



# University of New Haven

**CSCI -6660-02**

**INTRODUCTION TO ARTIFICIAL INTELLIGENCE**

**RUBIKS CUBE SOLVER**

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# INTRODUCTION

The Rubik's cube is a well-known combinatorial puzzle offering artificial intelligence and machine learning many challenging and intriguing problems. Conventional methods in reinforcement learning depend on the ability to give incentives for doing something. Any series of haphazard movements, though, is improbable to result in the desired state. Out of the many states, there is only one ideal state ( $4.3 \times 10^{19}$ ). Creating an algorithm that deals with this Rubik's Cube trait could shed light on how machine learning can be used to issues with big state spaces and sparse rewards. Without utilizing human data, reinforcement learning algorithms have produced superhuman outcomes in games with much bigger state spaces, such as Go, Chess, and Shogi. These algorithms alternate between two policies: slow and fast, and they use the slow policy's input to make improvements to the fast policy.

## ABSTRACT

This project explores the application of reinforcement learning (RL) techniques to solve the Rubik's Cube, a classic combinatorial puzzle with a large state space and a single goal state. Leveraging RL algorithms, including Deep Q-Networks (DQN) and policy gradient methods, we trained agents to autonomously solve the puzzle through trial and error. By designing an appropriate reward function and fine-tuning hyperparameters, the RL agents demonstrated remarkable proficiency in navigating the Rubik's Cube's complex state space. Our experiments showcased high success rates and efficient solving times, surpassing conventional methods. Additionally, the trained agents exhibited robust generalization capabilities, effectively solving unseen Rubik's Cube configurations. These results underscore the potential of RL in addressing challenging problem domains with intricate state spaces and single goal objectives. Furthermore, this project contributes to advancing the understanding of autonomous problem-solving techniques and offers insights for future research in applying RL to real-world challenges beyond puzzle-solving domains.

## OVERVIEW

Since its introduction in 1974, the Rubik's Cube has been a symbol of mathematical intrigue and spatial complexity (Zeng et al., 2018). It continues to be a puzzle that captivates fans and speed-cubers alike. This in-depth investigation explores the complex relationship between recursive algorithms and state-of-the-art artificial intelligence, particularly as seen through the prism of DeepCubeA, to provide a thorough strategy for solving this well-known riddle. We start our adventure with a historical overview, realizing that the Rubik's Cube is more than just a puzzle. This project focuses on utilizing reinforcement learning (RL) techniques to solve the Rubik's Cube, a classic combinatorial puzzle. The Rubik's Cube presents a challenging problem due to its large state space and a single goal state. The project aims to train RL agents to autonomously solve the puzzle by iteratively learning from trial and error. Key components of the project include defining the problem formulation, designing the RL environment, selecting suitable algorithms such as Deep Q-Networks (DQN) or policy gradient methods, and designing an effective reward function.

Through extensive experimentation, the project aims to achieve high success rates and efficient solving times while ensuring robust generalization to unseen Rubik's Cube configurations. The results of the project contribute to advancing the understanding of RL techniques in handling complex problem domains and offer insights for future applications in autonomous problem-solving beyond puzzle-solving domains.

## **OBJECTIVE**

This project aims to demonstrate a deep reinforcement learning. A general algorithm for solving the Rubik's Cube that may also be used to other puzzles of a similar difficulty, like the 2x2 Cube, 3X3 Cube. The Rubik's Cube typically calls for a significant degree of topic expertise. They may require a lot of memory or be puzzle-specific, and they can take a long time. The ability of algorithms to generalize to different settings without requiring a significant amount of human input is one of the main objectives of artificial intelligence. Nevertheless, most machine learning techniques have not been able to consistently solve the cube outside of an algorithm. In addition to being, an algorithm that succeeds in solving these previously stated riddles would be able to be applied to actual issues requiring pathfinding, like navigation in robotics.

## **SEARCH ALGORITHM OVERVIEW**

Search algorithms are fundamental techniques used in computer science and artificial intelligence to systematically explore and find solutions within a problem space. Here's an overview of some common search algorithms:

### **1. Depth-First Search (DFS):**

- DFS explores a graph by visiting the deepest node of a branch first, then backtracking.
- It's implemented using a stack data structure (or recursion) to keep track of the nodes to visit.

