AN AGENT-BASED MODEL OF CONSUMER BEHAVIOR BASED ON THE BDI ARCHITECTURE AND NEOCLASSICAL THEORY

Márcia Lourenço Baptista
Universidade de Lisboa,
marcia.baptista@ist.utl.pt

Carlos Roque Martinho
Universidade de Lisboa
carlos.martinho@ist.utl.pt

Francisco Lima
Universidade de Lisboa
francisco.lima@ist.utl.pt

Pedro Alexandre Santos
Universidade de Lisboa
pasantos@math.ist.utl.pt

Helmut Prendinger
National Institute of Informatics
helmut@nii.ac.jp

ABSTRACT

Agent-based models of consumer behavior open new possibilities in terms of the degree of realism and complexity of the simulation of markets. This technique brings several advantages over the traditional modeling approaches. This follows from the agent-based approach allowing the explicit modeling of the micro levels of intricacy of a market while enabling the emergence of the macro levels of market complexity. We propose an agent-based model of consumer behavior based on the Beliefs, Desires and Intentions (BDI) architecture and the neoclassical theory of utility maximization. The model allows simulating a dynamic environment of heterogeneous deliberative consumers. We show that the model can straightforwardly simulate different types of markets and economic phenomena such as price, income, substitution and complementary effects.

INTRODUCTION

In the field of agent-based computational economics (ACE), socio-economic settings are analyzed by creating computational models simulating the behavior of decision-makers – agents – which interact according to a number of prescribed rules (Tesfatsion 2001). Despite the growing body of research in ACE (Chen et al. 2012) the need for further improvements in computational agent-based economics is manifest, as noticed by Farmer and Foley (2009). This is particularly true for the area of consumer behavior modeling where traditional methods present limitations when having to describe both the micro and macro levels of market complexity (North et al. 2010).

Consumer markets have been simulated using different techniques from stochastic consumer behavior models (e.g. the NBD-Dirichlet approach, purchase incidence models, and purchase timing models) to econometric models (e.g., regression-based, Monte Carlo integration, and multinomial logit models). Nevertheless, as North et al. (2010) note, the traditional techniques do not model the interdependent behavior of consumers with sufficient level of detail. Agent-based modeling assumes itself as a viable and interesting option, not yet extensively explored. To address this possibility, we propose an agent-based model of consumer behavior.

This study attempts to provide further insights into 1) how to create an agent-based model in which choice is based on a deliberative architecture and on the neoclassical theory of consumer behavior and 2) how to simulate different economic phenomena such as substitution, complementary, price and income effects with an agent-based model.

BACKGROUND

The question which led to the creation of the research field of Agent-based Computational Economics (ACE) can be formulated as “Terming a specific approach to economics as agent-based may appear paradoxical. Isn't human behavior the foundation of economics – and shouldn't all economic theory be based on agents behavior in some sense?” (Brunn 2007). To address this problematic, a number of agent-based models of consumer behavior have been proposed. One of the most important models proposed is the framework of Janssen and Jager (1999). Its novelty lies in considering that distinct consumers engage in different cognitive processes – repetition, deliberation, imitation and social comparison – according to their level of purchase satisfaction and degree of uncertainty about product quality.

Other agent-based models of consumer behavior provide interesting perspectives on how to model the marketplace (Said et al. 2002, Schramm et al. 2010, Roozmand et al. 2011). An interesting example is CUBES (CUstomer BEhaviour Simulator) (Said et al. 2002). As a multi-agent system, CUBES explores how complex forms of interaction between consumers allow the emergence of different economic phenomena.

