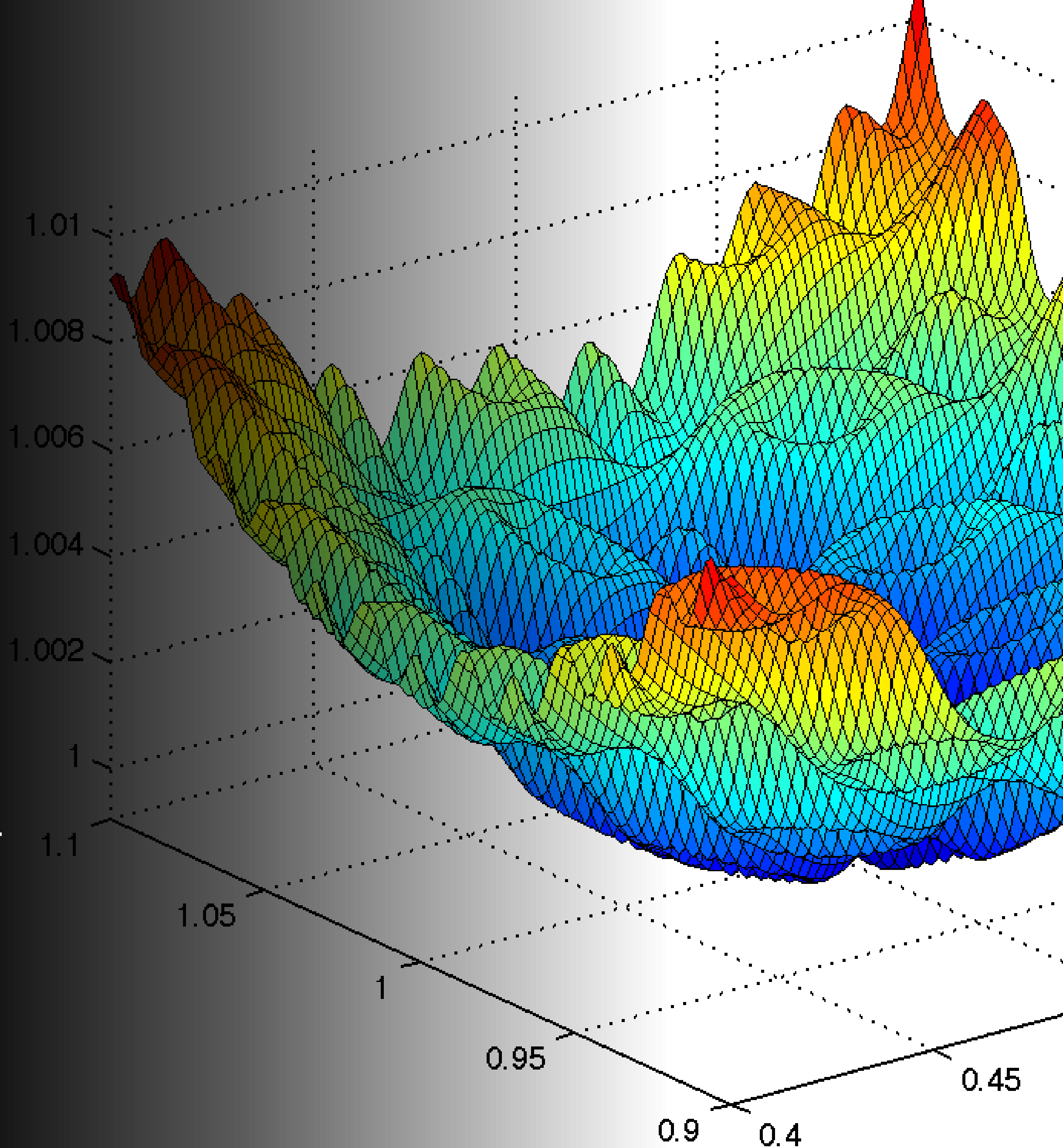
# CS 5/7320
## Artificial Intelligence

# Local Search
## AIMA Chapters 4.1 & 4.2

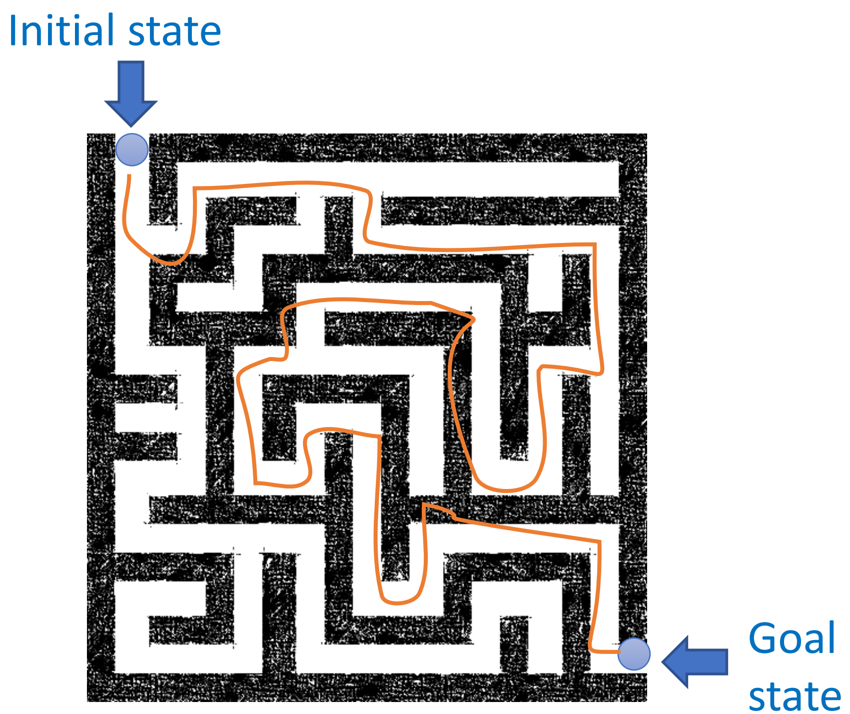
Slides by Michael Hahsler
based on slides by Svetlana Lazepnik
