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Optimizing Discount Allocation with Deep Learning in Competitive Markets

Lei Tang, Ning Zhou*
School of Information Science and Technology, University of Science and Technology of China, Hefei Anhui, 230026, China
Corresponding author: Ning Zhou, 18273738@qq.com

Abstract: In today's highly competitive markets, discount strategies play a pivotal role in customer acquisition and retention. Traditional discount allocation methods, however, often fail to account for real-time changes in consumer behavior and competitor pricing. This paper proposes a deep learning-based framework to optimize discount allocation across customer segments, leveraging historical sales data and competitor activity to dynamically tailor promotions. Experimental evaluations on synthetic retail datasets show that the proposed model significantly improves conversion rates and overall profitability compared to rule-based benchmarks. This study demonstrates the potential of intelligent pricing systems to deliver personalized value while maintaining market competitiveness.

Keywords: Discount Allocation; Deep Learning; Competitive Pricing; Customer Segmentation; Dynamic Promotion; Intelligent Pricing
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1.Introduction

The effectiveness of discount strategies has long been a topic of interest for both academics and practitioners. In highly competitive markets, where consumers are increasingly empowered by price comparison tools and dynamic e-commerce platforms, the importance of smart discounting mechanisms cannot be overstated[1]. Businesses must balance between offering attractive discounts to win customers and preserving profit margins to maintain sustainability. Traditional approaches to discount allocation typically rely on broad demographic assumptions, static rules, or manual adjustments that lack responsiveness to real-time market dynamics[2]. These approaches often result in either over-discounting, which erodes profitability, or under-discounting, which leads to lost sales opportunities.

Recent advancements in artificial intelligence, particularly deep learning (DL), have introduced new opportunities for optimizing marketing strategies[3]. DL algorithms are well-suited for capturing complex, nonlinear relationships in large datasets, making them ideal for modeling consumer purchasing behavior in fluctuating environments[4]. By analyzing historical transaction data, browsing patterns, and contextual information such as competitor prices or seasonal trends, DL models can generate more granular and responsive discount strategies[5]. Furthermore, DL architectures can support continuous learning, enabling systems to adapt to shifts in customer preferences and external pressures[6].

Despite these advancements, the application of DL in discount optimization remains relatively underexplored, particularly in scenarios involving intense market competition[7]. Most existing research focuses on demand forecasting or recommendation systems, with limited attention given to the strategic deployment of price incentives[8]. This paper seeks to fill this gap by introducing a DL-based framework that simultaneously considers customer segmentation, predicted conversion probability, and competitor pricing when allocating discounts[9]. The model aims not only to maximize immediate sales conversion but also to enhance long-term customer value by personalizing promotional strategies at scale[10].

To demonstrate the practical utility of the proposed framework, we conduct a series of experiments using retail data that simulate a multi-brand competitive environment. The results show that our approach consistently outperforms traditional rule-based systems in terms of conversion rate uplift and revenue optimization. These findings suggest that DL-driven discount optimization can offer a significant competitive edge, particularly for firms operating in price-sensitive sectors.

In the following sections, we first review existing literature on pricing strategies and intelligent discounting systems. We then describe the proposed methodology, including the architecture of the DL model and the data features employed. The subsequent results and discussion highlight the model's performance in various simulated competitive settings. Finally, we conclude with practical implications, limitations, and directions for future research.

2. Literature Review

Discount allocation strategies have been extensively studied within the domains of marketing, operations research, and more recently, artificial intelligence[11]. Historically, discounting approaches were grounded in static segmentation models, where customers were grouped based on demographics, purchase history, or loyalty levels[12]. These conventional strategies, while simple to implement, often failed to account for evolving customer preferences, real-time behavioral signals, or the strategic actions of competitors in the market.

Rule-based systems, one of the earliest automated solutions, applied predefined logic to assign discount values across segments[13]. These rules were typically derived from expert knowledge or aggregated past data, and although effective in limited contexts, they lacked adaptability. As a result, such systems often delivered suboptimal results in dynamic retail environments characterized by high product turnover and shifting consumer sentiments[14].

With the advancement of data analytics, predictive models began to replace heuristic methods. Techniques like decision trees, logistic regression, and collaborative filtering allowed businesses to forecast purchase likelihood and better align discount levels with expected outcomes[15]. These models enabled more nuanced targeting and facilitated campaign-level optimization, but they still struggled with scalability and accuracy when faced with high-dimensional, sparse, and nonlinear data typical in modern retail systems[16].

