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Research paper

Customer Retention: A Self Learning Approach

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Abstract

In the competitive business landscape, customer retention is crucial for business profitability, as acquiring new customers is significantly more expensive than retaining existing ones. Traditional retention strategies rely on static machine learning models that predict churn based on historical data, limiting their ability to adapt to changing customer behaviors. This study proposes a Self-Learning System powered by Reinforcement Learning (RL) to enhance customer retention dynamically. The proposed system analyzes customer data and segments individuals based on behavioral and transactional characteristics. It autonomously implements tailored retention strategies specific to each segment's needs, such as personalized discounts and loyalty rewards. A key innovation lies in the system's real-time learning capability, utilizing feedback from customer interactions to refine its decisions. Experimental results demonstrate that the proposed system adapts to evolving market conditions and improves retention rates compared to traditional models. These findings highlight the potential of AI-driven adaptive retention strategies in optimizing customer engagement and long-term business growth.

Keywords: *Customer Retention; Reinforcement learning; Market Basket Analysis; Churn Prediction.*

1. Introduction

Customer retention has become a critical focus for businesses due to the high cost of acquiring new customers compared to maintaining existing ones. Traditional churn prediction models, such as logistic regression and decision trees, rely on historical data to identify customers likely to leave. These models, while providing valuable insights, are inherently limited in their ability to adapt to the rapidly evolving nature of online customer behavior and market dynamics (Reichheld & Sasser Jr, 1990).

E-commerce is characterized by a vast amount of data and dynamic interactions. The rise of Reinforcement Learning (RL) offers a promising avenue for developing more adaptive and effective customer retention strategies. RL is a branch of machine learning that enables an agent to learn optimal actions through continuous interaction with an environment (Sutton & Barto, 2018). Unlike static models, RL-based systems can dynamically adjust retention strategies in response to real-time customer interactions and feedback, making them well-suited for the dynamic e-commerce environment. Additionally, Market Basket Analysis (MBA), a data mining technique that identifies relationships between frequently purchased items, can be integrated with RL to enhance retention efforts. By leveraging MBA insights, businesses can design personalized incentives, such as targeted discounts and loyalty programs, to reduce customer churn.

This research aims to bridge the gap between traditional static models and adaptive solutions by developing a Self-Learning Customer Retention System for businesses that integrates RL and Market Basket Analysis (MBA). The system dynamically segments customers and optimizes engagement strategies. The proposed system continuously learns from customer interactions, adapts to evolving behaviors, and applies personalized retention strategies based on real-time feedback. By doing so, this study provides a framework for improving customer satisfaction, reducing churn, and enhancing long-term business profitability.

2. Literature Review

Customer retention and churn prediction have been widely explored in both marketing and data science literature. Traditional machine learning models such as logistic regression, decision trees, and artificial neural networks (ANN) have been applied to classify customers based on the likelihood of churn (Lalwani et al., 2022; Tsai & Lu, 2009). While effective to an extent, these models are largely static and dependent on historical data, lacking adaptability in real-time environments.

In the context of customer segmentation, K-means, hierarchical clustering, and self-organizing maps have been extensively used to group customers based on behavioral and transactional data (Kansal et al., 2018; Hosseini & Shabani, 2015). These methods help in tailoring marketing strategies, but they do not dynamically adapt to behavioral shifts over time. Studies such as Cooil et al. (2008) and Hjort et al. (2013) emphasize the value of segmentation in predicting customer value, yet most approaches assume fixed patterns rather than learning from evolving customer data.