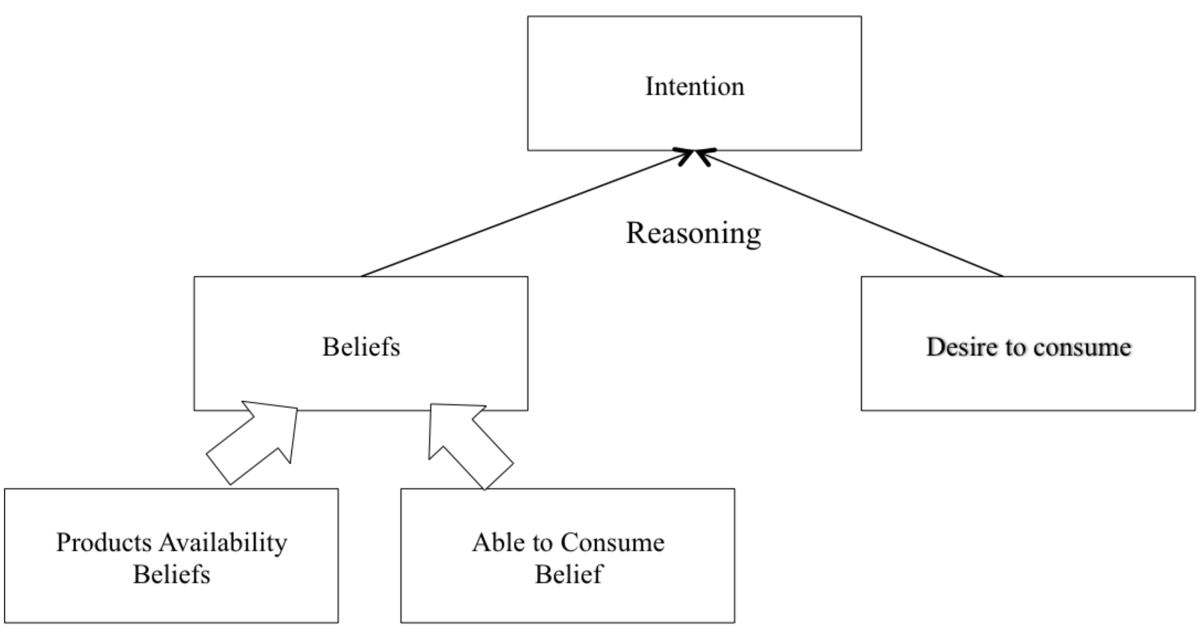
ARCHITECTURE

Our proposed architecture of consumer reasoning is inspired by the deliberative Beliefs, Desires and Intentions (BDI) architecture (Bratman 1987). Deliberative architectures allow agents to have an internal representation of the world to more easily perform their planning processes. Consumers often engage in deliberative processes to decide their next purchases and need to maintain information about the state of the marketplace. Accordingly, the BDI architecture is a suitable alternative to model the mind of a consumer.

As it is standard in the BDI architecture, each consumer represents the world by a set of structural elements. These elements are then used by the consumer’s planning system to select the optimal bundle of goods to purchase. The considered elements are described as follows (refer to Figure 1).

- **Beliefs** stand for the knowledge the consumer maintains about the world. Two types of beliefs are considered:
  - Availability belief: belief that a certain product is in stock at a certain store;
  - Able to consume belief: belief that the consumer can purchase at least one unit of a product.
- **Desires** stand for the motivations of the consumer. The consumer has the desire to consume enabled or disabled.
- **Intentions** stand for the consumer purchase plans. At each moment, the consumer can generate an intention for a bundle of product. According to the availability of products he may or may not accomplish its intentions.

Figure 1
BDI architecture of consumer agents.



The planning system of the consumer proceeds according to the following steps:

1. If the consumer has the desire to consume and believes he is able to consume, he proceeds to create a list of all the affordable bundles of goods.
2. The consumer assigns a utility value to affordable bundle of goods. Using a sorting algorithm the consumer selects its most preferred bundle as the one that maximizes his utility. In case of identical utilities, random values are used to decide. This preferred bundle of goods is selected as the consumer active intention.
3. All consumers attempt to accomplish their intentions in sequence according to a random assortment.
4. In the process of purchasing goods from different stores the consumer updates its beliefs and desires:
   a. Availability beliefs: if the consumer visited a store that no longer has a product in stock its availability belief is updated accordingly;
   b. Able to consume belief: after purchasing a product the consumer updates its current budget and according to the availability beliefs the consumer calculates if he is able to consume at least one additional unit of the product. The belief on being able to consume is updated accordingly;
   c. Desire to consume: if the consumer is able to consume then the desire to consume is enabled.

With this planning system, demand emerges from the indirect interaction of consumers. At the beginning of each planning phase, consumers do not have information regarding the intentions of other consumers nor the purchase sequence order. Accordingly, consumers plan their intentions based on the state of the world at the start of the planning stage. The purchases of other consumers may influence the availability of products and hence, have an impact upon the accomplishment of an intention of a consumer. This results in an effective interdependence between consumers.

