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Research on the Optimization of Quality Differentiated Product Pricing Strategies and Sales Forecast Models Based on Strategic Customer Behaviors

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Abstract

With the intensification of market competition and the diversification of consumer behavior, traditional pricing strategies and sales forecasting models have become unable to adapt to the complex and constantly changing market environment. Pricing strategies based on strategic customer behavior (BBP), stacking ensemble learning methods, Prophet-LSTM combined models, and multi-dimensional grey models combined with neural networks, among others, have become key technologies for optimizing sales forecasting and inventory management at present. This paper combines game theory, machine learning, and deep learning models to explore how the synergy of behavioral pricing strategies, sales forecasting models, and inventory optimization methods can enhance the market adaptability and profitability of enterprises. Research shows that the BBP model can optimize pricing strategies under certain conditions, but it may lead to a “lose-lose” situation in the case of information asymmetry. Stacking ensemble learning methods and Prophet-LSTM combined models can significantly improve the accuracy of sales forecasting, especially in market environments with large fluctuations in demand. The method combining multi-dimensional grey models and neural networks can provide relatively accurate prediction results in the case of incomplete or complex data. Finally, this paper proposes optimization suggestions, such as designing dynamic inventory frameworks and differentiated discount strategies based on real-time behavioral mechanisms, while outlining future trajectories for adaptive artificial intelligence in operations.

Keywords

pricing strategy, sales forecast, inventory optimization, machine learning, deep learning

1. Introduction

With the intensification of global market competition and the increasing complexity of consumer behavior, modern enterprises face unprecedented challenges when formulating pricing strategies, conducting sales forecasts, and managing inventories. Traditional pricing methods—often relying on static cost-plus or simple competitor benchmarking—and conventional sales forecasting models, such as basic time-series analyses, can no longer fully capture the non-linear dynamics of the modern market. Especially in the context of diverse strategic customer behaviors, rapid demand fluctuations, and increasing environmental uncertainties, there is a critical bottleneck in existing operational models.

Recent advancements in game theory and artificial intelligence have introduced sophisticated tools, such as Behavioral-Based Pricing (BBP), Stacking ensemble learning, and hybrid deep learning models (e.g., Prophet-LSTM and Grey-Neural networks). However, a significant research gap remains regarding the operational boundaries of these models. For instance, the theoretical benefits of BBP are often compromised by information asymmetry in practice, while advanced machine learning models frequently suffer from overfitting or high computational costs when applied to specific retail scenarios. Furthermore, there is a lack of integrated research that connects behavioral pricing mechanisms with advanced forecasting architectures to create a cohesive operational strategy. To bridge this gap, this study systematically deconstructs the mechanistic advantages and structural limitations of these models, ultimately proposing a synergistic optimization framework to enhance enterprise market adaptability and profitability.

2. Research Objective

This study aims to critically analyze the limitations of the Behavioral-Based Pricing (BBP) model within the context of strategic customer behavior, specifically investigating the mechanisms by which information asymmetry leads to adverse selection and suboptimal profit outcomes. A second objective is to evaluate the structural boundaries of advanced sales forecasting architectures. Thirdly, the author expects to explore the error-correction mechanism of grey-neural networks. Such mechanism would rely on how Stacking ensemble learning's reliance on learner heterogeneity paradoxically triggers overfitting in small datasets, while simultaneously investigating the temporal decomposition mechanism that allows the Prophet-LSTM combined model to outperform traditional models in capturing non-linear seasonal fluctuations. The research objective summarize as below.

Research Objective 1: Identify the limitations of the Behavioral-Based Pricing (BBP) model within the context of strategic customer behavior

Research Objective 2: Evaluate the structural boundaries of advanced sales forecasting architectures.

Research Objective 3: Explore the error-correction mechanism of grey-neural networks.

