
COMP6231 - COMPARING UNINFORMED AND HEURISTIC SEARCH METHODS

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1 Approach

In this report, are going to be detailed the research results obtained analysing and comparing different search algorithm used in order to solve the "Blocksworld tile puzzle" game by moving an agent (X) around a grid. In Figure 1, are shown the initial and final state of this problem.

Initial State	Final State
$\begin{bmatrix} - & - & - & - \\ - & - & - & - \\ - & - & - & - \\ A & B & C & X \end{bmatrix}$	$\begin{bmatrix} - & - & - & - \\ - & A & - & - \\ - & B & - & - \\ - & C & - & - \end{bmatrix}$

Figure 1: Blocksworld tile puzzle

Different tree searching techniques have been examined throughout this experiment such as: Breadth First Search (BFS), Depth First Search (DFS), Depth Limited Search (DLS), Iterative Deepening (ID) and their respective graph search equivalents. Additionally, an implementation of Bidirectional Search using two Breadth First Searchers starting from the initial and goal state will be provided. Of these different algorithms, just the Depth First Search implementations, the Iterative Deepening Graph Search and the Bidirectional Search proved to be not optimal (all the other implementations were able to find the shortest path to solve the problem).

In order to produce these results, Python has been chosen as preferred programming language. Throughout this experiment, different versions of the same code have been implemented in order to make sure the different algorithm were able to run as fast as possible and using the least possible amount of memory. As an example, a naive implementation of the Breadth First Search algorithm took about 7 hours to correctly solve this task, while the latest code version was able to solve this same problem in under 8 minutes (eg. by making a better use of data structures, creating a custom Deep Copy function and replacing for loops with list comprehension). An exhaustive demonstration of example outputs with a graphical demonstrations for the different tree and graph search methods is available in Appendix A.

Additionally, has been created a simple user interface in which the user can interactively choose which algorithm to use to solve the game, input the preferred board size, decide if or not to add obstacles and even try to solve the game himself (a simple example of the user interface is available in Appendix B). Furthermore, as a demonstration that both the tree and graph searchers were working as expected, in Appendix F is available a graphical representation of the first two tree levels of the A Star Search methods implemented. All the code used in order to reproduce these searching techniques is available in Appendix G.

In order to examine how the time complexity varies increasing the problem size/difficulty different approaches have been taken such as: varying the number of moves away from the goal state, the board size and the number of blocks in the problem.

2 Evidence

In this section, we will examine how well/bad different uninformed search strategies such as BFS, DFS and Iterative Deepening can perform in solving this task. Additionally, we will also compare them to an informed search strategy such as A Star. A collection of code outputs for these algorithms is available in Appendix A.

In order to implement these different algorithms, the "Artificial Intelligence: A Modern Approach" book [1] by Stuart Russel and Peter Norvig has been used as reference in conjunction with the course material and "Introduction to Algorithms" by Thomas H. Cormen et al. [2]. In Appendix C is additionally available a graphical representation of the steps taken by the agent in order to optimally solve this task.

The code used to create these algorithms has been divided into three main classes: Space, Game and MakeNode. The space class was used to create different grids in which the agent can move in, and was taking as input parameters the number of rows and columns we wanted our world to be formed of and a Boolean value indicating if we wanted to add or no obstacles in the grid. The Game class was instead inheriting the parameters from the Space class and was used to create the interactive graphical interface and to test if the different algorithms were working as expected. Finally, the MakeNode class was used to create new tree nodes and to store the state, parent, action, path depth and estimated cost associated with each node.

Each of the different tree algorithms, has then been created inside a single function which was taking as input parameter the initialised grid and the search mode the user wanted to use (eg. breath first, depth first, etc...). Depending on the mode selected it might have then been necessary to add other additional parameters (for example in Iterative Deepening was necessary to specify the mode and the maximum depth to reach). This same approach has also been used later on in order to create the graph search and bidirectional search methods (in other two separate functions).

All the tree search methods have been successfully tested using the start and goal states as shown in Figure 1.

2.1 Breadth First Search (BFS)

When using Breadth First Search, all the nodes are expanded at a given depth in the tree, before expanding any of the nodes at the next level. This can be implemented in Python by using a First-In-First-Out (FIFO) queue at the tree frontier. In this way, old nodes gets expanded first than newer nodes (which are deeper down in the tree).

The implementation results using BFS are shown in Listing 1. These results have been obtained by using Up, Left, Down, Right as nodes order expansion. Changing the order of these four operations would alternatively lead to different time complexities needed in order to solve the problem. In all the cases, BFS has proved to be able to always find the optimal path to the solution.

```
1 Scored Computational Time: 5251318
2 node Depth to reach goal state: 14
3 Estimated Path Cost: 14
4 Moves used to reach goal state ( 14 ) :
5 Root, Up, Left, Left, Down, Left, Up, Right, Down, Right, Up, Up, Left, Down, Left
```

Listing 1: Breadth First Search Solution

2.2 Depth First Search (DFS)

In Depth First Search, we aim instead to expand first the deepest node in the frontier (until there are no more successors available). In order to recreate this behaviour in Python, was made use of a Last-In-First-Out (LIFO) queue (expanding always the most recently generated nodes). One of the main problems associated with DFS, is that it is not complete (it might get stuck in an infinite loop). This can be fixed by using instead DFS graph implementation (as shown in the "Extras and limitations" section).

In Listing 2, are shown the result from DFS. In this case, the algorithm was able to solve the task but with a not-optimal solution. It has been necessary to run multiple times the method to record these results, as the algorithm was at times getting stuck in infinite loops (making exhaust all the memory available). In this case, the order of node expansion used in DFS has been randomised.

```
1 Scored Computational Time: 694
2 node Depth to reach goal state: 693
3 Estimated Path Cost: 693
4 Moves used to reach goal state ( 693 ) :
5 Root, Up, Up, Down, Up, Up, Down, Down, Down, Up, Left, Up, Up, Down, Right, ...
```

Listing 2: Depth First Search Solution

2.3 Iterative Deepening (ID)

When using Iterative Deepening, we aim to find the best depth limit (this is done by incrementally increasing the depth limit until a solution is found). In this way, we can be able to solve the problem by scoring a similar time complexity than BFS but reducing the space complexity needed. Also this time (as shown in Listing 3), Iterative Deepening has been proven to always find the optimal solution. In this occasion, I implemented this algorithm in Python by recursively calling the DFS function and setting a stop limit which is incremented by one every time the function is called (this time not randomising the order of node expansion).

```
1 Scored Computational Time: 12227545
2 node Depth to reach goal state: 14
3 Estimated Path Cost: 14
4 Moves used to reach goal state ( 14 ) :
5 Root, Up, Left, Left, Down, Left, Up, Right, Down, Right, Up, Up, Left, Down, Left
```

Listing 3: Iterative Deepening Solution

2.4 A Star Search

A Star Search is a type of informed search strategy which makes use of an evaluation function in order to considerably reduce the search space (Equation 1). In the evaluation function, the $g(n)$ represent the cost accumulated so far to reach a node and $h(n)$ represents the cost estimated using an heuristic to move from the current node to the end goal. In this case, the Manhattan distance (Equation 2) has been used as the heuristic of choice. I decided to make use of the Manhattan distance as heuristic, because it does never overestimate the cost to reach the goal, making A Star Tree search always optimal.

This heuristic has been implemented in Python by converting the current world state and the goal state into a one dimensional list, comparing the indices positions of the different respective letters in the world and taking the absolute value for each of them.

$$EvaluationFunction = g(n) + h(n) \quad (1)$$

$$ManhattanDistance = \sum_{i=1}^n |x[i] - y[i]| \quad (2)$$

The results obtained using A Star, are available in Listing 4. Additionally, as further evidence of the A Star method working, is available in Appendix F a graphical representation of the first two levels of the A Star tree and graph search.

```
1 Scored Computational Time: 2989
2 node Depth to reach goal state: 14
3 Estimated Path Cost: 14
4 Moves used to reach goal state ( 14 ) :
5 Root, Up, Left, Left, Down, Left, Up, Right, Down, Right, Up, Up, Left, Down, Left
```

Listing 4: A Star Search Solution

3 Scalability

Different approaches have been taken in order to examine how each of these different algorithms performs when varying the difficulty of the task. In this section, we will examine how increasing the node depth (the number of moves the agent is far from the goal state) affects the number of expanded nodes. In the "Extras and limitations" section, we will additionally also explore how changing the size of the board and the number of blocks in the problem can affect the scalability of the graph search methods.

In Figure 2, is examined the time complexity of Breadth First Search, Depth First Search, Iterative Deepening and A Star (in this graph the Y axis is in logarithmic scale to clearly show the differences between the different search methods).

The results obtained for DFS cannot be considered comparable with the other search methods due to the fact that this algorithm is not guaranteed to find the optimal solution (shortest path), therefore the Node Depth can't be controlled in this case. Additionally, due to the nature of this algorithm, has been necessary to run multiple times this method in order to obtained these graphs. In some cases, the execution of the algorithm had additionally to be stopped because of memory limitations and infinite loops, therefore, Figure 2 shows a quite optimistic summary of the time complexity taken by DFS to solve this task.

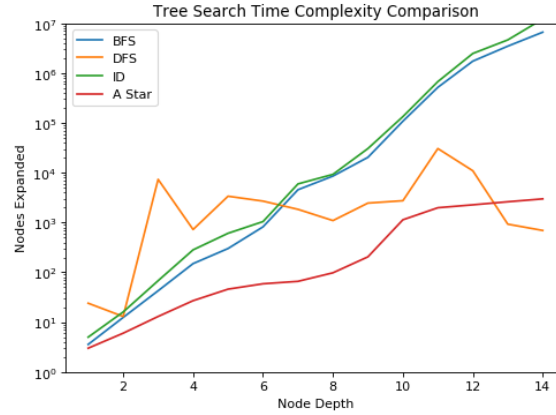


Figure 2: Tree Search Time Complexity Comparison

As we can clearly see from Figure 2, A Star is the algorithm which performed best in solving this task with the least time complexity (thanks to the Manhattan Distance Heuristic). In addition to this, we can also see that Iterative Deepening scored almost the same time complexity as Breadth First Search to solve the problem. In the case of Breadth First Search, it was necessary to run this experiment multiple times, changing everytime the order of nodes expansion to take an average of the time complexity.

