Simulation of Consumers Behavior Facing Discounts and Promotions

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Abstract: Discounts in stores are a powerful tools companies can use to create brand loyalty for products or increase sales during a short period of time. However, discounts are costly campaigns that result in complex effects on consumers, yielding unpredictable results and returns on investment. To maintain competitiveness, stores and brands have to use those campaigns and risk substantial investments. To gain a better understanding of the impact of discounts on consumer behavior, we argue that it is necessary to complement aggregated solutions with more granular, individually-centered approaches, such as agent-based modeling. In our study, we propose a new model based on social and psychological findings capable of replicating important and well-known emergent phenomena. This simulation model permits the study of behavioral responses to discounts and price strategy and can help companies to gain a clearer understanding of the effects of their different campaigns.

1 INTRODUCTION

In today's highly competitive business landscape, companies are well-aware of the indispensable role marketing plays in driving growth and establishing brand dominance. Companies have measured the importance and benefits of promotional campaigns, including discounts. One of the essential elements of marketing is offering promotional discounts and launching campaigns. These efforts not only attract and retain customers but also position the brand advantageously in the consumer's memory. To influence behavior, companies design campaigns as effective as possible by identifying the target population and the optimal means of promotion. Unfortunately, such campaigns are expensive and, if not executed correctly, can be of little use or even negatively influence the image of a brand or product. 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 to reduce costs and to better align with the potential demand. The use of computational models to evaluate marketing strategies is well acknowledged. (Negahban and Yilmaz, 2014; Axtell and Farmer, 2022; Said et al., 2002; Delre et al., 2007; Jager, 2007).

The effects of marketing campaign (marketing mix (Borden, 1964)) are mainly analyzed by statistical methods (Tellis, 2006; Wigren and Cornell, 2019) and machine learning algorithms (Tellis, 2006; Hung et al., 2019) 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 Multi-Agent Systems (MAS) perspective with its individual-centered approach via Agent-Based Modeling (ABM) facilitates the design and calibration of behaviors at a level of detail that allows a better understanding of the factors facing a marketing campaign. We also show that such an approach allows easier adaptation to changes in the environment such as the arrival or change of a product, thus providing robust and exploitable results.

In this article, 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. The great diversity of customer behaviors and promotional campaigns (price reduction, a percentage discount, vouchers, purchased/offered lots) motivates

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using ABM.

The rest of the paper is structured as follows. In the first part, we present the state of the art and highlight the significance of exploring the link between price evolution and consumer behavior. In the second part, we present an ABM for testing discount campaigns that rely on an individual utility function that each agent uses to evaluate products. The third part describes the design of computational experiments performed along with the results in relation to loyalty and sales volume evolution. Finally, the last part discusses the model's advantages, potential extensions, and future research avenues it affords, including considering social influence.

2 BACKGROUND: ABM IN MARKETING RESEARCH

The study of marketing strategies through simulation is not new. Prior research often relied on using equation-based or statistical approaches. Research on individual-centered ABM approaches highlighted the significance of behavioral differentiation. (Negahban and Yilmaz, 2014; Axtell and Farmer, 2022; Said et al., 2002; Delre et al., 2007; Jager, 2007).

- In (Delre et al., 2007) the launch of a product in a population is influenced by word-of-mouth (WOM), and The interaction possibilities are modeled via a "small world" (Watts–Strogatz) graph. In the model, when an agent adopts a new product, it tries to convince its neighbors to do the same. Word-of-mouth is a complex phenomenon and the models that study it integrate graphs to represent notions of social contacts, which agents can influence. We consider word-of-mouth, or in general social influence, is an area of study that offers new avenues of research but is not the primary focus of our current research objective. The confounding effects of the word-of-mouth mechanism with price dynamics would reduce the interpretability of the results, so we are primarily interested in understanding the impact of prices on different behaviors.
- There exist guidelines for modeling various marketing aspects in ABMs In (Negahban and Yilmaz, 2014), the authors propose an approach based on evaluating products according to a utility function. This allows model agents to evaluate items differently according to their characteristics. Thus, it becomes possible to create and modulate the characteristics of the agents, to reproduce behaviors classically observed in marketing.
- The use of ABM with individual behavioral parameters that regulate the diffusion of products is discussed in (Said et al., 2002). By exploring the parameter space, the authors reproduce stylized facts about consumers' brand choices, such as the emergence of an equilibrium between market shares and a lock-in effect of the market shares of a dominant brand or a cyclical competition between dominant brands.
- In (Jager, 2007), the authors apply marketing elements, including product, price, place of distribution, and promotion, in a social simulation model centered on individual behavior. In their model, agents have both individual and social preferences. Individual preferences are defined by the characteristics of each agent and social preferences are determined by looking at the consumption of socially connected individuals in a random graph. These four characteristics are fundamental in marketing and originate in (Borden, 1964).

