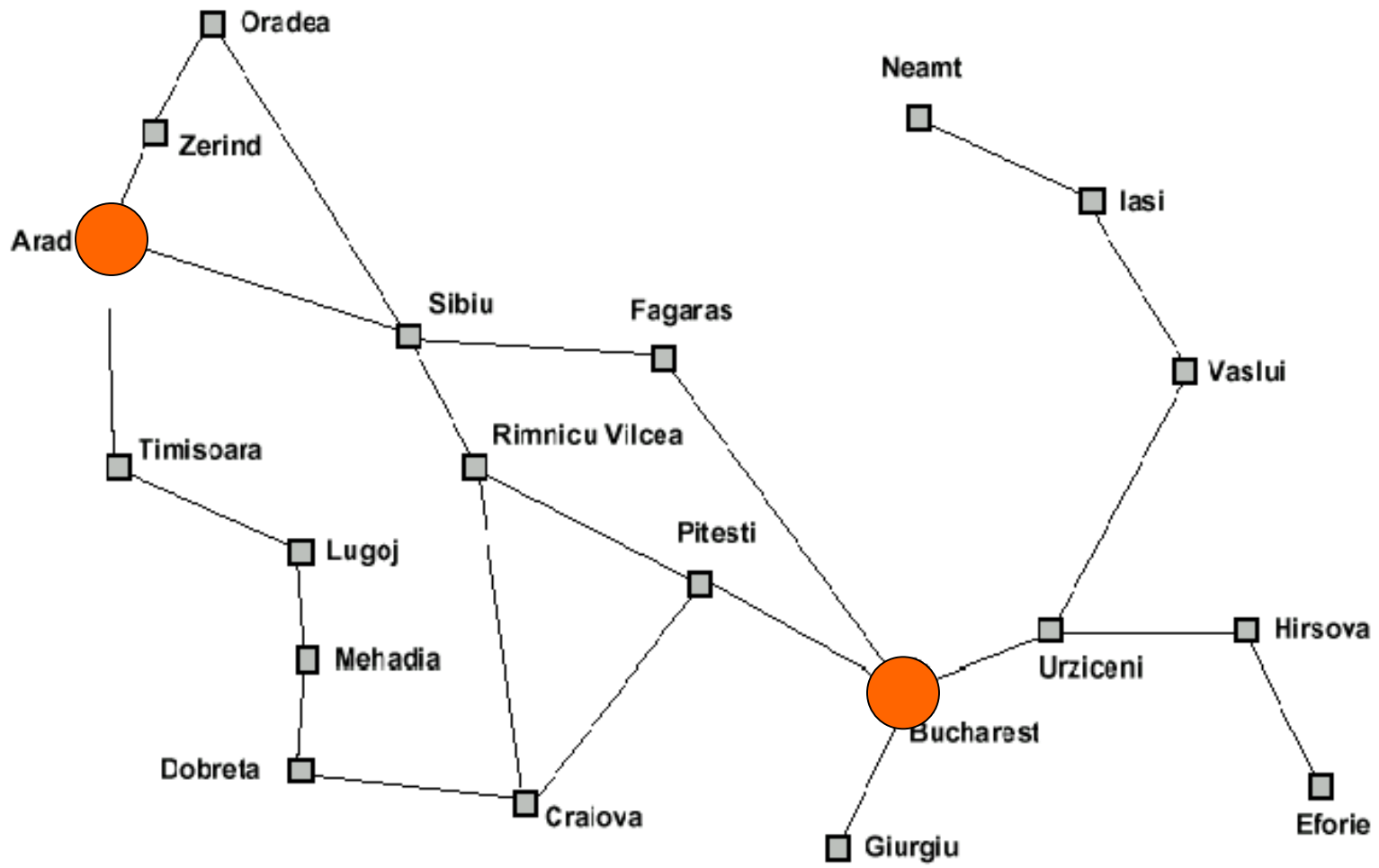# Recall: breadth-first search, step by step

Implementation of search algorithms

Function General-Search(problem, Queuing-Fn) **returns** a solution, or failure
    nodes ← make-queue(make-node(initial-state[problem]))
    loop do
        if nodes is empty **then return** failure
        node ← Remove-Front(nodes)
        if Goal-Test[problem] applied to State(node) succeeds **then return** node
        nodes ← Queuing-Fn(nodes, Expand(node, Operators[problem]))
    end

Queuing-Fn(*queue, elements*) is a queuing function that inserts a set of elements into the queue and <u>determines the order of node expansion</u>. Varieties of the queuing function produce varieties of the search algorithm.

