Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 30s (2025)
https://www.jneonatalsurg.com
OPEN ACCESS

Dynamic Pricing Predicting For Online Customers Using Machine Learning

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.Cite this paper as: A.V.Vamshi Krishna, Dr. Kandakatla Mahesh, (2025) Dynamic Pricing Predicting For Online Customers Using Machine Learning. *Journal of Neonatal Surgery*, 14 (30s), 465-471.

ABSTRACT

The goal of dynamic pricing, which is common in the business, is to maximise a company's long-term profitability by continuously adjusting the prices of its products and services. It functions adequately in an environment where pricing can be changed often, like online shopping.Understanding the connection between price and market reaction is crucial to dynamic pricing, which primarily aims to optimise prices.In this research, we use Improved XGBoost methods based on machine learning to solve the dynamic pricing problem. Classification and regression are handled by this supervised machine-learning approach. The true worth of algorithms for machine learning lies in their ability to be applied to new situations through trial and error. Using a dataset of online sales history data and statistical estimating approaches, we test how well the suggested strategy performs. Based on the results of the experiments, we can conclude that the proposed model and algorithms are suitable for dealing with the dynamic pricing problem, and that they give higher prediction performance.

Keywords: *Machine Learning; Dynamic Pricing, Predictive Modelling, Consumer Behavior.*

1. INTRODUCTION

Dynamic pricing, also known as rate optimisation, allows businesses to charge customers only for the things that they actually want. Competitor prices, supply, call and conversion fees, and revenue objectives are the main factors that most individuals use to decide the commodity's pricing [1]. Dynamic pricing, sales control, and role-level compensation difference were all terms used to describe the practice. Changing the prices that are directly related to the buyer's decision is yet another way to implement dynamic pricing. Another definition of dynamic pricing is the practice of charging different consumers varying rates for the same in-stock products based on their specific product preferences. A product's price is determined by the current market circumstances within the context of a commercial transaction; this practice is also known as real-time pricing. The phrase captures the essence of pleasure shopping as a whole, including the atmosphere of competition, the time of day, and how certain vendors adjust their prices according on the weather.

Retail, automobile, cellphone word of mouth, electricity, airline, and many more businesses use dynamic pricing. The retail business is seeing expansion due to improved access to client demand records, new technology that analyses customer habits to decide charges more efficiently, and decision-support tools for the next generation.

Reasons for this impact in the cellular network domain include rising levels of competition, falling naming fees, and the critical nature of the underlying network architecture. on addition, the influence on the car industry is a direct outcome of the synergy between various manufacturing techniques and stock selection, which results in a consumer-ready business prototype. Since the inception of centralised network connections, this novel concept of dynamic pricing has been in the spotlight [2]. In addition to integrating customer data into a comprehensive database, it assisted suppliers and customers in lowering menu pricing per item. Because of the rise of the Internet, customers may now seem like self-contained conveniences, and people also have more free time.

This notion of dynamic pricing, which incorporates online integration and automation using various ways, also benefits the vendors. Without the vendor's physical presence, registration costs are reduced, customer information is consolidated under one database, and the cost of publishing new catalogues is reduced. Furthermore, it is now more of a two-way street where buyers and sellers may communicate, rather than a closed system where reviews are only read and ignored. There are certain situations in which dynamic pricing as a service could be useful:

• Various prices.

• Availability on the market is not uniform.

In this scenario, distribution and controlling capital have less room for arbitrage, the rules are fair, and customers are willing to pay a premium for a higher quality product.

It can also be executed in sectors with low variable costs and high constant costs.

Changing product prices in response to market competition is a simple way to implement dynamic pricing. In a similar vein, expenses go down when call volumes are low and up when they are high. As a result, it's useful for setting fees and maximising the seller's profit. Technically speaking, another approach to dynamic pricing is the use of short-term cycles, namely temporary and permanent reductions. If a sale offers a certain price for a limited time but then goes back to its regular price the next day, we say that it is a temporary discount. A perpetual discount allows for a product's price to be lower than its present price in the future.

Due to its ability to streamline transactions, dynamic pricing has also grown in prominence across a variety of global businesses. The impact of dynamic pricing has been observed in several industries, including transportation, utilities, retail, online retail, cellular phone systems, sports, vehicle rental, and insurance, among many others. The list goes on and on. Electronic marketing, electronic procurement, electronic logistics, supply chain management, and business-to-business exchange structures have all made use of joint auctions, which are a component of dynamic pricing [4].

