

Artificial Intelligence

Local Search

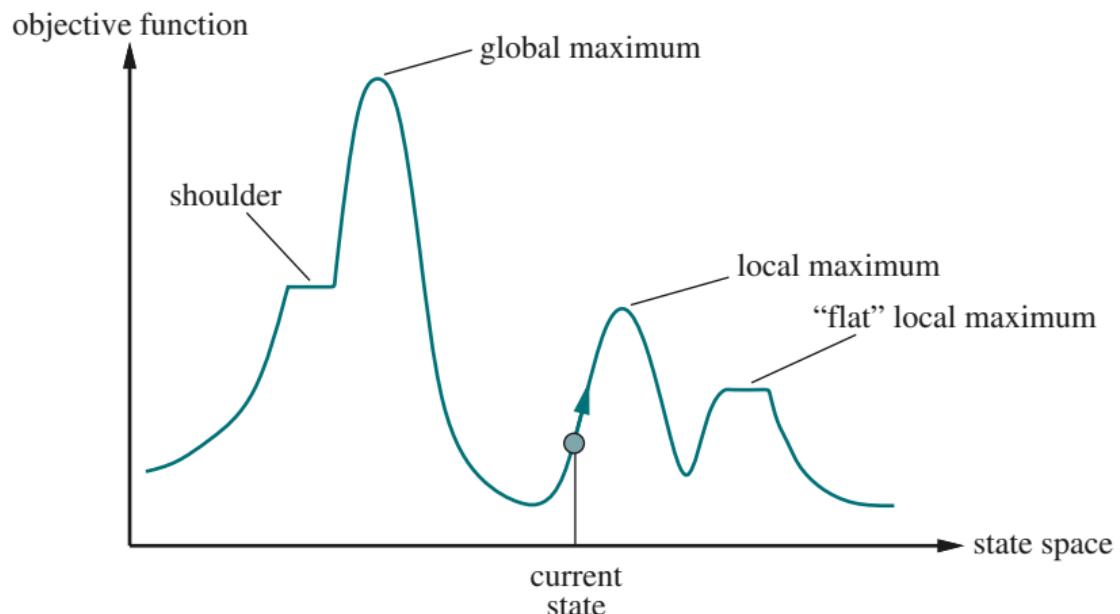
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Local Search

If you don't care about the path to a goal state, you can use **local search**.

- ▶ Search neighbors of current state, moving to best neighbor.
- ▶ Track only current state.
- ▶ Uses very little memory.
- ▶ Can find reasonable solutions in large or infinite state spaces.
- ▶ Often used for **optimization** problems – finding states that maximize or minimize an **objective function**.

