

# CS 205: Artificial Intelligence by Dr. Eamonn Keogh

## Project 1: 8 Puzzle problem Report

Name: Mohit Porwal

SID: 862325163

UCR mail id: [mporw002@ucr.edu](mailto:mporw002@ucr.edu)

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In completing this assignment, I referred the following resource:

1. The sample report pdf provided by the professor to make this report
2. For conceptual understanding, I referred to the Blind Search 1, Blind Search 2 and the Heuristic Search ppt slides by the professor.
3. For the layout of the program (UI), I referred the one provided in the sample report.
4. To learn about the `heapq` module, I referred the following YouTube video <https://www.youtube.com/watch?v=4hkJBcW5Ruk>
5. To learn about the Matplotlib library, I referred the official Matplotlib documentation <https://matplotlib.org/stable/index.html>
6. The Uniform Cost Search graph and the examples for tiles were taken from professor's slides

The entire code in this document is original, except for some subroutines that I imported from Python module

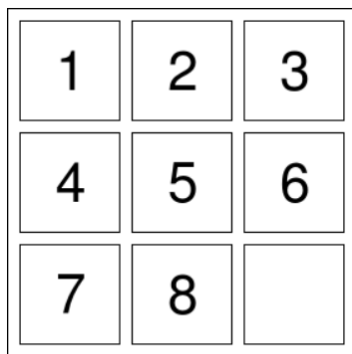
- a. `heapq` module to implement min heap priority queue
- b. `sys` to terminate the program
- c. `copy` to deepcopy all the object instances
- d. `time` to calculate the total time required for the search
- e. `itertools` to convert 2D list to 1D list
- f. `matplotlib` to plot the graphs

## **OUTLINE OF THIS REPORT**

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## Introduction

A sliding puzzle or a sliding tile puzzle is a mechanical puzzle consisting of  $N-1$  blocks of tiles where  $N$  is the total number of empty spaces in the puzzle. The standard and the most famous category in this are the 15 Puzzle problem where we have a board with  $4 \times 4$  dimension with 15 blocks of tiles placed on the board. The puzzle is a 2 dimensional board where we leave the last block empty. A smaller version of this puzzle is the 8-puzzle problem where we have a  $3 \times 3$  board which has 9 spaces and 8 of those spaces is occupied by the tiles and the last space is kept empty. The two figures, Figure 1 and Figure 2 shown below, illustrate how the puzzle looks in its standard setting or we can say, the goal state.



Goal state of Eight Puzzle Problem

The area of the board is divided into  $4 \times 4$  grid where each square of the grid holds a square tile. There are numbers from 1 to  $N-1$  on each tile. For 8 puzzle problem, the tiles are numbered from 1 to 8. There are some rules to solve this puzzle and the aim is to reach the goal state.

In the initial state, the tiles can be arranged in any random order (with one empty space). The aim is to reach the goal state from the initial distorted state. There are four operations allowed on each tile.

**Figure 1: 8 Puzzle Goal State**

The tile can be slides in four directions which are up, down, right and left. The tile can be moved by only 1 space at a time. Each movement will leave the previous tile with an empty space. In this way, by sliding, we need to reach the goal state.

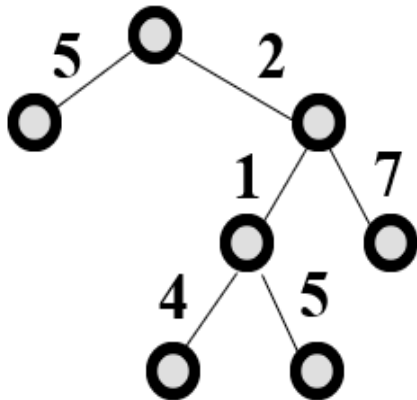


The 8-puzzle problem is a part of the course CS205: Artificial Intelligence, by Dr. Eamonn Keogh at University of California, Riverside. Our task in this project is to implement the 8-puzzle problem with 3 algorithms which are, Uniform Cost Search, A\* with misplaced tile heuristic and A\* with Manhattan distance heuristic. In the upcoming parts of the report, I have compared the performance of these three algorithms and also included my version of the code to implement this using Python programming language. Let us explore each algorithm in brief.

