An agent based simulation and data mining framework for scenario analysis of technology products

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Abstract

The objective of this study is to create a framework to simulate and analyze the effect of multiple business scenarios on the adoption behavior of a group of technology products. In our modeling framework, the adoption behavior of a technology will be influenced by it's value proposition in comparison to the other available technologies. We present the use of an agent based model in which potential adopters of a technology are allowed to be influenced by their local interactions within the social network of bounded agents. Additionally, consumers evaluate the value proposition of the available technologies based on the technologies attributes, including technologies attractiveness. We present a realistic case study that demonstrates the ability of this framework to model changes in market shares for a group of products in response to business scenarios such as new technology introduction, technology discontinuation and price changes. We also employ modern data mining approaches to derive actionable knowledge from the agent based simulation models.

Keywords: technology adoption, product diffusion, agent-based modeling, data mining.

1 Introduction

The revolution of digital technology has been propelling the processor market to support the demand for high performance, low cost computers. In keeping up with Moore's law, the number of transistors on a chip keep doubling about every two years. Processing power, measured in millions of instructions per second (MIPS), has steadily risen because of increased transistor counts. The pursuit of Moore's law has resulted in considerable advances in silicon-based technology. Simultaneous advances in process technology have resulted in higher yields, thus making it possible to produce less expensive, more powerful processors. With each technological breakthrough, chip manufacturers are able to introduce newer, better processors at a faster rate. Consequently, product life cycles have been considerably shortened as companies engage in a constant strife for pushing the technological benchmarks.

In this highly competitive market, multiple products with moderate differences in performance and price often compete for a unit of demand. Therefore, it is important to be cognizant of the fact that most business decision have the potential to affect the demand of any single product can potentially impact the entire group of competing products. Consider product pricing for example. Price is used as a knob to boost sales for certain products. When a higher technology product is made available to the consumers at a lower price, it has the potential to cannibalize the market demand for the products already competing at that lower price point. New product introduction and termination decisions can have similar consequences. Since product life cycles are short, changes in demand structure for products can have serious implications on scheduling of supply, manufacturing and distribution capacity. The occurrence of multiple business scenarios along with simultaneous price change decisions makes it very difficult to predict the their effect using simple intuition. As a result, models are required to capture the interaction effects of scenarios, thus aiding in quantifying their impact on the market share of certain price groups.

In this study, our aim is to create a framework that allows us to simulate and analyze the effect of multiple business scenarios on the adoption behavior of a group of technology products. We view diffusion as an emergent phenomenon that results from the interaction of consumers. To this note, we present the use of an agent based model in which potential adopters of a product are allowed to be influenced by their local interactions within the social network. Additionally, consumers evaluate the value proposition of the available products based on the products attributes, including price and switching costs. We encompass utility theory and discrete choice models in the decision making process for the consumers. Finally, we present a realistic case study that demonstrates the ability of this framework to model changes in market shares for a group of products in response to business scenarios such as new product introduction, product discontinuation and price changes. The models and other tools developed here are envisioned to be a part of a recommender system that provides insights into the effects various pricing and other business scenarios play on shaping market shares of different price groups at the macro level as well as those of individual CPUs. This necessiates a strategy to analyze and interpret the possible nonlinear relationships amongst the various parameters of the simulation model. We employ modern data mining approaches to derive actionable knowledge from the agent based simulation models.

The rest of the paper is organized as follows - Section 2 presents an overview of some existing modeling approaches. Sections 3, 4 and 5 provide a detailed description of our model based on the Overview, Design concepts, and Details (ODD) protocol of Grimm *et al.* [10]. Section 6 describes the methodology that was used to analyze the results and and Section 7 presents a case study based on the simulation model and the data mining tools.

2 Literature Review

Different analytical and empirical models have been proposed to address specific business scenarios that impact product demand. Empirical models such as the Cross Price Elasticity models ([5],[9]) have traditionally focused on modeling price demand relationships. These regression based approaches are suitable for products with longer life cycles. However, the technology substitution process poses unique challenges for modeling. Data sets are sparse due to short life cycles; a problem that is further aggravated as the substitution of products at different points in time results in considerable missing data.

