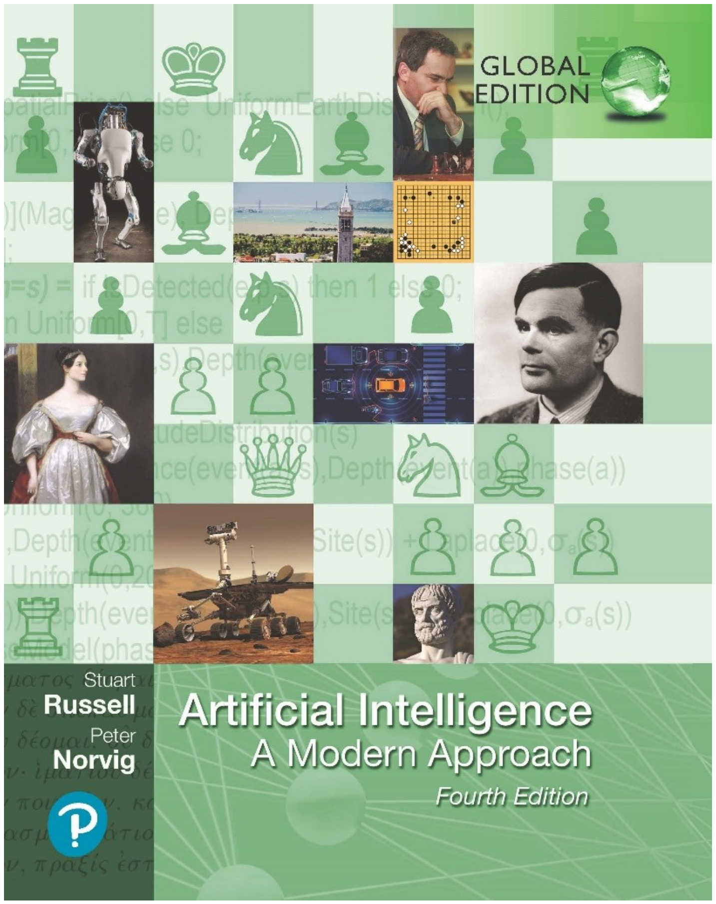
Artificial Intelligence: A Modern Approach

Fourth Edition, Global Edition



Chapter 4

Search in Complex Environments

Lecture Presentations: Artificial Intelligence

Adapted from:
"Artificial Intelligence: A Modern Approach, Global Edition", 4th Edition by Stuart Russell and Peter Norvig © 2021 Pearson Education.

Adapted for educational use at ACE Engineering College. Some slides customized by Mr. Shafakhatullah Khan Mohammed, Assistant Professor @ ACE Engineering College.
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Outline

- Local Search and Optimization Problems
  - Hill-climbing
  - Simulated annealing
  - Genetic algorithms
- Local search in continuous spaces
- Search with Nondeterministic Actions
- Search in Partially Observable Environments

Local Search and Optimization Problems

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

Then state space = set of "complete" configurations; find optimal
configuration, e.g., TSP
or, find configuration satisfying constraints, e.g., timetable

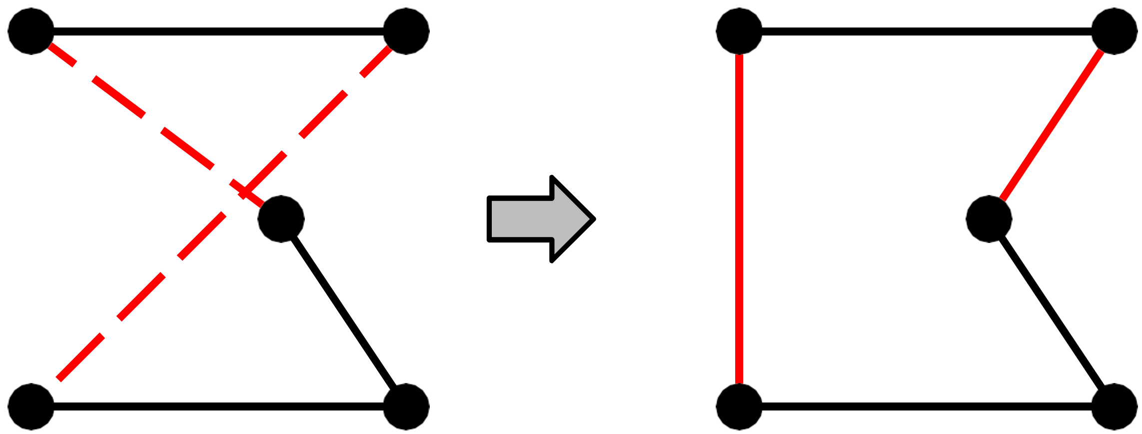
In such cases, one can use iterative improvement algorithms; keep a single "current" state, try to improve it

