

## Informed Search

- Blind search - no notion concept of the "right direction"
  - can only recognize goal once it's achieved
- Heuristic search — we have rough idea of how good various states are, and use this knowledge to guide our search
- Can find solutions more efficient than uninformed
- General approach is *best-first-search*
- A node is selected based on an *evaluation function  $f(n)$*
- A node that **seems** to be best is picked and it may not be the actual best

## Best First Search

- The Idea:
  - use an *evaluation function* for each node... estimate of "desirability"
  - Expand most desirable unexpanded node

### Implementation

- **Fringe**: is a queue sorted in decreasing order of desirability

### Special cases

#### Greedy

#### A\*

## Cost function $f(n)$

- A function  $f$  is maintained for each node
- $f(n) = g(n) + h(n)$ ,  $n$  is the node in the open list
- “Node chosen” for expansion is the one with least  $f$  value
- $g(n)$  is the cost from root  $S$  to node  $n$
- $h(n)$  is the estimated cost from node  $n$  to a goal
- For BFS:  $f = 0$ ,
- For DFS:  $f = 0$ ,
- For greedy  $g = 0$

## Greedy search

- Expands a node it sees closest to the goal
- $f(n) = h(n)$
- Resembles DFS in that it prefers to follow a single path all the way to the goal
- Also suffers from the same defects of DFS, it may stuck in a loop i.e. not complete As well as it is not optimal.

## Hill climbing

This is a *greedy* algorithm

Expands a node it sees closest to a goal

$$f(n) = h(n)$$

### The algorithm

select a heuristic function;

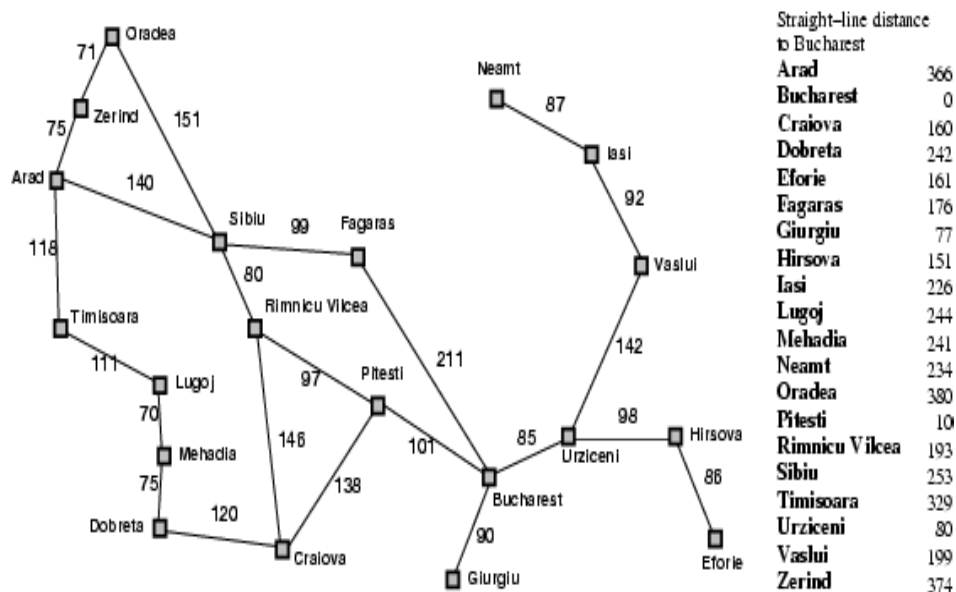
set C, the current node, to the **highest-valued** initial node;

**Loop until success or no more children(fail)**

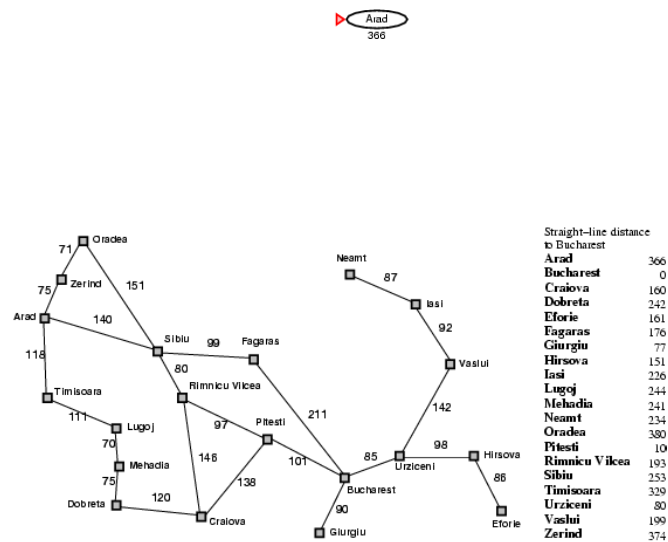
select N, the **highest-value** child of C;

return C if its value is better than the value of N;