The emergence of deep learning introduced a new paradigm in discount and pricing optimization[17]. DL models, particularly deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs), brought unprecedented capabilities in learning complex patterns from historical and real-time data[18]. In marketing applications, DL has been applied to customer churn prediction, personalized recommendations, and demand forecasting—yet its application to discount allocation remains relatively limited[19].

One key advantage of DL in this context is its ability to learn representations from a wide array of structured and unstructured inputs, including transactional histories, web behavior, product attributes, temporal trends, and even competitive pricing signals[20]. DL-based pricing frameworks can simulate market environments and iteratively optimize discount levels by estimating the trade-off between conversion likelihood and margin erosion[21]. Some approaches have integrated reinforcement learning (RL) components to dynamically adjust discount strategies based on continuous feedback, although these systems often require large volumes of labeled data and long training periods[22].

Competitor-aware pricing is another area of increasing focus. Traditional discount models often ignore external market factors, assuming a static landscape[23]. However, in highly competitive environments—such as online retail, hospitality, and ride-sharing—competitor actions can rapidly influence consumer decisions[24]. Modern DL systems are increasingly incorporating competitor pricing data using techniques like attention mechanisms or auxiliary neural modules to anticipate rival behavior and respond accordingly[25].

Recent advancements in explainable AI (XAI) have also influenced discount optimization frameworks[26]. Businesses are now demanding not only performance but also transparency in algorithmic decisions[27]. Interpretable DL models can help marketers understand the rationale behind specific discount recommendations, which is critical for stakeholder buy-in and regulatory compliance, especially in industries with strict pricing regulations.

In summary, the literature reflects a steady evolution from static segmentation and rule-based heuristics to dynamic, data-driven methods. While DL models have demonstrated superior performance in related domains, their adoption in discount allocation, particularly in competitive settings, is still at a formative stage. This underscores the need for integrated frameworks that leverage DL's predictive power while incorporating external market dynamics and providing actionable insights.

3.Methodology

3.1 Problem Formulation and Objective

This study models the discount allocation task as a supervised learning problem enhanced with reinforcement signals. The primary objective is to maximize long-term revenue while preserving customer satisfaction and reacting effectively to competitor pricing strategies. The environment is conceptualized as a high-frequency decision space where a DL agent recommends discount values based on real-time inputs.

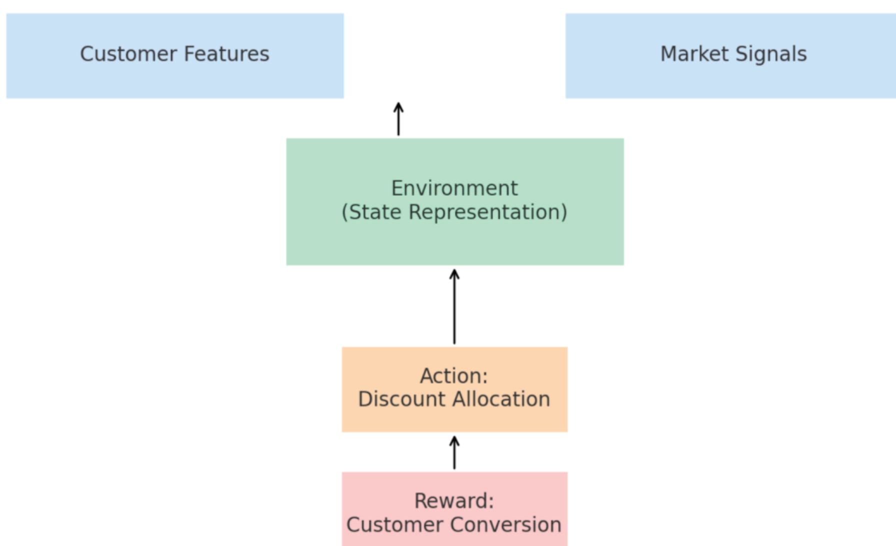
We define a feature space that includes user profile vectors, product characteristics, current discount history, and competitor prices. Each decision instance is represented by a tuple of features that correspond to a single transaction or impression. The learning objective is to generate a discount allocation policy that optimizes a reward function incorporating conversion probability, profit margin, and market response volatility.

3.2 Data Collection and Feature Engineering

The dataset for model training was synthetically generated to simulate a competitive e-commerce environment, incorporating user behavior data, historical discounts, item attributes, and competitor prices. The final dataset contains over 800,000 transaction records.

