases again at the end, forming an S-shaped curve. This phenomenon had been observed in both sociology and education.

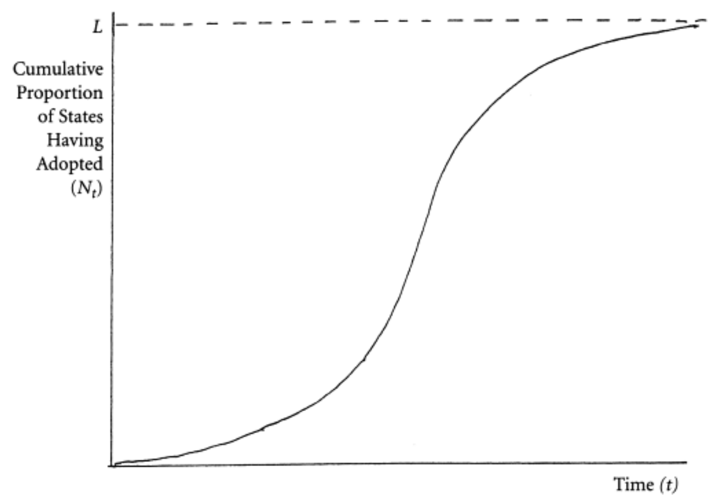


Figure 1. The S-shaped Curve in Innovation Diffusion by Rogers (1962)

Rogers's S-shaped curve is a theoretical model built to describe the adoption pattern of innovations. However, there are many studies that use empirical data to show the S-shaped curve in innovation diffusion. Griliches (1957) found that the percentage of corn planted with hybrid seed plotted over time is S-shaped. Brancheau and James (1990) did a field study and historical analysis of the diffusion of spreadsheet software in organizations, and show that the adoption rate of Spreadsheet has shown an S-shaped curve with a take-off point. Gurbaxani (1990) confirmed the S-shaped cumulative adoption curve in computing networks using BITNET as a model (Figure 2). BITNET is a university computer network founded in 1981. It allowed universities to send messages and files from point to point. The first connection was between City University of New York and Yale University, and later more and more universities started to use it. Gurbaxani finds out that the cumulative adoption of the BITNET computing network by universities shows an S-shaped curve. Furthermore, Gurbaxani and Mendelson (1990) showed that the adoption of information systems follows an S-shape curve in the early stage, and converges to an exponential pattern as the effects of decreasing price took over. Andersen (1999) studied empirically the long term evolution paths of individual technologies and showed that it follows an S-shaped growth path. Mingers (2008) fitted the citation pattern of over 600 papers published in six leading journals to S-curve models.

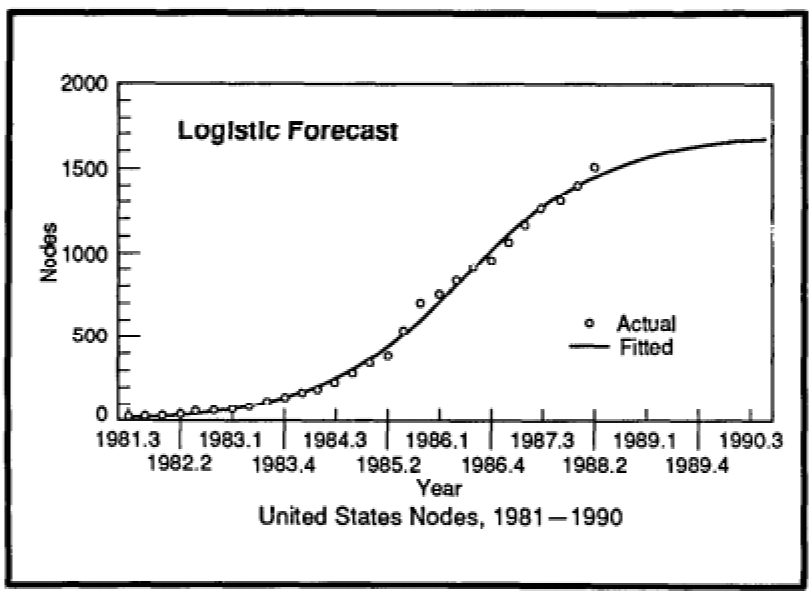


Figure 2. S-shaped curve fitted with BITNET data by Gurbaxani (1990)

Mansfield (1961) developed a simple model with a hypothesis—the probability that a firm adopts a new technique is an increasing function of the proportion of firms that have already adopted it and the profitability of doing so. In the beginning, there are few adopters and there is a high risk to adopt due to lack of information. However the profit is high, because the new technique can make the firm stand out in the market. Later, when more firms have adopted the new technique, the risk to adopt has become lower and adopting still provides good profit; the imitation rate reaches its maximum value in this phase. As a lot of firms have adopted the technique, the risk of adoption becomes increasingly lower at the end; however, the profit is also low since the competition among firms using this technique is high now. As a result, the imitation rate decreases to zero.

Another model about innovation diffusion rate, the Bass Model, was introduced by Bass (1969). In fact, the bell shaped curve in the Bass Model is the rate of imitation. If we measure the slope of the S-shaped curve and plot it over time, it will be bell shaped.

2.2 Models of the S-shaped Curve

Geroski (2000) disputes all types of models built to explain the emergence of S-shaped curve in innovation diffusion. The most popular model is the epidemic model, which builds on the theory that information diffusion drives innovation diffusion. This type of model usually assumes that the lack of information available about the new technology limits the speed of adoption. An important point is that for a new technology to be adopted, people need to both be aware of it and learn about how to use it by “word of mouth”. At each period a certain percentage of people will hear about the new technology, and that each non-adopter has a certain probability to make contact with previous users to learn information needed to use the technology effectively. This theory generates a logistic function that gives birth to the S-shaped curve. What’s more, according to empirical research in citation, the S-shaped curve is usually asymmetric, meaning that the tail at the end is longer. For example, Dixon (1980) claimed that the diffusion of hybrid seed is better fitted to an asymmetric S-curve. In asymmetric S-curve, the initial rise in citation is very rapid, however, it is followed by a slowing rate of citation over time, which may only tail off after 25 to 30 years. In order to explain the asymmetric S-shape, scholars introduce heterogeneous populations into the model, where there are "slower adopting population(s)" that cause the gradual increase in the tail. While the epidemic model can explain the asymmetric S-curve, an obvious problem is that it does not explain how the spread starts.

