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# 343H: Honors AI

Week 3 – Beyond classical search

# Today

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- Review of A\* and admissibility
- Graph search
- Consistent heuristics
- Local search
  - Hill climbing
  - Simulated annealing
  - Genetic algorithms
  - Continuous search spaces



DOTA)RU

MerkurysMusings.com

# Local Search Methods

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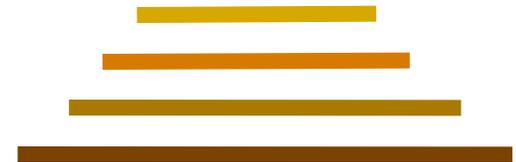
- Tree search keeps unexplored alternatives on the fringe (ensures completeness)
- Local search: improve what you have until you can't make it better
- Tradeoff: Generally much faster and more memory efficient (but incomplete)

# Types of Search Problems

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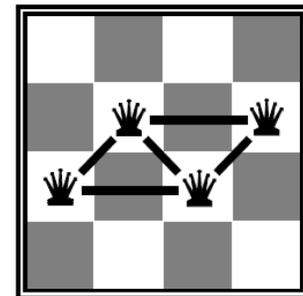
- **Planning problems:**

- We want a path to a solution (examples?)
- Usually want an optimal path
- *Incremental formulations*



- **Identification problems:**

- We actually just want to know what the goal is (examples?)
- Usually want an optimal goal
- *Complete-state formulations*
- Iterative improvement algorithms



