CSCI 3202: Intro to Artificial Intelligence

Lecture 12: Local Search

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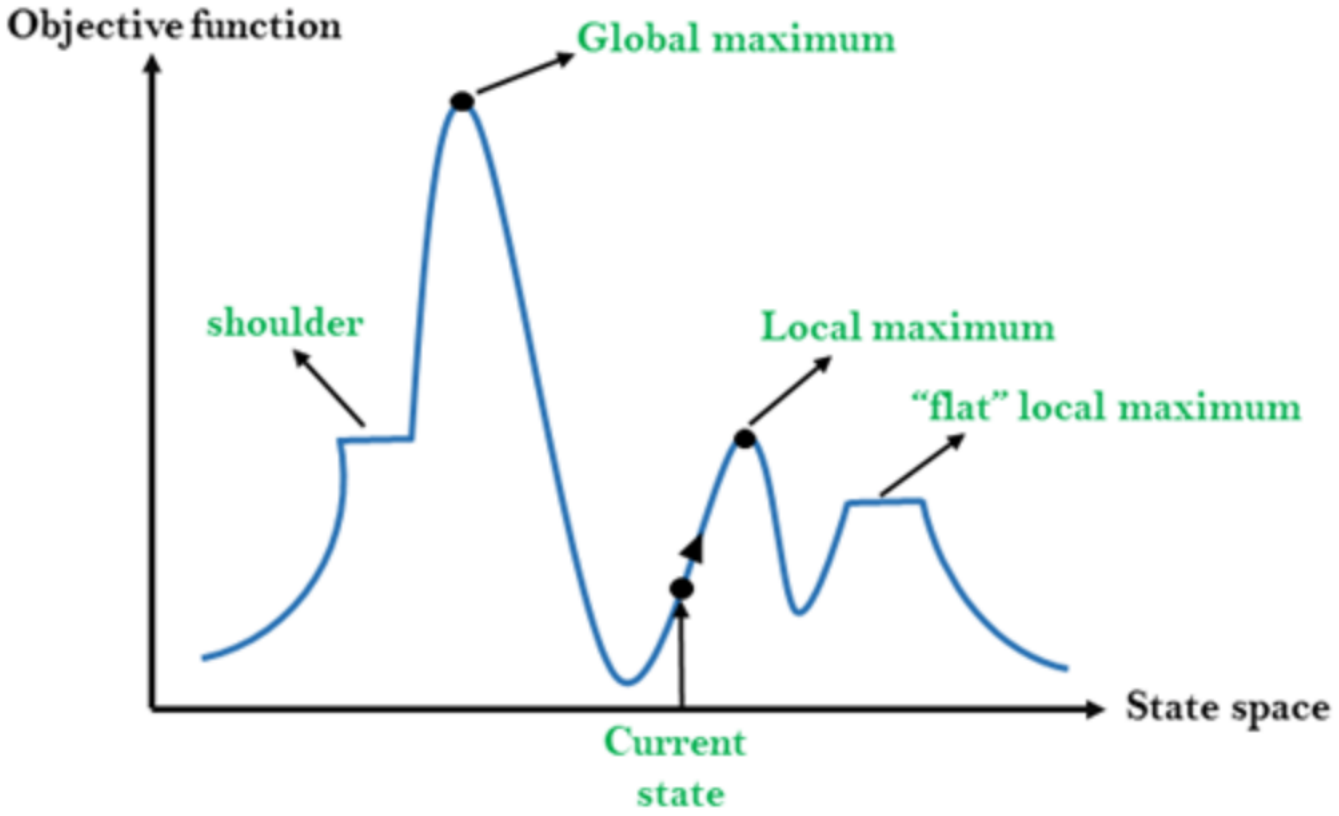
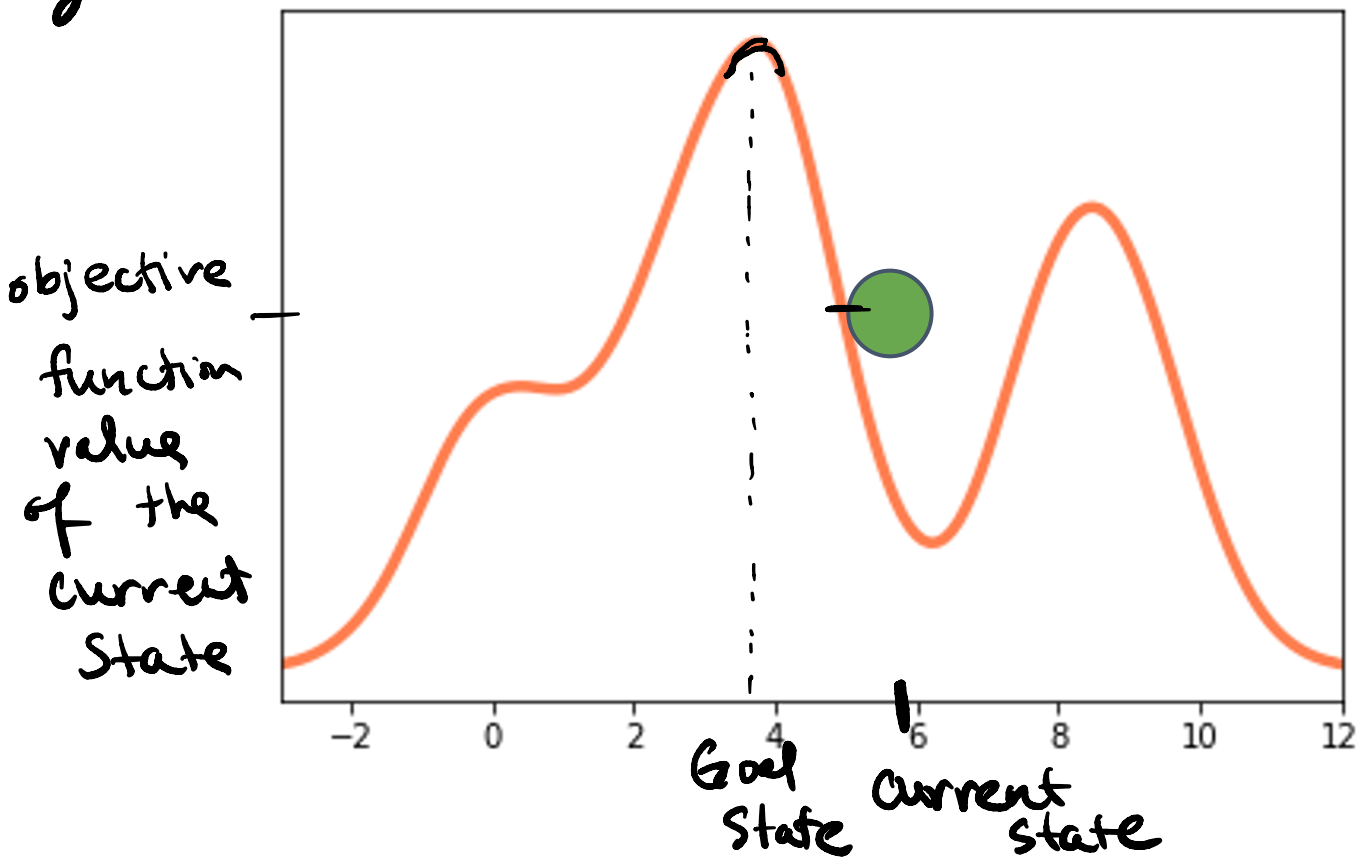


