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Deep Reinforcement Learning-Based Dynamic Pricing for Parking Solutions

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Introduction

The need for more effective car park management in public areas like healthcare facilities, shopping malls, and office buildings has been brought to light as a result of the rise in the number of automobiles in metropolitan areas. In order to optimize parking utilization and reduce traffic jams, this study combines dynamic pricing with real-time parking data. The practice of adjusting a product's or service's price in response to market trends is known as dynamic pricing. During both off-peak and peak hours, this strategy has the potential to manage vehicle traffic in the parking space. The dynamic pricing method has the ability to set the price of the parking fee to be higher during peak hours and lower during off-peak hours. This paper proposes a technique known as deep reinforcement learning-based dynamic pricing (DRL-DP). On an hourly basis, dynamic pricing is divided into episodes and shifted back and forth. Pricing control is seen as an incentive based on profits and parking utilization rates. In the context of a competitive parking market around the parking area, the simulation output demonstrates that the proposed solution is plausible and efficient.

Description

The rapid growth of private automobiles is a major issue in many metropolitan areas, particularly in major cities like London, Hong Kong, and Kuala Lumpur. The increasing number of automobiles has a negative impact not only on the local population but also on the surrounding environment. The need for parking spaces grows as the number of cars grows. New Strait Times conducted a survey that found that people spend about 25 minutes per day looking for parking in certain urban areas. The cars keep going around the area, wasting time looking for a free parking spot. Carbon dioxide emissions and fuel consumption rise as a result, contributing to climate change and the greenhouse effect. The more time a driver spent driving, the more people were stuck in traffic in that area. This sets off a chain reaction that aggraves other drivers and prolongs delays. After realizing the difficulties brought on by the increase in the number of automobiles, numerous academics have attempted to address the issues of traffic congestion and the significant demand for parking lots. Using technologies like sensors (loop or ultrasonic sensor), tickets, or e-payment systems, parking information, such as the availability of free parking spaces, can be received in real time. A chance to create a smart parking system with dynamic pricing is presented by this. By utilizing dynamic pricing, the parking vendor is able to offer price regulation that is adjustable based on a variety of time periods in order to maximize revenue while simultaneously increasing the utilization of parking spaces [1,2].

To control parking prices based on vehicle volume and occupancy rate, a deep reinforcement learning-based dynamic pricing (DRL-DP) model is proposed in this study. Reinforcement learning (RL) is recommended for environment modeling because it does not require raw labelled data. Throughout the experiments, RL enables sequential decision-making and provides a complete set of wise choices. In order to lessen traffic congestion and boost parking vendor profits, the dynamic pricing model monitors the various price plans and how they are applied in various contexts. The dynamic pricing model predicts vehicle volume and traffic congestion and distributes vehicle flows. The vehicle flows are distributed to non-peak hours by suppressing drivers' visits to a specific region during peak hours at specific intervals of the day. This increases the rate of parking utilization and reduces traffic jams. This is accomplished by lowering prices and offering incentives like cash back for parking fees. The deep learning agent will gain knowledge from the sequential selection of dynamic pricing in order to enhance the returned incentive in the subsequent episode. Dynamic pricing is a pricing strategy that has had a significant impact on our society because e-commerce is now a common business model. The Internet allows for any trade-off, reduces numerous physical costs, and has made it easier to enter the market. Numerous academics are now focusing on dynamic pricing in e-commerce due to the availability of huge amounts of data that reveal user behaviour [3].

Four e-commerce pricing strategies: time-based pricing, market segmentation, restricted rations, dynamic marketing, and combining the three types previously mentioned. On the other hand, Chen and Wang presented an e-commerce-specific dynamic pricing model that is based on data mining. The model was made up of three bottom-up layers: the data layer, the analytical layer, and the decision layer. Online bargaining is advantageous for both the seller and the buyer because the deal price agreed upon is higher than the seller's reserved price but lower than the buyer's reserved price. A bound regret over an infinite horizon was provided by the authors in addition to the Pareto-efficient and subgame-perfect equilibrium suggestions. They referred to regret as the anticipated cumulative profit loss compared to the ideal circumstance with a known demand model. However, when considering an oligopoly with dynamic pricing in the face of uncertain demand, they assumed that all vendors faced equal marginal costs [4,5].

Conclusion

In a multi-agent scenario, the other agents' strategies have an impact on the agent's optimal pricing strategy. A multi-agent reinforcement learning system that takes into account both the opponents' observed objective behaviors and their inferential intentions. For the purpose of taking into account dynamic pricing usage, order cancellation ratios, and various quality of service (QoS) levels in online networks, a novel continuous time model with price and time-sensitive demand was presented. Price and lead time-sensitive customers were at the heart of the suggested strategy, which involved two competing vendors. As two examples, they considered the situation in which there was no information and the situation in which there was partial information.

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Conflict of interest

No potential conflict of interest was reported by the authors.

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