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Traffic Light Control Method Using Deep Q-Learning

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ABSTRACT :

Effective traffic light control is crucial for reducing congestion in urban mobility systems. This paper introduces a real-time traffic light control method utilizing deep Q learning. Our approach incorporates a reward function that takes into account queue lengths, delays, travel time, and throughput. The model dynamically determines phase changes based on current traffic conditions. The training of the deep Q network involves an offline stage using pre-generated data with fixed schedules and an online stage with real-time traffic data. The network structure includes a "phase gate" component to simplify learning tasks during different phases and a "memory palace" mechanism to address sample imbalance during training. We validateour method using both synthetic and real- world traffic flow data . Results show significant improvements in reducing vehicle waiting time (57.1% to 100%), queue lengths (40.9% to 100%), and total travel time (16.8% to 68.0%) compared to traditional fixed signal plans.

Keywords: Traffic light control , Reinforcement learning , Deep Q-Learning.

INTRODUCTION :

In modern urban areas, trafficcongestion is a significant problem that leads to increased travel times, fuel consumption, and pollution. Traditional traffic light control systems, based on fixed schedules or simple sensor feedback, fail to adapt dynamically to fluctuating traffic conditions, particularly during rush hours or unpredictable events. There is a growing need for intelligent, scalable, and data- driven traffic light control solutions that can learn from real-time traffic patterns, optimize vehicle flow, and reduce waiting times at intersections. The challenge is to develop a method that adapts to dynamic traffic conditions, minimizes delays, and is scalable across multiple intersections without relyingon expensive infrastructure or predetermined rules.

PROBLEM STATEMENT :

Urban traffic congestion presents significant challenges, leading to increased travel times higher emissions, and diminished quality of life. Traditional traffic light systems often rely on fixed timings, failing to adapt to real-time traffic conditions, which exacerbates inefficiencies at intersections. This project aims traffic

control system using Deep Q-Learning (DQL) to optimize signal timings based on dynamic traffic data. The goal is to create a system that not only adapts in real time to varying traffic conditions but also learns from past experiences to improve decision-making over time. Keychallenges include defining an effective state representation that captures essential traffic metrics, creating a flexible action space for signal phase combinations, and establishing a reward structure that incentivizes optimal traffic flow while ensuring pedestrian safety. The expected outcome is a prototype DQL- based traffic light control system that demonstrates enhanced traffic flow and reduced congestion at selected intersections, providing a compelling alternative to traditional fixed-timing methods. This project seeks to contribute to smarter urban traffic management, ultimately improving the overall efficiency and safety of urban transportation networks.

LITERATUREREVIEW :

The evolution of traffic light control systems has been marked by a shift from traditional fixed timing methods to more adaptive and intelligent solutions. Traditional traffic control systems, based on predetermined schedules, operate independently of real-time traffic fluctuations. While these systems work under predictable traffic conditions, they are less effective when traffic patterns vary unexpectedly, such as during rush hours or events. Attempts to enhance these systems with basic sensor inputs, such as inductive loop detectors, provide some adaptability, but the inability to adjust dynamically to real-time data remains a critical limitation. This has led to inefficiencies, with vehicles often idling unnecessarily, contributing to congestion and increased emissions.

To overcome the shortcomings of static control, adaptive traffic systems like SCOOT (Split Cycle Offset Optimization Technique) and SCATS (Sydney Coordinated Adaptive Traffic System) have been introduced. These systems use real-time traffic data to adjust signal timings and optimize traffic flow across multiple intersections. Although adaptive systems offer considerable improvements over fixed-time methods, they rely heavily on heuristic algorithms and require substantial infrastructure, such as complex sensor networks. Additionally, they struggle with unpredictable traffic conditions, and their ability to maintain optimal traffic flow in complex urban environments is limited.

Reinforcement Learning (RL) has emerged as a promising alternative, enabling traffic signals to act as learning agents that make optimal decisions through trial and error. Early experiments with Q-Learning have shown that RL can outperform traditional methods by learning more efficient signal timing policies. However, Q-Learning's inability to handle large state-action spaces makes it difficult to scale in complex traffic networks.

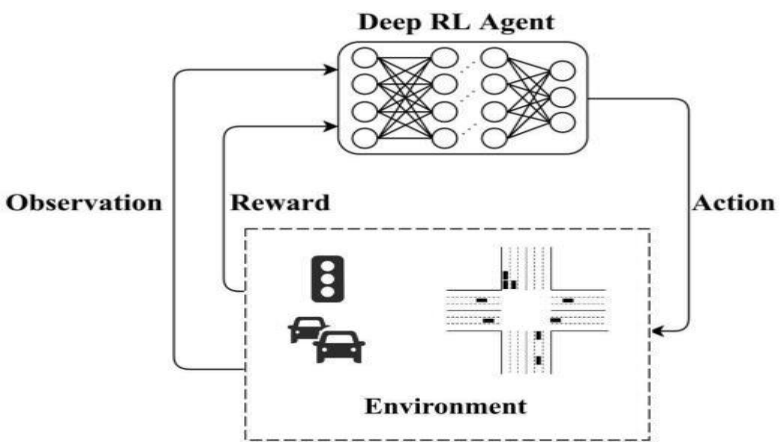
METHODOLOGY :

