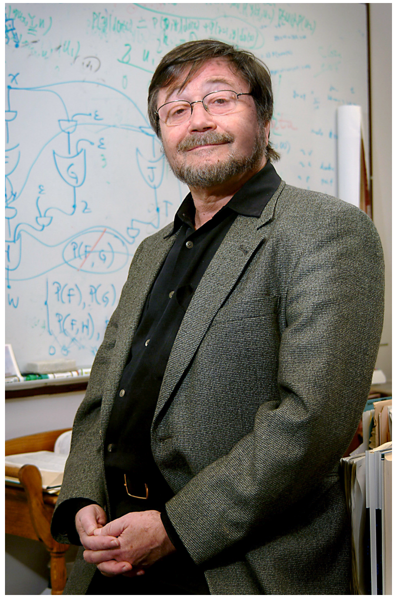

Artificial Intelligence

Local Search & Optimization

CS 444 – Spring 2021

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Much of this lecture is taken from
Dan Klein and Pieter Abbeel AI class at UC Berkeley

Announcements

- HW 2 is due tonight
- PA 1 is due this Monday, Feb 22
- First quiz is released today after class. It is due tomorrow by 5:00 pm tomorrow Friday).

Learning Objectives for Today

- Local Search
  - Hill Climbers
  - Evolutionary Algorithms
  - Beam Search

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Review of Search Problems/Methods so Far

- Uninformed and Informed Search
  - Systematic search
  - Assume finite state space (not always the case)
  - Environment may not be fully observable

