Artificial Intelligence

Informed Search

Chapter 4

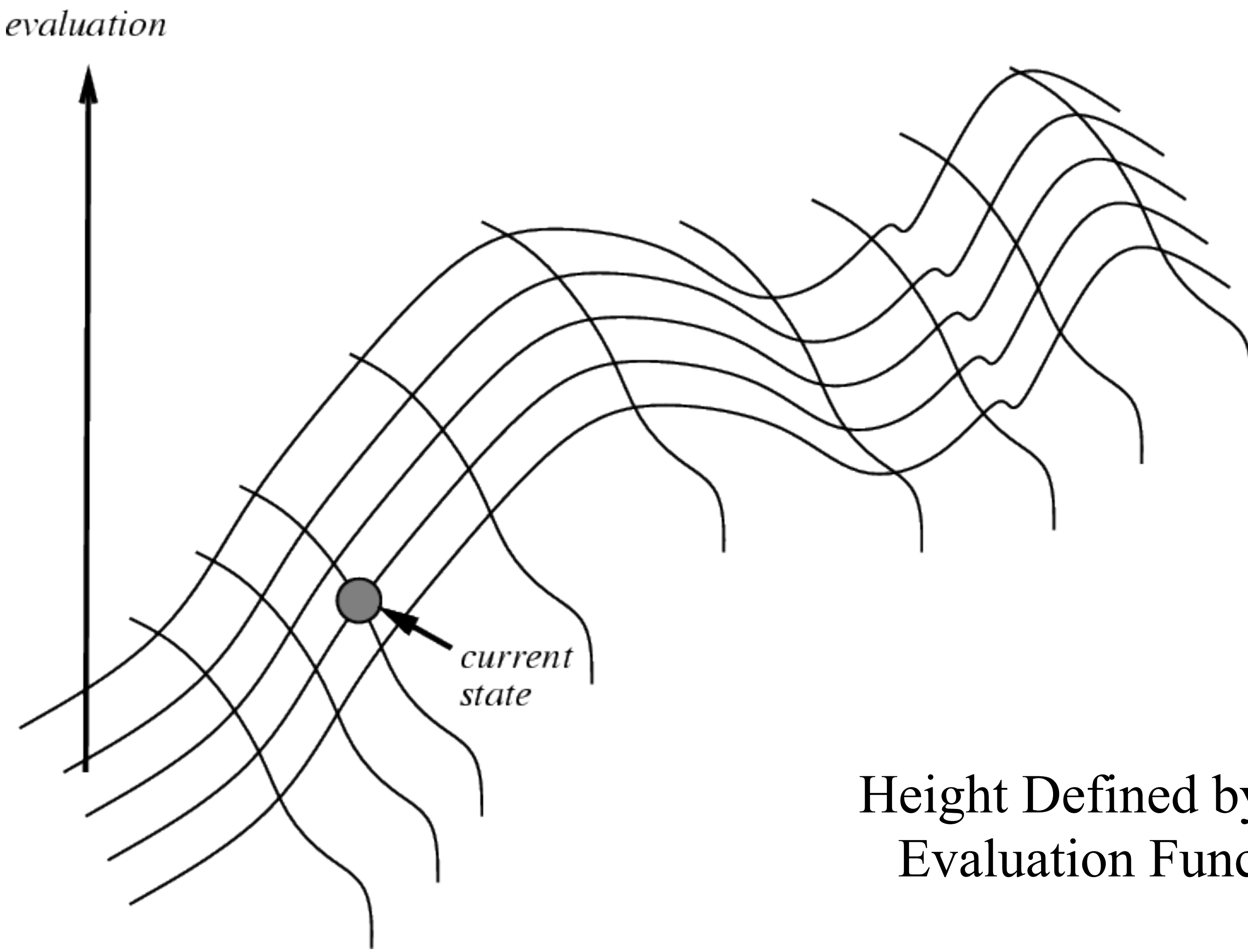
Adapted from materials by Tim Finin,
Marie desJardins, and Charles R. Dyer

Today's Class

- Iterative improvement methods
  – Hill climbing
  – Simulated annealing
  – Local beam search
- Genetic algorithms
- Online search

These approaches start with an initial guess at the solution and gradually improve until it is one.

