Applying Agent-Based Modeling to Business Simulations

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ABSTRACT

Although a number of agent-based models of consumer behavior have been proposed in recent years they are seldom adopted in most business games. The advantages of this approach are yet to be fully grasped by the business simulation community, who continues to favor equation-based models over the agent-based alternative. We review the major contributions to the field of agent-based models of consumer behavior. For illustration purposes we present a simple agent-based model of consumer behavior, which allows simulating context effects.

INTRODUCTION

It was with excitement that Ocean Quigley, Creative Director of Maxis, told Polygon that "Ten years ago, our ideas were just too ambitious, but after Spore shipped, we realized that we could actually do them — computers had finally gotten powerful enough". This was in 2012, after the announcement of SimCity simulation engine, GlassBox, a platform based entirely on agent-based modeling. With this simulation architecture, all moving objects in SimCity, from people to vehicles, were agents running on individual artificial intelligence. The Glassbox breakthrough was received with an apotheosis reaction by fans and gaming magazines. The increased realism provided by the platform generated high enthusiasm on the game current and future exploration and potential.

If the transition from equation-based models to agent-based models was swift in the case of SimCity, the same is not true for business simulations. Business simulations are serious games in which participants play the role of firm owners competing to sell their products against other firms (Summers 2004). These types of training simulations were created to assist managers or aspiring mangers in the development of their business and management skills. In contrast with other simulation games, such as SimCity, the primary purpose of these games is the promotion of learning. As such, the success of a business simulation is severely dependent on the degree of sophistication and verisimilitude of its simulation of the industry environment. Accordingly, the central element of these simulations is the model of the marketplace, that is, how the consumer demand is allocated to each competing firm.

Throughout the years, several techniques have been applied to model demand in business simulations. The traditional approach is the equation-based approach (Gold and Pray 2001) in which the macro behavior of the marketplace is simulated by a set of related equations. Alternative approaches have been proposed, such as the interpolation approach of Goosen and Kusel (1993) or the statistical approach of Carvalho (1995). Neither of these approaches has reached the same level of popularity and acceptance as the equation-based approach.

A novel technique, whose application has been much advocated, is agent-based modeling. Despite a number of scholars arguing about the advantages of agent-based modeling over equation-based modeling, very few agent-based models have been proposed in the field of business simulations. The few agent-based models proposed, such as the model of Umeda et al. (2009), lack the degree of sophistication of the more mainstream agent-based models of consumer behavior such as Schramm et al. (2010), and fail to explain the wide range of phenomena of the most recent equation-based models of demand such as the model of Cannon et al. (2012).

In this paper, we argue that agent-based modeling has unique characteristics, which can promote more (1) sophisticated, (2) realistic and (3) understandable business simulations. Concretely, we argue that more attention should be given to the explicit modeling of consumer behavior with agent-based modeling.