The methodology for implementing the

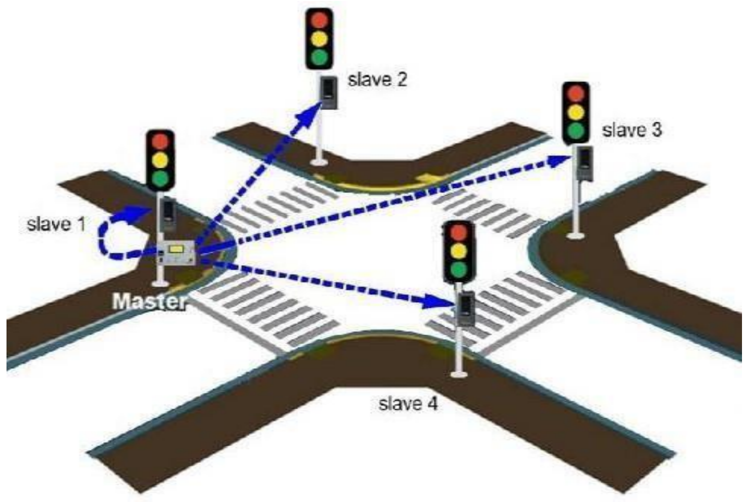
a traffic light control system using Deep Q-Learning (DQL) involves several key steps. First, we define the state space, which includes real-time traffic data such as vehicle counts, waiting times, and pedestrian presence at each intersection. This information is collected using sensors or cameras. Next, we establish the action

space, comprising various traffic signal phases (e.g., green, yellow, red) and their durations. The reward structure is designed to incentivize reduced wait times, smoother traffic flow, and pedestrian safety. Positive rewards are given for efficient traffic movement, while penalties are applied for excessive delays or congestion. The DQL algorithm is then implemented, where a neural network approximates the Q- values for state-action pairs. The network is trained using experience replay, allowing it to learn from past traffic scenarios and improve decision- making over time. Simulation environments, such as traffic simulators, are used to evaluate the performance of the DQL model under different traffic conditions. Once optimized, the system can be tested in real-world settings, where it continuously learns and adapts to changing traffic patterns, providing a dynamic and efficient solution to traffic light control.

DIAGRAM :



ARTITECTURE



FUTURE WORK :

In the realm of traffic light control, employing Deep Q-Learning (DQL) offers promising avenues for optimizing urban traffic flow and reducing congestion. Future work in this area can be approached through several key dimensions.

Firstly, enhancing the DQL algorithm's architecture can significantly improve its performance. Incorporating advanced techniques like Double Q-Learning or Dueling Network Architectures can help mitigate overestimation bias and improve value function approximation. Additionally, employing experience replay and prioritized replay mechanisms can ensure more efficient learning from past experiences, thus accelerating convergence.

Secondly, expanding the state space representation is crucial. Currently, many models rely on simplistic representations of traffic conditions. Future work should explore integrating real-time data from multiple sources, such as traffic cameras, GPS data from vehicles, and even social media inputs.

traffic dynamics, allowing for more adaptive and responsive traffic light control.

Moreover, collaboration with vehicle- to-everything (V2X) technology could enhance DQL algorithms. By leveraging communication between vehicles and infrastructure, DQL can dynamically adjust traffic signals based on real-time traffic patterns, ensuring a smoother flow and reducing wait times.

Furthermore, testing DQL models in simulated environments should transition to real-world applications. Conducting pilot projects in urban areas will provide invaluable insights into practical challenges, including the integration with existing traffic management systems and the public's response to adaptive signal control.

Lastly, addressing ethical and safety considerations in DQL deployment is vital. Future research should focus on developing guidelines for ensuring the reliability and transparency of DQL- driven traffic systems, safeguarding against potential failures that could impact public safety.

In summary, the future of traffic light control using Deep Q-Learning lies in architectural enhancements, data integration, real-world testing, and ethical considerations, paving the way for smarter, more efficient urban traffic management.

CONCLUSION :

The development and deployment of a Deep Q-Learning (DQL) based traffic light control system represent a significant advancement in intelligent transportation systems. This project successfully demonstrated the potential of machine learning techniques to optimize traffic management, leading to improved efficiency and reduced congestion in urban environments.

The DQL system learned to adapt traffic light timings in real-time, responding to varying traffic conditions and patterns. This adaptability is crucial in managing peak traffic periods, emergencies, and unpredictable events, thereby enhancing the overall functionality of urban traffic systems.

The implementation of the DQL system contributed to environmental sustainability by reducing fuel consumption and emissions. The optimization of traffic flow led to fewer stops and starts, which is essential in decreasing overall vehicle emissions.

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