Hill climbing on a surface of states



Height Defined by
Evaluation Function

Hill-climbing search

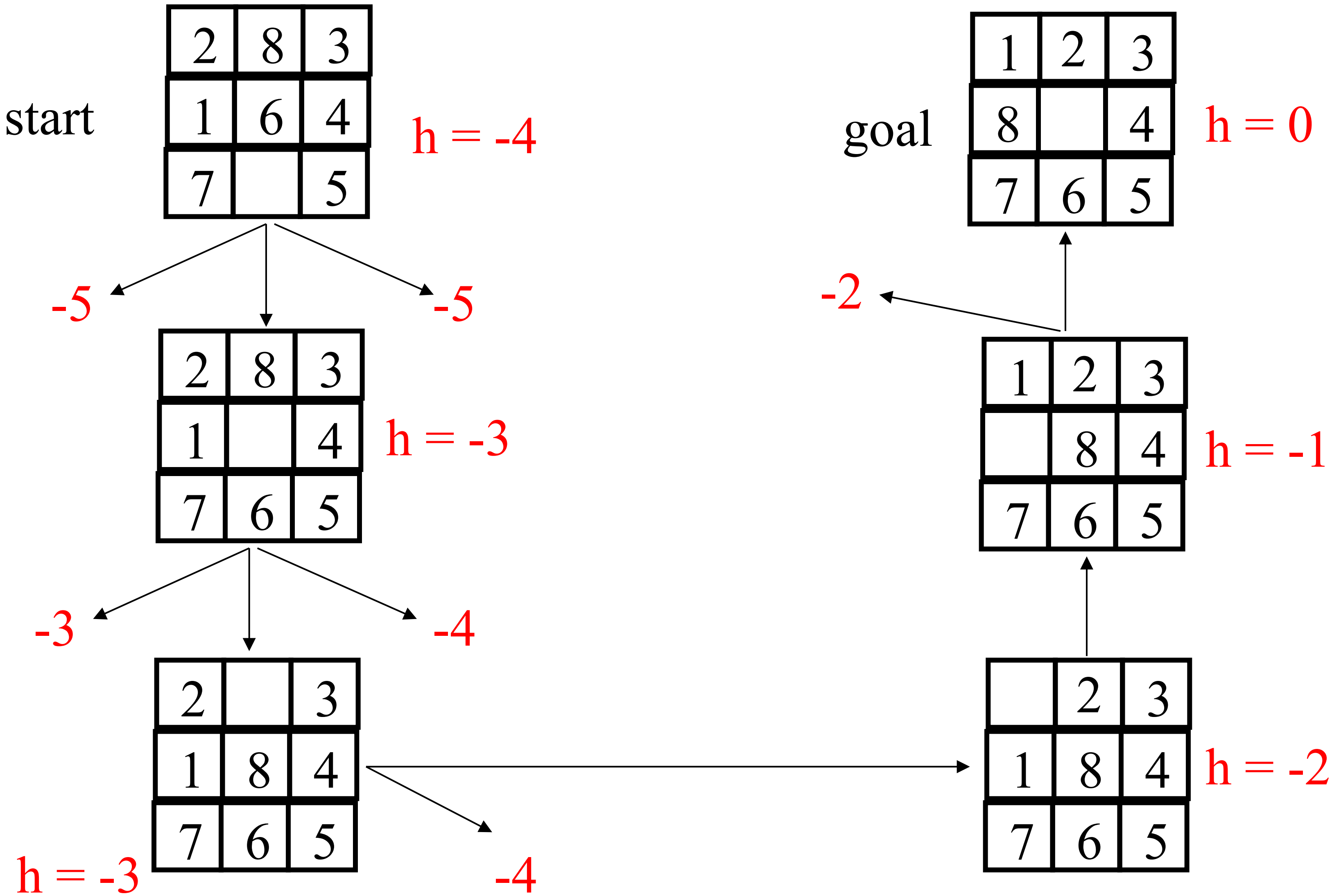
- Looks one step ahead to determine if any successor is better than the current state; if there is, move to the best successor.
- Rule:

