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Dynamic Pricing in Hospitality Industry Using Reinforcement Learning Approach

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ABSTRACT: A Reinforcement learning-based approach for dynamic hotel room pricing, utilizing a Deep Q-Network (DQN) agent. The DQN is recommend suitable pricing strategies that maximize daily earnings while minimizing the number of unoccupied rooms. Several factors, such as hotel demand, room type, and duration of stay, influence the pricing decisions. Hotel demand is predicted using a Random Forest model, which is trained on processed data to simulate realistic demand distributions. The method was tested using a real-world hotel bookings dataset, which was preprocessed before training. The DQN-driven pricing strategy outperforms both fixed pricing and rule-based approaches, leading to a 15-20% increase in profits and a significant reduction in empty rooms. The Discoveries show that dynamic pricing powered by reinforcement learning can effectively minimize revenue and occupancy in the hospitality industry. This work underscores the potential of AI-driven pricing models to adapt to market fluctuations and enhance operational efficiency. The model's effectiveness relies on high-quality data and successful training, offering considerable improvements over traditional pricing methods. The research adds to the growing body of work on AI applications in the hospitality sector, providing a valuable solution to the complex challenge of hotel room pricing..

KEYWORDS: Dynamic pricing, Deep Reinforcement Learning, Hospitality Industry, Deep Q-network, Revenue management.

I. INTRODUCTION

Dynamic pricing is widely used in retail and travel industries, but research in hotel pricing within the hospitality sector remains limited. Traditionally, hotel revenue management system have relied on rule-based methods without machine learning capabilities. While recent studies have explored stochastic models like Markov chain Monte Carlo(MCMC),these methods face challenges in scalability, personalization, and providing insights into customer behavior.

A Reinforcement learning approach using a Deep Q-Network(DQN) to optimize hotel room pricing. Reinforcement learning is effective for dynamic pricing because it can scale, personalize strategies, and be trained online without extensive historical data. The DQN agent is trained to maximize profits and minimize empty rooms by considering factors like demand, room type , booking time, and additional services.

Unlike traditional methods that rely on simulated demand,this approach uses real hotel booking data for demand forecasting . The machine learning-based demand calculation is scalable, adaptable, and transferable to various contexts.

II. RELATED WORK

Dynamic Pricing (DP) has been widely researched and applied across various industries, with the retail sector being one of the earliest adopters. In retail, most DP models assume demand follows specific distributions (e.g., Poisson, constant rate) or model it as a polynomial function dependent on price and product expiry. The airline and travel industry also heavily utilizes DP, with systems often combining demand forecasting methods (such as linear models or deep neural networks) with price optimization functions.

For our hotel room pricing use case, we employ a reinforcement learning-based Deep Q-Network (DQN) approach. Reinforcement learning, particularly Q-learning, has proven effective in price optimization tasks. While Q-learning works well for smaller action spaces, DQNs are more scalable and eliminate the need for memory-intensive Q-tables. DQNs are highly customizable, making them suitable for dynamic pricing problems with large action spaces.

Most previous reinforcement learning-based DP systems have focused on single-agent setups, but there has been some exploration of multi-agent price optimization in recent research. Our approach uses a single-agent DQN to optimize pricing for hotel rooms, maximizing profits across a one-month time period. Additionally, personalized DP approaches have been explored, where profit maximization occurs at the individual customer level. This paper contributes to the growing body of research on DP for hotel pricing, building on prior work that employed nonlinear programming or predefined probability distributions for price optimization. Factors such as demand elasticity, additional amenities, and booking time are found to influence pricing strategies in the hospitality sector.

III. METHADODOLOGY

The methodology for our study involves a structured life-cycling process divided into four interdependent steps to establish a Reinforcement Learning (RL)-based dynamic pricing framework. The first step focuses on analyzing real market scenarios to understand customer demands and preferences, using historical data and trends to identify key factors such as booking patterns and demand elasticity. This analysis provides essential feedback for creating a realistic RL environment. In the second step, the RL framework is defined by specifying its key components: the environment (a simulated market including variables like demand and room availability), states (system conditions such as occupancy levels and time intervals), actions (pricing strategies), and rewards (feedback mechanisms to incentivize profit and minimize vacant rooms). The third step involves configuring the agent using a Deep Q-Network (DQN) to interact with the environment, balancing exploration (trying new pricing strategies) and exploitation (applying proven strategies). Unlike traditional methods, the DQN approximates the value function using a neural network, ensuring scalability and eliminating memory-intensive Q-tables. Finally, the process incorporates feedback from the agent's performance to refine the environment and parameters iteratively, ensuring adaptability to evolving market conditions. This end-to-end methodology leverages real-world data and RL's flexibility to develop an optimized dynamic pricing strategy for hotel rooms.

IV. EXPERIMENTAL RESULTS

We developed a demand model using real hotel market data to simulate customer behavior and introduced a data simulation approach to replicate booking combinations based on lead times, enabling accurate market environment modeling and state updates. A pre-trained Deep Q-Network (DQN) model was trained over 30,000 episodes and evaluated for lead times ranging from 10 to 1 day before booking. The results showed that base prices generally increased as booking dates approached, reflecting higher demand, with an inverse relationship between base price and the number of bookings, consistent with market trends. A sharp price drop was observed in the final lead-time step (from 2 to 1 day) as hotels aimed to fill remaining vacancies, minimizing wastage. Discounts were minimal during peak demand periods but were introduced at the beginning and end of lead times to stimulate demand during low-booking phases. This approach effectively mirrors real-world hotel revenue management strategies, optimizing both pricing and occupancy

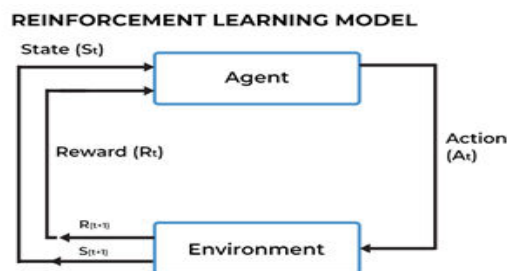


Fig1.Reinforcement Learning Model



Fig .2"Training Rewards Progression Over Episodes in DQN for Hotel Pricing Simulation"

V. CONCLUSION

Using real hotel market data, we developed a demand model to simulate customer behavior and introduced a data simulation approach to model booking combinations based on lead times. This enabled effective state updates and environment replication for pricing strategies.

A Deep Q-Network (DQN) was trained over 30,000 episodes and evaluated for lead times from 10 to 1 day before booking. Results showed that base prices generally increased as booking dates approached, reflecting higher demand, with an inverse relationship between base price and the number of bookings.

However, a sharp price drop occurred in the final lead-time step (2 to 1 day) as hotels sought to fill remaining vacancies. Discounts were applied at the start and end of lead times to stimulate demand but were minimal during peak periods. This strategy closely aligns with real-world hotel revenue management practices

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