This same analysis performed instead on BFS, DFS, ID, A Star graph search equivalents is available in the "Extras and limitations" section. Graph Search algorithms have been implemented in Python by creating a list storing all the visited world states and when expanding a node checking if any of the new states is already present in the visited list (in this way avoiding to visit a same state twice).

In Table 1, are summarised the main characteristics of the Uninformed Search methods covered in this section. For both Time and Space complexity has been made use of the Big O notation and of the following abbreviations:

- **b** = maximum branching factor.
- **d** = least cost solution depth.
- **m** = maximum state space depth.

Criterion	Breadth-First	Depth-First	Iterative Deepening
Worst Time	$O(b^d)$	$O(b^m)$	$O(b^d)$
Worst Space	$O(b^d)$	$O(bm)$	$O(b^{bd})$
Complete	Yes (if b finite)	No	Yes
Optimal	Yes (if cost=1 per step)	No	Yes (if cost=1 per step)

Table 1: Measuring problem-solving performance

A Star search has not been included in the Table 1 since it is an Heuristic Search and using different types of heuristics would lead to different time and space complexities. However, A Star has in general the following properties: the computational time is exponential in length of the optimal solution, in terms of space complexity it keeps all the expanded node in memory, it is complete and optimal.

The results obtained in this experiment perfectly matched with the summary in Table 1. In fact, Breadth First, Iterative Deepening and A Star demonstrated to be optimal and complete (as shown in the "Evidence" section) while Depth First not (eg. presence of infinite loops). Additionally, from the results obtained in Figure 2, we can see that as expected Breadth First and Iterative Deepening scored a similar time complexity when varying the problem difficulty (just outperformed by A Star thanks to the use of the Manhattan Distance as heuristic).

Overall, from this experiment we can clearly see that A Star demonstrated to be the search method which was best able to scale for different size problems while Depth First was the algorithm which had most problems in this ambit. One reason why Depth First, demonstrated to be not a suitable choice to solve this problem is that the maximum state space depth is larger than the least cost solution depth (**m** is larger than **d**). One of the main advantages although of using Depth First Search is his polynomial space complexity.

4 Extras and limitations

At completion of this project, different extras have been realised. Some examples are:

- Graph Search (BFS, DFS, Depth Limited Search, Iterative Deepening, A Star).
- Bidirectional Search (BFS-BFS).
- Varied Board Size.
- Varied Number of blocks in the game.
- Inclusion of obstacles in the world.
- User interface to let an user solve the different problems on their own.

In order to create the different graph search implementations, a list of the visited states has been created so to avoid to make the algorithm visit the same state twice. In this section, are provided three different methods to examine the scalability of the different graph search techniques: varying the number of moves away from the goal state, the number of blocks in the problem and the board size.

4.1 Varying the number of moves away from the goal state

As we can see from Figure 3, using graphs methods can considerably reduce the number of nodes expanded. In this case, also the Iterative Deepening graph search version demonstrated to not be optimal (this can be fixed by specifying in the algorithm to add in the visited list always the shortest path in case of any conflict). Additionally, on this graph has also been plotted the time complexity results scored using Depth Limited Graph Search with a limit of 50 for node depth. As shown in Figure 3, also in this case A Star demonstrated to be the algorithm which was best able to cope with different problem sizes.

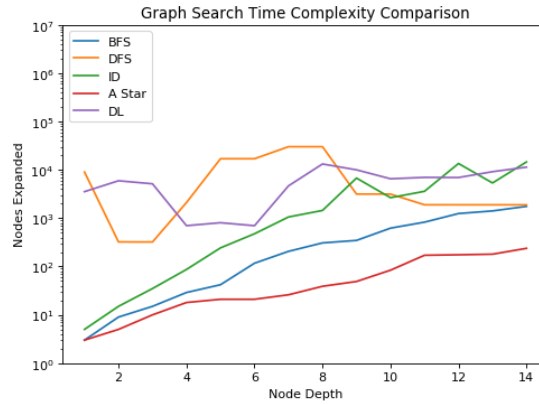


Figure 3: Graph Search Time Complexity Comparison

4.2 Varying the number of blocks in the problem and the board size

In this subsection, we will now examine how increasing iteratively the number of tiles of in the grid (Figure 4 (a)) and the board size (Figure 4 (b)) will increase the time complexity of the different algorithms implemented.

The time complexity registered using these two different approaches are shown respectively in Figure 5 (a) and (b). Also in this case, Depth First Search demonstrated to be the algorithm which performed less well when increasing the problem size. A Star instead demonstrated again to be the algorithm which was able to best scale.

In addition to this, in Appendix E (Graph Search problem difficulty with and without obstacles) is also available an analysis of how adding obstacles in the grid can affect the problem difficulty and time complexity needed in order to solve the Blocksworld tile puzzle in Graph and Bidirectional Search. Another example output demonstrating the use of obstacles in the grid is also available in Appendix B (Example Output: User Interface).

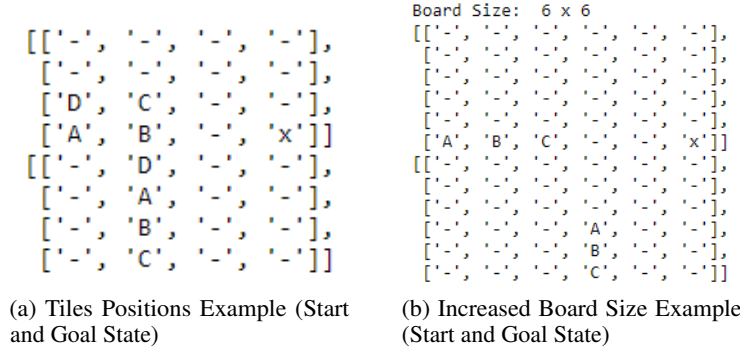


Figure 4: Varying complexity examples

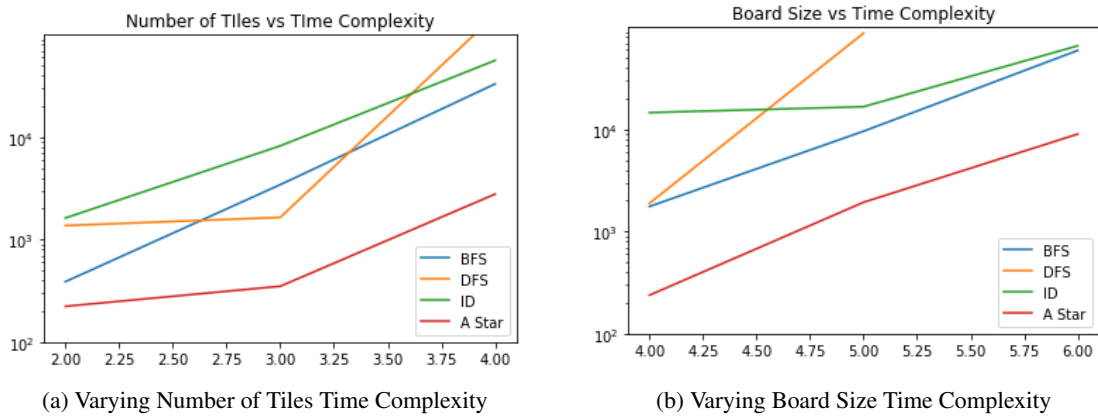


Figure 5: Time Complexity Varying problem difficulty

4.3 Bidirectional Search and Further Developments

Bidirectional Search was implemented by running simultaneously two different searchers (one starting from the start state and one starting at the goal state). In both searchers, a list of the visited states is stored and the search terminates if the frontiers of the two searches intersect (meaning that the two searchers met in the middle). The first intersection between the two searchers might although not be optimal, requiring therefore to do some additional search to check if there is any other short-cut across the gap. In this implementation, I decided to use two different Breadth First Searchers as searching algorithms. Examples of use of Bidirectional Search are available in Appendix A (A.10), Appendix D (D.6) and Appendix E.

Overall, this project had a successful outcome providing multiple insights about the different searching methods and in the comparison between the results expected from the theory and the actual ones from implementations. Although, some additional features in order to enhance this analysis can still potentially be added. Some examples of further advancements which can be added to this project are: space complexity analysis, use of a better heuristic for A Star and improving some of the graph search methods which were not optimal to become optimal by adding in the visited list always the shortest path in case of any conflict.

References

- [1] Artificial Intelligence: A Modern Approach (Third Edition). Stuart Russel and Peter Norvig. Accessed at: <https://www.cin.ufpe.br/tf2/artificial-intelligence-modern-approach.9780131038059.25368.pdf>, Nov 2019.
- [2] Introduction to Algorithms (Third Edition). Thomas H. Cormen et al. Accessed at: <http://kddlab.zjgsu.edu.cn:7200/students/lipengcheng/%E7%AE%97%E6%B3%95%E5%AF%BC%E8%AE%BA%EF%BC%88%E8%8B%B1%E6%96%87%E7%AC%AC%E4%B8%89%E7%89%88%E7%BC%89.pdf>, Nov 2019.

Appendix A Example Output: Tree & Graph Algorithms in action

In this section are provided example code outputs of the different tree algorithm in action. In the case of Breadth First search and A Star (Figure 2 and 3), is highlighted the difference between the two algorithms when trying to solve the Blocksworld tile puzzle. In the first case (Figure 2), is given equal importance to each branch of the tree, in the second case (Figure 3) the algorithm instead start early to focus on the branch which will most likely lead to the optimal solution. In all the other examples, will be instead shown the tree structure used to solve a simple problem (Figure 1), in this way it will be possible to show the full tree from the start state to the goal state. All these graphs have been created by storing the relevant results of each algorithm in a dictionary and plotting the results using the networkx Python library.