However, it should be noted that the models presented in (Delre et al., 2007; Said et al., 2002) do not explicitly integrate the price component, and that (Negahban and Yilmaz, 2014; Axtell and Farmer, 2022; Jager, 2007) do integrate the price, but are mainly interested in social influence without studying the price-behavior link, which is the central point of our work. Some properties are generally easier to model with ABMs than equational models. This is notably the case of social influence dynamics which requires explicit links between different individuals, as opposed to the notion of advertising, which can be explored with an equational model.

2.1 Modeling Individual Behavior

The modeling of a purchasing behavior process is based on two fundamental aspects: internal influences (characteristics specific to each individual that influence the desire to buy a given product) and external influences (e.g., advertising, promotion, word of mouth). In this work, we focus only on internal influences and price dynamics. It seems natural for most authors to use the price and quality of each product as an internal influence. (Hardie et al., 1993; Bawa, 1990; Seetharaman and Chintagunta, 1998; Cohen et al., 2020) propose to add additional criteria: loss aversion or inertia.

- loss aversion (prospect theory), is predicated on the notion that losing 1$ has more impact on a consumer than gaining 1$.
- inertia or brand loyalty, suggests that a consumer will not necessarily take the "best" product of-

fered, because it is also influenced by habitual behavior and brand loyalty.

(Hardie et al., 1993; Cohen et al., 2020) suggest using a reference product to consider loss aversion. This can be specific to each individual in a MAS model. The inertia can be simply considered by a reinforcement process or preferential attachment (Bawa, 1990; Seetharaman and Chintagunta, 1998). These aspects can be combined through a utility function used when evaluating a product ((Negahban and Yilmaz, 2014)). To combine these different notions, (Negahban and Yilmaz, 2014) suggests summing up the behaviors taken into account with a utility function used when evaluating a product.

2.2 The Impact of Promotion

Promotions undeniably increase sales volume (Blattberg et al., 1995) and induce asymmetrical impact on other products, along with diminishing returns on repeated promotions. The confounding effects of these different aspects motivate our work on evaluating a promotional campaign model. To this end, our model builds on an individual-centered modeling framework (Negahban and Yilmaz, 2014; Axtell and Farmer, 2022; Said et al., 2002; Delre et al., 2007; Jager, 2007) and augments it with loss aversion and inertia as (Hardie et al., 1993; Bawa, 1990; Seetharaman and Chintagunta, 1998; Cohen et al., 2020) to exhibit the classical impact properties of promotions described by (Blattberg et al., 1995).

3 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. For example, a percentage reduction in price or a ”by three get one free promotion”. The model is also capable of reacting to price changes outside a temporary promotion, or to the arrival of new products in the store. In this model, there is no spatial representation, the agents are omniscient and know all the products and their characteristics. 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.

3.1 The Product Model

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, $P(p, Qte, Qa, D)$:

- p represents the price,
- Qte is the quantity of product in one pack,
- Qa is the level quality,
- D represents a boolean variable indicating if there is a discount.

For more realism, products are regrouped into different categories. Let $C = c_1, c_2, \dots$ be a set of product categories. Let $C_i = P_1, P_2, \dots$ be a set of products representing a product category. Each pack belongs to a category $C_i \in C = C_1, C_2, \dots$

$$\forall P_j \exists C_i | P_j \in C_i, C_i \in C \quad (1)$$

The objective of the different agents is to choose, at most, one product in each category.

3.2 Customer/Agent Settings

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. Its behavior is based on its habits. An agent is characterized by internal parameters that differentiate it from its peers and individual history and cognitive references for each category. Let:

- l_h the length of the purchase history considered by the agent. (sliding window)
- $H_{i,a}$ a list of packs for each category corresponding to the purchase history.
  $P_{i,a,t}$ The product purchased by agent a in category C_i at time t $H_{i,a,t} = P_{i,a,t}$,
  at initialization $H_{i,a} = \{P_{i,a,-l_h}, P_{i,a,-l_h+1}, \dots, P_{i,a,-1}\}$. At time $t = l_h$, $H_{i,a} = \{P_{i,a,1}, P_{i,a,2} \dots, P_{i,a,l_h}\}$.
- $\lambda_{i,a}$ the need for each category C_i.
- $P_{ref,i}$ a reference product by category C_i as in (Hardie et al., 1993)
- $\beta_p, \beta_q, \beta_i, \beta_l$ Sensitivity to price, quality, inertia (the strength of habits) and promotions.

