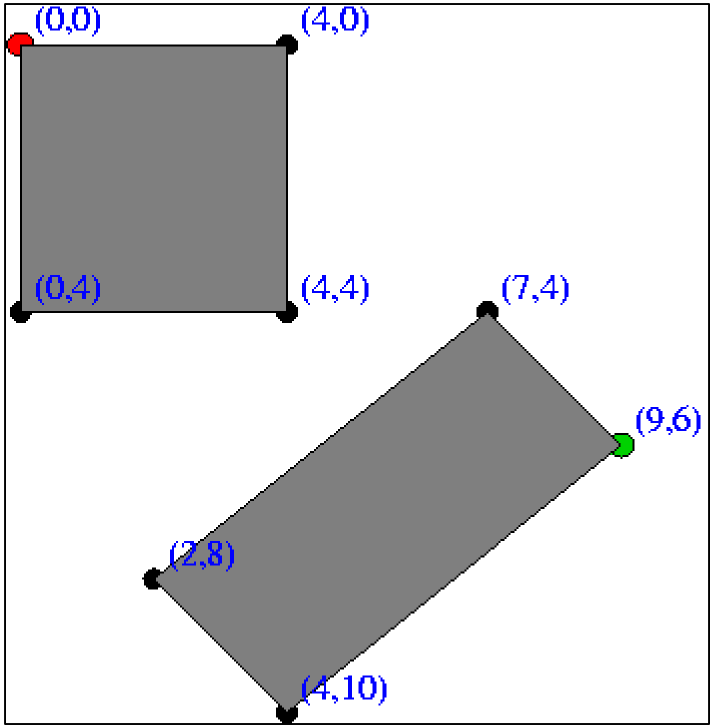
More on HW 2 (due Jan 22)

- Again, it must be in Python.
- For the A* algorithm, you will need an Open* list and a Closed list.
- States should have
  - the coordinates of the point
  - the g-value cost of the path from init to here
  - the h-value estimate of cost to goal
  - the parent state
  - (optional) list of successors

*Note: Python will have a fit if you call it Open.

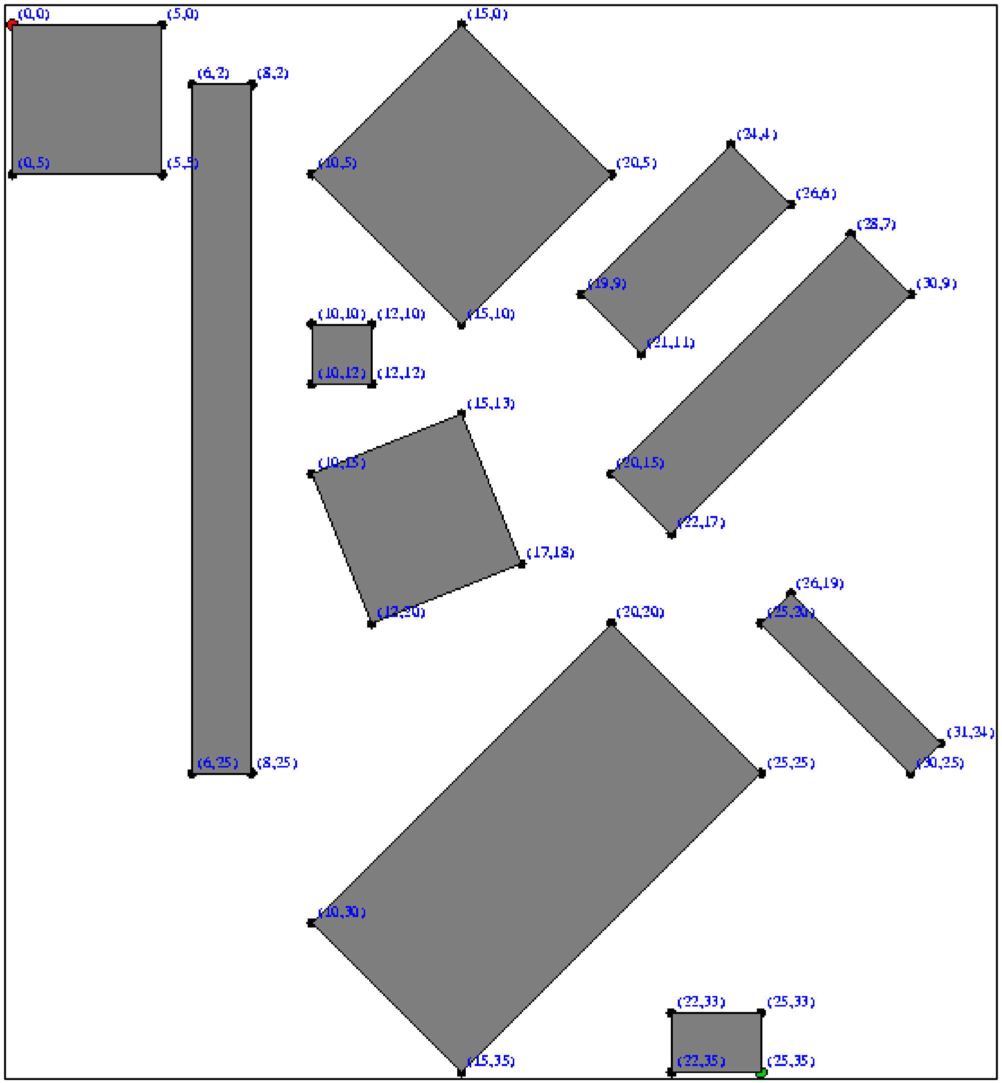
Input format Example

```
0 0
9 6
2
0 0 4 0 4 4 0 4
7 4 9 6 4 10 2 8
```



