Intelligent Urban Navigation Agent

DANIEL ALEJANDRO PRESIGA PRESIGA-20212020116

UNIVERSIDAD DISTRITAL FRANCISCO JOSÉ DE CALDAS

SYSTEMS SCIENCE FOUNDATIONS

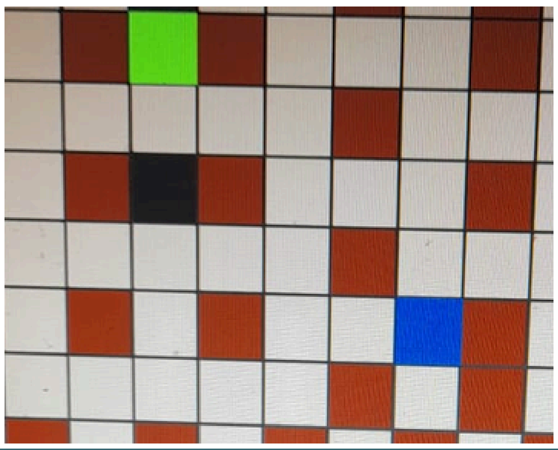
INTRODUCTION

Autonomous navigation in urban environments presents significant challenges due to chaotic traffic, traffic lights, and unpredictable obstacles.
Traditional rule-based systems struggle to adapt effectively in such conditions.
This project proposes an intelligent agent trained with Deep Q-Learning (DQN) that, through repeated interactions with a simulated environment (built using Gymnasium), learns to make legal and efficient decisions to reach a target.
The agent continuously analyzes its surroundings —such as speed, traffic lights, and nearby obstacles— to improve its behavior with every attempt.

EXPERIMENT

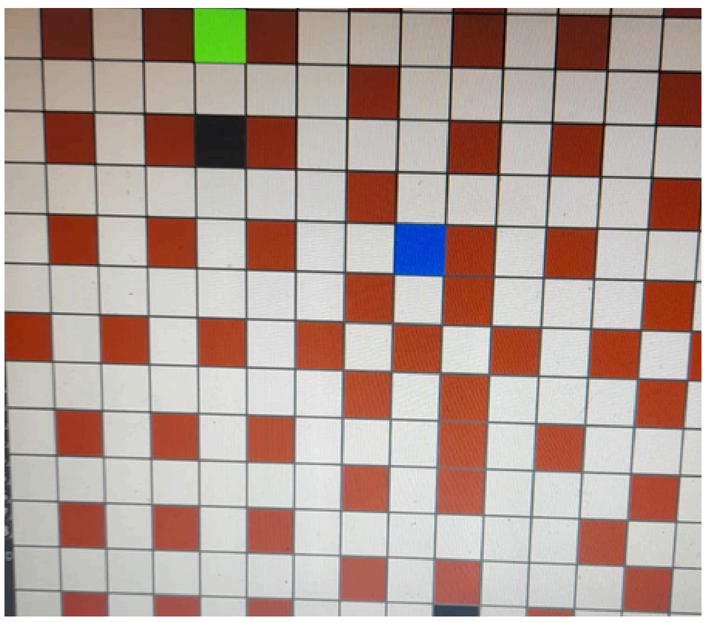
A simulated urban environment was built with obstacles and moderately complex routes.
The agent was trained directly within this environment using the Gymnasium library and Deep Q-Learning principles.
The reward function was designed to encourage efficient and legal navigation while penalizing collisions and inefficient behavior.
Several experiments were conducted by varying the number of training episodes (repetitions) to observe how the agent's learning and performance evolved over time.

```
episodes = 8000
alpha = 0.1
gamma = 0.99
epsilon = 1.0
epsilon_decay = 0.999
min_epsilon = 0.01
```



RESULTS

When trained with a low number of episodes, the agent tended to get stuck or loop repeatedly in the same area.
However, when trained with a high number of repetitions —such as 30,000 or more— the agent showed a clear ability to navigate more intelligently and reach the destination more reliably.
More training led to better movement, orientation, and goal-seeking behavior.



CONCLUSIONS

Although the final system lacks a polished interface and still requires improvements, it successfully fulfills its core function:
The agent learns from its virtual environment and improves over time.
This project provides a solid foundation for future work on advanced visualization, richer interactions, and real-world deployment.

REFERENCES

- Farama Foundation. Minigrid. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Duis at vestibulum ante. Nam id aliquet augue, et convallis quam. Nulla mauris odio, sagittis a lectus nec, imperdiet dignissim nunc. Aliquam condimentum lectus tristique, vehicula lectus eu, viverra diam.
- DigitalOcean. OpenAI Gym Tutorial. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Duis at vestibulum ante. Nam id aliquet augue, et convallis quam. Nulla mauris odio, sagittis a lectus nec, imperdiet dignissim nunc. Aliquam condimentum lectus tristique, vehicula lectus eu, viverra diam.
- FSNDZOMGA. Stable Baselines3 Guide. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Duis at vestibulum ante. Nam id aliquet augue, et convallis quam. Nulla mauris odio, sagittis a lectus nec, imperdiet dignissim nunc. Aliquam condimentum lectus tristique, vehicula lectus eu, viverra diam. ...