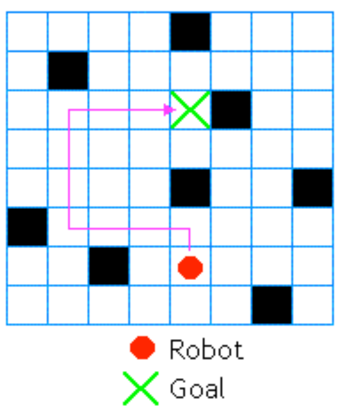
Local Search

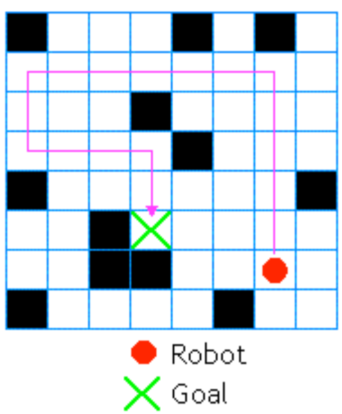
AI Class 6 (Ch. 4.1-4.2)

Based on slides by Dr. Marie desJardin. Some material also adapted from slides by Dr. Matuszek @ Villanova University, which are based on Hwee Tou Ng at Berkeley, which are based on Russell at Berkeley. Some diagrams are based on AIMA.

Bookkeeping

- HW 1 due last night
  - Grades within 1.5 weeks (hopefully sooner)
  - Discussions after grading
- HW 2 out tonight 11:59
  - Due 10/3, 11:59pm





Today's Class

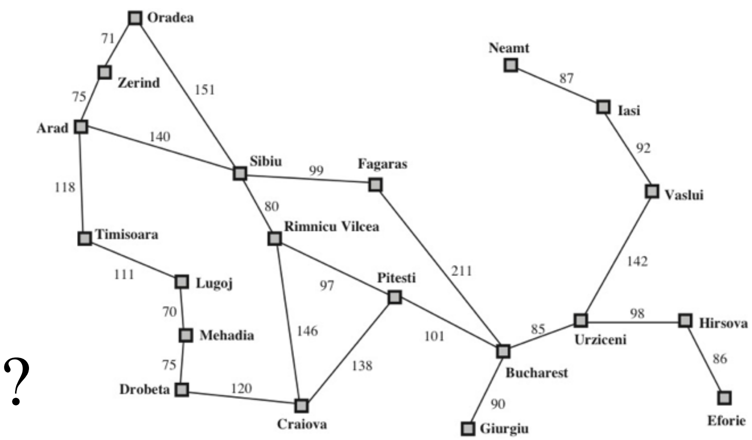
- Iterative improvement methods
- Hill climbing
- Simulated annealing
- Local beam search
- Genetic algorithms
- Online search

"If the path to the goal does not matter… [we can use] a single **current node** and move to neighbors of that node."

– R&N pg. 121

Admissibility

- Admissibility is a property of **heuristics**
  - They are *optimistic* – think goal is closer than it is
  - (Or, exactly right)



- Admissible algorithms can be pretty bad!

- Is $h(n)$: "1 kilometer" admissible?

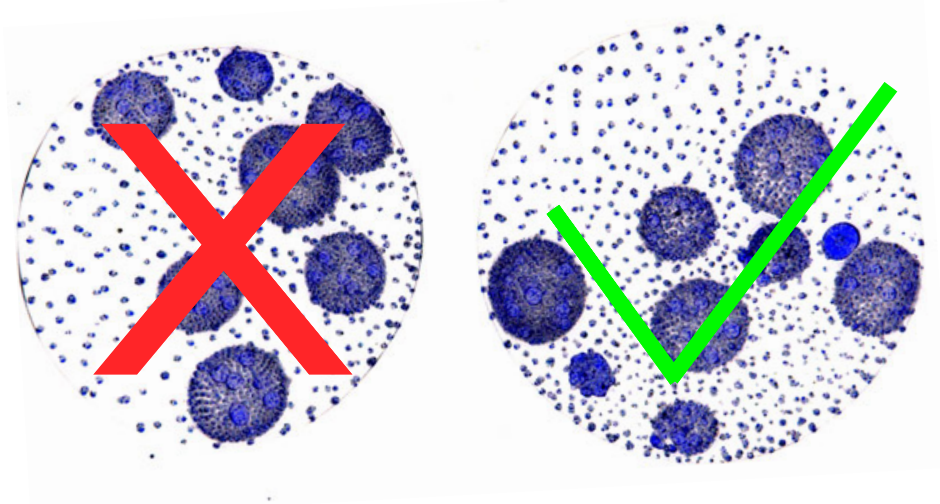
- Using admissible heuristics guarantees that the first solution found will be optimal, **for some algorithms** (A*).