Local Search

Suppose the path to the goal **doesn't matter** to us.

- look at our neighboring states
- compute the objective function value of the neighboring states
- choose state with max value to move to.



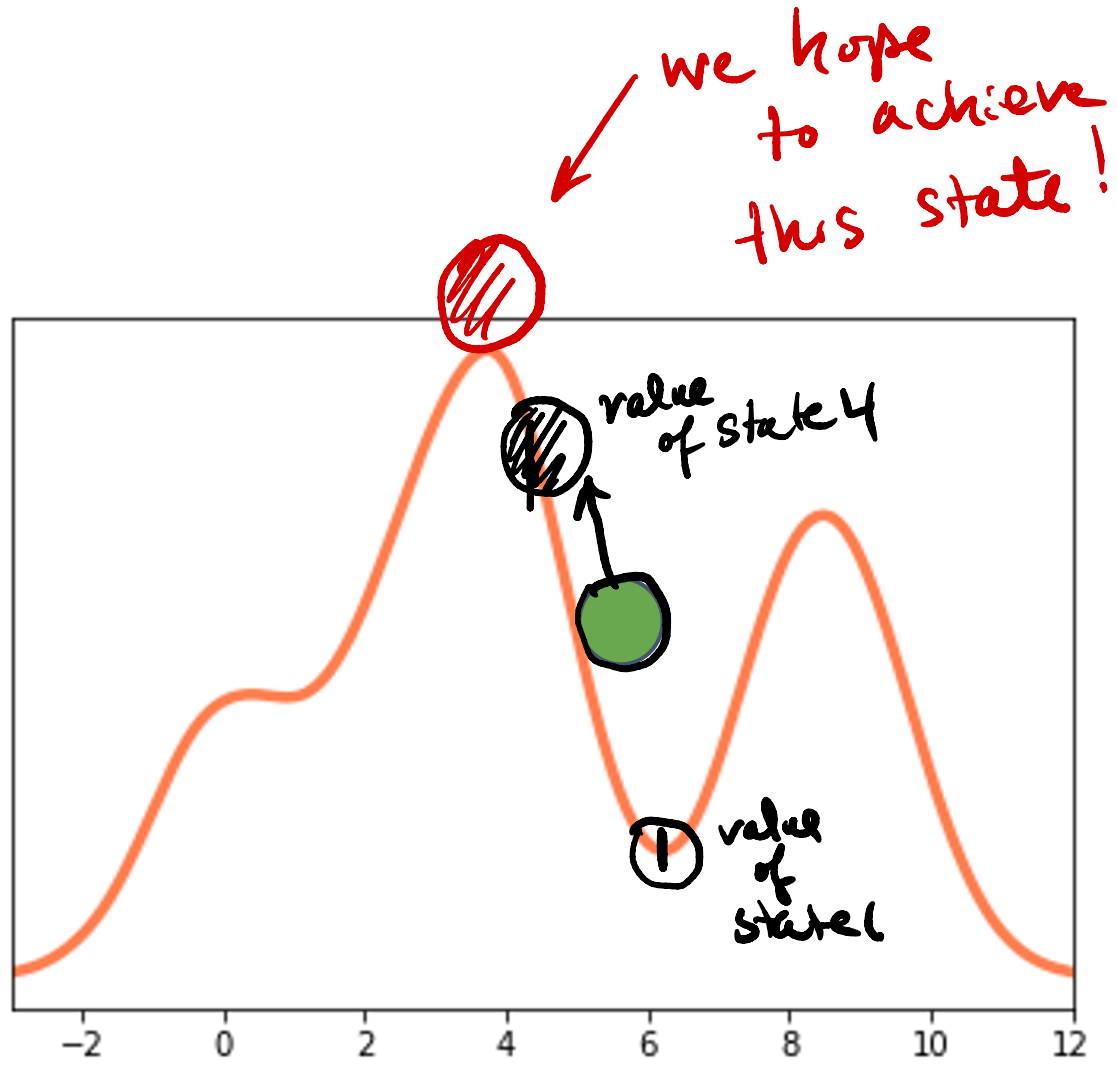
Local Search

Local search:

- Use only the current node/state
- And consider only moves to neighbor states
- Super memory efficient (only care about current state)
- Used widely for **optimization**

  Find the "best" state according to some **objective function**

  (think: minimizing a loss, or maximizing a utility)