Start Point
Goal Point
How many Rectangles.
Rectangle coordinates are given clockwise.

More Difficult Example



Has 4 known solutions with approximately the same cost.

You will just find 1 least cost solution and print the whole path with states and cumulative costs.

In Addition

- You must design your own custom data set and run your program on it, too. You will turn in a picture of your data set, similar to the pictures we give you of ours.
- Turn in commented source code, input and output from all 3 data sets, and your picture.

Beyond Classical Search

- Chapter 3 covered problems that considered the whole search space and produced a sequence of actions leading to a goal.

- Chapter 4 covers techniques (some developed outside of AI) that don’t try to cover the whole space and only the goal state, not the steps, are important.

- The techniques of Chapter 4 tend to use much less memory and are not guaranteed to find an optimal solution.

More Search Methods

- Local Search
  - Hill Climbing
  - Simulated Annealing
  - Beam Search
  - Genetic Search
- Local Search in Continuous Spaces
- Searching with Nondeterministic Actions
- Online Search (agent is executing actions)

Local Search Algorithms and Optimization Problems

- Complete state formulation
  - For example, for the 8 queens problem, all 8 queens are on the board and need to be moved around to get to a goal state
- Equivalent to optimization problems often found in science and engineering
- Start somewhere and try to get to the solution from there
- Local search around the current state to decide where to go next

Pose Estimation Example

- Given a geometric model of a 3D object and a 2D image of the object.
- Determine the position and orientation of the object wrt the camera that snapped the image.