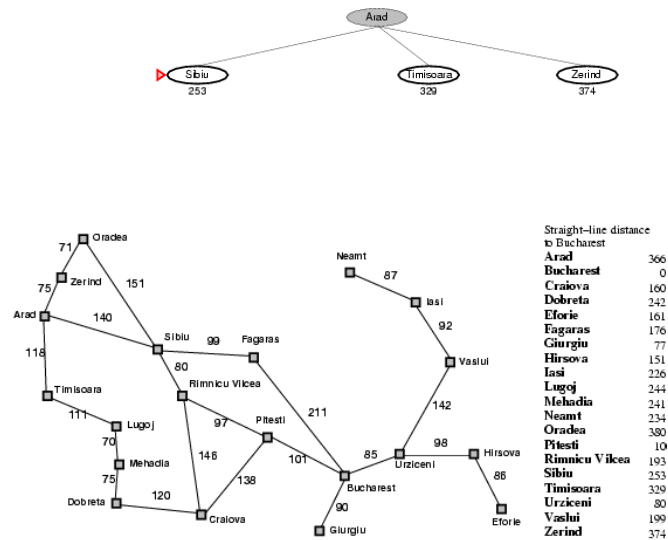
## Hill Climbing search example



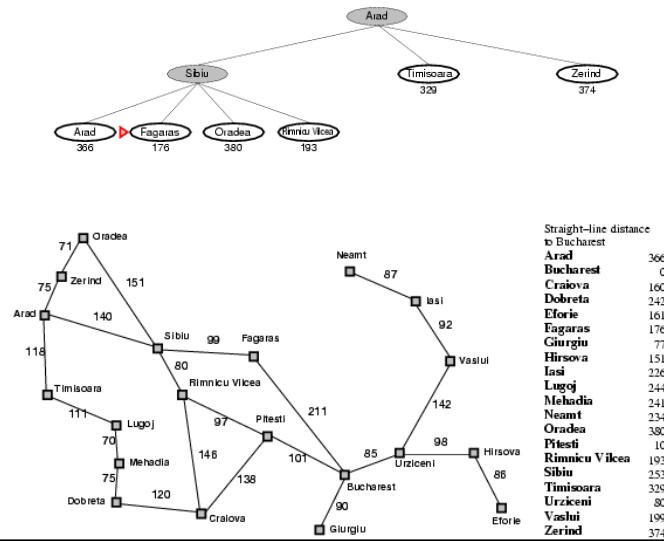
# Hill Climbing search example



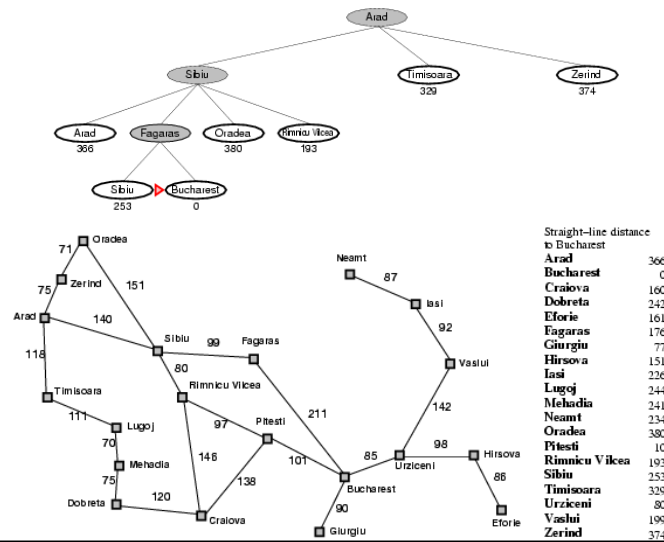
# Hill Climbing search example



# Hill Climbing search example



# Hill Climbing search example



## Hill climbing

### Complete:

No, Can get stuck in loop. Complete if loops are avoided.

