

# CSM6120 - 8 puzzle solver

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*Abstract*—The abstract goes here.

## I. INTRODUCTION

**I**N this report the created solution to the 8 puzzle solver will be discussed.

## II. STRUCTURE

The overall structure can be seen in the UML diagram, found in appendix A though C. In this section the structure of the program will be explained and the different classes and their uses. Detailed description methods will not be given please refer to the JavaDoc in appendix **ADD JAVADOC AS APPENDIX**.

The structure of this section is as follows: for every package used in the program the use of the package as well as the classes inside it is given followed by a section about the justification of the design choices.

### A. The *csM6120* Package

This package holds the Main class, aswell as the *State* and *FileManager* classes.

The class diagram for this can be found in Appendix A on page 6.

This package acts as entry point to the program where the input files are read and where the *State* class is located.

1) *Main*: The Main class is the entrance to the program. The main method takes command line arguments such as the path to the start state and goal state of the puzzle(in .txt files) and a string which specifies what algorithm to use. It creates instances of the *FileManager* object and *State* objects and calls the algorithm chosen by the user.

2) *State*: The State class holds variables and methods to manipulate and represent each state of the puzzle, that is the tile placement of the puzzle.

The tiles are interpreted as a simple *ArrayList*, this has been done in order to make manipulating the array easier.

The class holds methods to switch 2 given tiles(done based on their index in the *ArrayList*) as well as other common methods such as getters and methods to compare a state object to another.

These methods are used in the other algorithms incorporated in the program.

3) *FileManager*: The *FileManager* class holds methods to read input from a file, converts the strings into integers and then save it to the integer *ArrayList* in a *State* object. The main class instantiates a single *FileManager* object and than uses it to read the input files provided by the user.

4) *Justification*: The idea for the *csM6120 Package* was to have the methods which manipulate the input files all in one place. It was considered to move the *State* class to the *SearchTree* package, but considering it holds such a central role in the program the decision fell against it.

The *FileManager* class was created in order to have a separate class to handle input files, this was done in order to follow object orientated design structures.

### B. The *SearchTree* Package

This package holds classes which represent and generate the search tree.

The UML diagram for this can be found in appendix B on page 7

1) *TreeNode*: Objects of the *TreeNode* class represent nodes of the search tree.

Every *TreeNode* holds a *State* object as well as 2 *LinkedList*s. One *LinkedList* holding the children of one particular node, the other for holding its siblings.

The class has methods to add, get and remove nodes from those lists, as well as common methods such as returning if a list is empty.

2) *Graph*: The graph is used to generate the next step of the graph, by expanding all possible children from a particular *TreeNode* object and than add them to the *LinkedList* of children of said *TreeNode* object.

The *nextStep* method of this class checks where the empty tile is in a given *TreeNode* object, based on that it calls one of three possible functions which generate the children of the object.

3) *Justification*: The idea was to have all classes which represent or manipulate the nodes of the search tree in a single package. It was also decided to only have a class for the nodes of the tree and representing the connections to its children using a internal *LinkedList* rather than having a separate edge class which only links 2 nodes together. The reason this was done was for simplicity: using *LinkedList* methods like adding and returning makes it easier considering every node has a very limited, maximum of 4, number of possible children.

### C. *SearchAlgorithm* Package

This package holds all search algorithms implemented in the program, as well as all supporting classes needed for them.

The UML diagram for this package can be seen in appendix C on page 8.

In general all the search algorithms are build up much the same way, they take 2 parameters: a start and goal State object, these States are than used to create the first node of the search tree, the goal state gets saved in the current search algorithm object and is used to check if the goal state of the puzzle has been reached.

The algorithms use the classes from the SearchTree package(see section II-B) to generate the search tree.

At the beginning of each algorithm it is checked if the start state is equal the goal state, this might be a rare occurrence but a useful functionality non the less.

All algorithms also hold a list of all previous expanded nodes, which all new generated nodes are checked against in order to prevent infinity loops. That already visited nodes are created again is because the children to each node are generated without knowledge if such a node has been created before, so infinity loops would be created relatively early on in the search trees.

