Introduction to Artificial intelligence – HW1

Ofri Kleinfeld 302893680

Heuristic function choice:

The heuristic function we will choose to implement is the heuristic shown in class, known as “Manhattan distance”.

The heuristic scores a game state by summing the “Manhattan distance” of every panel, from its current position on the board, to its goal position on the board.

Formally we will denote:

So “Manhattan distance” score will be:

Heuristic function Characteristics:

1. The Manhattan distance heuristic is consistent.

Proof:

In each step of the algorithm, we change the position of exactly one panel.

Hence our heuristic score can improve only be 1.

So, it holds that , for state n and a successor state n’.

Since all the possible steps cost the same, and their cost equal exactly 1,

We get and the heuristic is consistent.

1. The Manhattan distance heuristic is admissible/under estimate.

Proof:

We will show that h(n) is always not higher than the real cost h\*(n).

The heuristic score will be equal exactly to the true cost from a given state to the goal state **only if we have a sequence of valid actions**, **where for** **each action the heuristic score doesn’t increase.**

For example, we can refer to the following state:

|  |  |  |
| --- | --- | --- |
| 1 | 2 | 3 |
| 4 | 5 |  |
| 7 | 8 | 6 |

Here h(n) = 1 and indeed we need a sequence of 1 action (UP), which decreases the heuristic function.

If we don’t have a sequence of actions that doesn’t increase the heuristic function, our estimated cost will be greater from the actual cost – because we will have to increase the estimated cost, before we will be able to decrease it.

For example, denote the following state:

|  |  |  |
| --- | --- | --- |
| 2 | 1 | 3 |
| 4 | 5 | 6 |
| 7 | 8 |  |

For this state h(n) = 2, but every step taken from this state will increase h(n). In order to switch the 1 and 2 panels we have to first move other panels from their goal position and hence increase the heuristic score.