with figures from the AIMA textbook.



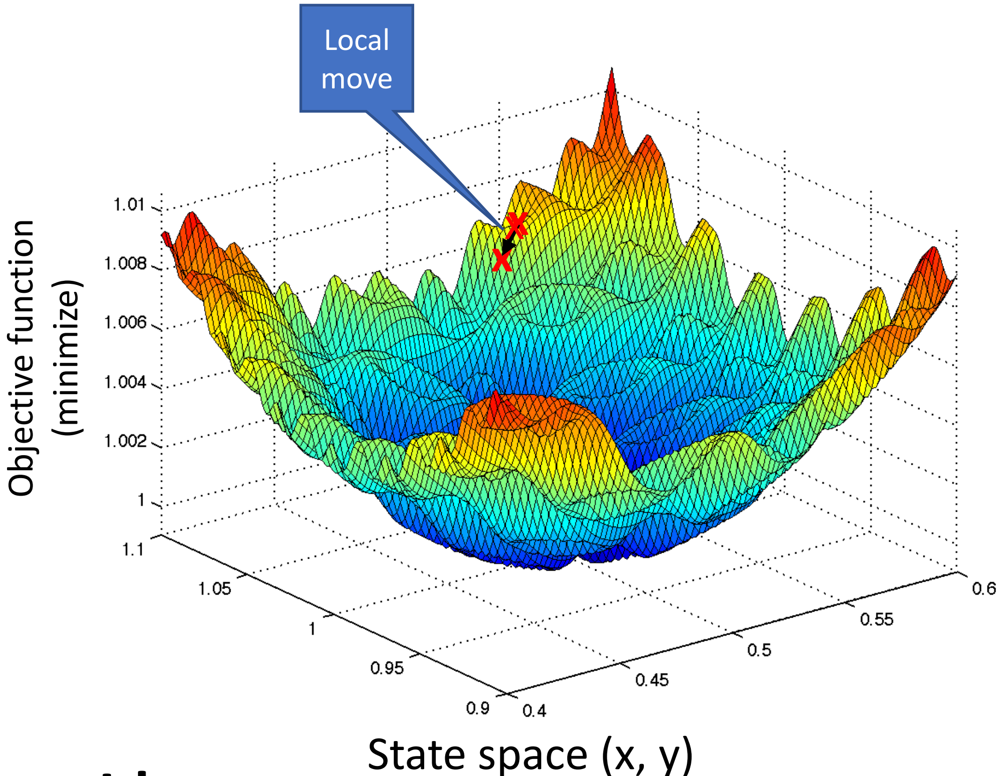
# Recap: Uninformed and Informed Search

Tries to find the
**best path**
from a
**given initial state**
to a
**given goal state.**