Market Basket Analysis (MBA) is another well-established technique in retail and customer analytics, aimed at uncovering associations between frequently purchased products. Methods like Apriori and FP-Growth algorithms have been used to generate association rules, aiding in recommendation systems and bundled offers (Boztuğ & Reutterer, 2008; Zamil et al., 2020). However, MBA is often used in isolation and rarely integrated into adaptive customer retention systems. More advanced applications of MBA, such as network-based models and multi-category analysis, show promise but remain underutilized in dynamic retention frameworks (Raeder & Chawla,2011; Musalem et.al., 2018). Recent studies have explored incorporating textual and behavioral data for churn prediction (Abou el Kassem et al., 2020) and combining Recency-Frequency-Monetary (RFM) analysis with association rules (Liu et al., 2018). However, these approaches still operate under predefined decision rules without learning adaptively from continuous feedback.
Reinforcement Learning (RL), a class of machine learning where agents learn through trial and error, has been recognized for its potential to optimize long-term customer value through sequential decision-making. Despite its relevance, the application of RL in marketing analytics is still in its nascent stages. Few studies attempt to use RL to modify customer engagement strategies in real time, and even fewer integrate RL with MBA or segmentation for retention optimization.
While prior research has successfully applied machine learning for customer churn prediction and segmentation, there is a lack of integrated frameworks that combine real-time adaptability with personalization. Existing models are largely static, unable to incorporate continuous behavioral feedback or adjust to changing market dynamics. Furthermore, most studies treat churn prediction, segmentation, and recommendation systems as siloed tasks. Specifically, the marketing analytics literature lacks:
- An adaptive, self-learning system that dynamically modifies retention strategies based on real-time feedback.
- Integrated use of Reinforcement Learning with traditional marketing techniques like MBA and behavioral segmentation.
- Empirical validation of such systems in the context of long-term customer engagement and retention improvement.

This study addresses these gaps by proposing and evaluating a Reinforcement Learning–based Self-Learning Customer Retention System that incorporates Market Basket Analysis and segmentation. By doing so, it contributes to both the methodological advancement of customer retention modeling and the theoretical discourse on adaptive marketing strategies.

3. Methodology

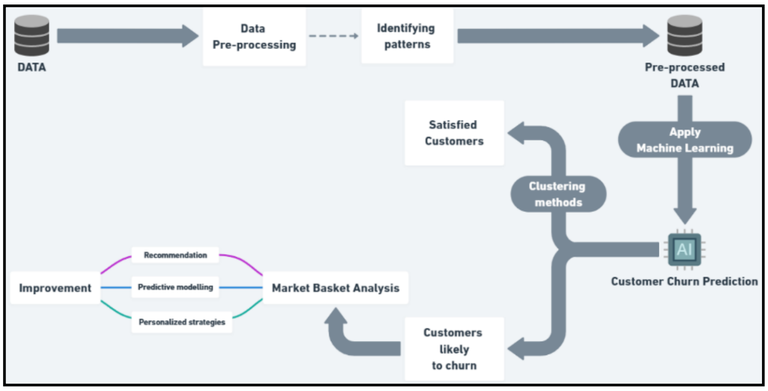

Fig. 1: Block Diagram of the Proposed System.

Figure 1 illustrates the different steps involved in the methodology, which are: data collection and preprocessing, Customer Churn Prediction Model, customer segmentation, Reinforcement Learning Model, and market basket analysis. Each step is explained below.

3.1. Data collection and preprocessing

The dataset used in this study comprises transactional, demographic, and behavioral information gathered from a multi-branch grocery retail environment. It combines detailed product-level sales data with customer attributes to support predictive modeling and personalized retention strategies.
Key Attributes:
- Customer information: Includes gender, city, state, region, and customer type (e.g., Member, Normal).
- Purchase behavior:
- Transaction-level data: Order ID, order date, quantity, product category (e.g., Health and Beauty, Beverages, Food Grains).
- Financials: Unit price, discount, total amount paid (Total), cost of goods sold (COGS), and profit.
- Engagement metrics: Purchase frequency, recency of purchase (Date, Order Date), and gross income.
- Product metadata: Product line and category (e.g., Electronic Accessories, Sports and Travel).
- Sales channel and payment mode: Includes branches, payment type (Cash, Credit Card, E-wallet).
- Following data collection, the Preprocessing Phase ensures the dataset's quality and usability. This involves cleaning the data by removing duplicates, handling missing values, and standardizing formats. Feature engineering creates additional informative attributes like average purchase value and engagement scores. The dataset is then normalized to ensure consistency and improve model performance during training.