State Space Landscape



Hill-Climbing Search

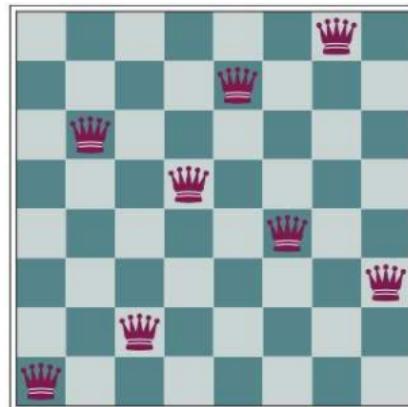
```
function HILL-CLIMBING(problem) returns a state that is a local maximum  
    current  $\leftarrow$  problem.INITIAL  
    while true do  
        neighbor  $\leftarrow$  a highest-valued successor state of current  
        if VALUE(neighbor)  $\leq$  VALUE(current) then return current  
      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

- ▶ Also known as **greedy local search**

The 8 Queens Problem

Complete-state formulation: row position for each of 8 columns, e.g., (a) below is

`<1, 6, 2, 5, 7, 4, 8, 3>`



(a)

18	12	14	13	13	12	14	14
14	16	13	15	12	14	12	16
14	12	18	13	15	12	14	14
15	14	14	14	13	16	13	16
14	14	17	15	14	14	16	16
17	14	16	18	15	15	15	15
18	14	15	15	15	14	14	16
14	14	13	17	12	14	12	18

(b)

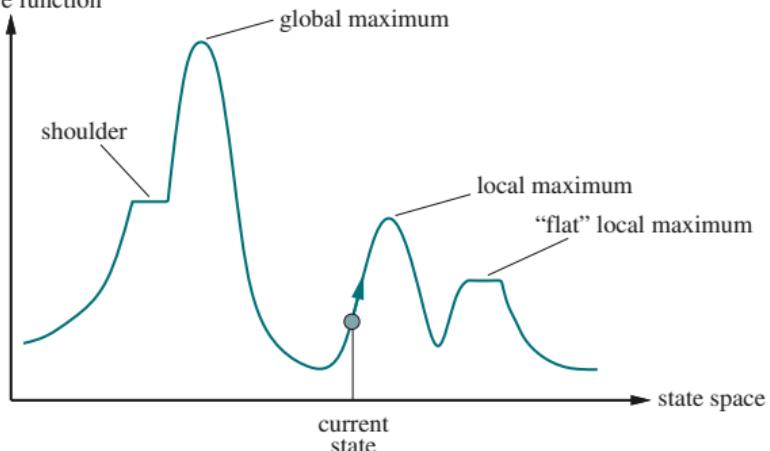
- ▶ Action: move a single queen to new row within column. Each state has $8^7 = 56$ successor states.
- ▶ Possible heuristic: number of pairs of attacking queens (even if blocked). (b) above has $h = 17$.
 - ▶ Useful to remember: $\binom{n}{k} = \frac{n!}{k!(n-k)!}$

Disadvantages of Hill-Climbing

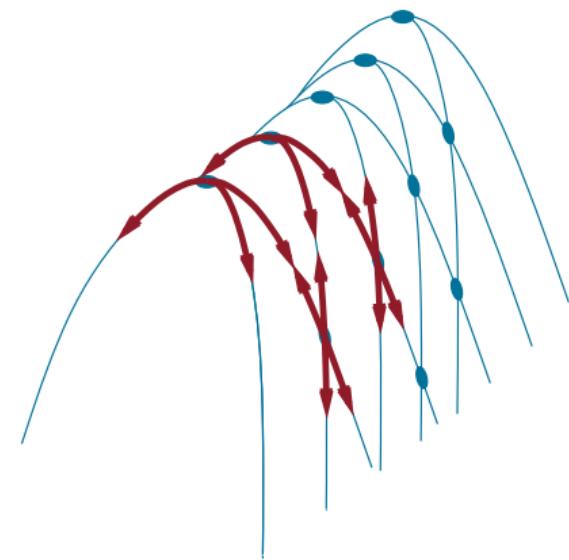
Susceptible to getting stuck in:

- ▶ local maxima
- ▶ ridges – sequences of local maxima
- ▶ plateaus, e.g., flat local maxima or shoulders.

objective function



Grid of states superimposed on ridge rising from left to right.



How to fix:

- ▶ Allow “sideways” moves
- ▶ Stochastic hill climbing chooses randomly from uphill moves.
- ▶ Random restart hill climbing restarts from multiple initial states.

Simulated Annealing