1) *Breadth-First search*: This class holds the breadth-first search algorithm.

This algorithm works using a first-come first served queue.

2) *Depth-First search*: This class holds the depth-first search algorithm.

It is in its structure very similar to the breadth-first search algorithm, however uses a last-in first-out stack.

3) *Greedy Best-First search*: This class holds the greedy best-first search algorithm.

It is in its structure very like the breadth-first or depth-first algorithms, however uses a priority queue. In the priority queue the elements are sorted according to its *natural ordering*, meaning from lower to higher numbers.

That way the treeNode which is closer to the goal state will be checked next. The priority queue uses the stateComparator class to sort its elements.

4) *A star algorithm*: This class holds the A star search algorithm.

This algorithm is similar to the greedy best-first algorithm in that it uses a priority queue, but it also uses a more advanced heuristic to decide which nodes to add to the queue in the first place.

This class holds 2 methods, one is the search algorithm in itself, the other is a method used to decide which treeNode object to add to the search queue. This is done using the Manhattan Distance heuristic. In the beginning of the algorithm the Manhattan Distance to the goal state is calculated and saved to a variable.

The addNode method than uses the current treeNode object and the goal State to calculate the Manhattan distance for each of the current treeNode's children. If the calculated Manhattan Distance is equal or less than the one calculated at the beginning of the algorithm the node is added to the search queue. Should the calculated distance be larger the child is discarded.

To calculate the Manhattan Distance the a ManhattanDistance

object is used.

5) *StateComparator*: This class holds the StateComparator method used to compare to states in a priority list. This class implements the *Comparator* interface.

It uses the String representation of a State objects state array to do the comparison.

6) *ManhattanDistance*: This class holds the methods used to calculate the Manhattan Distance.

During development of an early method to calculate the Manhattan Distance straight from a state array a number of problems have been found. The decision was made that a 2D representation of the array would be more fitting in order to calculate the Manhattan Distance.

However in order to avoid having to refactor all other algorithms the ManhattanDistance class holds methods to change an input arrayList to a simple array and after that to a 2 dimensional array.

The Manhattan Distance is calculated as such:

For each possible number of the puzzle find its index X and Y coordinates for each of the 2 input States. Then compare the X and Y coordinates of both indices and calculate the total difference in tiles.

Here 2 things must be noddod:

Depending on if the start State indices minus the goal State indices return a value less than zero or above, the formula gets flipped in order to prevent receiving a negative Manhattan Distance. The code for this is shown below:

---

```
if (startArray[i][j] == goalArray[i][j]) {
    continue;
} else if (startArray[i][j] - goalArray[i][j]
    < 0) {
    manhattanDistanceSum +=
        Math.abs(x_start - x_goal)
        + Math.abs(y_start - y_goal);
} else if (startArray[i][j] - goalArray[i][j]
    > 0) {
    manhattanDistanceSum += Math.abs(x_goal
        - x_start)
        + Math.abs(y_goal - y_start);
}
```

---

The other important thing to node is that empty/zero tile of the puzzle is ignored in the Manhattan Distance calculation, this is to accommodate the fact that at every iteration 2 tiles are switched.

7) *Justification*: It can be argued that the methods in the ManhattanDistance class are bad practice, as it would have been better to refactor all previously written algorithm to use 2D arrays rather than converting a State arrayList to a 2D array for every treeNode object.

However this decision was made as the use of a arrayList makes the use of the algorithms though out the program easier, thanks to Java's inbuilt arrayList methods.

Also since all arrayList have a limited size of 8, the computational cost for the conversion is constant and not large.

The list of expanded nodes which each class holds and all algorithms loop over at every iteration to check if the current nodes children already where created ones add a lot of computational overhead to each iteration.

While it gets apparent in breadth-first, however not as much in greedy best-first and A star search, this is not to much a problem because of the typical behaviour of these algorithms the overhead. But in depth-first search it causes massive computational overhead and causes long run times in order to find a solution.

The reason for that is the behaviour of the algorithm, unless in a few seldom instances the state space for depth-first search is much more massive than for the other algorithms.