  If there exists a successor s for the current state n such that

  - $h(s) < h(n)$ and
  - $h(s) \leq h(t)$ for all the successors t of n,

  then move from n to s. Otherwise, halt at n.
- Similar to Greedy search in that it uses $h()$, but does not allow backtracking or jumping to an alternative path since it doesn't "remember" where it has been.
- Corresponds to Beam search with a beam width of 1 (i.e., the maximum size of the nodes list is 1).
- Not complete since the search will terminate at "local minima," "plateaus," and "ridges."

Hill climbing example



f **(*n*) = -(number of tiles out of place)**

Exploring the Landscape

- **Local Maxima**: peaks that aren't the highest point in the space
- **Plateaus:** the space has a broad flat region that gives the search algorithm no direction (random walk)
- **Ridges:** flat like a plateau, but with drop-offs to the sides; steps to the North, East, South and West may go down, but a step to the NW may go up.

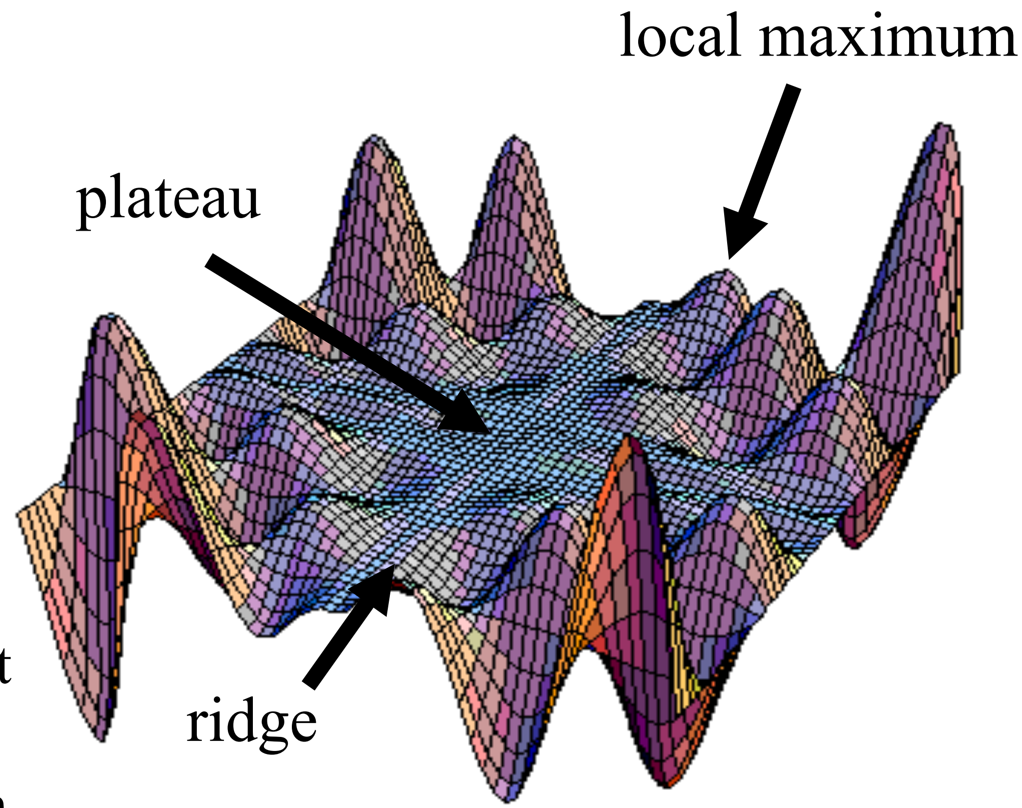
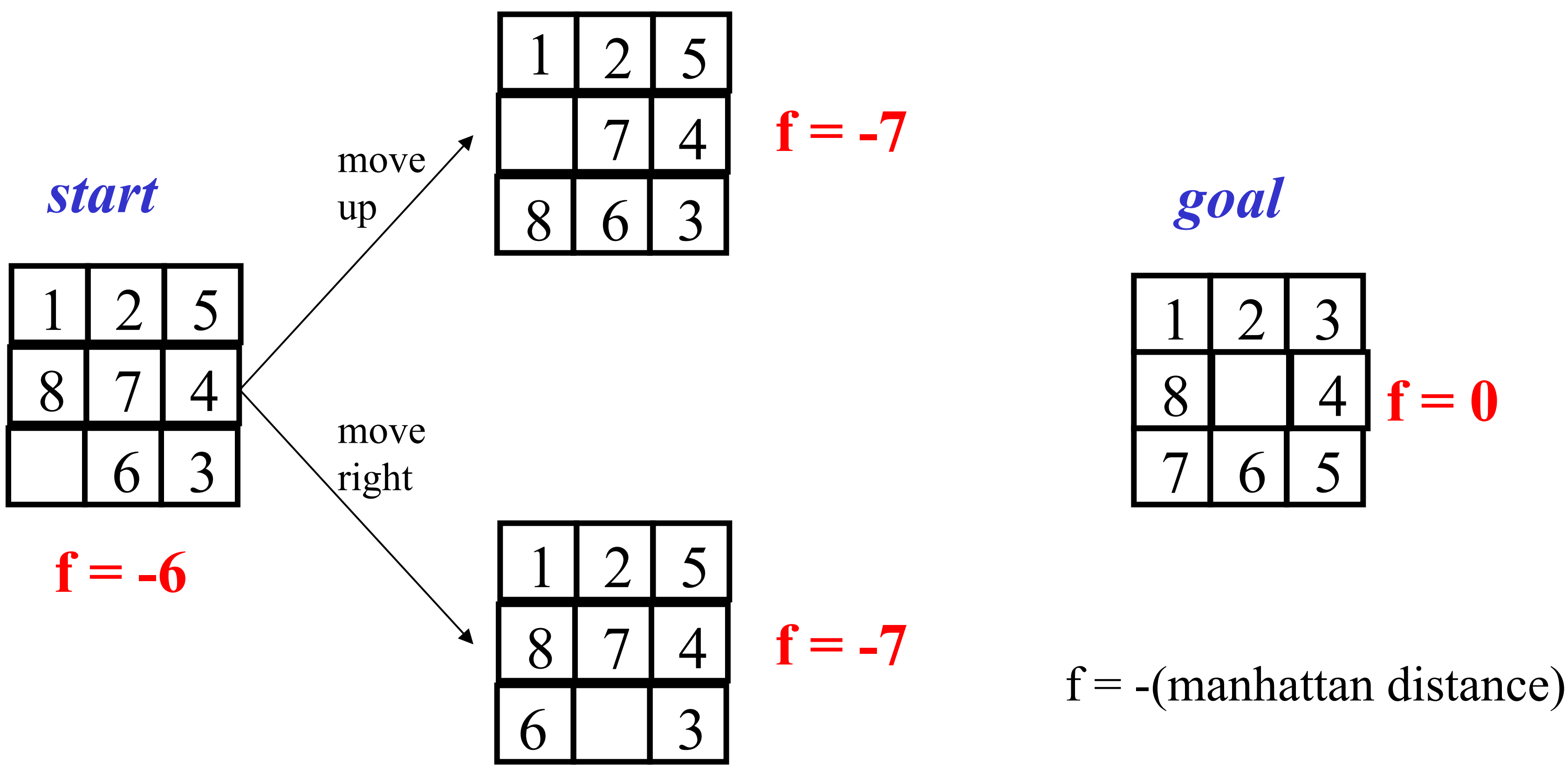