- Typically searches a large portion of the search space (needs time and memory).
- Often comes with optimality guarantees.



# Local Search Algorithms




- What if we do not know the goal state, but how "good" different states are? This is typically called the **objective function** → finding the best state is an **optimization problem**.
- We need a fast and memory-efficient way to find **the best/a good state.**

**Idea**:

- Improve the current solution by moving to a neighboring better state (a.k.a. performing a local move).
- This is fast and needs little memory (no search tree).

# Local Search Algorithms

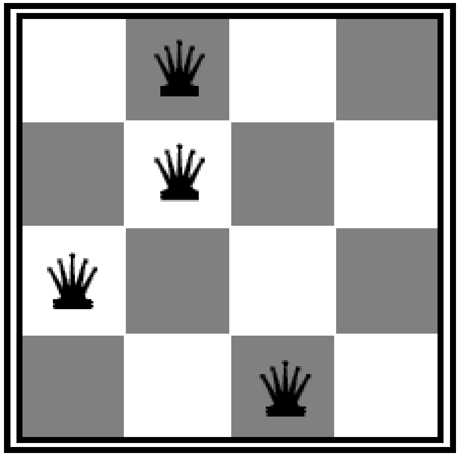
**Difference to search from the previous chapter:**

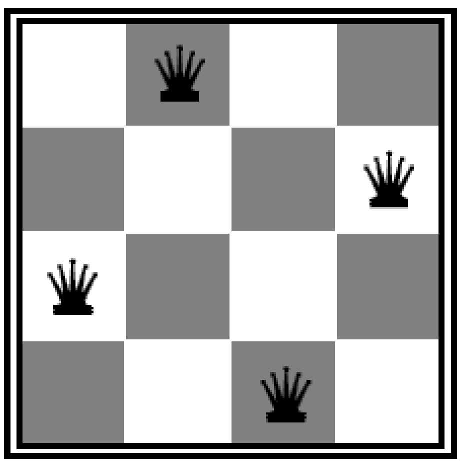
a) **Goal state is unknown** and needs to be identified.
b) Often no explicit initial state + **path to goal and path cost are not important.**
c) **No search tree**. Just stores the current state.

**Use in AI**

- **Utility-based agent**: Use utility as the objective function and always move to higher utility states. A greedy method used for complicated/large state spaces or online search.
- **Goal-based agent**: Identify a good goal state with a good objective function value before planning the path to that state.
- **General optimization**: Use for effective heuristic search in large or continuous spaces (with an infinite state space). E.g., learn neural networks.