So iterating over 10's of thousands of nodes in the list of expanded nodes takes a lot of time and computational power. Still the list needs to be maintained in order to avoid infinite loop problems.

### III. ANALYSIS

In this section the design choices will be analysed further. This includes the heuristic used as well as any problems encountered during the development cycle.

#### A. Manhattan Distance

For this program 2 heuristics where considered.

The first being simply the number of misplaced tiles, this heuristic is admissible as all misplaced tiles must be moved atleast once.

However it was decided to implement something more "advanced" in form of the Manhattan Distance heuristic, which is another common heuristic for these kind of problems [1].

The Manhattan Distance is admissible for this kind of problem as it either estimates the exact number of moves needed or underestimates the total path costs needed to find a solution.

The Manhattan Distance is calculated by the sum of the vertical and horizontal distances of between to tiles, because tiles can not move along diagonals.

#### B. Performance

In this section the performance of each algorithm with the 3 provided test cases is analysed.

It is interesting to note that the processing time varies between runs. While on the first run it is often a lot higher, the processing time reduces in the following couple of runs. until it either gets stable or varies between 2 values. All running times shown in this section are taken after 5 runs as it then appears to be stable.

The test cases used in this section are shown in table I. Test cases 1 through 3 are the ones supplied with the assignment description, test case 4 has been randomly generated.

TABLE I: Test cases used to test the program

Test case number	Test case representation
1	1 2 0
	3 4 5
	6 7 8
2	1 2 5
	3 0 4
	6 7 8
3	3 2 0
	6 1 5
	7 4 8
4	1 7 6
	3 6 2
	4 0 8

1) *Breadth-First search:* Table II shows the performance of Breadth-First search.

As the test result show the number of explored nodes increases significantly when more tiles are out of place. The processing time also increases.

While during test cases 1 - 3 the number of expanded nodes and the actual path cost to the goal, as well as the processing time, increases marginally from the easiest test case(1) to the more advanced one(3), the path cost, number of expanded nodes as well as the running time increases drastically when solving the randomly generated puzzle, represented as test case 4.

TABLE II: Performance of Breadth-First Search

Test case	Path Cost	Expanded Nodes	Running Time in nanosecond
1	3	7	5
2	29	53	7
3	67	114	11
4	58375	80176	90107

2) *Depth-First search:* Table III shows the performance of Depth-First search.

As can be seen the path cost is massive, a lot more than the in any other search algorithm implemented in the system. As well is the processing time. The reason for the immense path cost and processing time is the way children are added to nodes in the program, in combination with the working of Depth-First search.

It is likely that if nodes where added in a different way the path cost and processing time decrease. It could also be improved with implementing an abbreviation of Depth-First search, such as Depth-Limited search.

It is worth noting that the arguably more complex systems of Test Case 2, 3 and 4 actually have a lower path cost and lower computational time than the first one, where only 3 tiles are out of place.

TABLE III: Performance of Depth-First Search

Test case	Path Cost	Expanded Nodes	Running Time in nanosecond
1	169022	180688	1303747
2	139063	175713	1115838
3	111950	166823	895815
4	112545	167212	854431

3) *Greedy Best-First search*: Table IV shows the performance of the Greedy Best-First search algorithm.

As the table shows, in the first and easiest test case the algorithm performs with perfect accuracy, choosing the direct path to the goal state.

Test case 2 and 3 as well show a large improvement in path cost over Depth-First search, however shows, in some cases, worse performance than Breadth-First search. It can be seen that the extra computational overhead of sorting the priority queue causes the algorithm to perform marginal slower than Breadth-First search.

Also does the simple heuristic used in this algorithm not guarantee a better solution to the, as for test cases 2 and 3 the path cost and the number of expanded nodes is, though only minimal, larger than Breadth-First search.

It shows however that using a heuristic for more advanced search problems, represented here as test case 4, leads to far better performance than using an uninformed search.

TABLE IV: Performance of Greedy Best-First search

Test case	Path Cost	Expanded Nodes	Running Time in nanosecond
1	2	5	6
2	8	16	7
3	72	117	19
4	946	1379	100

4) *A star search*: Table V shows the performance of the  $A^*$  Algorithm.