**Figure 2: 15 Puzzle Goal State**

## Uniform Cost Search

Uniform Cost Search is a search algorithm which falls in the class of uninformed search algorithms. The algorithm chooses the path or a state with the least cost and then expands that state. So, the expansion of a node happens if it's the one with the lowest cost when compared to its sibling nodes. We can implement this using a Priority Queue data structure. Figure 3 below shows an illustration of the working of Uniform Cost Search.



The Uniform Cost Search has no heuristic to assist in its search hence the  $h(n)$  value for it will be equal to 0. Therefore, the cost function will be  $f(n) = g(n)$ , where  $g(n)$  is the cost from root node to current node. In this case, it will always be 1, because the cost of each operation in 8 puzzle is just 1. With  $h(n)$  as 0, it will act as Breadth-First-Search.

Figure 3: Uniform Cost Search graph

## The Misplaced Tile Heuristic

The A\* with misplaced tile heuristic calculates the number of misplaced tiles as a heuristic in our algorithm. The expansion of a particular node is decided on the basis of the cost function  $f(n) = g(n) + h(n)$  where  $g(n)$  is our cost of depth from initial state to current state and the  $h(n)$  is the misplaced tile heuristic. The  $h(n)$  is calculated by identifying the tiles in the current state which are not in their correct position when compared with the goal state. We sum up the count of all such tiles and that becomes our  $h(n)$ . We do not consider the blank state when counting the number of misplaced tiles.

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

In figure 4 and 5 example, the misplaced tiles are 7,4,2,5,6,8,3,1 which is total 8. Note that we are not considering the blank tile in the counting.

The final  $h(n)$  cost for this example will become 8.

Fig 4: Misplaced Tile Start

Fig 5: Misplaced Tile Goal

## The Manhattan Distance Heuristic

The A\* with Manhattan distance heuristic calculates the cost based on how far the misplaced tiles of the current state are from the goal state. For instance, if there are 3 tiles in the board that are not in their correct places, we can determine the number of steps or the amount of sliding that tile will require in order to reach the goal state. These number of steps are calculated for each misplaced tile and then summed up. The summation will be the final heuristic cost  $h(n)$  for that particular state. To illustrate this, we have an example.

3	2	8
4	5	6
7	1	

**Figure 6:**  
Manhattan Start State

1	2	3
4	5	6
7	8	

**Figure 7:**  
Manhattan Goal State

If we observe figure 6 which represents the current state and figure 7 which is goal state. The tile 3 is 2 spaces away from its goal state, the tile 1 is 3 spaces away, and the tile 8 is 3 spaces away. Therefore,  $3+3+2 = 8$ , this is our total  $h(n)$  for the current state.

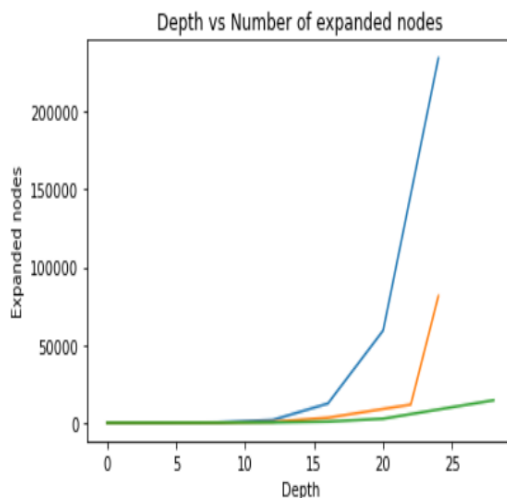
## Comparison of Algorithms based on Sample Puzzles