3.2. Customer churn prediction model

A machine learning-based Customer Churn Prediction Model is implemented to estimate the likelihood of customer churn. This model uses neural networks to analyze historical patterns in customer behavior, transactions, and demographics. The model outputs a churn probability for each customer. These probabilities help identify which customers will likely disengage, providing a basis for targeted retention efforts.

3.3. Customer segmentation

Based on the churn probability predicted in the previous phase, customers are segmented into defined categories as shown in fig. 2. The segmentation is further refined using clustering algorithms like K-Means or DBSCAN. Typically, the segments include:

Segment 0: Low-spending customers with frequent small purchases.

Segment 1: High-value customers with strong spending and engagement.

Segment 2: At-risk customers with low spending and engagement.

These customer segments are created based on churn probability ranges, ensuring that retention strategies can be customized effectively for each segment.

3.4. Reinforcement learning model

The core of the system is a Reinforcement Learning (RL) Model, which activates after segmentation. Each customer segment is treated as a distinct state in the RL environment. The model learns which retention actions (e.g., sending discounts, loyalty rewards, personalized offers) maximize long-term engagement and reduce churn. The RL model integrates Market Basket Analysis as part of its decision-making process. When it selects an action, it may choose to apply insights from market basket analysis to send personalized product recommendations or bundle offers. Each action's effectiveness is measured by a reward system:

+10 points for successful purchases or engagement.

+5 points for non-purchase interactions (e.g., website visits).

-10 points if the customer churns post-action.

Q-learning is used to update the Q-table, allowing the model to learn the optimal action for each customer segment. The model continuously adapts through a balance of exploration (trying new actions) and exploitation (applying known effective actions).

A feedback loop is established, where continuous customer interactions refine the Q-values, allowing the model to adapt to changing customer behaviors and market conditions in real time.

3.5. Market basket analysis

Market Basket Analysis is embedded within the RL model's action choices. The system identifies frequent product combinations and association rules using algorithms like Apriori or FP-Growth. These rules guide the recommendation of product bundles and offers:

For Segment 1 (loyal customers), loyalty points or combo offers are used to encourage repeat purchases.

For Segment 2 (at-risk customers), Buy-One-Get-One (BOGO) or discount strategies are applied to retain their interest.

For Segment 0, targeted discounts encourage increased basket size.

By combining segmentation, churn prediction, and association rules, the RL model makes intelligent, data-driven decisions that improve customer retention outcomes. The effectiveness of these strategies is monitored using metrics such as retention rate, engagement metrics, purchase frequency, and churn rate. These insights help refine the model and ensure adaptive learning based on real-time customer behavior.

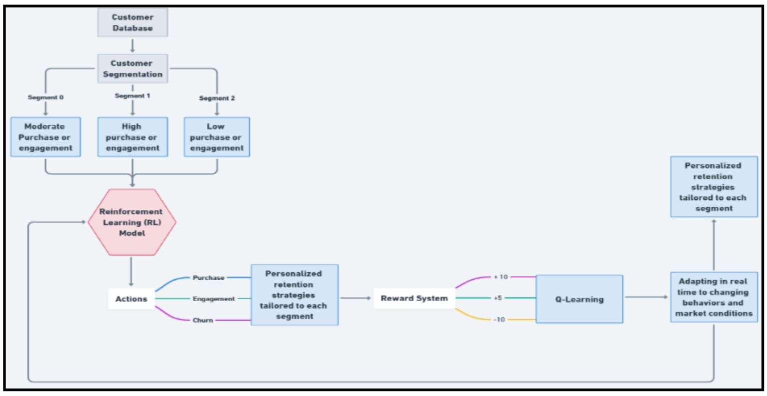

Fig. 2: Block diagram of the proposed system.

