University of New Haven

ARTIFICIAL INTELLIGENCE PROJECT ON

DECISION MAKING FOR CAB DRIVERS

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SUBMITTED TO

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RESEARCH QUESTION:

Reinforcement learning can be applied to enhance cab drivers' decision-making processes, helping them maximize earnings by strategically determining the best times and locations to accept rides. This approach considers real-world factors like fluctuating demand, time constraints, and fuel expenses.

INTRODUCTION:

Cab drivers in the transportation industry face significant obstacles in maximizing their daily income, even as the number of rides they provide increases. Rising operational costs, unpredictable traffic patterns, and fluctuating customer demand pose challenges to revenue optimization. Solving these issues is critical for enhancing driver profitability and improving the overall efficiency of urban transit systems.

This study presents a system based on Reinforcement Learning (RL) to help cab drivers make more informed decisions about ride selection and optimal route planning. By utilizing Deep Q-Learning, an advanced artificial intelligence technique, the system learns from past data while adapting to real-time conditions. This approach aims to boost drivers' earnings and reduce inefficiencies within the transportation networks.

RELATED LITERATURE:

Dynamic Ride-Hailing Optimization using Reinforcement Learning

Their Approach: This research frames vehicle repositioning as a semi-Markov Decision Process (SMDP) aimed at improving income efficiency for ride-hailing platforms. It emphasizes aligning supply with demand by relocating vehicles to high-demand regions using spatiotemporal data.

Our Approach: While their method focuses on repositioning, our project takes a broader perspective by equipping cab drivers to assess multiple ride options and select the most efficient routes in real time. Our approach incorporates urban variables such as traffic patterns and time limitations to enhance decision-making.

Source: https://ar5iv.org/html/2103.04555

Deep Reinforcement Learning for the Dynamic Vehicle Dispatching Problem

Their Approach: This study focuses on vehicle dispatch and repositioning to reduce idle cruising distances and better align supply with demand. It utilizes techniques such as deep Q-networks and proximal policy optimization to optimize vehicle actions.

Our Approach: Rather than emphasizing platform-level dispatching, our approach prioritizes individual cab drivers. It delivers tailored recommendations by dynamically analysing ride-specific rewards and operational expenses, offering a solution designed specifically for drivers.

Source: https://ar5iv.org/html/2307.07508

Value Function is All You Need: Unified Learning Framework for Ride-Hailing Platforms

Their Approach: This paper applies value-function approximation for the integrated optimization of dispatching and repositioning tasks. It leverages both real-time and offline learning to handle supply-demand dynamics on large ride-hailing platforms.

Our Approach: While their framework is designed for platform-wide optimization, our approach focuses on individual cab drivers. It enhances their earnings by utilizing reinforcement learning techniques to optimize route and ride choices, considering real-time and localized urban factors.

Source: https://ar5iv.org/html/2105.08791

APPROACH AND ALGORITHMS:

- Environment Simulation: The simulated environment represents a city with five locations, time of day, and day of the week.
- Deep Q-Learning Algorithm.
- A neural network estimates Q-values for all state-action pairs.

CHALLENGES AND WORKAROUNDS:

Challenge 1: Defining the ideal state representation

- **Current Approach:** Testing various state vectors to achieve a balance between comprehensiveness and efficiency
- **Next Steps:** Finalizing the state space design based on the results of preliminary testing

Challenge 2: Modelling realistic traffic conditions

- **Current Approach:** Beginning with basic traffic patterns for simplicity
- **Next Steps:** Intend to integrate more complex traffic patterns once the foundational functionality is in place.

Challenge 3: Stability issues during initial training tests

- **Current Approach:** Analysing hyperparameter configurations
- **Next Steps:** Plan to implement experience replay and optimize the network architecture.

GITHUB LINK:

https://github.com/minnuanna/AI-Project-