Graph color code

Green: Manhattan Distance Algorithm

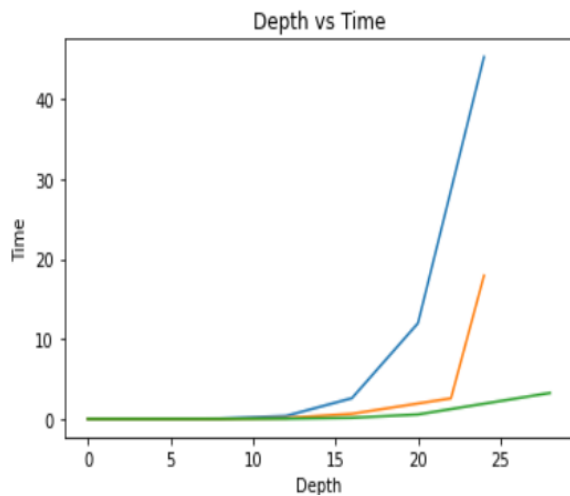
Orange: Misplaced Tile Algorithm

Blue: Uniform Cost Search Algorithm



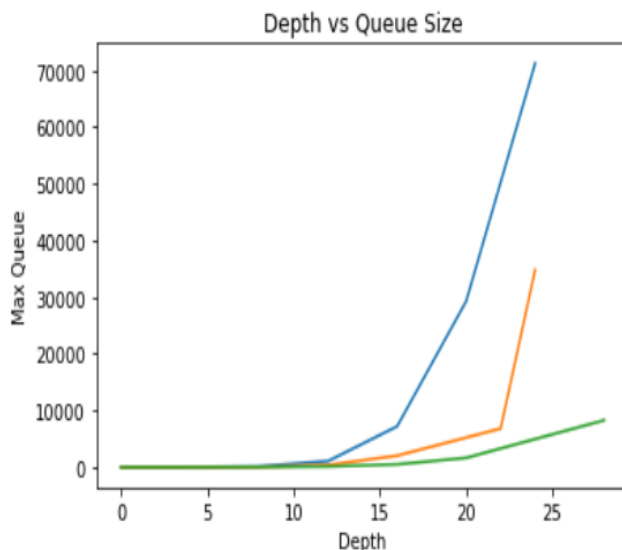
**Figure 8:** Depth vs Number of nodes expanded

As we can observe, the depth of the search increases with the number of nodes, especially for uniform cost search since it naively expands each and every state, in a breadth first search manner, rather than using some heuristic. The heuristic algorithms Manhattan and Misplaced tile expand far lesser nodes with the increasing depth since they smartly choose the least cost state. From the graph, it can be noted that Uniform Cost Search performs the worst and after depth 20, Manhattan expands far lesser nodes than the misplaced tile.



The depth vs time graph in figure 9, shows that the Uniform Cost Search performs the worst in terms of time as it increases the number of depths to the greatest extent. Misplaced tile's time complexity increases exponentially after node 20 since it has to calculate heuristic cost for a greater number of tiles now which takes time. Similar can be seen and concluded for Manhattan but it seems that the time complexity of Manhattan does not increase exponentially

**Figure 9: Depth vs Time**



When it comes to the queue size, it increases with depth after node 10 for all the three algorithms. Till node 10, the size of queue remains constant for all three algorithms. Even in this scenario, Manhattan distance performs orders of magnitude better than the other three algorithms.

**Figure 10: Depth vs Maximum Queue Size**

From the above graphs, it can be concluded that Manhattan Distance gives the best performance most probably because it is more intuitive as compared to the naïve uniform cost and the misplaced tile. The misplaced tile just counts the number of tiles not in their position but the Manhattan distance tells **how far** each tile is from the goal the goal state, thus giving an idea how far the overall state is from the goal state.