Another popular model used to generate S-shaped curve is the probit model, which emphasizes the adoption decisions of individuals. It is assumed that different people have different profits (x_i) in adopting the new technology, which follows a distributed function, for example normal distribution. One will adopt if his or her profit is greater than the threshold level which can also change over time. The combination of certain distribution function of x_i and how the threshold changes over time could yield an S-shaped curve. For example, if the distribution of x_i is bell-shaped and the threshold diminishes over time, then clearly adoption rate will increase first and then decrease, generating an S-shaped adoption curve. The most complicated part of this model is how to determine profits. In existing studies, firm size, suppliers, technological expectations, learning and searching costs, shifting costs, and opportunity costs are often considered in determining xi. The model identifies important determinants of firms' adoption decisions, and policy makers can use them to increase or decrease the diffusion rate of a new technology. However, probit models do not explicitly describe the interaction between individuals, but focus on profit and threshold instead. This is unsatisfying for people interested in studying innovation diffusion as a social process.

While epidemic model and probit model are non-strategic, there is a third type of models, called the strategic model, or Game-theoretic model, to generate S-shaped curve in innovation diffusion. For example, Jovanovic and Lach (1989) claimed that early entry has high revenue per unit of output, while late entry has lower entry and production cost due to learning by doing, but also lower benefits. These advantages are balanced off in equilibrium, and the competition generates S-shaped diffusion.

All these models trying to explain the S-shaped curve have advantages and limitations, depending on what is the focus of study. However, none of them has taken spatial components into consideration.

2.3 Other Studies on Innovation Diffusion

Many scholars pay attention to diffusion rate during the diffusion process, and try to analyze the mechanism behind the uneven spatial diffusion. They often study international trade, overseas R&D (research and development) cases, and problems involving innovation diffusion among countries with different levels of technology. Mansfield and Romeo (1980) present survey evidence in which U.S. multinationals reported the frequency and pace that their technology deployed in foreign affiliates reached host-country competitors. Fagerberg and Verspagen (1996) study the cross-country differences in GDP growth among countries in European Union, and developed the technology gap theory of economic growth. Haddad and Karrison (1993) study the technology spillovers of foreign firms in Moroccan, and point out that the hypothesis that foreign presence accelerated productivity growth in domestic firms might not always be true. Kokko (1996) uses the industry data from Mexican manufacturing to examine the productivity spillovers from competition between local firms and foreign affiliates, and find out that the spillovers from competition are rather determined by the simultaneous interactions between foreign and local firms. Keller (1996) studies innovation diffusion amount countries, and examines two questions: whether distance affects innovation diffusion, and if it does, how trend varies.

Other scholars are more interested in technology adopters, and focus on revealing the patterns and mechanism of innovation diffusion among the adopters. Scholars study innovation diffusion within the regions, and base their research on enterprises clusters and regional innovation networks. Abreu and

Henri (2004) employ techniques developed in spatial econometrics to analyze patterns of innovation diffusion and to detect clusters; they claim that technology levels are converging locally. Bart (2002) uses pattern citation data from European multinational firms to show that technology first diffuse to nearby area, and then to larger area; the technology diffuse in early period, but after two to three years, the diffusion has become very weak, which implies that innovation diffusion decay with distance. Andolfatto and Glenn (1998) developed a macroeconomic model using post-war U.S. data, in which individuals' behaviors are driven by their efforts to innovate and make use of others' innovation, and the model predicted the results for the post-war U.S. In sum, the empirical studies confirm the importance of space.

3. Methodology

3.1 Introduction to Agent-Based Modeling

The model I am using in this paper is an Agent-Based Model (ABM). ABM is a computational system that simulates the actions and interactions of autonomous agents and assesses the effects on the system. Kimura (2002) introduces the use of ABM to Regional Science. He points out that simulation has advantage over analytical methods for its ability to deal with dynamic phenomena and complex behaviors, and capture randomness. In recent years, there has been more and more research using ABM in Regional Science.

I would like to use ABM to build my spatial model mainly for two reasons. Firstly, I believe human interaction is crucial for innovation diffusion, and ABM is capable of simulating interactions among agents. Second, innovation and innovation diffusion arise in social networks, and ABM can assess the effects of individual interactions on the system as a whole. Last but not least, ABM is suitable for analysis of spatial problems for the fact that ABM is a computational model where space can be accommodated in a natural way.

3.2 The Model

A basic question about innovation and innovation diffusion is why the growth curve of the adopter population in a large society is often S-shaped. My purpose is to build a spatial model that generates the S-shaped curve, where location and distance from other individuals are taken into consideration. The scale I am looking at in this paper is country, since international diffusion may have many other barriers or information channels that are hard to capture.

In order to build a spatial model, I firstly generate a map with agents, which represent high-tech firms, randomly distributed on it (Figure 3). Some of them are isolated from others, while some of them are close to others, forming a "community". The map represents the reality that firms are located with a distance to other firms, and there are clusters where a group of firms are close to one another.

