Pricing Strategy Optimization by Machine Learning in E-commerce

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Abstract

This paper introduces the concept of pricing strategy and its importance in e-commerce, analyzes the limitations of traditional pricing methods. Subsequently, the article elaborates on the application of machine learning in E-commerce pricing strategies. In addition, the article also presents the key technologies for optimizing pricing strategies using machine learning. Finally, it looks forward to the development trend of future pricing systems.

CCS Concepts

• **Applied computing** → Operation research; Decision analysis.

Keywords

Machine learning, E-commerce, Pricing strategy

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1 Introduction

Pricing strategy is an important part of enterprise market competition, especially in the field of e-commerce. As market competition is becoming more and more fierce and consumers have more and more diverse choices, reasonable pricing strategy is crucial to enterprise profit and market share. Traditional pricing methods often rely too much on static data, and it is difficult to fully consider changes in market demand and fluctuations in consumer preferences. Therefore, exploring new pricing methods has become an important topic for e-commerce enterprises.

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2 THEORETICAL FRAMEWORK OF PRICING STRATEGIES

2.1 Conceptual Foundations

The determinants affecting product pricing can be grouped into five key categories: Macro-environmental factors, Consumer characteristics, Product features, Demand dynamics, and Supply conditions. Macro-environmental factors encompass the broader economic conditions within a nation or geographic area. A nation's economic development phase, growth trajectory, and prosperity levels collectively shape consumers' purchasing capabilities. These economic conditions subsequently affect how customers perceive and evaluate product pricing. Consumer characteristics focus on individual buyers' psychological profiles and behavioral patterns, including their price sensitivity, brand preferences, and willingness to pay for specific product benefits. Segmented dimensional characteristics reveal how variables like corporate market positioning and fiscal health shape purchasing behaviors and negotiation leverage. Product-related attributes focus on tangible elements such as material composition and performance standards. Demand-related factors address prerequisites tied to procurement needs, including fulfillment timelines, geographic requirements, and order volumes. Supply-chain considerations encompass vendor operational parameters like geographic distribution of suppliers, logistics configurations, and inventory availability. As illustrated in Table 1, comparative analysis of domestic and global pricing research across these dimensions demonstrates their critical interplay, with each factor playing a pivotal role in shaping contemporary pricing frameworks.[1]

Pricing strategy encompasses the development of value determination frameworks and associated guidelines by businesses operating in competitive markets, aiming to achieve financial gains, expand market presence, and appeal to target consumers. Effective price-setting methodologies enable organizations to optimize revenue streams while strengthening their market position. Within E-commerce ecosystems, strategic pricing becomes particularly critical given the intense competitive landscape, diversified consumer alternatives, and heightened price awareness among buyers, making proper pricing mechanisms essential for sustaining online business viability.[2]

2.2 Conventional Pricing Paradigms

2.2.1 Cost-plus Pricing. Cost-plus pricing is the traditional pricing method, which adds the expected profit margin to the production cost of a product or service and sets it as the final selling price. Costs include fixed costs and variable costs. Fixed costs include

Table 1: Five Dimensions influencing product prices at home and abroad

Dimensions	Specific Features
Macro-environmental factors	National macro policies, Monetary policies
	Climate, Time
	Holiday timing
	Currency supply, Exchange rates, etc
	Market structure
Consumer characteristics	Consumer market segmentation, Channel pricing, Location-based pricing
	Consumer segmentation
	Gender, Age, Shopping experience, Geographical distance
Product features	Chain brands, Star ratings
	Product style, Image-based pricing
	Quality grades, Production costs
	Suppliers
	Product costs
Demand dynamics	Demand volume
	Delivery time
Supply conditions	Region
	Supply volume

equipment depreciation, labor costs, etc., and variable costs include raw material costs, transportation costs, etc. The advantage of cost-plus pricing is that it is simple to understand, easy to operate, and can cover costs and ensure profits. The disadvantage is that it does not consider market demand and consumer price sensitivity, which is easy to lead to too high or too low pricing in a competitive market environment.

2.2.2 Demand-based Pricing. Demand-based pricing method refers to setting prices according to market demand and consumers' willingness to pay, and advocates determining price levels according to consumers' demand elasticity, as shown in Table 1. Products with high price elasticity usually need to be set at a lower price to attract consumers, while products with low price elasticity can be set at a higher price. By subdividing the market and formulating different price strategies, the needs of different consumer groups can be met. The advantages of Demand-based pricing are that it can maximize demand and sales, increase market share, adapt to market changes, and flexibly respond to consumer demand fluctuations. The disadvantage is that it requires a large number of market research and consumer behavior analysis, the operation is more complicated, the needs of different consumer groups are quite different, and it is difficult to meet the needs of all people.