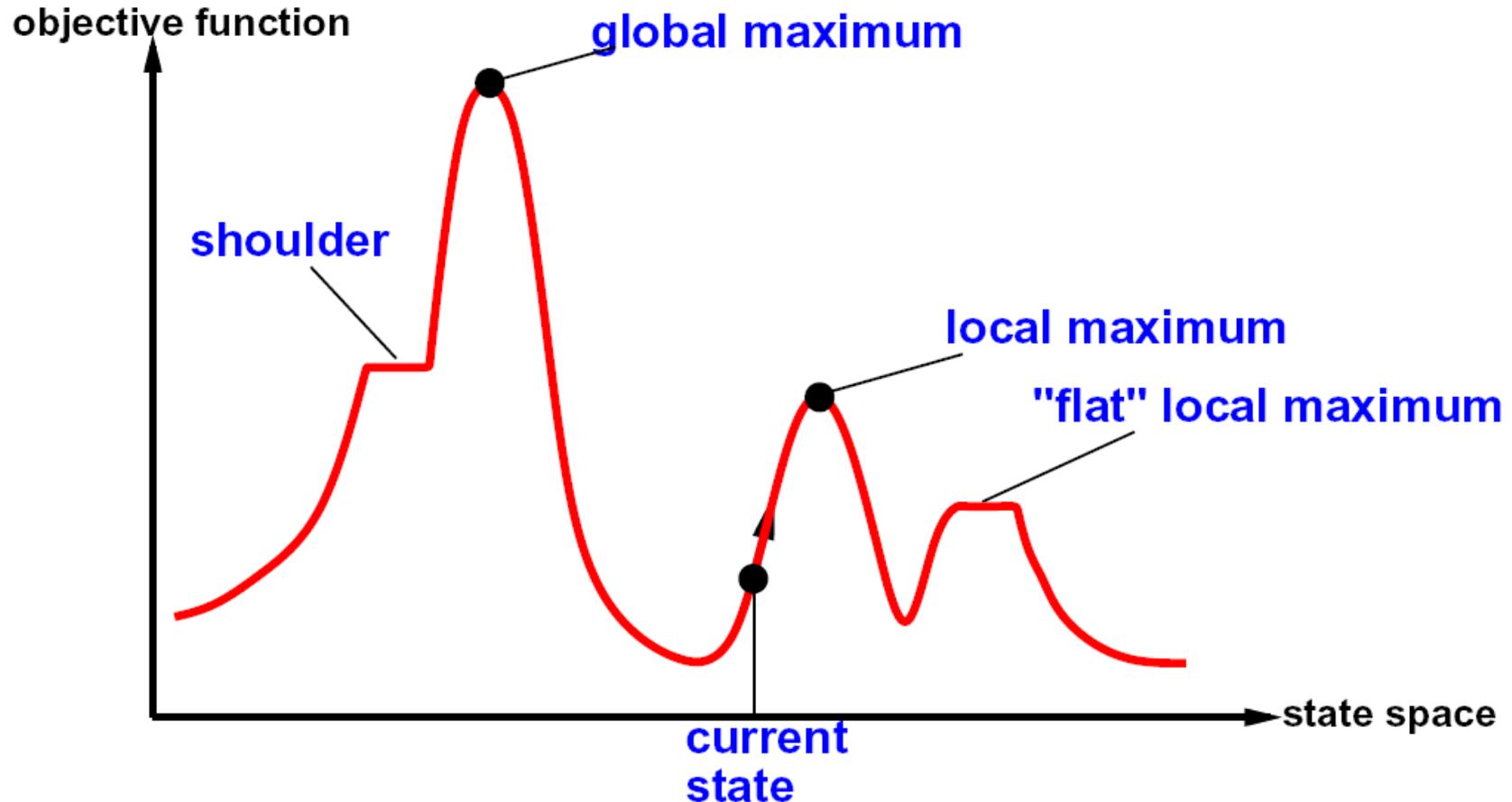
# Hill Climbing

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- Simple, general idea:
  - Start wherever
  - Always choose the best neighbor
  - If no neighbors have better scores than current, quit
- Why can this be a terrible idea?
  - Complete?
  - Optimal?
- What's good about it?

# Hill Climbing Diagram



- Sideways steps?
- Random restarts?

MOM????



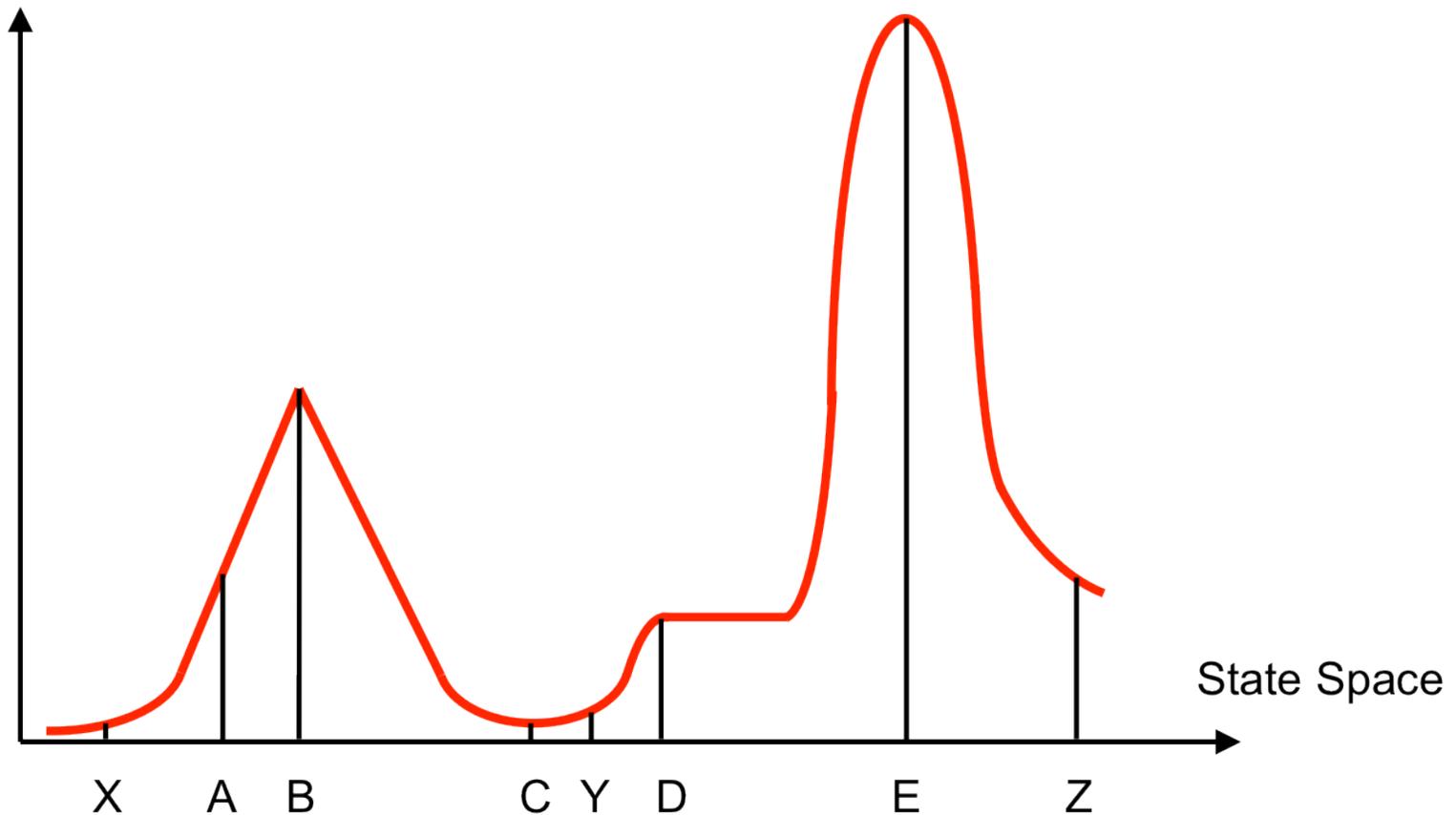
*“Many real problems have a landscape that looks more like a widely scattered family of balding porcupines on a flat floor, with miniature porcupines living on the tip of each porcupine needle, ad infinitum.” [Russell & Norvig]*