Local search algorithms operate by searching from a start state to neighboring states, without keeping track of the paths, nor the set of states that have been reached.

They are not systematic—they might never explore a portion of the search space where a solution actually resides.

Example: Travelling Salesperson Problem

Start with any complete tour, perform pairwise exchanges

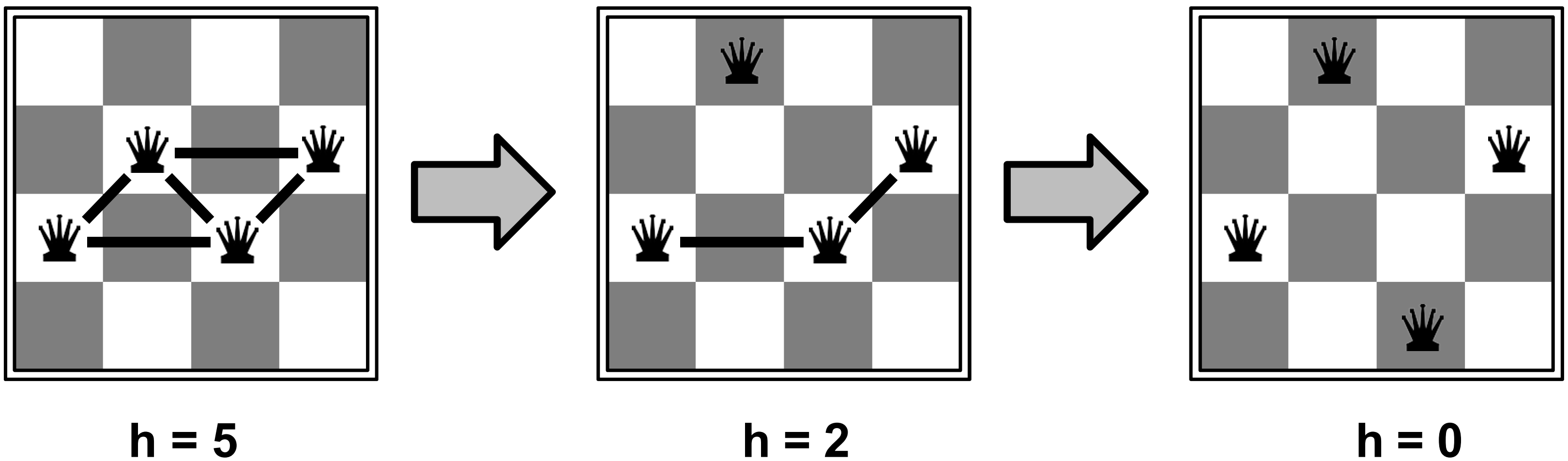


Variants of this approach get within 1% of optimal very quickly with thousands of cities

Example: n-queens

Put n queens on an $n \times n$ board with no two queens on the same row, column, or diagonal

Move a queen to reduce number of conflicts



Almost always solves n-queens problems almost instantaneously for very large n, e.g., $n = 1 million$

Hill-climbing (or gradient ascent/descent)

