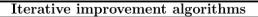
Workspace for 'chapter04b-1'

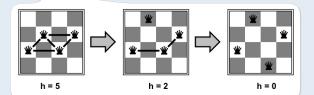
Page 1 (row 2, column 1)



In many optimization problems, **path** is irrelevant; the goal state itself is the solution

In such cases, can use iterative improvement algorithms; keep a single "current" state, try to improve it

N Queen



Hill-climbing (or gradient ascent/descent)

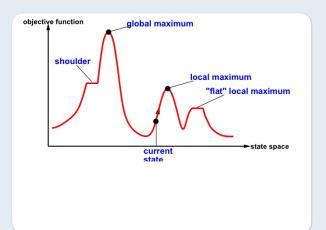
"Like climbing Everest in thick fog with amnesia"

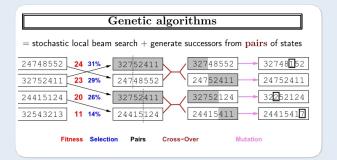
function Hill-Climbing (problem) returns a state that is a local maximum inputs: problem, a problem local variables: current, a node neighbor, a node $current \leftarrow \text{Make-Node}(\text{Initial-State}[problem])$ loop do $neighbor \leftarrow \text{a highest-valued successor of } current$ if $\text{Value}[\text{neighbor}] \leq \text{Value}[\text{current}]$ then return State[current] $current \leftarrow neighbor$ end

Simulated annealing

Idea: escape local maxima by allowing some "bad" moves but gradually decrease their size and frequency

 $\begin{aligned} & \textbf{function Simulated-Annealing}(\textit{problem}, \textit{schedule}) \ \textbf{returns a solution state} \\ & \textbf{inputs: problem}, \ \textbf{a problem} \\ & \textit{schedule}, \ \textbf{a mapping from time to "temperature"} \\ & \textbf{local variables: } \textit{current}, \ \textbf{a node} \\ & \textit{next}, \ \textbf{a node} \\ & \textit{T. a "temperature" controlling prob. of downward steps} \\ & \textit{current} \leftarrow \texttt{MAKE-Node}(\texttt{Initial-State}[\textit{problem}]) \\ & \textbf{for } t \leftarrow 1 \ \textbf{to} \propto \textbf{do} \\ & \textit{T} \leftarrow \textit{schedule}[t] \\ & \textbf{if } T = 0 \ \textbf{then return } \textit{current} \\ & \textit{next} \leftarrow \textbf{a randomly selected successor of } \textit{current} \\ & \Delta E \leftarrow \texttt{Value}[\textit{next}] - \texttt{Value}[\textit{current}] \\ & \textbf{if } \Delta E > 0 \ \textbf{then } \textit{current} \leftarrow \textit{next} \\ & \textbf{else } \textit{current} \leftarrow \textit{next} \ \textbf{only with probability } e^{\Delta E/T} \end{aligned}$





Workspace for 'chapter04b-1'

Page 2 (row 3, column 1)

Particle Swarm Optimization

- A particle (individual) is composed of:
- Three vectors:
 - The **x-vector** records the current position (location) of the particle in the search space,
- The **p-vector** records the location of the best solution found so far by the particle, and
- The **v-vector** contains a gradient (direction) for which particle will travel in if undisturbed.
- Two fitness values:
- The **x-fitness** records the fitness of the x-vector, and
- The **p-fitness** records the fitness of the p-vector.

Velocity calculation Swarm search

$$v_{id(t)} = \omega v_{id(t-1)} + c_1 \times rand() \times (p_{id} - x_{id}) + c_2 \times Rand() \times (p_{gd} - x_{id})$$

Position

$$update_{id(t)} = x_{id(t-1)} + v_{id(t)}$$

xid – current value of the dimension "d" of the dividual "i" vid – current velocity of the dimension "d" of the individual "i".

Pid – optimal value of the dimension "d" of the individual "i" so far.

Pgd – current optimal value of the dimension "d" of the

Particle Swarm Optimization The algorithm

- 1. Initialise particles in the search space at random.
- 2. Assign random initial velocities for each particle
- 3. Evaluate the fitness of each particle according a user defined objective function.
- 4. Calculate the new velocities for each particle.
- 5. Move the particles.
- 6. Repeat steps 3 to 5 until a predefined stopping criterion is satisfied.