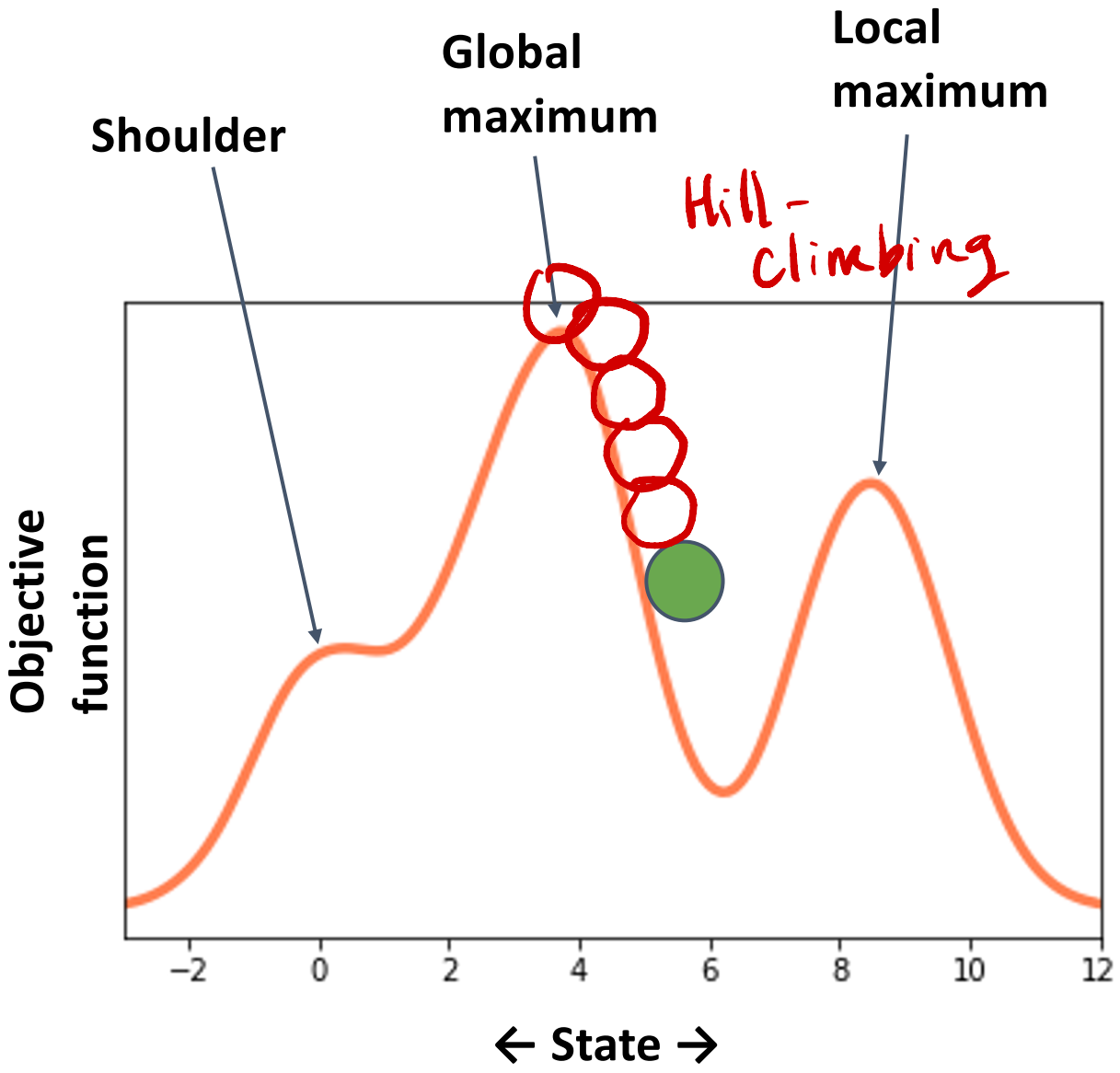


Local Search

Local search:

- Some terminology…

- A complete local search algorithm will always find the goal if one exists.
- An optimal local search algorithm will specifically find the global max or min.