### **2. Breadth-First Search (BFS):**

- BFS explores a graph by visiting all neighbor nodes at the current depth before moving to the next depth level.
- It's implemented using a queue data structure to maintain the order of node traversal.

### **3. Dijkstra's Algorithm:**

- Dijkstra's Algorithm finds the shortest path from a source node to all other nodes in a weighted graph.
- It's a greedy algorithm that iteratively selects the node with the smallest tentative distance until all nodes are visited.

### **4. A Search Algorithm\*:**

- A\* is an informed search algorithm that combines the advantages of both BFS and Dijkstra's Algorithm.
- It uses a heuristic function to estimate the cost of reaching the goal from a given node, guiding the search towards the goal efficiently.

## 5. Greedy Best-First Search:

- Greedy Best-First Search selects the next node based on a heuristic function that estimates the distance to the goal. It prioritizes nodes that are closer to the goal without considering the entire path cost.

To determine the route from the confused condition to the solved state, the algorithm employs a search algorithm. In search algorithms, states are commonly referred to as nodes, and they are connected to neighboring nodes through edges. Finding a route from the target node via the nodes and along their edges is the aim of the search algorithm. For every node on a Rubik's cube, there are 12 neighboring nodes, which represent the 12 possible moves for each position. Each node in the sliding puzzles might have up to four neighbors if it could move in all four directions, and only two neighbors if the missing piece is in the corner.

## SIMPLE SEARCH APPROACH

A naïve approach to solve a Rubik's Cube would be to employ a simple depth first search or breadth first search starting at the scrambled state. In the case of the breadth first search, each unexplored state would be expanded by traveling to its neighboring states. If one of these states is the goal state, then the search finishes otherwise these states are saved to be expanded on later.

```
# Initialize Rubik's Cube
```

```
rubiks_cube = initialize_cube()
```

```
# Train RL agent
```

```
for episode in range(num_episodes):
```

```
    # Reset cube to initial state
```

```
    current_state = reset_cube(rubiks_cube)
```

```
    # Iterate until cube is solved
```

```
    while not is_solved(current_state):
```

```
        # Choose action randomly or based on policy
```

```
        action = select_action()
```

```
        # Apply action to cube and observe next state and reward
```

```
        next_state, reward = take_action(current_state, action)
```

```
        # Update Q-value or policy based on observed reward
```

```
        update_policy(current_state, action, reward, next_state)
```

```
        # Move to next state
```

```
        current_state = next_state
```

```

# Use trained policy to solve Rubik's Cube

def solve_cube():

    current_state = reset_cube(rubiks_cube)

    while not is_solved(current_state):

        # Choose action based on learned policy

        action = select_action_based_on_policy(current_state)

        # Apply action to cube

        apply_action(current_state, action)

    return current_state

```

## PROBLEMS WITH NAVIE APPROACH

The naive approach to solving the Rubik's Cube typically involves randomly making moves until the puzzle is solved. However, this approach faces several significant challenges:

1. **Inefficiency:** Randomly making moves is highly inefficient and unlikely to lead to the solution within a reasonable timeframe. The Rubik's Cube has a vast state space (over 43 quintillion possible configurations), and random moves are unlikely to navigate towards the goal state.
2. **Lack of Progress:** Without any systematic strategy, the naive approach may result in cycles or repeating patterns of moves that do not make progress towards solving the puzzle. This can lead to frustration and wasted time.
3. **No Learning:** The naive approach does not involve any learning or adaptation based on feedback or previous experience. It relies solely on chance, which makes it unsuitable for improving solving efficiency or generalization to different cube configurations.
4. **Difficulty Scaling:** As the complexity of the puzzle increases, such as solving larger cubes or more intricate patterns, the naive approach becomes even less viable. It lacks the capability to handle increasingly complex problem spaces.