3.3 The Environment

The environment represents the store which includes the agents and the products. The agents interact with the environment by buying products. 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. The environment is therefore characterized by the following properties:

- β is the loss aversion parameter (identical for price and quality), $\beta > 1$.
- 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).

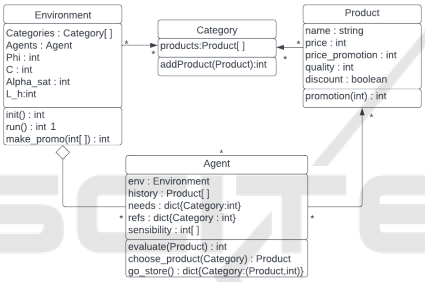


Figure 1: UML Conceptual Structure of the Model.

3.4 Hypothesis

We consider products as everyday consumer goods, which allows us to hypothesize that purchases are frequent and therefore that at each time step each agent questions the purchase. We could consider that a time step represents a week and that each customer arrives at the store each week to shop. It is assumed that the need (the $\lambda_{i,a}$) is computed using the average history of the quantities purchased: $\lambda_{i,a} = mean(H_{i,a}(qte))$. We exclude purchases of different packs in the same category to simplify the choice of agents. 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.

3.5 The Strategy for Choosing Packs

The strategy for pack selection depends on the preferences of agents. Agents can have distinct choices depending on their valuations.

3.5.1 Agent Preferences

At each time step, agents determine if they need a product of a specific category. An agent a evaluates C_i, by computing $B(C_i, t+1)$, the probability of needing a product of this category at time $t+1$. Finally, $N(C_i, t, t-n)$ is the quantity of the product the agent purchases in the last n steps.

$$sigmoid(x) = \frac{1}{1+e^{-x}} \tag{2}$$

$$B(C_i, t+1) = sigmoid\left(\frac{\lambda_{i,a}}{N(C_i, t, t-n)}\right) \tag{3}$$

Intuitively, this formula allows agent a to increase the probability of being interested in category C_i if it has purchased a small amount over the last few steps and inversely to reduce this probability if it has purchased more than usual lately.

3.5.2 The Evaluation of Packs

When an agent is interested in a product category, it evaluates all the packs, gives them a score, and chooses one. A high score means that the product matches the agent's expectations and is more likely to be chosen. The probability of purchase is proportional to the scores of the packs. For example, if we take 3 packs A, B and C with a score of 12, 6 and 2 respectively, the probability of purchase distribution will be 0.6 for A, 0.3 for B and 0.1 for C. Let c a pack category, P_c a pack within c, Pr_{P_c} the probability of the pack P_c to be chosen and $score_{P_c}$ the score of the pack.

$$Pr_{P_c} = \frac{score_{P_c}}{\sum_{i \in c} score_{P_i}} \tag{4}$$

To give a score to the packs, the agent uses his sensitivities and the parameters of the packs.

We define four utility functions U_1, U_2, U_3, U_4, one for each evaluated characteristic, respectively: price, quality, inertia, and promotion. The first two U_1 and U_2 compare the pack being evaluated with the reference pack on price and quality. It's in these formulas that loss aversion is taken into account. The third one considers the inertia, similar to the specification presented in (Bawa, 1990). Finally, the last function calculates the impact of a promotion. We then weigh the results of the four previous functions by the agent's sensitivities. The aggregate utility determines the score of the pack for this agent. The higher the score, the more the agent is interested in the pack.

