Autonomous Cybernetic Multi-Agent System for Traffic Intersection Control

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INTRODUCTION

Develop an autonomous agent capable of learning and adapting to a simulated environment using reinforcement learning. The agent will monitor two intersections with traffic lights with multiple traffic participants (cars, motorcycles, and pedestrians).

An autonomous agent will be designed to control and manage traffic lights in two intersections, with the goal of optimizing traffic flow with reinforcement learning in the simulation; the agent learns to respond to traffic lights by observing traffic conditions, in order to minimize waiting time and avoid traffic at the two points.

GOALS

Functional

1. Control and manage two intersections with traffic lights with multiply agent in the environment (pedestrians, vehicles).

2. Optimize traffic flow with the implementation of reinforcement learning.
3. Respond to different traffic flows and environment conditions (including initial conditions).

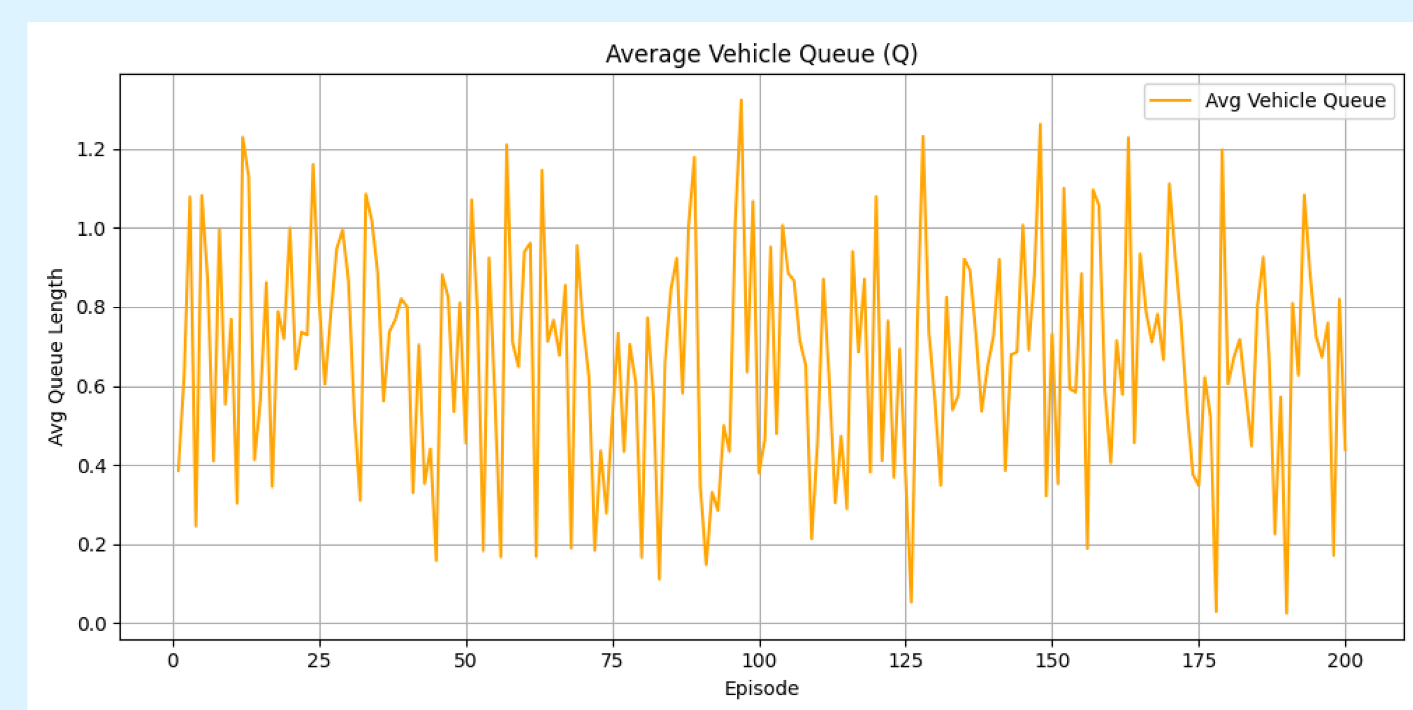
Non-Functional

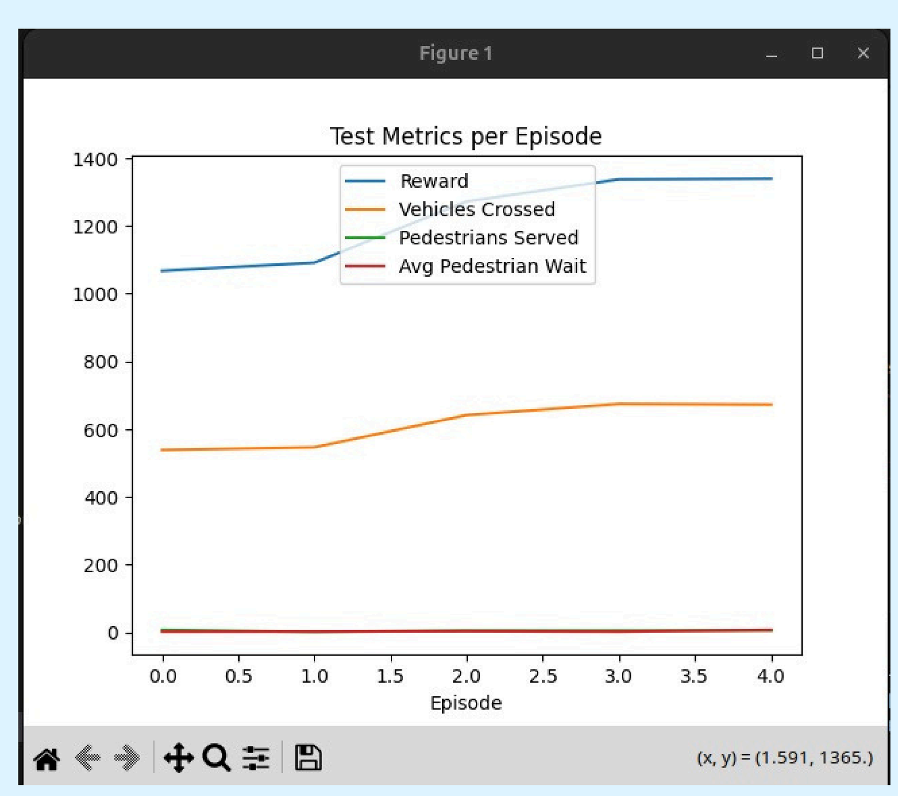
1. Scale from 2 to up to 10 intersections.

RESULTS

This graph shows the total reward obtained by the agent in each training episode. An initial
increasing trend is observed, indicating that the agent is learning. Then, there is a high
variability in the rewards, with high-performing episodes alternating with low-performing
ones. This could be due to ongoing exploration or a highly dynamic environment

This graph represents the average vehicle queue length per episode. The queue length re-
mains between 0.2 and 1.2, indicating that on average, there is no severe congestion. The
fluctuations may be caused by variations in traffic demand or suboptimal decisions in some
episodes

