Search – Chapter 4

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CS 4480

Beyond Classical Search

- Chapter 4
  - Hill Climbing
  - Simulated Annealing
  - Beam Search
  - Genetic Algorithms

Local search algorithms

- In many optimization problems, the path to the goal is irrelevant; the goal state itself is the solution
- State space = set of "complete" configurations
  - Find configuration satisfying constraints, e.g., n-queens
- In such cases, we can use local search algorithms
  - keep a single "current" state, try to improve it

Local search algorithms

- Does path matter?
  - Chess
  - Robot
  - 8 queens
  - Circuit design
  - Job scheduling

Optimization Problems

- Interested in Goal State – not how to get there
- Optimization Problems
  - State: vector of variables
  - Objective function from *set of states* to *real numbers*
  - Goal: find state that maximizes or minimizes the objective function
  - No goal test
  - No path cost
  - "Reproductive fitness" in nature
  - Local search may work well

Local search algorithms

- Basic Idea:
  - Use a single current state
  - Don't save paths followed
  - Generally move only to successors / neighbors of current state
- Generally require a complete state discription
- Pros:
  - Usually Constant Memory
  - Can often find reasonable solution in infinite or continuous state spaces

Example: *n*-queens

- Put *n* queens on an *n* × *n* board with no two queens on the same row, column, or diagonal

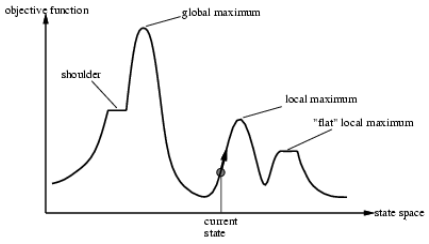
Hill-climbing search

- "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
```

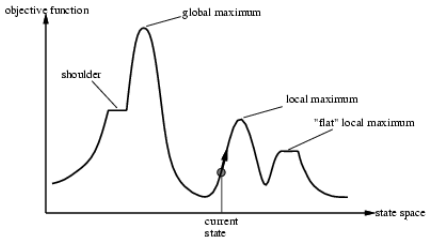
Hill-Climbing Search

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



Hill-Climbing Search

- If using cost function will want global minimum



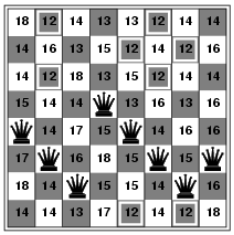
Hill-Climbing Search

- What to do when stuck?
- Stochastic Hill-Climbing
  - Choose successor at random
  - Probability based on steepness
- First Choice Hill-Climbing
  - Generate random successors until one is better

Hill-Climbing Search

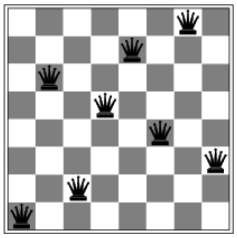
- What to do when stuck?
- Random-Restart Hill-Climbing
  - Series of hill-climbing searches from randomly generated initial states
  - Complete
  - Random sideways moves escape from shoulders
  - But loop on flat maxima

Hill-climbing search: 8-queens problem



- *h* = number of pairs of queens that are attacking each other, either directly or indirectly
- *h = 17* for the above state

Hill-climbing search: 8-queens problem



- A local minimum with *h = 1*

Simulated Annealing Search

- Anneal from

http://www.merriam-webster.com/dictionary/anneal

to heat and then cool (as steel or glass) usually for softening and making less brittle; *also* **:** to cool slowly usually in a furnace

Simulated Annealing Search

Idea:

- Use conventional hill-climbing techniques, but occasionally take a step in a direction other that that in which the rate of change is maximal
- As time passes, the probability that a down-hill step is taken is gradually reduced and the size of any down-hill step taken is reduced
- E.g. escape local maxima by allowing some "bad" moves but gradually decrease their frequency

Simulated Annealing Search

```
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^(Δ E/T)
```

Properties of simulated annealing search

- One can prove: If *T* decreases slowly enough, then simulated annealing search will find a global optimum with probability approaching 1
- Widely used in VLSI layout, airline scheduling, etc
  - VLSI: very large scale integration for creating integrated circuits

Local beam search

- Keep track of *k* states rather than just one
- Start with *k* randomly generated states
- At each iteration, all the successors of all *k* states are generated
  - If any one is a goal state, stop; else select the *k* best successors from the complete list and repeat.
- Not the same as k searches in parallel
- Problem: all k states may end up on same local hill
  - Choose the k successors randomly, biased toward good ones

Genetic algorithms

- A successor state is generated by combining two parent states
- Start with *k* randomly generated states (population)
- A state is represented as a string over a finite alphabet (often a string of 0s and 1s)
- Evaluation function (fitness function). Higher values for better states.
- Produce the next generation of states by selection, crossover, and mutation

Genetic algorithms

- Fitness function: number of non-attacking pairs of queens (min = 0, max = 8 × 7/2 = 28)
- 24/(24+23+20+11) = 31%
- 23/(24+23+20+11) = 29% etc

Genetic algorithms

Games vs. search problems

- "Unpredictable" opponent → specifying a move for every possible opponent reply
- Time limits → unlikely to find goal, must approximate