### Time complexity?

$O(b^m)$ , but with some good heuristic, it could give better results

### Space complexity?

$O(b^m)$ , keeps all nodes in memory

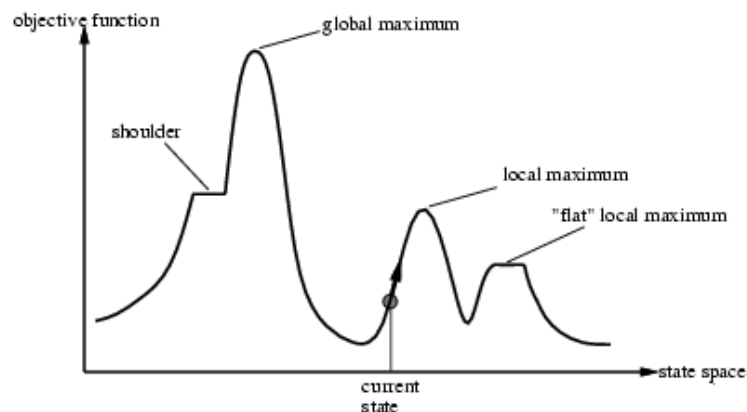
### Optimality?

No

e.g. Arad → Sibiu → Rimnicu Virea → Pitesti → Bucharest is shorter!

## Hill-climbing search

- Problem: depending on initial state, can get stuck in local maxima,...etc



## Problems with hill climbing

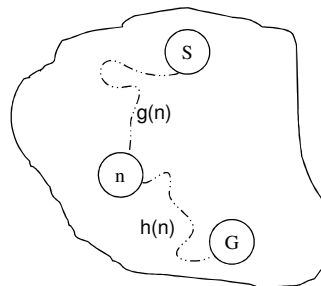
1. **Local maximum** problem: there is a peak, but it is lower than the highest peak in the whole space.
2. The **plateau** problem: all local moves are equally unpromising, and all peaks seem far away.
3. The **ridge** problem: almost every move takes us down.

### Solution:

**Random-restart** hill climbing is a series of hill-climbing searches with a randomly selected start node whenever the current search gets stuck.

## Algorithm A\*

- One of the most important advances in AI search algs.
- **Idea:** avoid expanding paths that are already expensive  
$$f(n) = g(n) + h(n)$$
- $g(n)$  = least cost path to  $n$  from  $S$  found so far
- $h(n)$  = estimated cost to goal from  $n$
- $f(n)$  = estimated total cost of path through  $n$  to goal



## The A\* procedure

Hill-climbing (and its improved versions) may miss an optimal solution. Here is a search method that ensures **optimality** of the solution.

### The algorithm

keep a list of partial paths (initially root to root, length 0);

#### repeat

succeed if the first path P reaches the goal node;

otherwise remove path P from the list;

extend P in all possible ways, add new paths to the list;

sort the list by **the sum of two values**: the real cost of P till now,  
and an estimate of the remaining distance;

prune the list by leaving only the shortest path for each node  
reached so far;

#### until

success or the list of paths becomes empty;

## The A\* procedure

A heuristic that never overestimates is also called **optimistic** or **admissible**.

We consider three functions with values  $\geq 0$ :

- $g(n)$  is the actual cost of reaching node  $n$ ,
- $h^*(n)$  is the actual *unknown* remaining cost,
- $h(n)$  is the optimistic estimate of  $h(n)$ .



## Admissible heuristics

- A heuristic  $h(n)$  is **admissible** if for every node  $n$ ,  $h(n) \leq h^*(n)$ , where  $h^*(n)$  is the **true** cost to reach the goal state from  $n$ .
- An admissible heuristic **never overestimates** the cost to reach the goal, i.e., it is **optimistic**.
- **Theorem**: If  $h(n)$  is admissible, A\* using is optimal.