Recall: breath-first search, step by step
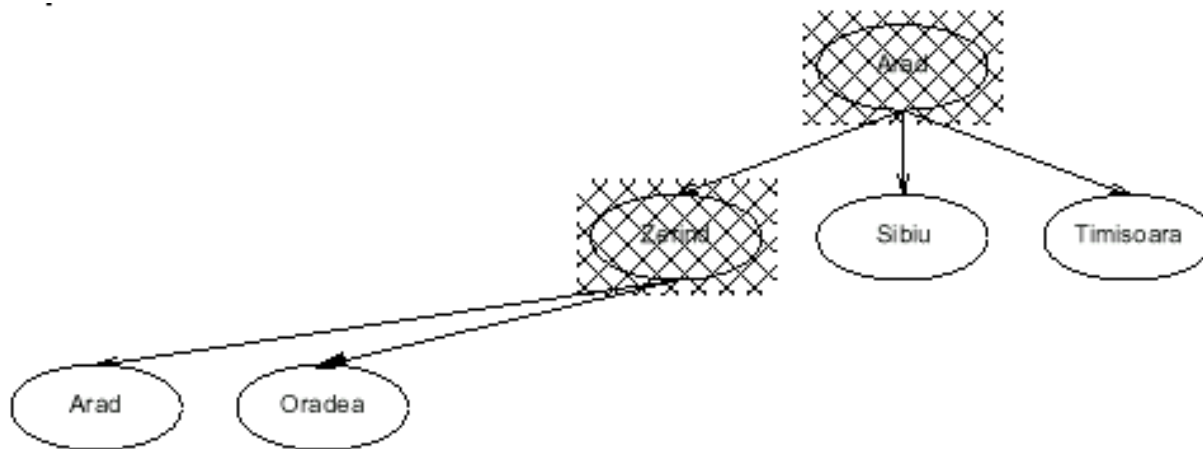
Breadth-first search

Node queue: initialization

#	state	depth	path cost	parent #
1	Arad	0	0	--

Breadth-first search

Node queue: add successors to queue end; empty queue from top

#	state	depth	path cost	parent #
1	Arad	0	0	--
2	Zerind	1	1	1
3	Sibiu	1	1	1
4	Timisoara	1	1	1

Breadth-first search

Node queue: add successors to queue end; empty queue from top

#	state	depth	path cost	parent #
1	Arad	0	0	--
2	Zerind	1	1	1
3	Sibiu	1	1	1
4	Timisoara	1	1	1
5	Arad	2	2	2
6	Oradea	2	2	2

(get smart: e.g., avoid repeated states like node #5)

Depth-first search
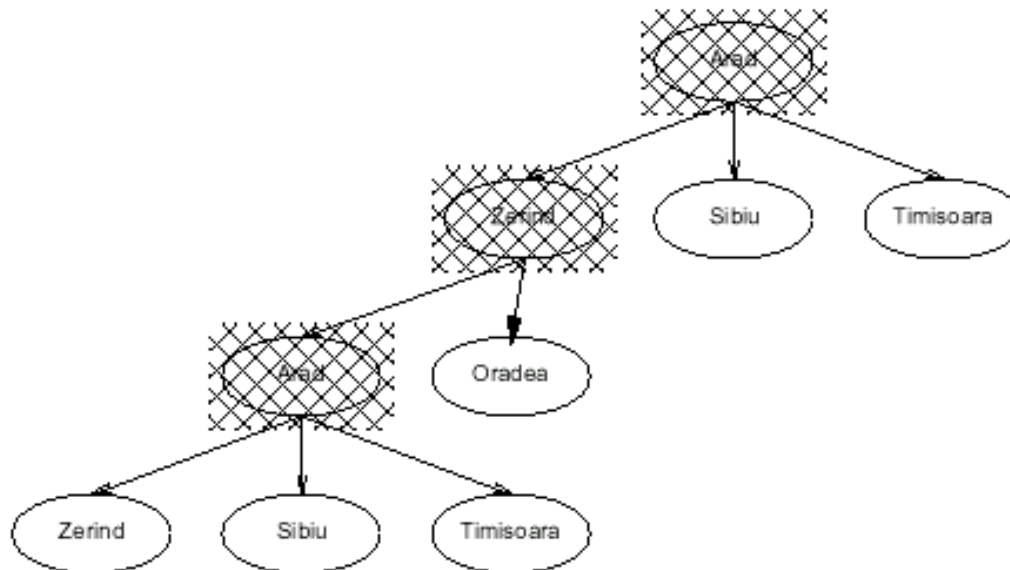
I.e., depth-first search can perform infinite cyclic excursions
Need a finite, non-cyclic search space (or repeated-state checking)

