Using Machine Learning and Improved Algorithms to Optimize E-commerce Pricing Models

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***Abstract*—E-commerce pricing models are key consideration for making purchases on the internet. Dynamic e-commerce pricing models, often used by online companies to boost sales and profitability, can greatly benefit them within the consumer market. This study aims to develop machine learning and improved algorithms that will help e-commerce platforms offer the right pricing models to customers. It focuses on companies with inventory leads but could also be useful for stockless online marketplaces. By using statistical and machine learning techniques, the study seeks to understand customer preferences in dynamic or adaptive product pricing based on various data sources such as visit characteristics, visitor traits, purchase history, site data, and context understanding. The article further provides a detailed explanation of how machine learning and improved algorithm may be used in optimizing e-commerce pricing models and revenue optimization.**

Keywords—E-commerce, Pricing Models, Machine Learning, Improved Algorithms, Sales Methods

I. Introduction

E-commerce pricing models have proven to be an effective strategy for optimizing price decisions in various enterprises, particularly within the e-commerce context. Unlike traditional static pricing techniques, dynamic pricing algorithms allow businesses to swiftly adjust their prices based on factors such as competitive pricing, market conditions, customer demand, and individual preferences. By adapting to changes in market dynamics, companies can use this technique to establish prices that both optimize value and reflect customers' willingness to pay. Machine learning techniques have revolutionized dynamic pricing by providing sophisticated data-driven methods for determining the optimal prices [1]. These approaches enable businesses to forecast customer behaviour in response to different price points using extensive datasets comprising historical sales data, consumer trends competitor pricing information, among other pertinent characteristics. By employing machine learning algorithms, businesses can uncover complex patterns and connections in the data that may not be immediately apparent using traditional statistical methodologies. Using machine learning techniques for dynamic pricing offers various advantages. First, due to their ability to handle large amounts of diverse data, businesses are able to collect and analyze a wide range of factors affecting pricing decisions. Second, machine learning models enable real-time adaptability and learning from new data, allowing for continual enhancement and modification of pricing methods. Lastly, by exposing non-linear correlations and interactions between variables, these techniques provide a more accurate understanding of pricing elasticity and customer behaviour. Therefore, detailed analysis remains imperative for the growth of these methods as well as artificial intelligence and allied sectors. In this article, we examine two aspects of machine learning concerning e-commerce pricing models: improved algorithms have shown impressive results in a variety of domains, providing unique benefits when modelling complex price dynamics [2]. By contrasting various machine learning techniques, we aim to highlight their relative benefits and drawbacks for dynamic pricing strategies, which could help optimize efficacy.

II. Related works

A. E-Commerce Pricing Models

As the e-commerce platform takes shape, the retail e-commerce industry is experiencing rapid growth. One of the key areas to focus on is the pricing model. While there has been researching on merchants' and retailers' pricing tactics, China has over time witnessed a surge in price competition across e-commerce platforms, with an increasingly evident impact of operating models on these platforms. This paper categorizes operational models into two groups: one where a platform sets the price and negotiates with suppliers (e.g., Amazon), and another where an e-commerce platform connects suppliers and customers, allowing suppliers (e.g., Alibaba) to set product prices. Both the operational model and the customer's perceived value influence the pricing model for products offered on these two types of e-commerce platforms. Factors such as wholesale price consideration, competition from second-type platforms, and negotiation skills when dealing with product suppliers should all be considered by first-type platforms when determining retail prices. Agent-based price modeling, which combines variables, agents, and rules through various computational methods, examines pricing for individuals or groups [3]. The inventory-based approach revolves around inventory levels combined with customer service; it can further be categorized into three types based on replenishment strategies - no replenishment inventory that determines fixed-inventory-based prices at specific points in time in meeting client needs.

The third type of pricing model is focused on customers and is described as being both strategic and shortsighted. Myopic consumers tend to purchase a product when its price is less than it's worth, while strategic customers take advantage of potential future price adjustments. Prices are determined using data collected on customer preferences and purchasing patterns through a data-driven methodology. The Game Theory Model comes into play when there are more sellers than consumers, considering other economic concepts. Utilizing e-market data, the machine learning model identifies customer preferences and trends, applying

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algorithms to optimize profitability. Any decision-making paradigm can be applied to a simulation model from the list provided or any other models available. The Auction Based Model for dynamic pricing requires six key components for proper function. These elements include a clear market structure between the buyers and the sellers, resources to be auctioned off during the process of trade, preference structure that includes agents stated views on product preferences, the bid structure that outlines the flexibility of resource requirements, market clearing that balances the prospects of supply and demand and lastly, information feedback that enables the bidders to adjust their offer based on the winning bid's price. The existing individual models could not have their effects combined effectively enough to address the Purchase Behavior problem comprehensively by utilizing dynamic pricing strategies. It is proposed in this current study that a framework should be developed which focuses on preserving dynamic pricing as an integral part of addressing the identified Purchase Behavior problem, in addition, to determining relevant customer groups along with estimating their most likely purchase range.

