

AI-Based Path Planning and Optimization

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Motivation & Purpose

In real-world domains such as robotics, autonomous driving, and delivery systems, intelligent agents must plan optimal paths in complex and uncertain environments. This project, AI Path Planner, explores both classical search algorithms and reinforcement learning to achieve efficient, adaptive, and goal-driven navigation on grid-based maps, highlighting the trade-offs between optimality, learning, and computational efficiency.

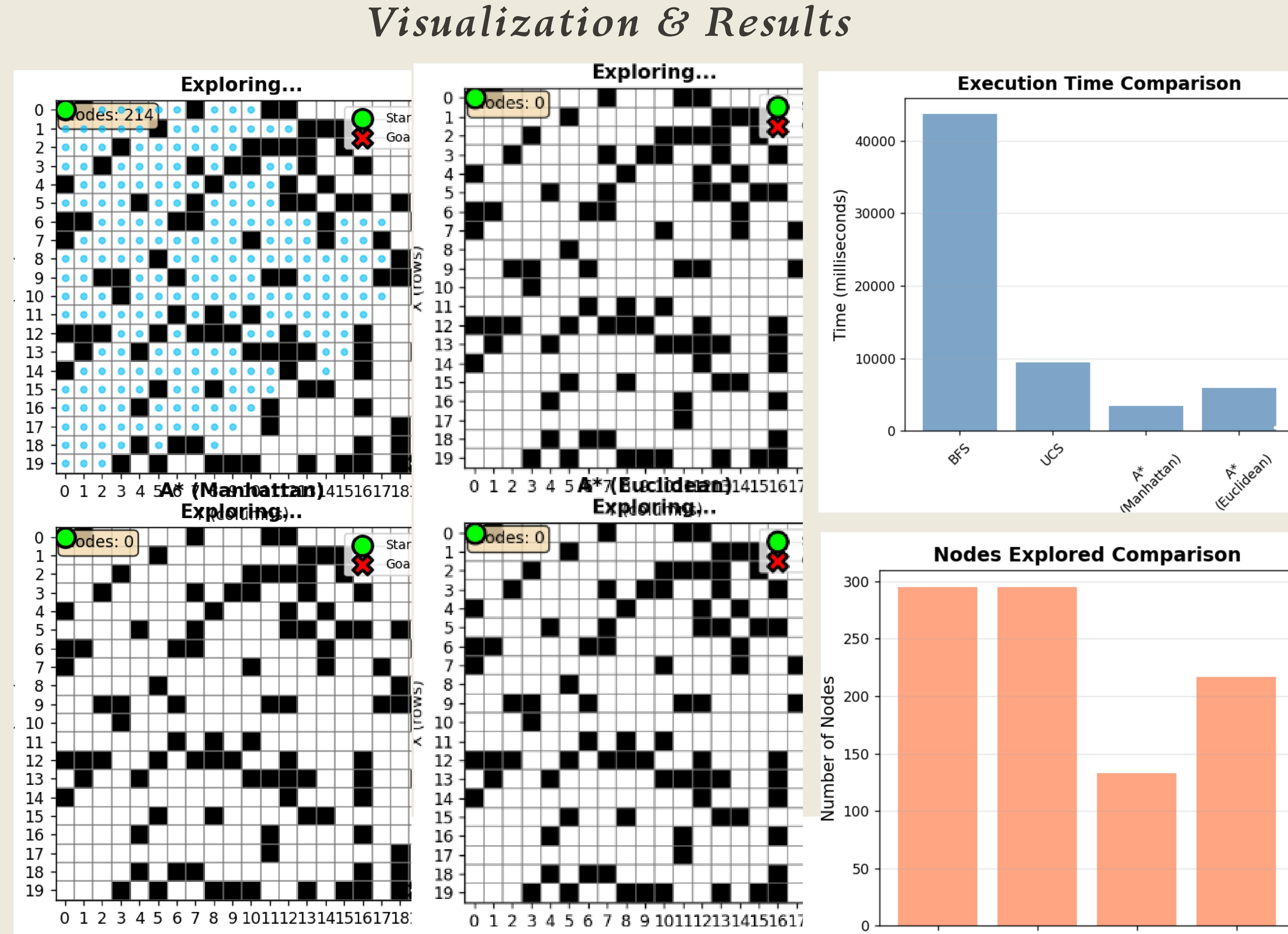
Project Overview

The system simulates an intelligent agent navigating a 20×20 grid world with obstacles representing real-world uncertainty. It compares classical search algorithms - BFS, UCS, and A* (Manhattan & Euclidean) alongside a Goal-Conditioned Q-Learning agent that learns routes through interaction.

Goal:

Evaluate each algorithm based on:

- Execution time
- Nodes explored
- Path cost
- Learning efficiency (for RL agent)

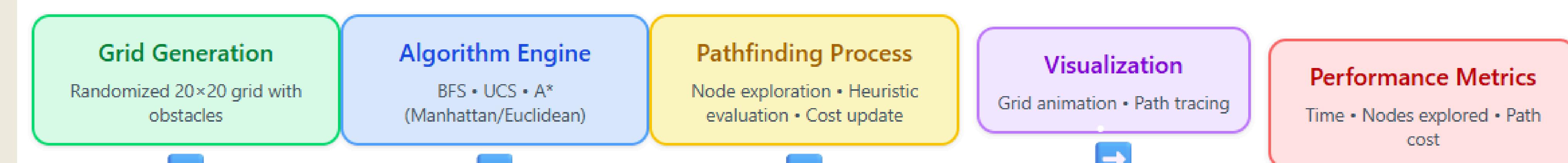


Analysis

All algorithms successfully found the optimal path, but A*(Manhattan) showed the highest efficiency, exploring 54.9% fewer nodes than BFS. UCS performed similarly to BFS in explored nodes but was faster. A*(Euclidean) maintained accuracy but was slightly slower due to floating-point calculations.

The extension to Goal-Conditioned Q-Learning showed how a trained agent can learn to navigate multi-goal routes with minimal exploration. While A* achieved a shorter path, RL explored far fewer nodes and executed faster after training, highlighting a trade-off between heuristic precision and learned efficiency.

AI Path Planner – Data Pipeline



Methods & Technologies

- **Programming Language:** Python 3.13
- **Libraries:** NumPy, Matplotlib, JSON
- **AI Concepts:** Search algorithms, heuristics, cost optimization
- **Visualization:** Real-time exploration updates and path reconstruction
- **Reinforcement Learning :** Goal-conditioned Q-Learning for adaptive pathfinding.

Conclusion

The AI Path Planner effectively combines classical search and learning-based methods to balance optimality and adaptability. While A*(Manhattan) remained the most optimal in static environments, the Goal-Conditioned Q-Learning agent demonstrated faster, experience-driven navigation with minimal exploration. This hybrid framework highlights how reinforcement learning can enhance traditional path planning for real-world robotics and autonomous systems.

References

- Russell & Norvig, Artificial Intelligence: A Modern Approach, 4th Edition
- UC Berkeley AI Materials (CS188)
- CMPT 310 Lecture Slides and Lab References