$(x)_+$ represents the maximum between 0 and x.

$$U_1 = G_p \times (\beta \times (p - p_{ref})_+ + (p_{ref} - p)_+) \quad (5)$$

$$U_2 = G_q \times (\beta \times (q - q_{ref})_+ + (q_{ref} - q)_+) \quad (6)$$

$$U_3 = G_i \times (10 \times nb_{bought} - nb_{bought}^2) \quad (7)$$

$$U_4 = G_d \times D \quad (8)$$

We note that the impact of the price decrease is calculated in U_1 and not U_4. We model with U_4 only the impact of the presence or not of a promotion.

$$U(P,a) = \sum_{k=1}^{n} U_k * \beta_{a,k} \quad (9)$$

3.5.3 The Purchase Quantity

Calculating the quantity purchased is independent of the internal quantity of each product. This calculation is used to decide the number of packs bought by the agent for the chosen pack. If $P(p, Qte, Qa, D)$ is the chosen product, and Qte is 100g, then the agent will use the formula 10 to calculate the desired quantity. The agent then buys three times the same product. In this formulation, $N(C_i,t)$ is the quantity purchased at time t of C_i.

$$Buy(P,t+1) = max(1, \lambda_{i,a} + N) \times S \quad (10)$$

$$N = \sum_{\tau=0}^{T} \frac{\lambda_{i,a} - N(C_i, t-\tau)}{T+1}) \quad (11)$$

$$S = Sat(U(P) - U(P_{ref},t)) \quad (12)$$

$$Sat(x) = \frac{C}{1 + e^{-\frac{X}{\alpha_{sat}} + log(C-1)}} \quad (13)$$

3.6 The Dynamics of the Model

The *Choose* method chooses a pack using a probability distribution proportional to the pack score. The `Qt` method uses equations 10 to 13 to compute the quantity that the agent a buys.

A trace of the execution of this algorithm can be found in the Jupyter sheet available at this address: https://github.com/cristal-smac/retail

Data: A the sets of agents;
C the sets of packs category;
$H_{(i,a,t)}$ the history of what agent A bought on category Ci at time t;
Result: Decision process used by each agent.
$t \leftarrow$ time step t;
for *all agents* $a \in A$ **do**
  a go to the store;
  for *all category* $c_i \in C$ **do**
    $H_{(i,a,t-l_h)} \leftarrow None$ (delete);
    $p \leftarrow B(c_i, t+1)$;
    $x \sim U(0,1)$;
    if $x > p$ **then**
      $H_{(i,a,t)} \leftarrow (None, 0)$
    else
      for *every product* $p \in c_i$ **do**
        $score(p) \leftarrow U(p,a)$;
        l append $(score(p), p)$;
      end
      $P_{i,a,t} \leftarrow$ Choose(l);
      $q \leftarrow$ Qt($Chos, ref$);
      $H_{(i,a,t)} \leftarrow (Chos, q)$;
    end
  end
end

Algorithm 1: Decision process.

4 EXPERIMENTS

In this section we show the model is capable to reproduce known marketing phenomena. 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.

The model is able to reproduce classical macroscopic promotional phenomena in marketing such as:

- The increase in the volume of sales of a product on promotion. This effect is fundamental according to (Blattberg et al., 1995).
- 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.

But above all, the model can reproduce phenomena that are observable only at the level of the agents, impossible to observe with an approach that would not be centered on the individual, such as :

- 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

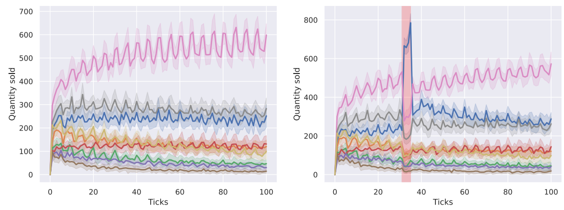


Figure 2: Quantity of sales as a function of time in a simulation. On the left without a promotion, on the right with a promotion of 40% between time steps 30 and 34.

brands. This influence also has effects on the loyalty of consumers to certain brands.

- How promotion impacts the acquisition and retention of new consumers, especially according to different profiles. For example, a promophile consumer will regularly change products if they are on promotion.

Within our experiments, it is discerned that the model adeptly reproduces renowned effects with considerable precision, thereby affirming the validity of our methodology.

4.1 Decline in Sales Volume of Other Products

The decline in sales of products that are not on promotion is also a common phenomenon. It is said that the promoted product "cannibalizes" the sales of other products of the same type. This effect can be seen in Figure 3. The drop in sales of non-promoted products ranges from 2 to 20 percent on average and varies by product and by similarity to the promoted product. The drop varies by the number of product in the category too. At least 1 product always has a sales decline of more than 0 percent.