Depth-first search

Node queue: initialization

#	state	depth	path cost	parent #
1	Arad	0	0	--

Depth-first search

Node queue: add successors to queue front; empty queue from top

#	state	depth	path cost	parent #
2	Zerind	1	1	1
3	Sibiu	1	1	1
4	Timisoara	1	1	1
1	Arad	0	0	--

Depth-first search

Node queue: add successors to queue front; empty queue from top

#	state	depth	path cost	parent #
5	Arad	2	2	2
6	Oradea	2	2	2
2	Zerind	1	1	1
3	Sibiu	1	1	1
4	Timisoara	1	1	1
1	Arad	0	0	--

Last time: search strategies

Uninformed: Use only information available in the problem formulation

- Breadth-first
- Uniform-cost
- Depth-first
- Depth-limited
- Iterative deepening

Informed: Use heuristics to guide the search

- Best first:
- Greedy search

- A* search

Last time: search strategies

Uninformed: Use only information available in the problem formulation
- Breadth-first
- Uniform-cost
- Depth-first
- Depth-limited
- Iterative deepening

Informed: Use heuristics to guide the search
- Best first:
- Greedy search -- queue first nodes that maximize heuristic "desirability" based on estimated path cost from current node to goal;
- A* search – queue first nodes that minimize sum of path cost so far and estimated path cost to goal.

This time

- Iterative improvement
- Hill climbing
- Simulated annealing

Iterative improvement

- In many optimization problems, path is irrelevant;
  the goal state itself is the solution.

- Then, state space = space of "complete" configurations.
  Algorithm goal:
  - find optimal configuration (e.g., TSP), or,
  - find configuration satisfying constraints (e.g., n-queens)

- In such cases, can use iterative improvement algorithms: keep a
  single "current" state, and try to improve it.

Iterative improvement example: vacuum world

Simplified world: 2 locations, each may or not contain dirt,
each may or not contain vacuuming agent.
Goal of agent: clean up the dirt.

If path does not matter, do not need to keep track of it.
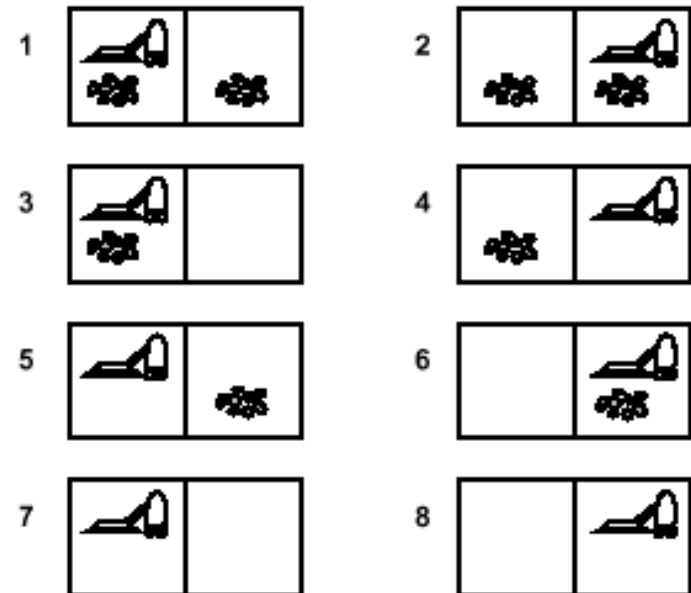
Single-state, start in #5. Solution??