The Bass diffusion model and its variants have been used for market analysis and demand forecasting of new products [2]. The model assumes that potential adopters of an innovation are influenced by two means of communication - mass media and word-of-mouth. Innovators tend to adopt a new technology as a consequence of external influences, whereas imitators are influenced by those who have already adopted. This model describes the process of how a new product gets adopted as an interaction between users and potential users. Fisher and Pry extended this single product model to a two product framework that represents the process by which a new technology product replaces or substitutes an older one in the market [6]. A drawback of these models lies in the underlying assumption of a homogeneous population and perfect mixing amongst individuals of the population [20]. However, it has been shown that many real world social networks represents a set of individuals with some pattern of interaction or ties between them.

Diffusion models have also been integrated with other learning algorithms to capture and analyze scenario information. For example, Yelland *et al.* used a combination of the Fisher and Pry models and Dynamic Linear Models [22] to capture the diffusion process as well as time series and seasonal components of product demand [24]. Meixell and Wu and Wu *et al.* proposed an approach to analyze demand scenarios in technology-driven markets where product demands are volatile, but follow a few identifiable life-cycle patterns [16, 23]. They demonstrated that products could be clustered by life-cycle patterns, and subsequently, within each cluster, identified leading indicator products that provided advanced indication of changes in demand trends. Using the Bass growth model and a Bayesian update structure, their proposed method provided a framework for scenario analysis by focusing on parametric changes of the demand growth model over time.

Several studies can be found on agent based modeling for diffusion of technology. Garcia provided a simple model to demonstrate agent based modeling in a competitive environment. This paper can be used as an introduction of using ABM as a learning tool in technology diffusion [8]. Ma and Nakamori built multi agent models to simulate complexities of macro-level from the interactions of micro-level in technological innovation. This paper describes technological innovation as an evolutionary process with consumers' incomplete information and diversity of their demand [14].

Recently, agent based models have been used to study the potential behavior of new electricity technologies. Hamilton *et al.* consider performance of the new technology versus the old technology and study effect of a specific spatial externality (fashion effect). They analyze the dynamics of technology diffusion among bounded agents with uncertainty by using agent based modeling [13]. An agent based model for a market game is presented by Zhang *et al.* to evaluate the effects of government strategies on promoting new electricity technologies in complex systems involving human behavior [25]. Agent based modeling enables us to evaluate different scenarios for policy making. Athanasiadis *et al.* used agent based modeling to control consumer demands by supporting interaction between consumers in a diffusion mechanism [1]. In another approach, advantages and disadvantages of optimization models and agent based modeling for technological change in different energy systems is compared[15].

The impact of the structure of a social network on the spread of innovations has been an actively researched issue. Montanari and Saberi considered competing alternatives when an agent adopts to a new behavior based on its neighbors. Also, in their model the pay off for agents increases with the number of neighbors who adopted the same choice [17]. Guardiola *et al.* consider upgrading cost in modeling diffusion of innovations in a social network [11]. Speed and other properties of diffusion are affected by network structure. Bohlmann *et al.* analyze network topologies and communication links between innovator and follower market segments in the diffusion process [3]. Rahmandad and Sterman compared agent-based and differential equation models and analyzed the effect of individual heterogeneity and different network topologies in the dynamics of diffusion [18]

3 State Variables and Scales

3.1 Agents

In order to model and investigate the adoption characteristics of a system involving multiple competing technology products, we consider a social network populated with technology adopters. Each agent in our model represents a buyer that chooses to adopts one technology over another. Agents are autonomous in their decision making but can be influenced to adopt a particular technology based on two primary elements -

1. Perception of product value - Each product has certain attributes that distinguish it from the others (Table 1). Examples of attributes for processors include to Price, Speed, Cache, etc. In addition to these attributes, newer processors may not be compatible with existing motherboard technology, thereby requiring a change in motherboard as well. As a consequence, there is a switching cost associated with certain processors.

2. Social influence - Since agents belong to a social network, they can interact with their neighbors and can therefore be persuaded to buy a particular product by their neighbors. Agents are influenced to buy a product based on the proportion of their connections who have adopted the same product as well as the average perception score for that product in their neighborhood.

The preference structure of each agent is assumed to be different. For instance, each agent believes that higher price is less desirable. However, their desirability may reduce at different rates. Also, agents can associate different weights to different attributes. Some may consider speed as being very important while others may base their decision only on the price of the products.

Agents are characterized by atomic variables that presented in Table 2.

Table 1: State Variables for technologies

Name	Value
Price	Between 80$ to 110$
Speed	Between 2.33 Ghz to 3.33 Ghz
Cache	Between 1 o 6
Switching cost	Between 0 $ to 100 $

3.2 Timescale

Agents update their perception of the available technologies on a continuous basis. Consequently, their influence towards a particular product is also updated continuously. However, decisions to change to a particular technology are driven by a Poisson process (Poisson (change-event-limit)) and are asynchronous.