B. Machine Learning and Improved Algorithms in e-Commerce Pricing Models

Machine reinforcement learning is analogous to human learning in that positive rewards enhance future behaviours while negative rewards weaken them. Machine learning aims to maximize cumulative reward by teaching the system how to formulate an action plan. In deep reinforcement learning, the agent selects and executes an action in the environment and receives a reward signal when the environment transitions to a new state [4]. The next action is then chosen based on this reward signal. In dynamic pricing research, deep reinforcement learning algorithms enable manufacturers to optimize overall returns over immediate transaction benefits. A machine learning architecture comprises four key components: value function, strategy, environmental model, and reward-punishment feedback. Dynamic pricing involves numerous complex environment-related elements. Previous studies on dynamic pricing using machine learning have primarily focused on specific environmental contexts categorized into two classes: value-based models and policy-based models. Value function-based machine learning often employs the Q-learning algorithm, SARSA algorithm, and Monte Carlo algorithm as its main iterative equations for updating Q-values as viewed by Nguyen et al., [5], E-commerce pricing research also frequently leverages these techniques as expressed in the Equation below:

$$\delta x = m^{x+1} + \gamma \max \Omega\ (n^{x+1},\varepsilon) - \Omega_t\ (x_t - \varepsilon_t) \qquad (1)$$

As provided in Equation 1, the vector Ω (nx+1,ε) serves as the state of the action values of pricing within a specified time (t), while the variables x serves as the reward values, γ the discounted factors, ε as the systems learning rate, εt detailing the time variance errors, and δx is the actionable state of the Equation. When the reward function and state transition probability are uncertain, the SARSA algorithm can iteratively determine the best action using the state-action value function [6]. Over time, it will converge to the optimal course of action and state-action value function with a high degree of certainty as long as the same state-action pair is repeatedly accessed. Since SARSA learns by taking cautious steps, its convergence may be relatively slow as expressed in Equation 2 below:

$$\Omega\ (n^{x+1},\varepsilon) = \Omega\ (n,\varepsilon) + \varepsilon\ \{\gamma + \gamma\Omega\ (n^{x+1},\varepsilon\} \qquad (2)$$

The Monte Carlo algorithm in the pricing model requires expertise to determine the optimal course of action; it does not necessitate full environmental knowledge. This expertise can be acquired online or through simulation techniques. The method calculates the frequency of state actions and future rewards in order to determine their values. It computes the average sample return using this technique based on the sample obtained, while noting down every state obtained, each with an average value of one [7]. The update rule for the value function is expressed as follows:

$$\Omega\ (m_t) = \Omega\ (m_{t+1}) + \varepsilon\ \{\gamma + \gamma\Omega\ (n^{x+1},\varepsilon\} \qquad (3)$$

As provided in this Equation, the reward values in the pricing model and time is established as a critical and fundamental parameter, a factor that is further compounded as:

$$x(n) = \text{Max}\sum_{\partial \in X}^{mt+1} xj \qquad (4)$$

$$x(n) = \text{Max}\sum_{\partial \in X}^{mt+1} xj\ \ (\varepsilon) \qquad (5)$$

The Monte Carlo method is particularly useful for repetitive tasks as sampling depends on the current strategy, which evaluates the benefits of recommended courses of action independently.

III. Methods

A. Proposed Machine Learning and Improved Algorithms for the Model

As provided herein, the proposed machine learning and improved algorithm in the optimization of e-commerce pricing models takes consideration of an amalgamation of varied techniques. Using machine learning techniques for dynamic pricing offers various advantages. First, due to their ability to handle large amounts of diverse data, businesses are able to collect and analyze a wide range of factors affecting pricing decisions [8]. These techniques play a critical role in identifying the element of appropriate pricing methods, client segments, and a prediction of the price ranges within a purchase period as frame worked in Figure 1.