MODEL OF CONSUMER PREFERENCES

As the consumer's utility function we propose the following general form where $x_1, \cdots, x_n$ represent the quantities of distinct products $1, \cdots, n$ which can be purchased at prices $p_1, \cdots, p_n$:

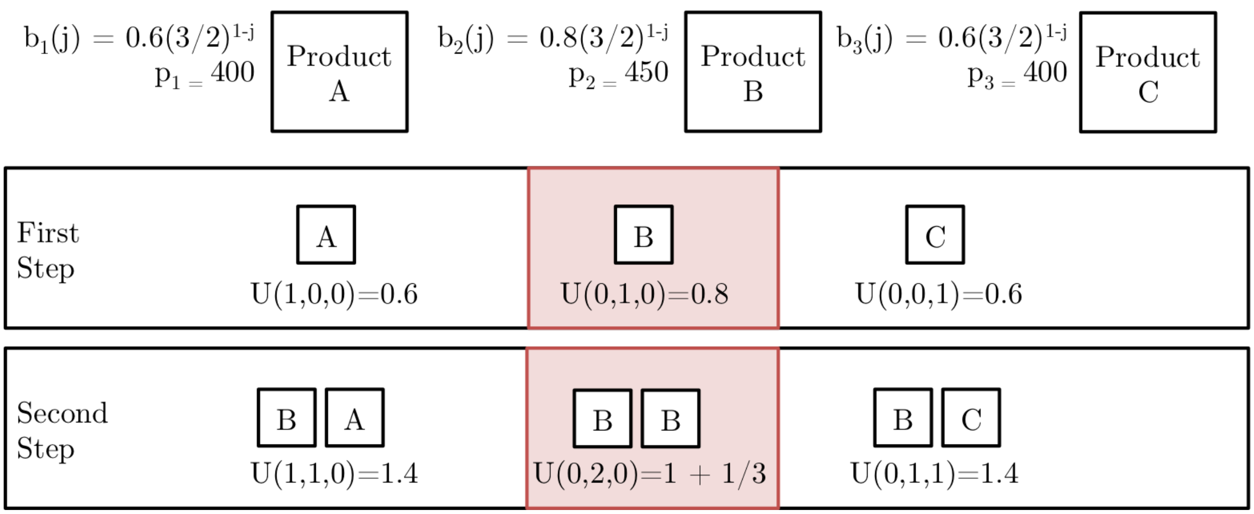
$$U(x_1, \cdots, x_n) = \sum_{j=1}^{x_1} b_1(j) + \cdots + \sum_{j=1}^{x_n} b_n(j) + \sum_{j=1}^{m} b_m(j) \quad \textbf{(1)}$$

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

In equation (1) the functions $b_i(j)$ represent the marginal utility of an jth additional unit of a product. To reflect the concept of diminishing marginal utility function $b_i(j)$ is positive and decreasing. Consumer satisfaction (utility) increases with the more units consumed. However, marginal utility decreases with units consumed.

An additional "virtual product" of quantity m was added to the bundle in equation (1). This was necessary to solve the problem of consumer satiation. In a real-world situation, consumers do not spend their entire budgets on a single product even if the product is sold at exceptionally low prices. This occurs since consumers can purchase products from alternative markets or save their budgets for future purchases. To address this situation, a composite product, representing all the other products the consumer may want to purchase, was added to the equation (1).

FIGURE 2
EXAMPLE OF ALGORITHM FOR FINDING PREFERRED INTENTION WITH BUDGET OF 1200 AND K=1.



We propose an efficient algorithm to select an intention (preferred bundle) from the set of all affordable bundles of goods. The algorithm uses a Greedy approach to solve the problem of finding the optimal bundle. It starts with an empty bundle of products and chooses successively the product to add to the bundle, according to the highest utility resulting from testing the addition of all currently affordable products. The variable K represents the number of products (of the same or of different kind) added to the bundle in each step of the algorithm and defines the complexity of the search and its efficiency. The higher the K variable the more likely is the algorithm to find an optimal solution. Figure 2 and Figure 3 provide examples of the execution of the algorithm for $K = 1$ and $K = 3$ (the composite product is disregarded in this example). It should be noted that in this particular scenario, the optimal solution is only found for $K = 3$.

SIMULATION OF ECONOMIC PHENOMENA

The agent-based technique allows simulating in a straightforward manner how simple differences at the consumer level lead to distinct emergent marketplace behavior. In this section we provide a few simple examples of markets (simulated with a C# program) with a single representative agent, which exhibit different economic behavior.

