


Local Search

Toolbox so far

- Uninformed search
 - BFS, DFS, Iterative deepening DFS, Uniform cost search
- Heuristic search
 - A*

Review

- Search:
 - Use in environments that are static, discrete, 100% observable, deterministic.
- Things we care about:
 - Completeness, optimality, time/space complexity.



it's not the
DESTINATION
that matters,
it's the
JOURNEY

New Idea: **Local Search**

- Can be used when path from start state to goal doesn't matter (only the goal matters).
- Process is slightly different than "normal" search:
 - Nodes/states are always complete solutions to the problem, not partial solutions.
 - One **current node** is maintained that has the best solution at the moment.
 - **Actions** generate new nodes with new complete solutions.

Local Search

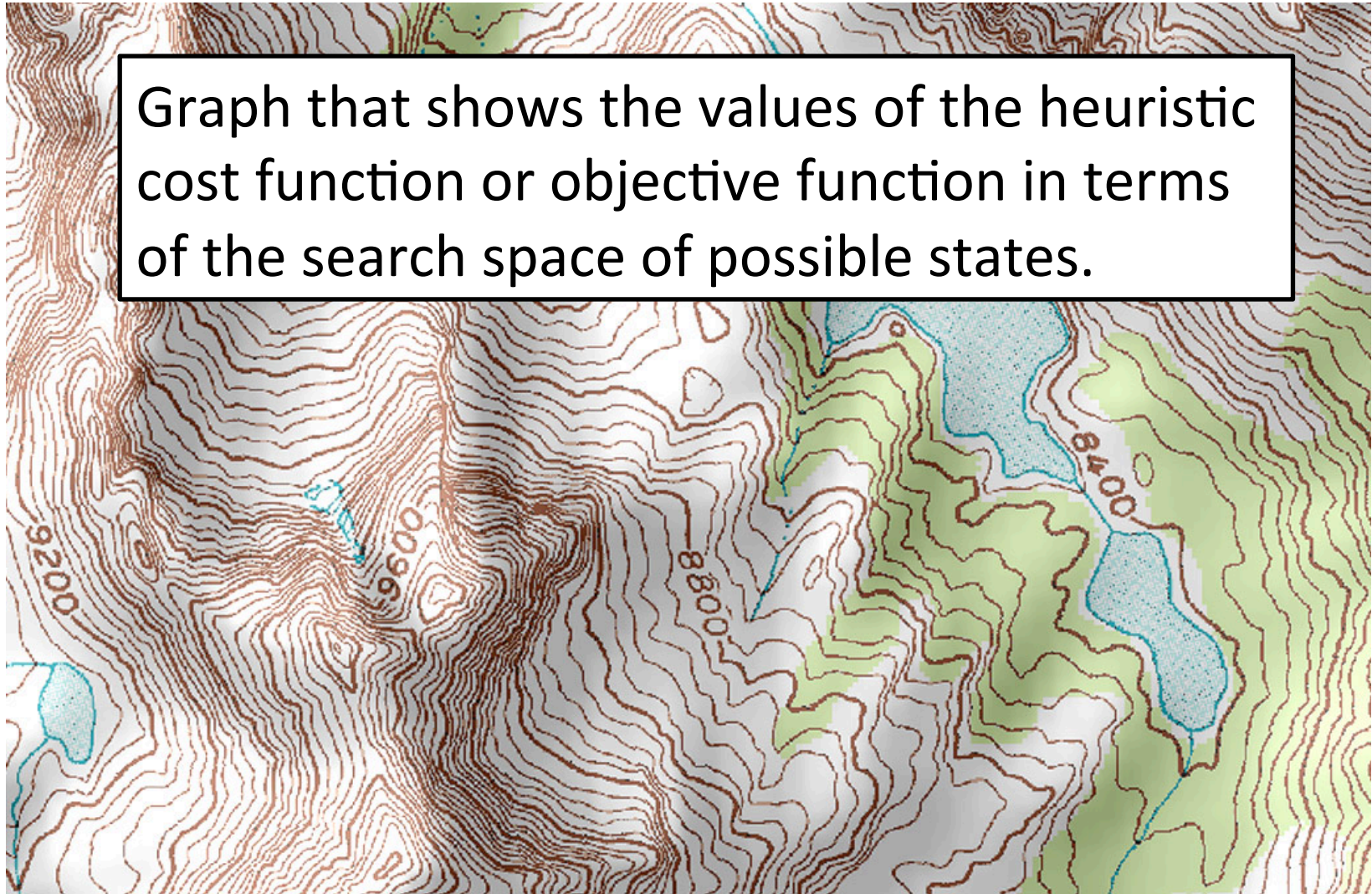
- Benefits:
 - Use very little memory, often constant.
 - Can search very large state spaces quickly.
- Useful in optimization problems.

State-space landscape



State-space landscape

Graph that shows the values of the heuristic cost function or objective function in terms of the search space of possible states.