In the context of yield management and revenue control, the airline's dynamic pricing software was investigated. As part of this process, we divided vacationers and travellers into three groups: regulars, occasionals, and hybrids. Dynamic pricing is also employed in the automotive industry to simplify production scheduling and inventory choices, which leads to improved supply chain control and greater total revenue outcomes. Consumers benefit from faster and easier access to products and the manufacturer's reputation rises thanks to dynamic pricing.

In order to observe the methods for dynamic pricing that are wanted, many methodologies should be applied. Using surveys or comments is the easiest and most usual way. A price suggestion function that approximate the wage/income ratio and consumers' willingness to pay was used to apply the two ways mentioned above. To find out first pricing tactics, there are other choices, such experimental auctions. The phasing approach is also influenced by the market type (mass or speciality). Skimming and penetration pricing are needed for each market.

Maximum usage pricing, segment pricing, uptime pricing, time of purchase pricing, and variation pricing are the five pricing methodologies that have been established to measure dynamic pricing. In differential pricing, the rate of a commodity is adjusted in response to the customer's willingness to pay. As a result, airlines and railways increasingly utilise high user charges, which customers are subject to during or close to peak hours. Setting extra for insufficient providers or for fixed transit times is the goal of provider time pricing. If the departure time of the flight is shorter when you make the ticket, the purchase price will be applied. Lastly, when there is an excessive amount of market uncertainty over a product, state pricing modifications take place.

2. EXISTING MODELS

These days, dynamic pricing is determined using a plethora of methods. Some had general purpose and applied to all product prices, while others were more targeted. The specific methods [5] that are available and the fees associated with them are as follows.

Agent-based modelling A method for analysing the expenses of a job or group using different calculation methodologies and tactics, agent-based modelling incorporates agents, suppliers, and policies. Stock grading and customer assistance are the foundation of the inventory-based algorithm. Another way to classify inventory is by replenishment vs. non-replenishment. The former entails making salary decisions based on a set stock at a given moment, while the latter includes gradually restocking according on demand and supply. In the second part, we have dependent and independent calls, which show how the demands of our customers change over time. Thirdly, the client is both strategically and myopic. Myopic consumers can make purchases when the price is lower than their value, and there's a smart purchase present that keeps the fortune fee lookin' good [6].

Data driven modeling

The pricing strategy of a data-driven model is based on insights about consumer tastes and habits. Several merchants compete for the business of an unmarried buyer in this game theory scenario, which incorporates economic principles. Using online marketplaces to target certain consumer options, patterns, and algorithms for revenue generation is a part of the machine learning paradigm. All iterations of the selection are compatible with the simulation model. Aside from that, any other specific style can be utilised as a template for copying [7].

For dynamic pricing to work in an auction-based approach, there are six essential components. There are four parts to the tender process: the first is the method of making the tender, the second is a clearly defined market structure between buyers and sellers, the third is the preferred form for the seller's product choice, and the fourth is the flexible bidding form. Market clearing, the process of matching supply and calls, is the sixth resource need. Statistical feedback signals are used to adjust the bid and reshape the bid pattern in accordance with the proposal [8].

With so many styles to choose from, it became impossible to combine the outcomes of several iterations, opening the door for dynamic pricing to tackle the issue of consumer behaviour from every angle. Consequently, we investigate potential framework developments that can forecast the greatest conceivable purchasing diversity while keeping dynamic pricing as the central issue. Choose the most suitable buyer persona. Environmentally friendly outcomes are anticipated from the framework [9].

The figure below shows the fundamental Dynamic pricing for online clients.