EFFECTS OF PRICE

Equations (1) and (2) can be used to simulate the different forms in which changes in price can influence the consumption of goods. More concretely, it allows the simulation of normal, Giffen and Veblen goods. The following equation provides a concrete example of a marginal utility function in which $\alpha_i \in \mathbb{R}^+$ represents the utility of the first unit of good while $\beta_i \in \mathbb{R}^+$ the rate at which marginal utility decays. The higher this second constant, the more rapidly marginal utility diminishes with the increase of units of the good:

$$b_i(j) = \alpha_i(\beta_i)^{1-j} \qquad \textbf{(3)}$$

We devised a concrete example of a market with two goods to study its indifference curves and demand curves (with I, p_1, p_2 standing for budget and price of product 1 and 2 respectively):

$$b_1(j) = \frac{3^{1-j}}{2},\ b_2(j) = \frac{3}{2} * \frac{3^{1-j}}{2},\ I = 1000, p_2 = 120 \qquad \textbf{(4)}$$

In this example, the demand curve of product 1 is downward slopping, except when the price is raised from 140 to 150 (refer to Figure 4). In that case the good displays a behavior similar to Giffen goods due to discrete choice. The case is analyzed in detail in Figure 5 (price of product 1 rises from 140 to 150). As can be seen in the same Figure, the law of demand would prevail in the continuous case.

FIGURE 3
EXAMPLE OF ALGORITHM FOR FINDING PREFERRED INTENTION WITH BUDGET OF 1200 AND K=3.

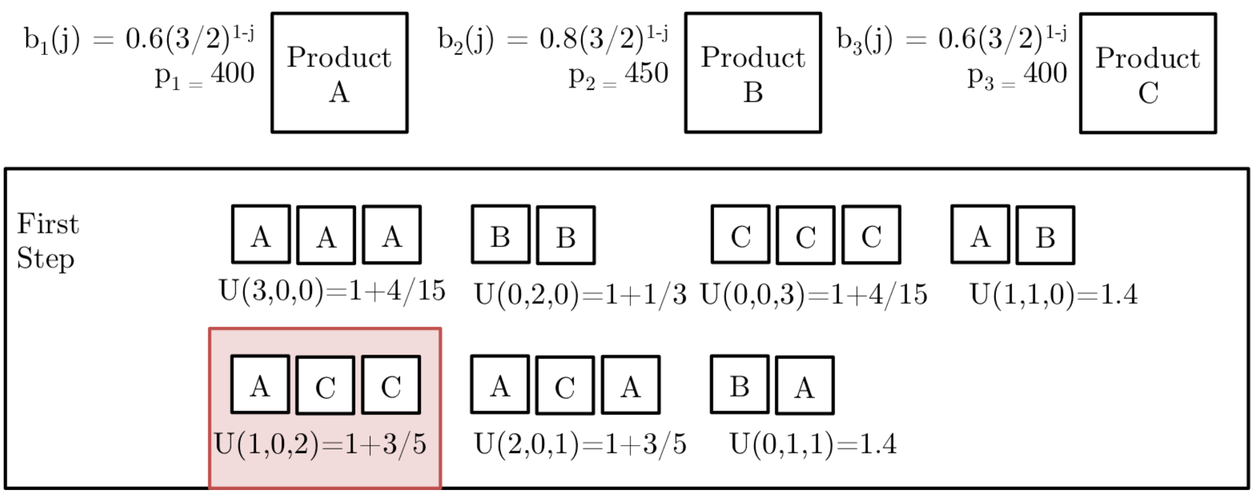


FIGURE 4
DEMAND SCHEDULE OF PRODUCT 1.