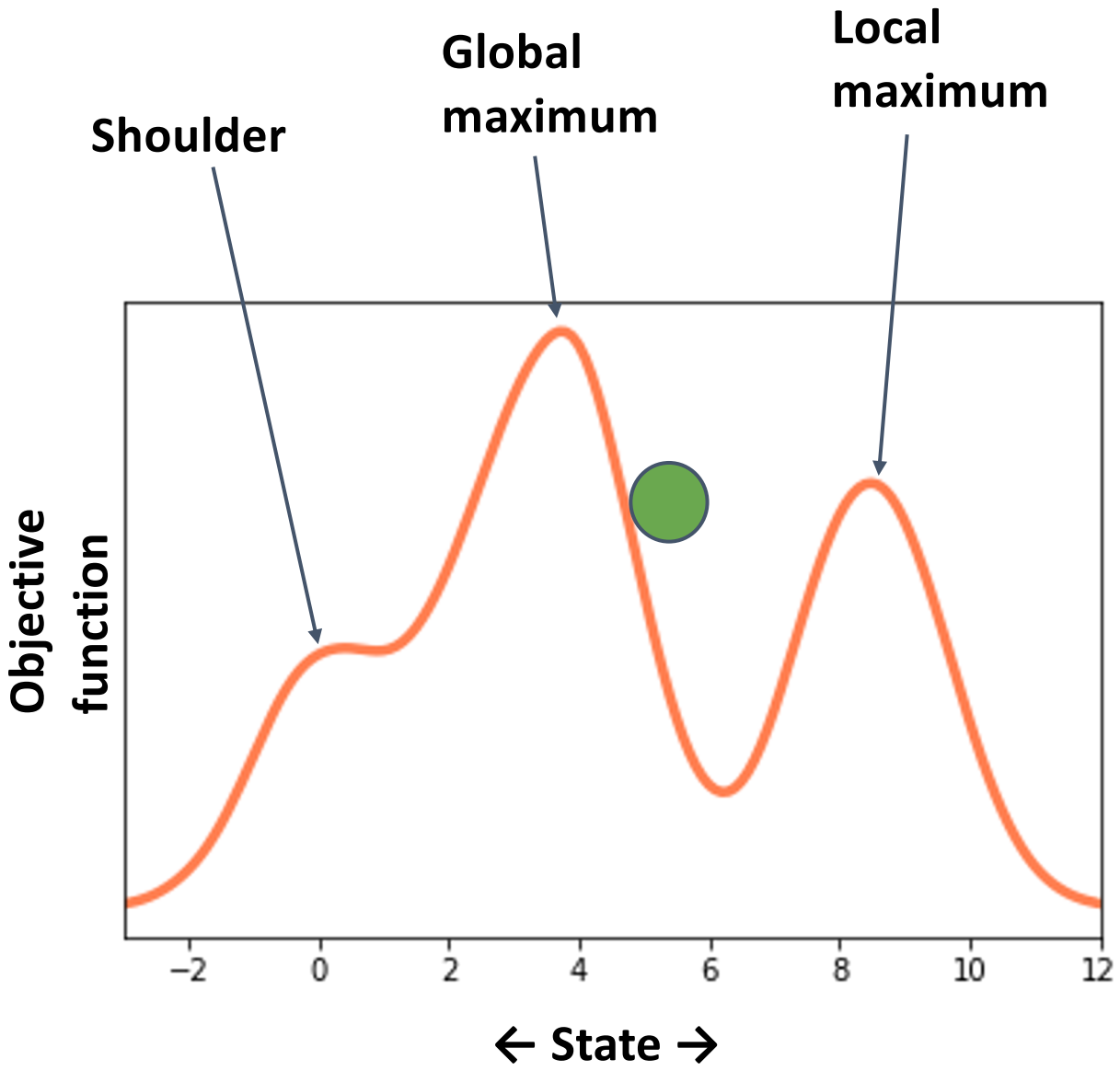


Hill Climbing

AKA: steepest ascent

Some words…

1) Start in some initial state
2) Get the neighbors of that state
3) Move to the neighbor with the best value of the objective function



Hill Climbing

Some potential issues…

- Hit a shoulder?
  (or local max.)