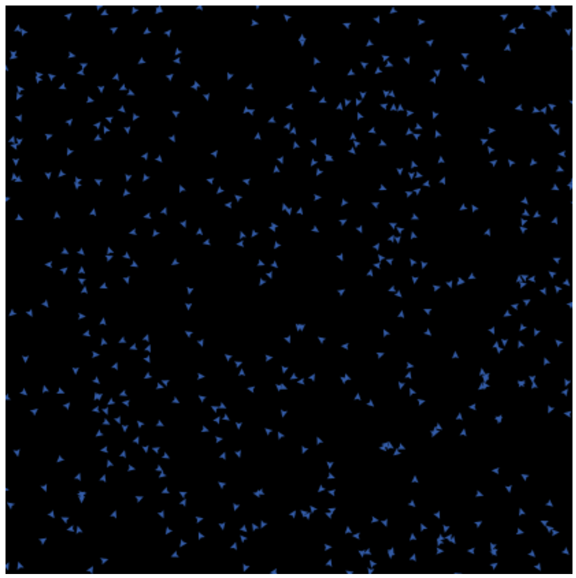


Figure 3. Map with agents randomly distributed on it

To simulate the innovation of new technology, at the beginning of the simulation, an agent will be randomly selected and "infected" with the new technology.

The next step is to think about how other firms, as potential adopters, get access to the new technology and adopt it. Following theories from epidemic models, for a firm to adopt a new technology, it needs both to be aware of the "hardware" and "software" of the technology. Hardware refers to the existence of the tool, machine or physical object that embodies the new technology; software refers to the information base needed to use the new technology, which is built through experience of using it. Software knowledge usually can only be obtained by face-to-face communication with another firm that has already adopted the new technology. Therefore, in my model, interaction between two agents represent face-to-face communication that can transmit software knowledge. This kind of interaction includes business cooperation, meetings, conferences, etc.

In each period, an agent will choose a partner to interact with following a probability function. Gravity model, as a stylized model often used in spatial interaction, is used to calculate the probability. The probability for agent i to choose agent j as partner is proportional to the distance between them to the power of α.

$$Prob(ij) \sim \frac{1}{d^{\alpha}}$$

Where d is the distance, and α is a parameter larger than 1 that could be adjusted. If two agents are placed on the same cell, the distance is set to be 0.25. This probability function accounts for the fact that high-tech firms usually interact with firms closer to themselves, while not eliminating the possibility to interact with firms further away. Also, as the distance increase, the bottom of the function will increase exponentially, causing the probability to interact to decrease tremendously. It accounts for the fact that firms prefer to interact in small communities.

Furthermore, I would like to include individual decisions and heterogeneity into the model. At the beginning, every firm has a probability which is randomly selected between 0 to 100% to adopt the new technology when they interact with a firm that already knows it. However, it is intuitive that when more firms have adopted the new technology, the risk of adopting it is getting lower, and therefore, firms should have a higher probability to adopt. In my model, when the percentage of firms adopted is higher than the probability to adopt, the probability changes to equal to the value of percentage adopted.

The flow chart (Figure 4) below explains the process. The code is in appendix.

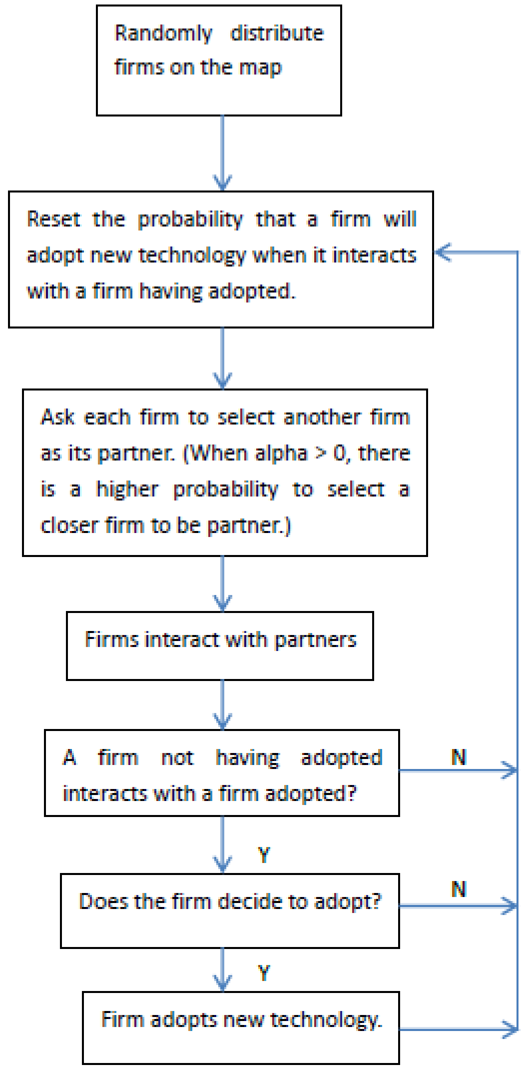


Figure 4. Flow Chart of the Spatial Model

3.3 Reference Objects

An important problem is that, agent based modeling is able to capture randomness, but at the same time, it is not transparent what cause the results. Even if the spatial model generates an S-shaped curve, it is not enough to argue that distance is driving the emergence of S-shape curve. Therefore, as a reference object, I will build a Model 2 that does not take spatial components into consideration. In this model, agents select partners randomly according to a uniform distribution. If spatial components should explain S-curve, Model 1 should generate an S-curve and Model 2 should not.

Another problem is that my model has agents randomly distributed on the map, but in reality, high-tech firms are not randomly distributed. Since this is a spatial agglomeration problem, and it has significant effect on the probability function, it should not be overlooked. I use empirical data of the number of U.S. firms by state from the Census to locate them on a U.S. map to build Model 3. The dataset contains the number of technological firms in each state. Technological firms are identified as those in the NAICS sector Professional, Scientific and Technical Services. In order to simplify computation to reduce computer power needed, there are two arrangements. Firstly, the agents are located in the geometric center of each state instead of the real location. Secondly, the number of firms in each state is divided by 500, so that the calculation will not take too long.

In the beginning, data of the number of firms in each state and a map of the continental United States are loaded into Netlogo. Then, agents are placed on the geometric centers of the states. In this model, we can choose in which state to have the initial innovation. Next, the firms will choose partners and interact with them just like the setting in Model 1.

4. Simulation Results

Model 1:

This is the spatial model I am developing to generate the S-shaped curve. In this model, agents are randomly distributed on the map. In a period, each agent will choose another agent to be its partner according to a probability function based on distance. If an agent interact with an infected agent, it will get infected.