## CODE ([https://github.com/L-E-A-R-N-E-R/8\\_Puzzle\\_Problem](https://github.com/L-E-A-R-N-E-R/8_Puzzle_Problem))

```
1 from copy import deepcopy
2 from itertools import chain
3 import time
4 import heapq as heap
5 import sys
6 import matplotlib.pyplot as plt
7
8 goal8 = [[1,2,3],[4,5,6],[7,8,0]]      #for 8 puzzle
9 goal15 = [[1,2,3,4],[5,6,7,8],[9,10,11,12],[13,14,15,0]]      #for 15 puzzle
10 goal24 = [[1,2,3,4,5],[6,7,8,9,10],[11,12,13,14,15],[16,17,18,19,20],[21,22,23,24,0]]      #for 24 puzzle
11 mapping = {}                          #to trace the path of parent states
12 mq_size=0                             #maximum size of queue
13
14 def main():
15
16     depth_samples = ( [[1,2,3],[4,5,6],[7,8,0]] , [[1,2,3],[4,5,6],[0,7,8]] , [[1,2,3],[5,0,6],[4,7,8]],
17
18                     [[1,3,6],[5,0,2],[4,7,8]], [[1,3,6],[5,0,7],[4,8,2]], [[1,6,7],[5,0,3],[4,8,2]],
19
20                     [[7,1,2],[4,8,5],[6,3,0]], [[0,7,2],[4,6,1],[3,5,8]] )
21
22     print("8 puzzle solver!\n\n")
23
24     print("The puzzle can be a default and also the one of your choice. Choose 1 for default or choose 2 for your own puzzle")
25
26     choice = int(input())
27
28     if(choice==1):
29
30         puzzle = [[1,3,6],[5,0,2],[4,7,8]]
31         print("The default puzzle looks something like this\n")
32         print(puzzle)
33
34
35
36     elif(choice==2):
37
38         print("Enter number of rows\n")
39         rows = int(input())
40         print("Enter number of columns\n")
41         cols = int(input())
42
43         print("Enter the elements one by one. Use zero to represent a blank element in the puzzle\n")
44
45         puzzlein = []
46         for i in range(rows):
47             inside = []
48             for j in range(cols):
49                 temp = int(input())
50                 inside.append(temp)
51             puzzlein.append(inside)
52
53         print("\n")
54         print("The puzzle entered by you looks something like this \n")
55
56         for z1 in range(rows):
57             for z2 in range(cols):
58                 print(puzzlein[z1][z2],end=" ")
59             print()
60
61         print("\n")
62
63         print("There are three ways to solve it! Please choose one of the following methods:\n\n")
64
65         print("1. Uniform Cost Search\n2. A* with the Misplaced Tile heuristic\n3. A* with Manhattan Distance heuristic\n")
66
67         method = int(input())
```





```

149
150         if(ele_row>0):
151             up_child = (cost,depth,up(matmat,ele_row,ele_col))
152             temp_tup_up = (tuple(map(tuple,up_child[2])))
153             if (temp_tup_up not in seen):
154                 child_states.append(up_child)
155
156         if(ele_row<len(matmat)-1):
157             down_child = (cost,depth,down(matmat,ele_row,ele_col))
158             temp_tup_down = (tuple(map(tuple,down_child[2])))
159             if (temp_tup_down not in seen):
160                 child_states.append(down_child)
161
162     final = []
163     for each_child in child_states:
164
165         each_child = list(each_child)
166         each_child[1] += 1
167         each_child = tuple(each_child)
168
169         if algorithm == 1:
170             each_child = list(each_child)
171             each_child[0] += 1
172             each_child = tuple(each_child)
173         if algorithm == 2:
174             h_n = misplaced_tiles(each_child[2])
175             each_child = list(each_child)
176             each_child[0] = each_child[0] + h_n + 1
177             each_child = tuple(each_child)
178         if algorithm == 3:
179             h_n = manhattan(each_child[2])
180             each_child = list(each_child)
181             each_child[0] = each_child[0] + h_n + 1

```

```

180         each_child = list(each_child)
181         each_child[0] = each_child[0] + h_n + 1
182         each_child = tuple(each_child)
183
184         final.append(each_child)
185
186     return final
187
188 def queueing_function(node_list,child_list):
189     global mq_size
190     for e in child_list:
191         heap.heappush(node_list,e)
192         if (len(node_list) > mq_size):
193             mq_size = len(node_list)
194     return node_list
195
196 def left(matrix1,p,q):
197
198     xten1 = deepcopy(matrix1)
199     tempo1 = xten1[p][q]
200     xten1[p][q] = xten1[p][q-1]
201     xten1[p][q-1] = tempo1
202
203     fedup1 = tuple((map(tuple,xten1)))
204
205     mapping[fedup1] = tuple((map(tuple,matrix1)))
206     return xten1
207
208 def right(matrix2,r,s):
209
210     xten2 = deepcopy(matrix2)
211     tempo2 = xten2[r][s]
212     xten2[r][s] = xten2[r][s+1]