# Quiz

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- Hill climbing on this graph:

Objective Function



# Hill climbing Mona Lisa

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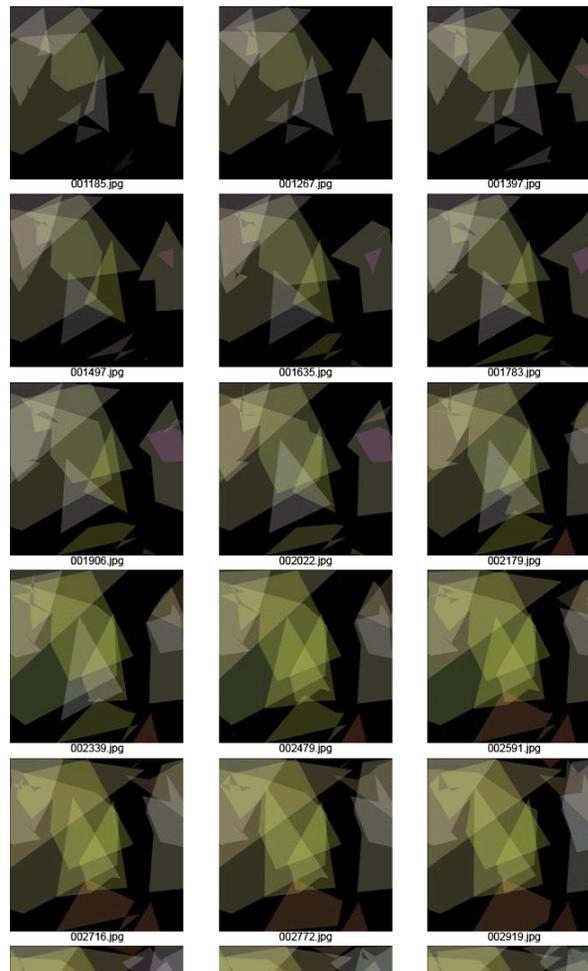
Could the computer paint a replica of the Mona Lisa using only 50 semi transparent polygons?