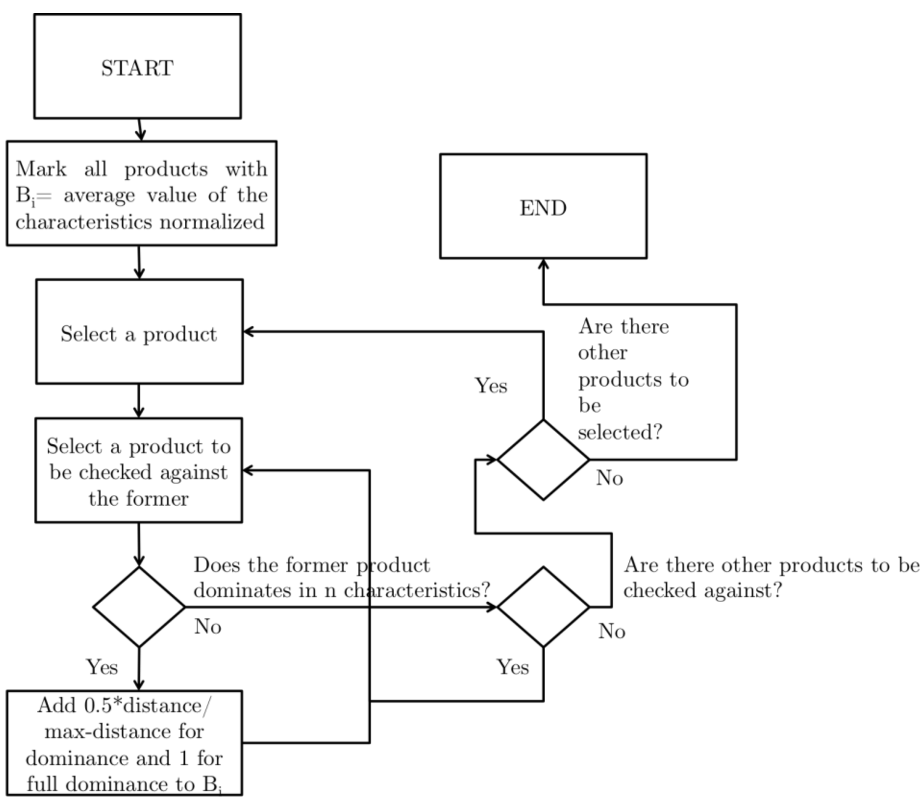
THE AGENT-BASED APPROACH AND BUSINESS SIMULATIONS

Equations are the oldest form of business simulations and the degree of sophistication of the latest equation-based demand models for business simulations is remarkable. Nevertheless, such types of models usually make use of mean values of simulation parameters and neglect the dynamics of the micro-level interactions. For instance, to calculate market demand, equation-based simulations usually resort to the mean values of the firms' decisions for marketing and research & development expenditures as well as price. Moreover, demand equations lack the ability to mimic in detail the complex interactions which may occur between consumers such as processes of product qualification/disqualification and word-of-mouth.

Agent-based modeling, in contrast with the equation-based approach, takes a bottom-up approach to the simulation of systems. Instead of describing the relationships between the modeled entities through the use of equations, agent-based modeling prescribes the individual behavior of the micro-level entities and their interaction rules. The emergent behavior is not codified, but instead emerges from the complex, non-linear interaction of the micro-level entities of the model, the agents.

The application of agent-based modeling to business

FIGURE 1
FLOWCHART FOR DEFINING PREFERENCES BI OF PRODUCTS WITH N CHARACTERISTICS.



simulations may be of great value for three particular reasons: the potential to increase complexity and realism in an unprecedented way and to provide highly detailed information about the simulation.

In recent years, the link between complexity and learning has been disputed (Hall and Cox 1994), and several authors have argued in favor of more simple simulations, which can promote better learning outcomes (Cannon 1995). This shift towards simpler simulations can be explained by the widespread acceptance of the complexity paradox — the pre-established notion that the participants of business simulations lose their ability to understand cause-effect relationships in increasingly complex simulations. We argue that this paradox only holds for business simulations with a black-box structure and hence, that transparent simulations preserve the link between complexity and the learning outcome of participants.

Traditional business simulations have a black-box structure (Machuca 2000), that is, the internal model that calculates the final outcome of the simulation, is kept hidden from the participants. From this follows that participants are often unable to base their decisions on a knowledgeable insight of the system's structure, relying instead on their intuition, operating by trial and error. As expected, as complexity increases so does the participant's inability to predict the outcome of their actions and effectively learn how to improve performance.

In contrast with traditional techniques of business simulations, agent-based models can provide new ways to present and understand data (Parunak et al. 1998). Rich agent-based data concerning the intentions, beliefs, desires of consumers as well as their complex interactions can profoundly reshape business simulations. This approach can allow more transparent simulations, which can become more complex, reaching exceptional levels of realism and sophistication, without sacrificing the successful learning experience of participants.