The result shows that the spatial model generates an asymmetric S-shaped curve (Figure 5). Also, when alpha is set between about 2 to 3, we get the best result, meaning asymmetric S-shaped curve. When alpha is larger than 5, the technology can not diffuse to most population after large number of periods.

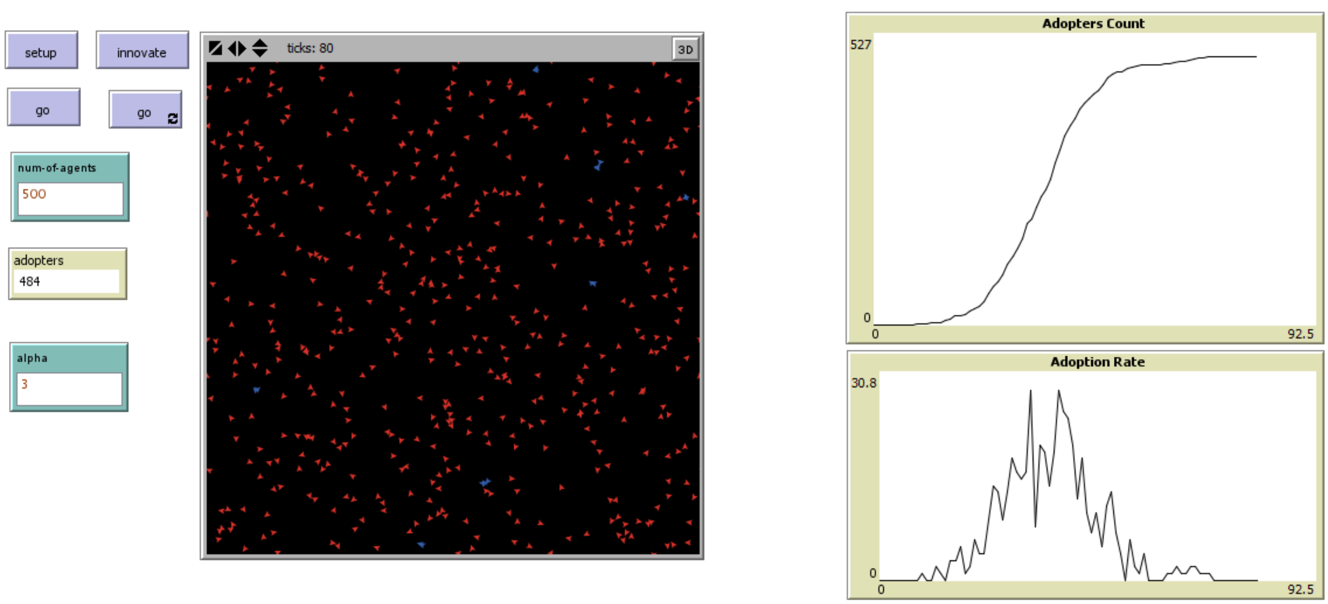


Figure 5. Simulation Results of the Spatial Model of Innovation diffusion

Model 2:

This model is designed as a reference object to the spatial model to prove that distance does play a role in generating S-shaped curve. In this model, agents are randomly distributed on the map. In a period, each agent will randomly choose another agent to be its partner, and then interact with the partner. If an agent interacts with an infected agent, it will get infected.

The result shows that the model does not generate an S-shaped curve, but an exponential curve instead. To be more specific, the curve lacks concavity at the tail (Figure 6).

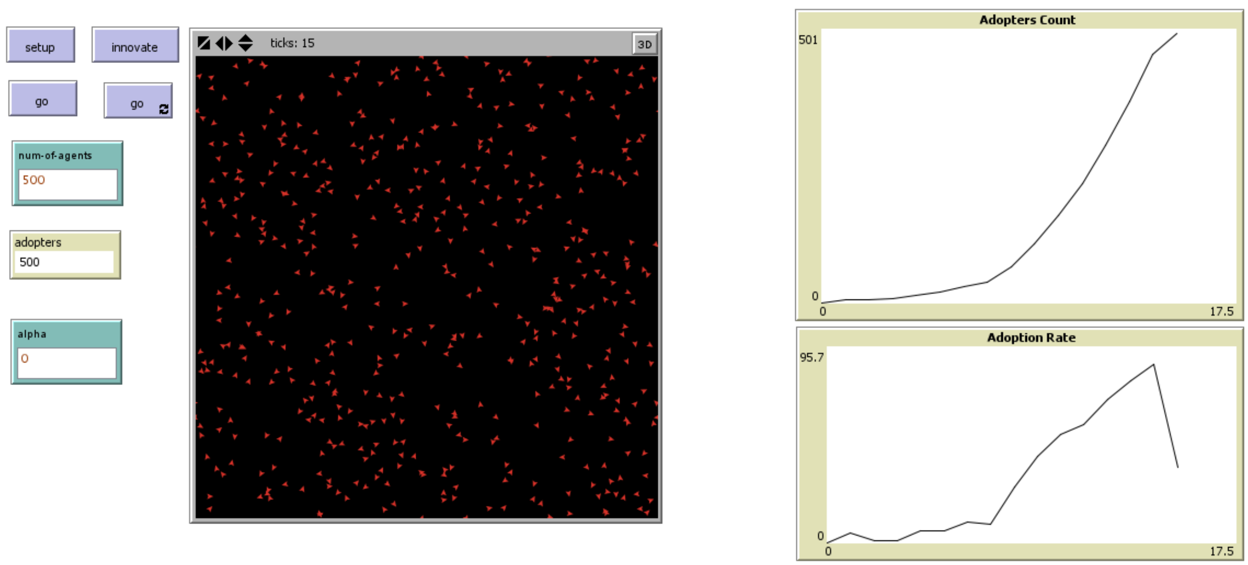


Figure 6. Simulation Result of Model 2

Model 3:

This model uses empirical data to build a map of the U.S. S. In this model, distance determines the probability that agents choose partners. The probability function used in this map is the same as the one used in Model 1.