# Hill climbing Mona Lisa

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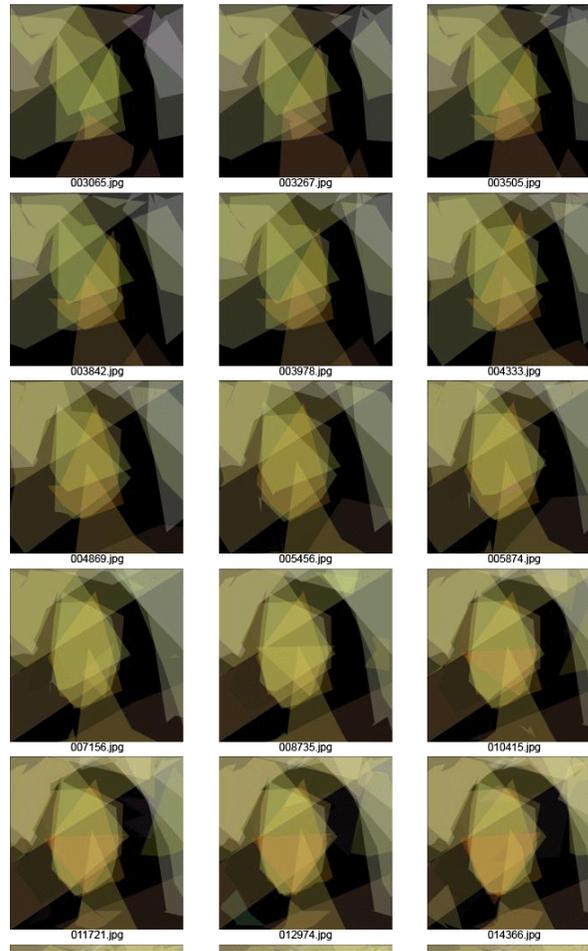
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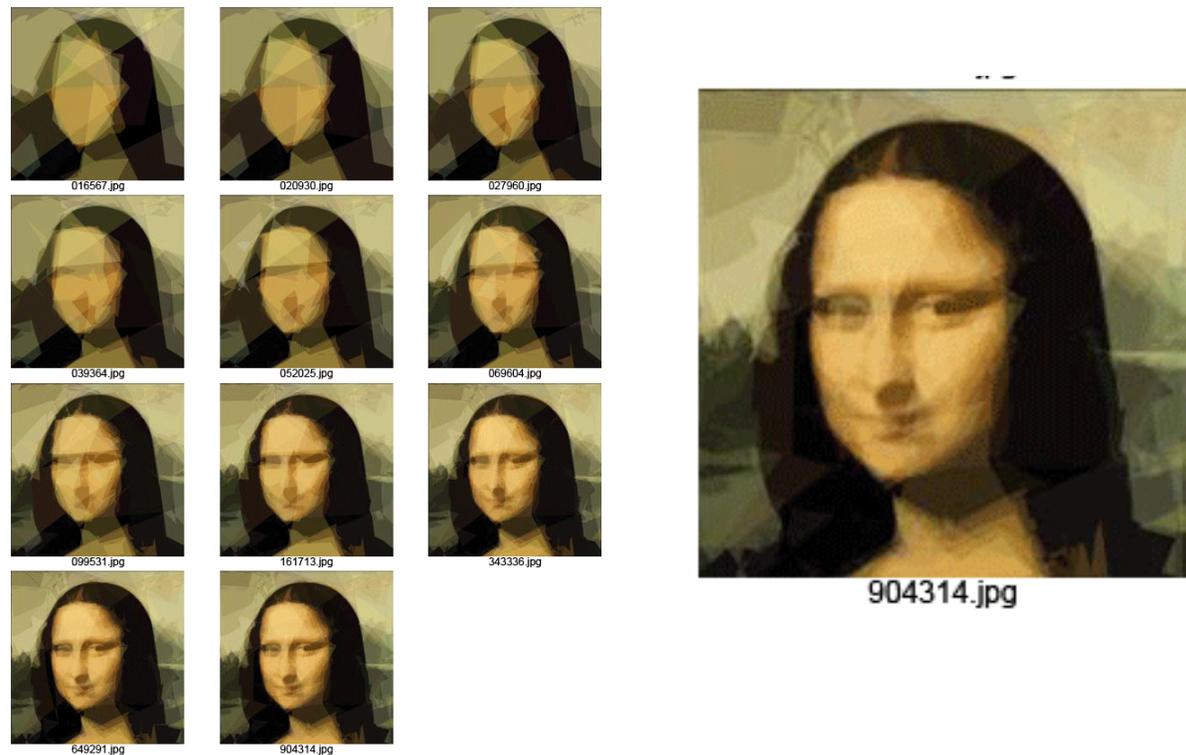
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# Hill climbing Mona Lisa