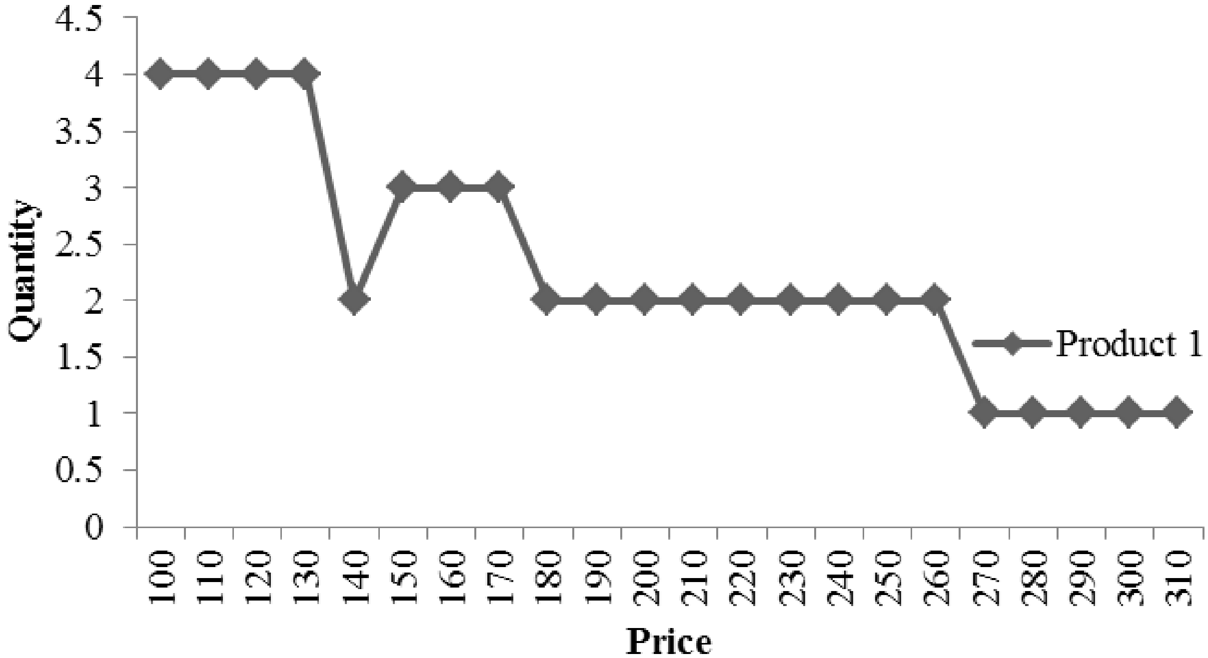


FIGURE 5
INDIFFERENCE CURVES FOR CONTINUOUS PREFERENCES AND PREFERRED BUNDLES (X1=2,X2=6 FOR P1=140; X1=3, X2=4 FOR P1=150) FOR DISCRETE PREFERENCES.

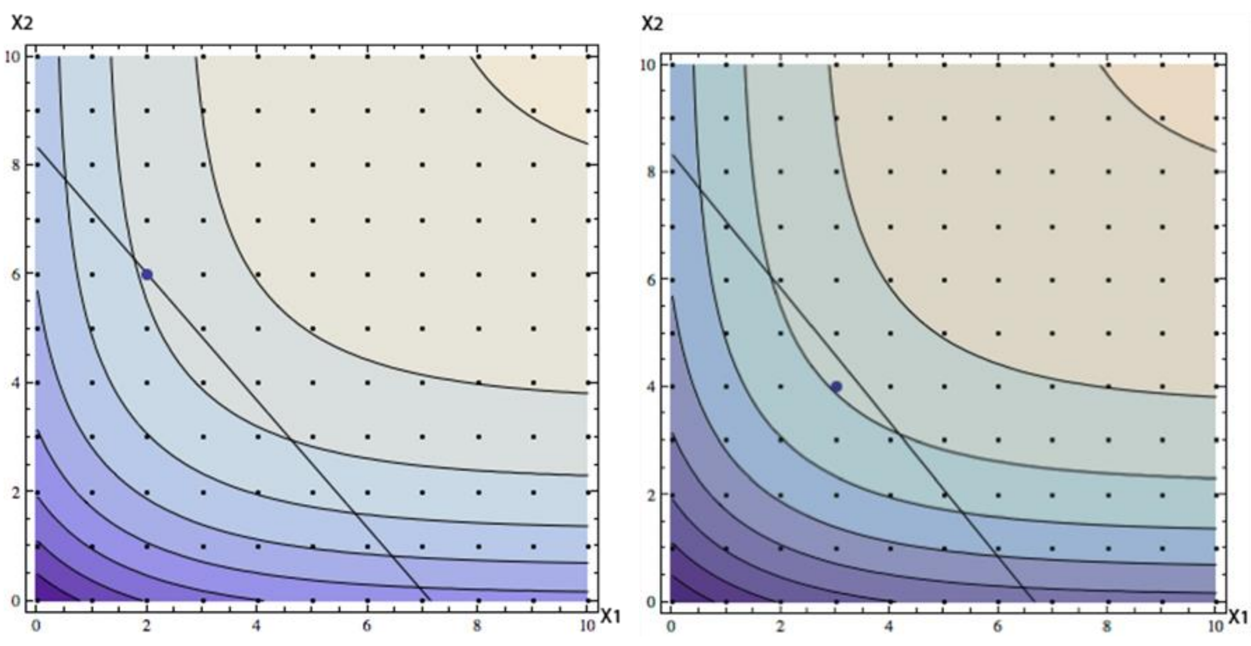


FIGURE 6
DEMAND SCHEDULE OF PRODUCT 3 (VEBLEN GOOD)