Image from: http://classes.yale.edu/fractals/CA/GA/Fitness/Fitness.html

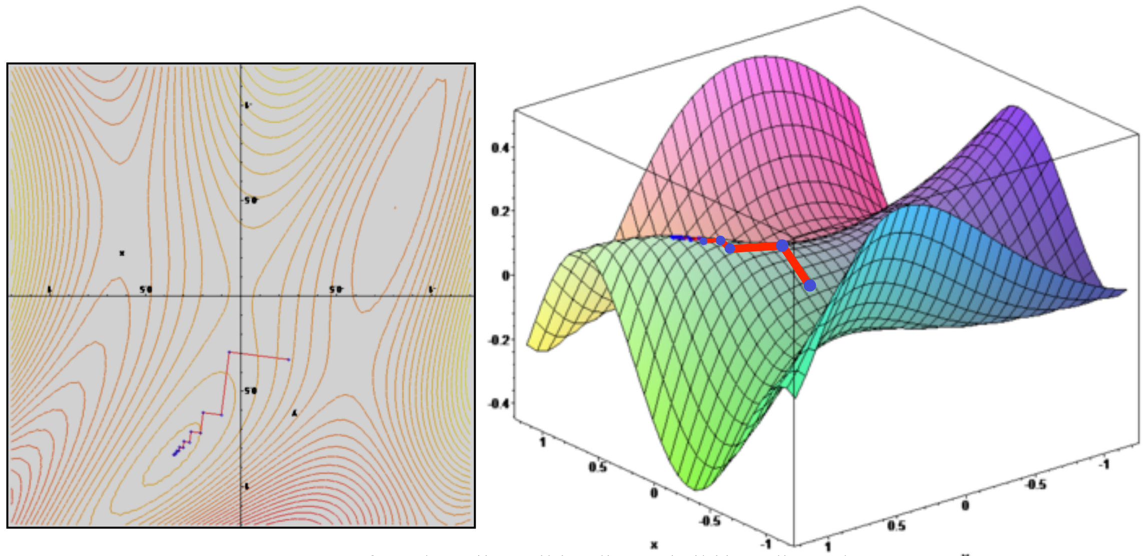
Drawbacks of hill climbing

- Problems: local maxima, plateaus, ridges
- Remedies:
  - **Random restart:** keep restarting the search from random locations until a goal is found.
  - **Problem reformulation:** reformulate the search space to eliminate these problematic features
- Some problem spaces are great for hill climbing and others are terrible.

Example of a local optimum



Gradient ascent / descent



Images from http://en.wikipedia.org/wiki/Gradient_descent

- Gradient descent procedure for finding the $arg_x \, min \, f(x)$
  - choose initial x_0 randomly
  - repeat
    - $x_{i+1} \leftarrow x_i - \eta f'(x_i)$
  - until the sequence $x_0, x_1, \ldots, x_i, x_{i+1}$ converges
- Step size η (eta) is small (perhaps 0.1 or 0.05)

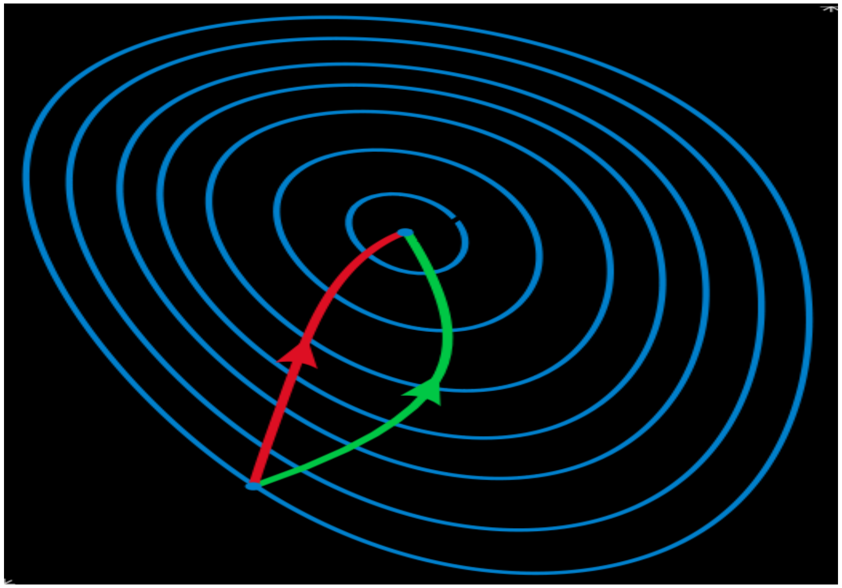
Gradient methods vs. Newton's method

- A reminder of Newton's method from Calculus:

  $x_{i+1} \leftarrow x_i - \eta f'(x_i) / f''(x_i)$

- Newton's method uses 2nd order information (the second derivative, or, curvature) to take a more direct route to the minimum.