AN AGENT-BASED MODEL TO SIMULATE CONTEXT EFFECTS

We propose a simple agent-based model based on the neoclassical theory of utility maximization. According to this theory, all consumers decide their next purchases according to a utility function. Consumers decide which bundle of products they wish to purchase by maximizing a utility function, which embodies their internal preferences. To reflect the inter-dependence between the quantities purchased of each product the following function can be used as the utility function of an individual agent:

$$U(x_1, \cdots, x_n) = \sum_{j=1}^{x_1} b_1(j) + \cdots + \sum_{j=1}^{x_n} b_n(j) \qquad (1)$$

$$b_i(j) \in \mathbb{R}^+, b_i(j+1) \leq b_i(j) \qquad (2)$$

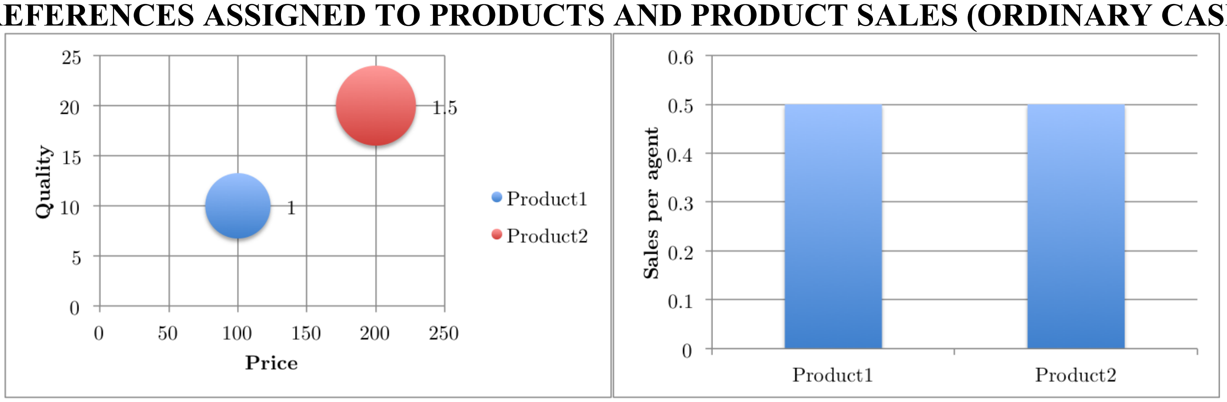
$$p_1 x_1 + \cdots + p_n x_n \leq I \qquad (3)$$

In equation (1), $x_1, \cdots, x_n$ represent the quantities of distinct products $1, \cdots, n$ that can be purchased at prices $p_1, \cdots, p_n$ and $b_i(j)$ the marginal utility function. Equation (2) expresses that utility increases with units while marginal utility decreases with units (concept of diminishing marginal utility). Equation (3) expresses the budget restriction (I) the agent faces.

A topic related to consumer demand that has attracted much attention is context effects — changes of demand solely due to the availability of more or less product options (Trueblood et al 2013). Context effects are usually explained at the level of the basic reasoning processes of the consumers. Agent-based models are therefore more suitable to model context effects than traditional equation-based models. There are two major reasons for this. First, they allow modeling the reasoning process of a consumer explicitly. Second, they allow modeling more straightforwardly how the availability of product choice can influence distinctively different consumers.

We propose a simple agent-based model to illustrate the attraction, compromise and similarity effects. We assume

FIGURE 2
PREFERENCES ASSIGNED TO PRODUCTS AND PRODUCT SALES (ORDINARY CASE).



the following marginal utility function:

$$b_i(j) = B_i * 2^{1-j} \qquad (4)$$

Context effects can be simulated with an algorithm, which defines preferences B_i of a product. We consider that each product has an array of n characteristics with price being one of them. The two steps of the algorithm are the following (Figure 1 illustrates the algorithm with a flowchart):