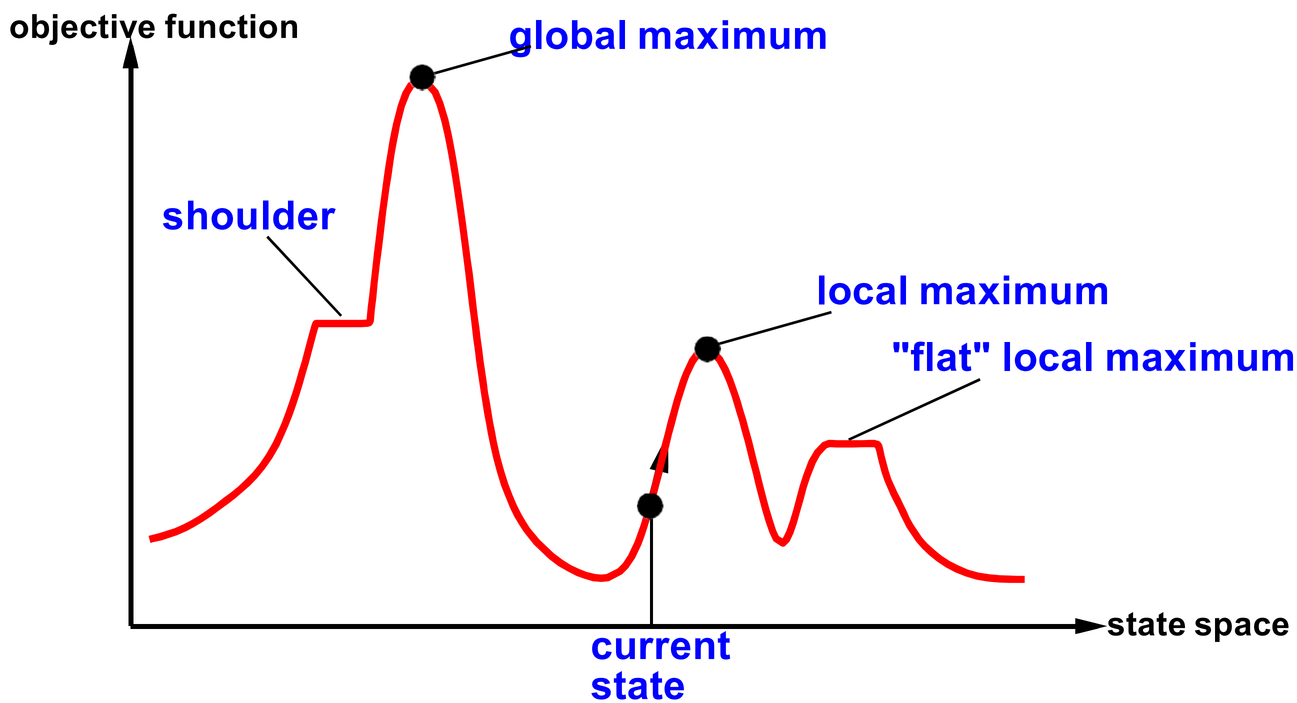
"Like climbing Everest in thick fog with amnesia"

```
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 ← Make-Node(Initial-State[problem])
    loop do
        neighbor ← a highest-valued successor of current
        if Value[neighbor] ≤ Value[current] then return State[current]
        current ← neighbor
    end
```

Hill-climbing contd.

Useful to consider state space landscape



Random-restart hill climbing overcomes local maxima—trivially complete

Random sideways moves 😊 escape from shoulders ☹ loop on flat maxima

Simulated annealing

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

```
function Simulated-Annealing( problem, schedule) returns a solution state
    inputs: problem, a problem
            schedule, a mapping from time to "temperature"
    local variables: current, a node
                     next, a node
                     T, a "temperature" controlling prob. of downward steps

    current ← Make-Node(Initial-State[problem])
    for t ← 1 to ∞ do
        T ← schedule[t]
        if T = 0 then return current
        next ← a randomly selected successor of current
        ΔE ← Value[next] – Value[current]
        if ΔE > 0 then current ← next
        else current ← next only with probability e^(ΔE/T)
```

Properties of simulated annealing

At fixed "temperature" T, state occupation probability reaches Boltzman distribution

$$p(x) = a e^{\frac{E(x)}{kT}}$$

T decreased slowly enough $\Longrightarrow$ always reach best state x^*

because $e^{\frac{E(x^*)}{kT}} / e^{\frac{E(x)}{kT}} = e^{\frac{E(x^*)-E(x)}{kT}}$ � 1 for small T

Is this necessarily an interesting guarantee??