As provided in Figure 1, the proposed model primarily encompasses the provided stages that play a critical role in determining the pricing approach and strategy. The first process primarily involves the collection of data within a provided online marketplace. This process considers an array of schemas that include the correspondences of pricing such as the market rates, product categories, purchasing amounts, and brands among other key factors.

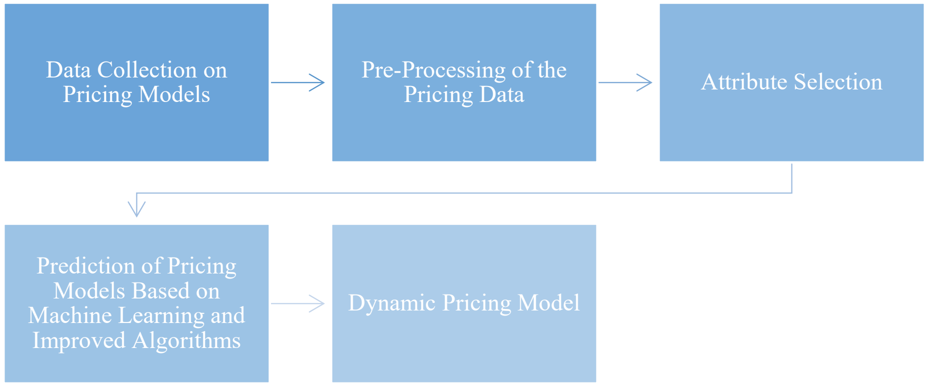

Figure 1: Processes Involved in Pricing

B. Pre-Processing of the Pricing Data

All the collected data collected on different pricing models is in this case analyzed for its relevance to the price forecast. Preprocessing is also necessary to create data sheets for the instruments needed for analysis. The inquiry utilized tools such as R, SAS, as well as Excel. Additional variables must be designed to provide more relevant data since the original data was provided is not continuous. These resulting variables include purchase by firm, buy by brand, buy by quantity, buy by category, buy by offer, and buy by channel. They were determined by totaling the purchase amount made by the client and dividing it accordingly based on offers, category, quantity, business, brand, and channel that were considered in their purchases [9]. After eliminating anomalies, the combined data underwent several analytical examinations. Selecting attributes to execute client segmentation involves considering repeat customers for the present analysis. Recurring pricing models for customers are analyzed based on their purchase quantity to detect commonalities among them and categorize similar consumer types. A clustering method is selected, detailing the need for attributes [10]. The use of a K-means clustering model and algorithm as detailed in Table I establishes the coefficient and the variations of the pricing models.

TABLE I CLUSTERS FORMED FROM THE PRICING DATA

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Frequency	2785	6468	89046	89760
Price by Offer	2.68	0.48	1.68	0.65
Pricing by Category	2.15	0.26	3.89	1.78
Pricing by Quality	2.87	0.86	3.68	1.98
Pricing by Channel	2.93	0.98	2.65	2.08
Pricing by Market Needs	2.87	1.38	2.16	2.86
Pricing by Demand	3.26	1.72	2.82	3.28

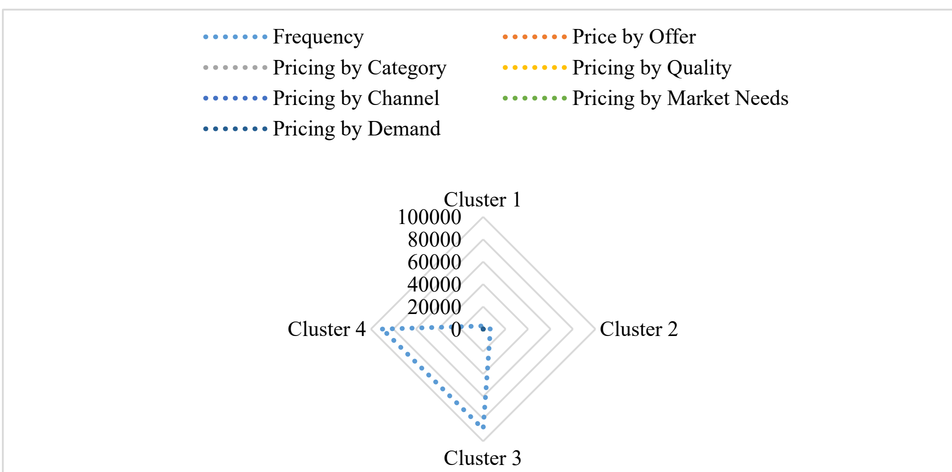

Figure 2: Clusters from Pricing Data

Figure 2 identifies the pricing categories form the basis for establishing dynamic price ranges for each segment. Dynamic pricing utilizes statistical and machine learning techniques to determine the appropriate price range for each segment.