Initial State	Final State
$\begin{bmatrix} - & X & - & - \\ - & - & A & - \\ - & B & - & - \\ - & C & - & - \end{bmatrix}$	$\begin{bmatrix} - & - & - & - \\ - & A & - & - \\ - & B & - & - \\ - & C & - & - \end{bmatrix}$

Figure 1: Simple Grid

A.1 Tree Breadth First Search

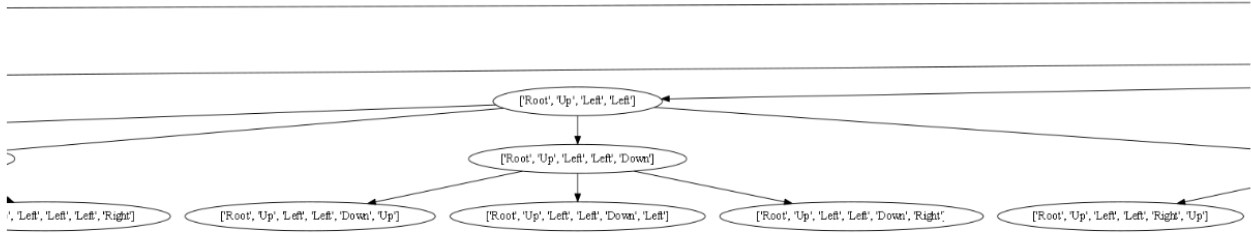


Figure 2: Tree Breadth First Search

A.2 Tree A Star Search

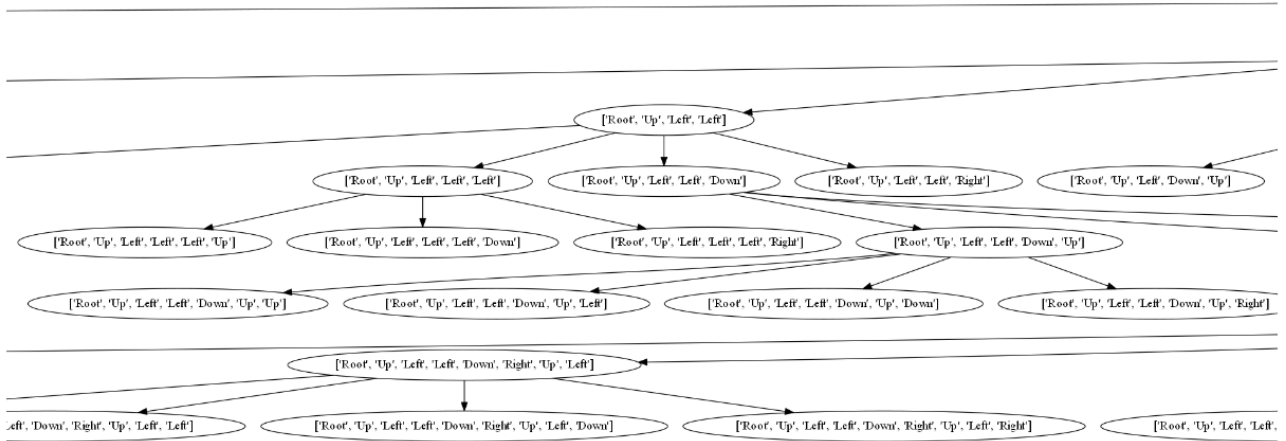


Figure 3: Tree A Star Search

A.3 Tree Depth First Search

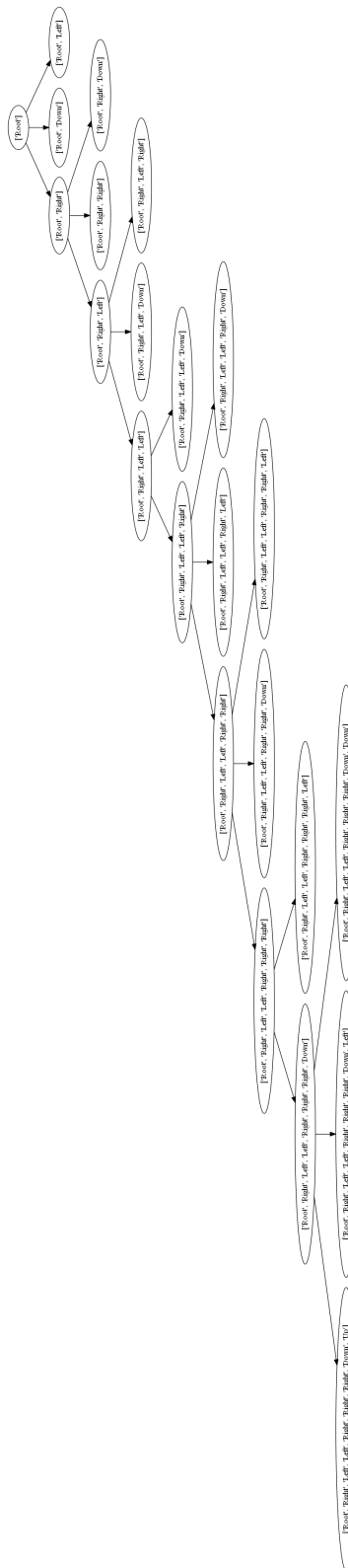


Figure 4: Tree Depth First Search

A.4 Tree Iterative Deepening Search

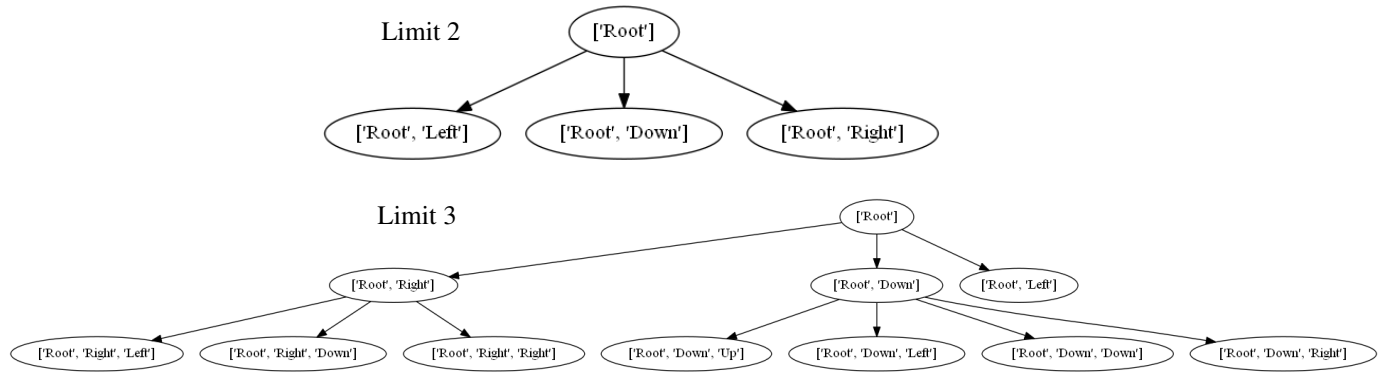


Figure 5: Tree Iterative Deepening Search

A.5 Graph Breadth First Search

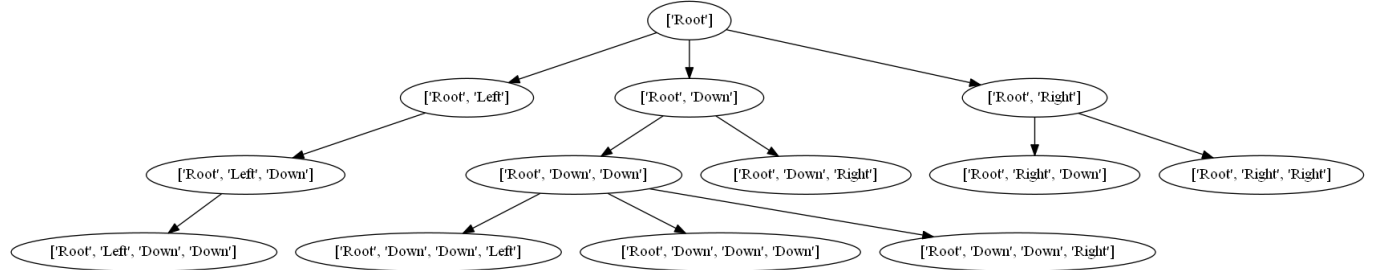


Figure 6: Graph Breadth First Search

A.6 Graph Depth First Search

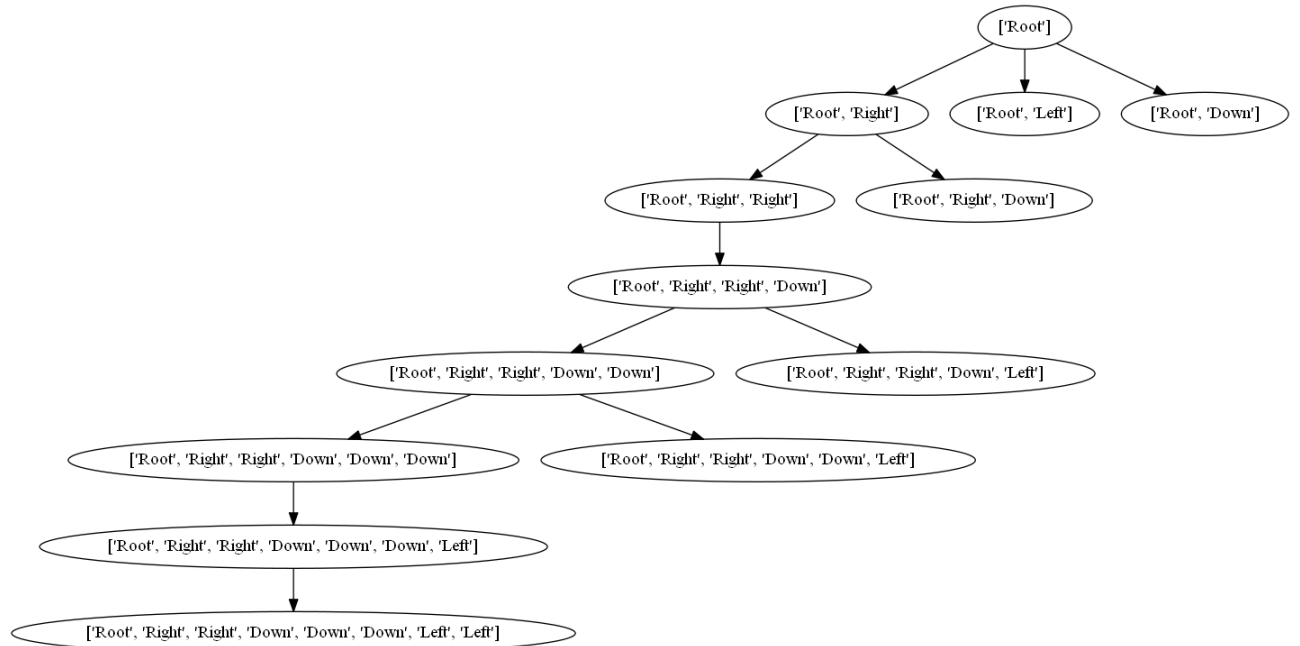


Figure 7: Graph Depth First Search

A.7 Graph Depth Limited Search

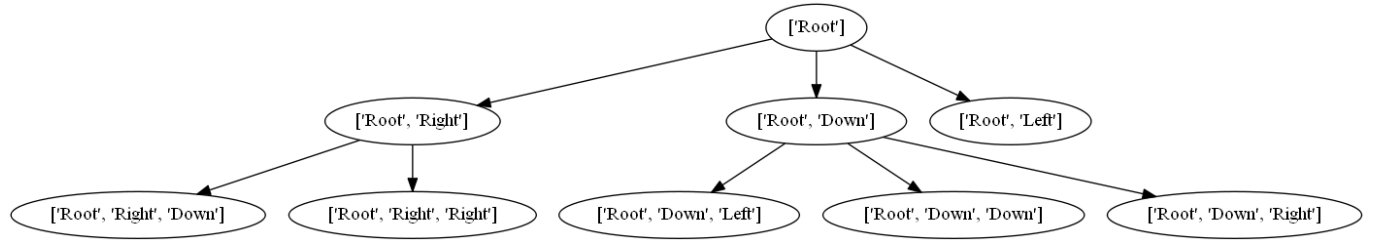


Figure 8: Graph Depth Limited Search

A.8 Graph Iterative Deepening Search

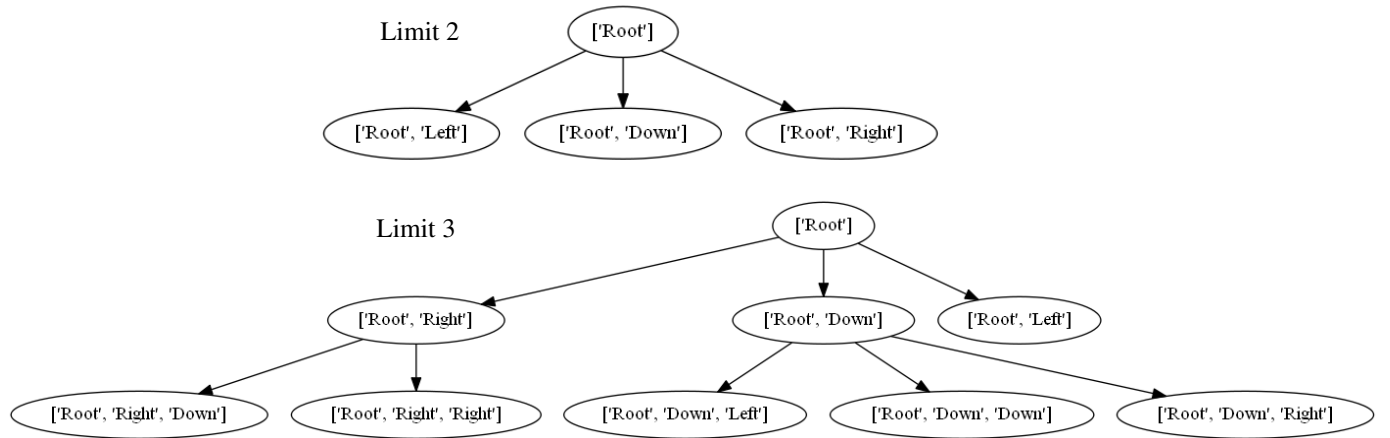


Figure 9: Graph Iterative Deepening Search

A.9 Graph A Star Search

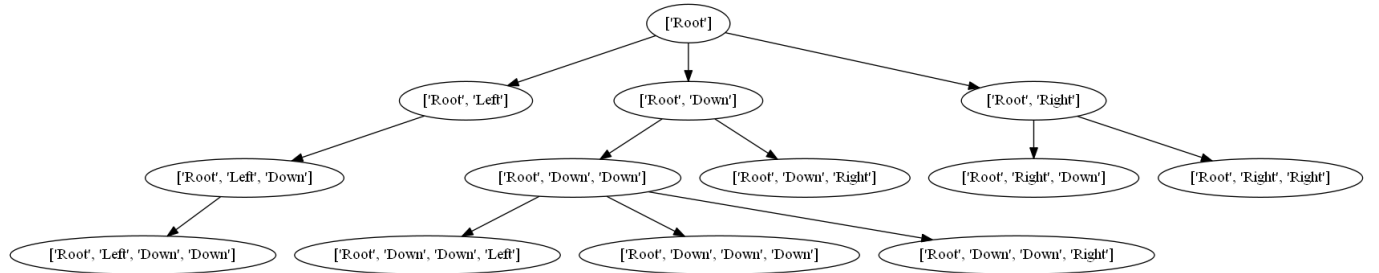


Figure 10: Graph A Star Search

A.10 Bidirectional Search

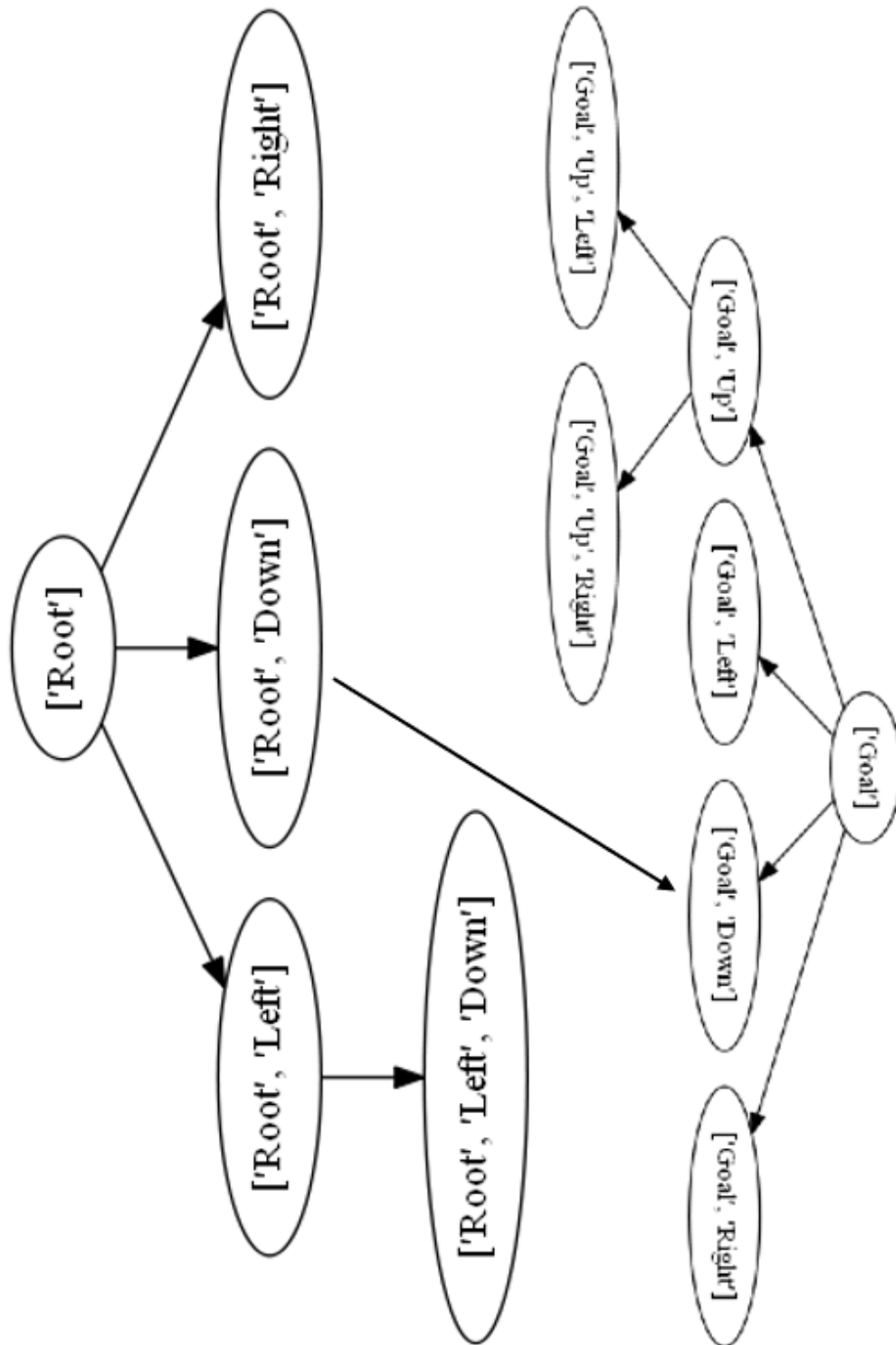


Figure 11: Bidirectional Search

Appendix B Example Output: User Interface

```
1 Welcome to my Blocksworld tile puzzle solver
2 What game matrix size do you prefer? (minimum 4*4)
3 Number of rows: 5
4 Number of columns: 5
5 Do you want to use Tree (0), Graph Search (1) or Bilateral Search (2)?
6 1
7 Do you want to add obstacles in the world? (yes/no)yes
8 Do you want to play the game yourself? (yes/no)
9 yes
10 Use a to move left, d to move right, w to move up, z to move down and e to escape
    the game
11 [['-', '-', '-', '-', '-'],
12  ['- ', '-', '-', '-', '%'],
13  ['- ', '-', '-', '-', '-'],
14  ['- ', '-', '-', '%', '-'],
15  ['- ', 'A', 'B', 'C', 'x']]
16 Choose Direction: w
17 [['-', '-', '-', '-', '-'],
18  ['- ', '-', '-', '-', '%'],
19  ['- ', '-', '-', '-', '-'],
20  ['- ', '-', '-', '%', '-'],
21  ['- ', 'A', 'B', 'C', '-']]
22 Choose Direction: w
23 [['-', '-', '-', '-', '-'],
24  ['- ', '-', '-', '-', '%'],
25  ['- ', '-', '-', '-', 'x'],
26  ['- ', '-', '-', '%', '-'],
27  ['- ', 'A', 'B', 'C', '-']]
28 Choose Direction: a
29 [['-', '-', '-', '-', '-'],
30  ['- ', '-', '-', '-', '%'],
31  ['- ', '-', '-', 'x', '-'],
32  ['- ', '-', '-', '%', '-'],
33  ['- ', 'A', 'B', 'C', '-']]
34 Choose Direction: z
35 Invalid move, try again
36 Choose Direction: d
37 [['-', '-', '-', '-', '-'],
38  ['- ', '-', '-', '-', '%'],
39  ['- ', '-', '-', '-', 'x'],
40  ['- ', '-', '-', '%', '-'],
41  ['- ', 'A', 'B', 'C', '-']]
42 Choose Direction: e
43 End of the game!
44 Which algorithm do you want to use to solve the Blocksworld tile puzzle?
45 0: Breadth First Search
46 1: Depth First Search or Limited Depth Search