Devised by Metropolis et al., 1953, for physical process modelling

Widely used in VLSI layout, airline scheduling, etc.

Local beam search

Idea: keep k states instead of 1; choose top k of all their successors

Not the same as k searches run in parallel!
Searches that find good states recruit other searches to join them

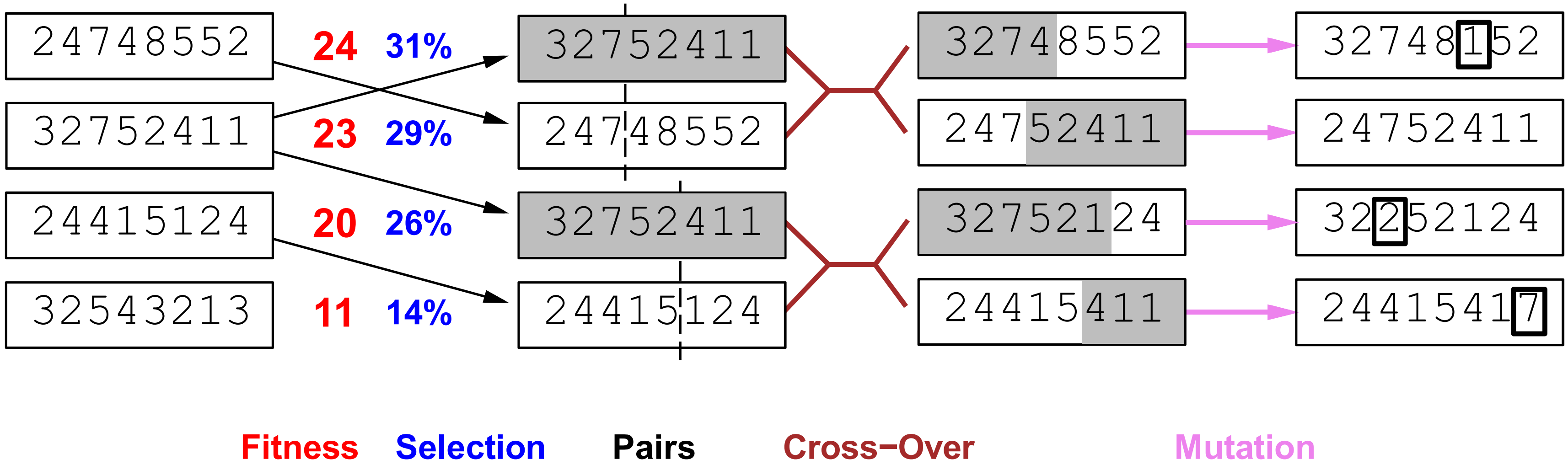
Problem: quite often, all k states end up on same local hill

Idea: choose k successors randomly, biased towards good ones

Observe the close analogy to natural selection!