IV. RESULTS

Supervised learning is more effective as it can achieve higher accuracy by utilizing past data. Having a distinct pricing range for each area will help draw attention to specific groups due to their unique characteristics. The regression equation developed for the cluster is as follows:

$$x_m (D_m, P_r) = \frac{xr,\beta 1-\delta 2}{\delta 1\,(\delta 2-\delta 1)} \tag{6}$$

$$\prod x = (D_m, P_r)\ [2 - \frac{xr-ym}{\delta 3-\delta 1}] \tag{7}$$

Given this, the variables and functions marked in the Equations above denote the pricing models established. For the convenience of this, an assumption is therefore made on the related costs of production through the determination of a constant [11]. To optimize the maximal price, a price response element and function denoted as r and m is in this case derived as provided below:

$$x_m = \frac{\mu 1}{3\mu 2}\, xr + \frac{\mu 1}{2\mu a2} xm \tag{8}$$

$$x_r = \frac{1}{2} xm + \frac{1}{2}(\gamma 2 - \gamma 1) + \frac{1}{2} x^t \tag{9}$$

As provided in the Equations above, the functions are typically used in the expression of the pricing model. Each cluster will have a unique price range, as the pricing for each group is determined by the customer's purchasing power. The buying power is recalculated each time a customer makes a repeat purchase, and then the customer is categorized into a specific cluster based on their spending patterns. Once categorized, customers are offered prices within their estimated range. Table II displays the results of variable-based regression to calculate buying power for each of the four groups. A decent overall variation among clusters was considered when estimating the price ranges. These models also help identify each buyer's specific price range.

TABLE II REGRESSION OUTCOMES OF THE OPTIMIZED PRICING MODEL FOR CLUSTERS

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4
C: Constant	0.0675	0.1670	0.0398	0.0867
Price by Offer	0.1685	0.2865	0.4863	0.0547
Pricing by Category	0.2564	0.3856	0.4876	0.0674
Pricing by Quality	0.3574	0.4890	0.5697	0.2684
Pricing by Channel	0.6584	0.6586	0.6583	0.6832
Pricing by Market Needs	0.0657	0.8653	0.6981	0.1673
Pricing by Demand	0.3685	0.9865	0.7632	1.9826
R-Square	0.4768	0.98	1.85	1.96
Pricing Model Range	\$600-\$1000	\$1200-1500	\$2500-\$3000	\$4500-\$5000

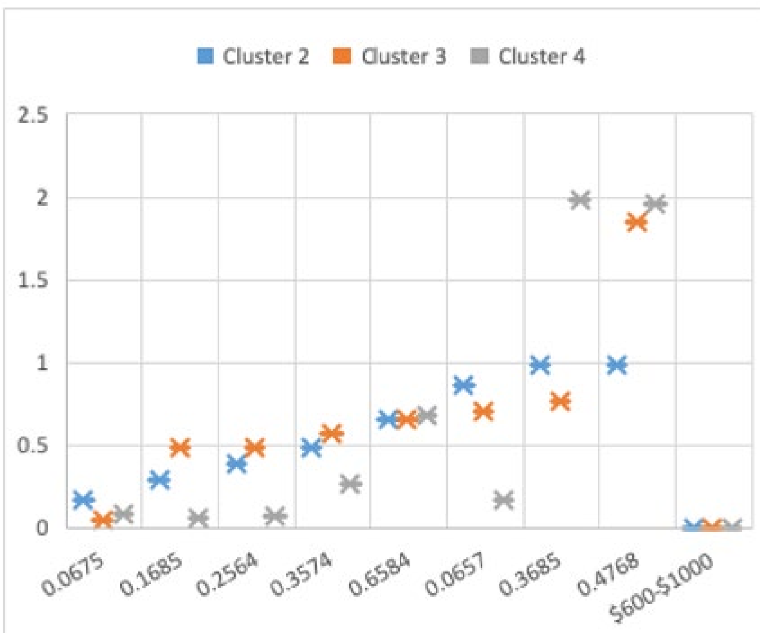

Figure 3: Regression Outcomes of the Price Models

At this stage, Table II provides an acceptable consumer group and an appropriate price range in mind, the dynamic pricing approach utilizes logistic regression to predict the likelihood of a customer purchasing the product. Using the previously provided framework as a foundation as detailed in Figure 3, employing a binary predictor is ideal for determining the customer's final purchasing behavior [12]. The dataset was utilized to generate outcomes through multiple regression logistic regression focused on both purchasing power and in price prediction.