3.3 Landscape

The landscape represents a discrete community populated with interacting, autonomous agents. The model is constructed on a scale-free network. The population parameter controls the number agents on the network. At any given time, each agent adopts one of the technologies A, B, or C. The edges show relationship between consumers where node degree distribution follows a power law. The community is randomly seeded according to initial percentage of technology B and C (Figure 1).

4 Process overview and scheduling

A brief outline of the process is given below. Specific sub-processes are explained in more detail later:

1. At initialization, majority of the agents own or have adopted Technology A. Technology A is representative of an older product. A proportion of the population also owns products B and C. This proportion is controlled using the B-initial and C-initial parameters. Technologies B and C represent newer products that are currently being launched. Therefore, the B-initial and C-initial parameters control the number of early adopters in the market for these products.

2. At each time increment agents update their level of satisfaction in utility function based on technology attributes

3. A change event is generated for agents according to internal time clock with Poisson (change-event-limit),

4. Agents compare their current utility with their utility threshold

Table 2: State Variables for Agents

Name	Description	Value
utility-threshold	A limit for utility to switch to another technology	A random number less than a user defined variable (utility-threshold-limit)
coeff-price	Makes agents risk-averse (coeff $>$ 1) or risk-seeking (coeff $<$ 1)for price desirability	A random number less than a user defined variable (coeff-price-UL)
coeff-speed	Makes agents risk-averse (coeff $<$ 1) or risk-seeking (coeff $>$ 1)for speed desirability	A random number less than a user defined variable (coeff-speed-UL)
coeff-cache	Makes agents risk-averse (coeff $<$ 1) or risk-seeking (coeff $>$ 1)for cache desirability	A random number less than a user defined variable (coeff-cache-UL)
coeff-switch	Makes agents risk-averse (coeff $>$ 1) or risk-seeking (coeff $<$ 1) for switch desirability	A random number less than a user defined variable (coeff- switch - UL)
budget	The amount of money that agents own at each time	A random number less than a user defined variable (max-initial-budget). A random value (less than max-budget-increment) is added to it at each time.
change-event	The time in which agents check their utility to make decision	A random Poisson number less than a user defined variable (change-event-limit)
w-price, w-speed, w-cache, w-switch-cost	Weight of technology variables in the additive utility function	A normal random number with mean 1 and standard-deviation 0.2
w-attractiveness	Weight of attractiveness in the additive utility function	A normal random number with mean 1 and standard-deviation 0.2

