Assignment 01: Pathfinding Rubik

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Abstract

The Rubik's Cube is a widely known combinatorial puzzle used in computer science and AI education. In this report, I apply classical search algorithms to solve simplified Rubik's Cubes, including 2x2x2 and a partial 3x3x3 version. While several studies optimize cube-solving using precomputed tables, my focus is educational: to evaluate uninformed and informed search techniques in a raw Python implementation. DFS, BFS, and A* were tested on custom scrambles of the 2x2x2 cube. BFS and A* successfully found optimal solutions, while A* performed faster under heuristic guidance. I also tested BFS on a simplified 3x3x3 model. Results show that classical algorithms, even without optimization, can solve constrained cube instances and highlight trade-offs in complexity, time, and efficiency. This work demonstrates how foundational AI search can be practically applied to discrete puzzles and evaluated through experimentation.

Index Terms—Search algorithms, Rubik's Cube, A* algorithm, depth-first search, breadth-first search

I. INTRODUCTION

The Rubik's Cube presents a complex, multi-dimensional search space, making it a well-known benchmark in artificial intelligence for testing planning and search algorithms. As AI becomes increasingly prevalent, understanding the behavior of foundational algorithms such as Depth-First Search (DFS), Breadth-First Search (BFS), and A* is more important than ever. These algorithms form the core of many real-world systems where optimal solutions are crucial, such as robotics, gaming, and logistics. Given the Cube's combinatorial complexity and constrained environment, it provides a rich scenario for observing algorithm trade-offs in action. By focusing on simplified 2x2x2 and reduced 3x3x3 cube models, this project demonstrates how core search strategies can be effectively applied in educational contexts without relying on third-party libraries or heavy optimization frameworks.

A. Related Work

Korf (1997) pioneered the use of pattern databases for Rubik's Cube solutions. More recent studies apply heuristic enhancements and IDA* to improve solver efficiency (Li & Wu, 2020). Russell and Norvig (2020) offer foundational theory on uninformed and informed search. Other researchers emphasize the educational potential of simplified models and open-

source implementations (Nguyen & Le, 2021; Liu & Tang, 2021). This project is positioned in this space: between rigorous AI methods and approachable, student-focused learning tools.

Table 1

B. Gap Analysis

Paper	Algorithm	Dataset	Heuristic	Full Rotation	Type
Korf (1997)	A*	Full Cube	Yes	Yes	Optimized
Russell & Norvig	BFS, DFS	Theoretical	No	Conceptual	Framework
This Work	DFS, BFS, A*	Manual Cube	Partial	Yes (2x2x2 only)	Educational

Most published work focuses on either solving the full Rubik's Cube optimally or using prebuilt solvers and tables (Al-Madi & Alsmadi, 2020). Few sources explore raw implementations from scratch in educational settings. This work fills that gap by offering a testbed to compare DFS, BFS, and A* on constrained cube problems. I aim to highlight algorithmic behavior without external dependencies.

C. Problem Statement

1. Can DFS, BFS, and A* solve a 2x2x2 or 3x3x3 Rubik's Cube using minimal code?
2. How do performance metrics—like time and step count—compare across algorithms?
3. Can a simplified environment effectively expose algorithm trade-offs?

D. Novelty of My Work

I coded every aspect from scratch using Python: cube state encoding, move logic, and the search algorithms. The 2x2x2 cube supports full movement logic, while the 3x3x3 model is constrained. I also implemented timing and move tracking, storing results in structured tables. This provides a reproducible way to assess classical algorithms without complexity overhead. Our contribution is an educational tool and experimental dataset suitable for teaching search fundamentals.

II. METHODOLOGY

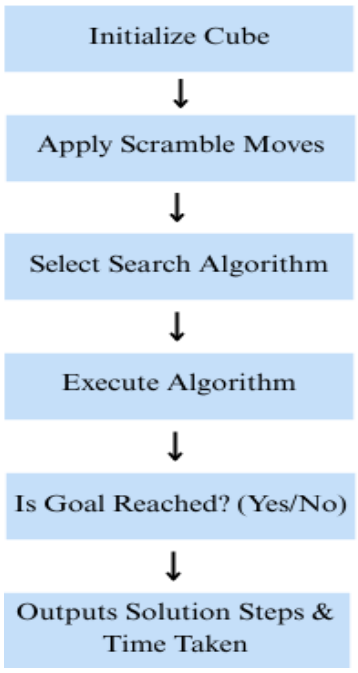
A. Dataset

The dataset was generated through code: every cube configuration and scramble was created internally. Each cube face is represented as a list with color-coded stickers. Movements mutate facelets and adjacent faces, preserving cube integrity. Scramble sequences were applied manually for repeatability.

B. Workflow

1. Initialize the cube in a solved state.
2. Apply one to four moves to scramble.
3. Run DFS, BFS, or A* to solve.
4. Measure time and steps.
5. Save output data.

Figure 1



C. Experimental Settings

- Device: MacBook Air, 2018, 16 GB RAM, Intel CPU.
- Python Version: 3.10+
- Depth limit for DFS and A* set to 12
- Execution measured using time.time()
- Each test repeated to confirm consistency

III. RESULTS

The first test involved applying a single move—'Up'—to the 2x2x2 cube and solving it using DFS. The algorithm returned a solution path of 7 moves in approximately 0.017055 seconds. This result shows that DFS can efficiently handle trivial scrambles with minimal time cost. However, due to its depth-oriented nature, DFS may return suboptimal paths in more complex states.