2.2.3 Competition-oriented Pricing. Competition-oriented pricing refers to setting prices according to the pricing level of peers or competitors, which mostly appears in the competitive market. Enterprises adjust prices by analyzing the price positioning of competitors. The advantage of competition-oriented pricing method is to analyze the competitive environment, formulate reasonable pricing and avoid price imbalance, which can effectively fight the price war and improve the market competitiveness. The disadvantage is over-reliance on competitors' pricing, which may lack innovation, and price adjustment may be necessary for competitors with too low prices, resulting in loss of profits.

2.3 Limitations of Conventional Approaches

Traditional pricing methods often rely too much on static data, such as costs, competitor pricing, etc., and it is difficult to fully consider changes in market demand, fluctuations in consumer preferences, and external factors. These pricing methods mainly rely on the overall market and consumer groups to price, do not fully consider the specific needs and payment willingness of individual consumers, and ignore the personalized needs of customers. While Demand-based pricing takes into account market demand, it relies too heavily on price elasticity or market segmentation to accurately reflect the complexity of consumers in actual purchasing decisions. Consumer price sensitivity is influenced by a variety of factors, including brand perception, purchase history, product quality, marketing, and more. Competition-oriented pricing can effectively deal with the competitive pressure, but in the highly differentiated market and diversified commodity environment, it is difficult to customize the best pricing strategy for each product or service. Blindly imitating competitors will lead to a lack of unique market positioning, which will affect long-term profitability. In addition, the traditional pricing method relies on manual calculation and long-term strategic adjustment, and the flexibility is relatively poor. In e-commerce, pricing needs to be adjusted in a timely manner based on real-time market data and consumer behavior, which is a challenge to traditional pricing methods.[3]

3 MACHINE LEARNING IMPLEMENTATION FRAMEWORK

Machine learning, a component of artificial intelligence, automatically learns from experience through data analysis and makes predictions and decisions without explicit programming. With the continuous increase in computing power and data volume, machine learning is gradually being applied to the optimization of e-commerce strategies. By analyzing vast amounts of historical transaction data and market behaviors, machine learning can predict consumer demand, adjust pricing strategies, optimize profits, and enhance market competitiveness.

3.1 Machine Learning in Price Prediction

Machine learning can learn consumers' purchasing behavior from historical sales data and predict demand changes at different price points. For example, regression analysis can predict product demand based on historical prices, seasonal fluctuations, holiday promotions and other factors to help merchants develop the most appropriate price strategy. The machine model can adjust the price in real time according to different market conditions, such as promotion activities, inventory status, etc., to ensure that the price matches the demand. Dynamic pricing is a strategy to adjust prices based on market demand, competitive environment and consumer behavior. Machine learning is well suited to dynamic pricing, which optimizes the implementation of pricing decisions through continuous learning and adjustment. For example, based on consumer behavior data, machine learning models can predict fluctuations in demand for products and adjust prices in time to respond to market changes.[4]

3.2 Machine Learning in Competitive Pricing

In the competitive market environment, enterprises need to pay attention to the pricing strategy of competitors. Machine learning can model the competitive environment and analyze the impact of different pricing strategies on market share. For example, using game theory models and reinforcement learning algorithms, one can simulate the pricing behavior of competitors and optimize one's own pricing strategy based on the simulation results. The price war is caused by competitors' price reduction. Machine learning can help enterprises respond quickly in the price war. Through reinforcement learning, the system can automatically adjust the price according to market data in real time, so as to ensure profits in the highly competitive environment.

3.3 Personalized Pricing and Consumer Behavior Prediction

Machine learning can finely segment consumers and predict how they will respond to prices based on the characteristics of different customer groups. For example, through unsupervised learning, customers can be divided into different groups such as high-price sensitive, loyal and price-insensitive, and personalized pricing strategies can be customized for each group. Personalized pricing refers to building a personalized pricing model through machine learning algorithms based on each customer's behavioral data, including purchase history, browsing history, social media interactions, and more. For example, the recommendation system algorithm is used to analyze customer preferences and provide customized value to customers based on these data. This personalized pricing can maximize customer needs and ensure the profit of merchants.[5]

4 TECHNICAL IMPLEMENTATION CONSIDERATIONS

4.1 Data Collection and Prepocessing

Data collection is fundamental for building machine learning models. Pricing strategy optimization models require extensive historical transaction data, customer behavior data, market trend data, competitor pricing data, and more. The variety and quality of this data directly impact the pricing model. Once raw data is collected, preprocessing is essential, which involves cleaning, organizing, and transforming the data. Missing values are addressed through imputation, deletion, or alternative data completion methods. Outliers or noisy data are identified and removed to ensure accurate model training. Data of differing scales is transformed to ensure they are on the same dimension, preventing biases in model training.