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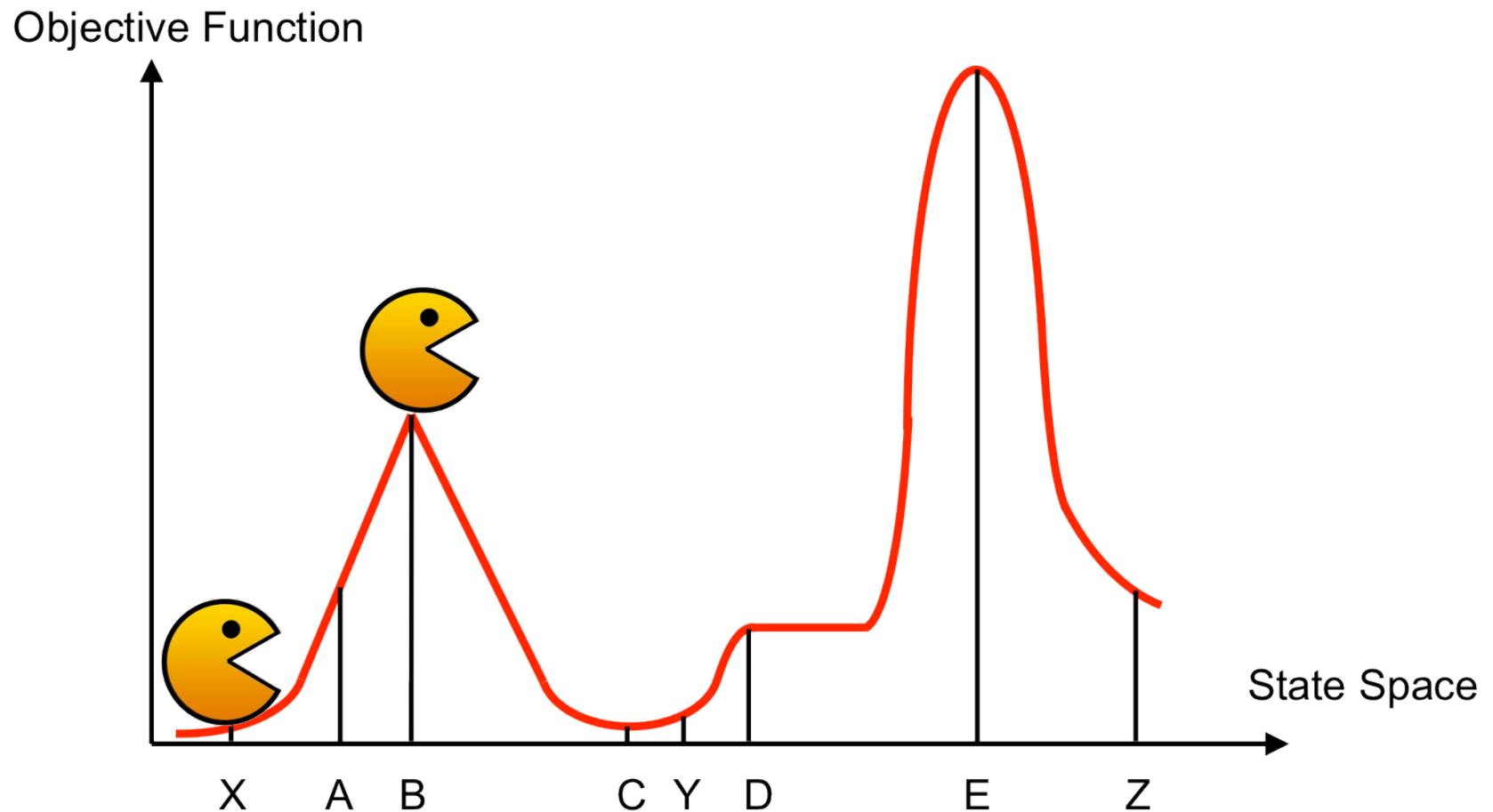
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- <http://rogersaling.com/2008/12/07/genetic-programming-evolution-of-mona-lisa/>