47 2: Iterative Deepening
48 3: A Star
49
50 3
51 [['-', '-', '-', '-', '-'],
52  ['- ', '-', '-', '-', '%'],
53  ['- ', '-', '-', '-', '-'],
54  ['- ', '-', '-', '%', '-'],
55  ['- ', 'A', 'B', 'C', 'x']]
56 [['-', '-', '-', '-', '-'],
57  ['- ', '-', '-', '-', '-'],
58  ['- ', '-', 'A', '-', '-'],
59  ['- ', '-', 'B', '-', '-'],
60  ['- ', '-', 'C', '-', '-']]
61 Nodes Generated (Space Complexity: 721 )
```

```

62 Scored Computational Time: 494
63 Node Depth to reach goal state: 18
64 Estimated Path Cost: 18
65 Moves used to reach goal state ( 18 ) :
66 Root, Up, Up, Left, Left, Down, Down, Left, Up, Right, Down, Right, Right, Up, Up
    , Left, Left, Down, Left
67 Graphical representation of moves:
68 [0,
69 ['-', '-', '-', '-', '-'],
70 ['-', '-', '-', '-', '%'],
71 ['-', '-', '-', '-', '-'],
72 ['-', '-', '-', '-', '%'],
73 ['-', 'A', 'B', 'C', 'x'],
74 ['-', '-', '-', '-', '-'],
75 ['-', '-', '-', '-', '%'],
76 ['-', '-', '-', '-', '-'],
77 ['-', '-', '-', '-', '%'],
78 ['-', 'A', 'B', 'C', '-'],
79 ['-', '-', '-', '-', '-'],
80 ['-', '-', '-', '-', '%'],
81 ['-', '-', '-', '-', 'x'],
82 ['-', '-', '-', '-', '%'],
83 ['-', 'A', 'B', 'C', '-'],
84 ['-', '-', '-', '-', '-'],
85 ['-', '-', '-', '-', '%'],
86 ['-', '-', '-', 'x', '-'],
87 ['-', '-', '-', '-', '%'],
88 ['-', 'A', 'B', 'C', '-'],
89 ['-', '-', '-', '-', '-'],
90 ['-', '-', '-', '-', '%'],
91 ['-', '-', 'x', '-', '-'],
92 ['-', '-', '-', '-', '%'],
93 ['-', 'A', 'B', 'C', '-'],
94 ['-', '-', '-', '-', '-'],
95 ['-', '-', '-', '-', '%'],
96 ['-', '-', '-', '-', '-'],
97 ['-', '-', 'x', '-', '%'],
98 ['-', 'A', 'B', 'C', '-'],
99 ['-', '-', '-', '-', '-'],
100 ['-', '-', '-', '-', '%'],
101 ['-', '-', '-', '-', '-'],
102 ['-', '-', 'B', '-', '%'],
103 ['-', 'A', 'x', 'C', '-'],
104 ['-', '-', '-', '-', '-'],
105 ['-', '-', '-', '-', '%'],
106 ['-', '-', '-', '-', '-'],
107 ['-', '-', 'B', '-', '%'],
108 ['-', 'x', 'A', 'C', '-'],
109 ['-', '-', '-', '-', '-'],
110 ['-', '-', '-', '-', '%'],
111 ['-', '-', '-', '-', '-'],
112 ['-', 'x', 'B', '-', '%'],
113 ['-', '-', 'A', 'C', '-'],
114 ['-', '-', '-', '-', '-'],
115 ['-', '-', '-', '-', '%'],
116 ['-', '-', '-', '-', '-'],
117 ['-', 'B', 'x', '-', '%'],
118 ['-', '-', 'A', 'C', '-'],
119 ['-', '-', '-', '-', '-'],
120 ['-', '-', '-', '-', '%'],
121 ['-', '-', '-', '-', '-'],
122 ['-', 'B', 'A', '-', '%'],
123 ['-', '-', 'x', 'C', '-'],
124 ['-', '-', '-', '-', '-'],

```

```

125 ['-', '-', '-', '-', '%'],
126 ['-', '-', '-', '-', '-'],
127 ['-', '-', 'B', 'A', '%', '-'],
128 ['-', '-', 'C', 'x', '-'],
129 ['-', '-', '-', '-', '-'],
130 ['-', '-', '-', '-', '%'],
131 ['-', '-', '-', '-', '-'],
132 ['-', '-', 'B', 'A', '%', '-'],
133 ['-', '-', 'C', '-', 'x'],
134 ['-', '-', '-', '-', '-'],
135 ['-', '-', '-', '-', '%'],
136 ['-', '-', '-', '-', '-'],
137 ['-', '-', 'B', 'A', '%', 'x'],
138 ['-', '-', 'C', '-', '-'],
139 ['-', '-', '-', '-', '-'],
140 ['-', '-', '-', '-', '%'],
141 ['-', '-', '-', '-', 'x'],