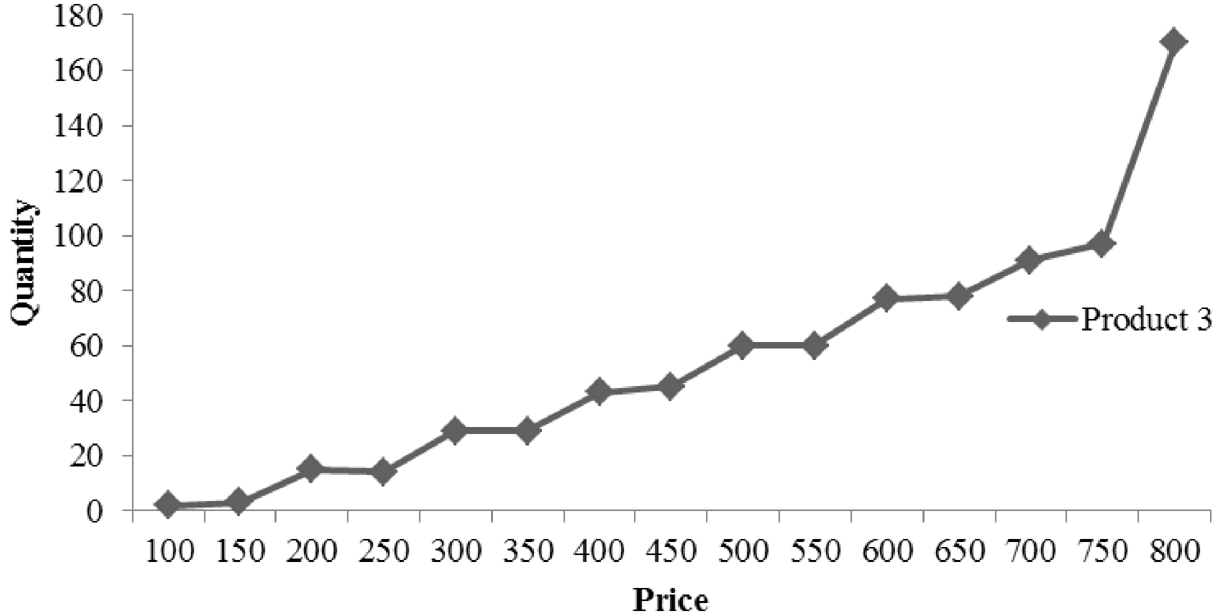
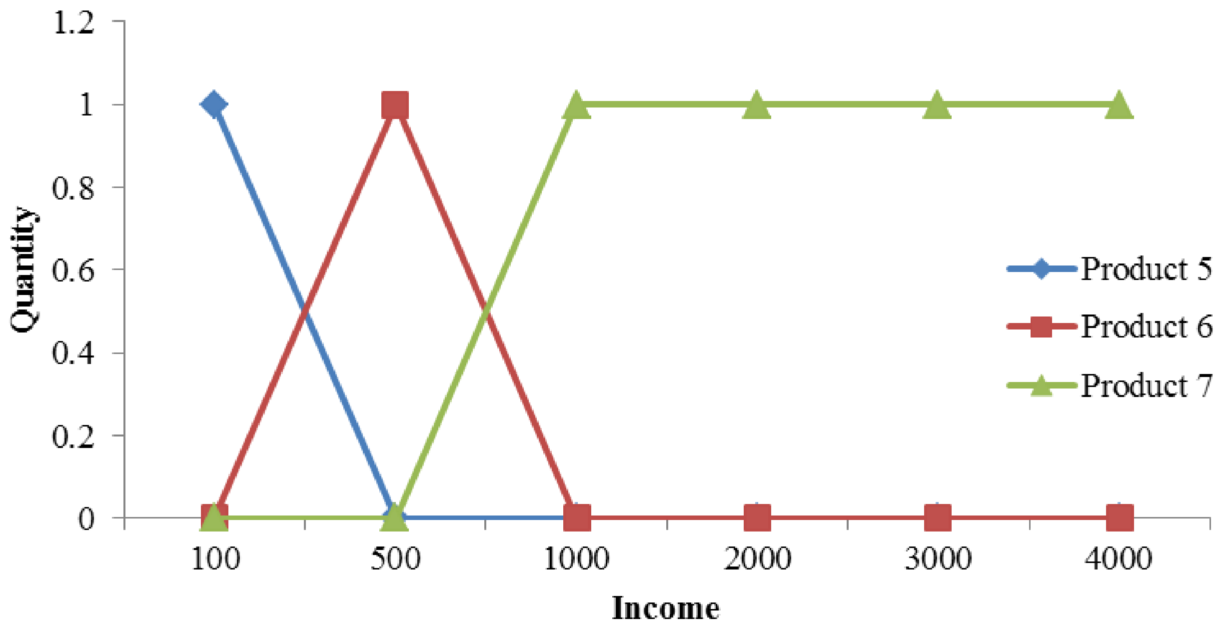