# Example:
# *n*-Queens Problem



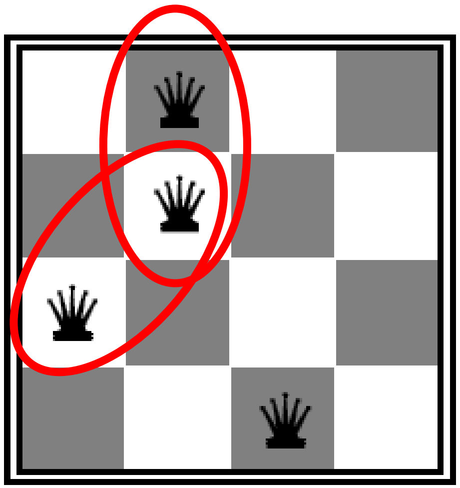


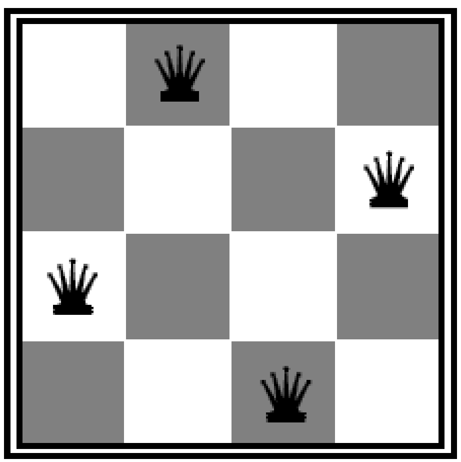
- **Goal**: Put $n$ queens on an $n \times n$ board with no two queens on the same row, column, or diagonal.

- **State space:** All possible $n$-queen configurations. **How many are there?**

- What is a possible **objective function**?

2 conflicts





0 conflicts

# Example: *n*-Queens Problem

- **Goal**: Put $n$ queens on an $n \times n$ board with no two queens on the same row, column, or diagonal

- **State space:** all possible $n$-queen configurations:
  4-queens problem: $\binom{16}{4} = 1820$

- What is a possible **objective function**?

**Minimize the number of pairwise conflicts**

**Note:** this can be seen as a heuristic used in informed search, but it may not be an admissible heuristic.


# Example: Traveling salesman problem

- **Goal**: Find the shortest tour connecting a given set of cities
- **State space:** all possible tours (states are not individual cities!)
- **Objective function:** minimize the length of the tour

Note: We have solved a different problem with uninformed/informed search! Each city was defined as a state and the path was the solution.


# Hill-Climbing Search aka Greedy Local Search

**Idea:** keep a single “current” state and try to find better neighboring states.

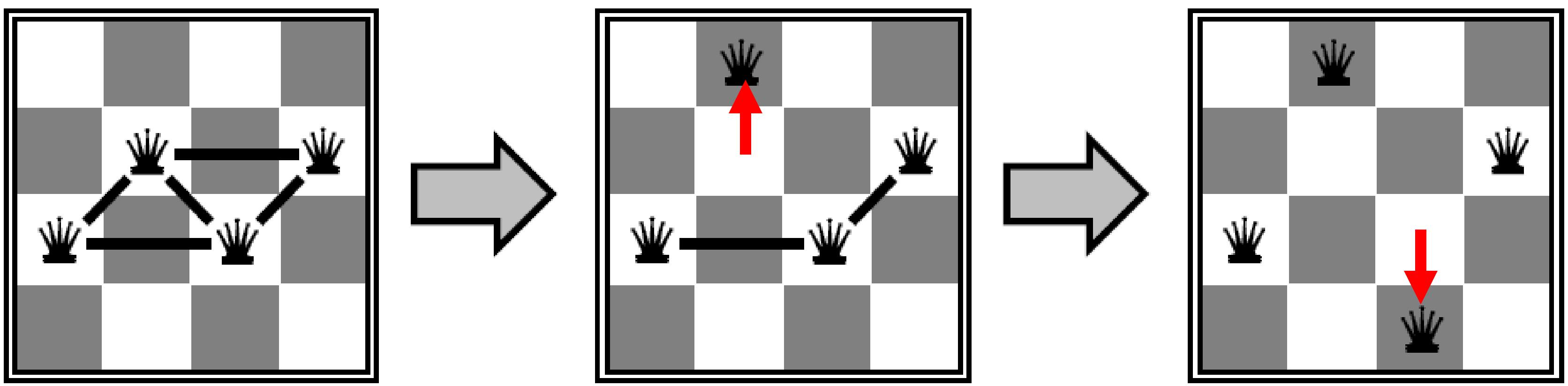
# Example: *n*-Queens Problem

- **Goal:** Put $n$ queens on an $n \times n$ board with no two queens on the same row, column, or diagonal.
- **State space:** all possible $n$-queen configurations. We can restrict the state space: Only one queen per column.
- **Objective function:** minimize the number of pairwise conflicts.

State space is reduced from 1820 to $4^4 = 256$

What is a possible local improvement strategy?