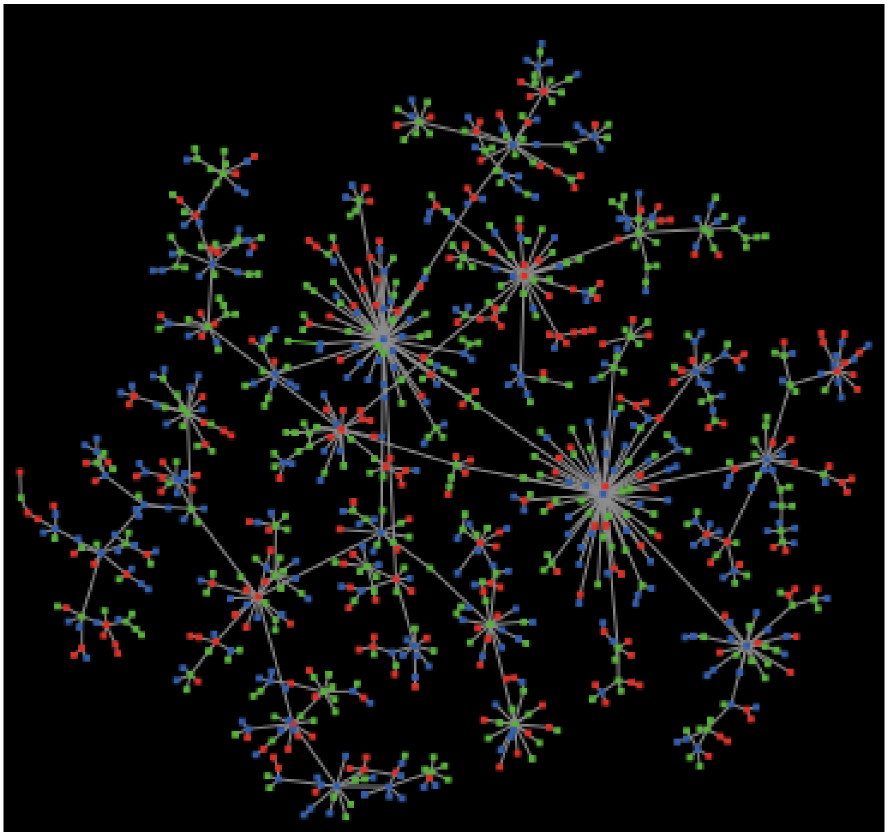

Figure 1: Example of a scale-free network. Each node represents a consumer that owns Technology A (red), Technology B (green) or Technology C (blue)

5. If ratio of utility for technology K to current technology is greater than their utility-threshold they may adopt the new technology

6. Agents check their available budget before switching

7. At each time interval, budget of each agent increase by a random amount if it does not buy a new technology. Once the agent buys the new technology, its budget is set to zero.

In summary, agents update their utility and budget on a continuous time scale. However, decisions to switch to an alternative technology are made only when a signal is generated for that specific agent according to its Poisson process. Some probabilities are considered for switching to cover levels of irrationality.

5 Design Concepts

1. Emergence: Population dynamics emerge from the behavior of agents.

2. Sensing and Interaction: Each agent has information regarding the attributes of the products in the market. As a consequence, they have ready information regarding the price of each product at any point in time. Additionally, agents are able to view their neighbors and check what proportion of their neighbors have adopted which product. They can also query their neighbors and check their utility values for the competing technologies. These two sources on information factor into the amount of social influence in the agents decision making process. Agents also know their utility-threshold, current type, available budget, and required coefficients to calculate desirability.

3. Fitness: Agents measure their desirability towards each product and change their behavior based on the utility functions after change event time.

Table 3 shows inputs and initial parameters in the simulation model.

Table 3: Inputs and Initial parameters

Variables	Default Value (Range)
population	0-5000
B-initial	0-1
C-initial	0
beta	0-15
utility-threshold-limit	0-10
coeff-price-UL	0-5
coeff-cache-UL	0-5
coeff-speed-UL	0-5
coeff-switch-UL	0-5
max-budget-increment	1-5
max-initial-budget	0-100
change-event-limit	0-100
price (A,B,C)	80-110
speed (A,B,C)	2.33-3.33
cache (A,B,C)	{2,4,6}
switch-cost-C	1-100

5.1 Sub-models

Here, we discuss three sub-processes in more detail. Specifically, we will focus on the attractiveness updating, satisfaction updating process, and the technology switching process.Together, these processes make up the decision making engine of the agents.

Computing social influence: The decision to buy a particular technology product can be influenced by the agents neighbors. Here neighbors are defined as directly connected agents. We assume that agents are more likely to buy a particular technology if a large proportion of their neighbors have already adopted it. We allow all agents to update their valuation of all products even though they may have adopted a particular product. This is important since pricing decisions and other external stimuli can make certain products more attractive at a later point in time. Hence, even though an agent may have adopted one product, he may infact recommend some other product to his neighbor. Therefore, the social influence (local-attractiveness) as defined for each agent towards technology K is computed as the average utility for technology K in the neighborhors times the proportion of neighbors that have already adopted technology K.

Utility update: Along with social influence, the agents base their decisions on product attributes. Each agent has this notion of desirability of the product and its attributes. For example, agents will generally consent that higher values of speed make the product more desirable. At the same time price is an attribute that has a negative impact on desirability. When the agents target a maximum value of attributes we used eq. 1 (to calculate desirability function of speed and cache). We apply eq. 2 when the target is the minimum value (to calculate desirability function of price and switching cost).

$$D_{k_n} = (\frac{y_n - L_n}{U_n - L_n})^{coeff_n}, \tag{1}$$

$$D_{k_n} = (\frac{U_n - y_n}{U_n - L_n})^{coeff_n}, \tag{2}$$

where, n is technology attributes (price, speed, cache, switch-cost) and K is technology type (A, B, C).

Each agent has a different desirability coefficient for each product attribute. This induces heterogenity in the shape of the desirability function. Figure 2 shows the range of those functions for risk-averse and risk-seeking agents in both maximum and minimum targets.

