Decentralized Traffic Lights Agents for Pedestrian Safety

Members

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Problem Statement

Traditional traffic lights at urban intersections operate on fixed cycles or manually tuned heuristics, which often result in inefficient vehicle movement and long pedestrian wait times. These methods do not adapt to dynamic traffic or pedestrian patterns.

This project proposes a single RL agent that learns to control a traffic light at one intersection, making real-time decisions based on current traffic and pedestrian conditions. The goal is to reduce overall waiting times for both cars and pedestrians, while avoiding unsafe crossing conditions or excessive congestion.

Vehicles and pedestrians will be modeled as automated agents that follow simple rule-based logic (e.g., arrive at random intervals, wait for green signals, cross or pass). The RL agent will observe the environment state and decide when to switch or maintain the signal phases.

Feasibility: Why is RL Suitable?

Reinforcement Learning is well-suited to this setting because:

- The environment is dynamic and partially observable (car and pedestrian arrivals vary over time).
- The agent must learn a policy that balances conflicting needs: keeping wait times low for both types of agents while ensuring safety.
- Unlike rule-based systems, RL can adapt to emerging traffic patterns without being hard-coded.

Bi-Weekly Milestones

Date	Deliverable
15th October	Build basic custom Gym environment: simulate arrivals, crossings, rule-based agent logic. Finalize reward structure
27th October	Demo 1: Submit environment demo with random traffic light control
30th October	Begin Q-Learning agent integration. Prepare logging tools for wait times, signal switches and unsafe conditions
15th November	Train RL agent with baseline reward. Evaluate initial performance and tune hyperparameters
30th November	Experiment with different reward functions and traffic scenarios. Compare with fixed timer baseline
1st December	Demo 2: Submit performance demo showing trained RL agent behaviour and comparative results
7th December	Submit final project report with detailed methodology, experimental results and future work discussion

References

1. Wei, H., Zheng, G., Yao, H., & Li, Z. (2019). *CoLight: Learning Network-Level Cooperation for Traffic Signal Control*. arXiv:1905.05717
2. Chu, T., Wang, J., Codeca, L., & Li, Z. (2019). *Multi-Agent Deep Reinforcement Learning for Traffic Signal Control*. arXiv:1903.04527
3. PressLight: *Learning Max Pressure Control to Coordinate Traffic Signals in Arterial Network*. arXiv:1905.02146
4. Mannion, P. et al. (2016). *Experimental Comparison of Reinforcement Learning Algorithms for Adaptive Traffic Signal Control*. Autonomic Road Transport Support Systems.