Result shows that the model does generate an S-shaped curve, though it looks different from the curve in Model 1 (Figure 7).

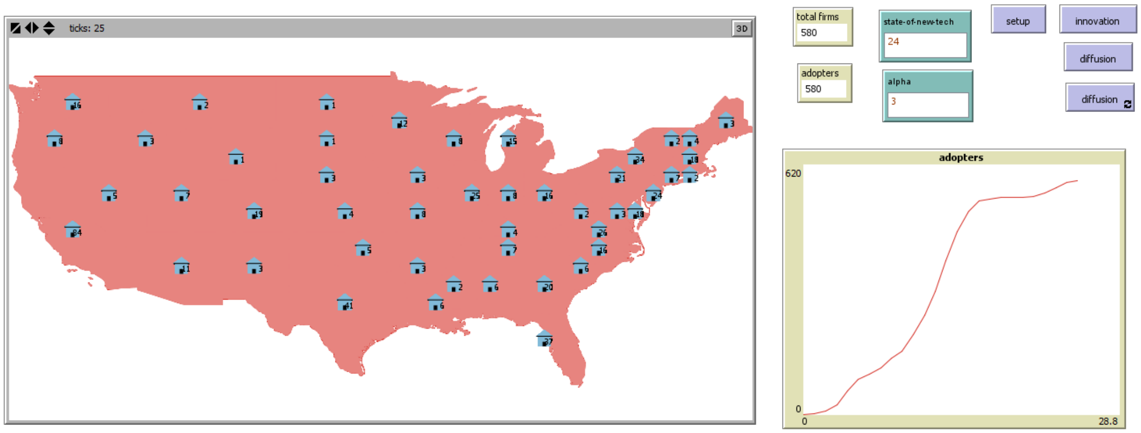
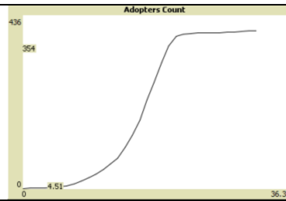
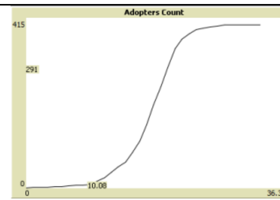
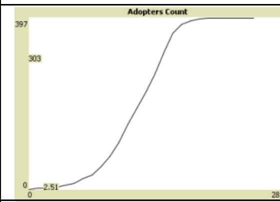
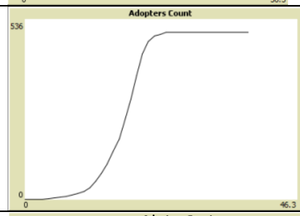
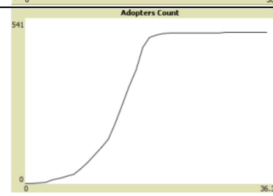
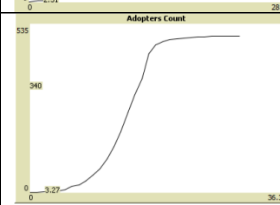
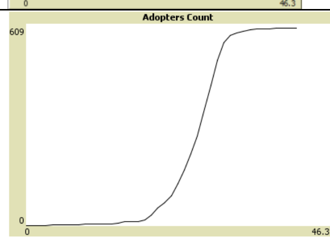
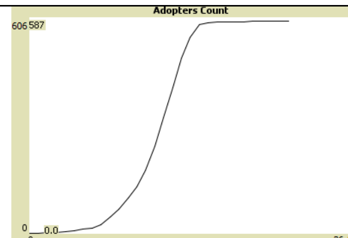
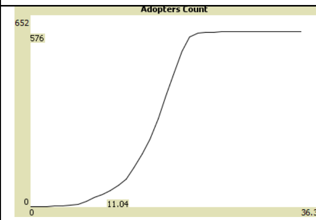
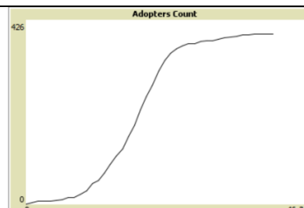
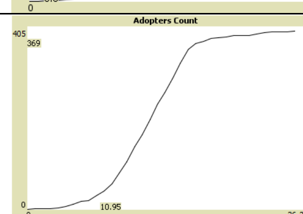
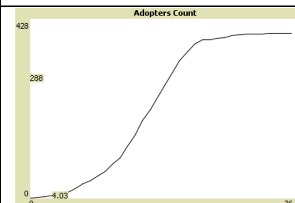
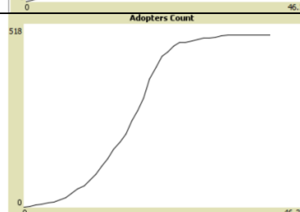
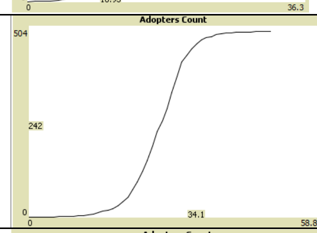
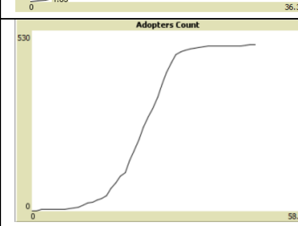
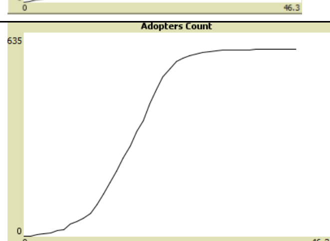
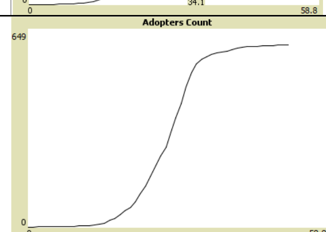
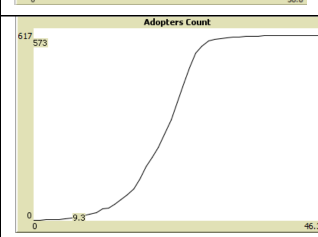
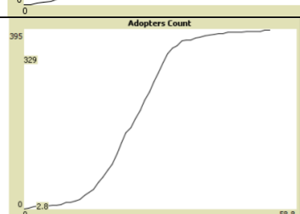
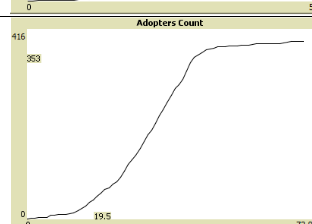
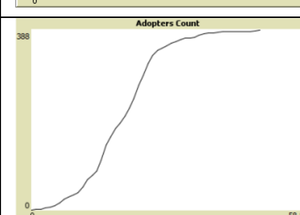