Multiple-state, start in {1, 2, 3, 4, 5, 6, 7, 8}
e.g., *Right* goes to {2, 4, 6, 8}. Solution??

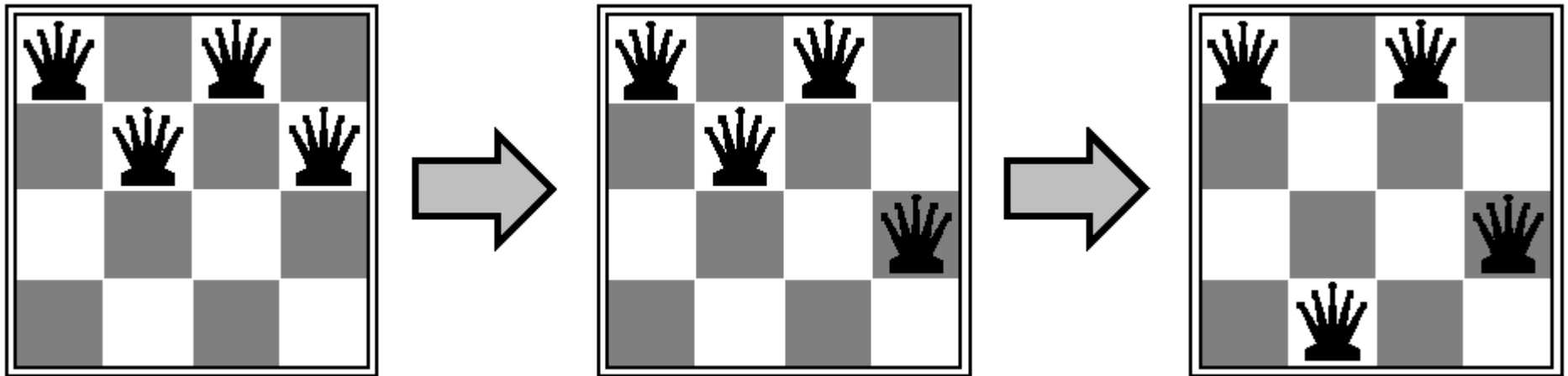Contingency, start in #5
Murphy's Law: *Suck* can dirty a clean car-
pet
Local sensing: dirt, location only.
Solution??

Iterative improvement example: n-queens

- **Goal:** Put n chess-game queens on an n x n board, with no two queens on the same row, column, or diagonal.

- Here, goal state is initially unknown but is specified by constraints that it must satisfy.

Hill climbing (or gradient ascent/descent)

- Iteratively maximize "value" of current state, by replacing it by successor state that has highest value, as long as possible.

"Like climbing Everest in thick fog with amnesia"

function HILL-CLIMBING(*problem*) **returns** a solution state
    inputs: *problem*, a problem
    local variables: *current*, a node
                     next, a node

    current ← MAKE-NODE(INITIAL-STATE[*problem*])
    loop do
        next ← a highest-valued successor of *current*
        if VALUE[next] < VALUE[current] **then return** *current*
        current ← *next*
    end