## Admissible heuristics

E.g., for the 8-puzzle:

- $h_1(n)$  = number of misplaced tiles
- $h_2(n)$  = total Manhattan distance  
(i.e., no. of squares from desired location of each tile)

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

- $h_1(S) = ?$
- $h_2(S) = ?$

## Admissible heuristics

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7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

- $h_1(S) = ?$  8
- $h_2(S) = ?$   $3+1+2+2+2+2+3+3+2 = 18$

## Admissible heuristics

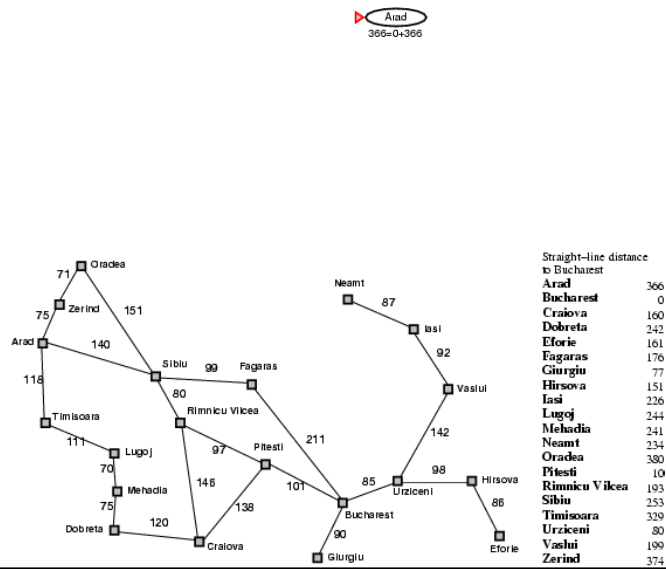
- If  $h_2(n) \geq h_1(n)$  for all  $n$ , both are admissible
- Then  $h_2$  dominates  $h_1$  and is usually better for search

Typical Costs

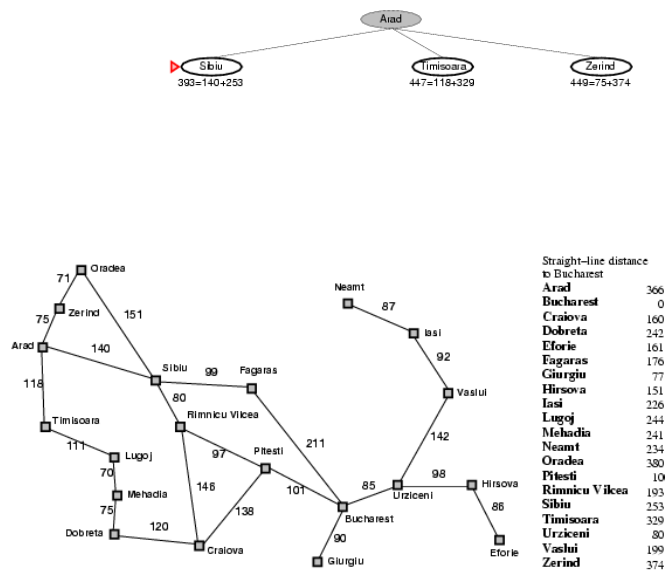
- $d = 14$  IDS = 3,473,941 nodes
  - $A^*(h_1) = 539$  nodes
  - $A^*(h_2) = 113$  nodes
- $d = 24$  IDS ~ 54,000,000,000 nodes
  - $A(h_1) = 39,135$  nodes
  - $A(h_2) = 1,641$  nodes

Remark: Given  $h_1$  and  $h_2$  any two admissible functions  
then  $h(n) = \max \{h_1(n), h_2(n)\}$  is also admissible