Admissibility and Optimality

- Intuitively:
  - When A* finds a path of length *k*, it has already tried **every other path which can have length ≤ k**
  - Because all frontier nodes have been sorted in ascending order of $f(n)=g(n)+h(n)$
- Does an admissible heuristic guarantee optimality for greedy search?
  - Reminder: $f(n) = h(n)$, always choose node "nearest" goal
  - No sorting beyond that

Local Search Algorithms

- Sometimes the path to the goal is irrelevant
  - Goal state itself is the solution
  - ∃ an **objective function** to evaluate states
- In such cases, we can use local search algorithms
- Keep a single "current" state, try to improve it



Local Search Algorithms

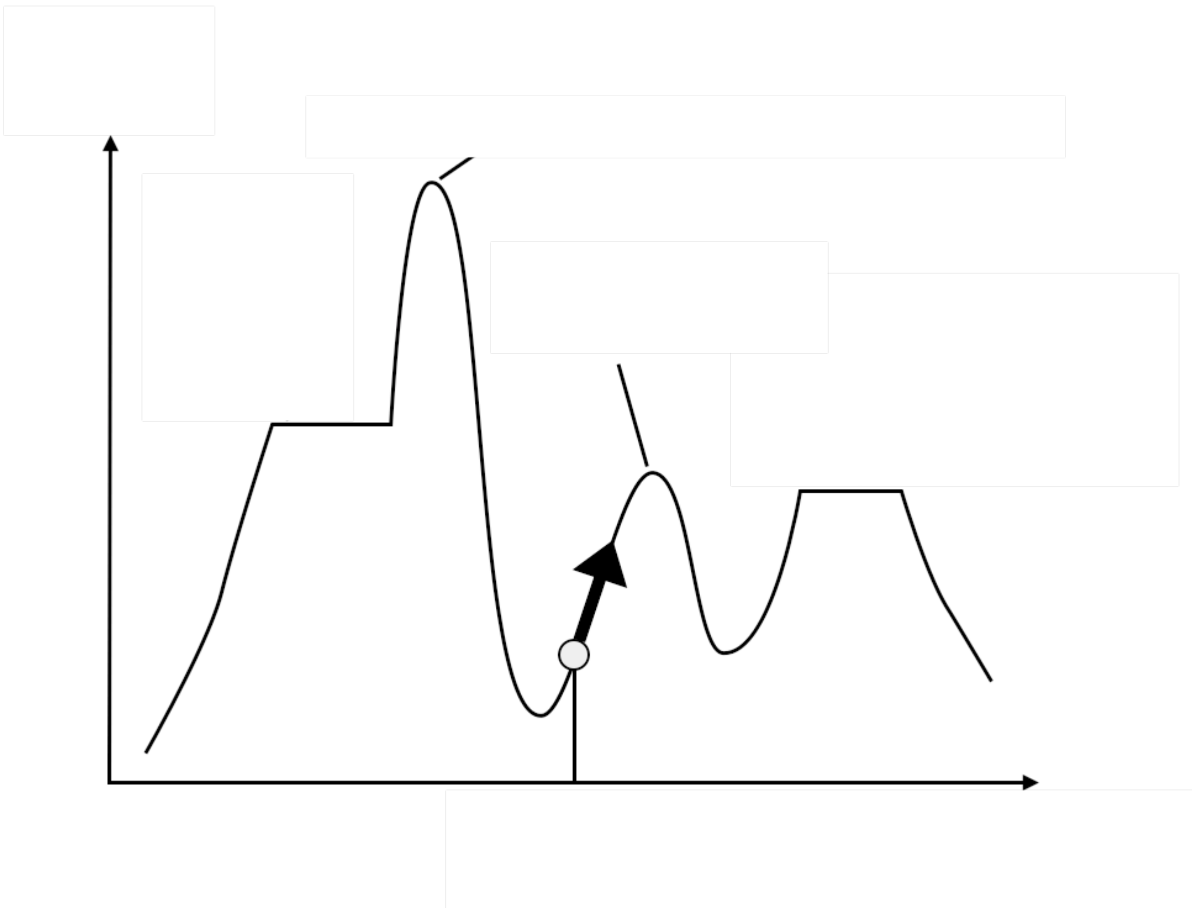
- Sometimes the path to the goal is irrelev
  - Goal state itself is the solution
  - ∃ an **objective function** to evaluate states

Very efficient!

Why?

- State space = set of "complete" configurations
  - That is, all elements of a solution are present
  - Find configuration satisfying constraints
  - Example?
- In such cases, we can use local search algorithms
- Keep a single "current" state, try to improve it

What Is This?