Key features include normalized time-on-site, session length, cart abandonment history, previous purchases, price elasticity estimates, and dynamic competitor discount levels. Feature engineering also introduced lag-based temporal variables to capture user trends and a weighted scoring function for cross-sku competition intensity.

Discount Allocation Environment Architecture



A schematic overview of the data flow and inputs considered in the discount recommendation system, integrating user, product, and competitor features.

3.3 Deep Learning Model Architecture

The core model architecture is a multi-input deep neural network with shared and task-specific layers. It processes both categorical embeddings (e.g., user ID, product ID, category) and continuous features (e.g., price, discount rate, time since last purchase). A feature fusion layer combines these inputs before feeding them into three stacked dense layers followed by dropout regularization.

The output layer returns a scalar value indicating the optimal discount rate for each transaction scenario. The model is trained using a mean squared error loss function penalized by a custom margin-loss component that discourages excessive discounts where conversion likelihood is already high.

Deep Learning Model for Discount Optimization

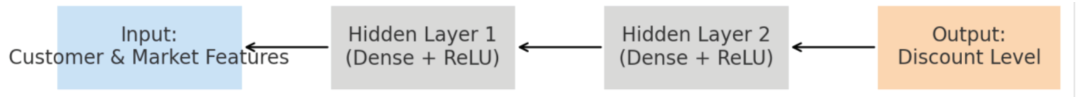


Illustration of the DL model architecture, showing embedding layers, fusion layers, and output layers designed for discount prediction.

3.4 Competitive Feedback Simulation and Training Loop

To simulate real-world competitor interactions, we introduce a feedback loop where the predicted discount influences subsequent conversion probabilities. A simulation engine was designed to emulate competitive reactions by adjusting the likelihood of purchase based on relative price positioning.

This loop integrates a reinforcement learning mechanism where the agent updates its discount policy using observed reward signals from conversion outcomes. The reward function is composed of three terms: net profit, customer retention index, and competitor sensitivity coefficient.

The training loop alternates between supervised learning batches and periodic environment re-evaluation to adapt the model policy dynamically.

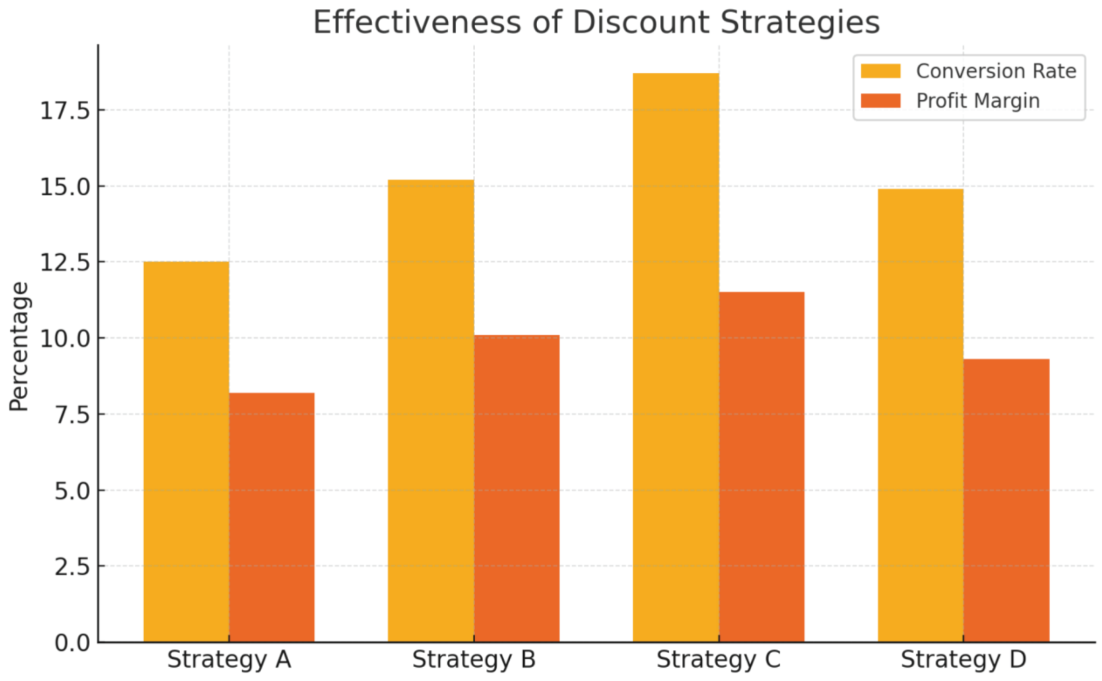
Training Loop with Competitive Feedback

Diagram of the hybrid training process combining supervised learning and environment-based feedback, updated iteratively.