For each agent, the utility of a technology K is computed as a weighted average of the desirabilities of the product attributes and the local-attractiveness as shown in Equation 3. In addition to having different desirability functions, agents can assign different importance (weight, W_n) to different attributes that make up the utility function. In this form, we assume an additive utility function.

$$Utility_K = \frac{\sum_n W_n D_{k_n}}{\sum_n W_n}, \tag{3}$$

where, n is technology attributes from Table 1 including the attractiveness and W's are weight of technology attributes from Table 2.

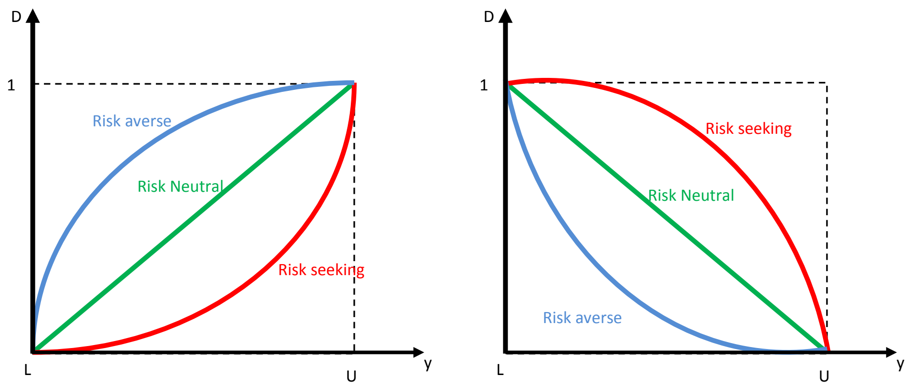

Figure 2: Desirability functions showing (left) risk-averse agents ($coeff < 1$) and risk-seeking agents ($coeff > 1$) for targeting maximum, (right) risk-averse agents ($coeff > 1$) and risk-seeking agents ($coeff < 1$) for targeting minimum

Technology switching: Each agent is assigned a different value for their utility threshold. The utility threshold is a measure of how much better the newer technology is compared to their existing technology for the agents to consider switching. After a change event is trigerred, the agents check their ratio of utility for technology K to their currently adopted technology. If this ratio exceeds the utility threshold, and the agent has enough money to buy the new product, then they consider buying it. A set of different decision environments arise at this point.

- If an agent only has money to buy one of the new technologies (say B) and the ratio of its utility for technology B to current technology is greater than the threshold, it will adopt this technology with probability K.
- If an agent has money to buy both technologies and only ratio of its utility for Technology K to current technology is greater that the threshold, it will adopt to this technology with probability K and adopt to the other technology with probability K' (this shows its irrationality).

  If an agent has money to buy both technologies and ratio of its utility for both technologies to current technology is greater that the threshold, it will adopt to one of those technology with some probability. This probability, eq. 4, is larger for technology with higher utility,

$$Prob_k = \frac{e^{\beta Utility_k}}{e^{\beta Utility_k} + e^{\beta Utility_{k'}}}, \tag{4}$$

  where, beta represents how sensitive the agents are to differences utilities. The higher beta shows the more sensitive agents to the dynamics of technology attributes.

6 Analysis Methodology

In order to characterize the adoption behavior of new technologies under different competitive environments, a method is required to summarize and quantify the impact of each predictor. Feature selection techniques are based on the idea that the information content in high dimensional data sets is actually contained in a small subset of relevant covariates (predictors). Modern data mining learners such as Support Vector Machines [12] and tree based ensemble methods ([21], [4]) have proven to be very successful in filtering out irrelevant covariates from the data set while preserving its relevant features.

In addition to being effective at feature selection, support vector machines and tree based methods are very competitive at the prediction stage. These methods have been proven to be useful in capturing nonlinear relationships between the covariates and the response of interest. We will demonstrate the use of Random Forests (RF) [4] for feature selection and predictive modeling.

The next step after developing empirical models is to attempt to understand the nature of the dependence of your response on the joint values of the relevant covariates [19]. Here, we try to identify the range or level(s) in the important predictors that drive the most significant changes in the response. For example, we may be interested in identifying the specific region in the covariate space that is associated with higher adoption for a particular technology. Visualization of the predicted function $f(X)$ over the entire covariate space is a powerful tool in interpretation the model as it provides a comprehensive summary of the the dependency of the response on the joint values of the input variables [19]. However, such visualization is only possible for up to four dimensional views. Many machines learning algorithms lack this interpretability for more than three variables.