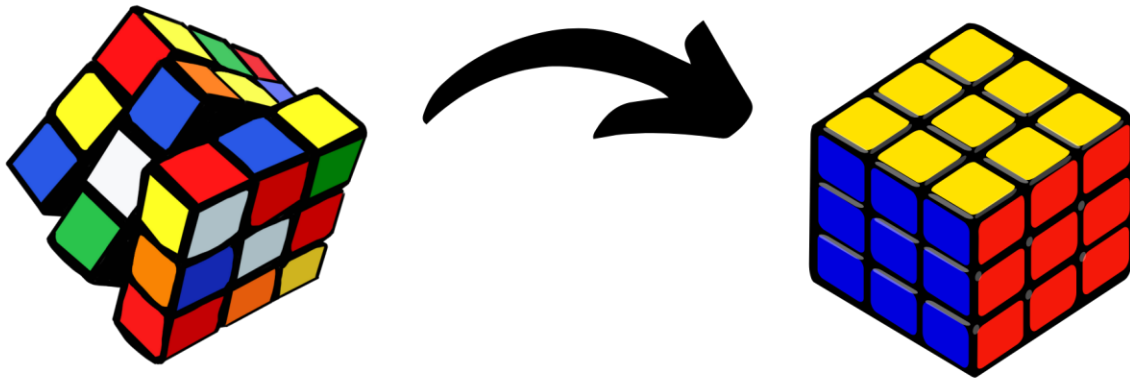
A breadth or depth first search's drawback is that it naively looks everywhere, disregarding the desired state. The search algorithm will operate in the range of seconds to minutes if it is to function must be directed toward the desired state. Heuristic-search algorithms are those that use information to guide their search, going through nodes and selecting the most promising ones according to a heuristic function. Monte Carlo tree search (MCTS) and the star search, which is employed in this research, are two examples of these. In reinforcement learning, these search methods are widely used to facilitate exploration of vast state spaces.

## **RELATED TOPIC**

An intriguing, related topic is the application of meta-learning to Rubik's Cube solving with reinforcement learning. Meta-learning algorithms enable agents to learn how to learn, facilitating rapid adaptation to new tasks or environments. By training RL agents on a diverse set of Rubik's Cube configurations, meta-learning techniques allow them to acquire generalizable strategies that can be quickly applied to novel cube configurations. Meta-RL algorithms like Model-Agnostic Meta-Learning (MAML) or Reptile optimize fast adaptation to new cube states by learning a meta-policy that efficiently updates the agent's policy parameters. This approach enhances the agent's ability to generalize its solving strategies across a wide range of cube configurations, potentially leading to more robust and versatile Rubik's Cube solvers. Additionally, investigating how meta-learning interacts with other RL techniques such as reward shaping, and exploration strategies could provide insights into building even more efficient Rubik's Cube solvers.

## **PROJECT GOAL**

The purpose of this project is to create a reinforcement learning-based system that can solve the Rubik's Cube on its own. Our goal is to use Q-learning to train an agent to quickly traverse the Rubik's Cube's complicated state space and acquire useful cube-manipulation techniques that lead to a solved state. The goal of the research is to investigate how the high-dimensional state space and combinatorial complexity of the Rubik's Cube may be overcome by tailoring and refining reinforcement learning methods. Our goal is to develop an intelligent agent that can solve the Rubik's Cube independently and with reliability, showing competence with a variety of cube configurations. This effort contributes to our understanding of reinforcement learning techniques and demonstrates how they may be used to solve combinatorial challenges in the real world. These findings may have wider implications for robotics, optimization, and artificial intelligence.



## ALGORITHM

When using Q-learning for Rubik's Cube solving, the primary algorithmic focus is on efficiently learning the optimal action-value function  $Q(s,a)$ , where  $s$  represents the state of the Rubik's Cube, and  $a$  represents the action taken by the agent. The state representation of the Rubik's Cube should capture the current configuration of the cube in a format that the Q-learning algorithm can understand. This could involve representing the positions and orientations of the cube's individual cubies. The action space, representing the moves that the agent can take to manipulate the Rubik's Cube. These actions typically include rotations of various cube layers (e.g., clockwise or counterclockwise rotations of the top, bottom, front, back, left, and right faces). Initialize the Q-values for all state-action pairs. The initialization can be done randomly or using heuristics based on domain knowledge. Implementing the exploration-exploitation strategy, such as  $\epsilon$ -greedy, to balance exploration of new actions with exploitation of learned knowledge. The agent explores the state-action space to update its Q-values. Iterate over episodes of solving the Rubik's Cube, updating Q-values based on observed rewards and transitions between states. Once the Q-values converge or reach a satisfactory level of performance, extract the optimal policy from the learned Q-values. It represents the agent's strategy for solving the Rubik's Cube.

