Understanding the Impact of Promotions on Consumer Behavior

Extended Abstract

Jarod Vanderlynden
Univ. Lille, CNRS, Centrale Lille, UMR 9189 CRIStAL, F-59000 Lille
fifty-five, Paris
France
jarod.vanderlynden.etu@univ-lille.fr

Philippe Mathieu
Univ. Lille, CNRS, Centrale Lille, UMR 9189 CRIStAL, F-59000 Lille
France
philippe.mathieu@univ-lille.fr

Romain Warlop
fifty-five
Paris, France
romain@fifty-five.com

ABSTRACT

Marketing is a complex tool companies use to publicize new products and build consumer loyalty. However, cost-effective understanding and prediction of marketing campaign influence on consumers' behavior are necessary to maintain an effective business strategy. To understand the impact of the diversity of profiles and human behaviors, it is necessary to supplement aggregated solutions with the design of granular, individual-centered Agent-Based Models suitable for describing behavioral diversity. In this article, we propose a new model that reproduces customer loyalty as an emergent phenomenon while also demonstrating the effects of price wars on consumer loyalty. The model facilitates measuring the increase in sales during discounts, the drop in competitors' sales, the negative effects of discount repetition and also complex phenomenon as decoy effect. Introducing a new product, a "decoy", in a competitive category can raise the sales of an existing product.

KEYWORDS

Consumer's behavior, Agent-based model, Simulation, Marketing

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1 INTRODUCTION

Marketing campaigns are designed to be as effective as possible by identifying the target population and the optimal means to use leverage marketing campaigns to influence behavior. As with many costly and complex phenomena, measuring the impact of conceived campaign strategies in a computational laboratory prior to real-world deployment is preferable. The use of computational models to evaluate marketing strategies is well acknowledged. [1, 8, 9, 15, 18, 19, 25]. The effects of marketing campaigns [5] are mainly analyzed by statistical methods [23, 24] and machine learning algorithms [10, 14, 23] to analyze customer segmentation and to support decision-making. However, these approaches are limited in understanding the impact of fine-grained consumer behaviors or supporting exploratory modeling analysis of campaign strategies under various scenarios. We argue that Agent-Based Modeling (ABM) facilitates the design, adaptation and calibration of behaviors at a level of detail that allows a better understanding of the factors facing a marketing campaign [20]. We consider the context of a supermarket with the objective of understanding the consumers' behaviors through their adaptive reactions over time to changes in prices or packaging of products. To do so, we propose a model focused on individuals, allowing the deployment of promotional campaigns at a chosen date and duration through simulation, and measuring its impact on various populations. Interactions are based on criteria originating from different disciplines: loss aversion from social sciences (Prospect theory [11, 16]), inertia from marketing influencing the choice of brands [2, 6], and evaluation of quality from economic sciences [17]. This article proposes a model capable of considering such aspects, following [8, 18, 19] ABM rules. However, the primary subject of our study is price dynamics. We show in this paper that our agent-based model, provides a sound framework for understanding the impact of collective behavior. Our model is self-adaptive to changes in the environment : new products, price changes, new marketing campaign. The model can therefore effectively help explore the consequences of different "what if" scenarios. The rest of the paper is structured as follows. In the first part, we present our ABM model. The second part describes the computational experiments. Finally, the last part discusses the model's advantages, potential extensions and future research.

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2 SPECIFICATION OF THE MODEL

In this article, we focus on a model of a store by which it is possible to simulate different discounts on different products. We do not take into account the geographical positioning of the store and the products, nor the social influence, in order to focus on the influence of price and promotions. We start by presenting the *packs* (products) and the agents that constitute the store's customers, followed by the specification of the environment that characterizes the store and its products. The model dynamics is based on a behavioral model, involving the strategies and mechanisms used by agents to reason and make decisions about product selection.

A pack represents any product in a supermarket. This product can be sold alone or in a pack. This information is represented by the characteristic *quantity* In our model, it is represented by a quadruple, $P(p, Qty, Qa, D)$: price, quantity, quality, a boolean variable for discount. Products are regrouped into different categories. An agent, $a(H_i, \lambda_i, P_{ref_i}, (\beta_p, \beta_q, \beta_i, \beta_l))$, represents an entity (a person, a family or other) who shops regularly in the store. This entity