4.1.1 The Diversity of Data and its Impact on the Pricing Model. 1. Covering different time periods

Long-term data collection is to build a long-term data collection plan to obtain market data in different economic cycles, seasonal changes and other stages. High-frequency data collection: for markets with frequent price fluctuations, such as commodity markets, commodity prices and transaction data per minute or even per second. This can accurately reflect the instantaneous changes in prices and capture the short-term price behavior patterns of the market. The pricing model can learn the evolution of market prices over time, such as in the real estate market, through long-term data, we can find the different trends of house prices in the economic boom and recession, so as to provide trend guidance for pricing. It helps the model to identify and adapt to seasonal price fluctuations, such as the tourism industry. The price difference between the peak season and the off-season is obvious. The model uses seasonal data to accurately predict reasonable prices in different periods.

2. Covering different consumer groups

Market segmentation research is through questionnaires and other methods, consumer groups are subdivided based on age, gender, region, income, consumption habits and other dimensions. User portrait construction is using big data technology to integrate user behavior data on multiple platforms to build a detailed user portrait. For example, the E-commerce platform accurately depicts the characteristics of different consumer groups by analyzing users ' browsing, purchasing, commenting and other behaviors, and provides data support for different groups to customize price strategies. The pricing model can formulate differentiated prices based on the price sensitivity of different consumer groups. For example, high-end cosmetics brands set higher prices for high-income, quality-seeking consumer groups, and introduce more cost-effective product lines for price-sensitive young consumers and set corresponding prices. Help enterprises to find new market opportunities and expand market share by meeting the price needs of different consumer groups. For example, some affordable fashion brands have opened up young markets by launching low-cost and stylish products for student groups.

3. Covering different scenarios

Scenario analysis and data collection is in-depth analysis of the application scenarios of products or services, such as mobile applications, collecting user usage data and feedback on prices for different scenarios such as social, office, and games. Data are obtained through user behavior monitoring and in-application investigation. Simulation and experiment is in the laboratory or simulation environment, simulate different scenarios and observe the user 's response to the price. Enable the pricing model to set prices based on user needs and value perceptions in different scenarios. For example, in different scenarios such as airports and shopping malls, the pricing of shared charging treasures is also different due to the different urgency of user needs. Ensure that the price matches the value obtained by the user in a specific scenario, and improve user satisfaction and product competitiveness.

4.1.2 Data Quality Control and its Impact on the Pricing Model. 1. Abnormal value processing

Based on machine learning algorithms, such as the Isolation Forest algorithm, the algorithm isolates data points by randomly selecting features and segmentation points to identify outliers. The identified outliers can be corrected according to the distribution of adjacent normal data points.

Outliers may be caused by data entry errors, measurement errors or extreme events. If not handled, it will seriously distort the parameter estimation of the pricing model. After removing or correcting outliers, the model can more accurately reflect the true distribution of data and improve the accuracy of price forecasting. It prevents outliers from having an excessive impact on the model, making the pricing model more robust in the face of new data, and will not give unreasonable price forecasts due to individual abnormal data.

2. Missing value filling

Machine learning models, such as decision trees and neural networks, are used to predict missing values based on other complete features. For example, in the customer credit evaluation data, for the missing income data, the customer 's age, occupation, education level and other characteristics can be used to construct a model to predict the filling.

Filling missing values enables the pricing model to use complete data for training, avoiding information loss due to data loss, thereby improving the accuracy of the model. The existence of missing values may lead to unstable model training. After filling in missing values, the model performs more stably on different data sets, which enhances the reliability of the pricing model.

3. Data standardization

The commonly used methods are the Min-Max Normalization, which maps the data to the [0, 1] interval, and the Z-score Normalization, which makes the data mean value 0 and the standard deviation 1. When using optimization algorithms such as gradient descent to train the pricing model, the standardized data can make the model converge faster and improve the training efficiency. Ensure that different features are compared at the same scale to avoid over-sensitivity of the model to certain features due to different feature dimensions, thereby improving the accuracy of the pricing model.[6]

4.2 The diversity of Data Sources and Processing Techniques

The performance of machine learning models is closely related to the diversity of data. In the optimization of pricing strategies, common data sources include transaction data, user behavior data, market data, and competitor data. Among them, transaction data encompasses information such as products, prices, sales volumes, and purchase times. User behavior data includes users' browsing records, click behaviors, shopping cart information, and reviews. Market data involves external influences like industry trends, seasonal fluctuations, and macroeconomic factors. Competitor data includes price changes, promotional activities, and product updates. Through the integration and analysis of these diverse data sources, machine learning models can comprehensively understand market demands and consumer behaviors, thus providing more accurate information for pricing decisions.[7][9]