Different in this table compared to the previous once is that an extra column has been added in to show the Manhattan Distance value which was calculated at the beginning of the algorithm.

As the table shows for test cases 1 and 2 the estimated Manhattan Distance was reached precisely. On test case 3 the algorithm had to explore 21 nodes in order to find the goal state, while the estimated Manhattan Distance was 6 notes. This shows that the heuristic is admissible as it does not overestimate the path cost.

The processing time is similar to Greedy Best-First and Breadth-First search. Even for the more advanced puzzle (test case 3).

However test case 4 shows that a good heuristic does not always leads to a goal state.

No solution could be found for this test case, however the Manhattan Distance is estimated to be 11.

As the other test case work fine there is no reason to believe

that the algorithm itself it faulty, but rather that  $A^*$  simply is not able to find a solution to every puzzle.

TABLE V: Performance of A star search

Test case	Manhattan Distance	Patch cost	Expanded nodes	Running Time in nanosecond
1	2	2	4	6
2	4	4	7	7
3	6	21	28	11
4	11	/	/	5

### C. Problems

In this subsection the problems encountered in the development cycle are discussed, as well as how they were solved.

1) *Infinite loop*: Early during the development process, after implementing Breadth-First and Depth-First search, a problem with the graph generation was encountered. The problem was that states which were already encountered got generated again.

The reason for was that no method was implemented to check if nodes were already generated. This led to infinite long search trees.

Listing 1: Solution to the Infinite Search Tree Problem

```

while (node.childrenIsEmpty() != true) {
    /*
     * Add the current node to a an ArrayList
     * of expanded nodes
     */
    if (expanded.contains(node.getState().
        getStringToString()) ==
        false) {
        expanded.add(node.getState().
            getStringToString());
    }
    String s = node.peekChild().getState().
        getStringToString();
    if (expanded.contains(s) == false) {
        expanded.add(s);
        searchQueue.add(node.getFirstChild());
    } else {
        node.removeFirstChild();
    }
}

```

The solution to that is shown in listing 1.

With these few lines of code all expanded nodes are saved to a arrayList of expanded nodes, which than gets iterated through every iteration to check if a newly generated state already exists. If it does not the state will be added to the search queue/stack as well as to the list of expanded nodes. This piece of code, although modified in case of the  $A^*$  algorithm, is included in all algorithms.