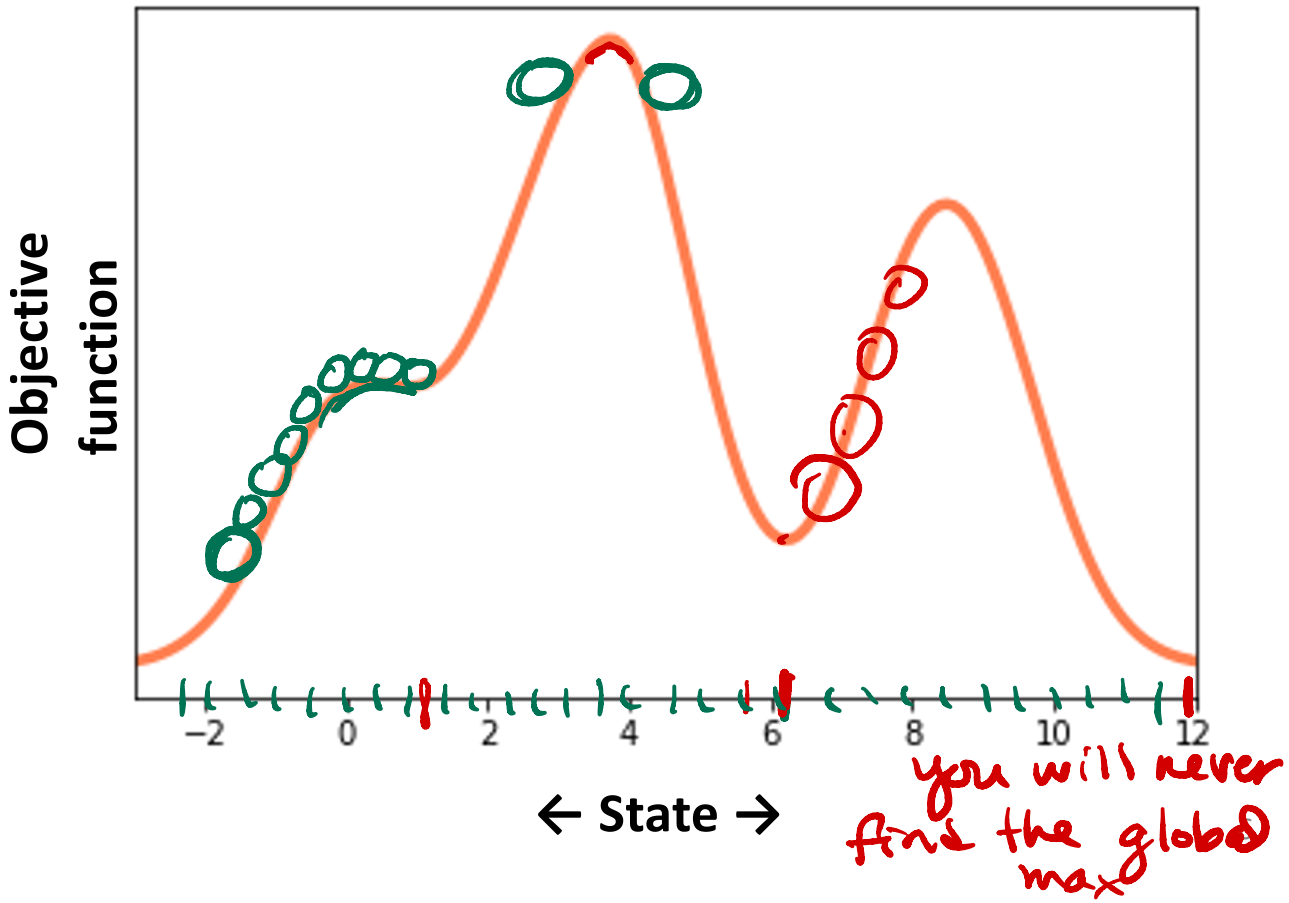
→ Permit **sideways moves**?