```

```

212     xten2[r][s] = xten2[r][s+1]
213     xten2[r][s+1] = tempo2
214
215     fedup2 = tuple((map(tuple,xten2)))
216
217     mapping[fedup2] = tuple((map(tuple,matrix2)))
218     return xten2
219
220 def up(matrix3,t,u):
221
222     xten3 = deepcopy(matrix3)
223     tempo3 = xten3[t][u]
224     xten3[t][u] = xten3[t-1][u]
225     xten3[t-1][u] = tempo3
226
227     fedup3 = tuple((map(tuple,xten3)))
228
229     mapping[fedup3] = tuple((map(tuple,matrix3)))
230     return xten3
231
232 def down(matrix4,v,w):
233
234     xten4 = deepcopy(matrix4)
235     tempo4 = xten4[v][w]
236     xten4[v][w] = xten4[v+1][w]
237     xten4[v+1][w] = tempo4
238
239     fedup4 = tuple((map(tuple,xten4)))
240
241     mapping[fedup4] = tuple((map(tuple,matrix4)))
242     return xten4
243

```

```

244 def manhattan(two_d):
245
246     dict = {1:[0,0], 2:[0,1], 3:[0,2], 4:[1,0], 5:[1,1], 6:[1,2], 7:[2,0], 8:[2,1]} #to create this mapping for puzzle of a
247     cost_of_one_state = 0
248
249     for ice in range(len(two_d)):
250         for juice in range(len(two_d)):
251             if(two_d[ice][juice]!=0):
252                 r = ice
253                 c = juice
254                 linear = dict.get(two_d[ice][juice])
255                 cost_of_one_state += abs(linear[0]-r) + abs(linear[1]-c)
256
257     return cost_of_one_state
258
259 def misplaced_tiles(tile_cost):
260
261     count = 0
262     calculation = list(chain.from_iterable(tile_cost))
263
264     for element in calculation:
265         if(element!=0):
266             position = calculation.index(element)
267             if((element-position)!=1):
268                 count+=1
269
270     return count
271
272 def plotter(testers,option):
273
274     exp_node_testers_uniform = []
275     depth_testers_uniform = []
276     max_queue_testers_uniform = []
277     time_testers_uniform = []

```

```

277 time_testers_uniform = []
278
279 exp_node_testers_misplaced = []
280 depth_testers_misplaced = []
281 max_queue_testers_misplaced = []
282 time_testers_misplaced = []
283
284 exp_node_testers_manhattan = []
285 depth_testers_manhattan = []
286 max_queue_testers_manhattan = []
287 time_testers_manhattan = []
288
289 for algos in range(1,4):
290
291     for looping in testers:
292
293         exp_node,d,mqsz,t = general_search(looping,algos)
294
295         if algos==1:
296             depth_testers_uniform.append(d)
297             max_queue_testers_uniform.append(mqsz)
298             time_testers_uniform.append(t)
299             exp_node_testers_uniform.append(exp_node)
300
301         if algos==2:
302             depth_testers_misplaced.append(d)
303             max_queue_testers_misplaced.append(mqsz)
304             time_testers_misplaced.append(t)
305             exp_node_testers_misplaced.append(exp_node)
306

```

```

307
308     if algos==3:
309         depth_testers_manhattan.append(d)
310         max_queue_testers_manhattan.append(mqsz)
311         time_testers_manhattan.append(t)
312         exp_node_testers_manhattan.append(exp_node)
313
314     #Depth and nodes expanded
315     plt.plot(depth_testers_uniform,exp_node_testers_uniform)
316     plt.plot(depth_testers_misplaced,exp_node_testers_misplaced)
317     plt.plot(depth_testers_manhattan,exp_node_testers_manhattan)
318     plt.title("Depth vs Number of expanded nodes")
319     plt.xlabel("Depth")
320     plt.ylabel("Expanded nodes")
321     plt.show()
322
323     #Depth and time
324     plt.plot(depth_testers_uniform,time_testers_uniform)
325     plt.plot(depth_testers_misplaced,time_testers_misplaced)
326     plt.plot(depth_testers_manhattan,time_testers_manhattan)
327     plt.title("Depth vs Time")
328     plt.xlabel("Depth")
329     plt.ylabel("Time")
330     plt.show()
331
332     #Depth and maximum queue size
333     plt.plot(depth_testers_uniform,max_queue_testers_uniform)
334     plt.plot(depth_testers_misplaced,max_queue_testers_misplaced)
335     plt.plot(depth_testers_manhattan,max_queue_testers_manhattan)
336     plt.title("Depth vs Queue Size")
337     plt.xlabel("Depth")
338     plt.ylabel("Max Queue")
339     plt.show()
340
341
342 if __name__ == "__main__":
343     main()
344