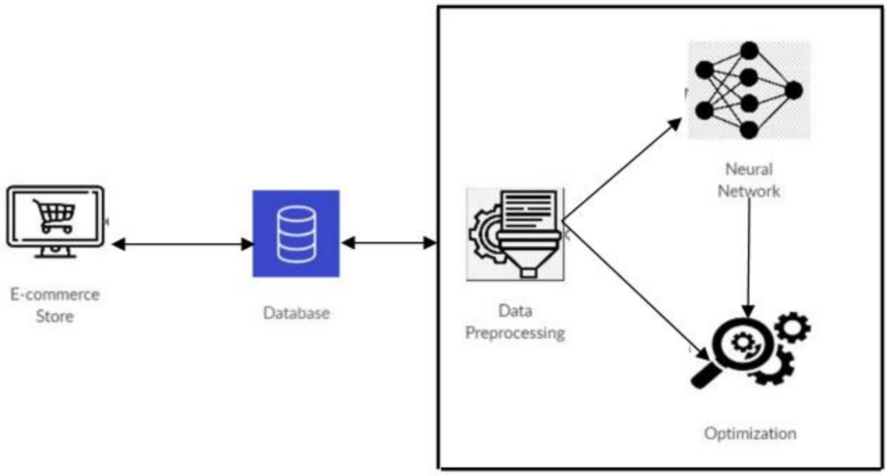

Fig.1 Basic structure for Dynamic pricing on e-commerce

3. PROPOSED MODEL

Three approaches are used in the proposed model: understanding the client, setting fair prices, and predicting the customer's probable investment within that range. In Figure 2, you can see the framework.

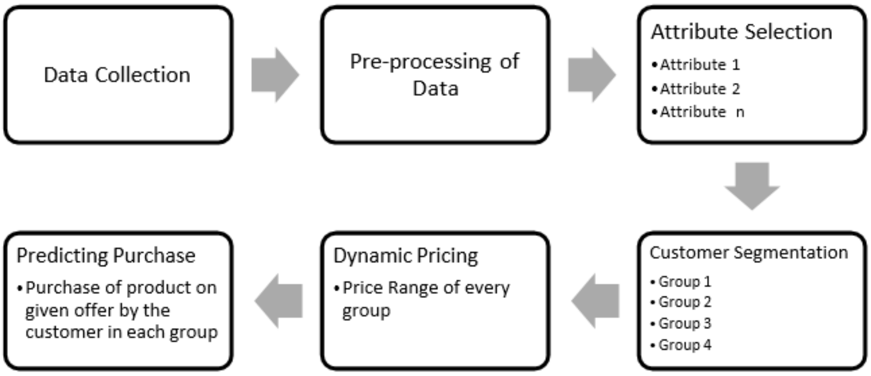

Figure 2 shows the suggested architecture for online client purchase prediction using dynamic pricing. The following procedures for ascertaining the pricing system and investing behaviour of online clients were included in the offered model:

a) Data Collection

This is the first and foremost stage of the framework. Collecting information from many sources and storing it in an appropriate database is essential. In order to conduct our research, we selected a portion of the internet market. Two datasets are described in the table below.

Table 1.datasets using a part of a data schema from an online marketplace

Customer ID	Store Chain	Store Department	Product Category	Product Company	Product Brand	Purchase Date	Product Size	Product Measure	Purchase Quantity	Purchase Amount

Offer ID	Product Category	Product Quantity	Product Company	Offer/price Value	Product Brand

A user's whole transaction history is stored in the first schema, which is a database representing transactions. On the other hand, Schema 2 is associated with an offer database that assigns a certain supplier type to each product, beauty, or discount. A marketing approach based on requirements. The transactional database provided clear information for the majority of the variables used to represent the identifying target audience, which included customer, chain, department, beauty, agency, mark, length, and length. Both the frequency and amount of purchases are seen to be continually fluctuating. The most serious bid in the bid database also included a set price and amount of merchandise, but other bids were more detailed. In a database that included about 2.4 million confirmed users, there were 350 million transactions. Those clients who were able to take advantage of the deals the most quickly and easily were considered in the deal. Consequently, we have a history of offering a wide range of rates to cater to different types of clients, organisations, and logos when it comes to acquiring items.

b) Pre-Processing

This part involves preprocessing all of the acquired statistics in a methodical way based on how important they are to the price prediction. In order to create statistics tables for individual assessment tools, preprocessing is also required. This is done with the use of R, SAS, and Excel. Because records didn't have to be stored constantly, additional variables could be created to capture more important data. Purchasing on a price (POR), category (PCT), quantity (PQT), organisation (PCY), brand (PBD), and channel (PBD) basis are the derived variables. Buy from (PCN). To get them, we tally up all the things a client has bought and then divide that amount by the number of presents they have ordered broken down by product, class, quantity, organisation, brand, and channel. Data was prepared for the several analytical tests by removing outliers and rolling up the remaining data.