→ "Convergence" criteria?

→ **Stochastic** hill climbing

→ Random **restart**

→ simulated annealing



Hill Climbing

Some pseudocodes…

```
class state:

    # we need to be able to keep track of states and their associated
    # objective function values


class problem:

    # We want to include everything that defines the problem here:
    # - initial state
    # - current state
    # - what is the objective function we're trying to maximize/minimize?
    # - what are the choices of action that we have?
    # - what do we need to know to select our action?


def hill_climb(problem, number of iterations):

    for t in some number of iterations:
        1. get a list of our available moves
        2. which move optimizes the objective function?
        3. do that move; update our state
        4. possible goal/convergence check
```

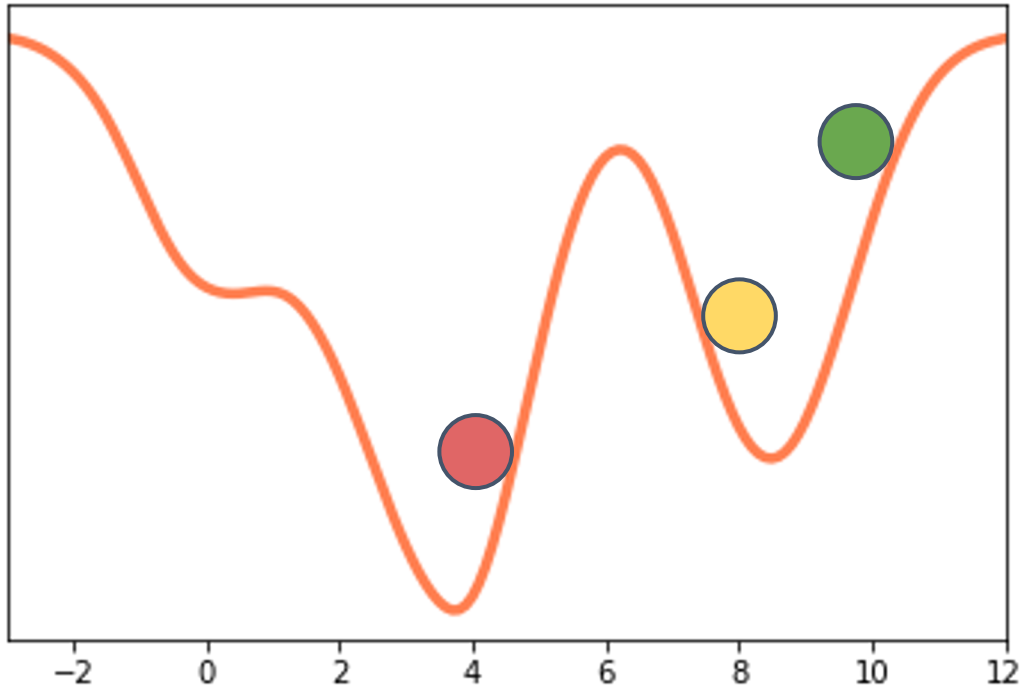
Annealing – Metallurgy

Visualization of what happens when you heat treat (e.g. Anneal) a metal: Video

Simulated Annealing

Trying to find global **minimum** (in this case)

- Propose **random** moves
- Accept with a probability that depends on:
  1) "temperature”
  2) how “good” the move is
     - ➢ Accept move without question if it’s better than our current situation
     - ➢ Accept move with some probability < 1 if it’s worse



Simulated Annealing

Visualization of Simulated Annealing: Video

Meant to mimic the slow cooling of metals.