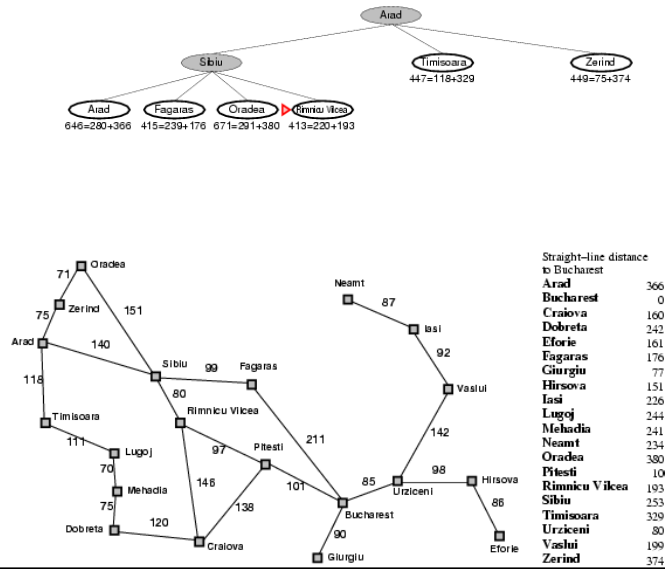
# A\* search example



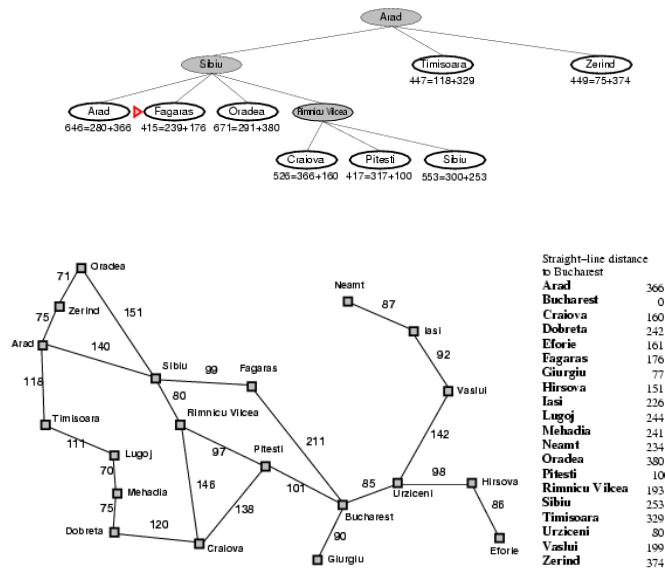
# A\* search example



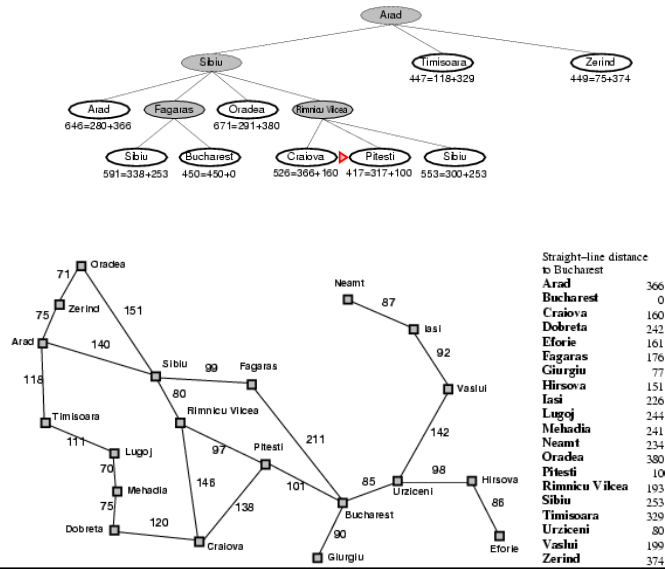
# A\* search example



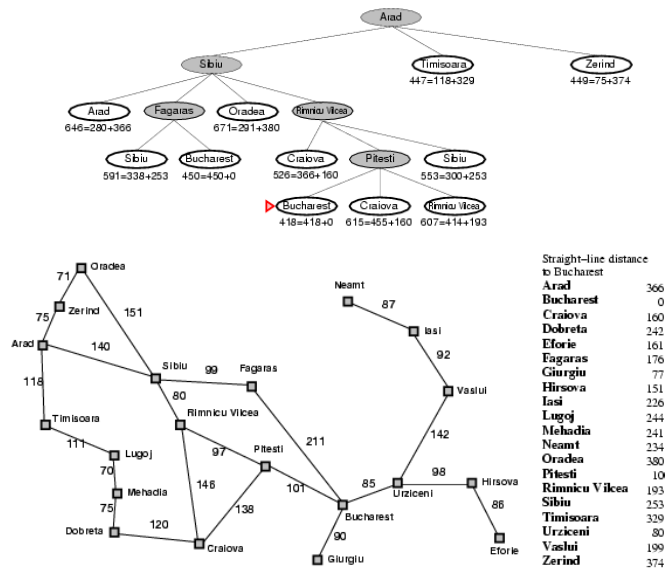
# A\* search example



# A\* search example



# A\* search example



## Properties of A\*

- Complete?