4.2 Impact of Repeated Promotions

The model also shows the frequency of promotions wields a profound influence on their efficacy. A saturation of promotions tends to attenuate the peak sales they typically induce. This can be attributed to the evolving consumer evaluation of products; as they grow accustomed to incessant discounts, their propensity to transition between products during a discount diminishes. This effect can be seen in our model as described by 3

4.3 Testing the Robustness of the Model

To test and show how the model can behave, and it's adaptation to different cases, we make 3 other test :

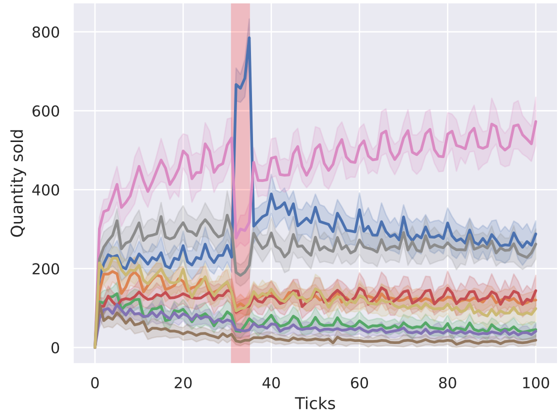
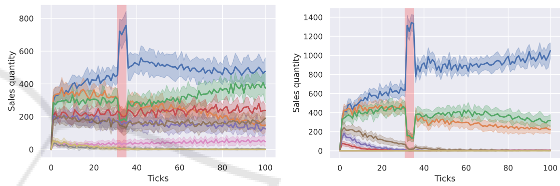
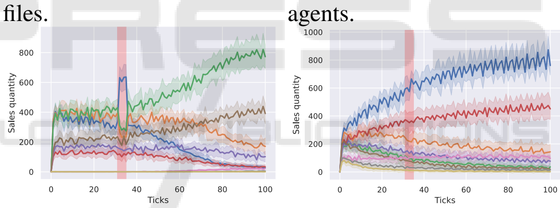


Figure 3: Quantity of sales as a function of time in a simulation with a promotion of 40% on the Pack 0 between time steps 30 and 34.



(a) Evenly distributed profiles. (b) Only discount oriented agents.



(c) Only price, quality oriented agents. (d) Only inertial/loyal agents.

Figure 4: Simulations of 100 time steps, making a 40% discount between time step 30 and 34 on all simulations. We very the sensibilities of the agents in each simulation. In 4a a simulation with the 5 profiles presented earlier evenly distributed. In 4b a simulation with only discount oriented agents (promophile). In 4c a simulation with only price, quality oriented agents and finally in 4d a simulation with only inertial/loyal agents.

what happens when profiles of agents change, how the duration of discount impact the results and we test the difference between a temporary price reduction and a discount.

4.3.1 What Happens when You Change the Behavior/profiles of Agents

We vary the proportions of the different agent profiles and test new ones to observe the effects of these agent's parameters on the model.

On simulations in figure 4 we observe that the pro-

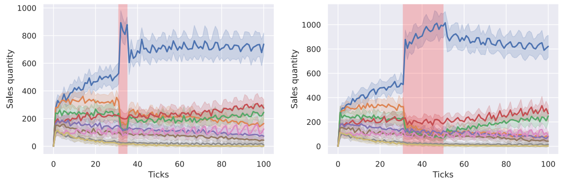


Figure 5: Simulations of 100 time steps, making a 20% discount between time step 30 and 34 on the left and a 20% discount between time step 30 and 50 on the right.

mophile profiles are very impacted by the promotion, but are also more likely to be loyal. Indeed, on the same promotion of 40% on the same time steps with the same agents and the same packs, we observe a short term increase in sales of 78% for the promotion on classic profiles against 116% for the promotion on only promophile profiles. Similarly, in the long term, we see an increase from 28% for classic profiles to 79% for promophile profiles. Finally, if price and quality agents' sensibilities are exacerbated, we obtain agents who are very oriented towards the quality/price ratio. This ratio is better during a promotion, which means that we always see an increase in sales during the promotion, but since the agents are very oriented towards the quality/price ratio, they tend to quickly turn to the pack with the best ratio. Finally, the so-called inertial or loyal agents are not impacted by the promotion. These simulations show that a variation of the agents' sensitivities leads to different results, but always consistent with what we model.

4.3.2 The Impact of the Duration of a Discount

The duration of a discount corresponds to the number of ticks the discount lasts. The simulations of figure 5 shows longer discounts have greater impact. The long discount last 20 ticks compared to 4 ticks for the other. However, it is important to note that we go from a peak sale of 78% to a peak sale of 110% for the same amount of discount. Finally, the length of the promotion leads to a stronger loyalty. Indeed, the inertia has time to set in, the customers have in a way made the product part of their consumption habits.