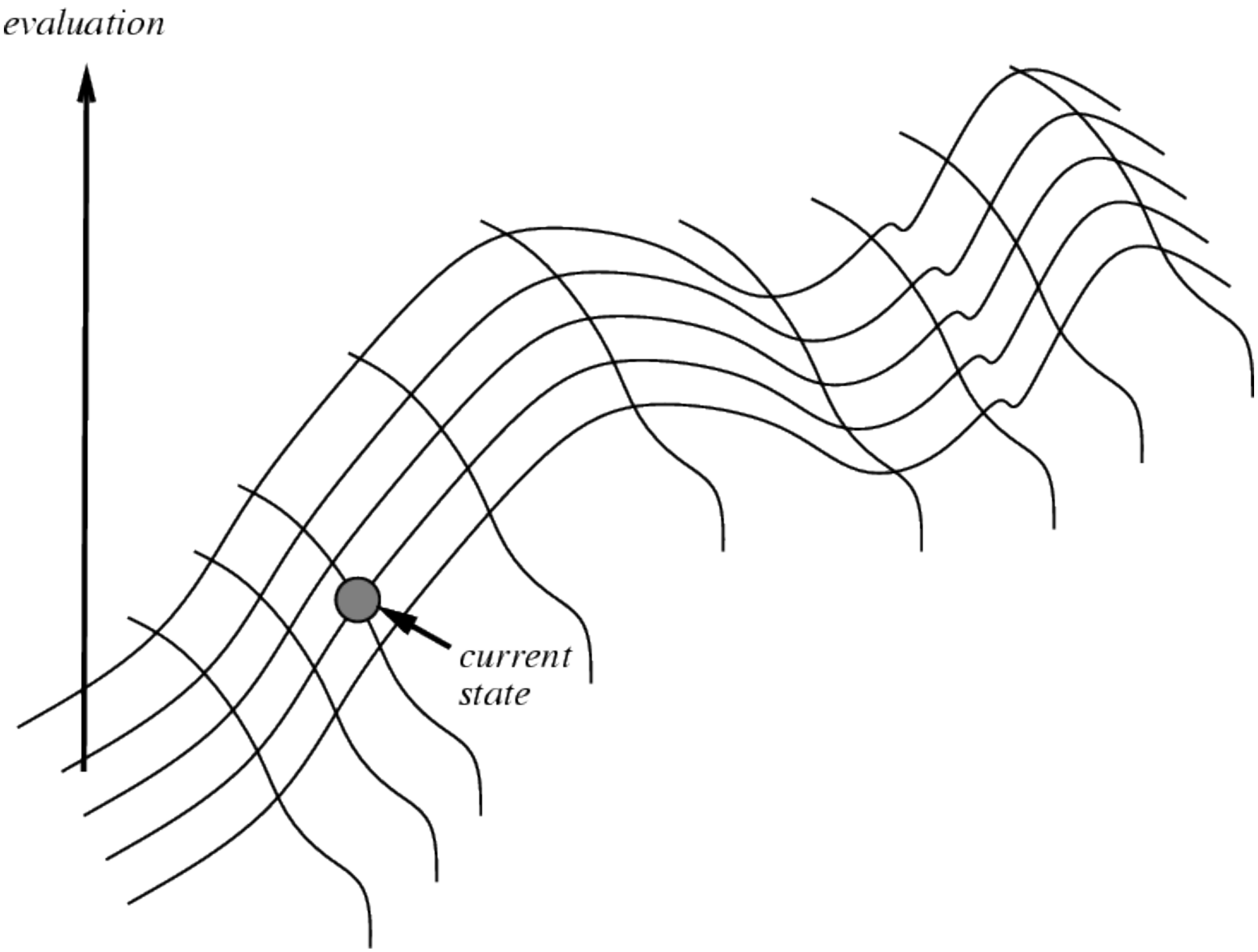


Iterative Improvement Search

- Start with an initial guess
- Gradually improve it until it is legal or optimal
- Some examples:
  - Hill climbing
  - Simulated annealing
  - Constraint satisfaction

Hill Climbing on State Surface

- Concept: trying to reach the "highest" (most desirable) point (state)
- "Height" Defined by Evaluation Function



Hill Climbing Search

- If there exists a successor s for the current state n such that
  - $h(s) < h(n)$
  - $h(s) \leq h(t)$ for all the successors t of n,