```

## SAMPLE OUTPUT:

### a. Traceback for Depth 8 with misplaced tile heuristic

8 puzzle solver!

The puzzle can be a default and also the one of your choice. Choose 1 for default or choose 2 for your own puzzle

1

The default puzzle looks something like this

[[1, 3, 6], [5, 0, 2], [4, 7, 8]]

There are three ways to solve it! Please choose one of the following methods:

1. Uniform Cost Search
2. A\* with the Misplaced Tile heuristic
3. A\* with Manhattan Distance heuristic

3

The best state to expand with a  $g(n) = 0$  and  $h(n) = 0$  is...

[1, 3, 6]  
[5, 0, 2]  
[4, 7, 8]

The best state to expand with a  $g(n) = 8$  and  $h(n) = 1$  is...

[1, 3, 6]  
[0, 5, 2]  
[4, 7, 8]

The best state to expand with a  $g(n) = 8$  and  $h(n) = 1$  is...

The best state to expand with a  $g(n) = 8$  and  $h(n) = 1$  is...

[1, 3, 6]  
[5, 2, 0]  
[4, 7, 8]

The best state to expand with a  $g(n) = 10$  and  $h(n) = 1$  is...

[1, 0, 6]  
[5, 3, 2]  
[4, 7, 8]

The best state to expand with a  $g(n) = 10$  and  $h(n) = 1$  is...

[1, 3, 6]  
[5, 7, 2]  
[4, 0, 8]

The best state to expand with a  $g(n) = 15$  and  $h(n) = 2$  is...

[1, 3, 0]  
[5, 2, 6]  
[4, 7, 8]

The best state to expand with a  $g(n) = 15$  and  $h(n) = 2$  is...

[1, 3, 6]  
[4, 5, 2]  
[0, 7, 8]

The best state to expand with a  $g(n) = 17$  and  $h(n) = 2$  is...

[0, 3, 6]  
[1, 5, 2]  
[4, 7, 8]

The best state to expand with a  $g(n) = 17$  and  $h(n) = 2$  is...

[1, 3, 6]  
[5, 2, 8]  
[4, 7, 0]

The best state to expand with a  $g(n) = 19$  and  $h(n) = 2$  is...

[1, 3, 6]  
[5, 7, 2]  
[4, 8, 0]

The best state to expand with a  $g(n) = 21$  and  $h(n) = 2$  is...

[0, 1, 6]  
[5, 3, 2]  
[4, 7, 8]

The best state to expand with a  $g(n) = 21$  and  $h(n) = 2$  is...

[1, 3, 6]  
[5, 7, 2]  
[0, 4, 8]

The best state to expand with a  $g(n) = 21$  and  $h(n) = 2$  is...

[1, 6, 0]  
[5, 3, 2]  
[4, 7, 8]

The best state to expand with a  $g(n) = 21$  and  $h(n) = 3$  is...

[1, 0, 3]  
[5, 2, 6]  
[4, 7, 8]

The best state to expand with a  $g(n) = 21$  and  $h(n) = 3$  is...

[1, 3, 6]  
[4, 5, 2]  
[7, 0, 8]

The best state to expand with a  $g(n) = 26$  and  $h(n) = 4$  is...

[1, 2, 3]  
[5, 0, 6]  
[4, 7, 8]

The best state to expand with a  $g(n) = 26$  and  $h(n) = 4$  is...