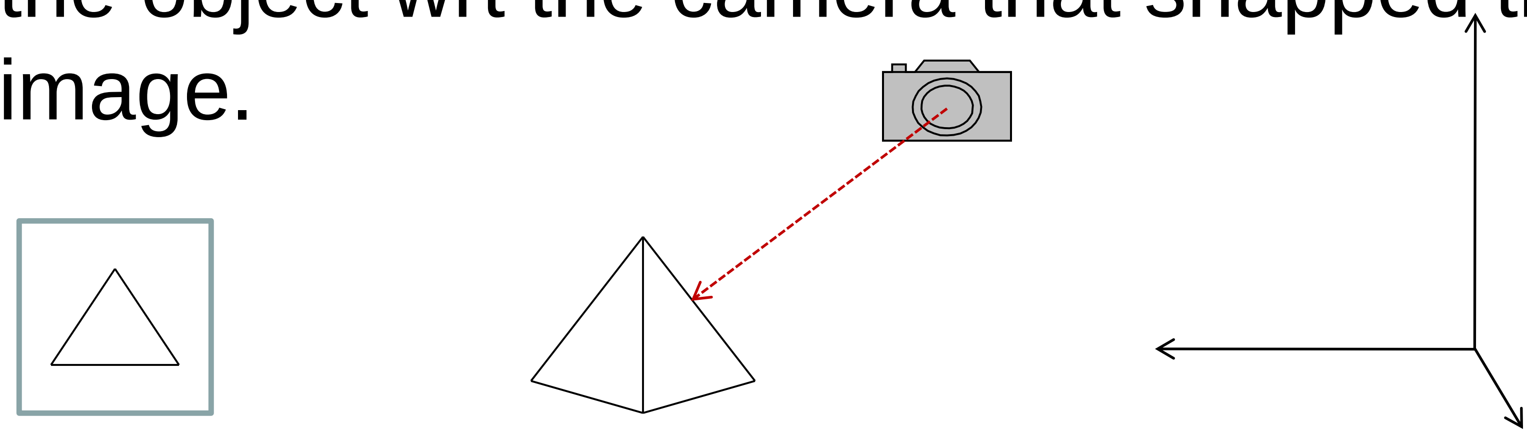


image 3D object

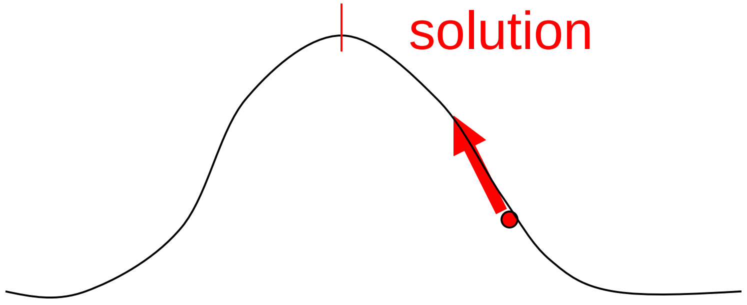
- State (x, y, z, θx, θy, θz)

Gradient

- What is the gradient of a function?
- In 1D. Function $f(x)$. Gradient $f'(x)$, the derivative.
- In 2D. Function $f(x,y)$. Gradient (∂x, ∂y)
- e.g. $f(x) = x^2$. $f'(x) = ?$

Hill Climbing

"Gradient ascent"



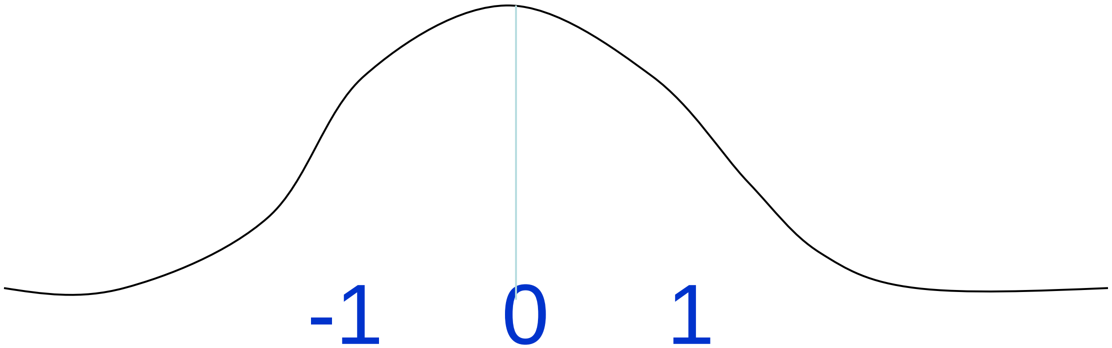
Note: solutions shown here as max not min.

Often used for numerical optimization problems.