- Move one queen within its column to reduce conflicts



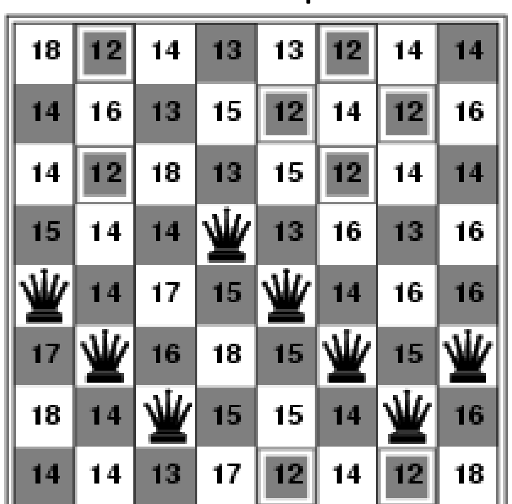
h = 5 h = 2 h = 0

# Example: *n*-Queens Problem

- **Goal:** Put *n* queens on an *n* × *n* board with no two queens on the same row, column, or diagonal.
- **State space:** all possible *n*-queen configurations. We can restrict the state space: Only one queen per column.
- **Objective function:** minimize the number of pairwise conflicts.

What is a possible local improvement strategy?

- Move one queen within its column to reduce conflicts




*h* = 17
best local improvement has h = 12

Note that there are many options, and we have to choose one!

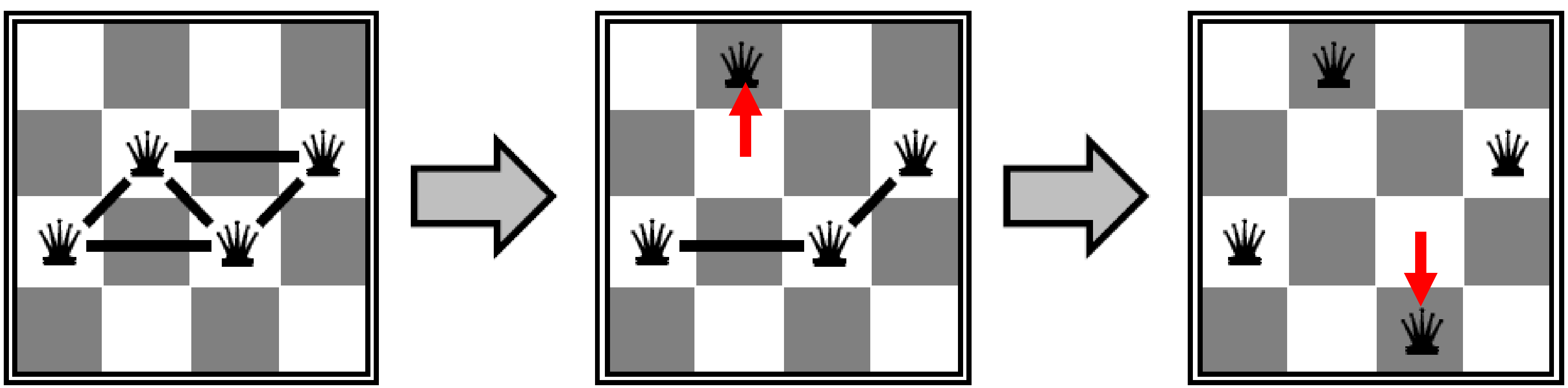
# Example: *n*-Queens Problem

Optimization problem: find the best arrangement $a$

$$a^* = \operatorname{argmin}_a \ \text{conflicts}(a)$$

s.t. $a$ has one queen per column

Remember: This makes the problem a lot easier.



