

# CSE3013 Artificial Intelligence

## Module-3: Local Search

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SCOPE

Local Search

Hill-Climbing Search

Simulated annealing

# Local Search

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- Up to now, single category of problems:
  - observable, deterministic, known environments
  - where the solution is a sequence of actions
- Now these assumptions are relaxed
- **Local search**- evaluate and modify one or more current states rather than systematically exploring paths from an initial state
- Useful when only the solution state is relevant, not the path cost to reach it

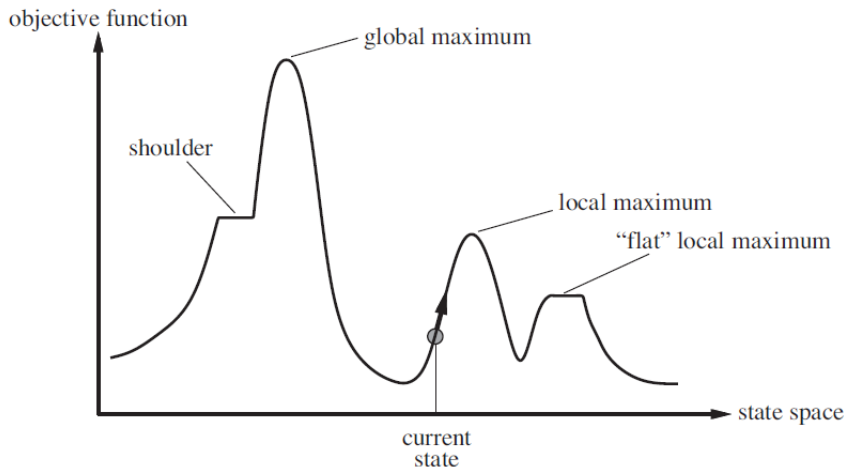
# When local search?

- Up to now, paths to goal states and various alternatives are memorized
- Systematic exploration of the search space
- Path to the goal is also part of the solution
- For many problems, path to the goal is irrelevant
  - N-queens problem
  - integrated-circuit design
  - factory-floor layout
  - job-shop scheduling
  - automatic programming
  - telecommunications network optimization
  - vehicle routing
  - portfolio management.
- If the path to the goal does not matter, we might consider a different class of algorithms, which do not worry about paths at all

## Local search- features

- Local search algorithms operate using a single **current node** (rather than multiple paths) and generally move only to neighbors of that node
- Typically, the paths followed by the search are not retained
- Advantages: -
  1. They use very little memory—usually a constant amount
  2. They yield solutions in large or infinite state spaces for which systematic algorithms are unsuitable
- Especially useful for **optimization problems**, to find the best state for a given **objective function**

# State-space landscape



# Terminologies

- **State-space landscape:** State-space v/s objective function/heuristic cost function plot
  - Has **location** (defined by the state) and **elevation** (defined by the value of the heuristic cost function or objective function)
- If elevation corresponds to cost, then the aim is to find the lowest valley—a **global minimum**
- If elevation corresponds to an objective function, then the aim is to find the highest peak—a **global maximum**
- Local search algorithms explore this landscape
- Local search varieties:
  - **Complete local search** algorithm always finds a goal if one exists
  - **Optimal** algorithm always finds a global minimum/maximum



# Hill-Climbing Search

- Steepest ascent version
- Is a loop that continually moves in the direction of increasing value—that is, uphill
- Terminates when it reaches a “peak” where no neighbor has a higher value
- Does not look ahead beyond the immediate neighbors of the current state

# Hill-climbing search algorithm

```
function HILL-CLIMBING(problem) returns a state that is a local maximum  
    current  $\leftarrow$  MAKE-NODE(problem.INITIAL-STATE)  
    loop do  
        neighbor  $\leftarrow$  a highest-valued successor of current  
        if neighbor.VALUE  $\leq$  current.VALUE then return current.STATE  
        current  $\leftarrow$  neighbor
```

- Greedy local search  $\rightarrow$  it grabs a good neighbor state without thinking ahead about where to go next
- Local maxima  $\rightarrow$  a local maximum is a peak that is higher than each of its neighboring states but lower than the global maximum
- Ridges  $\rightarrow$  result in a sequence of local maxima that is very difficult for greedy algorithms to navigate
- Plateaux  $\rightarrow$  a plateau is a flat area of the state-space landscape

# Difficulties in hill-climbing

- Local maxima
- Ridges
- The algorithm halts If it reaches a plateau where the best successor has the same value as the current state
- Allow sideways move- but can result in infinite loop, if not a shoulder
- Solution  $\rightarrow$  Limit the number of sideways moves

# Hill-climbing variations

- We discussed steepest ascent now
- Stochastic hill-climbing  $\rightarrow$  chooses at random from among the uphill moves; the probability of selection can vary with the steepness of the uphill move
- First-choice hill climbing  $\rightarrow$  implements stochastic hill climbing by generating successors randomly until one is generated that is better than the current state
  - good strategy when a state has many (e.g., thousands) of successors
- Random-restart hill climbing  $\rightarrow$  conducts a series of hill-climbing searches from randomly generated initial states, until a goal is found
  - Useful as all other hill-climbing versions are **incomplete**—often fail to find a goal when one exists because they can get stuck on local maxima

# Simulated annealing

- Hill climbing with no downward movement to lower value or higher cost is **incomplete**, due to local maximum
- Purely random walk—that is, moving to a successor chosen uniformly at random from the set of successors—is complete but extremely inefficient
- Hybrid of hill climbing and random walk  $\rightarrow$  efficiency and completeness

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

**inputs:** *problem*, a problem

*schedule*, a mapping from time to “temperature”

*current*  $\leftarrow$  MAKE-NODE(*problem*.INITIAL-STATE)

**for**  $t = 1$  **to**  $\infty$  **do**

$T \leftarrow$  *schedule*( $t$ )

**if**  $T = 0$  **then return** *current*

*next*  $\leftarrow$  a randomly selected successor of *current*

$\Delta E \leftarrow$  *next*.VALUE – *current*.VALUE

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

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

# Algorithm

- Temperature in annealing is mapped to time here
- Instead of picking the best move the algorithm picks a random move. If the move improves the situation, it is always accepted
- Otherwise, the algorithm accepts the move with some probability less than 1
- The probability decreases exponentially with the “badness” of the move—the amount  $\Delta E$  by which the evaluation is worsened
- The probability also decreases as the “temperature”  $T$  goes down
- “bad” moves are more likely to be allowed at the start when  $T$  is high, and they become more unlikely as  $T$  decreases

# More local search algorithms

- Local beam search
- Genetic algorithms

Thank you...