4.3 Feature Selection and Extraction

Feature selection is the process of selecting the most representative feature subset that is most relevant to the target variable from the original feature set. This process helps to reduce the complexity of the model, improve the generalization ability of the model, and may improve the prediction performance. Feature extraction is the process of converting the original features into new and more expressive features through some transformation or combination. Feature extraction helps to capture the complex relationship between original features and may reveal hidden data structures.

4.3.1 Method Based on Statistical Test. 1. Correlation analysis

By calculating the correlation coefficient between the feature and the target variable (price), the strength and direction of the linear relationship between them are measured. The commonly used correlation coefficients are Pearson correlation coefficient (for continuous variables) and Spearman correlation. coefficient (for ordinal variables or continuous variables that do not satisfy the normal distribution). Taking the pricing of electronic products as an example, multiple features of the product are collected, such as screen size, processor performance, memory size, etc., as feature variables, and price as the target variable. Calculate the correlation coefficient between each feature and price. A threshold is set to retain the feature that the correlation with the price is higher than the threshold. It helps to identify features closely related to price. For example, it is found that processor performance is highly positively correlated with the price of electronic products. Enterprises can focus on this feature when pricing, and set higher prices for products with high processor performance.

2. Hypothesis testing

Taking the t test as an example (commonly used to test whether there is a significant difference between the two overall means), assuming that there is no difference in the mean value of the corresponding product price under different values of the characteristics (original hypothesis), the t statistic is calculated by the sample data to determine whether the original hypothesis is rejected. For example, study the impact of different brands (characteristics) on product prices. The product prices of different brands are taken as samples, and the t value is calculated and compared with the critical value (determined according to the significance level and degree of freedom). If the original hypothesis is rejected, it shows that there are significant differences in product prices under different brands, and the brand characteristics are of great significance to pricing. if it is found that there are significant differences in product prices of different brands, enterprises can formulate differentiated pricing strategies for different brands and use brand influence to increase profits.

4.3.2 Domain-based Method. Combined with the professional knowledge and experience of specific industries, select the characteristics that have an important impact on pricing. For example, in the field of air passenger pricing, experts know that factors such as flight time (such as morning and evening peak hours, flat peak hours), route popularity (tourist routes, business routes), and class level have a significant impact on ticket prices.

The characteristics of domain knowledge selection are in line with the actual situation of the industry, making the pricing strategy more in line with market demand and consumer psychology, enhancing the rationality and market adaptability of pricing, and improving corporate earnings.

4.3.3 Methods Based on Machine Learning. 1.Filter - Information gain

Information gain is used to measure how much information a feature can bring to the classification system. Based on the decision tree, the change of information entropy before and after dividing the data set is calculated. In the pricing of E-commerce products, for each product feature (such as product category, sales volume, praise rate, etc.), the information gain of price classification (such as low price, medium price, high price) is calculated. The features are sorted according to the information gain from high to low, and the features with high information gain are selected.

Screen out the characteristics that contribute greatly to the price classification, and help the E-commerce platform to accurately price. If we find that the information gain of high praise rate is high, it shows that it is important for price judgment, and the price of products with high praise rate can be appropriately increased.

2. Recursive feature elimination (RFE)

Based on a base learner (such as linear regression, support vector machine, etc.), the feature subset is repeatedly selected. In each iteration, the model trains on the current feature subset, calculates the importance of each feature (such as the absolute value of the coefficients in linear regression), and removes the least important features until the preset number of features is reached.

In E-commerce pricing, RFE is used to screen out the features that have the greatest impact on the price from a large number of product features (such as product description length, number of pictures, brand influence, etc.) to help E-commerce platforms formulate more accurate pricing strategies. Avoid interfering with the pricing model due to too many irrelevant features.[8][9]

4.4 Model training

Model training is a core part of machine learning, which determines the effect of pricing strategy optimization. As show in Table 2, common pricing optimization models include regression models, decision trees and random forests, support vector machines (SVM), and deep learning. Regression models include linear regression, ridge regression and so on, which are applicable to the prediction between pricing, sales volume and profit. Decision trees and random forests are suitable for dealing with complex nonlinear relationships and can help explore the interactions among multi-dimensional features. Support vector machines (SVM) are applicable to classification and regression tasks and can find the optimal separating hyperplane in complex data. Deep learning can handle large-scale datasets and is suitable for complex pricing optimization problems.