## IV. DISCUSSION

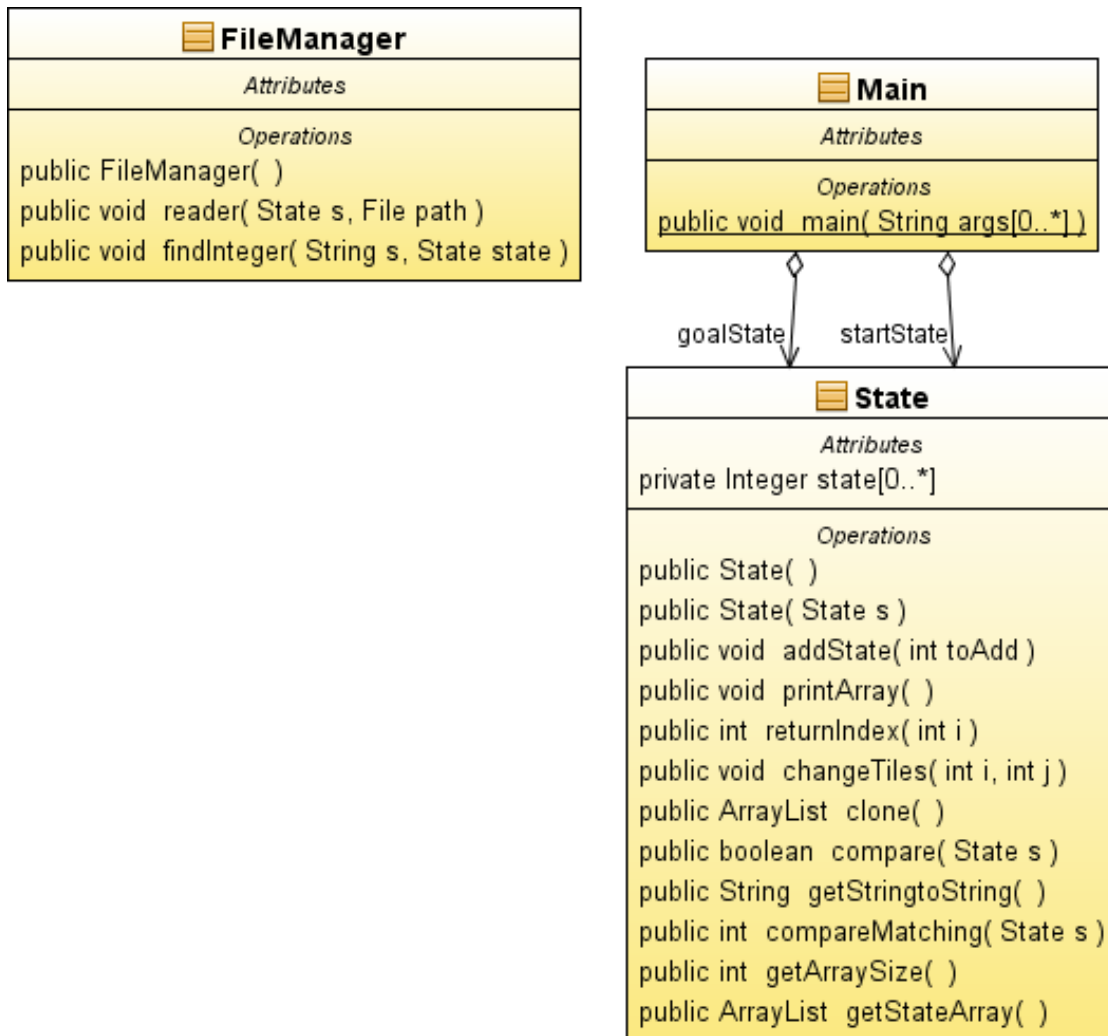
Section III shows the analysis of each algorithm and its performance on each of the 4 test cases.

Inherently one could see it as a comparison of uninformed search VS informed search, with 2 examples for each type of search. It shows that for simple puzzles uninformed search methods perform equally well or better than some informed search algorithms, both in time and space complexity. It is however on the more advanced puzzles that the informedness of an heuristic shows an drastic improvement over uninformed strategies.

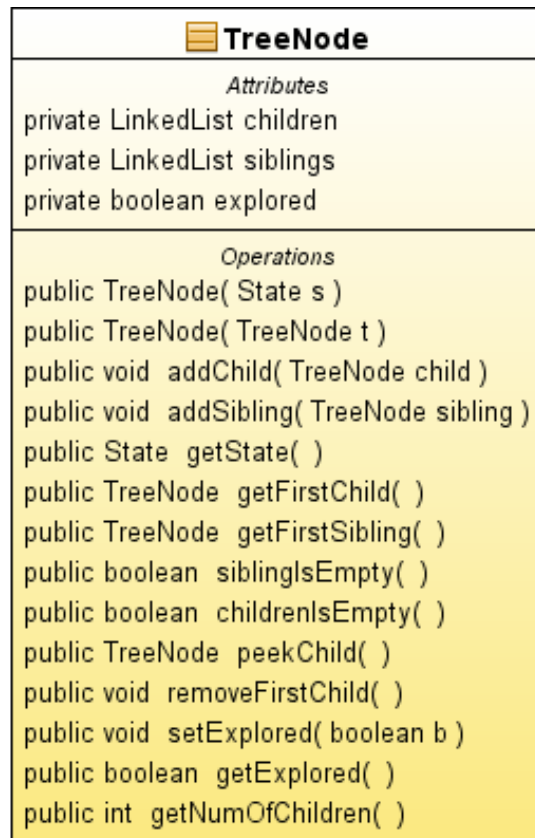
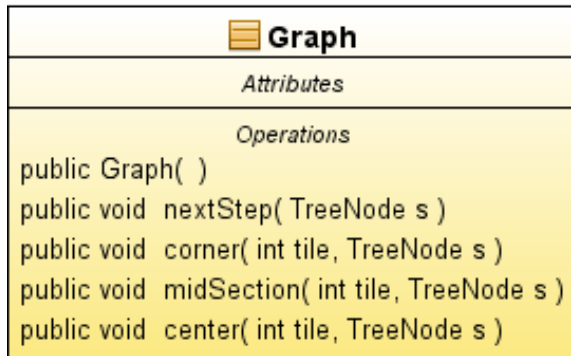
It also shows that an advanced heuristic can both perform better or worse than a simple heuristic. An example of that would be a direct comparison of Greedy Best-First vs  $A^*$  search.  $A^*$  uses a more advanced heuristic which leads to better results in the most test cases but it fails to find a solution for the last test case.