c) Attribute Selection

User segmentation is carried out with the use of attributes that need to be determined upon in this step. The new buyer's demographic profile, buying history, purchasing objectives, context, and characteristics should be employed as a multitude of qualities derived from chosen data. But previous research has accounted for the fact that the most loyal consumers always seem to have a plan B. For returning clients, the most important metrics are POR, PCT, PQT, PCN, and QUANTITY PURCHASED. The purpose of these attributes is to categorise users according to their shared characteristics.

d) Customer Grouping

The only criterion for customer classification is the mutually agreed upon credentials. For the purpose of depicting user similarities, K-means clustering policies are employed. Table 2 and Figure 3 show that the institution developed clusters. The basic model accounts for the majority of the facts with an 83% coefficient. Table 2. Segmenting customers with K-means clustering

Variables	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Frequency	4688	132307	86255	18129
RMS-SD	1.43	0.48	0.65	0.92
Variable 1 - POR	1.34	0.13	0.35	0.92
Variable 2 - PCT	1.45	0.21	0.35	0.76
Variable 3 - PQT	1.78	0.14	2.89	1.34
Variable 4 - PCY	1.88	0.25	0.35	1.12
Variable 5 - PBD	1.92	0.19	0.35	2.14
Variable 6 - PCN	2.19	0.12	0.13	0.43

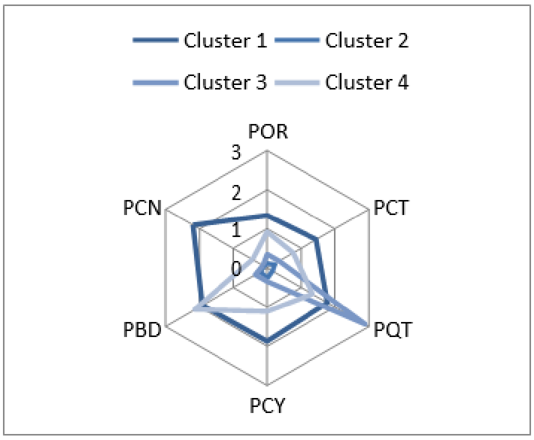

Figure.3 Clusters formed for the various customers

e) Dynamic Pricing

Based on the various client categories, a dynamic pricing range is determined for each stage. The correct price range for each section is determined using machine learning and statistical methods in dynamic pricing. Because more precise results may be obtained from past data, controlled information is a more efficient way to get it. By setting separate price points for each category, you can better cater to their unique needs. Here is the cluster regression equation:

$$P_i = \beta_0 + \beta_1 POR_i + \beta_2 PCT_i + \beta_3 PQT_i + \beta_4 PCY_i + \beta_5 PBD_i + \beta_6 PCN_i$$

Pi, i. is the cluster salary, whereas the Hs are the neutral variables and slope coefficients for each cluster of men or women. Each cluster may be distinguished by a unique pricing range, which is determined by the purchasing power of the consumer. A customer's spending and purchasing habits are used to group their electrical purchases into a certain cluster when they make recurrent purchases from the shop. The consumer is shown the recommended pricing, which is likely to vary depending on the cluster. Table 2 displays the outcomes of the regression analysis for the four groups defined by the variables pertaining to the purchase of energy. To account for the range of earned salaries, the cluster-specific variable is decent enough. And it is from these styles that we derive the salary range of our unique clients.

f) Predictive Modeling

This step involved applying dynamic methods with the Improved XGBoost algorithm to forecast, given a suitable client group and pricing range. Extreme gradient boosting is abbreviated as XGBoost. In many ways, it's like gradient enhancing machines, except it's quicker and more accurate. Having said that, the model is strict about using only numerical variables and requires a matrix format for input. To use XGBoost's dynamic pricing in online stores, one must use the algorithm to forecast the best prices depending on a number of criteria. The term "dynamic pricing" refers to a method of optimising income by making real-time adjustments to prices based on variables like demand and competition. XGBoost may help you determine if a consumer is likely to buy your product and how much to charge for it. Here's a general explanation on how to utilise it. In light of the aforementioned framework, a binary predictor is a good fit as it aids in determining the customer's ultimate purchasing behaviour. With the use of multiple regression, the data set was used to compute the outcomes for the suggested strategy that is based on purchasing power and price prediction. A train set and a test set were created from the whole dataset in a ratio of 4:1. Figure 4 shows the region beneath the curve.