V. CONCLUSION

As found in this article, e-commerce pricing models are key consideration for making purchases on the internet. Dynamic e-commerce pricing models, often used by online companies to boost sales and profitability, can greatly benefit them within the consumer market. This study aims to develop machine learning and improved algorithms that will help e-commerce platforms offer the right pricing models to customers. It focuses on companies with inventory leads but could also be useful for stockless online marketplaces. As provided herein, the proposed machine learning and improved algorithm in the optimization of e-commerce pricing models takes consideration of an amalgamation of varied techniques. Using machine learning techniques for dynamic pricing offers various advantages. First, due to their ability to handle large amounts of diverse data, businesses are able to collect and analyze a wide range of factors affecting pricing decisions.

REFERENCES

[1] M. Sarkar et al, "Optimizing E-Commerce Profits: A Comprehensive Machine Learning Framework for Dynamic Pricing and Predicting Online Purchases," Journal of Computer Science and Technology Studies, vol. 5, no. 4, pp. 186–193, Dec. 2023, doi:https://doi.org/10.32996/jcsts.2023.5.4.19.

[2] Yerragudipadu Subbarayudu, G. Vijendar Reddy, K. Raj, K. Uday, M.D. Fasiuddin, and P. Vishal, "An efficient novel approach to E-commerce retail price optimization through machine learning," vol. 391, pp. 01104, Jan. 2023, doi:https://doi.org/10.1051/e3sconf/202339101104.

[3] C. Yin and J. Han, "Dynamic Pricing Model of E-Commerce Platforms Based on Deep Reinforcement Learning," Computer Modeling in Engineering & Sciences, vol. 127, no. 1, pp. 291–307, 2021, doi:https://doi.org/10.32604/cmes.2021.014347.

[4] J. Bauer and D. Jannach, "Optimal pricing in e-commerce based on sparse and noisy data," Decision Support Systems, vol. 106, pp. 53–63, Feb. 2018, doi: https://doi.org/10.1016/j.dss.2017.12.002.

[5] R. Gupta and C. Pathak, "A Machine Learning Framework for Predicting Purchase by Online Customers based on Dynamic Pricing," Procedia Computer Science, vol. 36, pp. 599–605, Jan. 2014, doi:https://doi.org/10.1016/j.procs.2014.09.060.

[6] J. Nanduri, Y. Jia, A. Oka, J. Beaver, and Y.-W. Liu, "Microsoft Uses Machine Learning and Optimization to Reduce E-Commerce Fraud," INFORMS Journal on Applied Analytics, vol. 50, no. 1, pp. 64–79, Jan. 2020, doi: https://doi.org/10.1287/inte.2019.1017.

[7] M. Zaghloul, S. Barakat, and A. Rezk, "Predicting E-commerce customer satisfaction: Traditional machine learning vs. deep learning approaches," Journal of Retailing and Consumer Services, vol. 79, p. 103865, Jul. 2024.

[8] L. Nguyen et al. "E-commerce Price Suggestion Algorithm - A Machine Learning Application," 2022. Accessed: May 15, 2024. [Online]. Available: https://ieomsociety.org/proceedings/2022india/609.pdf

[9] D. T. Tran and J.-H. Huh, "New machine learning model based on the time factor for e-commerce recommendation systems," The Journal of Supercomputing, Nov. 2022, doi: https://doi.org/10.1007/s11227-022-04909-2.

[10] Q. Zhao, Y. Zhang, D. Friedman, and F. Tan, "E-commerce Recommendation with Personalized Promotion," Proceedings of the 9th ACM Conference on Recommender Systems - RecSys '15, 2015, doi: https://doi.org/10.1145/2792838.2800178.

[11] A. Ali Salamai, A. Abdulrahman Ageeli, and E.-S. M. El-kenawy, "Forecasting E-Commerce Adoption Based on Bidirectional Recurrent Neural Networks," Computers, Materials & Continua, vol. 70, no. 3, pp. 5091–5106, 2022, doi: https://doi.org/10.32604/cmc.2022.021268.

[12] M. T. Ballestar, P. Grau-Carles, and J. Sainz, "Predicting customer quality in e-commerce social networks: a machine learning approach," Review of Managerial Science, vol. 13, no. 3, pp. 589–603, Dec. 2018, doi: https://doi.org/10.1007/s11846-018-0316-x.