# Accepting bad moves

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# 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*]

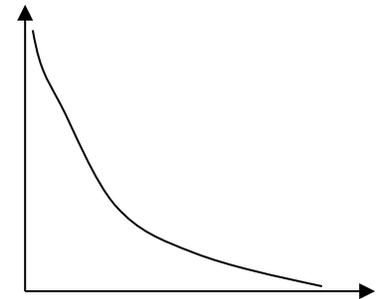
**if** *T* = 0 **then return** *current*

*next* ← a randomly selected successor of *current*

$\Delta E$  ← VALUE[*next*] – VALUE[*current*]

**if**  $\Delta E > 0$  **then** *current* ← *next*

**else** *current* ← *next* only with probability  $e^{-\Delta E/T}$



# Simulated Annealing

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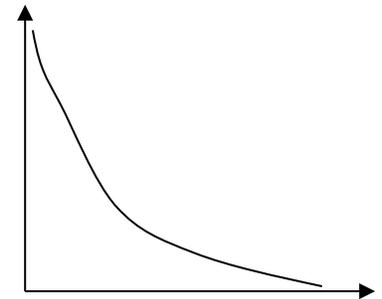
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# Simulated Annealing

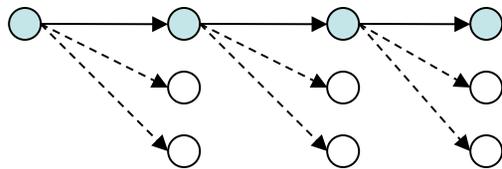
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- Theoretical guarantee:
  - Stationary distribution:  $p(x) \propto e^{-\frac{E(x)}{kT}}$
  - If T decreased slowly enough, will converge to optimal state!
- Is this an interesting guarantee?
- Sounds like magic, but reality is reality:
  - The more downhill steps you need to escape, 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

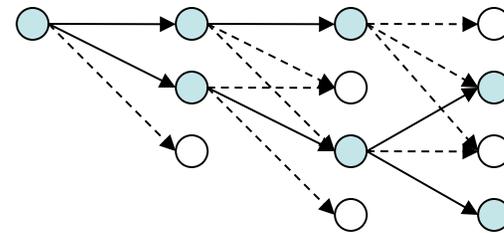
# Beam Search

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- Like greedy hillclimbing search, but keep K states at all times:



Greedy Search



Beam Search

- Variables: beam size, encourage diversity?
- The best choice in many practical settings