- The second-order information is more expensive to compute, but converges quicker.



Contour lines of a function
Gradient descent (green)
Newton's method (red)
Image from http://en.wikipedia.org/wiki/Newton's_method_in_optimization

Simulated annealing

- Simulated annealing (SA) exploits an analogy between the way in which a metal cools and freezes into a minimum-energy crystalline structure (the annealing process) and the search for a minimum [or maximum] in a more general system.
- SA can avoid becoming trapped at local minima.
- SA uses a random search that accepts changes that increase objective function f, **as well as** some that **decrease** it.
- SA uses a control parameter T, which by analogy with the original application is known as the system "**temperature.**"
- T starts out high and gradually decreases toward 0.

Simulated annealing (cont.)

- A “bad” move from *A* to *B* is accepted with a probability

$$P(\text{move}_{A\rightarrow B}) = e^{(f(B)-f(A))\ /\ T}$$

- The higher the temperature, the more likely it is that a bad move can be made.
- As *T* tends to zero, this probability tends to zero, and SA becomes more like hill climbing
- If *T* is lowered slowly enough, SA is complete and admissible.

The simulated annealing algorithm

```
function SIMULATED-ANNEALING(problem, schedule) returns a solution state
  inputs: problem, a problem
          schedule, a mapping from time to "temperature"
  static: current, a node
          next, a node
          T, a "temperature" controlling the probability 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)
```

Local beam search

- Begin with *k* random states
- Generate all successors of these states
- Keep the *k* best states

- Stochastic beam search: Probability of keeping a state is *a function* of its heuristic value

Genetic algorithms

- Similar to stochastic beam search
- Start with *k* random states (the *initial population)*
- New states are generated by "mutating" a single state or "reproducing" (combining via crossover) two parent states (selected according to their *fitness)*
- Encoding used for the "genome" of an individual strongly affects the behavior of the search

- Genetic algorithms / genetic programming are a large and active area of research

In-Class Paper Discussion

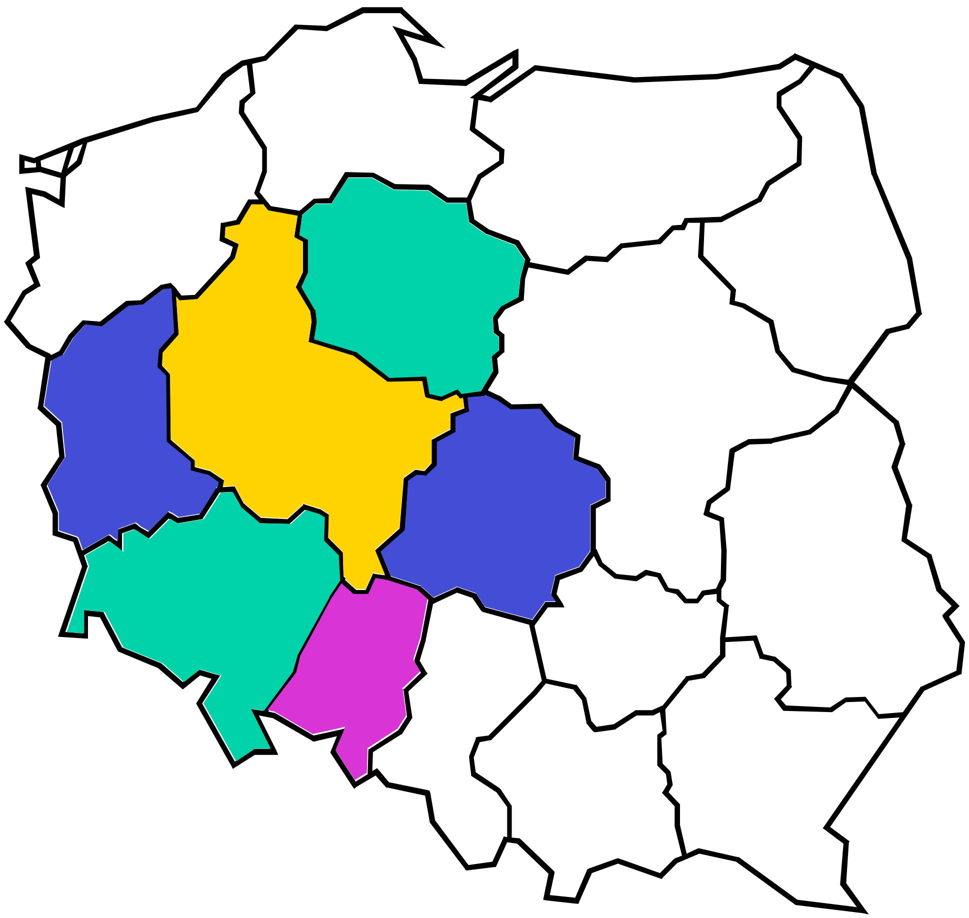
Stephanie Forrest. (1993).