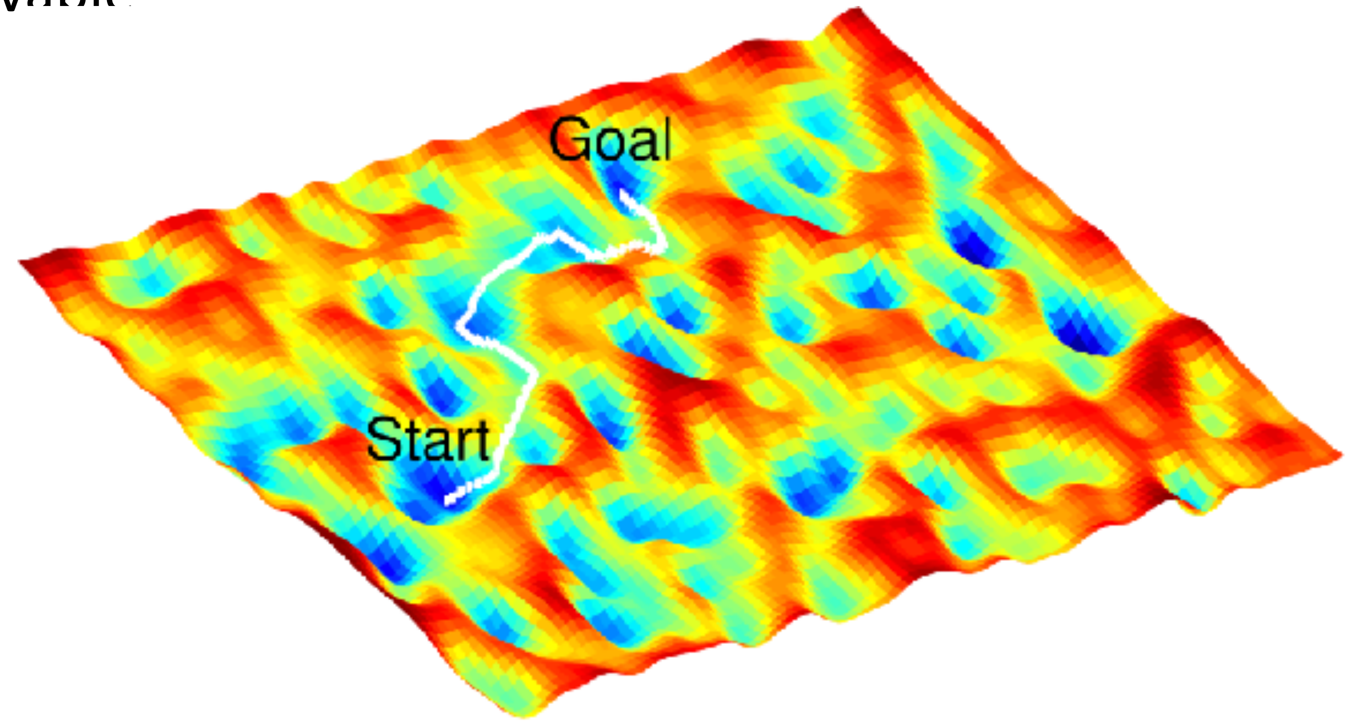


Figure from Berkley AI

Local Search

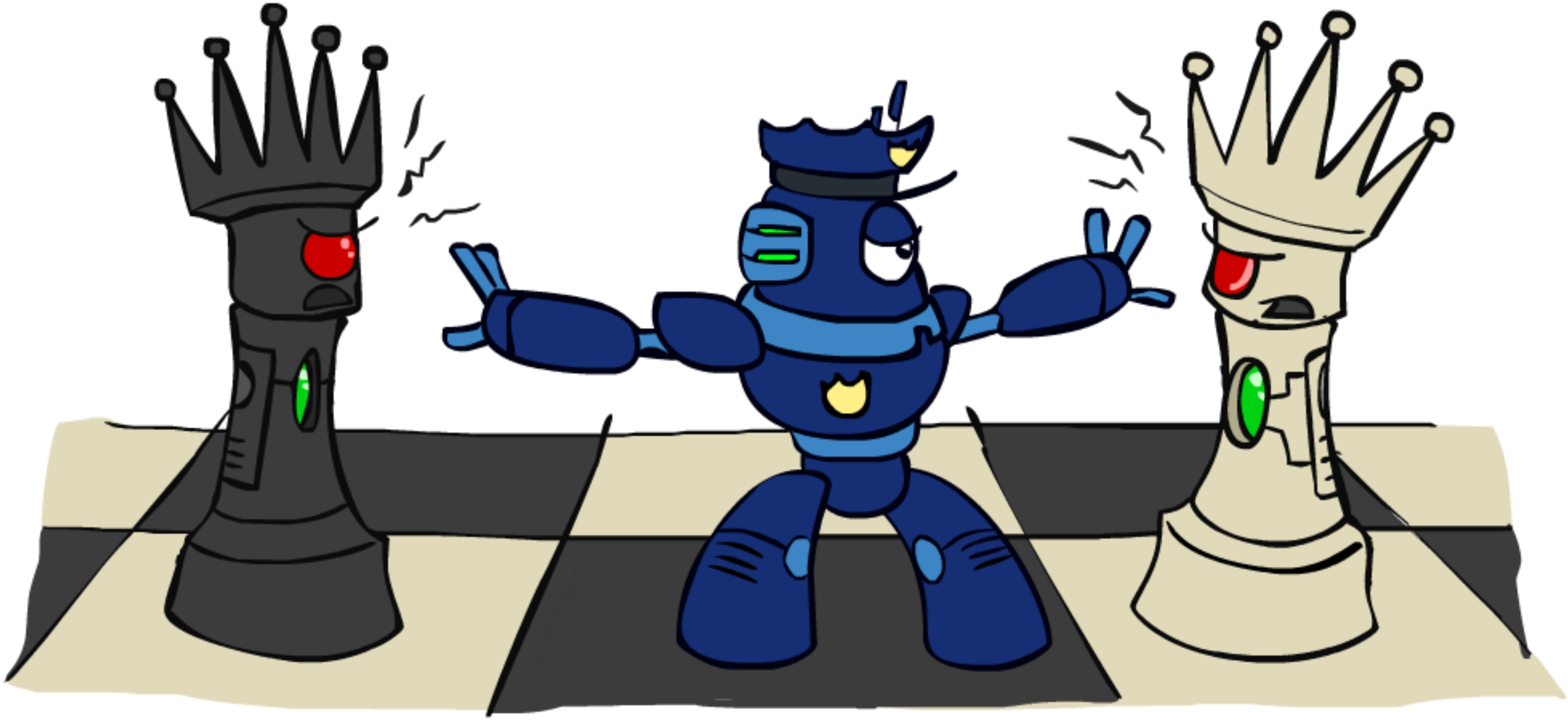
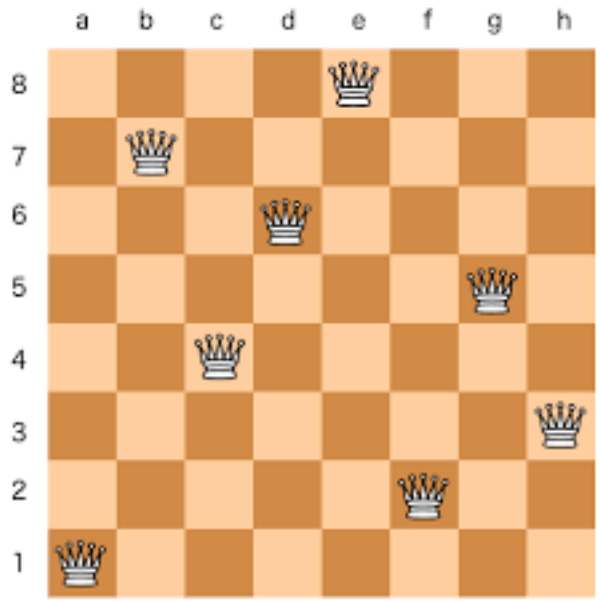
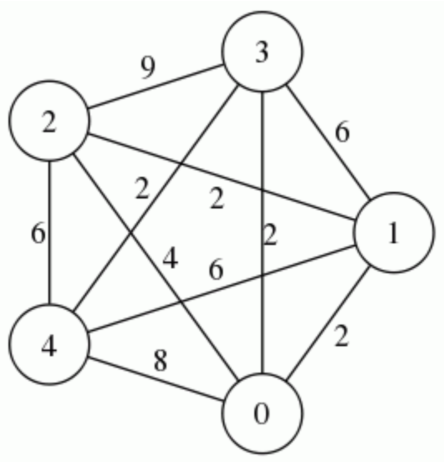


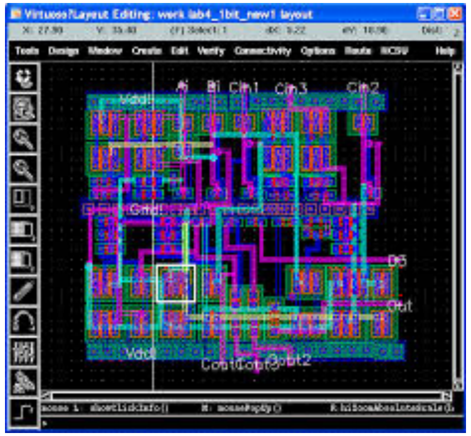
Figure from Berkley AI

Other Problems to Solve?