Genetic algorithms

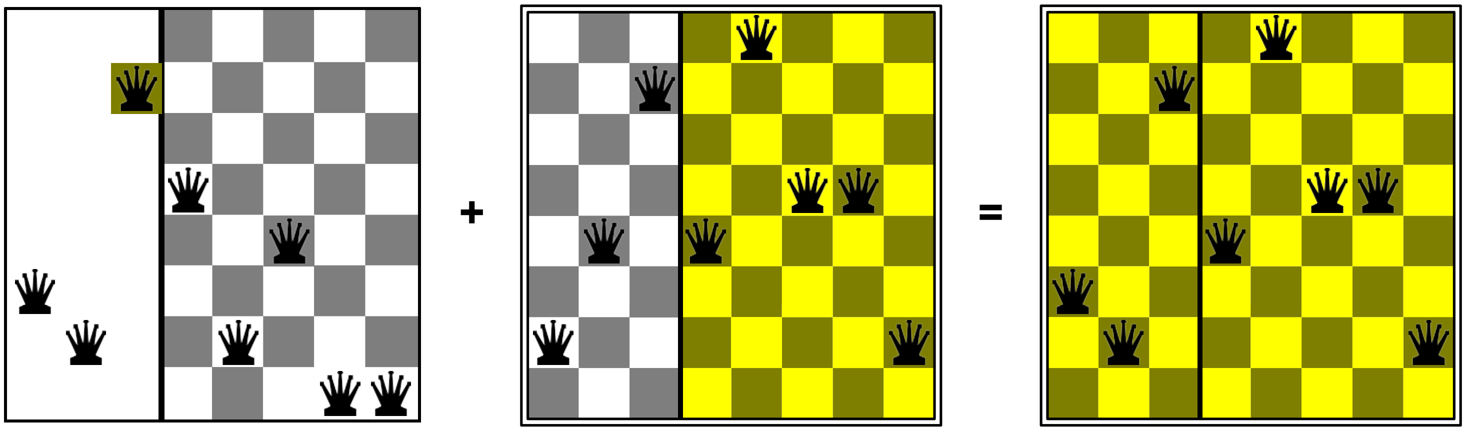
= stochastic local beam search + generate successors from pairs of states



Genetic algorithms contd.

GAs require states encoded as strings (GPs use programs)

Crossover helps iff substrings are meaningful components



GAs /= evolution: e.g., real genes encode replication machinery!

Continuous state spaces

Suppose we want to site three airports in Romania:

– 6-D state space defined by (x_1, y_2), (x_2, y_2), (x_3, y_3)

– objective function $f(x_1, y_2, x_2, y_2, x_3, y_3)$ =
sum of squared distances from each city to nearest airport

Discretization methods turn continuous space into discrete space, e.g., empirical gradient considers $\pm\delta$ change in each coordinate

Gradient methods compute

$$\nabla f = \left(\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial y_1}, \frac{\partial f}{\partial x_2}, \frac{\partial f}{\partial y_2}, \frac{\partial f}{\partial x_3}, \frac{\partial f}{\partial y_3}\right)$$

to increase/reduce f, e.g., by $\mathrm{x} \leftarrow \mathrm{x} + \alpha\nabla f(\mathrm{x})$

Sometimes can solve for $\nabla f(\mathrm{x}) = 0$ exactly (e.g., with one city).
Newton–Raphson (1664, 1690) iterates $\mathrm{x} \leftarrow \mathrm{x} - \mathrm{H}_f^{-1}(\mathrm{x})\nabla f(\mathrm{x})$
to solve $\nabla f(\mathrm{x}) = 0$, where $\mathrm{H}_{ij} = \partial^2 f / \partial x_i \partial x_j$

Search with Nondeterministic Actions

Agent doesn't know the state its transitioned to **after action**, the environment is **nondeterministic**.

Rather, it will know the possible states it will be in, which is called "**belief state**"

Examples:

- The **erratic vacuum world** (if-then-else) steps. If statement tests to know the current state.
- **AND-OR** search trees. Two possible actions (**OR nodes**). Branching that happens from a choice (**AND nodes)**.
- **Try, try again**. A cyclic plan where minimum condition (every leaf = goal state & reachable from other points in the plan)

Search in Partially Observable Environments

Problem of partial observability, where the agent's percepts are not enough to pin down the exact state**.**

Searching with no observation: Agent's percepts provide **no information at all**, sensorless problem (or a conformant problem).

- Solution: sequence of actions, not a conditional plan

Searching in partially observable environments requires a function that **monitors** or **estimates** the environment to maintain the belief state.

Summary

Local search methods keep only a **small number of states** in memory that are useful for optimization.

In **nondeterministic environments**, agents can apply **AND–OR search** to generate contingency plans that reach the goal regardless of which outcomes occur during execution.

Belief-state is the set of **possible states** that the agent is in for **partially observable environments**.

Standard search algorithms can be **applied directly to belief-state** space to solve **sensorless** problems.