# Genetic Algorithms

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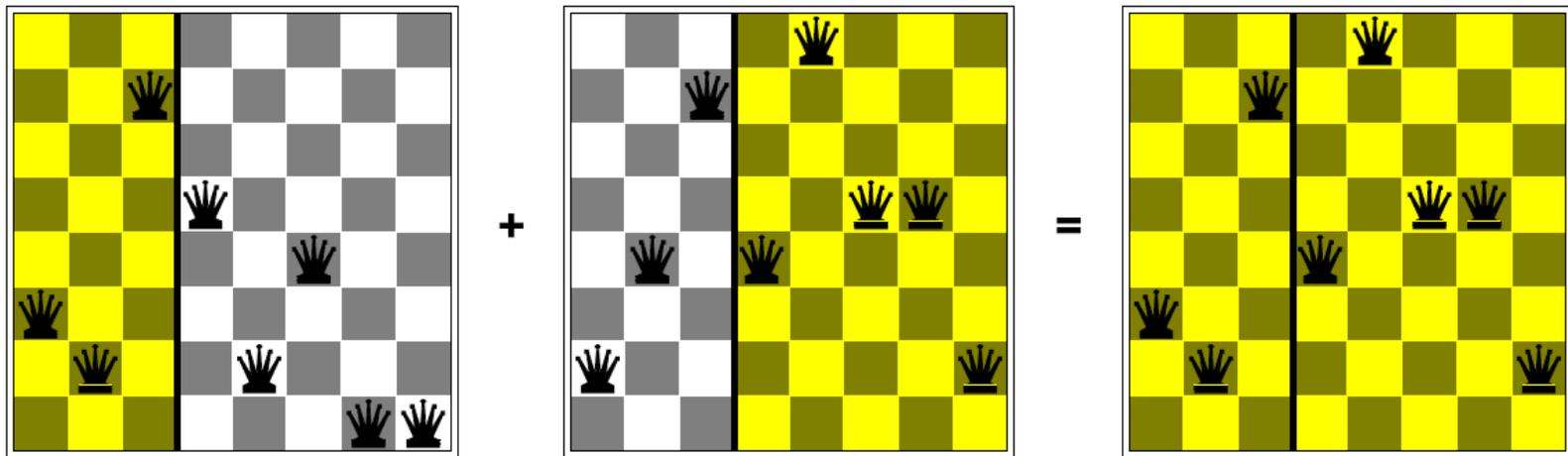
24748552	24
32752411	23
24415124	20
32543213	11

Fitness

- Genetic algorithms use a natural selection metaphor
- Like beam search (selection), but also have pairwise crossover operators, with optional mutation

# Example: N-Queens

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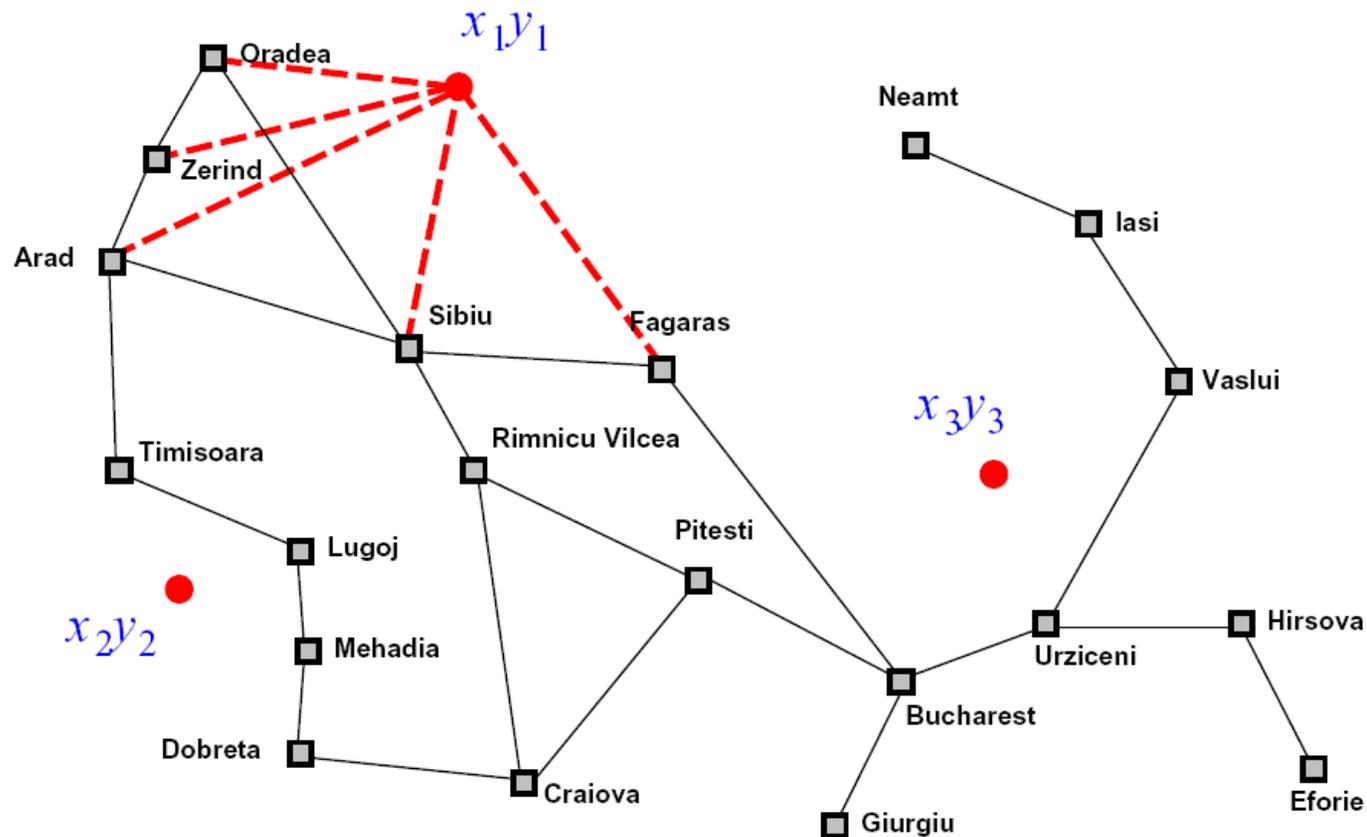
- Why does crossover make sense here?
- When wouldn't it make sense?
- What would mutation be?
- What would a good fitness function be?