- Traveling Salemans Problem
- Placing N-queens on a chessboard so no queens can "attack" each other
- Design the layout of a circuit board
- Protein structure prediction







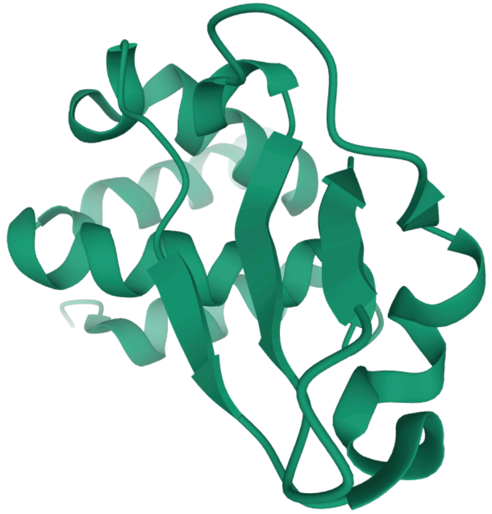


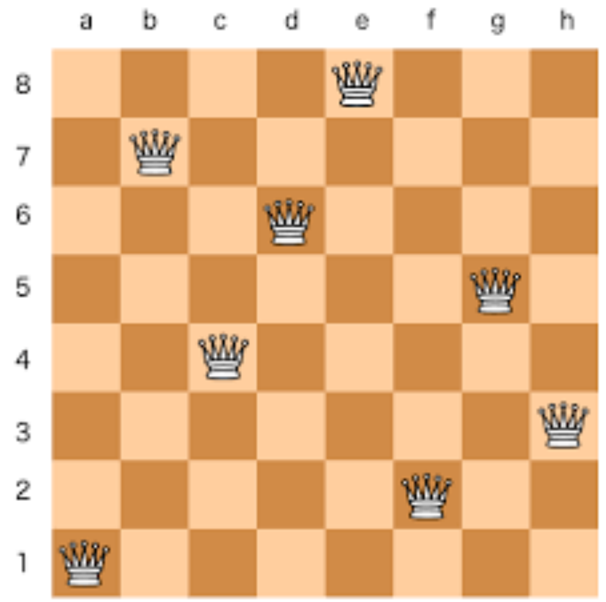
Figure from Berkley AI

Optimization Problems

Key Difference from problems so far?

- The goal itself is the solution. **No path required**
- The state space is a set of **complete** solutions.

Find the optimal configuration.



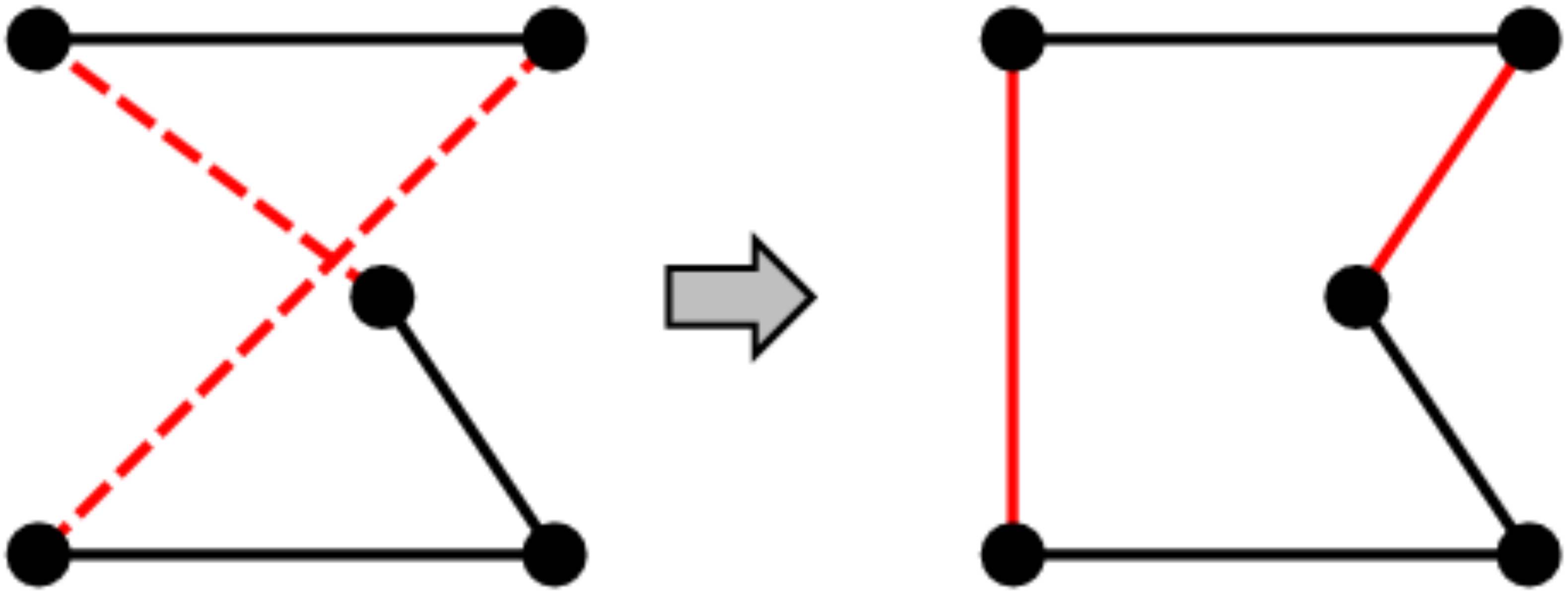
Key idea: **Iterative improvement**

- Keep a single "current" state, try to improve it. That is, no memory of what has been found so far, hence, sometimes called (memory-less) local search
- **Iterative** refers to iterating between states
- **Improvement** refers to later states improving some objective/goal function or satisfying more