How does it work?

In continuous space, the gradient tells you the direction in which to move uphill.

Numeric Example



- Normal distribution with 0 mean and 1 SD
- $f(x) = c\ e \wedge (-1/2)x^2$
- $f'(x) = -x\ c\ e \wedge (-1/2)x^2$
- $f'(1)$ comes out negative, ie. move backward
- $f'(-1)$ comes out positive, ie. move forward.

AI Hill Climbing

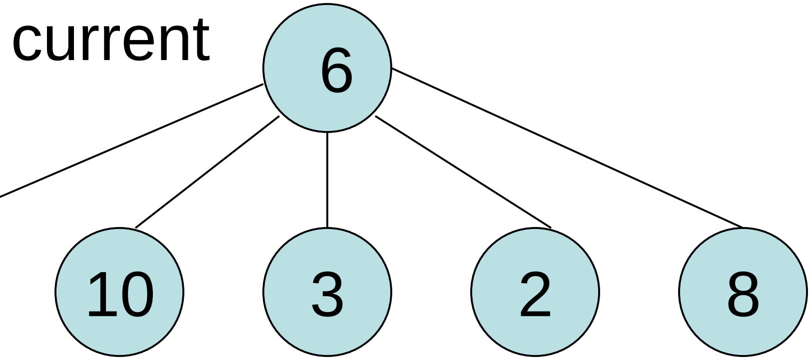
Steepest-Ascent Hill Climbing

- *current* ← start node
- loop do
  - *neighbor* ← a highest-valued successor of *current*
  - if *neighbor*.Value <= *current*.Value then return *current*.State
  - *current* ← *neighbor*
- end loop

At each step, the current node is replaced by the best (highest-valued) neighbor.

This is sometimes called greedy local search.

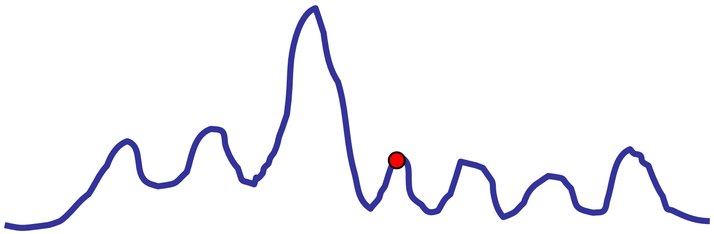
Hill Climbing Search



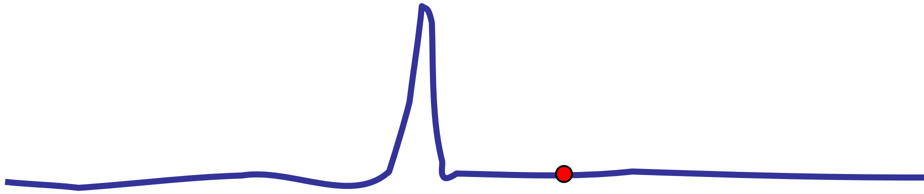
What if current had a value of 12?

Hill Climbing Problems

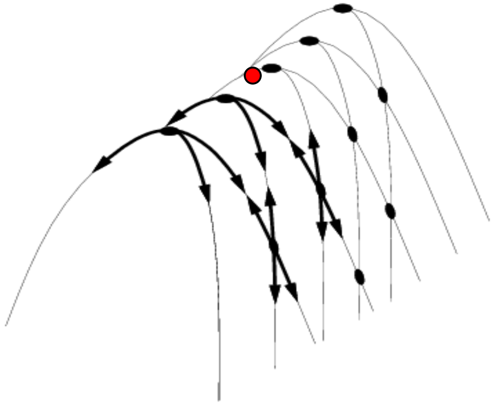
Local maxima



Plateaus



Diagonal ridges



What is it sensitive to?
Does it have any advantages?