142 ['-', '-', 'B', 'A', '%', '-'],
143 ['-', '-', 'C', '-', '-'],
144 ['-', '-', '-', '-', '-'],
145 ['-', '-', '-', '-', '%'],
146 ['-', '-', '-', 'x', '-'],
147 ['-', '-', 'B', 'A', '%', '-'],
148 ['-', '-', 'C', '-', '-'],
149 ['-', '-', '-', '-', '-'],
150 ['-', '-', '-', '-', '%'],
151 ['-', '-', '-', 'x', '-', '-'],
152 ['-', '-', 'B', 'A', '%', '-'],
153 ['-', '-', 'C', '-', '-'],
154 ['-', '-', '-', '-', '-'],
155 ['-', '-', '-', '-', '%'],
156 ['-', '-', 'A', '-', '-'],
157 ['-', '-', 'B', 'x', '%', '-'],
158 ['-', '-', 'C', '-', '-'],
159 ['-', '-', '-', '-', '-'],
160 ['-', '-', '-', '-', '%'],
161 ['-', '-', 'A', '-', '-'],
162 ['-', '-', 'x', 'B', '%', '-'],
163 ['-', '-', 'C', '-', '-']

```

Listing 5: Graphical User Interface

Appendix C Example Output: Optimal Solution

1 Graphical representation of moves:

```
2 [['-', '-', '-', '-'],
3  ['- ', '- ', '- ', '- '],
4  ['- ', '- ', '- ', '- '],
5  ['A', 'B', 'C', 'x'],
6  ['- ', '- ', '- ', '- '],
7  ['- ', '- ', '- ', '- '],
8  ['- ', '- ', '- ', 'x'],
9  ['A', 'B', 'C', '- '],
10 ['- ', '- ', '- ', '- '],
11 ['- ', '- ', '- ', '- '],
12 ['- ', '- ', 'x', '- '],
13 ['A', 'B', 'C', '- '],
14 ['- ', '- ', '- ', '- '],
15 ['- ', '- ', '- ', '- '],
16 ['- ', 'x', '- ', '- '],
17 ['A', 'B', 'C', '- '],
18 ['- ', '- ', '- ', '- '],
19 ['- ', '- ', '- ', '- '],
20 ['- ', 'B', '- ', '- '],
21 ['A', 'x', 'C', '- '],
22 ['- ', '- ', '- ', '- '],
23 ['- ', '- ', '- ', '- '],
24 ['- ', 'B', '- ', '- '],
25 ['x', 'A', 'C', '- '],
26 ['- ', '- ', '- ', '- '],
27 ['- ', '- ', '- ', '- '],
28 ['x', 'B', '- ', '- '],
29 ['- ', 'A', 'C', '- '],
30 ['- ', '- ', '- ', '- '],
31 ['- ', '- ', '- ', '- '],
32 ['B', 'x', '- ', '- '],
33 ['- ', 'A', 'C', '- '],
34 ['- ', '- ', '- ', '- '],
35 ['- ', '- ', '- ', '- '],
36 ['B', 'A', '- ', '- '],
37 ['- ', 'x', 'C', '- '],
38 ['- ', '- ', '- ', '- '],
39 ['- ', '- ', '- ', '- '],
40 ['B', 'A', '- ', '- '],
41 ['- ', 'C', 'x', '- '],
42 ['- ', '- ', '- ', '- '],
43 ['- ', '- ', '- ', '- '],
44 ['B', 'A', 'x', '- '],
45 ['- ', 'C', '- ', '- '],
46 ['- ', '- ', '- ', '- '],
47 ['- ', '- ', 'x', '- '],
48 ['B', 'A', '- ', '- '],
49 ['- ', 'C', '- ', '- '],
50 ['- ', '- ', '- ', '- '],
51 ['- ', 'x', '- ', '- '],
52 ['B', 'A', '- ', '- '],
53 ['- ', 'C', '- ', '- '],
54 ['- ', '- ', '- ', '- '],
55 ['- ', 'A', '- ', '- '],
56 ['B', 'x', '- ', '- '],
57 ['- ', 'C', '- ', '- '],
58 ['- ', '- ', '- ', '- '],
59 ['- ', 'A', '- ', '- '],
60 ['x', 'B', '- ', '- '],
61 ['- ', 'C', '- ', '- ']]
```

Listing 6: Graphical Representation of the optimal path to reach the goal state

Appendix D Graph Search evidences

In this section, are provided evidences of the graph search methods running (in the same way as it was done in the "Evidence" section for the Tree search methods). The shortest action sequence for all the complete methods has also been provided. Also in this case, the start and goal state are the ones represented in Figure 1.