Figure from Berkley AI

Example: Traveling Salesman Problem (TSP)

Start with any complete tour, perform pairwise exchanges

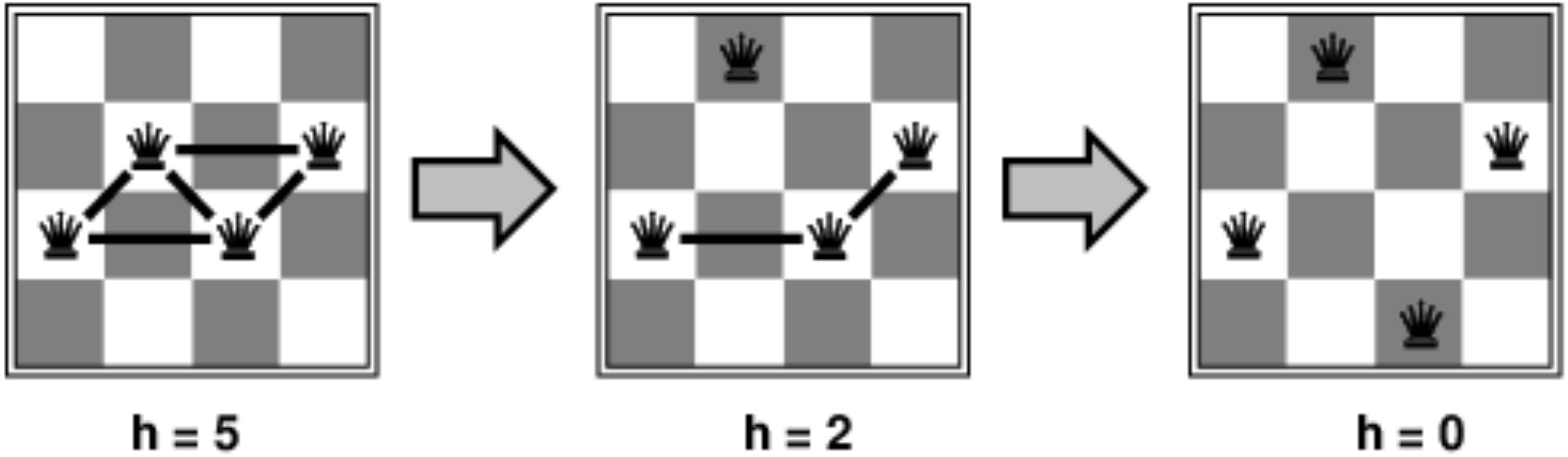


Variants of this approach get within **1%** of the optimal solution very quickly (even with thousands of cities)

Example: n-queens

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

Move a queen to reduce number of conflicts.



Local search techniques can solve this problem almost instantaneously for very large n (n = 1 million) (recall an 8x8 board has 8^8 states (≈ 17 million states).

Hill Climbing Algorithm

- Simple, general idea:
  - Start wherever
  - Repeat: move to the best neighboring state
  - If no neighbors better than current, quit

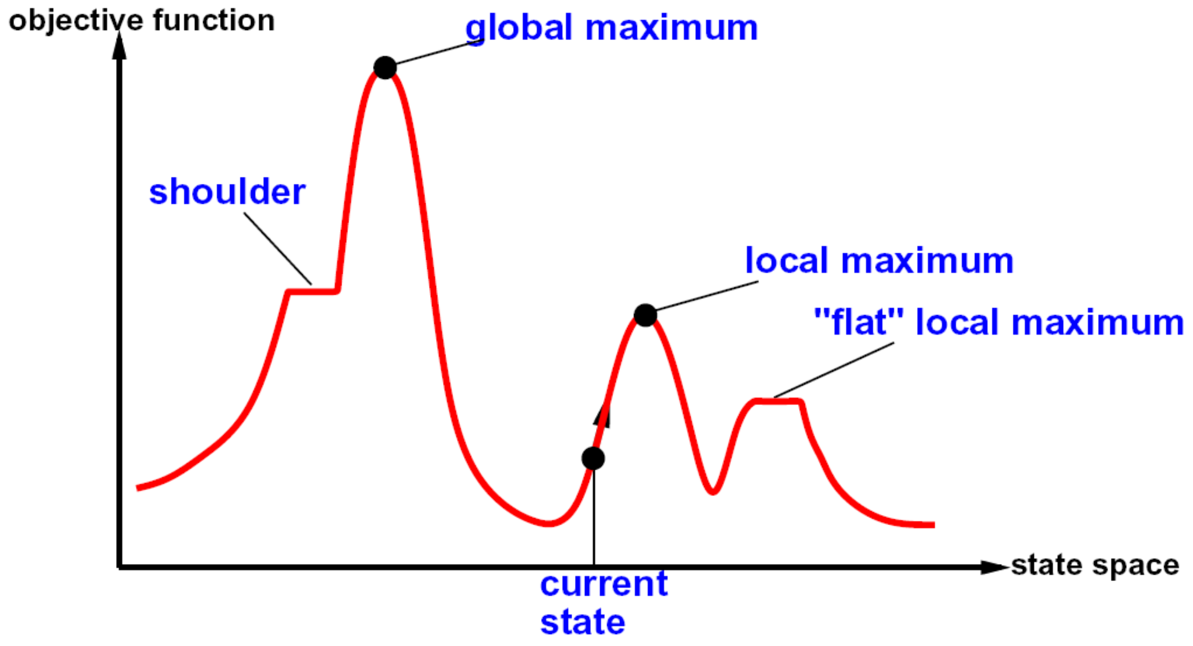
- What's bad about this approach?
  - Complete?
  - Optimal?