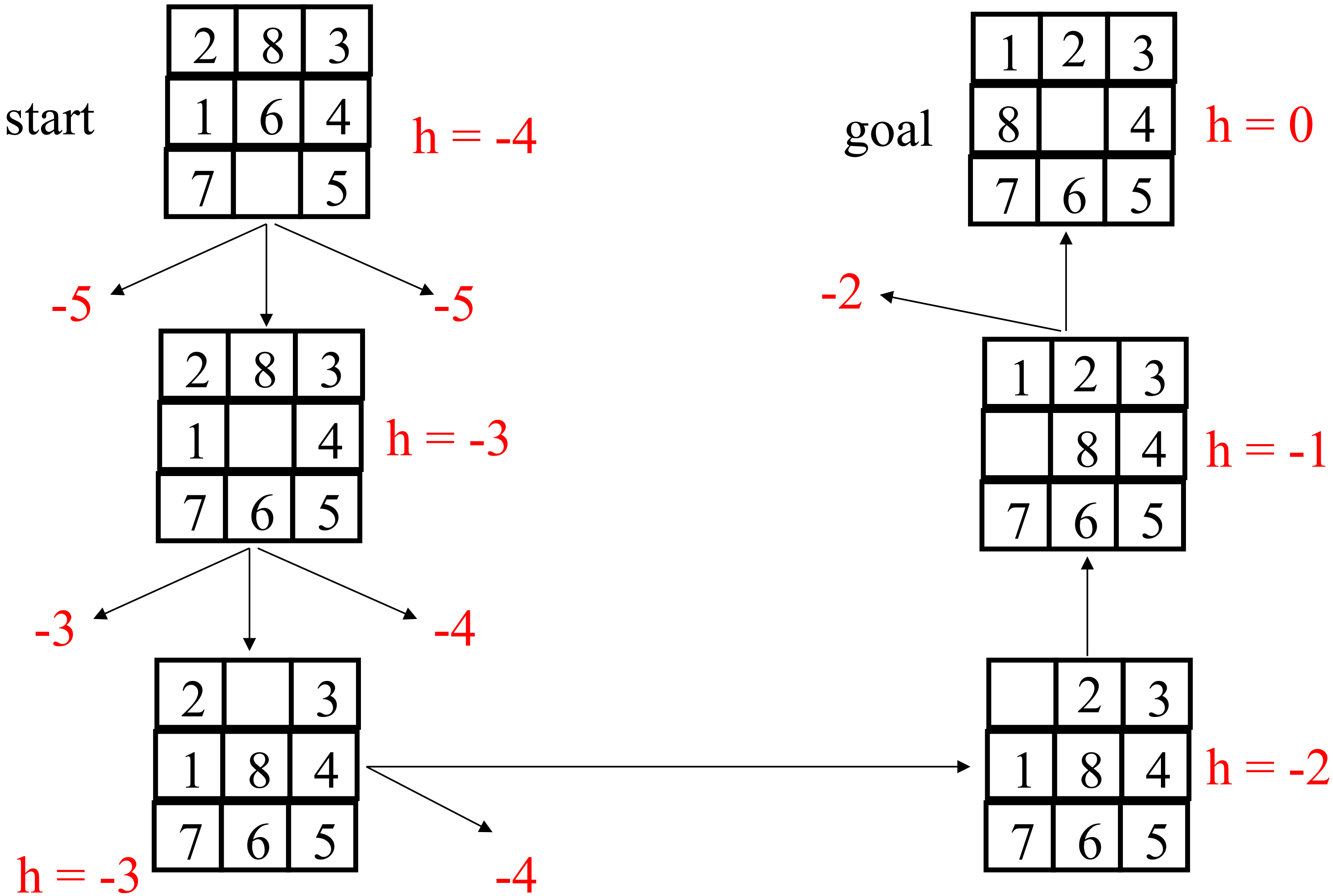
  then move from n to s. Otherwise, halt at n.

- Look one step ahead to determine if any successor is "better" than current state
  - If so, move to the best successor

- A kind of Greedy search in that it uses h
  - But, does not allow backtracking or jumping to an alternative path
  - Doesn't "remember" where it has been.

- Not *complete*
  - Search will terminate at local minima, plateaux, 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:**
  - 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.