Figure 7. Simulation Result of Model 3

To do robustness check, I repeated the test using different alphas and numbers of agents. When alpha is smaller than 2, the effect of distance is too small, and when alpha is larger than 3, the effect is too large that it takes too much time for the innovation to spread. Therefore, I am using alpha equal to 0, 2, 2.5, and 3 in the tests. When alpha is equal to 0, it is the case when distance has no effect.

In order to get a reliable result, I want to have a bigger sample size, which means more agents. However, to reduce computation, the number should not be too big. After some trials, I find 500 to be a balanced number. I am using 400, 500, and 600 agents in the tests. Also, I am running each test with the same alpha and number of agents for three times to have different spread of agents.

The results (Table 1) show that, when alpha is 2 to 3, or in other words (distance matters), I observe an S-shaped curve. When alpha is 0 (distance does not matter), there is no S-shaped curve observed.

Alpha	Number of agents	1th test	2nd test	3rd test
2	400			
2	500			
2	600			
2.5	400			
2.5	500			
2.5	600			
3	400			

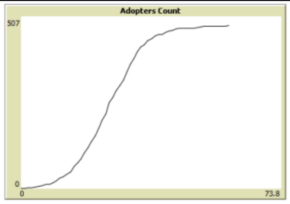
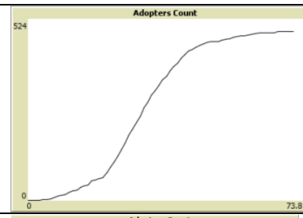
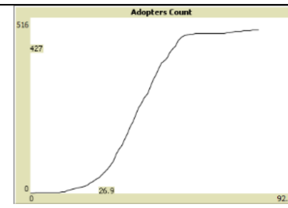
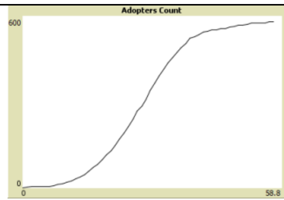
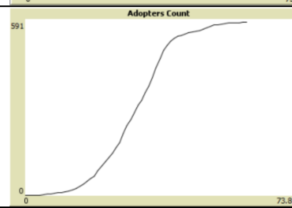
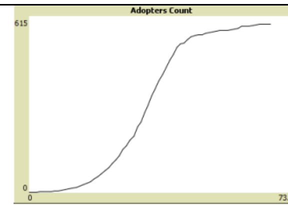
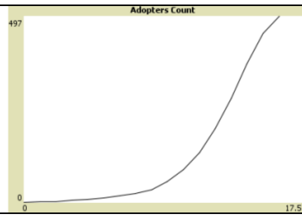
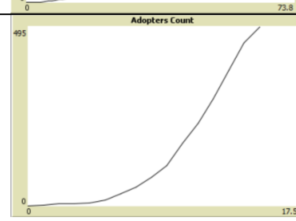
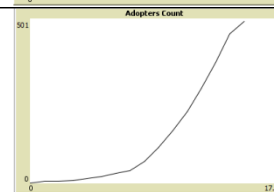
3	500			
3	600			
0	500			

Table 1. Robustness Check

5. Explanations of the Observations

In this part, I will focus on exploring the story behind the emergence of S-shaped curve in Model 1. Model 2 is used to help understand the difference. I will also talk about the implications and limitations of Model 3 in the next section.

The results show that a spatial model does generate the asymmetric S-shaped curve in innovation diffusion as described in existing literature. Furthermore, a model with some settings except considering distance does not generate the asymmetric S-shaped curve. The problem is that the curve can not generate concavity at the tail, or the tail is also not long enough. The result suggests that distance does play an important role in the emergence of an S-shaped curve in innovation diffusion.

In the spatial model, the best result is obtained when alpha is between 2 and 3. This number represents the impact of distance. When the impact is zero as in model 2, there is no S-shaped curve. When the impact is too strong, firms often refuse to communicate outside of their groups and the technology can only diffuse to very limited firms after a lot of periods. When alpha is set between 2 to 3, distance does affect diffusion but is not so strong to prevent distanced communication. The S-shaped curve emerges in this instance.

To take a further step in understanding the spatial diffusion of technology, I am interested in exploring the story behind the simulation. In some sense, my model is similar to the epidemic model, for we both believe that innovation diffusion drives innovation diffusion, and we are both concerned about the social process of innovation diffusion and emphasize on interaction between firms. One of the questions that epidemic model has difficulties answering is how did the initial infection start? In my spatial model, the initial infection is very intuitive. Since the effect of distance is very strong, the new technology often diffuses to individuals in the same cell, or nearby cells if the inventor is isolated, in the first few ticks. This is consistent with the regional network-based industrial system described by

Saxenian (1996) in her book *Regional Advantage*. Regional network-based industrial system is usually formed inside a high-tech cluster, like Silicon Valley. Individual firms in the system, regardless of its size, are encouraged to communicate actively with other firms in the system and adapt to changing technologies. As a result, local firms are usually the first to get access to, both its hardware and software, and adopt new technologies. This type of network-based system has been proven to be beneficial for high-tech clusters' development, and more and more high-tech clusters are developing towards that direction.