- What's good about it?

Figure from Berkley AI

Hill Climbing

function Hill-Climbing(problem) **returns** a state (local optimum)
    inputs: problem, a problem
    local variables: *current (a node)*
        neighbor (a node)
    current ← MAKE-NODE(INITIAL-STATE [problem])
    loop do
        neighbor ← a successor of current
        If Value[neighbor] **is not better than** Value[current]
            then return State ← [current]
        current ← neighbor
    end



Hill Climbing Generating Neighboring States

How is the neighbor of a current state generated? **Varies with approach…**

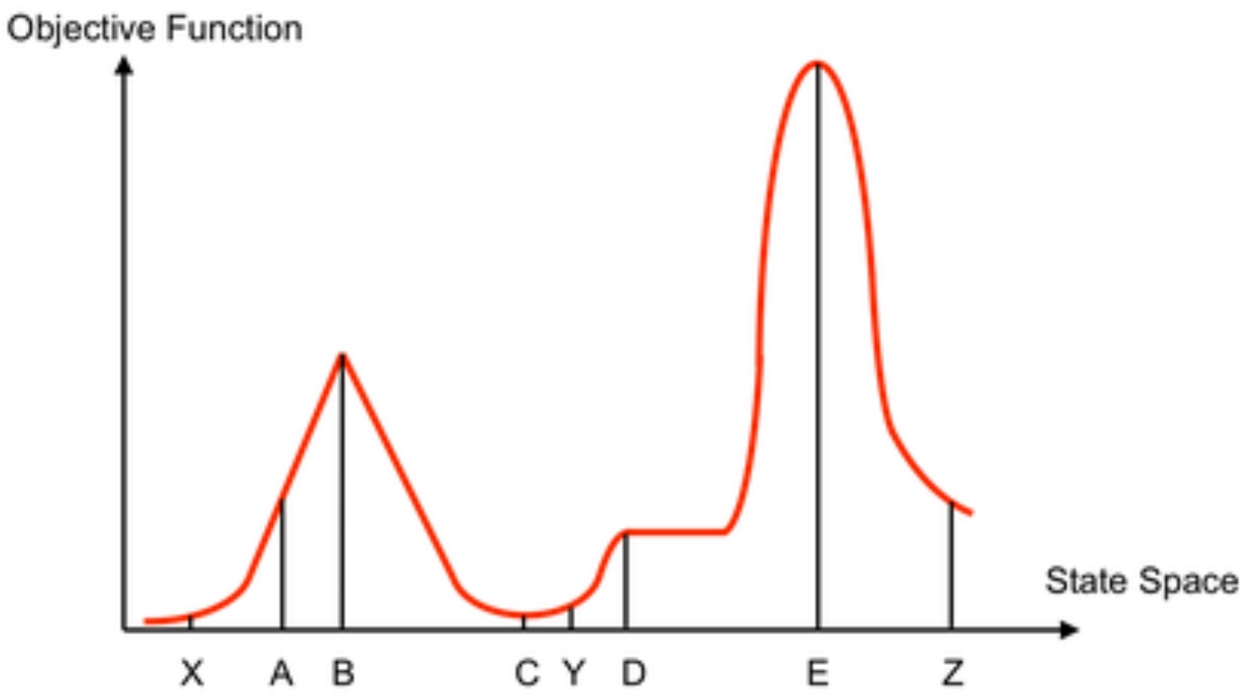
If state space is discrete and neighbor list is finite, all neighbors of a current state can be considered:

- **Steepest hill climbing**: compare best neighbor to current
- **First-choice hill climbers** use the first choice that is improves on current

What if neighbors cannot be enumerated? What if state space is continuous?

- **Stochastic hill climbing**: generate neighbor at random (continuous spaces, perform a small perturbation to generate neighbor)
- **Gradient-based variants**: for continuous state spaces
  - (Conjugate) Gradient Descent/Ascent
  - Other numerical optimization algorithms (beyond scope of CS 444)