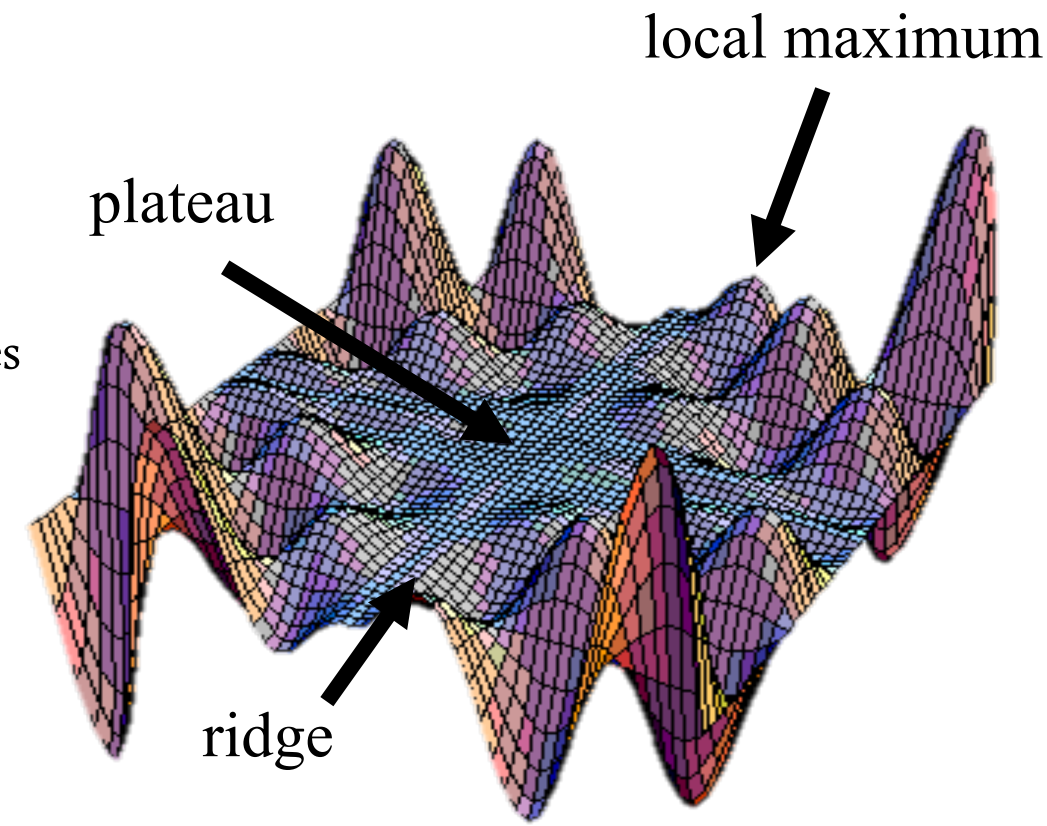
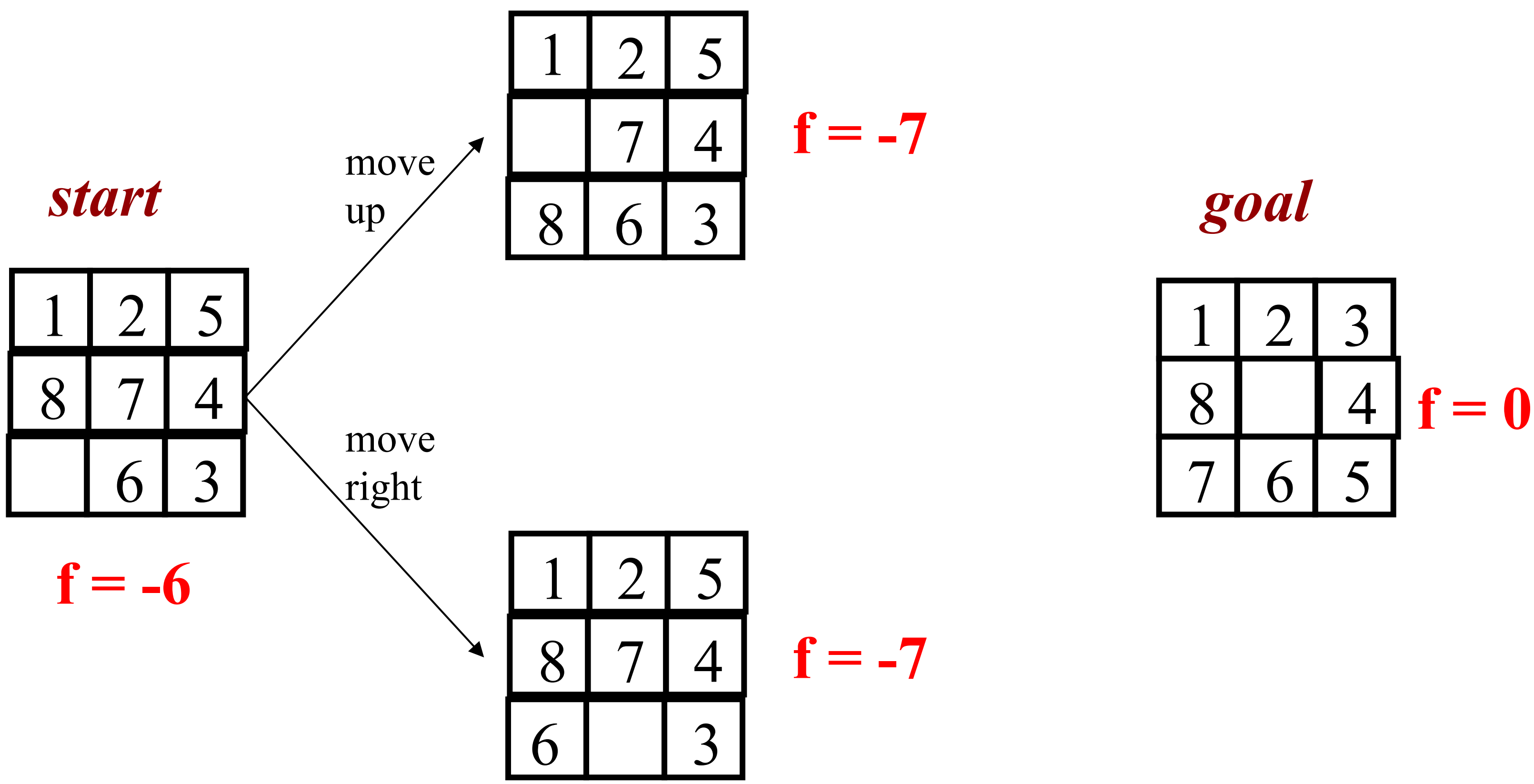