Further, I want to look into how the adoption rate change over time. To begin with, I am curious about the story behind the emergence of the concave curve in the first half of the S-shaped curve. As shown in my model and observed in many empirical researches, the adoption rate is slow and the acceleration of the increasing adoption rate is low but also increasing, forming a concave curve. Why is this happening? As observed in both Model 1 and Model 2, the adopter count increase exponentially in this stage. This phenomenon can be simply explained by the fact that the more agents infected, the more infected firms to infect others.

However, this may only be part of the cause of the concave curve in Model 1. If we look at the adopter rate, we can see that in Model 1 the rate jumped up to a much higher level at some point, while in Model 2 the rate increases more smoothly (Figure 8). Recall that previous research has pointed out the importance to break through in the early stage, and after getting certain market share the technology will automatically diffuse increasing rapidly until it reaches next stage. In the spatial model of innovation diffusion, the curve before the lowest point represents the early stage of diffusion, when the regional network-based industrial system is dominating, meaning that the technology mainly diffuses inside clusters or a local region. However, as the technology manages to diffuse to further firms, it has planted a new seed there and created a channel to spread innovation. This reminds me of the theory of Weak Ties introduced by Granovetter (1973) and further explored by Easley and Kleinberg (2010). The theory of weak ties is developed in social network analysis. A weak tie is a weak relationship between two individuals, and one feature that makes a weak tie important is that it usually connects two groups of individuals that are otherwise separate. And by “group”, it means some individuals of strong ties, meaning strong relationship, with each other. The weak tie allows information to float from one group to another group, and this has significant structural effects that ripple through a population as a whole. In my spatial model, the weak relationship can be seen as a connection between two individuals that are far away from each other, and therefore, are in different clusters or regions. As one of the adopters interacts with another firm located outside of its region, it is creating a weak tie between them. This new infected firm will then begin to infect other firms nearby and causing the adoption rate to increase to a higher level. The emergence of more and more weak ties may explain for the more and more rapidly increasing adoption rate and acceleration that we observe in the concave part of the S-shaped curve.

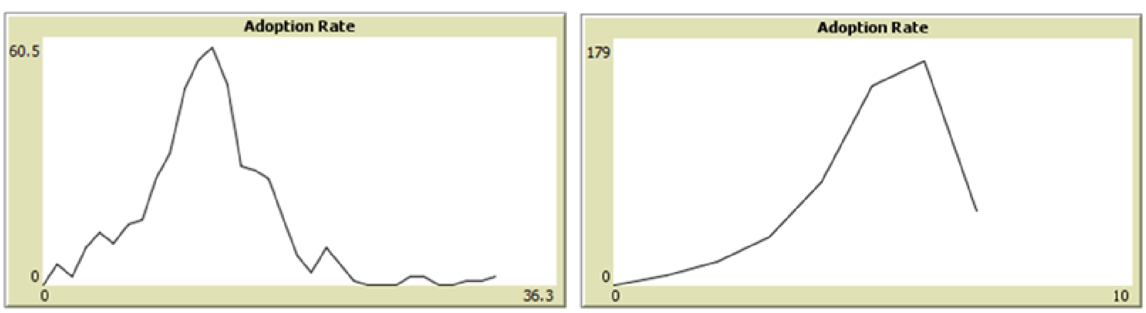


Figure 8. Adoption Rate in Model 1 (left) and Model 2 (right)

Secondly, I am interested in the story behind the emergence of the asymmetric concave curve in the second half of the S-shaped curve. There are two questions, one is why the adoption rate goes down, causing convexity; the other is why it is asymmetric. In my model, convexity often occurs when more than 80% of the population has adopted the technology. Those “left out” are usually firms in small local groups (Figure 9). They are encouraged to interact with individuals in their own group, but they do not reach out much to others outside. They are more resistant to a new technology. Since they do not have a large population in the group, it is harder, though not impossible, for one of their group members to interact with adopters and get infected with the new technology. The existence of these groups causes the adoption rate to slow down when the "easier" firms have already adopted. Note that, not every small group adopts late in the process. Saxenian (1996) also points out that some clusters have regional culture that is more stable and self-reliant. These small groups could enjoy intimacy inside the groups, but do not have an advantage in adopting new technologies rapidly. However, once a member has adopted, it can spread fast inside the community. On the other hand, it is obvious that as the percent adopted reached 80%, there are not many firms left to become new adopters in each period. The lack of population to infect combined with the resistance of small groups cause the convexity to occur. Since it takes a long period to infect the more resistant groups, the S-curve is asymmetric.

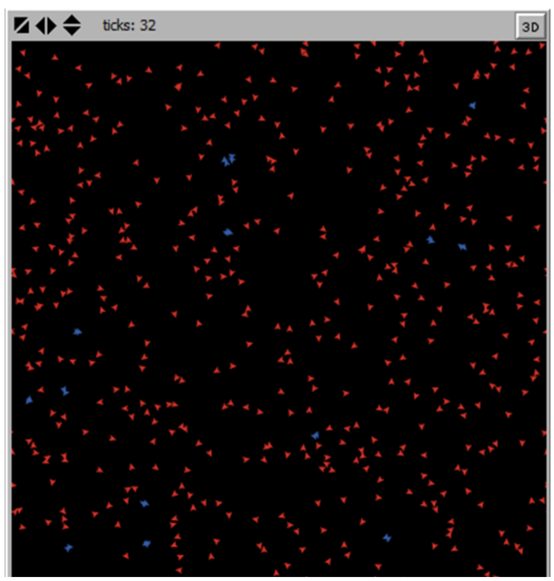


Figure 9. Small groups which are more resistant to new technology

6. Policy Implications

My research shows that distance may play an important role in the diffusion of innovation. There are several implications for policy makers to promote high-tech industry development.

Firstly, develop high-tech parks and encourage communication among different firms. Even though the internet has changed how people exchange information, face-to-face communication is still necessary to transmit tacit knowledge, for example, experience learned in using the new technology. It is also easier to persuade people to adopt a new technology when they learn about it in person. High-tech parks can reduce the cost to communicate with people in the same industry as well as those in different industries. It provides a good opportunity for people to learn and spread innovation.