Hill Climbing Quiz



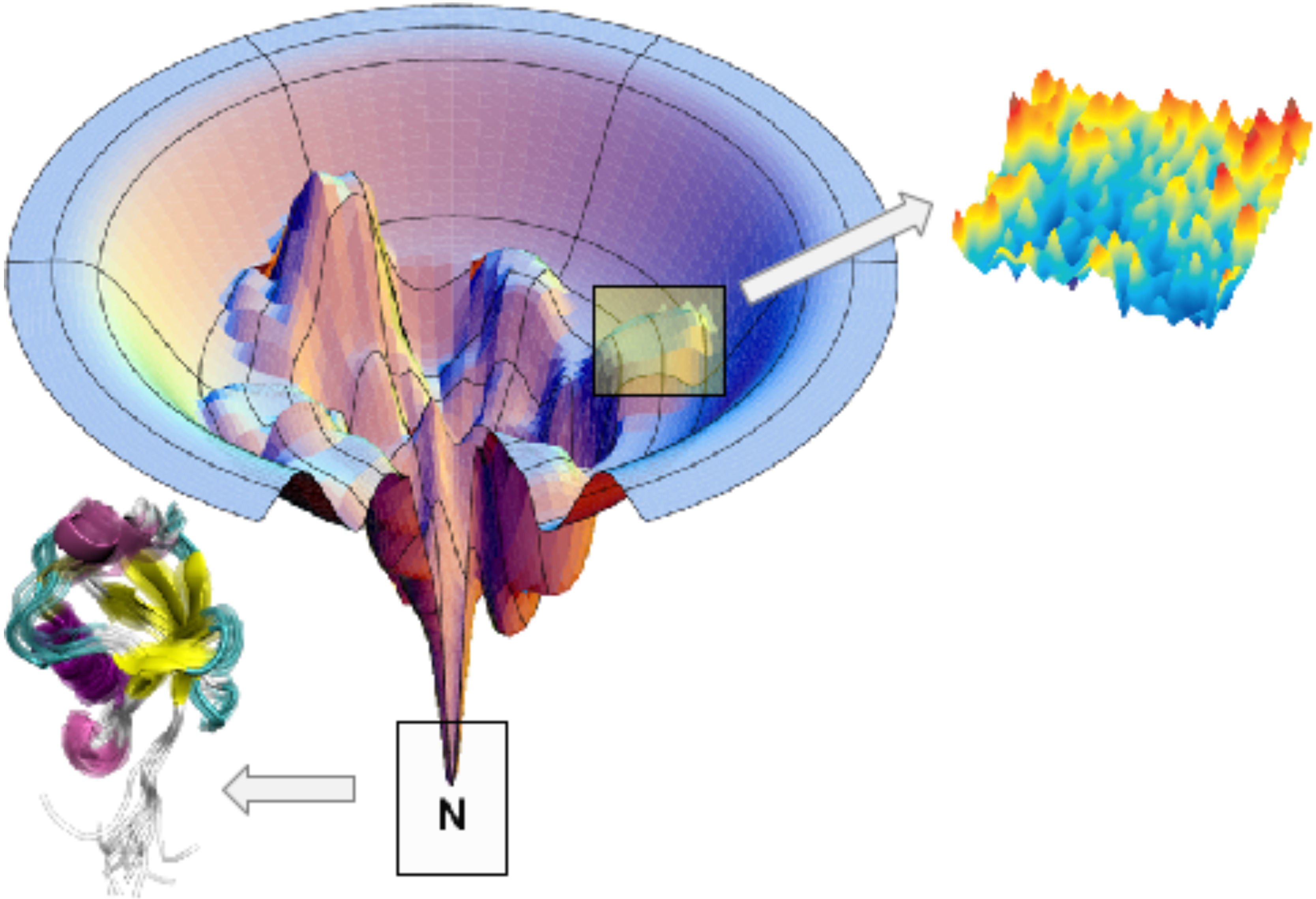
Starting from X, where do you end up ?

Starting from Y, where do you end up ?

Starting from Z, where do you end up ?

Figure from Berkley AI

Challenging Hill Climbing Landscape



Funnell landscape from Ken Dill

Dealing with Local Optima

Randomization:

- Random/multi restart allows embarrassing parallelization
- Iterated Local Search (ILS)

Memory-less randomized/stochastic search optimization:

Monte Carlo search

Simulated Annealing Monte Carlo

Memory-based randomized search:

- Memory via search structure
  - List: tabu search
  - Tree-/graph based search
- Memory via population
  - Evolutionary search strategies
  - Evolutionary Algorithms (Eas)
  - Genetic Algorithms (GA)

Figure from Berkley AI

Random-Restart Hill Climbers

Idea: Launch multiple hill climbers from different initial states/configurations.

Bonus: Amenable to embarrassing parallelization.

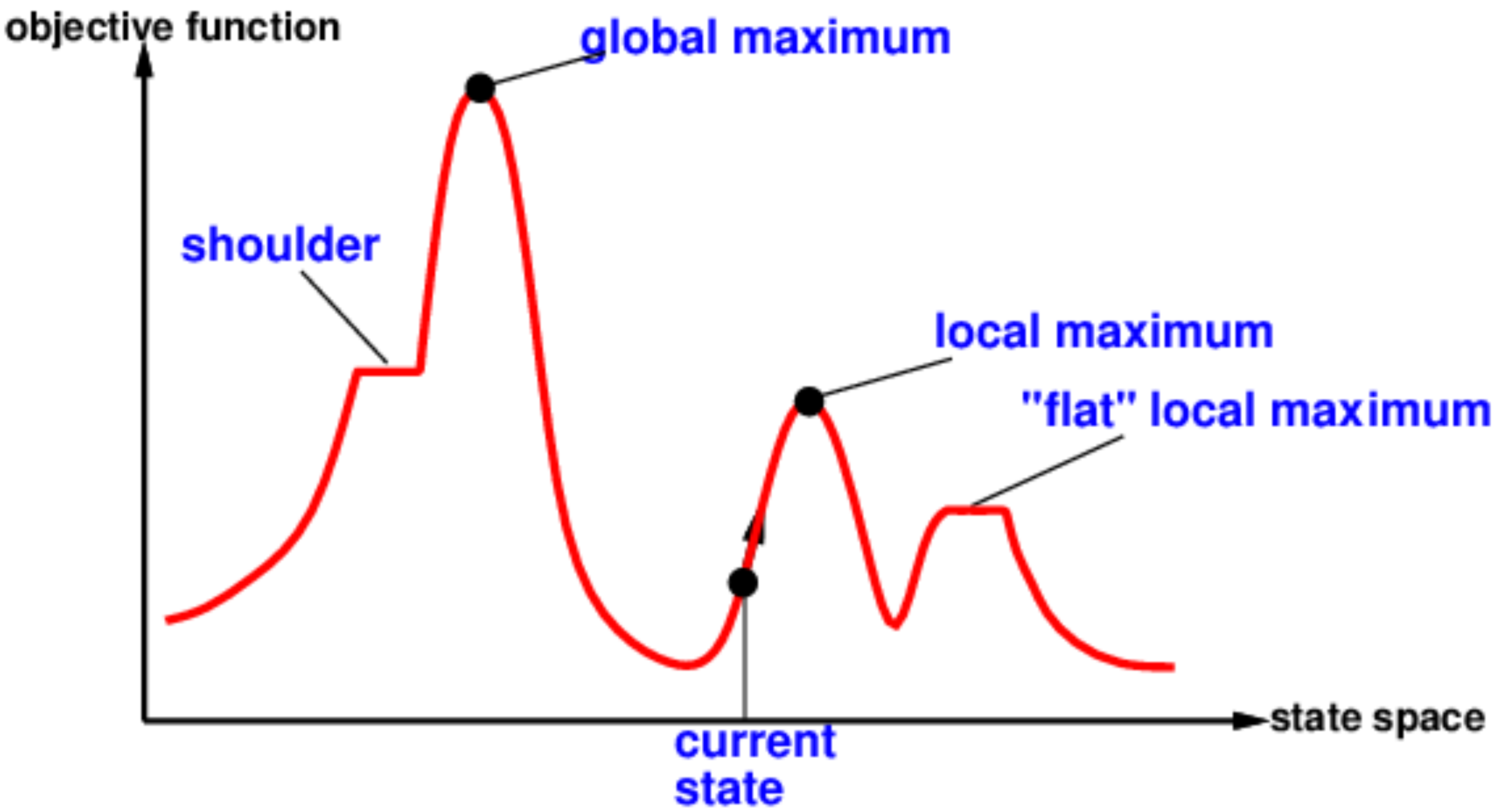
Take-away: It is often better to spend CPU time exploring the space, then carefully optimizing from an initial condition.