```
function SIMULATED-ANNEALING(problem, schedule) returns a solution state
    current  $\leftarrow$  problem.INITIAL
    for t = 1 to  $\infty$  do
        T  $\leftarrow$  schedule(t)
        if T = 0 then return current
        next  $\leftarrow$  a randomly selected successor of current
         $\Delta E \leftarrow \text{VALUE}(\textit{current}) - \text{VALUE}(\textit{next})$ 
        if  $\Delta E > 0$  then current  $\leftarrow$  next
        else current  $\leftarrow$  next only with probability  $e^{\Delta E / T}$ 
```

- ▶ Based on annealing in metallurgy – gradually cooling metals or glass to reach a low-energy crystalline state.
- ▶ Think in terms of gradient descent.
- ▶ Similar to hill climbing, but picks a random move and
 - ▶ accepts it if its better,
 - ▶ if not better, accept with probability < 1 .
- ▶ Probability of accepting a worse move depends on:
 - ▶ how much worse the move is, ΔE , and
 - ▶ the current “temperature,” T .

If T decreases sufficiently slowly, then the Boltzman distribution, $e^{\frac{\Delta E}{T}}$, ensures that all the probability is concentrated on the global maxima, so the algorithm finds a global maximum probability approaching 1.

Genetic Algorithms

A kind of **local beam search**: tracking k states instead of just one.

Elements of genetic algorithms:

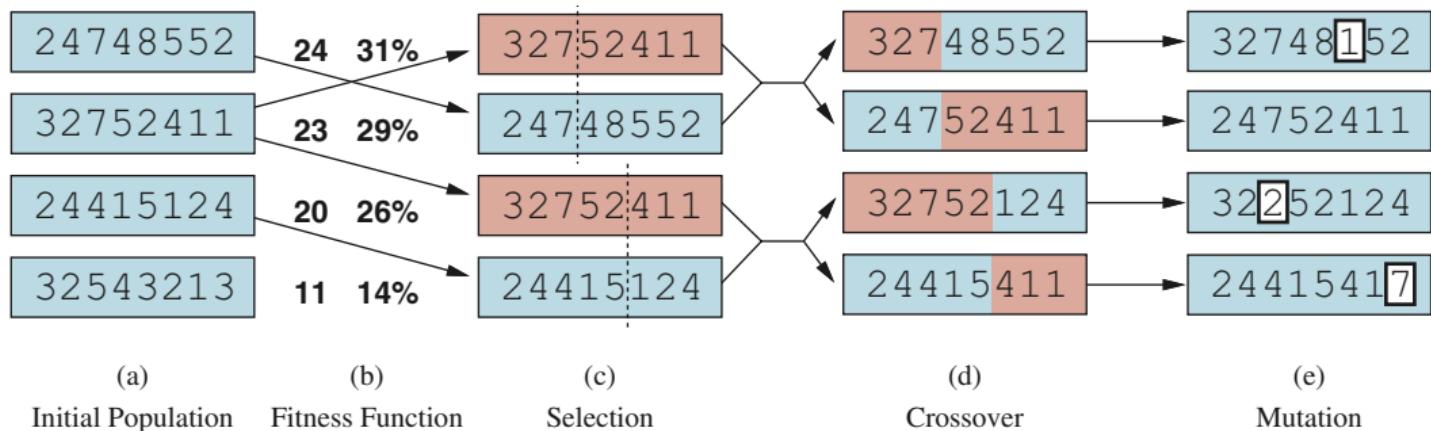
- ▶ Fitness function.
- ▶ Population size.
- ▶ Candidate representation:
 - ▶ Typically a string (vector) over a finite alphabet.
 - ▶ **Evolution strategies**: sequence of real numbers.
 - ▶ **Genetic programming**: computer programs.
- ▶ Mixing number, ρ : number of “parents” from which to generate new candidates. When $\rho = 1$, stochastic beam search.
- ▶ Selection process for choosing “parents.”
- ▶ Recombination procedure.
- ▶ Mutation rate.
- ▶ Composition of next generation.
 - ▶ Elitism: choose top-scoring candidates.
 - ▶ Culling: eliminate bottom-scoring candidates.

A Genetic Algorithm

```
function GENETIC-ALGORITHM(population, fitness) returns an individual
repeat
    weights  $\leftarrow$  WEIGHTED-BY(population, fitness)
    population2  $\leftarrow$  empty list
    for i = 1 to SIZE(population) do
        parent1, parent2  $\leftarrow$  WEIGHTED-RANDOM-CHOICES(population, weights, 2)
        child  $\leftarrow$  REPRODUCE(parent1, parent2)
        if (small random probability) then child  $\leftarrow$  MUTATE(child)
        add child to population2
    population  $\leftarrow$  population2
until some individual is fit enough, or enough time has elapsed
return the best individual in population, according to fitness
```

```
function REPRODUCE(parent1, parent2) returns an individual
n  $\leftarrow$  LENGTH(parent1)
c  $\leftarrow$  random number from 1 to n
return APPEND(SUBSTRING(parent1, 1, c), SUBSTRING(parent2, c + 1, n))
```

Genetic Algorithm on 8-Queens Problem



Crossover in the 8-queens Problem