Solving the Problems

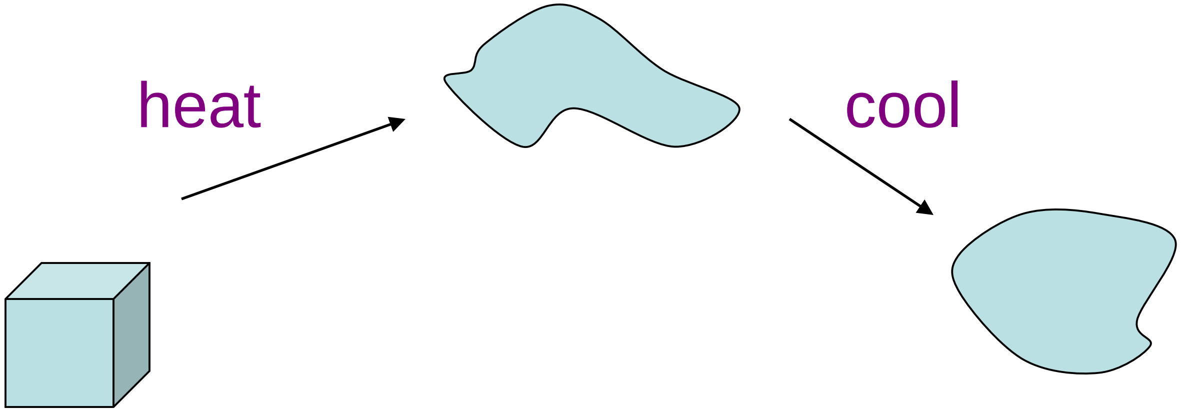
- Allow backtracking (What happens to complexity?)
- Stochastic hill climbing: choose at random from uphill moves, using steepness for a probability
- Random restarts: “If at first you don’t succeed, try, try again.”
- Several moves in each of several directions, then test
- Jump to a different part of the search space

Simulated Annealing

- Variant of hill climbing (so up is good)
- Tries to explore enough of the search space early on, so that the final solution is less sensitive to the start state
- May make some downhill moves before finding a good way to move uphill.

Simulated Annealing

- Comes from the physical process of annealing in which substances are raised to high energy levels (melted) and then cooled to solid state.



- The probability of moving to a higher energy state, instead of lower is

$$p = e^{(-\Delta E/kT)}$$

where ΔE is the positive change in energy level, T is the temperature, and k is Bolzmann's constant.

Simulated Annealing

- At the beginning, the temperature is high.
- As the temperature becomes lower
  - kT becomes lower
  - $\Delta E/kT$ gets bigger
  - $(-\Delta E/kT)$ gets smaller
  - $e^{(-\Delta E/kT)}$ gets smaller
- As the process continues, the probability of a downhill move gets smaller and smaller.

For Simulated Annealing

- ΔE represents the change in the value of the objective function.
- Since the physical relationships no longer apply, drop k. So $p = e^{(-\Delta E/T)}$
- We need an annealing schedule, which is a sequence of values of T: $T_0, T_1, T_2, \ldots$

Simulated Annealing Algorithm

- *current* ← start node;

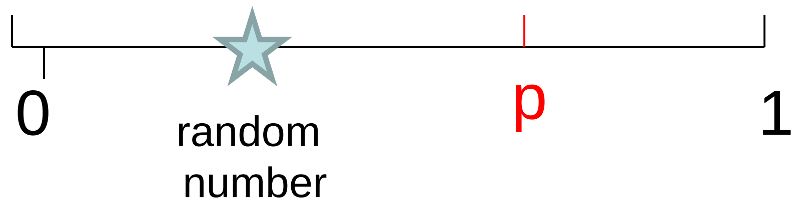
- for each T on the schedule /* need a schedule */

  - *next* ← randomly selected successor of *current*
  - evaluate next; it it's a goal, return it
  - ΔE ← *next*.Value – *current*.Value /* already negated */
  - if $\Delta E > 0$
    - then *current* ← *next* /* better than current */
    - else *current* ← *next* with **probability** $e^{(\Delta E/T)}$

How would you do this probabilistic selection?