4. Results

4.1. Customer churn prediction and segmentation

Figure 3 presents a Power BI dashboard analyzing customer churn across multiple dimensions using a transactional dataset of 1000 customers, revealing a churn rate of 18.8%. The dashboard segments churn data by gender, product line, payment method, city, and churn reason. Notably, "High Price" was the leading cause of churn (49.44%), followed by "Better Alternatives" (20%) and "Poor Service" (12.78%).

Figures 4 and 5 show that female customers accounted for 52.22% of churn, slightly higher than male customers (47.78%), indicating a potential gender-based variance in churn behavior.

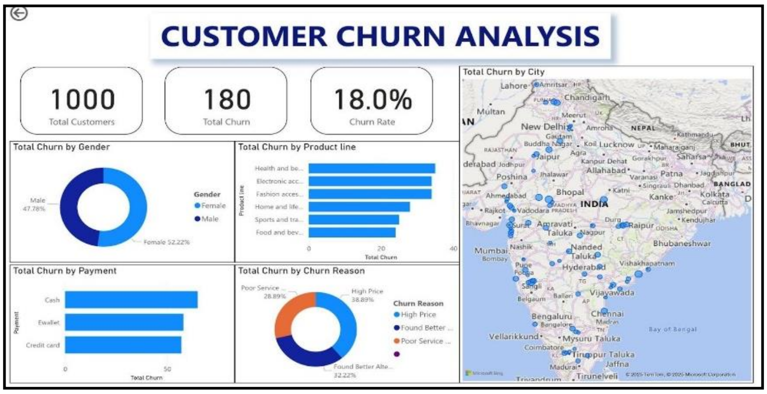

Fig. 3: Customer Churn Analysis Dashboard.

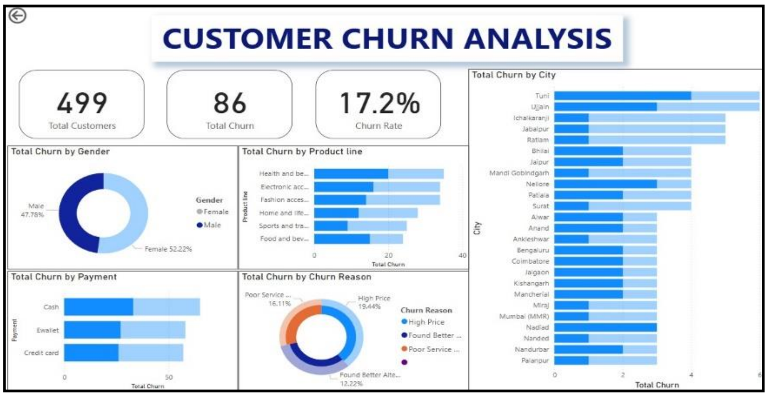

Fig. 4: Total Churn by Gender – Male.

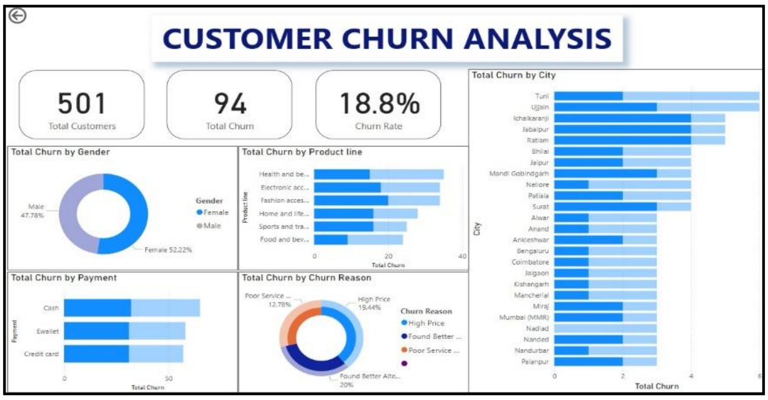

Fig. 5: Total Churn by Gender – Female.