[1, 3, 6]  
[4, 5, 2]  
[7, 8, 0]

The best state to expand with a  $g(n) = 27$  and  $h(n) = 3$  is...

[1, 3, 6]  
[5, 2, 8]  
[4, 0, 7]

The best state to expand with a  $g(n) = 27$  and  $h(n) = 3$  is...

[3, 0, 6]  
[1, 5, 2]  
[4, 7, 8]

The best state to expand with a  $g(n) = 28$  and  $h(n) = 4$  is...

[0, 1, 3]  
[5, 2, 6]  
[4, 7, 8]

The best state to expand with a  $g(n) = 28$  and  $h(n) = 4$  is...

[1, 3, 6]  
[4, 0, 2]  
[7, 5, 8]

The best state to expand with a  $g(n) = 29$  and  $h(n) = 3$  is...

[1, 3, 6]  
[5, 7, 0]  
[4, 8, 2]

The best state to expand with a  $g(n) = 30$  and  $h(n) = 5$  is...

[1, 2, 3]  
[0, 5, 6]  
[4, 7, 8]

The best state to expand with a  $g(n) = 31$  and  $h(n) = 3$  is...

[1, 6, 2]  
[5, 3, 0]  
[4, 7, 8]

The best state to expand with a  $g(n) = 36$  and  $h(n) = 5$  is...

- [1, 3, 6]
- [0, 4, 2]
- [7, 5, 8]

The best state to expand with a  $g(n) = 36$  and  $h(n) = 5$  is...

- [5, 1, 3]
- [0, 2, 6]
- [4, 7, 8]

The best state to expand with a  $g(n) = 36$  and  $h(n) = 8$  is...

- [1, 2, 3]
- [4, 5, 6]
- [7, 8, 0]

Expanded nodes: 37

Depth: 8

Maximum size of queue: 29

0.02

Choose 1 to plot the graph, 0 to terminate

## b. Traceback for Depth 4 with Manhattan Distance

---

8 puzzle solver!

The puzzle can be a default and also the one of your choice. Choose 1 for default or choose 2 for your own puzzle

2

Enter number of rows

3

Enter number of columns

3

Enter the elements one by one. Use zero to represent a blank element in the puzzle

1

2

3

5

0

6

4

7

8

The puzzle entered by you looks something like this

1 2 3

5 0 6

4 7 8

---

There are three ways to solve it! Please choose one of the following methods:

1. Uniform Cost Search
2. A\* with the Misplaced Tile heuristic
3. A\* with Manhattan Distance heuristic

3

The best state to expand with a  $g(n) = 0$  and  $h(n) = 0$  is...

[1, 2, 3]

[5, 0, 6]

[4, 7, 8]

The best state to expand with a  $g(n) = 4$  and  $h(n) = 1$  is...

[1, 2, 3]

[0, 5, 6]

[4, 7, 8]

The best state to expand with a  $g(n) = 6$  and  $h(n) = 1$  is...

[1, 0, 3]

[5, 2, 6]

[4, 7, 8]



The best state to expand with a  $g(n) = 6$  and  $h(n) = 1$  is...

[1, 2, 3]  
[5, 6, 0]  
[4, 7, 8]

The best state to expand with a  $g(n) = 6$  and  $h(n) = 1$  is...

[1, 2, 3]  
[5, 7, 6]  
[4, 0, 8]

The best state to expand with a  $g(n) = 7$  and  $h(n) = 2$  is...

[1, 2, 3]  
[4, 5, 6]  
[0, 7, 8]

The best state to expand with a  $g(n) = 9$  and  $h(n) = 2$  is...

[0, 2, 3]  
[1, 5, 6]  
[4, 7, 8]

The best state to expand with a  $g(n) = 9$  and  $h(n) = 3$  is...

[1, 2, 3]  
[4, 5, 6]  
[7, 0, 8]

The best state to expand with a  $g(n) = 10$  and  $h(n) = 4$  is...

[1, 2, 3]  
[4, 5, 6]  
[7, 8, 0]

Expanded nodes: 9

Depth: 4

Maximum size of queue:9

0.01

Choose 1 to plot the graph, 0 to terminate