Hill climbing
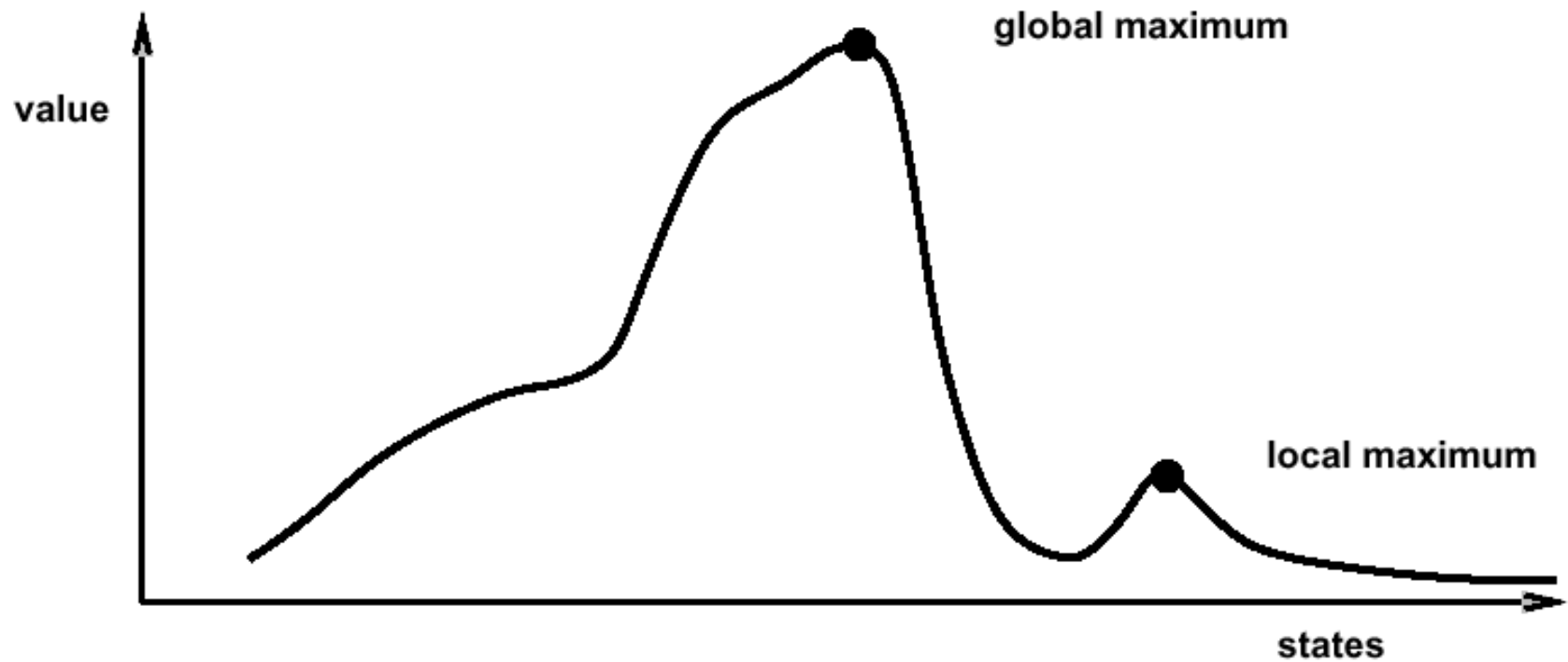
- Note: minimizing a "value" function v(n) is equivalent to maximizing –v(n),

  thus both notions are used interchangeably.

- Notion of "extremization": find extrema (minima or maxima) of a value function.

Hill climbing

- **Problem:** depending on initial state, may get stuck in local extremum.

Minimizing energy

- Let's now change the formulation of the problem a bit, so that we can employ new formalism:

  - let's compare our state space to that of a physical system that is subject to natural interactions,

  - and let's compare our value function to the overall potential energy E of the system.

- On every updating we have $\Delta E \leq 0$

- Hence the dynamics of the system tend to move E toward a minimum.

- We stress that there may be different such states — they are *local* minima. Global minimization is not guaranteed.