4.3.3 The Difference Between a Temporary Price Reduction and a Discount

Figure 6 shows the difference between a discount and a temporary price reduction. A price reduction that is not posted as a discount has less impact. The short-term impact of the promotion is 76% additional sales (during the promotion) versus 45% for the discount, and the long-term impact is 28% additional sales for the promotion (loyalty) versus 20% for the discount. Indeed, promophile agents do not perceive this discount as a promotion. Only price-oriented agents are really sensitive to this kind of change.

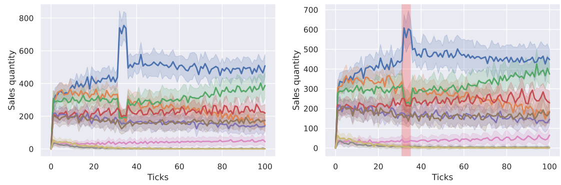


Figure 6: Simulations of 100 time steps, making a 20% discount between time step 30 and 34 on the left and a 20% price reduction between time step 30 and 50 on the right.

5 MODEL CAPABILITIES

In this section, we explore the practical applications of our model and demonstrate its ability to inform decision-making processes in pricing strategies. Leveraging the power of computational simulation, we uncover valuable insights into optimizing discounts : when to apply them, how much to offer, and the interplay of competitive products in the market.

We propose an experiment involving 3 packs of the same category, directly competing with each other. It is noteworthy that the price-quality ratio is the same for each of the packs to avoid a domination of one pack in the simulation. The number of simulation time steps, the number of agents, their parameters, and the timings at which promotions for packs B and C are carried out are fixed. The goal is to test various promotions for pack A, calculate the profits (the selling price minus a lower value representing the cost of the pack) for this pack, and determine the best promotions to carry out.

To test different promotions, we initially conducted a random search and then implemented a genetic algorithm. We justify the use of a genetic algorithm because the number of possible promotions is very large and we cound't find the optimal solution in a reasonable time. In this experiment, in each simulation, we propose conducting up to 10 different promotions for Pack A throughout the simulation at variying time steps. Given the simulation duration of 100 time steps, there are up to C_{20}^{100} possible promotion moments and 100^{10} possible promotion power (in %). Even when excluding promotions at a loss, this number remains substantial.

Firstly, it emerges from this experiment that in our model under these experimental conditions, it is more profitable for the profits generated by pack A if its promotions do not coincide with the promotions of packs B and C. Additionally, we observe that conducting a rather strong promotion (around 40%) at the very beginning of the simulation, from time steps 0 to 10, increases the profits of Pack A. It is noteworthy that there are no other promotions on packs B and C at this specific moment. Finally, the model demonstrates that it is necessary to conduct at least a second promotion later in the simulation, often just after the promotions of B and C, to prevent these promotions from impacting the sales of A.

In conclusion, our experimental findings suggest that, within the specified experimental conditions of our model, it is more advantageous for the profits generated by pack A to schedule its promotions independently of those for packs B and C and to use the promotion sparingly.

6 DISCUSSION

In this paper, we show in section 4 that the agent-based approach proposed in section 3 is able to reproduce emerging phenomena known in marketing such as the increase in sales volume, the ”cannibalization” linked to competition or the changes in customers behavior caused by the rapid repetition of promotions. Moreover, the individual-centered approach allows us to show phenomena that are only observable at the individual level, such as loyalty during a promotion or the effects of price wars directly on consumers. We show the model's ability to reproduce general stylized marketing facts and to adapt to different scenarios. In this way, we propose a form of learning that allows us to start from a known scenario, and run a complete simulation of different scenarios that we would like to explore. Scenario exploration is facilitated by access to simulated data similar to real data (sales receipts).

In order to deepen the model, it is possible to add a system of social influence similar to those described in the section 2, which would allow agents to exchange and interact with each other in order to influence each other. Moreover, it is possible to give the agents only a partial knowledge of the products, so the agents would have to discover themselves the products they do not know or be socially influenced. Finally, it would be interesting to study the notion of similarity between products and to see, according to this similarity, the competition generated and the effects of promotions.

The proposed model has the possibility to easily integrate real data (via history) which would improve the realism, and apply the model to concrete scenarios. We justify its adaptability to the data through the global parameters built into the model.

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