h = 5 h = 2 h = 0

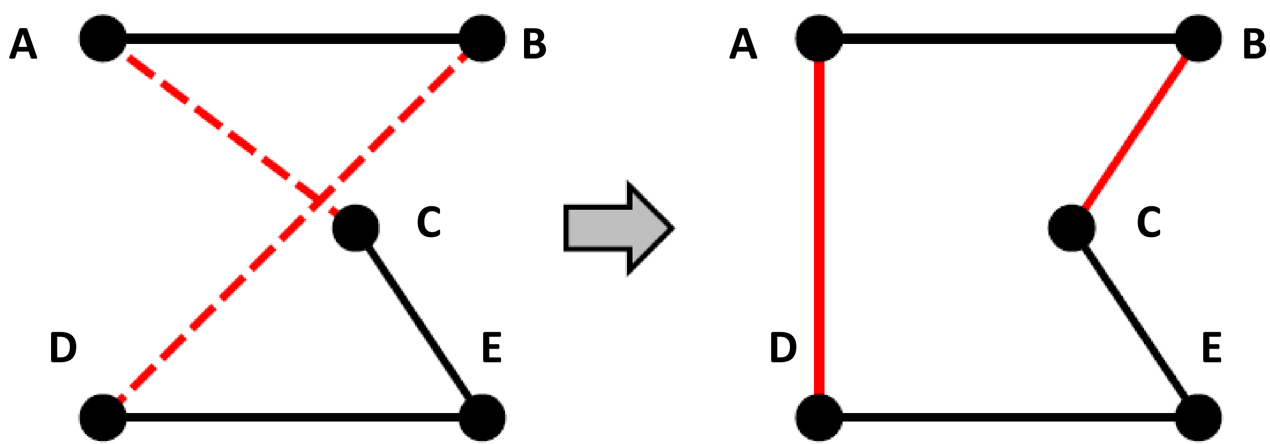
# Example: Traveling Salesman Problem

- **Goal:** Find the shortest tour connecting n cities
- **State space:** all possible tours
- **Objective function:** length of tour

What's a possible local improvement strategy?

- Start with any complete tour, perform pairwise exchanges.

Permutation: **ABDEC** **ABCED**



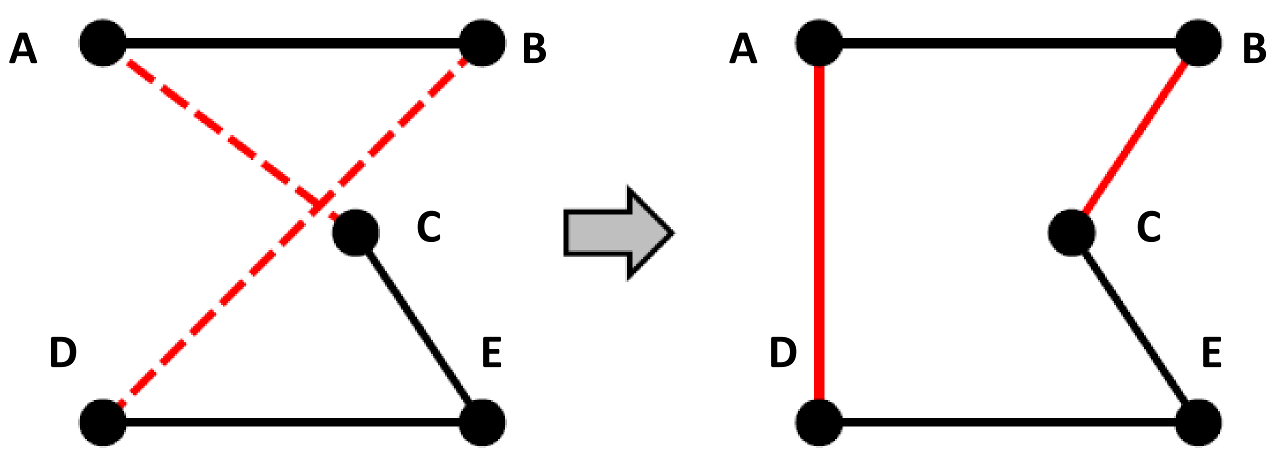
# Example: Traveling Salesman Problem

Optimization problem: Find the best tour $\pi$

$$\pi^* = \operatorname{argmin}_{\pi} \ \ \mathrm{tourLength}(\pi)$$

s.t. $\pi$ is a valid permutation (i.e., sub-tour elimination)

Permutation: **ABDEC** **ABCED**



# Hill-Climbing Search (= Greedy Local Search)

**function** HILL-CLIMBING(*problem*) **returns** a state that is a local maximum
  *current* ← *problem*.INITIAL
  **while** *true* **do**
    *neighbor* ← a highest-valued successor state of *current*
    **if** VALUE(*neighbor*) ≤ VALUE(*current*) **then return** *current*
    *current* ← *neighbor*