Basin of

Attraction for C

A

D

B

E

C
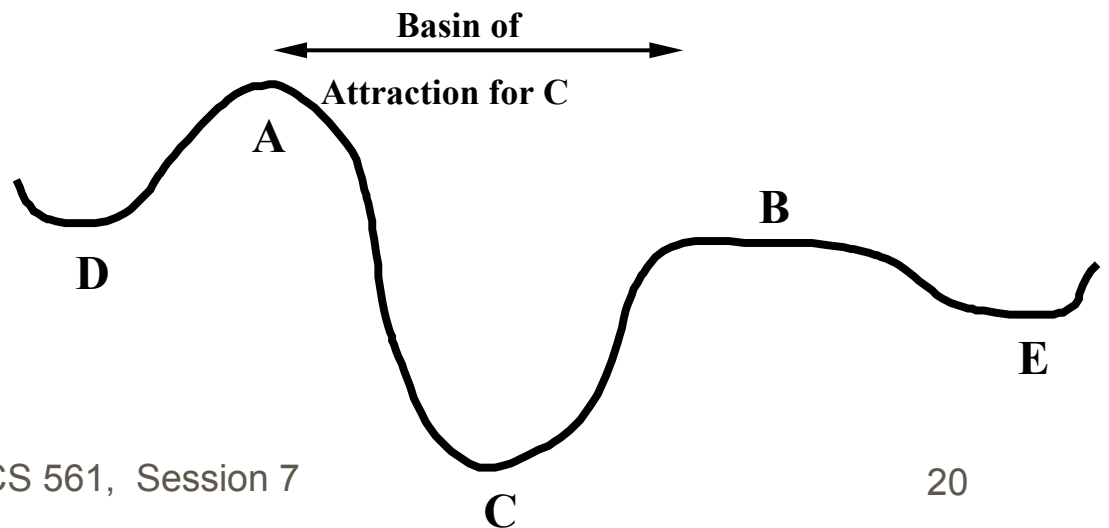
Boltzmann machines

h

A

B

D

E
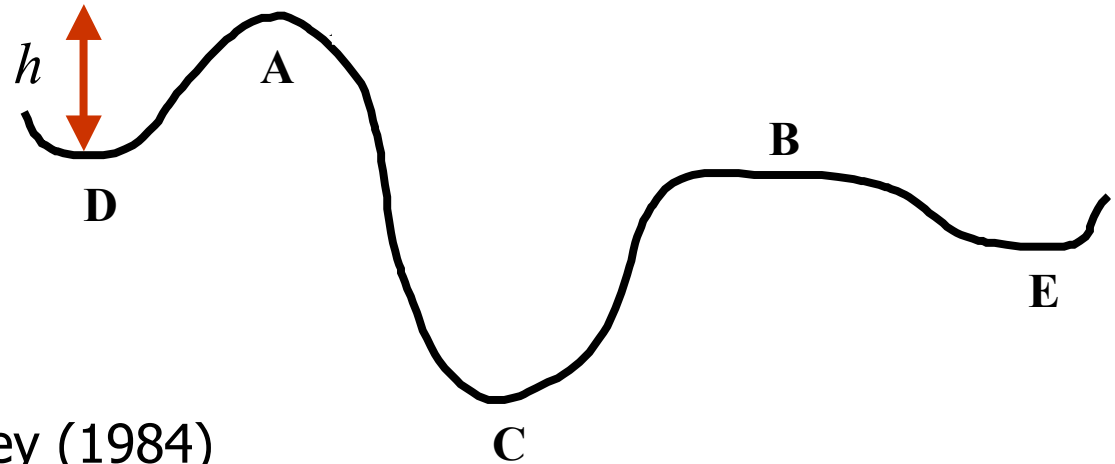
The Boltzmann Machine of
Hinton, Sejnowski, and Ackley (1984)
uses simulated annealing to escape local minima.

C

To motivate their solution, consider how one might get a ball-bearing traveling
along the curve to "probably end up" in the deepest minimum. The idea is to
shake the box "about h hard" — then the ball is more likely to go from D to
C than from C to D. So, on average, the ball should end up in C's valley.

Simulated annealing: basic idea

- From current state, pick a **random** successor state;

- If it has better value than current state, then "accept the transition," that is, use successor state as current state;

- Otherwise, do not give up, but instead flip a coin and accept the transition with a given probability (that is lower as the successor is worse).

- So we accept to sometimes "un-optimize" the value function a little with a non-zero probability.

Boltzmann's statistical theory of gases

- In the statistical theory of gases, the gas is described not by a deterministic dynamics, but rather by the probability that it will be in different states.

- The 19th century physicist Ludwig Boltzmann developed a theory that included a probability distribution of temperature (i.e., every small region of the gas had the same kinetic energy).

- Hinton, Sejnowski and Ackley's idea was that this distribution might also be used to describe neural interactions, where low temperature T is replaced by a small noise term T (the neural analog of random thermal motion of molecules). While their results primarily concern optimization using neural networks, the idea is more general.