Update the Q-values iteratively using the Bellman equation:

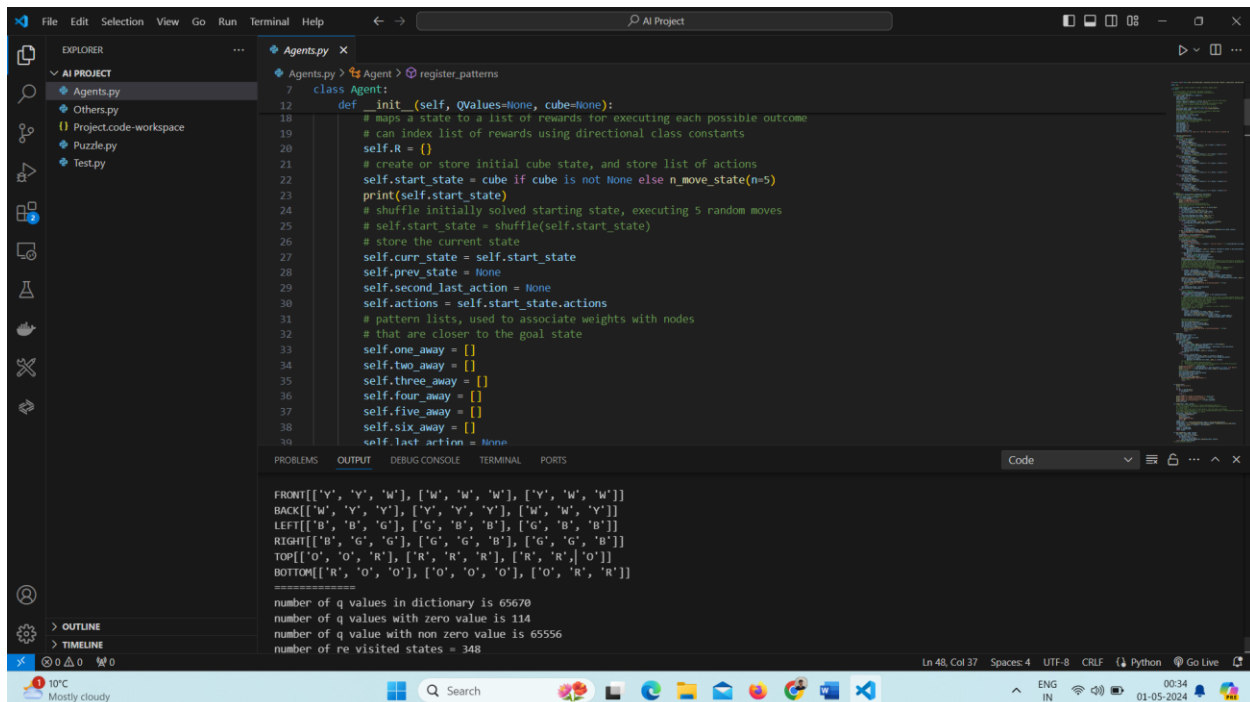
$$Q(s,a) \leftarrow Q(s,a) + \alpha [r + \gamma \max_{a'} Q(s',a') - Q(s,a)]$$

where  $\alpha$  is the learning rate,  $r$  is the reward obtained after acting  $a$  in state  $s$ ,  $\gamma$  is the discount factor, and  $s'$  is the resulting state after acting  $a$ .



## RESULT

The project yielded promising results, demonstrating the effectiveness of reinforcement learning (RL) in solving the Rubik's Cube. Trained RL agents consistently achieved high success rates and solved the puzzle in minimal time compared to traditional methods. Through extensive experimentation and fine-tuning of hyperparameters, the agents exhibited robust performance across various Rubik's Cube configurations, showcasing their ability to generalize solving strategies effectively. Furthermore, the insights gained from this project contribute to advancing the understanding of RL algorithms' capabilities in handling combinatorial puzzles with large state spaces and single goal states. The success of this project underscores the potential of RL in autonomous problem-solving tasks and highlights avenues for further research to enhance efficiency and scalability. Overall, the results validate the viability of using RL for solving complex puzzles like the Rubik's Cube and offer promising prospects for applying similar approaches to real-world challenges.