D.1 Graph Breadth First Search

```
1 Scored Computational Time: 1757
2 Node Depth to reach goal state: 14
3 Estimated Path Cost: 14
4 Moves used to reach goal state ( 14 ) :
5 Root, Up, Left, Left, Down, Left, Up, Right, Down, Right, Up, Up, Left, Down, Left
```

Listing 7: Graph Breadth First Search

D.2 Graph Depth First Search

```
1 Scored Computational Time: 1890
2 Node Depth to reach goal state: 1836
3 Estimated Path Cost: 1836
4 Moves used to reach goal state ( 1836 ) :
5 Root, Left, Left, Left, Up, Right, Right, Right, Down, Left, Left, Left, Up, Up,
6 Right, Right, ...
```

Listing 8: Graph Depth First Search

D.3 Graph Depth Limited Search

```
1 Scored Computational Time: 11385
2 Node Depth to reach goal state: 49
3 Estimated Path Cost: 49
4 Moves used to reach goal state ( 49 ) :
5 Root, Left, Left, Left, Up, Right, Right, Right, Down, Left, Left, Left, Up, Up,
6 Right, Right, Right, Down, Down, Left, Up, Right, Down, Left, Up, Right, Up, Left,
7 Left, Down, Right, Up, Left, Down, Right, Right, Up, Left, Up, Left, Down, Down,
8 Right, Down, Left, Up, Right, Up, Left, Up
```

Listing 9: Graph Depth Limited Search

D.4 Graph Iterative Deepening Search

```
1 Scored Computational Time: 14595
2 Node Depth to reach goal state: 20
3 Estimated Path Cost: 20
4 Moves used to reach goal state ( 20 ) :
5 Root, Left, Left, Up, Left, Down, Right, Right, Right, Up, Left, Left, Down, Right
6 ,Up, Left, Left, Up, Right, Down, Right
```

Listing 10: Graph Iterative Deepening Search

D.5 Graph A Star Search

```
1 Scored Computational Time: 238
2 Node Depth to reach goal state: 14
3 Estimated Path Cost: 14
4 Moves used to reach goal state ( 14 ) :
5 Root, Up, Left, Left, Down, Left, Up, Right, Down, Right, Up, Up, Left, Down, Left
```

Listing 11: Graph A Star Search

D.6 Bidirectional Search

```
1 Scored Computational Time: 4812
2 Node Depth to reach goal state: 30
3 Estimated Path Cost: 30
4 Moves used to reach goal state ( 30 ) :
5 Root, Up, Left, Left, Down, Left, Up, Right, Down, Right, Up, Left, Left, Down,
6 Right, Up, Left, Down Down, Down, Left, Left, Up, Right, Up, Right, Down, Down,
7 Left, Left, Up,
```

Listing 12: Bidirectional Search

Appendix E Graph Search problem difficulty with and without obstacles

In Figure 12, are shown the time complexity and the node depth required by the different algorithms in order to solve the Blocksworld tile puzzle.

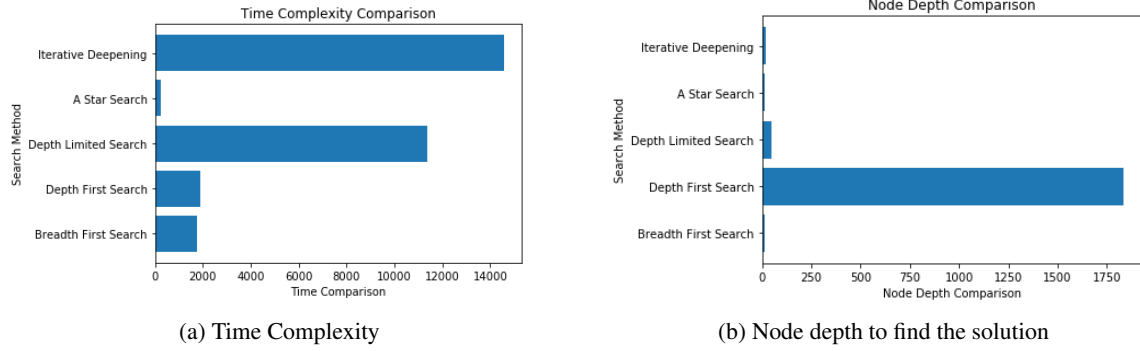


Figure 12: Graph Search to solve Blocksworld tile puzzle without obstacles

Adding obstacles in the world (Figure 13) led instead to the results shown in Figure 14. Therefore, in this example adding obstacles in the grid made overall easier for the different graph algorithms to solve this problem.

Initial State with Obstacles

$$\begin{bmatrix} - & - & - & \% \\ - & - & - & - \\ - & - & \% & - \\ A & B & C & X \end{bmatrix}$$

Figure 13: Blocksworld tile puzzle with Obstacles

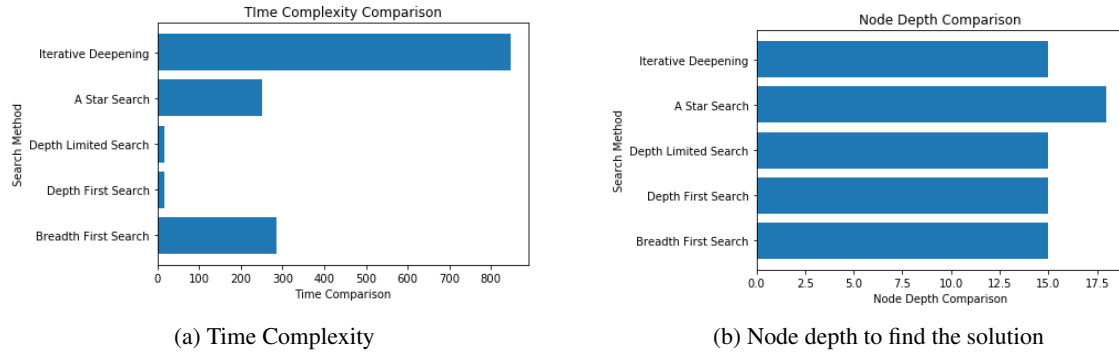


Figure 14: Graph Search to solve Blocksworld tile puzzle with obstacles

Trying to solve this same problem, with and without obstacles, using Bidirectional Search led instead to the results shown in Figure 15.

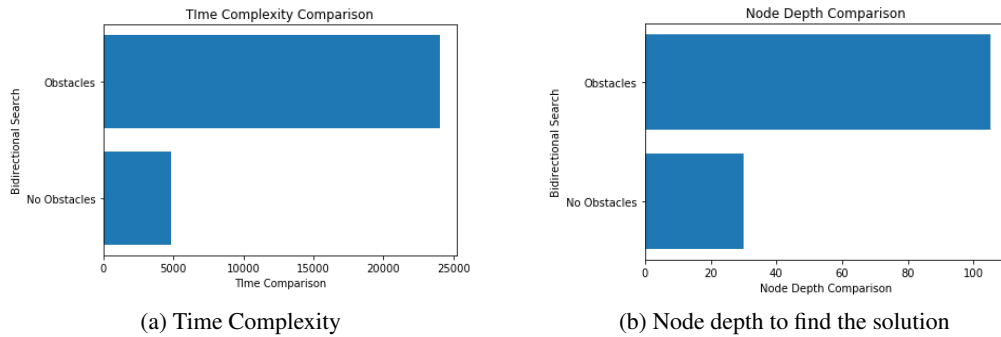


Figure 15: Bidirectional Search to solve Blocksworld tile puzzle with and without obstacles

Appendix F Example Output: A Star

Figure 16 and 17 have been realised by taking the code output shown respectively in Figure 18 (a) and (b) and rearranging it in a tree like structure. This example output has been created by taking the first two levels of the tree used by A Star in order to solve the Blocksworld tile puzzle.