Boltzmann distribution

- At thermal equilibrium at temperature T, the Boltzmann distribution gives the relative probability that the system will occupy state A vs. state B as:

$$\frac{P(A)}{P(B)} = \exp\left(-\frac{E(A)-E(B)}{T}\right) = \frac{\exp(E(B)/T)}{\exp(E(A)/T)}$$

- where E(A) and E(B) are the energies associated with states A and B.

Simulated annealing

Kirkpatrick et al. 1983:

- Simulated annealing is a general method for making likely the escape from local minima by allowing jumps to higher energy states.

- The analogy here is with the process of annealing used by a craftsman in forging a sword from an alloy.

- He heats the metal, then slowly cools it as he hammers the blade into shape.
  - If he cools the blade too quickly the metal will form patches of different composition;
  - If the metal is cooled slowly while it is shaped, the constituent metals will form a uniform alloy.

Simulated annealing in practice

- set T
- optimize for given T
- lower T   (see Geman & Geman, 1984)
- repeat

Simulated annealing in practice

- set T
- optimize for given T
- lower T   (see Geman & Geman, 1984)
- repeat

- Geman & Geman (1984): if T is lowered sufficiently slowly (with respect to the number of iterations used to optimize at a given T), simulated annealing is guaranteed to find the global minimum.

- Caveat: this algorithm has no end (Geman & Geman's T decrease schedule is in the 1/log of the number of iterations, so, T will never reach zero), so it may take an infinite amount of time for it to find the global minimum.

Simulated annealing algorithm

- Idea: Escape local extrema by allowing "bad moves," but gradually decrease their size and frequency.

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 the probability of downward steps

current ← MAKE-NODE(INITIAL-STATE[*problem*])
for $t \leftarrow 1$ **to** ∞ **do**
    $T \leftarrow schedule[t]$
    if $T=0$ **then return** *current*
    next ← a randomly selected successor of *current*
    $\Delta E \leftarrow$ VALUE[*next*] – VALUE[*current*]
    if $\Delta E > 0$ **then** *current* ← *next*
    else *current* ← *next* only with probability $e^{\Delta E / T}$

Note: goal here is to maximize E.

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Algorithm when goal is to minimize E.

Note on simulated annealing: limit cases

- Boltzmann distribution: accept "bad move" with $\Delta E < 0$ (goal is to maximize E) with probability $P(\Delta E) = \exp(\Delta E / T)$

- If T is large: $\Delta E < 0$

  $\Delta E / T < 0$ and very small

  $\exp(\Delta E / T)$ close to 1

  accept bad move with high probability

- If T is near 0: $\Delta E < 0$

  $\Delta E / T < 0$ and very large

  $\exp(\Delta E / T)$ close to 0

  accept bad move with low probability

Note on simulated annealing: limit cases

- Boltzmann distribution: accept "bad move" with $\Delta E < 0$ (goal is to maximize E) with probability $P(\Delta E) = \exp(\Delta E / T)$

- If T is large:
  $\Delta E < 0$
  $\Delta E / T < 0$ and very small
  $\exp(\Delta E / T)$ close to 1
  accept bad move with high probability

  Random walk

- If T is near 0:
  $\Delta E < 0$
  $\Delta E / T < 0$ and very large
  $\exp(\Delta E / T)$ close to 0
  accept bad move with low probability

  Deterministic down-hill

Summary

- Best-first search = general search, where the minimum-cost nodes (according to some measure) are expanded first.

- Greedy search = best-first with the estimated cost to reach the goal as a heuristic measure.
    - Generally faster than uninformed search
    - not optimal
    - not complete.

- A* search = best-first with measure = path cost so far + estimated path cost to goal.
    - combines advantages of uniform-cost and greedy searches
    - complete, optimal and optimally efficient
    - space complexity still exponential

Summary

- Time complexity of heuristic algorithms depend on quality of heuristic function. Good heuristics can sometimes be constructed by examining the problem definition or by generalizing from experience with the problem class.

- Iterative improvement algorithms keep only a single state in memory.

- Can get stuck in local extrema; simulated annealing provides a way to escape local extrema, and is complete and optimal given a slow enough cooling schedule.