Image from: http://classes.yale.edu/fractals/CA/GA/Fitness/Fitness.html

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; others are terrible

Example of a Local Optimum



f = -(manhattan distance)

Some Extensions of Hill Climbing

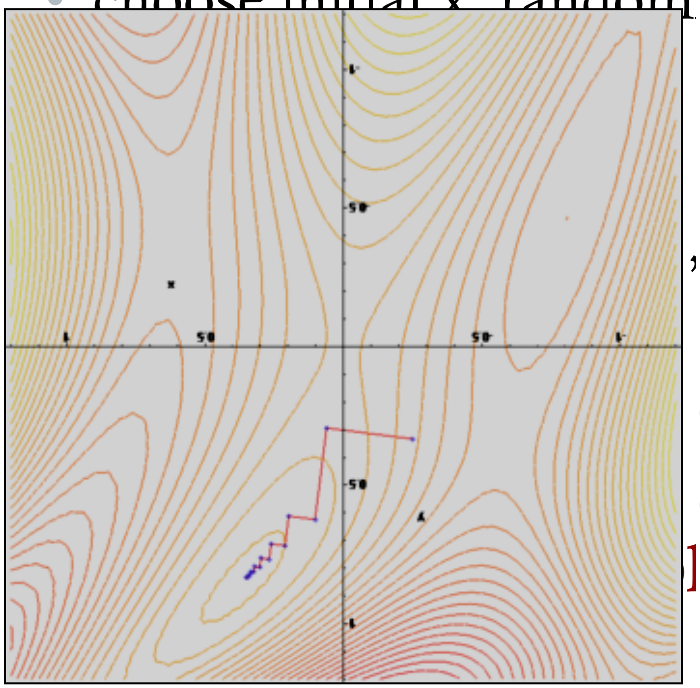
- Simulated Annealing
  - Escape local maxima by allowing *some* "bad" moves but gradually decreasing their frequency
- Local Beam Search
  - Keep track of k states rather than just one
  - At each iteration:
    - All successors of the k states are generated and evaluated
    - Best k are chosen for the next iteration