Each new solution x_j is accepted with a temperature dependent probability.

probability function →

$$P_T = \begin{cases} 1 & \text{if } f(x_j) \le f(x_i) \\ e^{\frac{f(x_i)-f(x_j)}{kT}} & \text{if } f(x_j) \ge f(x_i) \end{cases}$$

new state is better → move with prob 1

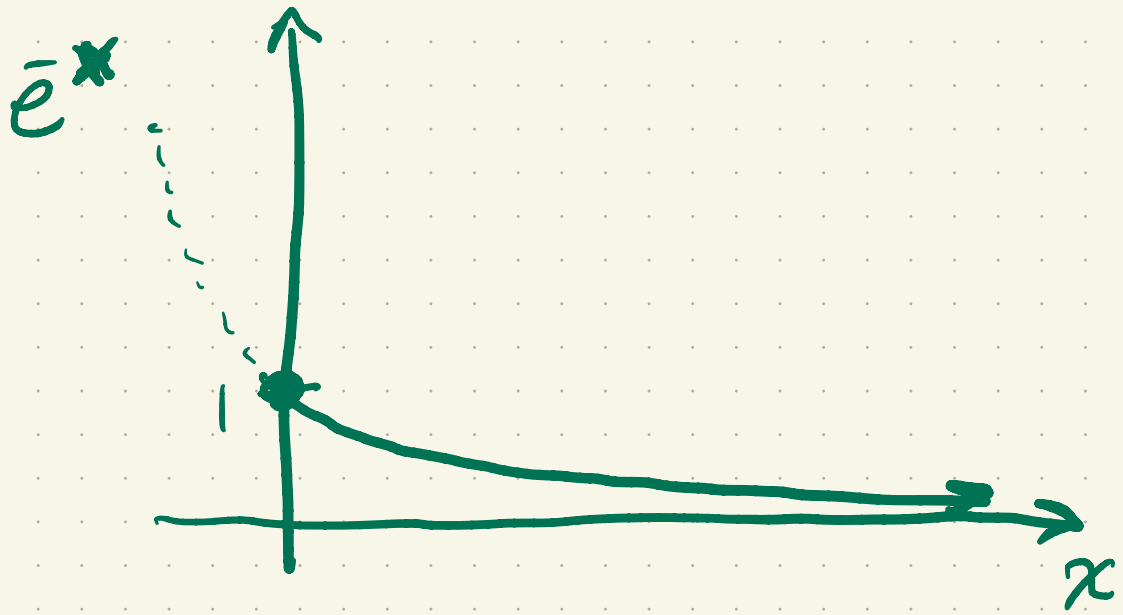
new is worse, you still might move there with prob > 0

f - objective function value

x_i, x_j states

T - current Temperature
k - Boltzmann constant

❖ Further reading - optimization is a huge area, we are only scratching the surface



e^{-x} will always provide an output between 0 and 1

S^* : proposed state

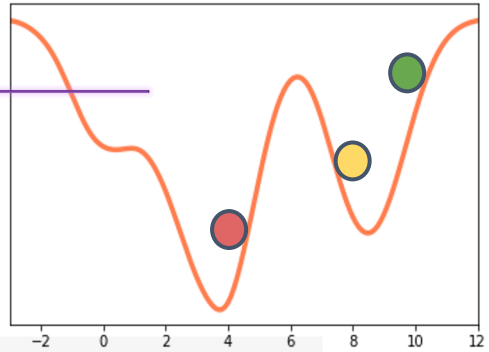
S_t : current state

minimize

$$f(S^*) > f(S_t)$$

$$P_{accept} = e^{\frac{-\Delta E}{T(t)}}$$

Simulated Annealing



Some pseudocode…

```
def schedule(time):
    '''some sort of mapping from time to temperature, to represent how we should be
    "cooling off" - that is, accepting wacky solutions with lower and lower probability'''
    # math goes here
    return temperature


def simulated_annealing(problem, some number of iterations):

    for t in some number of iterations:
        #1. update the "temperature", T(t) = schedule(time)
        #2. which moves can we make from the current node?
        #3. pick a random move
        #4. calculate difference in objective function between
        #   proposed new state and the current state (deltaE)
        #5. if proposed new state is better than the current state,
        #   then accept the proposed move with probability 1
        #6. otherwise...
        #         ACCEPT the move with probability exp(-deltaE/T(t)),
        #     or REJECT with prob 1-exp(-deltaE/T(t))
```

Next Time

- *Optimization!*
- *Genetic algorithms!*

But first…