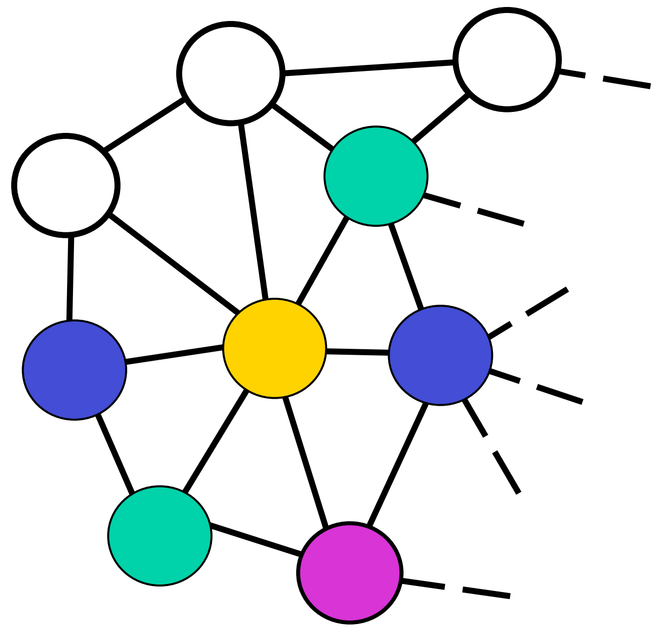
Genetic algorithms: principles of natural selection applied to computation.

Science 261 (5123): 872–878.

Class Exercise:

Local Search for Map/Graph Coloring





Online search

- Interleave computation and action (search some, act some)
- Exploration: Can't infer outcomes of actions; must actually perform them to learn what will happen

- Competitive ratio = Path cost found* / Path cost that could be found**
  * On average, or in an adversarial scenario (worst case)
  ** If the agent knew the nature of the space, and could use offline search

- Relatively easy if actions are reversible (ONLINE-DFS-AGENT)
- LRTA* (Learning Real-Time A*): Update $h(s)$ (in state table) based on experience
- More about these issues when we get to the chapters on Logic and Learning!

Summary: Informed search

- **Best-first search** is general search where the minimum-cost nodes (according to some measure) are expanded first.
- **Greedy search** uses minimal estimated cost $h(n)$ to the goal state as measure. This reduces the search time, but the algorithm is neither complete nor optimal.
- **A* search** combines uniform-cost search and greedy search: $f(n) = g(n) + h(n)$. A* handles state repetitions and $h(n)$ never overestimates.
  - A* is complete and optimal, but space complexity is high.
  - The time complexity depends on the quality of the heuristic function.
  - IDA* and SMA* reduce the memory requirements of A*.
- **Hill-climbing algorithms** keep only a single state in memory, but can get stuck on local optima.
- **Simulated annealing** escapes local optima, and is complete and optimal given a "long enough" cooling schedule.
- **Genetic algorithms** can search a large space by modeling biological evolution.
- **Online search** algorithms are useful in state spaces with partial/no information.