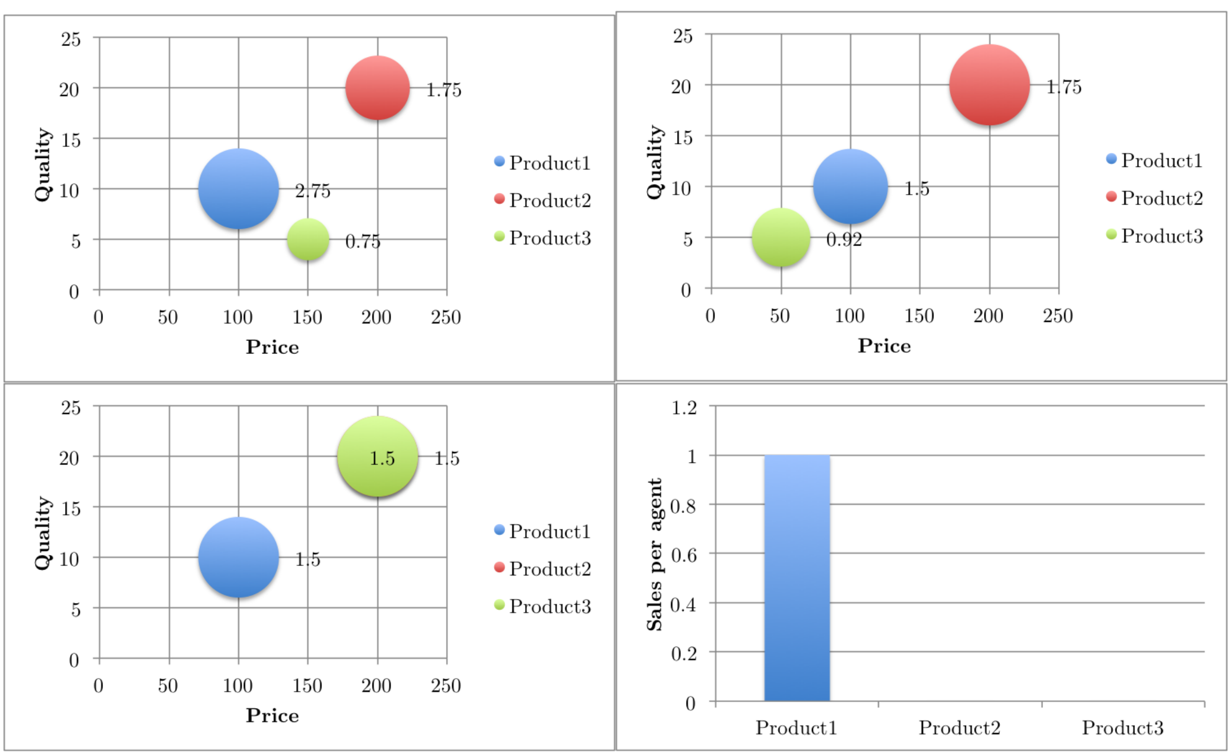
1. For each product preference B_i is calculated to be equal to the mean value of the normalized values of each product characteristic (except price).
2. A random product is selected. This product is checked against all the other products. If the product dominates another analyzed product in all dimensions its preference B_i is increased by one. If not, for each dimension of the product, it adds $\frac{distance*0.5}{max-distance}$, with the $max - distance$ being defined as the larger difference between the value of product and the value of the other products in that dimension. This step is repeated for all the remaining products.

The following figures present concrete examples of the instantiation of the algorithm in different scenarios. Figure 2 depicts the traditional scenario when there are context effects. In the scenario of Figure 3a a third product introduces the attraction effect. Figure 3b presents another example in which the third product introduces the compromise effect. Finally, Figure 3c illustrates how the third product introduces the similarity effect. All these effects lead to product 1 being sold more as depicted in Figure 3d.

CONCLUSION

Demand evolves not as a result of a set of isolated purchase decisions of individual consumers but rather as the result of repeated interactions between complex webs of interrelated buyers over time. To understand such a lively complex system it is essential to fully grasp not only the intricate details of the consumers' individual reasoning processes but also their dynamic, interactive processes. Equation-based modeling has shown to be less than suitable for understanding complex economic phenomena. This paper describes an alternative approach to equation-based modeling, agent-based modeling. This approach entails the simulation of consumers as autonomous conscious agents that interact with each other in the dynamic environment of an economic market. We contend that this approach is better suited to model demand in business simulations and should

FIGURE 3
PREFERENCES OF PRODUCTS
(ATTRACTION, COMPROMISE AND SIMILARITY EFFECTS).



be further explored in the future.

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