Probabilistic Selection

- Select *next* with probability p



- Generate a random number
- If it’s <= p, select *next*

Simulated Annealing Properties

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

$$p(x) = \alpha e\text{\^{}}(E(x)/kT)$$

- If T is decreased slowly enough (very slowly), the procedure will reach the best state.

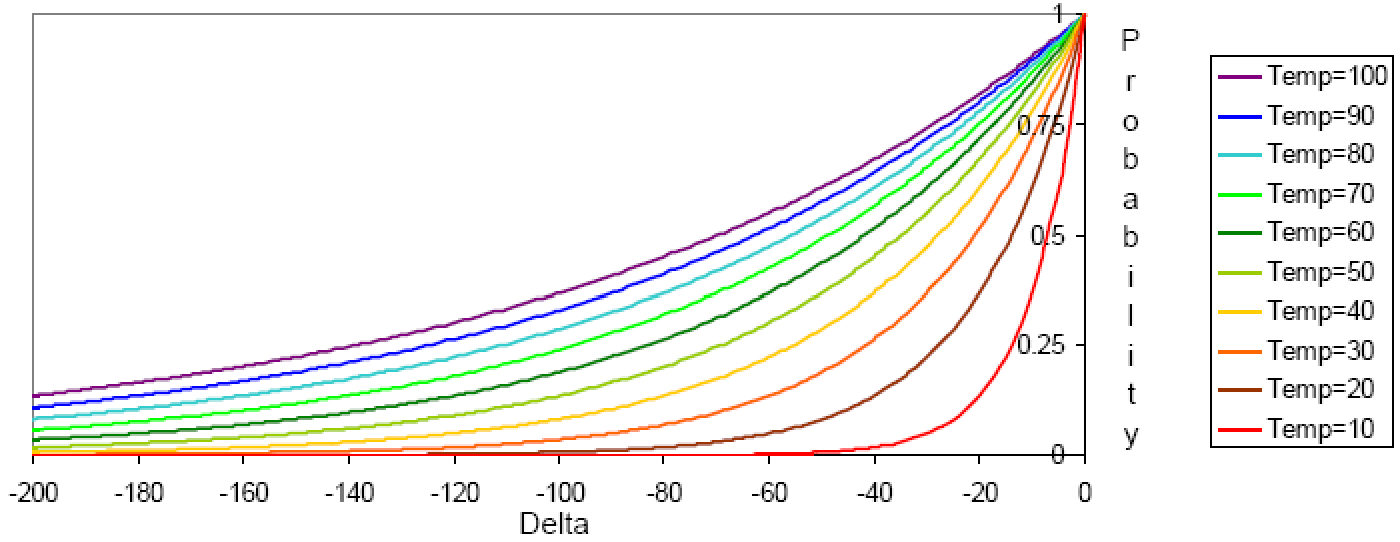
- Slowly enough has proven too slow for some researchers who have developed alternate schedules.

Simulated Annealing Schedules

- Acceptance criterion and cooling schedule

if (delta>=0) accept

else if ($random < e^{delta/Temp}$) accept, else reject /* 0<=random<=1 */



Initially temperature is very high (most bad moves accepted)

Temp slowly goes to 0, with multiple moves attempted at each temperature

Final runs with temp=0 (always reject bad moves) greedily “quench” the system

Simulated Annealing Applications

- Basic Problems
  - Traveling salesman
  - Graph partitioning
  - Matching problems
  - Graph coloring
  - Scheduling
- Engineering
  - VLSI design
    - Placement
    - Routing
    - Array logic minimization
    - Layout
  - Facilities layout
  - Image processing
  - Code design in information theory

Local Beam Search

- Keeps more previous states in memory
  - Simulated annealing just kept one previous state in memory.
  - This search keeps k states in memory.

    - randomly generate k initial states
    - if any state is a goal, terminate
    - else, generate all successors and select best k
    - repeat

Local Beam Search

Coming next: Genetic Algorithms, which are motivated by human genetics. How do you search a very large search space in a fitness oriented way?