Post-churn prediction, customers were clustered into three segments:

- High Spend, Moderate Satisfaction: Highest revenue contributors but only moderately satisfied—ideal for loyalty enhancement.
- Moderate Spend, High Satisfaction: Highly satisfied but lower spenders—good candidates for upselling.
- Low Spend, Low Satisfaction: Least engaged—requires basic retention efforts.

This segmentation supported personalized strategy deployment. Figure 6 displays average total spending per segment, while Figure 7 illustrates the average customer rating, further informing targeted retention actions.

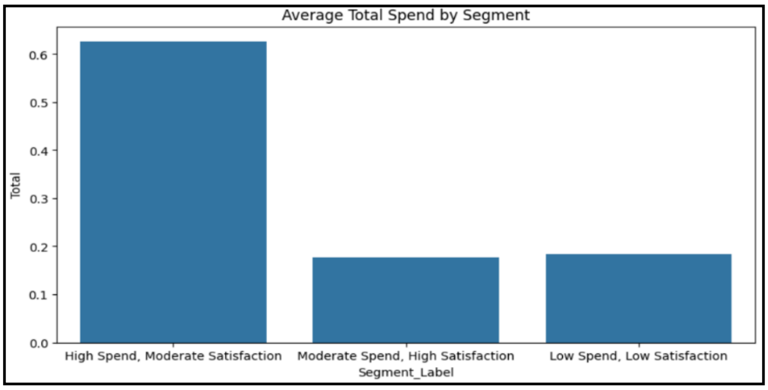

Fig. 6: Average Total Spends by Segment.

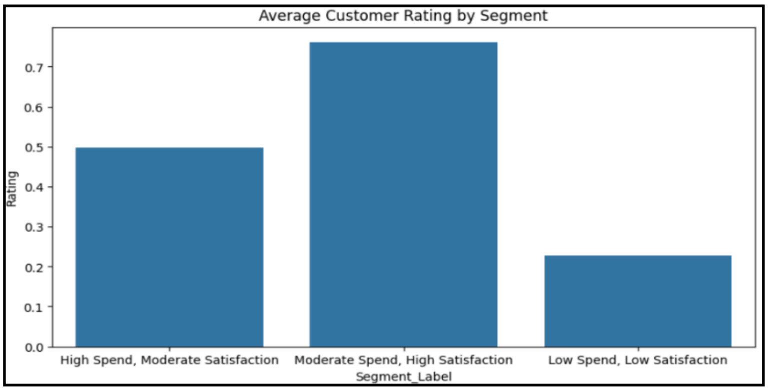

Fig. 7: Average Customer Rating by Segment.

Figure 8 and Figure 9 illustrate the Q-tables learned by the reinforcement learning agent. Figure 8 shows the initial Q-values, where each row represents a customer segment and each column an action. The values reflect expected cumulative rewards, helping the agent determine the most effective strategy over time. Figure 9 presents the Q-table after extensive training, with significantly higher and more stable values (e.g., 929.19, 926.85), indicating convergence. This demonstrates that the RL agent effectively learned to select optimal long-term retention actions through continuous interaction and feedback from the environment.

```
Final Q-Table:
Segment_0: [41.17453388 14.87757038  9.49503104 10.73536919]
Segment_1: [33.59900543 13.84852425 10.42642114  7.441742  ]
Segment_2: [38.30974322  9.60958475 14.22822134  8.33899468]
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Fig 8: Q-Table.

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Learned Q-Table:
[[818.86621529 700.74206622 929.19891576]
 [523.18660007 731.46940397 926.85523554]
 [552.86610781 754.30197908 929.32022373]]
```

Fig. 9: Learned Q-Table.