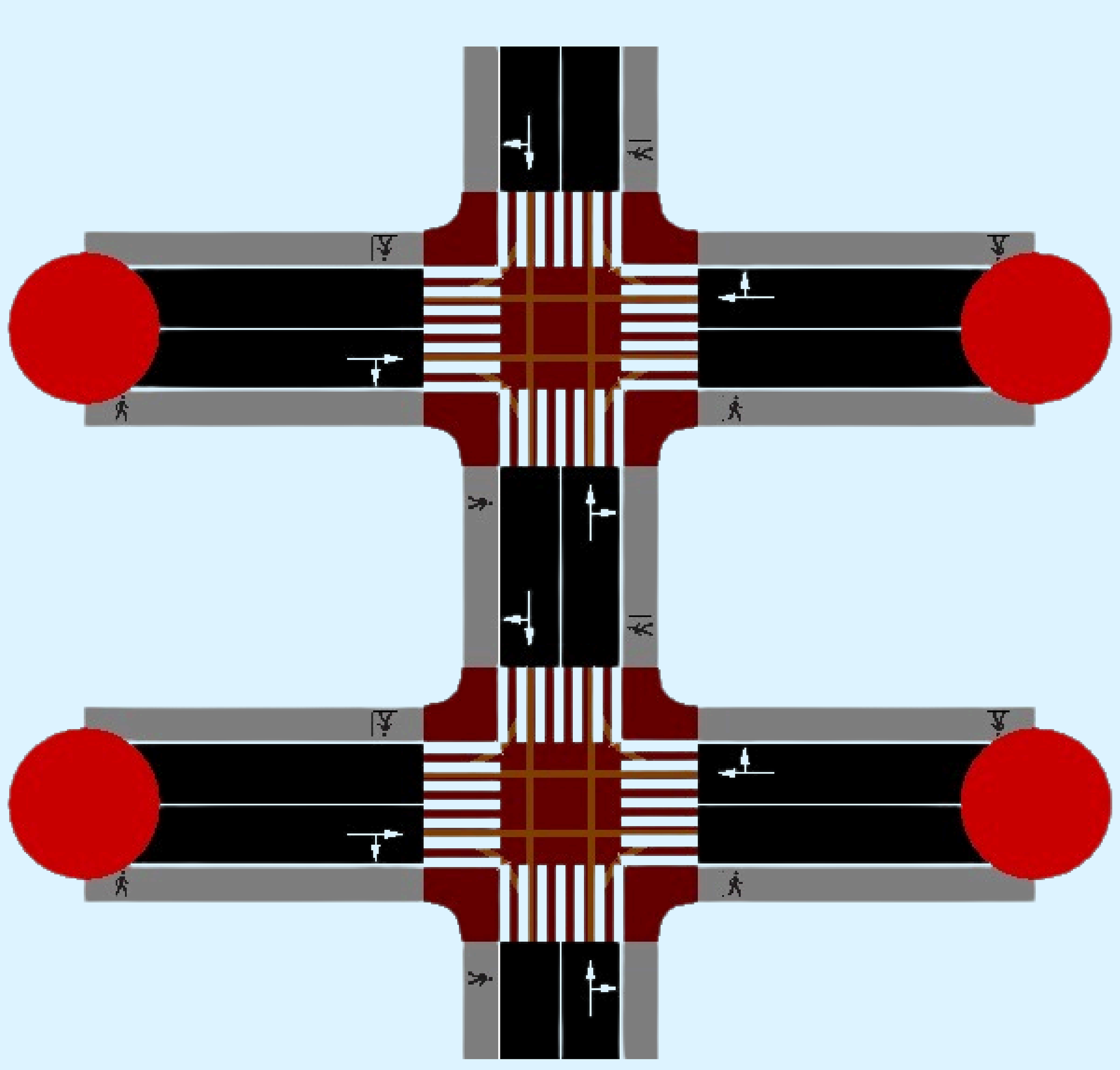




This graph displays various performance metrics of the Q-learning agent during the test phase, evaluated over 5 episodes.

- Reward (blue line): The total reward shows a consistent increase, indicating that the agent performs better over time by making more optimal decisions.
- Vehicles Crossed (orange line): The number of vehicles successfully crossing the intersection also increases across episodes, reaching a plateau. This reflects improved traffic flow management by the agent.
- Pedestrians Served (green line): The number of pedestrians served remains relatively stable with a slight upward trend, showing the agent maintains attention to pedestrian crossing needs.
- Average Pedestrian Wait (red line): The average waiting time for pedestrians remains low and consistent throughout the test, suggesting that the system prioritizes minimizing pedestrian delays.

PROPOSED SOLUTION



RL agent that controls traffic lights at two simulated intersections, optimizing vehicular and pedestrian flow. It uses an algorithm such as DQN or PPO, processing traffic data (vehicles, pedestrians) to decide on light changes.

CONCLUSIONS

The autonomous cybernetic multi-agent system successfully demonstrates how reinforcement learning and feedback control can be integrated to optimize traffic flow and pedestrian safety at intersections. By using Q-learning and DQN, the agents adapt to dynamic traffic conditions, reducing average wait times and improving system efficiency without requiring manual intervention. This project lays the groundwork for scalable, intelligent urban traffic management systems capable of self-regulation and real-time adaptation.

BIBLIOGRAPHY

1.Tutorial: An Introduction to Reinforcement Learning Using Open AI Gym (s. f.). https://www.gocoder.one/blog/rl-tutorial-with-openai-gym/

2. Lin, R. (2022, 3 march). Create your own environment using the OpenAI Gym library –GridWorld. Medium. https://reneelin2019.medium.com/create-your-own-environment-using-the-openai-gym-library-gridworld-8ca9f18e00a4