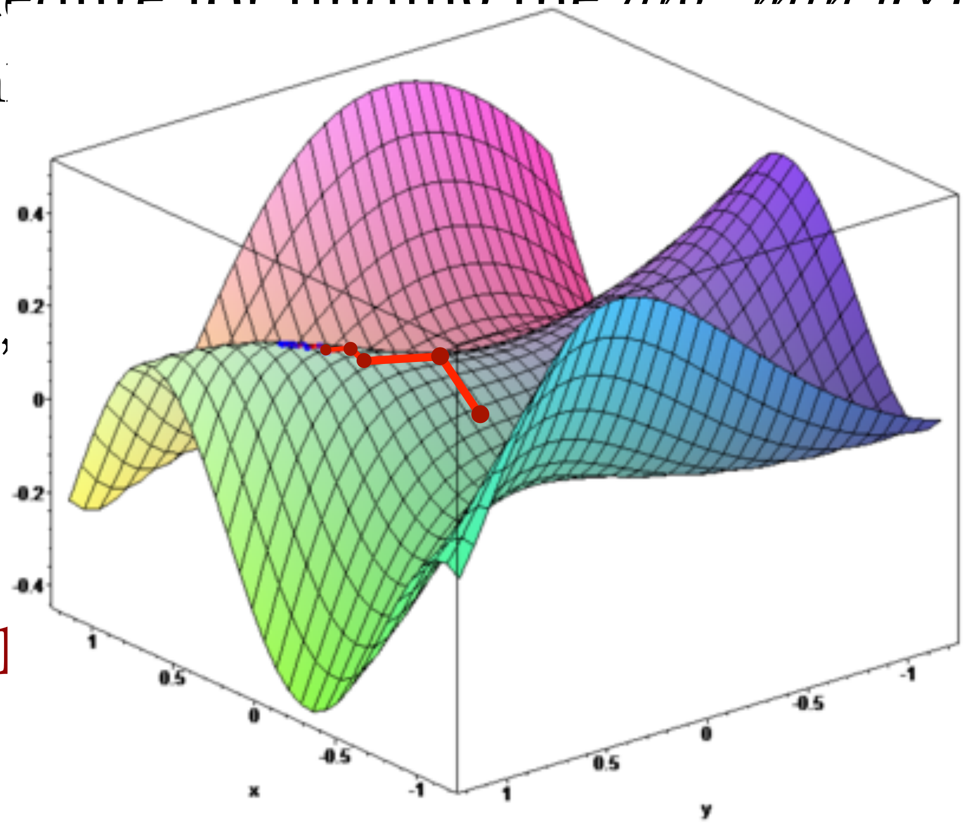
Some Extensions of Hill Climbing

- Stochastic Beam Search
  - Chooses semi-randomly from “uphill” possibilities
  - “Steeper” moves have a higher probability of being chosen
- Random-Restart Climbing
  - Can actually be applied to any form of search
  - Pick random starting points until one leads to a solution
- Genetic Algorithms
  - Each successor is generated from two predecessor (parent) states

Gradient Ascent / Descent

- Gradient descent procedure for finding the *arg min f(x)*
  - choose initial x_0 random





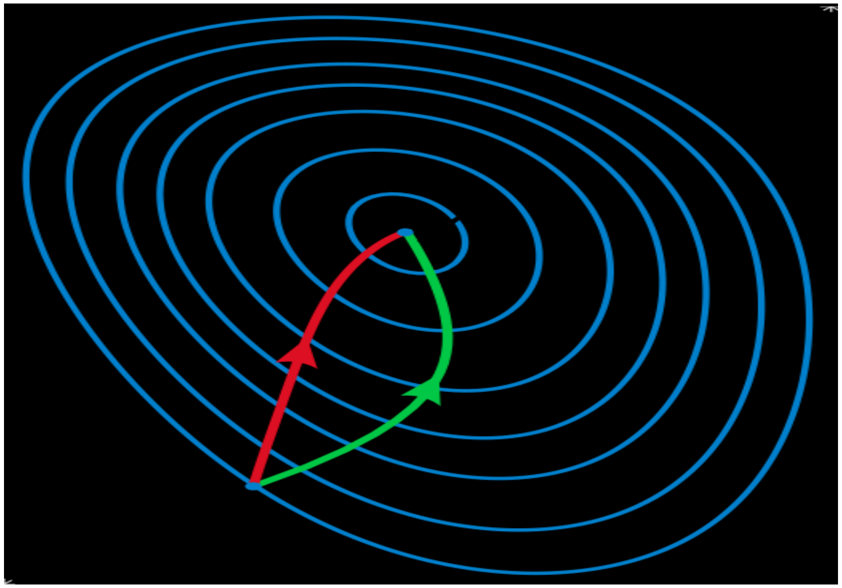
 Images from http://en.wikipedia.org/wiki/Gradient_descent

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 2^{nd} 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 more quickly.



Contour lines of a function
Gradient descent (green)
Newton's method (red)

Images from http://en.wikipedia.org/wiki/Newton's_method_in_optimization

Simulated Annealing

- Simulated annealing (SA): analogy between the way metal cools into a minimum-energy crystalline structure and the search for a minimum generally
  - In very hot metal, molecules can move fairly freely
  - But, they are slightly less likely to move out of a stable structure
  - As you slowly cool the metal, more molecules are "trapped" in place
- Conceptually: Escape local maxima by allowing some "bad" (locally counterproductive) moves but gradually decreasing their frequency

Simulated Annealing (II)

- Can avoid becoming trapped at local minima.
- Uses a random local search that:
  - Accepts changes that increase objective function *f*
  - **As well as** some that **decrease** it
- Uses a control parameter T
  - By analogy with the original application
  - Is known as the system "**temperature**"
- T starts out high and gradually decreases toward 0

Simulated Annealing (IIII)

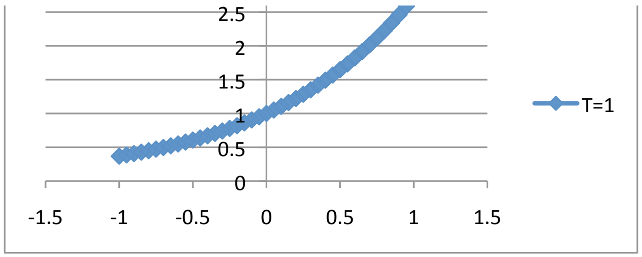
- $f(s)$ represents the quality of state n (high is good)
- A "bad" move from A to B is accepted with a probability

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

  - (Note that $f(B) - f(A)$ will be negative, so bad moves always have a relatively probability less than one. Good moves, for which $f(B) - f(A)$ is positive, have a relative probability greater than one.)