Hill climbing algorithm

- Loop that looks at all possible neighbors of the current state, and picks the one that increases the optimization function the most.

```
function HILL-CLIMBING(problem) returns a state that is a local maximum
```









```
  current ← MAKE-NODE(problem.INITIAL-STATE)
```

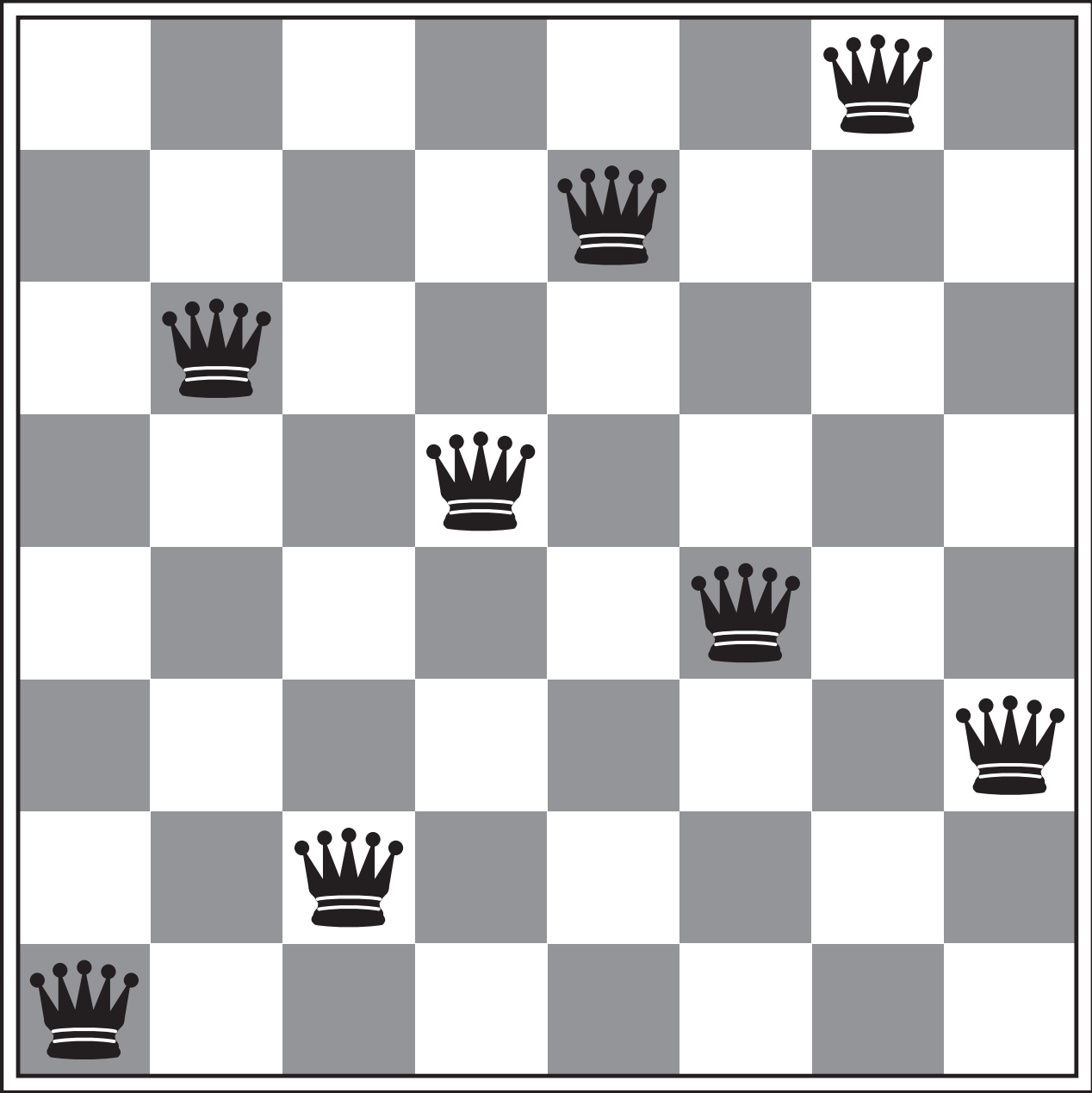
```
  loop do
```

```
    neighbor ← a highest-valued successor of current
```

```
    if neighbor.VALUE ≤ current.VALUE then return current.STATE
```

```
    current ← neighbor
```