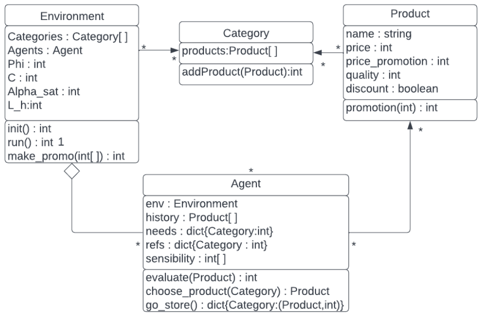

Figure 1: UML Conceptual Structure of the Model

has for each category a history (H_i), a need (λ_i), a reference pack, real of created (P_{ref_i}) and 4 β representing Sensitivity to price, quality, inertia (the strength of habits) and promotions. The environment represents a store. We use the environment parameters to modulate the global functioning of the model, e.g., increasing the significance of promotion or increasing the capacity of loss aversion [2, 7, 11, 21]. The environment is therefore characterized by the following properties:

β is the loss aversion parameter, $\beta > 1$.

C defines limit for the purchase quantity, $C >= 1$.

α_{sat} represents the saturation parameter.

l_h is the length of the purchase history.

G_p, G_q, G_i, G_d represent the impact regulation parameters: price, quality, inertia, and promotion (discount).

2.1 Hypothesis

We regard products as typical consumer commodities, which leads us to assume that purchases occur frequently. Each agent consider their purchase decision at each time step. It is assumed that the need (the $\lambda_{i,a}$) is computed using the average history of the quantities purchased: $\lambda_{i,a} = mean(H_{i,a}(Qty))$. We eliminate the possibility of purchasing different packs within the same category. This is equivalent to excluding the purchase of two similar packs, but of different brands. Each agent chooses, at each time step, at most one pack in each category. This assumption does not prevent agents from buying the same pack multiple times or from not buying anything.

2.2 Decision process

Agents uses preferences to choose packs they'll buy. This process is defined in 3 steps, the evaluation of categories, evaluation/choice of a pack using a utility function and choice of the number of pack. In each steps, agents use the same process. At each time step, all the agents visit the store, and for each category, each agent determines if this category interests it or not according to a probability. On each chosen category agents then evaluates all the packs using their utility function and chose one pack to buy and in which quantity. The differences in agent's behavior comes from the use of their internal parameters in the utility function.

The code, description and examples can be found at the Jupyter sheet available at this address: https://github.com/cristal-smac/retail

3 EXPERIMENTS

All our experiments are performed with the same environmental parameters. On the same experiment, the agents and products have the same characteristics to allow comparison. The procedure to generate the agents and products are randomized procedures. The agents are categorized according to their sensitivities. All experiments are performed several times (20) for more accuracy. We show that in the same situation (similar agents and products), two identical promotions have almost the same effect.

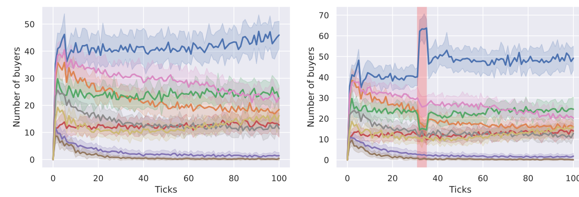

Figure 2: Number of buyers for each product as a function of time in a simulation. On the left without a promotion, on the right with a promotion of 40% between ticks 30 and 34.

The model is able to reproduce macroscopic promotional phenomena such as: The increase in the volume of sales of a product on promotion. This effect is fundamental according to [4]. Cannibalization, which corresponds to the decrease in sales of products competing with a product discounted during a discount. Repeated promotions on the same product have a lesser impact with each new promotion. Multiple successive promotions change the reference price of the agents. The price war is a phenomenon with macroscopic impacts, but also microscopic impacts by changing the perceptions that consumers have of certain brands. How promotion impacts the acquisition and retention of new consumers, 2 especially according to different profiles. The decoy effect [13, 26], a psychological phenomenon where the introduction of an inferior option makes one of the existing options seem more attractive. Finally, our results are of the same order of magnitude as the elasticities actually observed by [3, 12, 22].

4 CONCLUSION

In closing, we've been able to point the effects of our seven global model parameters. We found that the decline in sales depends on various factors such as product similarity and the number of products in the category. This level of detail is valuable for businesses. Furthermore, an intriguing findings is the counterintuitive impact of the consumer global price parameter. While one might assume that this parameter would be a dominant factor in increasing sales volume, our results revealed that it had a negative impact on the raise of sales volume during discount periods. This underscores the importance of understanding the interplay of various parameters for more precise calibration and more accurate predictions. Looking to the future, there are multiple avenues for enhancing the model's capabilities. One such avenue is the integration of social influence systems, allowing agents to interact and influence each other's purchasing decisions.

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