Why?

Repeated restarts give a global view of the state space (instead of just the local one provided by each climber).

Drawback? The hill climbers do not talk to one another.

Escaping a local maximum/minimum



How to escape from a local minimum?

Make a random move – this is what we call **Iterated Local Search (ILS)**

Figure from Berkley AI

Local Beam Search

Idea: Don't keep just a single state, keep *k* states.

Not the same a *k* searches in parallel!

Search that finds good states recruits other searches to join them

Generate *k* starting states at random.

REPEAT

For each state *k* generate a successor state

Pick the best *k* states from the set of 2*k states (the originals and the "offspring"*

Issues/Problems?

Quite often, all k states end up on some local "hill"

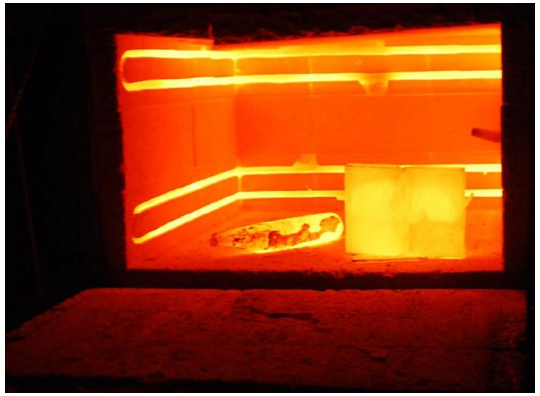
Solution: choose k successors randomly (biased towards "good" states". This is call Monte Carlo sampling (robotics/computer vision use this in particle filters).

Simulated Annealing

- Idea: Escape local maxima by allowing downhill moves
  - But make them rarer as time goes on

```
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)
```



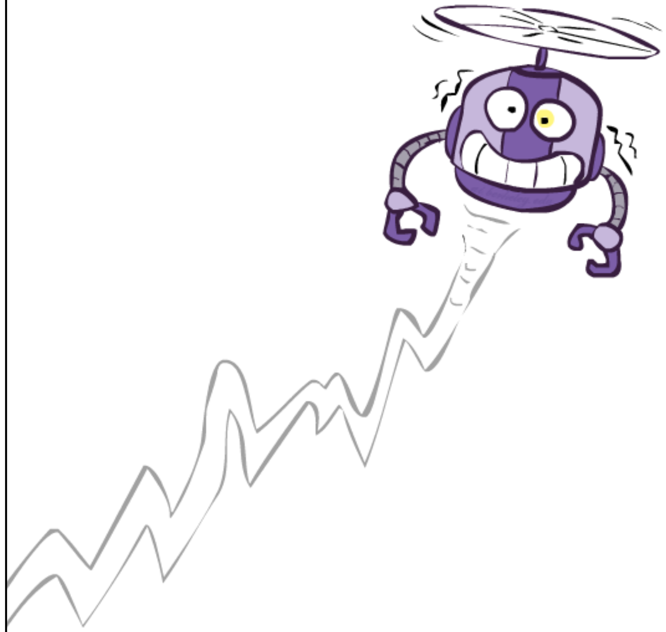


Figure from Berkley AI

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Simulated Annealing

- Theoretical guarantee:
  - Stationary distribution: $p(x) \propto e^{\frac{E(x)}{kT}}$
  - If T decreased slowly enough, will converge to optimal state!
- Is this an interesting guarantee?
- Sounds like magic, but reality is reality:
  - The more downhill steps you need to escape a local optimum, the less likely you are to ever make them all in a row
  - People think hard about *ridge operators* which let you jump around the space in better ways