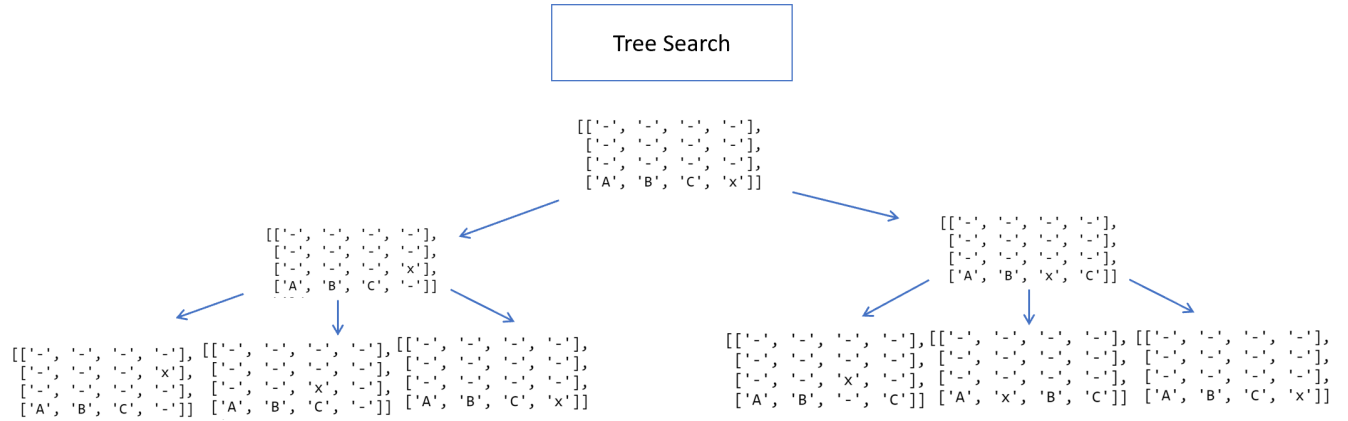


Figure 16: A Star Tree Search

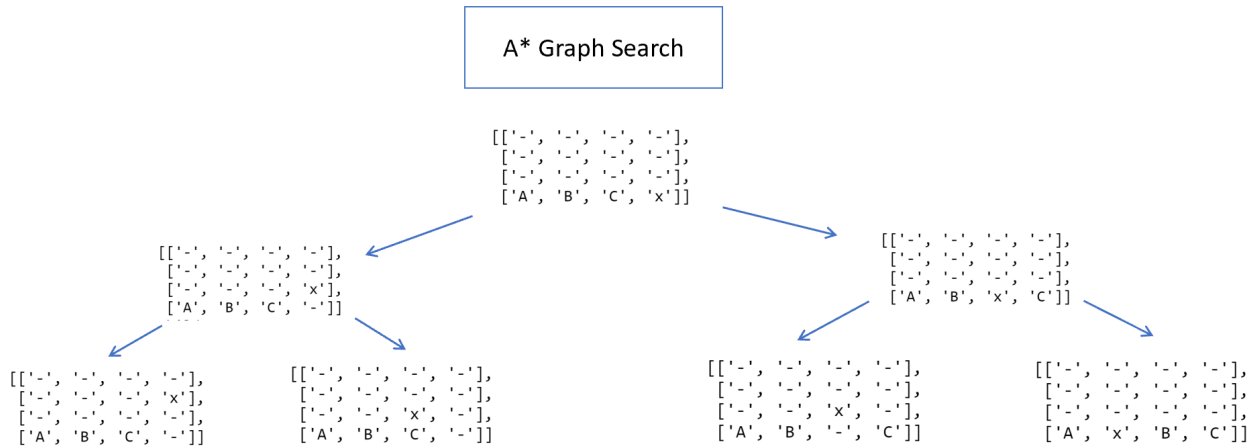


Figure 17: A Star Graph Search

Appendix G Code

This project has been structured in 2 main files: Foundations.py and Blocksworld_tile_puzzle.py. In Foundations.py are included some of the basic functions which are used to create and update the world the agent is moving in and check if the current world state is equal to the goal state. In Blocksworld_tile_puzzle.py are instead implemented the different search techniques. A third file (start.py), used to create the interactive user interface, is additionally included in the attached Zip Folder (this has not been added here because of its length). In addition to this, in the zip folder are also available the Jupyter Notebooks used in order to create the graphs used in this report.

```
1 import numpy as np
2
3
4 def world(n, m):
5     grid = np.chararray((n, m))
6     grid = [['-' for j in i] for i in grid]
7     return grid
8
9
10 def move_up(w, player):
11     if player[0] > 0:
12         if w[player[0] - 1][player[1]] != '%':
13             a = w[player[0] - 1][player[1]]
14             w[player[0] - 1][player[1]] = w[player[0]][player[1]]
15             w[player[0]][player[1]] = a
16             player[0] = player[0] - 1
17             return w, player
18         else:
19             return 0, 1
20     else:
21         return 0, 1
22
23
24 def move_down(w, player):
25     if player[0] < len(w) - 1:
26         if w[player[0] + 1][player[1]] != '%':
27             a = w[player[0] + 1][player[1]]
28             w[player[0] + 1][player[1]] = w[player[0]][player[1]]
29             w[player[0]][player[1]] = a
30             player[0] = player[0] + 1
31             return w, player
32         else:
33             return 0, 1
34     else:
35         return 0, 1
36
37
38 def move_left(w, player):
39     if player[1] > 0:
40         if w[player[0]][player[1] - 1] != '%':
41             a = w[player[0]][player[1] - 1]
42             w[player[0]][player[1] - 1] = w[player[0]][player[1]]
43             w[player[0]][player[1]] = a
44             player[1] = player[1] - 1
45             return w, player
46         else:
47             return 0, 1
48     else:
49         return 0, 1
50
51
52 def move_right(w, player):
53     if player[1] < len(w) - 1:
54         if w[player[0]][player[1] + 1] != '%':
```

```

55         a = w[player[0]][player[1] + 1]
56         w[player[0]][player[1] + 1] = w[player[0]][player[1]]
57         w[player[0]][player[1]] = a
58         player[1] = player[1] + 1
59         return w, player
60     else:
61         return 0, 1
62 else:
63     return 0, 1
64
65
66 def solution_check(w, sol):
67     h = [k for i, j in zip(w, sol) for k, z in zip(i, j) if k != z]
68     return len(h)

```

Listing 13: Foundations.py

```

1 import pprint
2 import random
3 import numpy as np
4 from Foundations import world, move_up, move_down, move_left, move_right,
    solution_check
5 from IPython.display import clear_output
6 from collections import deque
7 import time
8 from operator import attrgetter
9 import copy
10
11 start = time.time()
12
13
14 class Space:
15     def __init__(self, m, n, obstacles=False):
16         self.m = m
17         self.n = n
18
19         grid = world(self.n, self.m)
20
21         if obstacles is False:
22             grid[self.n - 1][self.m - 2] = 'C'
23             grid[self.n - 1][self.m - 3] = 'B'
24             grid[self.n - 1][self.m - 4] = 'A'
25             grid[self.n - 1][self.m - 1] = 'x'
26             self.player = [self.n - 1, self.m - 1]
27         else:
28             grid[self.n - 1][self.m - 2] = 'C'
29             grid[self.n - 1][self.m - 3] = 'B'
30             grid[self.n - 1][self.m - 4] = 'A'
31
32             grid[self.n - 4][self.m - 1] = '%'
33             grid[self.n - 2][self.m - 2] = '%'
34             grid[self.n - 1][self.m - 1] = 'x'
35             self.player = [self.n - 1, self.m - 1]
36
37         self.w = grid
38
39     def solution(self):
40         grid = world(self.n, self.m)
41
42         grid[self.n - 1][self.m - 3] = 'C'
43         grid[self.n - 2][self.m - 3] = 'B'
44         grid[self.n - 3][self.m - 3] = 'A'
45         return grid
46
47

```

```

48 class Space2:
49     def __init__(self, m, n, obstacles=False):
50         self.m = m
51         self.n = n
52
53         grid = world(self.n, self.m)
54
55         if obstacles is False:
56             # Final Grid
57             grid[self.n - 1][self.m - 3] = 'C'
58             grid[self.n - 2][self.m - 3] = 'B'
59             grid[self.n - 3][self.m - 3] = 'A'
60             grid[self.n - 2][self.m - 2] = 'x'
61             self.player = [self.n - 2, self.m - 2]
62         else:
63             # Obstacles Grid
64             grid[self.n - 1][self.m - 3] = 'C'
65             grid[self.n - 2][self.m - 3] = 'B'
66             grid[self.n - 3][self.m - 3] = 'A'
67             grid[self.n - 4][self.m - 1] = '%'
68             grid[self.n - 2][self.m - 2] = '%'
69             grid[self.n - 3][self.m - 2] = 'x'
70             self.player = [self.n - 3, self.m - 2]
71
72         self.w = grid
73
74
75 class Game(Space):
76     def __init__(self, m, n, obstacles=False):
77         super().__init__(m, n, obstacles)
78
79     def __repr__(self):
80         game = True
81         pprint.pprint(self.w)
82         clear_output(wait=True)
83         while game is True:
84             val = input("Choose Direction: ")
85             if val == 'a':
86                 clear_output(wait=True)
87                 check1, check2 = move_left(self.w, self.player)
88                 if check1 != 0:
89                     self.w, self.player = check1, check2
90                     pprint.pprint(self.w)
91             else:
92                 print("Invalid move, try again")
93             elif val == 'd':
94                 clear_output(wait=True)
95                 check1, check2 = move_right(self.w, self.player)
96                 if check1 != 0:
97                     self.w, self.player = check1, check2
98                     pprint.pprint(self.w)
99             else:
100                 print("Invalid move, try again")
101             elif val == 'w':
102                 clear_output(wait=True)
103                 check1, check2 = move_up(self.w, self.player)
104                 if check1 != 0:
105                     self.w, self.player = check1, check2
106                     pprint.pprint(self.w)
107             else:
108                 print("Invalid move, try again")
109             elif val == 'z':
110                 clear_output(wait=True)
111                 check1, check2 = move_down(self.w, self.player)

```

```

112         if check1 != 0:
113             self.w, self.player = check1, check2
114             pprint.pprint(self.w)
115         else:
116             print("Invalid move, try again")
117     elif val == 'e':
118         game = False
119         return ('End of the game!')
120     else:
121         print('Wrong Entry')
122
123
124 # play = Game(4, 4)
125 # print(play)
126
127
128 class MakeNode:
129     def __init__(self, state, parent, action, path_depth, estimated_cost):
130         self.state = state
131         self.parent = parent
132         self.path_depth = path_depth
133         self.action = action
134         self.estimated_cost = estimated_cost
135
136
137 def heuristic(world, sol, depth):
138     w = [item for sublist in world for item in sublist]
139     s = [item for sublist in sol for item in sublist]
140     manhattan = 0
141     manhattan += abs(w.index('A') - s.index('A')) + abs(w.index('B') - s.index('B')) + abs(w.index('C') - s.index('C'))
142     return manhattan + depth
143
144
145 def expand_node(problem, node, mode, sol, visited=0):
146     if mode == 3:
147         up = MakeNode(move_up([x[:] for x in problem.w], [x for x in problem.player]), node.parent + problem.w,
148                        node.action + ', Up', node.path_depth + 1,
149                        heuristic(problem.w, sol, node.path_depth))
150         down = MakeNode(move_down([x[:] for x in problem.w], [x for x in problem.player]), node.parent + problem.w,
151                         node.action + ', Down', node.path_depth + 1,
152                         heuristic(problem.w, sol, node.path_depth))
153         left = MakeNode(move_left([x[:] for x in problem.w], [x for x in problem.player]), node.parent + problem.w,
154                         node.action + ', Left', node.path_depth + 1,
155                         heuristic(problem.w, sol, node.path_depth))
156         right = MakeNode(move_right([x[:] for x in problem.w], [x for x in problem.player]), node.parent + problem.w,
157                          node.action + ', Right', node.path_depth + 1,
158                          heuristic(problem.w, sol, node.path_depth))
159         res = [node for node in [up, left, down, right] if node.state[0] != 0]
160         if visited != 0:
161             res = [i for i in res if i.state[0] not in visited]
162         return res
163     else:
164         up = MakeNode(move_up([x[:] for x in problem.w], [x for x in problem.player]), node.parent + problem.w,
165                        node.action + ', Up', node.path_depth + 1, node.
166                        estimated_cost + 1)
167         down = MakeNode(move_down([x[:] for x in problem.w], [x for x in problem.player]), node.parent + problem.w,

```



```

167         node.action + ', Down', node.path_depth + 1, node.
estimated_cost + 1)
168     left = MakeNode(move_left([x[:] for x in problem.w], [x for x in problem.
player])), node.parent + problem.w,
169         node.action + ', Left', node.path_depth + 1, node.
estimated_cost + 1)
170     right = MakeNode(move_right([x[:] for x in problem.w], [x for x in problem
.player])), node.parent + problem.w,
171         node.action + ', Right', node.path_depth + 1, node.
estimated_cost + 1)
172     res = [node for node in [up, left, down, right] if node.state[0] != 0]
173     if mode == 0:
174         return res
175     elif mode == 1:
176         res = random.sample(res, len(res))
177         return res
178     elif mode == 4:
179         res = [i for i in res if i.state[0] not in visited]
180         return res
181
182
183 def search(problem, mode, depth=np.inf, obstacles=False):
184     computational_time = 0
185     gen = []
186     sol = [x[:] for x in problem.solution()]
187     if mode == 3:
188         fringe = [MakeNode([problem.w, problem.player], [0], 'Root', 0, heuristic(
problem.w, sol, 0))]
189     else:
190         fringe = deque([MakeNode([problem.w, problem.player], [0], 'Root', 0, 0)])
191     diff = solution_check(problem.w, sol)
192     if ((diff == 1) and (obstacles is False)) or ((diff == 3) and (obstacles is
True)):
193         return 0, computational_time, None, None, None
194     elif mode == 0:
195         while True:
196             if len(fringe) == 0:
197                 return np.inf, computational_time, None, None, None
198             else:
199                 node = fringe.popleft()
200                 problem.w, problem.player = node.state[0], node.state[1]
201                 computational_time += 1
202                 diff = solution_check(node.state[0], sol)
203                 if ((diff == 1) and (obstacles is False)) or ((diff == 3) and (
obstacles is True)):
204                     print("Nodes Generated (Space Complexity:", sum(gen), ")")
205                     return node.path_depth, computational_time, node.action, node.
parent + node.state[0], node.estimated_cost
206                 else:
207                     new = expand_node(problem, node, 0, sol)
208                     fringe.extend(new)
209                     gen.append(len(new))
210                     if (computational_time % 50000) == 0:
211                         print('Time:', computational_time)
212     elif mode == 1:
213         while True:
214             if len(fringe) == 0:
215                 return np.inf, computational_time, None, None, None
216             else:
217                 node = fringe.pop()
218                 problem.w, problem.player = node.state[0], node.state[1]
219                 computational_time += 1
220                 diff = solution_check(node.state[0], sol)