The attributes of the algorithm play a big role as well. Depth-First search has very large time and space complexity, but is still guaranteed to find a solution as the search space is finite. Breadth-First search performs much better in every test case, however in the worst case scenario it would have the same time and space complexity as Depth-First search. Greedy Best-First performs better for some test cases however has for the simplest puzzles worse time complexity.  $A^*$  has the best time and space complexity of all algorithms implemented in this program however, as already mentioned, fails to find a solution for the most advanced test case. Whereas the other algorithms, even depth-first search, find a solution.

APPENDIX A  
CSM1620 PACKAGE UML

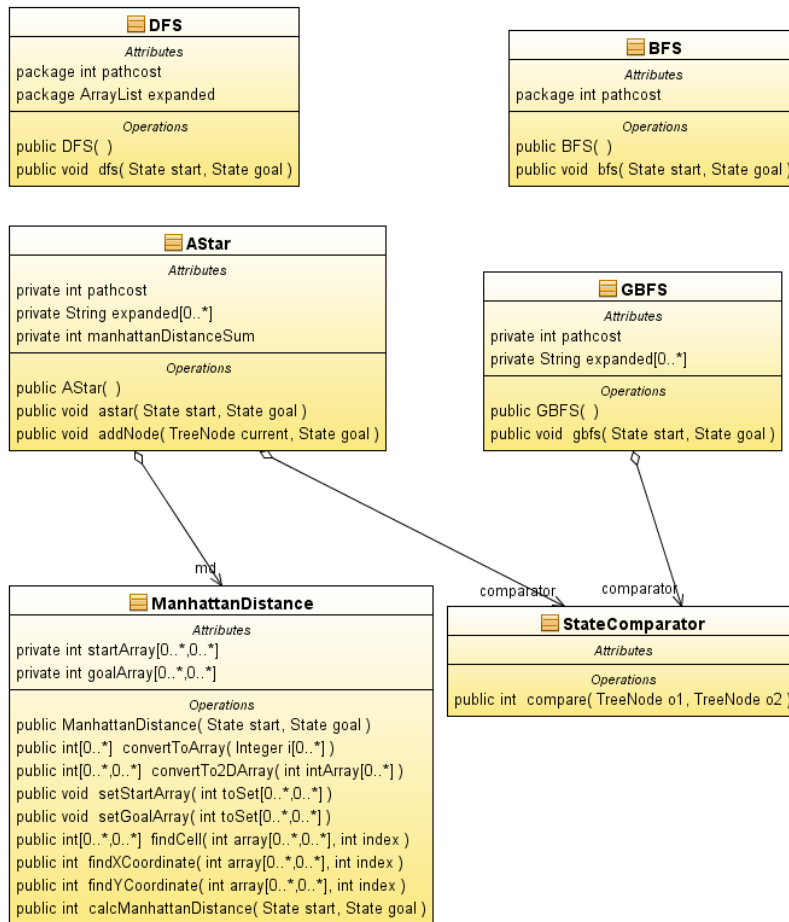


APPENDIX B  
SEARCHTREE PACKAGE UML



## APPENDIX C

### SEARCHALGORITHM PACKAGE UML





## REFERENCES

- [1] S. J. Russell and P. Norvig, *Artificial intelligence: a modern approach (3rd edition)*. Prentice Hall, 2009.