

ASSIGNMENT 4

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Simulated Annealing (SA) is a generic probabilistic metaheuristic for the global optimization problem of applied mathematics, namely locating a good approximation to the global minimum of a given function in a large search space.

- A. Input is given in a file in the following format. Read the input and store the information in a matrix. Configuration of the start state and the goal state can be anything. For example, given below, T1, T2, ..., T8 are tile numbers, and B is blank space.

Start State

T4	T1	T2
T7	T5	B
T8	T6	T3

Goal State

T1	T2	T3
T4	T5	T6
T7	T8	B

- B. **Input:** Input should be taken from an input file and processed as a matrix. Other inputs are Temperature variable T, heuristic function, neighborhood generating function, probability function to decide state change, and a cooling function.
- C. **Output:** All the following results should be stored in an output file:
- The success or failure message
 - Heuristics chosen, Temperature chosen, cooling function chosen, Startstate, and Goal state.
 - (Sub) Optimal Path (on success)
 - Total number of states explored.
 - Total amount of time taken.
- D. Objective functions to be checked:
- $h_1(n)$ = Number of displaced tiles.
 - $h_2(n)$ = Total Manhattan distance.

Solution:

Simulated Annealing -

Simulated annealing is a method for solving unconstrained and bound-constrained optimization problems. The method models the physical process of heating a material and then slowly lowering the temperature to decrease defects, thus minimizing the system energy.

At each iteration of the simulated annealing algorithm, a new point is randomly generated. The distance of the new point from the current point, or the extent of the search, is based on a probability distribution with a scale proportional to the temperature. The algorithm accepts all new points that lower the objective, but also, with a certain probability, points that raise the objective. By accepting points that raise the objective, the algorithm avoids being trapped in local minima, and is able to explore globally for more possible solutions.

Algorithm:

function SIMULATED-ANNEALING (problem, schedule) return a solution state

input: problem, a problem

schedule, a mapping from time to temperature

local variables: current, a node.

next, a node.

T, a “temperature” controlling the probability of downward steps

current \leftarrow MAKE-NODE (INITIAL-STATE [problem])

for t \leftarrow 1 to ∞ do

T \leftarrow schedule[t]

if T = 0 then return current

next \leftarrow a randomly selected successor of current

$\Delta E \leftarrow$ VALUE [current] – VALUE [next]

if $\Delta E > 0$ then current \leftarrow next

else current \leftarrow next only with probability $e^{-\Delta E / T}$

Heuristic search

This technique is designed to solve problems quickly but does not guarantee an optimal solution but gives a good solution.

Number of displaced tiles

Every tile out of place must be moved at least once in order to arrange them into the goal state.

Manhattan distance

It is the summation of the absolute difference between of goal's x and y coordinates and current x and y coordinates.

Q.1) Check whether the heuristics are admissible.

Yes, heuristics are admissible.

Q.2) What happens if we make a new heuristics $h_3(n) = h_1(n) * h_2(n)$.

When we combine these two heuristics code is not giving any output it is going into an infinite loop (iterations are increased)

Q.3) What happens if you consider the blank tile as another tile?

When we consider the blank tile as another tile it will take almost the same time (increases but very small), and the path will remain the same.

Q.4) What if the search algorithm got stuck into the Local optimum? Is there any way to get out of this?

If the temperature in the annealing process is not lowered slowly and enough time is not spent at each temperature, the process could get trapped in a local optimum.

- Simulated Annealing picks the move randomly
- If the situation improves then accept the move
- Otherwise, accept the move with some probability
- Probability decreases as the temperature goes down
- The probability decreases exponentially with the badness of the move
- Bad moves are more likely to be allowed at the start when temperature is high, and they are unlikely when temperature decreases

Using the probability function we can get out of the local optimum.

CASE1: $h_1(n)$ = Number of displaced tiles.

This heuristic is admissible.

Cooling Function	Linear Function
TMAX	30
Total Number of states explored	10
Search Status	Successful
(sub) optimal Path length	9
Time Taken	0.022929 sec.

Cooling Function	Negative Exponential Function
TMAX	30
Total Number of states explored	10
Search Status	Successful
(sub) optimal Path length	9
Time Taken	0.025932 sec.

CASE2: $h_2(n)$ = Total Manhattan distance

This heuristic is admissible.

Cooling Function	Linear Function
TMAX	30
Total Number of states explored	10
Search Status	Successful
(sub) optimal Path length	9
Time Taken	0.023921 sec.

Cooling Function	Negative Exponential Function
TMAX	30
Total Number of states explored	10
Search Status	Successful
(sub) optimal Path length	9
Time Taken	0.024936 sec.

Q.5) Compare Hill Climbing (previous assignment) and the Simulated Annealing with respect to optimality, completeness, and running time complexity (only for this specific problem).

Hill Climbing

	Number of displaced titles	Total Manhattan distance
Total number of states explored	9	9
Total number of states to optimal path	10	10
Optimal Path Cost	9	9
Time Taken for Execution	0.000447 sec.	0.000589 sec.

Simulated Annealing

	Number of displaced titles	Total Manhattan distance
Total number of states explored	9	9
Total number of states to optimal path	10	10
Optimal Path Cost	9	9
Time Taken for Execution	0.000568 sec.	0.000628 sec.

We are find that hill climbing and Simulated Annealing take the same optimal path but hill climbing is faster than Simulated Annealing.