FIGURE 7
VARIATION OF QUANTITY OF PRODUCT 5, 6 (INFERIOR GOODS) AND 7 (NORMAL GOOD) WITH INCOME.



Equations (1) and (2) can also be used to simulate Veblen goods. As the price of a Veblen good increases so does the quantity demanded. Nevertheless and in contrast with Giffen goods, this occurs due to a status effect. Consumers interpret the high price as a signal of high quality, or in other words, of high utility, moving the demand schedule to the right. Veblen goods can be modeled by introducing a marginal utility function variable with the price of the product ($b_i(j,p)$). The higher the good's price, the higher the signaled utility. The following equations provide a concrete example of a market with two products, where product 3 is a Veblen good. As shown in Figure 6 the quantity demanded of product 3 increases with its price.

$$b_3(j,p_1) = \frac{3^{1-j}}{2} * p_3{}^2, b_4(j,p_4) = p_4, I = 200\,000, p_4 = 250 \quad \textbf{(5)}$$

EFFECTS OF INCOME

Equations (1) and (2) can be used to simulate how changes in income can influence consumption. We present an example of a market with three economic goods in which two of them (product 5 and 6) are inferior goods (refer to Figure 7):

$$b_5(j) = \frac{3^{1-j}}{2}, p_5 = 100, b_6(j) = 9 * \frac{3^{1-j}}{2}, p_6 = 500, b_7(j) = 81 * \frac{3^{1-j}}{2}, p_7 = 1000 \quad \textbf{(6)}$$

INDEPENDENT GOODS

The simulation of independent goods is achieved by modeling consumers with different budget restrictions for each good. The following equations describe how two independent goods can be represented by modifying equations (1) and (2):

$$U(x_1,x_2) = \sum_{j=1}^{x_1} b_1(j) + \sum_{j=1}^{x_2} b_2(j) \quad \textbf{(7)}$$

$$x_1 p_1 = I_1, x_2 p_2 = I_2, I_1 + I_2 = I \quad \textbf{(8)}$$

The existence of two distinct budget restrictions allows that cross elasticity ($e_{1,2}, e_{2,1}$) is set to zero for both products. This defines the products as independent goods since the parcels Δx_1 and Δx_2 are set to zero:

$$e_{1,2} = \frac{\frac{\Delta x_1}{x_1}}{\frac{\Delta p_2}{p_2}} = 0, \; e_{2,1} = \frac{\frac{\Delta x_2}{x_2}}{\frac{\Delta p_1}{p_1}} = 0 \quad \textbf{(9)}$$

SUBSTITUTION AND COMPLEMENTARY EFFECTS

Equations (1) and (2) can be slightly modified to allow the simulation of substitute goods. The following equations show how it is possible to model perfect substitute goods (10) and general substitute goods (11).

$$U(x_1,x_2) = \sum_{j=1}^{x_1+x_2} b_1(j) \quad \textbf{(10)}$$

$$U(x_1,x_2) = \sum_{j=1}^{x_1} b_1(j) + \sum_{j=1}^{x_2} b_2(j) \quad \textbf{(11)}$$

Complementary goods can be simulating by introducing a virtual complementary product to utility function (1) with r_1, r_2 representing the ratio of products 1 and 2 which compose the complementary product 12:

$$(x_1,x_2) = \sum_{j=1}^{x_1} b_1(j) + \sum_{j=1}^{x_2} b_2(j) + \sum_{j=1}^{\min(\frac{x_1}{r_1},\frac{x_2}{r_2})} b_{12}(j) \quad \textbf{(12)}$$

CONCLUSION

The agent-based approach is a novel perspective on how to simulate consumer behavior. It allows a more realistic simulation of the behavior of markets. Simple rules describing the micro behavior of consumers can simulate the complex emergent behavior of markets.