Friedman [7] developed a graphical summary referred to as partial dependence plots to add interpretability to any "black box" learning methods. Partial dependence functions represent the effect of the variable subset on the predicted response ($f(X)$) after accounting for the average effects of the other variables. Plotting the partial dependence of $f(X)$ on its most relevant covariates can reveal how the response behaves in different regions of the covariates. We will use such plots to interpret the results from the Random Forest model.

7 Scenario Analysis

A semiconductor chip manufacturer currently has two technologies in the 80 \$ - 110 \$ price range. Technology A, which is the older of the two technologies currently dominates the market share in this price group. At the beginning of the simulation, a small percentage of early adopters own Technology B. The company decides to terminate the production of technology A and launches a new technology - Technology C. Technologies A and B are compatible with the same socket type i.e. they can be interchanged on the same motherboard. However, technology C requires a different socket type. Hence, a switching cost, equivalent to that of buying a new motherboard is associated with buying Technology C. Customers who currently own Technology A, are now faced with three options. Stay with Technology

Table 4: Simulated market conditions

Factor	Levels
Speed-A	2.66
Speed-B	2.93%
Speed-C	3.13%
Cache-A	2
Cache-B	2
Cache-C	4

Table 5: Fixed parameters and their initial values

Factor	Levels
Population	1500
B-initial	20 %
C-initial	5 %
beta	15
max-initial-budget	60 $
max-budget-increment	2 $
change-event-limit	50

A, switch to Technology B or switch to Technology C.

7.1 Effect of Price

To simulate a real life market condition, we assume that the technological attributes of the three products are fixed. Specifically, we are interested in the effect of relative pricing of the three products on the adoption of technology C. To conduct this analysis, we fixed the speed and cache of the products as per the settings summarized in Table 4. Other simulation parameters that were held constant during the runs are summarized in Table 5. To simulate the effect of price, we varied the price for each product starting from 80 to 110 in increments of 5 $. A total of 5 replicates were run at each combination of the prices. After each run, we noted the maximum share of the market that Technology C captured. This is the response variable of interest. A Random Forest model was built to analyze the effects of pricing on this response.

The Random Forest model yeilds high prediction accuracy. The model reduced the prediction error from a base error of 0.219 to 0.029 (Out Of Bag). To interpret the results, we discuss the dependency plots of each pricing variable. Figure 3 shows the dependency of the adoption for Technology C on the prices for two technologies, after accounting for the price for the third. The figure on the extreme right is the dependency plot based on the price for Technology A and B after accounting for the effect of price of Technology C. It can be seen from the response surface and contour plot that a significant of non-linear interaction exists in the model. Also, based on this figure, we notice that the adoption of Technology C is significantly more sensitive to the price of product B than to that of product A. We can also notice regions in the contour plot that are conducive to the uptake of Technology C. As the price advantage for C increases, its adoption success increases.

