ISyE 6740 - Spring 2025
Project Proposal

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1 Introduction

Urban traffic congestion is a growing problem, leading to increased travel times, higher fuel consumption, and elevated levels of pollution. Traditional traffic light systems operate using fixed schedules or sensor-based activation, which may not effectively adapt to real-time traffic fluctuations. This project will investigate the use of Reinforcement Learning (RL) to optimize traffic signal timings dynamically, with the goal of reducing congestion and improving traffic efficiency. By leveraging machine learning techniques, I aim to design an adaptive traffic control system capable of responding intelligently to varying traffic conditions.

2 Problem Statement

The current methods for managing traffic signals often rely on predefined rules or time-based sequencing, which do not adapt well to changing traffic patterns. As urbanization accelerates, the increasing number of vehicles on the road intensifies congestion problems. The primary research questions for this project are:

- Can reinforcement learning effectively optimize traffic light timings to reduce congestion and improve traffic flow in real-world scenarios?
- How does an RL-based traffic control system compare to traditional fixed-schedule traffic lights in terms of efficiency and congestion mitigation?

The success of this project will be measured by improvements in average vehicle wait times, overall traffic throughput, and system adaptability to different traffic conditions.

3 Data Source

For training and evaluating the RL model, I will utilize open-source and publicly available datasets, including:

- **SUMO (Simulation of Urban Mobility)**: A widely used traffic simulator that provides realistic traffic flow models and allows for experimentation with different control strategies
- **OpenTraffic API**: Provides real-time and historical traffic data from various cities, useful for validating the RL model
- **City-specific transportation department datasets**: Datasets from cities such as New York City, Los Angeles, or Atlanta may provide insights into real-world traffic behavior
- **Synthetic data generation**: Simulated traffic environments with configurable parameters will be used for initial training and testing

By combining real-world and synthetic data, I aim to develop a robust model that generalizes well to different urban environments.

4 Methodology

My approach involves the following structured steps:

4.1 Traffic Environment Simulation

I will use SUMO or a similar traffic simulation tool to create realistic traffic environments for training the RL model. This simulation will include intersections, multiple traffic lanes, and varying vehicle arrival rates.

4.2 Reinforcement Learning Model

I plan to implement RL algorithms such as:

- **Deep Q-Networks (DQN)**: A value-based RL algorithm suitable for optimizing discrete decision-making processes like traffic light control
- **Proximal Policy Optimization (PPO)**: A policy-gradient-based approach that may provide better stability in continuous decision-making

The RL agent will be trained using feedback from the environment, with rewards based on reduced congestion and lower vehicle wait times.

4.3 State and Action Space Definition

State Space: The input to the RL model will include real-time traffic conditions such as:

- Number of vehicles in each lane approaching the intersection
- Average vehicle waiting time
- Current traffic signal phase

Action Space: The possible actions include:

- Changing the traffic signal to a different phase
- Keeping the current signal unchanged
- Adjusting signal durations dynamically

4.4 Reward Function Design

The reward function will be designed to incentivize:

- Minimization of vehicle waiting time
- Reduction of overall congestion levels
- Efficient traffic flow across intersections

A well-defined reward function will help the RL agent learn an optimal control policy that balances throughput and fairness across different traffic flows.

5 Evaluation and Final Results

The effectiveness of the RL-based traffic signal control system will be evaluated based on the following key performance indicators:

- **Average Vehicle Waiting Time**: Reduction in wait times compared to traditional fixed-time signal control.
- **Traffic Throughput**: Increase in the number of vehicles passing through intersections within a given time frame.
- **Adaptability**: The model's ability to handle sudden changes in traffic conditions.
- **Computational Feasibility**: Evaluation of the model's performance in real-time scenarios and its practicality for real-world deployment.

I will conduct experiments using both simulated and real-world datasets to benchmark the RL model against traditional methods.

6 Conclusion

This project aims to demonstrate the potential of reinforcement learning in dynamically optimizing traffic light control. By training an RL-based traffic management system, I anticipate improvements in reducing congestion and improving overall traffic efficiency. The results from this project could pave the way for smarter, AI-driven traffic signal systems in real-world urban settings.