Despite its advantages and potential over the possible alternatives, such as stochastic and econometric models, the agent-based technique has yet to be extensively applied to model consumer behavior. We propose a flexible architecture of consumer behavior, which attempts to integrate research from the areas of economics, marketing, artificial intelligence and engineering. We intend to facilitate the task of modeling and simulating artificial markets.

Despite microeconomics laying the foundations of consumer behavior with the neoclassical theory of utility maximization it does not prescribe how the needs of consumers are generated and how consumers sense and interact in the marketplace. This information is however critical to simulate an artificial market. Consequently we proposed a deliberative architecture, inspired by the BDI architecture, to embody the consumer preferences – represented by the utility function. This synergy between the areas of artificial intelligence and economics results in a powerful abstraction of consumer behavior.

The proposed architecture intends to represent an efficient and flexible alternative to simulate a multitude of economic outcomes. With this architecture it is possible to simulate a wide range of economic phenomena such as the effects of changes in price and income as well as substitute and complementary effects. A close replication of real markets is possible by the simulation of a wide range of economic goods. Our proposed model provides the designer of the artificial market more freedom to conceive the simulation.

The deliberative agent-based architecture distinguishes itself from the remaining modeling alternatives by the provision of a large amount of high fidelity information regarding the building blocks of the economic market – the consumer itself. In contrast with other techniques, such as stochastic behavior models, the application of the agent-based approach allows that, in our architecture, micro information regarding the consumer, such as its successful and unsuccessful intentions, interactions and purchase plans can be stored and used for further research.

Given its characteristics, the architecture presented here can serve as a valuable learning and research tool. It can be used as the underlying model of business games to enhance the management skills of business students or as a tool to conduct economic experiments enabling the prediction of market trends.

FUTURE RESEARCH

Perhaps one of the chief advantages of using the agent-based approach is the possibility to explore the interaction between the agents. In the field of agent-based consumer behavior this possibility was further investigated, among others, by Janssen and Jager (1999) and Said et al. (2002), who simulated interaction effects such as processes of imitation and of recommendation/ disqualification of products in their models of agent-based consumer behavior. In our architecture, consumers interact by influencing each other via their consumption acts. We intend to further research this topic in our future line of work by developing direct interaction processes between the agents, namely imitation and word-of-mouth processes.

REFERENCES

Bratman, M., 1987. *Intentions, Plans, and Practical Reason*. Cambridge, MA: Harvard University Press.

Bruun, C., 2007. *Agent-based Computational Economics*. Handbook of Research on Nature Inspired Computing for Economics and Management, 183.

Chen, S., Chang, C., Du, Y., 2012. Review: Agent-based economic models and econometrics. *The Knowledge Engineering Review* 27 (2), 187–219.

Farmer, J., Foley, D., 2009. The economy needs agent-based modelling. *Nature* 460 (7256), 685–686.

Janssen, M., Jager, W., 1999. An integrated approach to simulating behavioural processes: A case study of the lock-in of consumption patterns. *Journal of Artificial Societies and Social Simulation* 2 (2), 21–35.

North, M., Macal, C., Aubin, J., Thimmapuram, P., Bragen, M., Hahn, J., Karr, J., Brigham, N., Lacy, M., Hampton, D., 2010. Multiscale agent-based consumer market modeling. *Complexity* 15 (5), 37–47.

Roozmand, O., Ghasem-Aghaee, N., Hofstede, G. J., Nematbakhsh, M. A., Baraani, A., Verwaart, T., 2011. Agent-based modeling of consumer decision making process based on power distance and personality. *Knowledge-Based Systems* 24 (7), 1075–1095.

Said, L., Bouron, T., Drogoul, A., 2002. Agent-based interaction analysis of consumer behavior. In: Proceedings of the *first international joint conference on Autonomous agents and multi-agent systems*, IFAAMAS, pp. 184–190.

Schramm, M. E., Trainor, K. J., Shanker, M., Hu, M. Y., 2010. An agent-based diffusion model with consumer and brand agents. *Decision Support Systems* 50 (1), 234–242.

Tesfatsion, L., 2001. Introduction to the special issue on agent-based computational economics. *Journal of Economic Dynamics and Control* 25 (3), 281–293.