Yes (unless there are infinitely many)

- Time/Space?

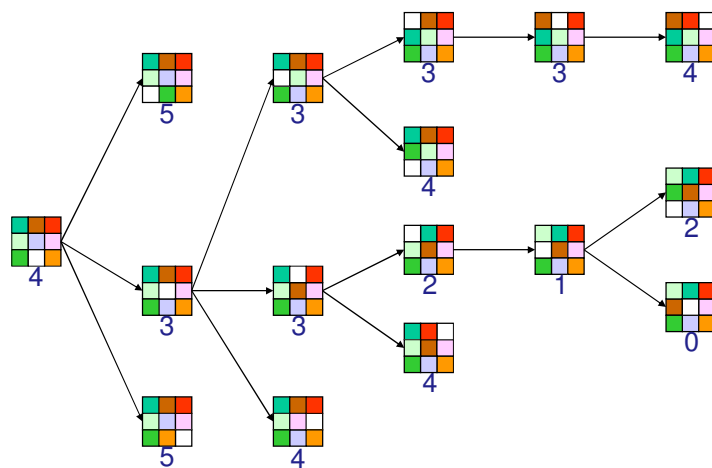
- Exponential mostly

- Optimal?

Yes

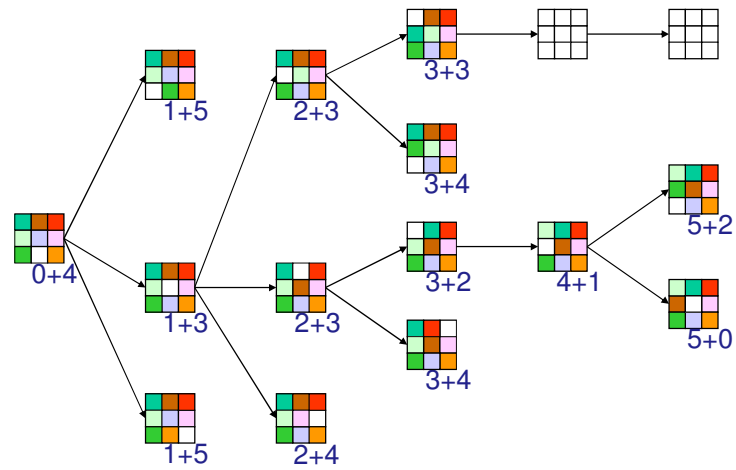
## 8-Puzzle

$f(N) = h(N)$  = number of misplaced tiles



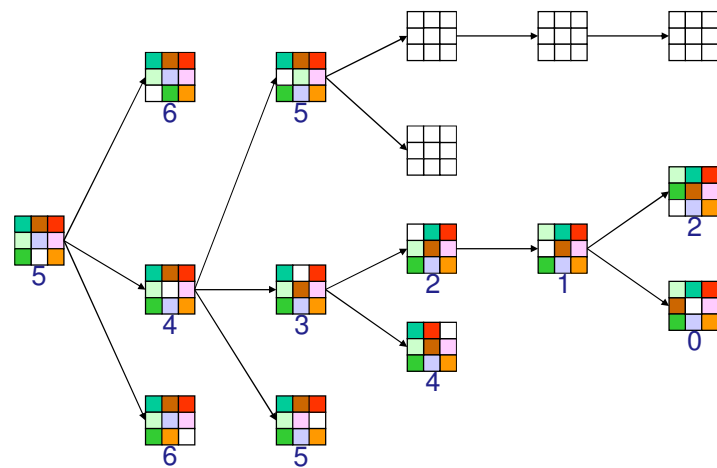
## 8-Puzzle

$f(N) = g(N) + h(N)$   
with  $h(N)$  = number of misplaced tiles



## 8-Puzzle

$f(N) = h(N) = \sum \text{distances of tiles to goal}$



## Local Search Algorithms

- In many optimization problems, *path* is irrelevant
- the goal state itself is the solution
- Ex: The 8-queen problem, the final configuration of the queens is the important not the order they were put
- Operates using only single current state, rather than multiple paths.
- Find Optimal Configuration ( satisfies the constraints)
- Use *iterative improvement algorithms*
- A **Complete** local search algorithm finds a goal if exists
- An **Optimal** algorithm finds the global minimum or maximum