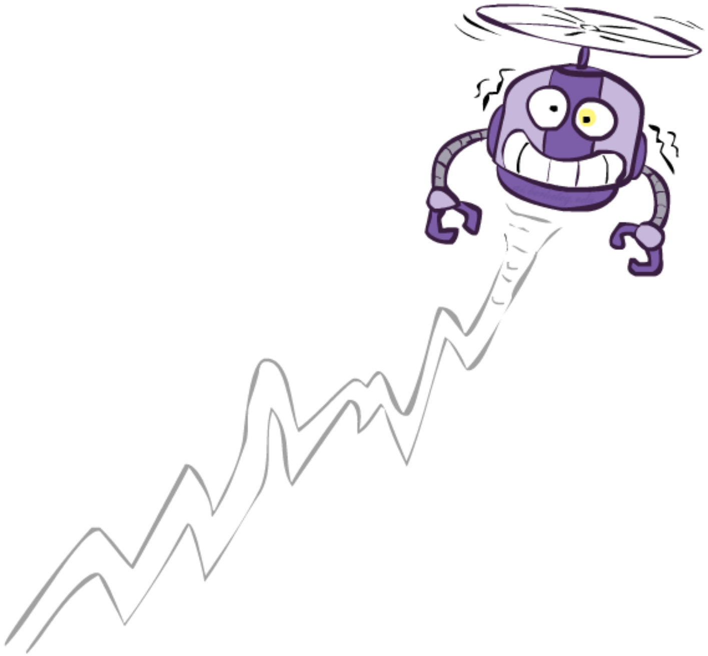
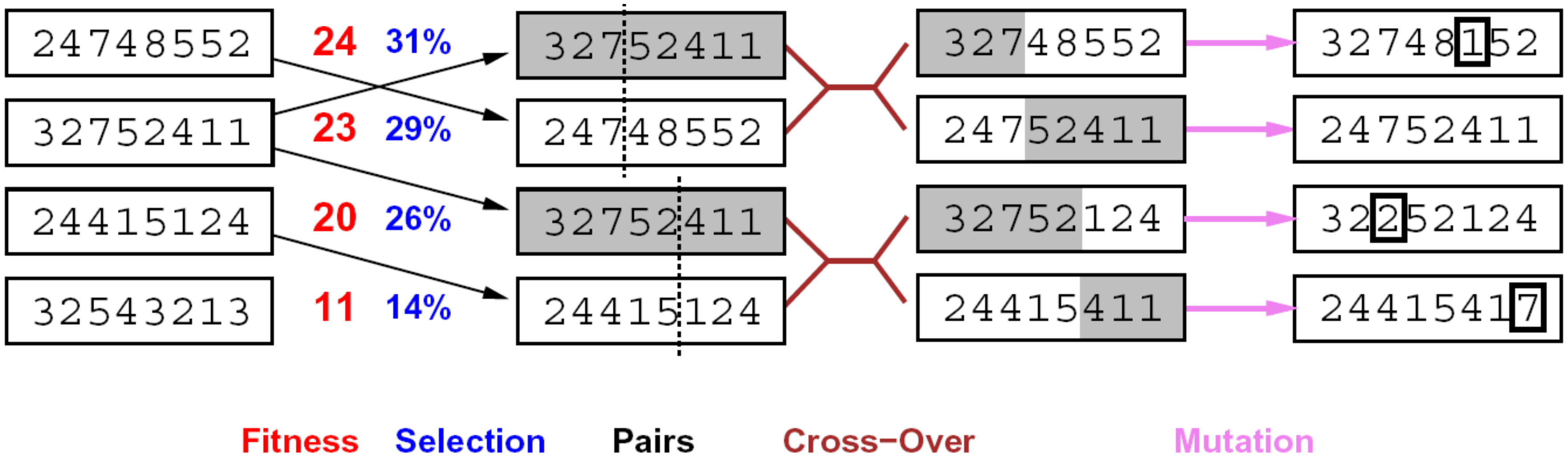
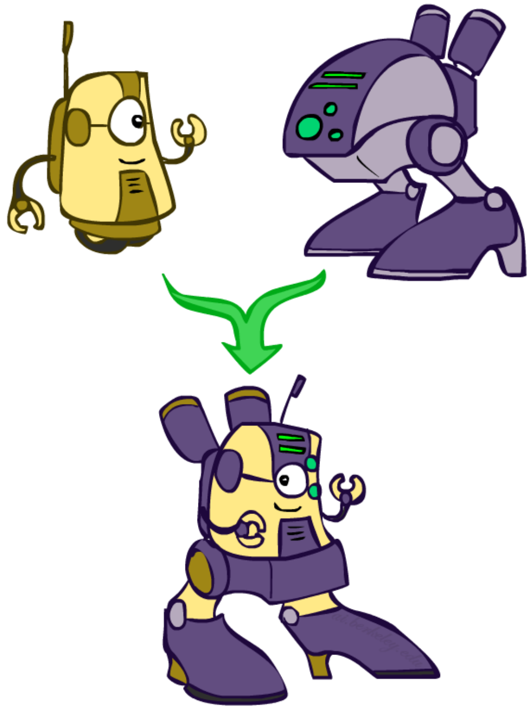


Figure from Berkley AI

Genetic Algorithms





- Genetic algorithms use a natural selection metaphor
  - Keep best N hypotheses at each step (selection) based on a fitness function
  - Also have pairwise crossover operators, with optional mutation to give variety
- Possibly the most misunderstood, misapplied (and even maligned) technique around