Secondly, encourage communication and cooperation between firms far from others. Policy makers can arrange industry associations and meetings to bring firms together. This can build a bridge between different groups of firms, and allow them to learn about new ideas that they have little contact with.

Thirdly, support new firms and help them to spread new ideas. The S-shaped curve shows that it is most difficult for a new technology to gain its first supporters. In order to open up the situation, policy makers should take actions to help at the early stage. The government can provide funding, office space, and tax preference to start-ups. Start-ups are usually very innovative and full of new ideas, but they need more resources to succeed. Further, the government can build more incubators near universities. The industry-university-research cooperation mode has been very effective in bringing innovations from universities to the market.

Last but not least, protect intellectual property rights, especially at the middle stage when the technology is widely accepted. At the middle stage, the technology has become popular and the adoption rate is fastest. The cost and risk of adoption has become lower and people are using it. This situation brings the problem of plagiarism. When an innovation is popular, other firms may try to copy it and improve it. This phenomenon can damage the interest of the innovator, and as result, discourage firms from innovating. The government should create a mechanism to protect innovation and punish plagiarism.

7. Limitations and Future Studies

A major limitation of my spatial model is that the map is built with firms randomly distributed. However, in reality, high-tech firms are never randomly distributed. Although my model does generate some random clusters, it is still far from the real map. Since my model does take distance as a major factor, and agglomeration effects are involved, this problem could be significant to the result. Although Model 3 does try to use empirical data in building the model, it is hard to argue that it is indeed a better model than Model 1. The reason is that Model 3 places all the agents in the geometric center of the states, which decreases the distance between firms in the same state and eliminates isolated firms. If I could obtain the real data of high-tech firms' distribution in the U.S. or other countries, I could have developed a more realistic map. However, there are two difficulties in achieving this, one is the difficulty of obtaining such big data, and the other is to simulate with such big data requires a very powerful computer. A solution to the problems is to design a simplified map using real data.

Another limitation of my model, though not as significant as the first one, is that I did not account for different types of firms. I did include heterogeneity of firms in the sense of assigning different adaptation, or willingness to adopt new technology, to different firms. However, it will also be interesting to think about different types of organizations that play different roles in innovation diffusion. To think about this problem, it is important to understand how technology diffuses among different organizations in the real world. Organizations involved in innovation diffusion can be classified in to four groups: research and development institutes, headquarters, producers, and services providers. OECD report (1999) points out that in most cases firms do not innovate in isolation, but in production and manufacturing networks. Most innovation activities involve multiple organizations and start in the complementation and integration of different specialized knowledge.

To give an example of how innovation works among different organizations, I did a study on the case of Stanford University in 1950s. Stanford University took three actions to open up a new situation in Silicon Valley. First, Stanford Research Institute was established to do research in national defense and provide innovations to companies in the west coast. Second, Stanford University opened courses to local companies and encouraged engineers to take courses in classrooms in their companies. This action keeps engineers updated with new technologies, and allows them to maintain relationship with the university. Third, Stanford Industrial Park, which was built as a source of income for the university in the beginning, had promoted cooperation between the university and companies.

In the future, I can develop a more detailed and realistic spatial model of innovation diffusion by using empirical firm data, identifying different organizations, and to simulate the interactions among different organizations. Never the least, the simplified spatial model of technology I presented in this paper provides meaningful implications about geographical proximity in innovation diffusion.

Appendix

This part contains the code for the spatial model of innovation diffusion. It runs in Netlogo.

```
globals [
  partner-variable      ;;this is a temporary variable used to select partner
  pick                  ;;this is a temporary variable used to select partner
  adopters              ;;counts the number of firms adopted the new tech
  adopters0             ;;this is a temporary variable used to calculate adoption rate
  percent-adopted       ;;percentage of firms adopted the new tech
  adoptionRate          ;;speed of adoption
  ]


turtles-own [
  tech                  ;;0 if the agent does not know the new tech, 1 otherwise
  others                ;;all other agents except itself
  partner               ;;partner to interact in this round
  porb-to-interact      ;;probability to interact with another turtle. this variable changes every round
  adaptation            ;;probability to adopt a new tech when the agent has access to it
  ]


to setup
  clear-all
  reset-ticks
  crt num-of-agents [setxy random-xcor random-ycor  set tech 0 set color blue set adaptation random-
float 1]
end
```

```
to innovate
  ask one-of turtles [set tech 1  set color red]
end

to go

   ;; reset adpatation. If more agents have adopted the new tech, there is a higher probability for agents to adopt.
   set adopters count turtles with [tech = 1]
   set percent-adopted adopters / num-of-agents
   ask turtles [
     if adaptation < percent-adopted
         [ set adaptation percent-adopted]]

  ;;ask each agent to find a partner
  ask turtles [
    set porb-to-interact 0 ;;agent does not interact with itself
    set others turtles with [self != myself]
    ask others
      [ set porb-to-interact 0 ;;reset the variable for this round
        let d distance myself
        if d = 0 [set d 0.25]
        set porb-to-interact 1 / d ^ alpha ]

    ;;picking partner. see Lottery Example for the logic behind this method
    set pick random-float (sum [porb-to-interact] of others)
    set partner nobody
    set partner-variable nobody
```

```
ask others
  [ if partner-variable = nobody
      [ ifelse porb-to-interact > pick
        [ set partner-variable self ]
        [ set pick (pick - porb-to-interact) ]
     ] ]
set partner partner-variable
]

ask turtles [if partner = nobody [print "no partner"]]  ;;make sure everyone has a partner to interact



;;ask each agent to interact with its partner. Agent has a probability to learn new tech if its partner has already adopted
ask turtles [

  if tech < [tech] of partner [
    let x random-float 1
    if adaptation > x [set tech 1 set color red]
]]

set adopters0 adopters
set adopters count turtles with [tech = 1]
set adoptionRate adopters - adopters0
if adopters = count turtles [stop]
tick
end
```

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