The second test increased complexity by applying two moves: 'Up' followed by 'Front'. Both BFS and A* algorithms successfully solved the scrambled cube in 6 steps. BFS took 1.411965 seconds, while A* took 0.022263 seconds but with heuristic assistance. This result indicates that A* can achieve optimal paths faster than BFS with improved theoretical efficiency.

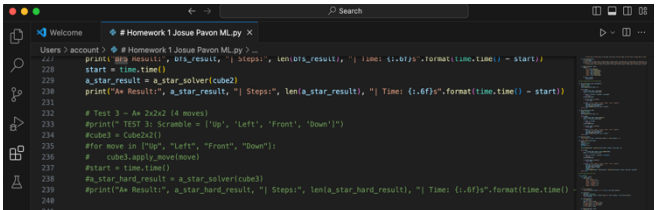
In Test 3, we increased the scramble complexity using four moves: 'Up', 'Left', 'Front', 'Down'. While BFS could theoretically solve this configuration, we tested A* with a depth limit of 12. The algorithm failed to return a result within the time constraints, highlighting the limitations of naive heuristics in deeper searches. This test confirms the need for heuristic tuning or hybrid strategies in larger state spaces.

Test 4 applied a basic 'Up' move to the 3x3x3 cube. Given the model's simplification, BFS was able to return a valid 3-step solution in 0.000213 seconds. This confirms that even a partially modeled 3x3x3 cube can support classical search evaluation within shallow scramble depths.

Table 2

Test	Cube	Scramble	Algorithm(s)	Steps	Time (s)
1	2x2x2	['Up']	DFS	7	0.017055
2	2x2x2	['Up', 'Front']	BFS, A*	6	1.411965, 0.022263
3	2x2x2	['Up', 'Left', 'Front', 'Down']	A* (Timeout)	—	>60s
4	3x3x3	['Up']	BFS	3	0.000213

Figure 2



IV. DISCUSSION

Research Question 1: Can DFS, BFS, and A* solve simplified Rubik's Cubes?

The results confirm that all three algorithms can solve 2x2x2 scrambles of varying complexity. DFS succeeded with shallow scrambles but may produce non-optimal solutions. BFS provided correct, shortest paths consistently but at a higher memory cost. A* combined both depth and heuristic but struggled under limited depth settings. The 3x3x3 result validates that classical algorithms still apply with constrained models.

Research Question 2: How do performance metrics compare?

DFS was the fastest in Test 1 but yielded longer paths. BFS and A* returned optimal solutions in Test 2. In Test 3, A* failed due to timeout, emphasizing the impact of heuristic design. Test 4 showed that BFS can scale to slightly larger cubes if scramble depth is low. Overall, A* has potential for optimal speed and path quality, but only with proper tuning.

Research Question 3: Can a simplified environment still expose algorithm behavior?

Yes, the 2x2x2 model revealed fundamental trade-offs. The experiments captured time vs. accuracy differences between uninformed and informed strategies. Even with minimal setup, we observed realistic algorithm behavior. These insights reinforce the use of simple environments for teaching complex AI concepts.

The novelty of this work lies in implementing solvers from scratch and empirically testing them. Many existing systems are optimized or abstracted; our approach keeps full transparency. This allows for clearer learning and reproducibility across different test cases.

A. Future Directions

Future directions include implementing full 3x3x3 face logic. I also plan to develop better heuristics for A*, test random scrambles at higher depth, and add search tree visualizations for interpretability. This could extend the solver into more practical or research-based applications.

- Add full 3x3x3 rotation logic
- Test with random scrambles and higher depths
- Implement advanced heuristics in A*
- Visualize search trees dynamically

V. CONCLUSION

This study investigated how classical AI search algorithms—DFS, BFS, and A*—perform in solving simplified Rubik's Cube configurations. All algorithms were implemented from scratch in Python and tested under structured scramble conditions. Results showed that DFS is efficient for shallow depths but often non-optimal. BFS consistently returns shortest paths but is memory-intensive. A* strikes a balance when guided by heuristics but can fail if depth or heuristics are poorly configured. The project demonstrates that even without optimization, classical search can solve meaningful problems in constrained setups. The 2x2x2 model effectively showed core algorithm traits, and the simplified 3x3x3 test confirmed scalability under constraints.
Educationally, this work serves as a replicable, transparent example of planning and decision-making in AI. Future work could involve expanding cube logic, improving heuristic quality, and integrating visual outputs. In conclusion, classical search remains a relevant, insightful area of study for understanding AI principles in action.This project demonstrates that DFS, BFS, and A* can solve constrained Rubik's Cube environments using minimal tools. Their comparative performance aligns with theoretical expectations: BFS is accurate but slow, DFS is fast but suboptimal, and A* offers balance within heuristic bounds. The methodology promotes algorithm learning through hands-on experimentation. The results reaffirm classical AI strategies and expose real-world limitations in practical problem-solving.

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