4.2. Market basket analysis for personalized recommendations

Figure 10 showcases a web interface that integrates churn prediction and Market Basket Analysis to deliver personalized retention strategies. Upon entering an Order ID, the system displays customer details, churn probability (e.g., 0.33), and tailored product recommendations based on association rules (e.g., fresh food, grains, vegetables). A targeted offer (e.g., 30% off + free gift) is also generated based on customer segmentation. This demonstrates the system's ability to translate real-time analytics into actionable, personalized interventions for customer retention.

Enter Order ID

OD77 Submit

Customer Information

Field	Details
Order ID	OD77
Customer Name	Arvind
Category	Fruits & Veggies
Purchases	veggies, fruits, organic
Region	Central
Sales	₹1250
Churn Probability	0.33
Churn Segment	0
📌 Personalized Recommendations	fresh, food, vegetables, grains, staples
🎁 Special Offer	30% off your next order + Free Gift!

Fig. 10: Web Interface That Displays Market Basket Analysis.

5. Discussion

The proposed Reinforcement Learning (RL)-based system significantly outperformed traditional models in both effectiveness and efficiency. Customer Retention Rate (Figure 11): The RL-based system achieved the highest customer retention rate at 81.2%, significantly outperforming logistic regression (70.8%), decision trees (70.0%), and the baseline approach (54.8%). This demonstrates the RL model's ability to dynamically tailor strategies for different customer segments, leading to superior retention outcomes.

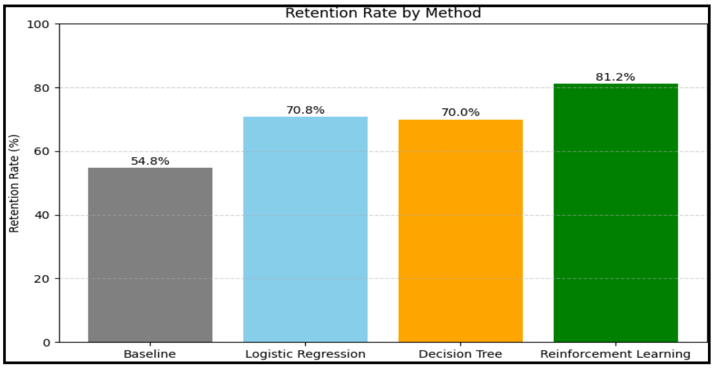

Fig. 11: Retention Rate by Method.

Similarly, the churn rate shown in Figure 12 decreased drastically to 18.8% under the RL strategy, compared to 29.2% and 30.0% under logistic regression and decision tree models, respectively, and 45.2% in the baseline case. These results confirm that targeted interventions generated by the RL agent were more effective in reducing attrition.

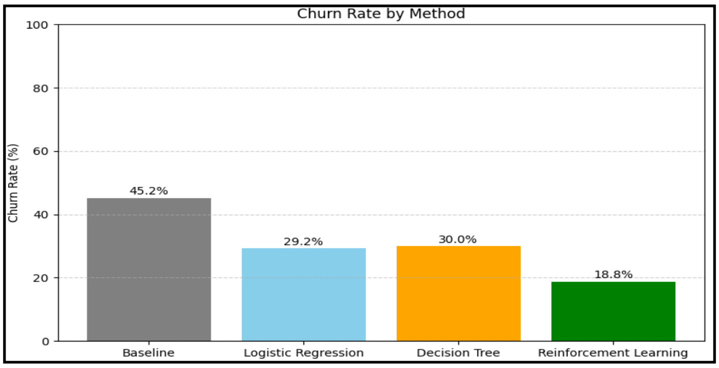

Fig. 12: Churn Rate by Method.

The system also demonstrated substantial financial benefits in Figure 13. A 48.2% increase in Customer Lifetime Value (CLTV) and an impressive 712% Return on Investment (ROI) were observed. These outcomes suggest that the long-term rewards learned by the RL model contribute not only to customer engagement but also to overall business profitability.