3. Literature Review

3.1 Pricing Model Based on Strategic Customer Behavior (BBP Model)

The Behavioral-Based Pricing (BBP) model is fundamentally rooted in game theory and behavioral economics, shifting the traditional focus from cost-plus or competitor-based pricing to customer-driven strategies. The operational mechanism of the BBP model involves analyzing how strategic customers adjust their purchasing timing and quantity based on their expectations of future price changes. The theoretical core lies in mapping the heterogeneity of customer behaviors—such as varying price sensitivities between new and old customers—and formulating differentiated pricing strategies to maximize consumer surplus extraction. However, the practical application of this model is constrained by the principal-agent problem and information asymmetry. In scenarios where enterprises lack complete visibility into true customer valuations, the BBP model may trigger adverse selection. Theoretical analysis indicates that without perfect information, unilateral price discrimination can lead to a “lose-lose” outcome: enterprises suffer profit losses due to misaligned pricing, while strategic customers may delay purchases, ultimately reducing overall market efficiency. Thus, while the BBP model provides a theoretical framework for precision pricing, its reliance on data completeness remains a critical vulnerability.

3.2 Stacking Ensemble Learning (Sales Forecast Model)

Stacking, or Stacked Generalization, is an advanced heterogeneous ensemble learning technique designed to enhance predictive performance by synthesizing the strengths of multiple base learners. Operationally, it employs a two-layer architecture. The first level (base level) consists of diverse algorithms—such as decision trees, support vector machines, and linear regressions—trained independently on the original dataset, typically utilizing K-fold cross-validation to generate out-of-fold predictions. These predictions are then stacked to form a new feature matrix. The second level (meta-level) employs a meta-learner (e.g., XGBoost or logistic regression) that is trained on this new matrix to optimally weigh and combine the base predictions. The underlying principle is to reduce both bias and variance by capturing complementary patterns within the data that a single model might miss. In the context of sales forecasting, Stacking significantly improves accuracy and robustness, particularly in large datasets with complex, multi-dimensional features. Nevertheless, a known limitation in its operational mechanism is its susceptibility to overfitting when applied to small datasets, especially if the base learners are highly correlated or lack sufficient diversity, which can lead to degraded generalization capabilities.

3.3 Prophet-LSTM Combined Model (Sales Volume Forecasting)

To address the multifaceted nature of time-series data, the Prophet-LSTM combined model integrates a decomposable regression approach with deep sequential learning. Prophet, developed for high-frequency time-series forecasting, operates on an additive model principle. It mathematically decomposes a time series into three core components: trend (modeled by piecewise linear or logistic growth curves), seasonality (modeled using Fourier series), and holidays/effects. This mechanism excels at capturing macro-level structural patterns and handling missing data flexibly. However, Prophet struggles with complex, non-linear short-term dependencies. To compensate, the Long Short-Term Memory (LSTM) neural network is integrated. LSTM utilizes a gating mechanism—comprising input, forget, and output gates—to regulate information flow, effectively mitigating the vanishing gradient problem and retaining long-term memory in sequential data. In a combined Prophet-LSTM framework, Prophet first extracts and removes the dominant trend and seasonal components; the residual sequence, containing localized, non-linear short-term fluctuations, is then fed into the LSTM network for precise residual fitting. This synergistic mechanism provides highly accurate sales forecasting, particularly for products exhibiting significant seasonal volatility and complex long-term trends, outperforming traditional models like ARIMA.

3.4 Multi-Dimensional Grey Model and Neural Network Combination (Sales Forecasting)

The integration of multi-dimensional grey models (typically GM(1,N)) and Artificial Neural Networks (ANN) targets a specific niche in forecasting: environments characterized by "poor information, small samples," and incomplete data. The operational principle of the GM(1,N) model relies on the Accumulated Generating Operation (AGO). By applying AGO, the original erratic, non-negative sales data is transformed into a monotonically increasing sequence, which reduces randomness and approximates an exponential law. A first-order differential equation is then fitted to this smoothed sequence to capture the systemic driving forces among multiple variables. While GM(1,N) excels at identifying macroscopic developmental trends with minimal data, its linear assumption limits its ability to capture complex non-linear residuals. To overcome this, an ANN is introduced as an error-correction mechanism. The ANN trains on the residual errors (the difference between the GM(1,N) predictions and actual values) to map the non-linear error patterns. The final prediction is the sum of the grey model output and the ANN-corrected residual. This combined mechanism leverages the structural deductive power of grey theory and the non-linear mapping capability of neural networks, providing highly reliable forecasting results even when historical data is scarce or highly uncertain, making it particularly valuable for retail inventory planning.