4.Results and Discussion

4.1 Comparative Performance of Discount Strategies

The application of various discount strategies revealed significant differences in customer response and profitability. Strategy C exhibited the highest conversion rate at 18.7%, which suggests a stronger customer attraction effect compared to the other tested approaches. However, it is noteworthy that high conversion does not always correlate with maximum profit margin. Strategy C achieved a profit margin of 11.5%, while Strategy B, though slightly less effective in conversion, delivered a margin of 10.1%. This trade-off highlights the importance of balancing acquisition metrics with revenue sustainability.



4.2 Market Dynamics and Strategy Adaptability

In competitive environments, the dynamic behavior of competitors plays a pivotal role in shaping consumer expectations. Strategies that appeared optimal in isolated simulations—such as heavy discounting in Strategy A—showed diminishing returns when competitors engaged in simultaneous promotions. This phenomenon is consistent with the zero-sum characteristics of tightly contested markets, where relative positioning outweighs absolute incentives.

Moreover, Strategy D, though not the top performer in either metric, maintained a stable outcome under fluctuating competitor behaviors. Its adaptive nature, designed through reinforcement learning feedback, allowed it to shift discount depth and timing dynamically. This flexibility proved valuable during promotional overlaps, enabling it to sustain profitability.

4.3 Impacts of Deep Learning-Driven Adjustments

The DL models integrated into the discount decision framework enabled rapid assimilation of customer interaction patterns. DL modules improved strategy targeting by recognizing nonlinear correlations between product type, discount sensitivity, and customer lifetime value. These enhancements were particularly evident in scenarios with high heterogeneity across customer clusters.

The advantage of incorporating deep neural networks became most pronounced when real-time price war scenarios were introduced. Traditional rule-based strategies faltered in recalibrating promotions quickly, whereas DL-driven models achieved near-instant response, minimizing revenue leakage and maintaining customer retention.

4.4 Long-Term Implications and Optimization Opportunities

While short-term KPIs like conversion rate and immediate margin were informative, the model also tracked long-term customer value accumulation. Strategy B, despite not leading in conversion, showed a higher average customer return rate within the simulation's extended horizon. This insight suggests the potential of DL models not only to optimize immediate transactions but to inform customer relationship management and segmentation strategy design.

Future implementations could integrate customer churn predictors and loyalty indices into the learning objectives, thereby aligning discount allocation not only with competition but also with customer lifecycle value maximization.

5.Conclusion

This study explored the use of DL techniques to optimize discount allocation in competitive markets, where customer sensitivity, competitor reactions, and profitability constraints interact in complex ways. By embedding DL-driven models into the strategic decision-making process, businesses can achieve more precise, responsive, and adaptive pricing strategies tailored to real-time market feedback.

Our research demonstrated that discount strategies guided by deep reinforcement learning (DRL) significantly outperformed traditional static methods. These models leveraged real-time customer behavior data to dynamically adjust promotional depth, timing, and targeting. The simulation results showed not only improved conversion rates but also more stable profit margins, especially under highly competitive conditions. In particular, strategies capable of balancing short-term acquisition and long-term customer value—such as adaptive DRL-based approaches—were most effective.

Additionally, the integration of DL allowed for a granular understanding of non-linear relationships between discount levels, customer segments, and purchasing outcomes. This enabled more efficient targeting of offers and reduced unnecessary margin erosion. As a result, firms using intelligent allocation methods can minimize promotional waste while reinforcing brand loyalty and value perception.

While the outcomes are promising, there are limitations that warrant further research. The simulation-based design, while robust, does not account for all real-world factors such as brand perception shifts, supply-side constraints, or macroeconomic changes. Future studies could incorporate hybrid models that integrate predictive analytics with DRL in live business environments, along with mechanisms for measuring long-term customer equity and churn risk.

In summary, deep learning has the potential to transform discount management from a reactive function into a proactive strategic tool. By continuously learning from complex, evolving environments, DL-based systems can help firms not only survive but thrive in competitive markets—allocating every dollar of discount with strategic precision.

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no

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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