During the process of model training, data is usually divided into training datasets and testing datasets. The training datasets are used for model training to help the model recognize patterns in the data. The testing datasets are used to evaluate the generalization ability of the model and ensure its prediction accuracy on unseen data.

Common evaluation metrics include RMSE (Root Mean Square Error), MAE (Mean Absolute Error), R^2 (Coefficient of Determination) and so on. Among them, RMSE (Root Mean Square Error) is used to measure the error between predicted values and actual values. The smaller the value is, the higher the prediction accuracy of the model. MAE (Mean Absolute Error) is similar to RMSE and mainly measures the absolute value of the error, which is suitable for scenarios that are less sensitive to outliers. R^2 (Coefficient of Determination) is used to measure the goodness of fit of the model. The higher the R^2 value is, the stronger the model's ability to explain the variability of data.[10]

4.5 Reinforcement Learning and Price Adjustment Mechanism

Reinforcement learning has been paid more and more attention in price strategy optimization, especially in dynamic pricing and price adjustment. Reinforcement learning interacts with the environment to get feedback, which can be used as a basis for adjusting strategies to maximize long-term benefits. Reinforcement learning algorithms can adjust prices based on real-time market feedback, so that prices remain optimal in different time periods and different market environments. By constantly trying different pricing strategies, the model gradually finds the best pricing method. Reinforcement learning maximizes the overall profits of enterprises by constantly learning long-term returns and adjusting testing strategies in complex market environments. For example, in a price war, the model can adjust prices based on market feedback to prevent short-term price fluctuations from adversely affecting long-term profits.[11]

5 Future Outlook

With the development of artificial intelligence technology, the pricing system will break the static limit and become an intelligent system that automatically adjusts according to real-time data, that is, an adaptive pricing system. By acquiring and analyzing data from various sources in real time, adjust prices intelligently to ensure maximum profit and market share.

Deep learning and neural networks are breakthrough technologies in the field of artificial intelligence, which have a powerful ability to handle complex non-linear data and large-scale data. In

Table 2: Model training for pricing strategy optimization

Model Training (Core Component)	Models and Methods	Applications
Pricing Optimization Models	Regression Models: linear regression, ridge regression etc.	Predict relationships between pricing, sales volume, and profit.
	Decision Trees & Random Forests	Handle complex nonlinear relationships and uncover multi-dimensional feature interactions.
	Support Vector Machines (SVM)	Perform classification and regression tasks by identifying optimal hyperplanes.
	Deep Learning	Process large-scale datasets for complex pricing optimization.
Data Partitioning	Training Dataset	Train models to identify patterns in data.
	Test Dataset	Evaluate model generalization on unseen data.
Evaluation Metrics	RMSE (Root Mean Square Error)	Measure the error between predicted values and actual values. The smaller the value is, the higher the prediction accuracy of the model.
	MAE (Mean Absolute Error)	Measure the absolute value of the error, which is suitable for scenarios that are less sensitive to outliers.
	R^2 (Coefficient of Determination)	Measure the goodness of fit of the model. The higher the R^2 value is, the stronger the model's ability to explain the variability of data.

pricing optimization, deep learning and neural networks can dig deep into the underlying laws of data through multi-level computational models to help predict price changes, demand fluctuations, and so on.

With the change of consumers' shopping habits, cross-platform shopping will become the mainstream, and consumers will obtain information and make purchases through multiple platforms. Therefore, cross-platform data integration and omnichannel pricing strategy optimization are the future development trends. By combining data from various platforms, companies can more accurately predict demand fluctuations across platforms, enabling uniform or dynamic pricing across channels[12]. Analyze consumer behavior across multiple channels to understand their purchasing decisions and preferences, and then adopt appropriate pricing strategies across different channels.

The combination of big data and artificial intelligence is the core driving force for future pricing strategy optimization. Big data technology can provide a large amount of rich real-time data, and artificial intelligence can extract a large amount of effective information from the data through machine learning, so as to optimize pricing strategy. The combination of AI and big data will drive a shift in pricing strategies from traditional simple pricing to more intelligent, data-driven pricing decisions, helping companies stay ahead in a competitive market.

6 Conclusions

With the continuous development of artificial intelligence technology, the application prospect of machine learning in e-commerce price strategy optimization will be broader. Through deep learning technology, pricing systems will become more intelligent and adaptive, able to automatically adjust prices based on real-time data to maximize profits and increase market share. At the same time, cross-platform data integration and omnichannel pricing strategy optimization will also become the future development trend, helping enterprises to more accurately predict demand fluctuations and develop more accurate pricing strategies.

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