Typically, we start with a random state

Variants:

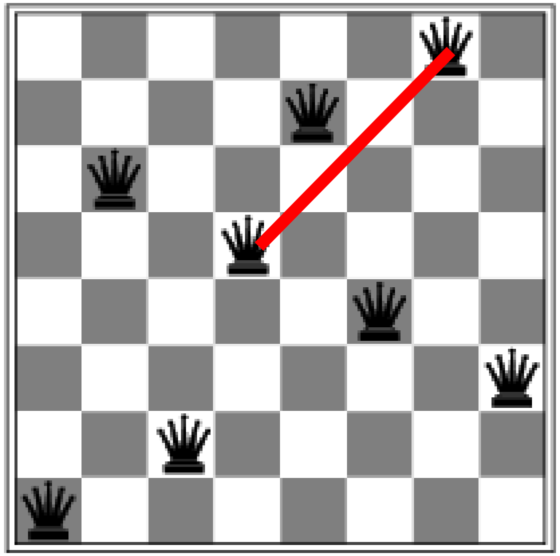
- **Steepest-ascend hill climbing**
  - Check all possible successors and choose the highest-valued successors.
- **Stochastic hill climbing**
  - choose randomly among all uphill moves, or
  - generate randomly one new successor at a time until a better one is found = first-choice hill climbing – **the most popular variant**, this is what people often mean when they say "stochastic hill climbing"
- **Random-restart hill climbing** – to deal with local optima
  - Restart hill-climbing many times with random initial states and return the best solution.

# Hill-Climbing Search

Hill-climbing search is similar to greedy best-first search with the objective function as a (maybe not admissible) heuristic.

Is it complete/optimal?