# Exercise 4.1

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# Continuous Problems

- Placing airports in Romania
  - States:  $(x_1, y_1, x_2, y_2, x_3, y_3)$
  - Cost: sum of squared distances to closest city



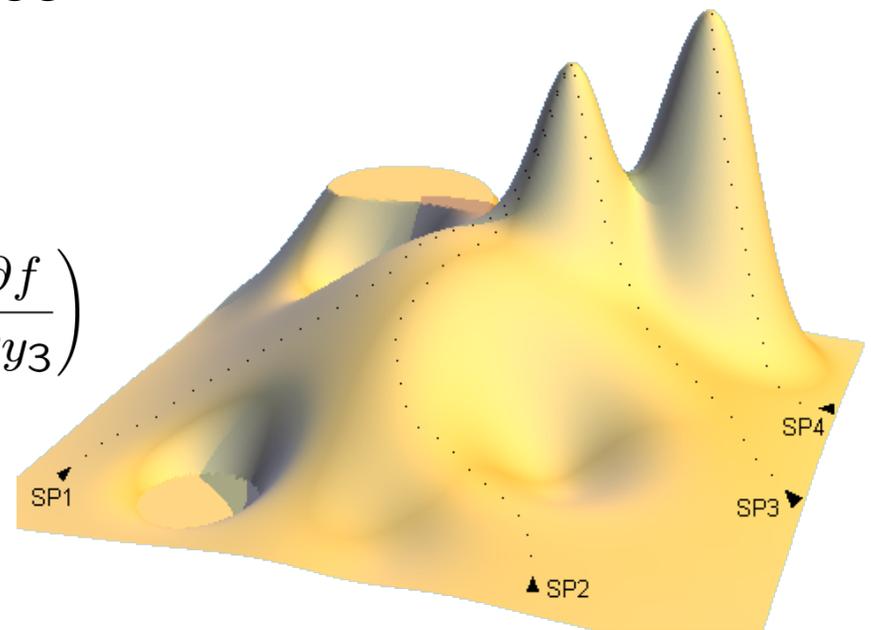
# Gradient Methods

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- How to deal with continuous (therefore infinite) state spaces?
- Discretization: bucket ranges of values
  - E.g. force integral coordinates
- Continuous optimization
  - E.g. gradient ascent

$$\nabla f = \left( \frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial y_1}, \frac{\partial f}{\partial x_2}, \frac{\partial f}{\partial y_2}, \frac{\partial f}{\partial x_3}, \frac{\partial f}{\partial y_3} \right)$$

$$x \leftarrow x + \alpha \nabla f(x)$$



# Summary

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- Graph search
  - Keep closed set, avoid redundant work
- A\* graph search
  - Optimal if  $h$  is consistent
- Local search: Improve current state
  - Avoid local min traps (simulated annealing, crossover, beam search)