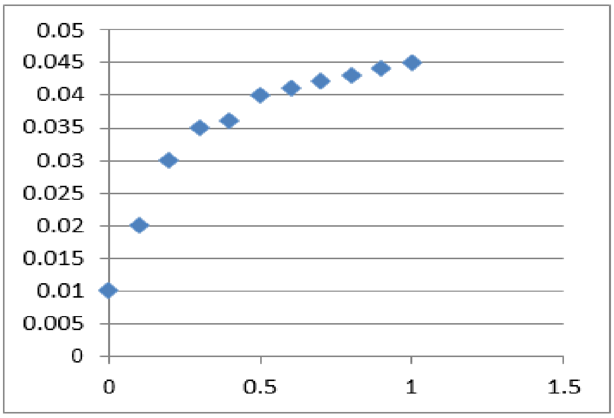

Figure.4 ROC curve for Improved XGBoost classifier

Model Training with XGBoost:

• Train a regression model with the help of the XGBoost algorithm. Regression problems are well-suited to XGBoost, and it is capable of handling complicated data connections.

Assign the product's price as the dependent variable and its attributes as the independent variables that should be considered while setting the price.

Validation:

Use a different validation set to see how well the suggested model works. The model's ability to generalize to previously unknown data is enhanced by this set.

4. RESULT

In order to forecast purchases and the potential income gains, the framework created for price prediction is examined. Our suggested model identified a more effective revenue generating method with less mistakes in forecasting client purchases for the same product given at a fixed price for a certain set of consumers. In Figure 5, you can see the outcomes. The aforementioned model is capable of accurately forecasting the buyer's actions. Supervised learning will assist find the right answers for consumer behaviour as time goes on and more data is collected, and it will give more accurate findings.

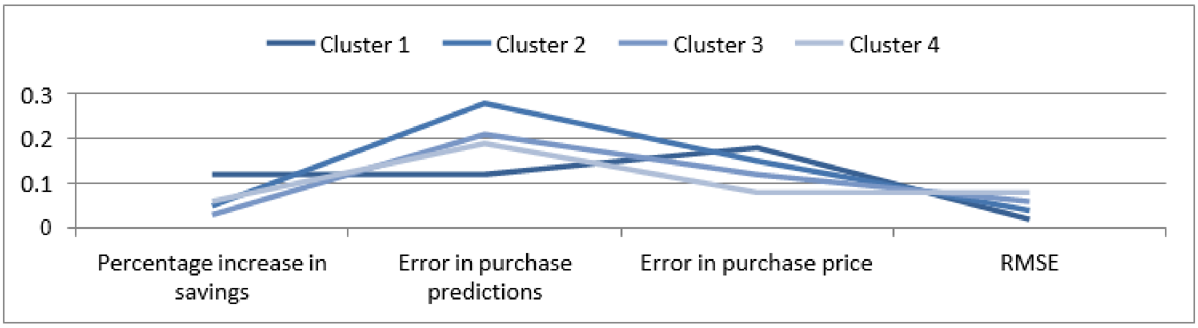

Fig.5Analysis of the results obtained from the analysis

Price optimization logic

The Xgboost regressor has provided us with the anticipated costs for every client. This will serve as the starting point for the pricing. Using aggregated data from many clients based on day, time, etc., the model may often be adjusted periodically or in batches in a production setting.

5. CONCLUSION

To anticipate an online shopper's buying behaviour by suggesting a suitable price range based on Dynamic Pricing, the suggested framework has been developed utilising the potent tools of Machine Learning, Data Mining, and Statistical Methods. This study presents the XGBoost model, which has been evaluated on a sizable dataset for an e-commerce company. The outcomes are encouraging enough to warrant a comprehensive implementation of the framework. A more accurate pricing range that works for the business and its customers is being established, and the mistake rate is going down. Adapting the fundamental structure to unique needs opens it up to use in a wide range of online-based enterprises. It is probable that the outcomes of the ongoing work will be addressed in the subsequent section of this research.

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