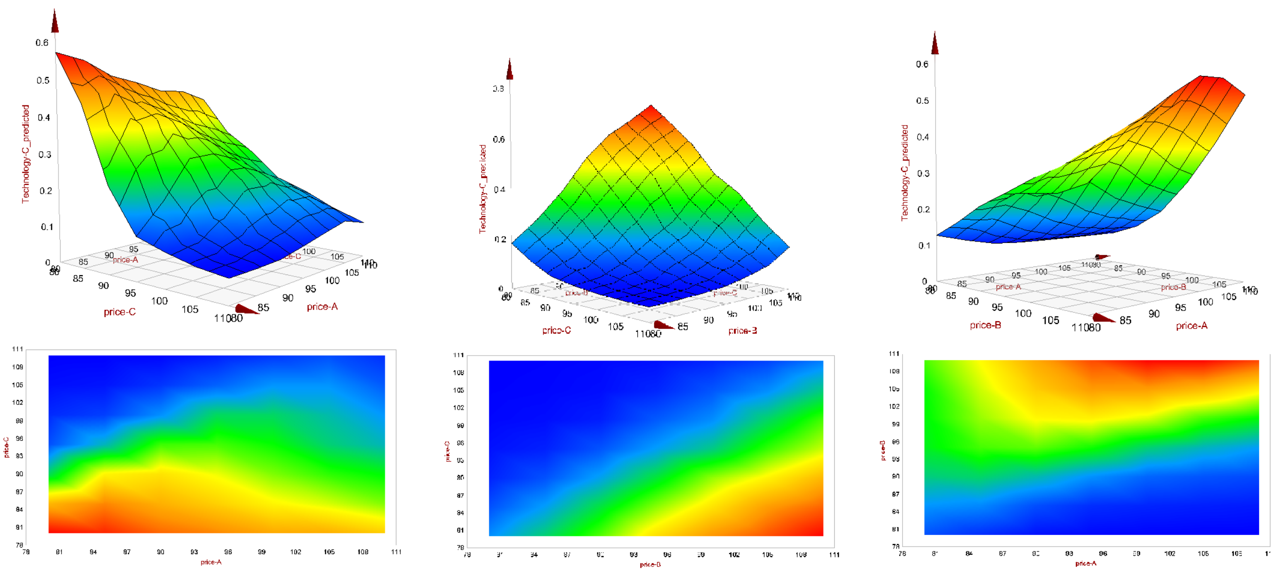

Figure 3: Dependency plot showing the relative price effects on the adoption of Technology C. (Left) Price-C vs Price A, (Middle) Price-C vs Price-A, (Right) Price-B vs Price A.

7.2 Effect of introducing a new product on existing products

Here, we try to study the effects of a new product introduction on the adoption behavior of a technology. We simulate situations in which technology C, having a variety of attribute levels is introduced into a market where Technology B is already competing. We try and study the scenarios under which Technology B still competes successfully and those which result in a failed adoption. Therefore, we will try and analyze the impact of a new product introduction on the market share captured by Technology B. The following experiment was carried out to analyze this scenario. We held the attributes of Technology A and B constant at the settings shown in Tables 5 and 6. Under these market conditions, we launch Technology C. The attributes for Technology C are varied between runs to simulate the introduction of products with different value proposition. The values over which the attributes for Technology C were varied is given in Table 8. Again, five replicates were conducted at each setting.

The Random Forest model for Technology B reduced the error from 0.05 to 0.03. The effect of price, speed and cache of Technology C on the adoption of Technology B can be visualized using partial dependency plots. Figure 4 shows that Technology B captures a

Table 6: Simulated market conditions prior to New Product Introduction

Factor	Levels
Price-A	90 $
Price-B	95 $
Speed-A	2.33 Ghz
Speed-B	2.66 Ghz
Cache-A	2 M
Cache-B	2 M

Table 7: Introductory attributes for Technology C

Factor	Levels
Price-C	{80 85 90 95 100 105 110} $
Speed-C	{2.33 2.5 2.7 2.9 3.1 3.33} Ghz
Cache-C	{2,4,6} M

lower share of the market when Technology C is introduced at the highest speed and lowest price settings. Similarly, higher cache and low price settings result in lower market share for Technology B. However, in general, we can identify a large portion in the contour plots that allw successful adoption of Technology B. Figure 5 shows the adoption curves for the three technologies when Technology C is introduced at the best settings for Speed and Cache with varying Prices. It canbe seen the as the introductory price for Technology C is reduced, the market share for Technology B reduces.

8 Conclusion

In this paper we presented a method that allows us to characterize the adoption behavior of new technologies under different competitive environments, and summarize and quantify the impact of each predictor. We studied diffusion as an emergent phenomenon that results from the interaction of consumers. This research encompassed utility theory and discrete choice models in the decision making process for the irrational consumers. We employed feature selection techniques based on the idea that the information content in high dimen-

Table 8: Market conditions for analyzing the effect of social influence

Factor	Levels
Price-C	{80 85 90 95 100 105 110} $
Speed-C	{2.33 2.5 2.7 2.9 3.1 3.33} Ghz
Cache-C	{2,4,6} M