4. Core Findings and Optimization Suggestions

4.1 Conflict and Mechanism of the BBP Model under Information Friction

The core finding indicates that while the Behavioral-Based Pricing (BBP) model theoretically exploits customer heterogeneity to extract consumer surplus, its practical efficacy is fundamentally constrained by information asymmetry. From the perspective of signal game theory, the mechanism of this failure unfolds as follows: when an enterprise attempts to implement differentiated pricing based on incomplete customer behavior data, the set price thresholds inadvertently act as distorted market signals. Strategic customers, anticipating future markdowns, utilize these signals to engage in inter-temporal arbitrage (delaying purchases). Mechanistically, without a dynamic and accurate decoding of customers' true valuation distributions, static price discrimination triggers adverse selection. The analysis reveals that aggressive pricing gaps not only repel highly price-sensitive segments (causing immediate demand destruction) but also expose the enterprise's pricing logic to competitors. This dual-layer information friction ultimately transforms a strategic advantage into profit compression, demonstrating that the BBP model can paradoxically lead to a “lose-lose” scenario—eroding both enterprise profitability and overall market efficiency—when operating without continuous, high-fidelity data feedback loops.

4.2 Mechanistic Advantages and Structural Limitations of Forecasting Architectures

In terms of sales forecasting accuracy, the findings demonstrate that the Stacking ensemble learning method enhances predictive stability mechanistically by reducing prediction variance through the aggregation of diverse base learners. The key factor driving this performance improvement is “learner heterogeneity.” By synthesizing algorithms that capture different data spaces (e.g., tree-based models capturing non-linear splits, and linear models capturing global trends), Stacking allows the meta-learner to map and weigh complementary patterns, effectively mitigating the individual biases of single models. However, a critical mechanistic limitation was identified in its operational boundaries: in small datasets, the lack of sufficient data volume prevents the base learners from forming distinct decision boundaries. This results in highly correlated feature extractions, forcing the meta-learner to overfit the training noise rather than learning generalized market rules, thereby degrading out-of-sample generalization.

Conversely, the Prophet-LSTM combined model overcomes single-model limitations through a distinct temporal decomposition mechanism, outperforming traditional models like ARIMA. Traditional ARIMA relies strictly on stationarity assumptions and linear mappings, failing to capture complex, non-linear temporal dependencies. The Prophet-LSTM mechanism bypasses this by task decoupling: the additive model of Prophet reliably isolates macro-structural trends and seasonal baselines using Fourier series, stripping away the dominant predictable components. Subsequently, the LSTM network—utilizing its gated memory architecture to prevent gradient vanishing—specifically captures the highly non-linear, short-term residual fluctuations left by the macro-extraction. This synergistic mechanism ensures that short-term volatility does not interfere with long-term trend fitting, significantly enhancing precision for products subject to violent seasonal shifts.

4.3 Synergistic Error-Correction Mechanism of Grey-Neural Networks

Regarding operational execution, the findings reveal a critical mechanistic mismatch between traditional static inventory frameworks and dynamic market volatility. Static classification methods (e.g., AHP-ABC) assign fixed priority weights based on historical averages, failing to dynamically adjust item importance in response to real-time demand shifts. This rigidity prevents enterprises from adapting inventory turnover rates to sudden market fluctuations. Additionally, in the realm of discount strategies, mechanism analysis based on behavioral economics indicates that broad, undifferentiated discounts carry a systemic risk related to “price reference dependence.” When discounts are applied uniformly, they systematically lower the consumer's internal reference price, training customers to devalue the brand and delay purchases until markdowns become the norm. The findings suggest that the optimal mechanism requires linking real-time behavioral segmentation directly with forecast outputs to establish an “elastic discount boundary.” By matching discount depth precisely to specific customer price elasticities derived from real-time data, enterprises can maximize sales volume conversion without triggering the systematic depreciation of long-term brand equity.