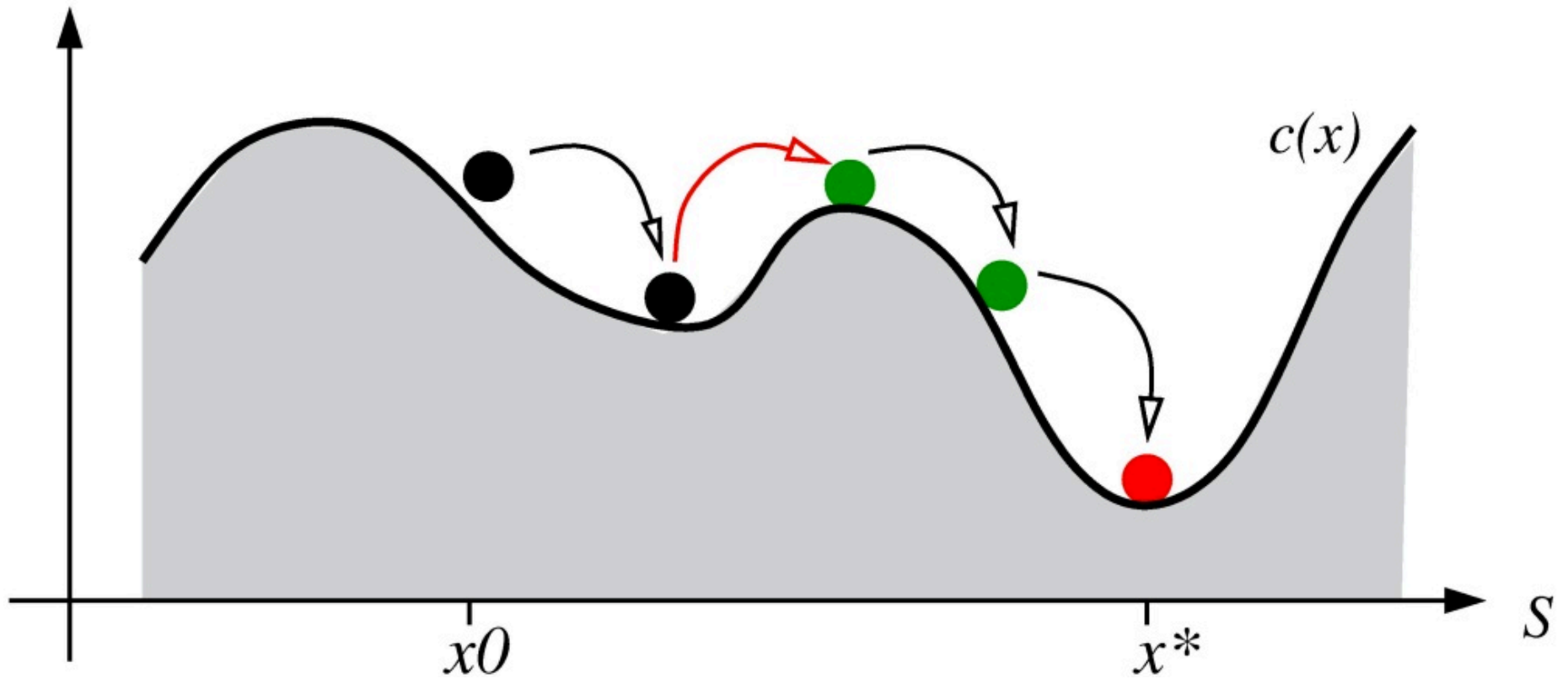
18	12	14	13	13	12	14	14
14	16	13	15	12	14	12	16
14	12	18	13	15	12	14	14
15	14	14		13	16	13	16
	14	17	15		14	16	16
17		16	18	15		15	
18	14		15	15	14		16
14	14	13	17	12	14	12	18



Variants

- Stochastic hill climbing
- Random-restart hill climbing

Simulated annealing



function SIMULATED-ANNEALING(*problem*, *schedule*) **returns** a solution state

inputs: *problem*, a problem

schedule, a mapping from time to “temperature”

current ← MAKE-NODE(*problem*.INITIAL-STATE)

for $t = 1$ **to** ∞ **do**

$T \leftarrow \text{schedule}(t)$

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

next ← a randomly selected successor of *current*

$\Delta E \leftarrow \text{next.VALUE} - \text{current.VALUE}$

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

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

Temperature
gets lower
over time

Probability is lower
with smaller T ,
and lower with
bigger $\text{abs}(\text{delta-E})$

Beam search

- Variation of hill climbing
 - Use k current states
 - Generate all of their successors
 - Take k best
- Variation: stochastic beam search
 - Adds in probabilistic idea from simulated annealing.
 - Same as above, but take k best successors based on probability.

Genetic algorithms

- Variation on stochastic beam search.
- Successor states are generated using two parent states, not one. (Crossover)
- Mutation: Randomly modifies a current state.

function GENETIC-ALGORITHM(*population*, FITNESS-FN) **returns** an individual

inputs: *population*, a set of individuals

FITNESS-FN, a function that measures the fitness of an individual

repeat

new_population \leftarrow empty set

for $i = 1$ **to** SIZE(*population*) **do**

$x \leftarrow$ RANDOM-SELECTION(*population*, FITNESS-FN)

$y \leftarrow$ RANDOM-SELECTION(*population*, FITNESS-FN)

child \leftarrow REPRODUCE(x , y)

if (small random probability) **then** *child* \leftarrow MUTATE(*child*)

add *child* to *new_population*

population \leftarrow *new_population*

until some individual is fit enough, or enough time has elapsed

return the best individual in *population*, according to FITNESS-FN