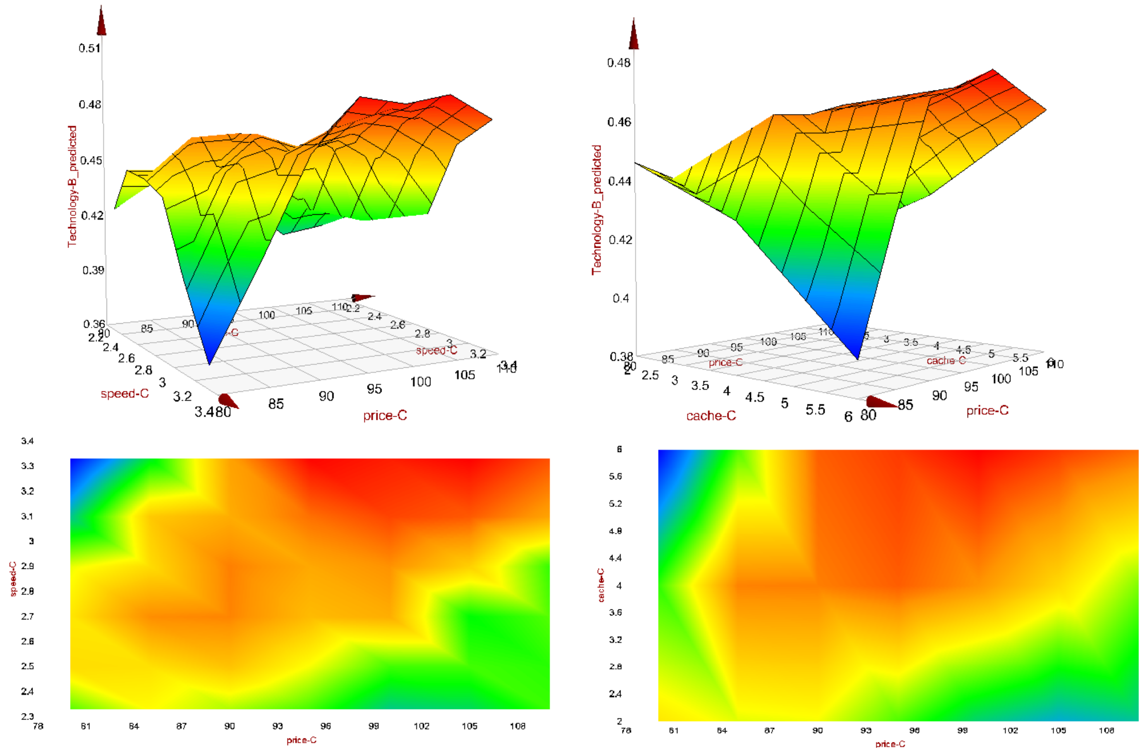

Figure 4: Dependency plot showing the effect of new product introduction on the adoption of Technology B. (Left) Speed-C vs Price-C, (Right) Price-C vs Cache-C.

sional data sets is actually contained in a small subset of relevant covariates (predictors). This study identified the range or level in the important predictors that drive the most significant changes in the response. The models and other tools developed here are envisioned to be a part of a recommender system that provides insights into the effects various pricing and other business scenarios play on shaping market shares. We developed a strategy to analyze and interpret the possible nonlinear relationships among the various parameters of the simulation model. Future research can consider larger number of technologies in the system. Also, simultaneously introducing more than one technology may leads to new results.

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The original model is developed in *NetLogo 4.1.1*. The implementation and source code can be found in the model archive of *www.openabm.org*.

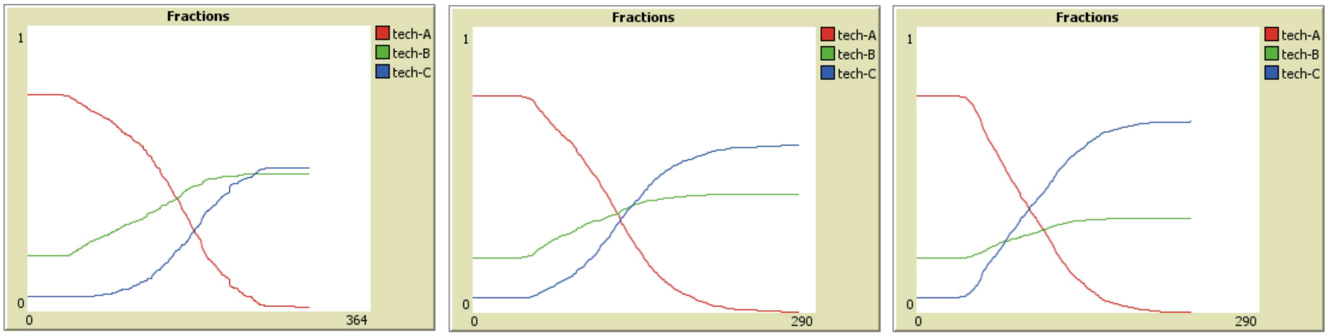

Figure 5: Adoption curves under different price settings at Speed = 3.33 Ghz and Cache = 6 M. (Left) Price-C = 110 $, (Middle) Price-C = 95 $, (Right) Price-C = 80 $

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