- Temperature
  - 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.

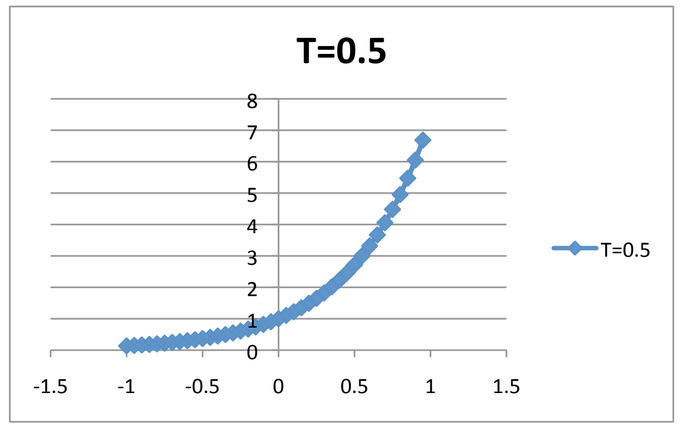
Visualizing SA Probabilities

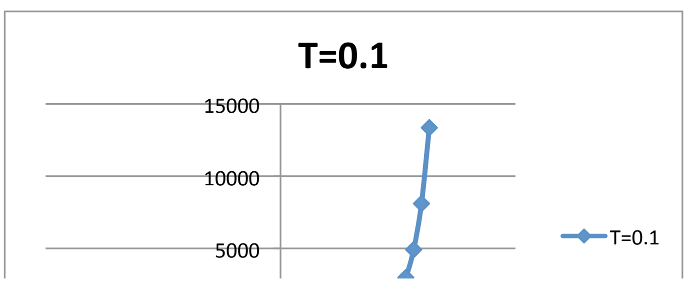


p(neg) =
0.1422741

[-1,1] ratio =
49.402449

p(neg) =
0.0202419





[-1,1] ratio =
294267566

The Simulated Annealing Algorithm

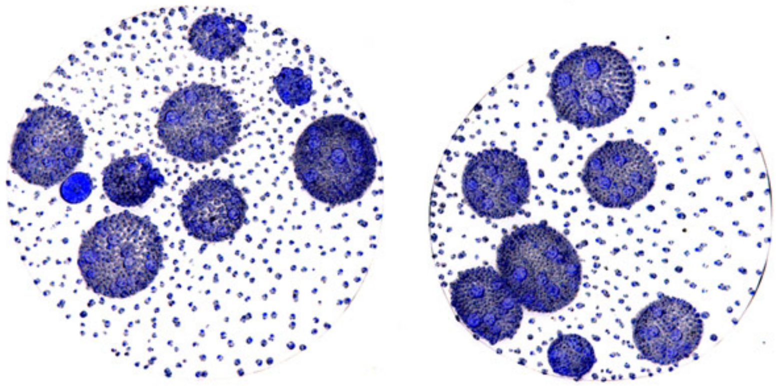
```
function SIMULATED-ANNEALING(problem, schedule) returns a solution state
   inputs: problem, a problem
           schedule, a mapping from time to "temperature"
   static: current, a node
           next, a node
           T, a "temperature" controlling the probability of downward steps

   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
  - *k*, instead of one, current state(s)
- 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
  - More likely to keep “better” successors

Genetic Algorithms



- The Idea:
  - New states are generated by "mutating" a single state or "reproducing" (somehow combining) two parent states
  - Selected according to their **fitness**
- Similar to stochastic beam search
- Start with *k* random states (the **initial population***)*
  - 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

Class Exercise: Local Search for N-Queens

Q					
	Q				
		Q			
			Q		
				Q	
					Q

(more on constraint satisfaction heuristics next time...)

Tabu Search

- Problem: Hill climbing can get stuck on local maxima
- Solution: Maintain a list of *k* previously visited states, and prevent the search from revisiting them
- Why not always do this?

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
- LRTA* (Learning Real-Time A*): Update $h(s)$ (in state table) based on experience
- More about online search and nondeterministic actions next time…

Summary: Informed Search

- **Best-first search** is general search where the minimum-cost nodes are expanded first.
- **Greedy search** uses minimal estimated cost $h(n)$ to the goal state as measure
- Reduces the search time, but 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.
  - 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.