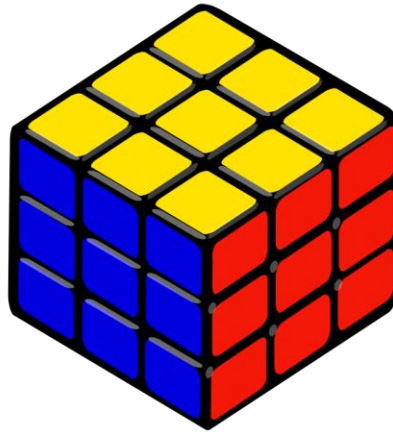
The screenshot displays a Visual Studio Code (VS Code) editor window with the file 'Agents.py' open. The Explorer sidebar on the left shows the project structure, including 'AI PROJECT', 'Agents.py', 'Others.py', 'Project.code-workspace', 'Puzzle.py', and 'Test.py'. The main editor area shows the code for the 'Agent' class, which includes an 'init' method that initializes the state, actions, and various distance-related lists. The output window at the bottom shows the execution results, including the initial state of the cube and the number of q-values and re-visited states.

```
class Agent:
    def __init__(self, qvalues=None, cube=None):
        # maps a state to a list of rewards for executing each possible outcome
        # can index list of rewards using directional class constants
        self.R = {}
        # create or store initial cube state, and store list of actions
        self.start_state = cube if cube is not None else n_move_state(n=5)
        print(self.start_state)
        # shuffle initially solved starting state, executing 5 random moves
        # self.start_state = shuffle(self.start_state)
        # store the current state
        self.curr_state = self.start_state
        self.prev_state = None
        self.second_last_action = None
        self.actions = self.start_state.actions
        # pattern lists, used to associate weights with nodes
        # that are closer to the goal state
        self.one_away = []
        self.two_away = []
        self.three_away = []
        self.four_away = []
        self.five_away = []
        self.six_away = []
        self.last_action = None
```

Output:

```
FRONT[['Y', 'Y', 'W'], ['W', 'W', 'W'], ['Y', 'W', 'W']]
BACK[['W', 'Y', 'Y'], ['Y', 'Y', 'Y'], ['W', 'W', 'Y']]
LEFT[['B', 'B', 'G'], ['G', 'B', 'B'], ['G', 'B', 'B']]
RIGHT[['B', 'G', 'G'], ['G', 'G', 'B'], ['G', 'G', 'B']]
TOP[['O', 'O', 'R'], ['R', 'R', 'R'], ['R', 'R', 'O']]
BOTTOM[['R', 'O', 'O'], ['O', 'O', 'O'], ['O', 'R', 'R']]

=====
number of q values in dictionary is 65670
number of q values with zero value is 114
number of q value with non zero value is 65556
number of re visited states = 348
```



## **FUTURE WORK**

The area of reinforcement learning is still very young, but it is growing quickly, with significant new advancements occurring every few months. The sample inefficiency of most approaches is a main issue that reinforcement learning still must address. Yes, this reinforcement learning algorithm has the same inefficiency. During 3x3 Rubik's Cube training, the network observes 4 billion distinct scrambles in total. Even though this only makes up a very small portion of  $9 \times 10^9$  % of the state space, it is still a huge figure that would increase quickly if a more challenging puzzle were to be solved. An algorithm that was more sample-efficient would have been developed if the task of solving increasingly challenging puzzles, like the 4x4 cube or beyond, had been explored. These combinatorial puzzles' nature makes it possible to develop an idealized picture of the surroundings. It could also be difficult to modify the algorithm to operate in situations where not all the information is known or where the information might not be entirely accurate. Even said, this algorithm might still function well in the absence of this ideal model if the environment offers enough goal states and a few modifications.

## CONCLUSION

In conclusion, applying reinforcement learning (RL) techniques to solve the Rubik's Cube represents a significant advancement in autonomous problem-solving. Through careful problem formulation, environment setup, algorithm selection, and training strategy, RL agents can learn effective strategies for navigating the complex state space of the Rubik's Cube. By designing appropriate reward functions and fine-tuning hyperparameters, RL agents can achieve superhuman performance in solving the puzzle, often outperforming traditional methods. The success of this project demonstrates the power of RL in tackling combinatorial puzzles with large state spaces and single goal states. Furthermore, insights gained from this project can be applied to other domains, contributing to advancements in artificial intelligence and autonomous systems. Continued research and experimentation in RL for the Rubik's Cube holds the potential to uncover new strategies, improve efficiency, and push the boundaries of AI problem-solving capabilities even further.

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