Reinforcement Learning for Traffic Signal Optimization in SUMO Simulations

Using Deep Q-Learning to control traffic lights and improve traffic flow in diverse urban layouts using SUMO

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Problem Statement

The Problem

Urban intersections are typically managed with static traffic lights, which do not adapt to real-time traffic flow

Project Goal

Can an RL agent be trained to generalize across various simulated traffic maps and optimize signal control to minimize:

- Waiting time
- Traffic congestion
- Teleports and vehicle stops?

Challenges

- Varying map complexities
- Malformed or incomplete traffic light logic
- Simulation stability

Methodology

Environment Setup

- Used SUMO simulator with TraCI to control traffic lights
- Wrapped in OpenAI Gym environment TrafficEnv
- Observation: 19D vector (phases, density, queue)
- Action: Switching phases for each traffic light

Algorithm

Deep Q-Learning (via Stable-Baselines3)

Improvements Made:

- Validated traffic light logic dynamically
- Safe phase-setting wrapper
- Reward tuning (waiting, arrivals, stops, utilization)

Evaluation

Ran RL agent across 12 different .sumocfg files, each a unique city layout

Data & Results

Synthetic Data from SUMO Configs:

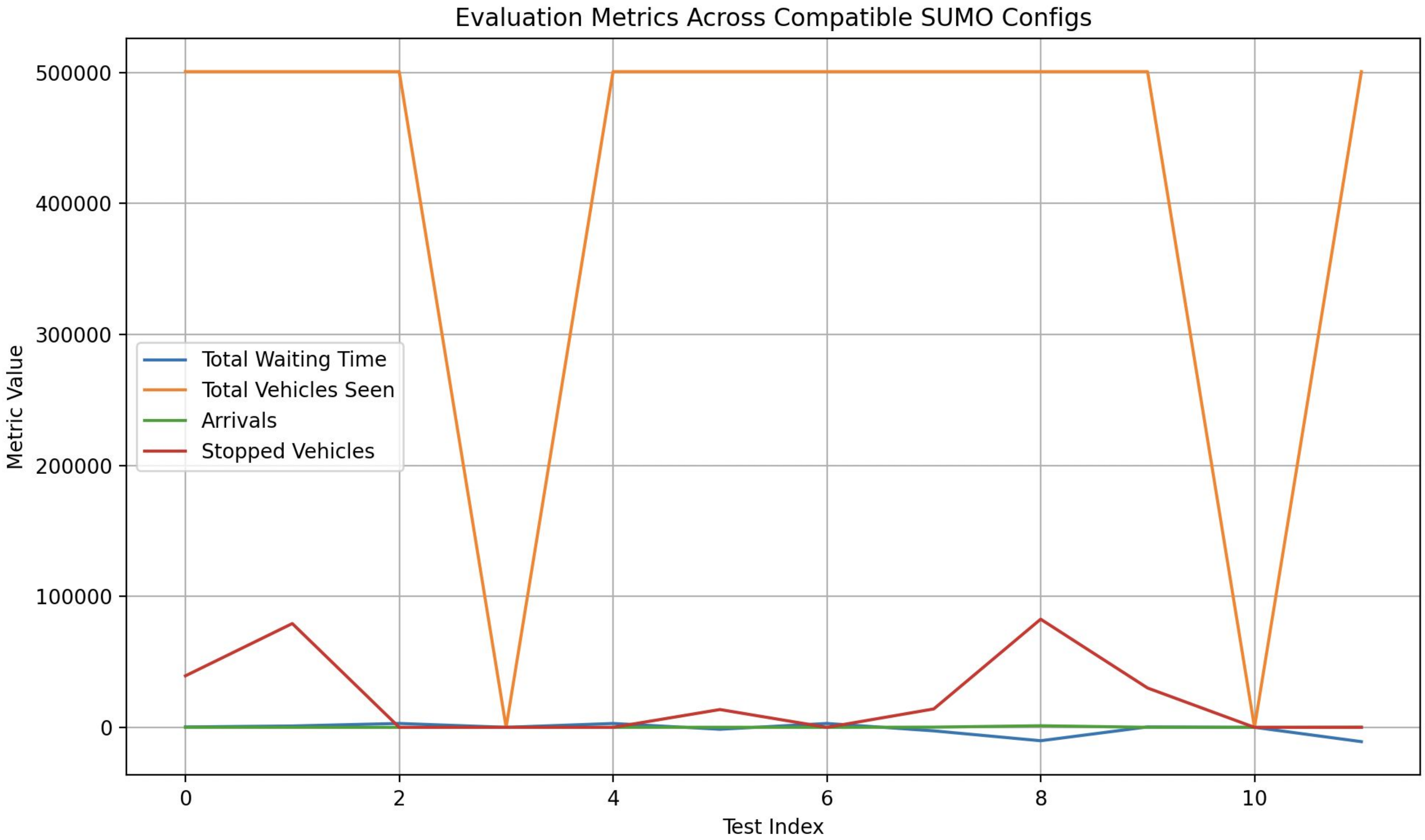
Tested maps like fkk_in, highway, cross, DRT, A10KW

Some Sample Results

- A10KW: 1211 arrivals, wait=0.00
- fkk_in: 44 arrivals, wait=293.11
- DRT: 0 arrivals, wait=2979.41
- highway: 158 arrivals, wait=0.00

Conclusion

- RL agent generalized well in structured maps
- Poor performance on configs with missing traffic logic
- Safe handling, reward design, and filtering were key
- Foundation laid for real-world deployment and deeper RL exploration


Evaluation Metrics Across Compatible SUMO Configs
500000
400000
300000
200000
100000
0
Metric Value
0
2
4
6
8
10
Test Index
Total Waiting Time
Total Vehicles Seen
Arrivals
Stopped Vehicles