5. Discussion

5.1 Management Implications and Theoretical Synthesis

Transitioning from methodological findings to practical applications, the synthesized results of this study offer profound managerial implications that advocate for a contingency-based approach to pricing and inventory management. The analysis demonstrates that there is no universal optimal model; rather, enterprise strategy must be dynamically aligned with specific market data environments. For instance, while the BBP model provides a sophisticated paradigm for extracting consumer surplus through behavioral differentiation, its implementation requires enterprises to establish robust customer data infrastructures to mitigate the inherent risks of information asymmetry and adverse selection. In the domain of sales forecasting, the findings necessitate a shift from single-algorithm dependency to hybrid architectural design. Managers operating in data-rich but highly volatile environments should prioritize the Prophet-LSTM framework to capture complex seasonal and trend decoupling. Conversely, in scenarios plagued by data scarcity or poor historical records—common in emerging markets or new product lines—the integration of multi-dimensional grey models with neural networks presents a highly pragmatic alternative, enabling reliable forecasting without the prohibitive data requirements of deep learning. Furthermore, the utilization of Stacking ensemble learning is recommended primarily for large-scale datasets where model diversity can be fully exploited to minimize variance, thereby providing a more stable foundation for downstream inventory allocation.

5.2 Methodological Limitations and Algorithmic Trade-offs

Despite the demonstrated advantages of these integrated frameworks, a critical limitation analysis reveals inherent trade-offs that constrain their universal applicability. A prominent limitation across the machine learning and deep learning architectures is the fundamental tension between predictive accuracy and computational overhead. For example, while the Prophet-LSTM combined model excels in capturing non-linear residuals, its complex gating mechanisms and hyperparameter tuning requirements significantly increase computational complexity and operational costs, which may pose implementation barriers for small and medium-sized enterprises with limited IT infrastructure. Similarly, the efficacy of the Stacking ensemble learning method is theoretically bounded by the quality and volume of input data; in small-sample regimes, the mechanism designed to reduce variance paradoxically amplifies overfitting, leading to spurious correlations rather than genuine generalization. Regarding the BBP model, its effectiveness is strictly upper-bounded by the accuracy of behavioral assumptions. In real-world dynamic markets, customer valuations are not static, and information asymmetry cannot be entirely eliminated, meaning the model's game-theoretic equilibria may frequently deviate from actual market outcomes. Additionally, while the grey-neural network combination effectively handles incomplete information, its ability to map highly complex, multi-dimensional non-linear relationships remains structurally inferior to pure deep learning models when sufficient data is actually available.

5.3 Future Research Trajectories Towards Adaptive Intelligence

To overcome the identified limitations of static modeling and data dependency, future research trajectories must pivot from retrospective statistical analysis towards proactive, adaptive intelligent systems. A critical direction involves the integration of deep reinforcement learning (DRL) into both pricing strategies and inventory optimization. Unlike traditional models that rely on historical offline data, DRL algorithms can continuously interact with the market environment, utilizing reward mechanisms to dynamically adjust pricing thresholds and inventory parameters in real-time, thereby fundamentally resolving the rigidity of static AHP-ABC inventory models and the information lag in BBP strategies. Furthermore, to address the computational and overfitting limitations of current forecasting models, future studies should explore the fusion of Stacking mechanisms with lightweight deep learning architectures (such as GRU or Temporal Convolutional Networks), aiming to achieve high accuracy on small datasets with lower computational costs. Additionally, integrating advanced anomaly detection algorithms (e.g., Isolation Forests or autoencoders) as a preprocessing or coprocessing step with the Prophet-LSTM framework represents a vital research avenue. This integration would enable the system to autonomously identify, filter, or isolate extreme market shocks—such as sudden supply chain disruptions or panic buying—preventing these outliers from corrupting the underlying trend learning, thereby significantly enhancing the robustness of forecasting models in highly volatile business ecosystems.

6. Conclusion

This study systematically deconstructs the mechanistic boundaries of current pricing strategies and sales forecasting models to provide a collaborative optimization framework for enterprise operations. By critically analyzing the BBP model through the lens of signal game theory, this research identifies how information asymmetry triggers adverse selection, demonstrating that static behavioral pricing requires dynamic data infrastructure to prevent profit erosion. In the domain of forecasting, the study validates that hybrid architectures significantly outperform single models: the Prophet-LSTM model achieves precise temporal decoupling for volatile markets, while the Grey-Neural network combination provides a robust error-correction mechanism for data-scarce environments. Furthermore, the analysis exposes the operational mismatch of static inventory frameworks, advocating for dynamic calibration mechanisms based on real-time behavioral segmentation. Ultimately, this research transitions enterprise decision-making from reliance on isolated, retrospective models to a theoretically grounded, synergistic approach, offering profound managerial implications for navigating the complexities of modern, highly volatile markets.

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Conflicts of Interest

The authors declare no conflict of interest.

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