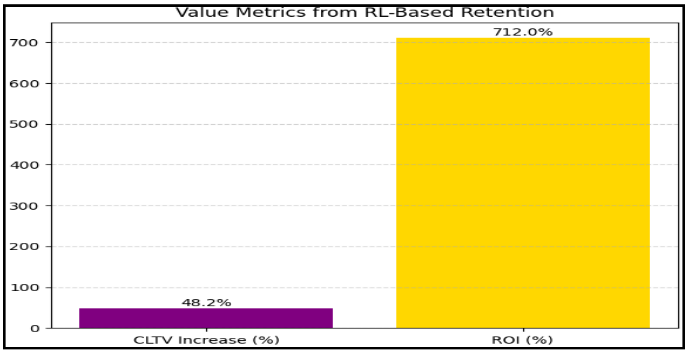

Fig. 13: Value Metrics from RL-Based Retention.

Furthermore, uplift modeling (shown in Figure 14) revealed that the treated group (customers who received RL-based interventions) exhibited a 46.4% purchase probability, compared to 29.2% in the control group, producing a 58.9% relative uplift. This supports the claim that the RL model not only retains customers but also drives higher purchase behavior.

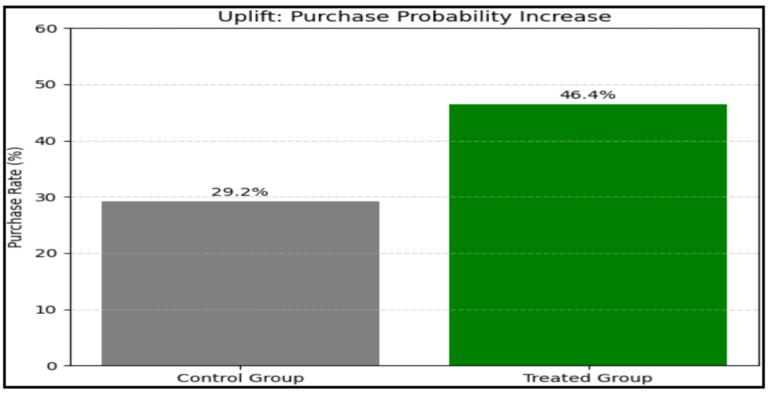

Fig. 14: Uplift Purchase Probability Increase.

These findings validate the potential of reinforcement learning in customer retention systems. Just as CNN model performance varies with epochs and layer configuration, the RL model's efficiency can be further improved through tuning of parameters such as discount factors, exploration rates, and reward functions. Continuous training and interaction with live customer environments may further refine action policies and increase performance over time.

6. Conclusion

This study presents a Self-Learning Customer Retention System that integrates Reinforcement Learning (RL) and Market Basket Analysis (MBA) to dynamically optimize retention strategies. Unlike traditional static churn prediction models, the proposed system continuously learns from customer interactions, allowing businesses to implement adaptive retention strategies such as personalized discounts, loyalty rewards, and targeted engagement efforts.

The key contributions of this research include the development of a novel self-learning retention framework that evolves based on real-time feedback. By integrating RL with MBA, the system enables personalized and data-driven retention strategies that adapt to customer behavior changes. Additionally, the proposed framework enhances adaptability and scalability, making it applicable to various industries seeking to improve customer engagement and reduce churn.

While the current model effectively reduces churn, several enhancements can further improve its performance. Multi-channel integration can be explored to incorporate data from multiple customer touchpoints, such as social media, mobile apps, and customer service interactions, providing a more comprehensive understanding of customer behavior. Deep learning techniques can also be utilized for advanced customer segmentation, enabling more precise targeting of retention strategies based on complex behavioral patterns.

Another potential improvement is the implementation of AI-driven dynamic pricing strategies, which would allow businesses to optimize pricing based on customer preferences, purchase history, and market trends. Additionally, expanding the scalability of the system and adapting it to industry-specific requirements such as e-commerce, finance, and telecommunications can further enhance its real-world applicability. By addressing these areas, future research can refine retention strategies, helping businesses build stronger customer relationships and maintain long-term competitiveness in dynamic market environments.

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