```

```

221         if ((diff == 1) and (obstacles is False)) or ((diff == 3) and (
obstacles is True)):
222             print("Nodes Generated (Space Complexity:", sum(gen), ")")
223             return node.path_depth, computational_time, node.action, node.
parent + node.state[0], node.estimated_cost
224         else:
225             if node.path_depth < depth:
226                 if depth == np.inf:
227                     new = expand_node(problem, node, 1, sol)
228                     fringe.extend(new)
229                     gen.append(len(new))
230                 else:
231                     new = expand_node(problem, node, 0, sol)
232                     fringe.extend(new)
233                     gen.append(len(new))
234                 if (computational_time % 50000) == 0:
235                     print('Time:', computational_time)
236     elif mode == 2:
237         iteration = 0
238         r = copy.deepcopy(problem)
239         for i in range(depth):
240             print("Depth: ", i)
241             depth, complexity, moves, history, cost = search(copy.deepcopy(r), 1,
i)
242             iteration += complexity
243             if moves is not None:
244                 return depth, iteration, moves, history, cost
245         return 1, computational_time, None, None, None
246     elif mode == 3:
247         while True:
248             if len(fringe) == 0:
249                 return np.inf, computational_time, None, None, None
250             else:
251                 fringe.sort(key=attrgetter('estimated_cost'))
252                 node = fringe.pop(0)
253                 problem.w, problem.player = node.state[0], node.state[1]
254                 computational_time += 1
255                 diff = solution_check(node.state[0], sol)
256                 if ((diff == 1) and (obstacles is False)) or ((diff == 3) and (
obstacles is True)):
257                     print("Nodes Generated (Space Complexity:", sum(gen), ")")
258                     return node.path_depth, computational_time, node.action, node.
parent + node.state[0], node.estimated_cost
259                 else:
260                     new = expand_node(problem, node, mode, sol)
261                     fringe.extend(new)
262                     gen.append(len(new))
263                     if (computational_time % 50000) == 0:
264                         print('Time:', computational_time)
265             else:
266                 print("Select an adequate mode: \n")
267                 print(" 0: Breadth First Search \n 1: Depth First Search or Limited Depth
Search \n "
268                     "2: Iterative Deepening \n 3: A Star \n")
269                 return None, None, None, None, None
270
271 def graph_search(problem, mode, depth=np.inf, obstacles=False):
272     computational_time = 0
273     gen = []
274     sol = [x[:] for x in problem.solution()]
275     if mode == 3:
276         fringe = [MakeNode([problem.w, problem.player], [0], 'Root', 0, heuristic(
problem.w, sol, 0))]

```

```

278     visited = [problem.w]
279 else:
280     fringe = deque([MakeNode([problem.w, problem.player], [0], 'Root', 0, 0)])
281     visited = [problem.w]
282     diff = solution_check(problem.w, sol)
283     if ((diff == 1) and (obstacles is False)) or ((diff == 3) and (obstacles is
True)):
284         return 0, computational_time, None, None, None
285     elif mode == 0:
286         while True:
287             if len(fringe) == 0:
288                 return np.inf, computational_time, None, None, None
289             else:
290                 node = fringe.popleft()
291                 problem.w, problem.player = node.state[0], node.state[1]
292                 computational_time += 1
293                 diff = solution_check(node.state[0], sol)
294                 if ((diff == 1) and (obstacles is False)) or ((diff == 3) and (
obstacles is True)):
295                     print("Nodes Generated (Space Complexity:", sum(gen), ")")
296                     return node.path_depth, computational_time, node.action, node.
parent + node.state[0], node.estimated_cost
297                 else:
298                     new = expand_node(problem, node, 4, sol, visited)
299                     fringe.extend(new)
300                     gen.append(len(new))
301                     visited.extend([i.state[0] for i in new])
302                     if (computational_time % 50000) == 0:
303                         print('Time:', computational_time)
304     elif mode == 1:
305         while True:
306             if len(fringe) == 0:
307                 return np.inf, computational_time, None, None, None
308             else:
309                 node = fringe.pop()
310                 problem.w, problem.player = node.state[0], node.state[1]
311                 computational_time += 1
312                 diff = solution_check(node.state[0], sol)
313                 if ((diff == 1) and (obstacles is False)) or ((diff == 3) and (
obstacles is True)):
314                     print("Nodes Generated (Space Complexity:", sum(gen), ")")
315                     return node.path_depth, computational_time, node.action, node.
parent + node.state[0], node.estimated_cost
316                 else:
317                     if node.path_depth < depth:
318                         new = expand_node(problem, node, 4, sol, visited)
319                         fringe.extend(new)
320                         gen.append(len(new))
321                         visited.extend([i.state[0] for i in new])
322                         if (computational_time % 50000) == 0:
323                             print('Time:', computational_time)
324     elif mode == 2:
325         iteration = 0
326         r = copy.deepcopy(problem)
327         for i in range(depth):
328             print("Depth: ", i)
329             depth, complexity, moves, history, cost = graph_search(copy.deepcopy(r
), 1, i)
330             iteration += complexity
331             if moves is not None:
332                 return i, iteration, moves, history, cost
333         return 1, computational_time, None, None, None
334     elif mode == 3:
335         while True:

```

```

336         if len(fringe) == 0:
337             return np.inf, computational_time, None, None, None
338         else:
339             fringe.sort(key=attrgetter('estimated_cost'))
340             node = fringe.pop(0)
341             problem.w, problem.player = node.state[0], node.state[1]
342             computational_time += 1
343             diff = solution_check(node.state[0], sol)
344             if ((diff == 1) and (obstacles is False)) or ((diff == 3) and (
obstacles is True)):
345                 print("Nodes Generated (Space Complexity:", sum(gen), ")")
346                 return node.path_depth, computational_time, node.action, node.
parent + node.state[0], node.estimated_cost
347             else:
348                 new = expand_node(problem, node, 3, sol, visited)
349                 fringe.extend(new)
350                 gen.append(len(new))
351                 visited.extend([i.state[0] for i in new])
352                 if (computational_time % 50000) == 0:
353                     print('Time:', computational_time)
354             else:
355                 print("Select an adequate mode: \n")
356                 print(" 0: Breadth First Graph Search \n 1: Depth First Graph Search or
Limited Depth Graph Search \n "
357                     "2: Iterative Deepening Graph Search \n 3: A Star Graph Search \n")
358                 return None, None, None, None, None
359
360 def bi_search(problem, mode, problem2):
361     computational_time = 0
362     fringe = deque([MakeNode([problem.w, problem.player], [0], 'Root', 0, 0)])
363     goal_fringe = deque([MakeNode([problem2.w, problem2.player], [0], '', 0, 0)])
364     visited = [problem.w]
365     visited2 = [problem2.w]
366     if mode == 0:
367         while True:
368             node = fringe.popleft()
369             node2 = goal_fringe.popleft()
370             if node.state[0] == node2.state[0]:
371                 a = node2.action.split(',')
372                 a.reverse()
373                 node2.parent.pop(0)
374                 b = [node2.parent[i:i+len(node2.state[0])] for i in
range(0, len(node2.parent), len(node2.state[0]))][::-1]
375                 return node.path_depth + node2.path_depth,
computational_time, node.action+', '.join(a), node.parent + \
node.state[0] + sum(b, []), node.estimated_cost
376             + node2.estimated_cost
377             problem.w, problem.player = node.state[0], node.state[1]
378             computational_time += 1
379             new = expand_node(problem, node, 4, 0, visited)
380             fringe.extend(new)
381             visited.extend([i.state[0] for i in new])
382             problem2.w, problem2.player = node2.state[0], node2.state[1]
383             new2 = expand_node(problem2, node2, 4, 0, visited2)
384             goal_fringe.extend(new2)
385             visited2.extend([i.state[0] for i in new2])
386
387             if (computational_time % 50000) == 0:
388                 print('Time:', computational_time)
389
390
391 # problem = Space(4, 4, obstacles=True)
392 # pprint.pprint(problem.w)

```

```

394
395 # problem2 = Space2(4, 4, obstacles=True)
396 # pprint.pprint(problem2.w)
397
398 # depth, complexity, moves, history, cost = bi_search(problem, 0, problem2)
399
400 problem = Space(4, 4, obstacles=False)
401 pprint.pprint(problem.w)
402 pprint.pprint(problem.solution())
403
404 depth, complexity, moves, history, cost = search(problem, 2, 30, obstacles=False)
405
406 # depth, complexity, moves, history, cost = graph_search(problem, 2, 300,
407     obstacles=False)
408
409 if depth == 0:
410     print('Initial state is equal to goal state')
411 elif depth == np.inf:
412     print('Searched Tree, no possible result')
413 elif complexity is None:
414     print("Please follow the instructions to run the simulation")
415 else:
416     print('Scored Computational Time:', complexity)
417     print('node Depth to reach goal state:', depth)
418     print("Estimated Path Cost:", cost)
419     print('Moves used to reach goal state (', str(moves).count(','), ') :\n',
420         moves)
421     print('Graphical representation of moves:')
422     pprint.pprint(list(history))
423 end = time.time()
424 print("Elapsed Time = %s" % (end - start))

```

Listing 14: Blocksworld_tile_puzzle.py