- No – can get stuck in local optima

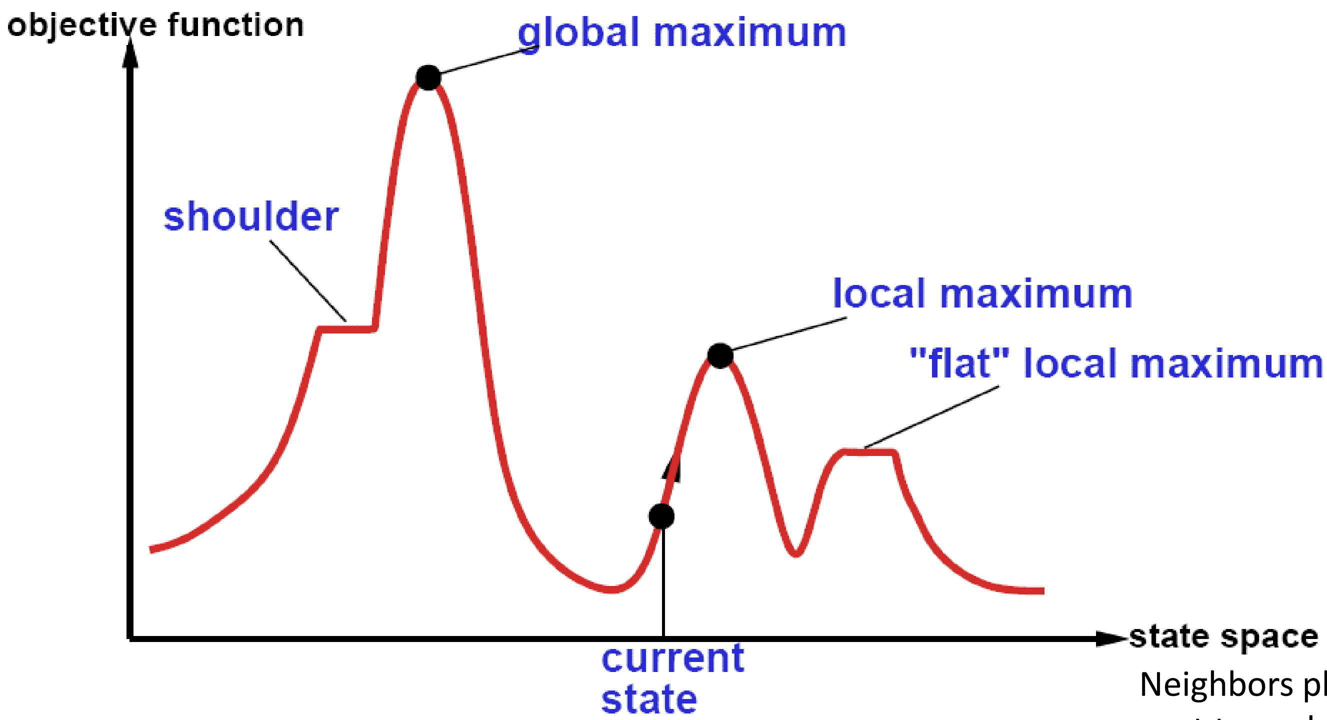


Example: local optimum for the 8-queens problem. No single queen can be moved within its column to improve the objective function.

*h* = 1

# The State Space "Landscape"

Maximization problem




Neighbors placed next to each other

How to escape local maxima?

→ Random restart hill-climbing can help.

What about "shoulders" (called "ridges" in higher dimensional space)?

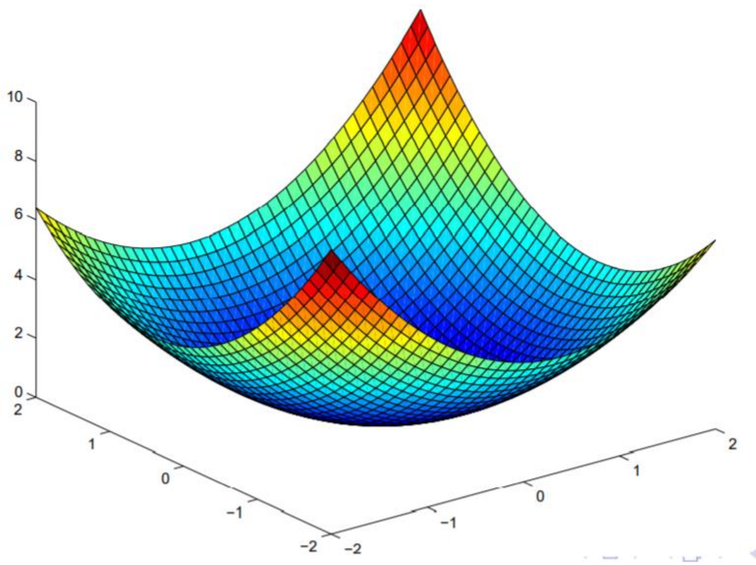
What about "plateaus"?

→ Hill-climbing with sideways moves.

# Convex vs. Non-Convex Optimization Problems

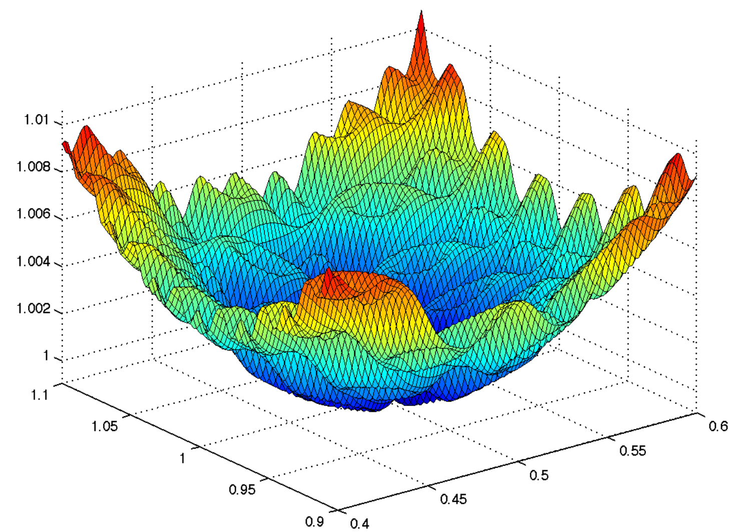
Minimization problem

Convex Problem




One global optimum + smooth function → calculus makes it easy

Non-convex Problem



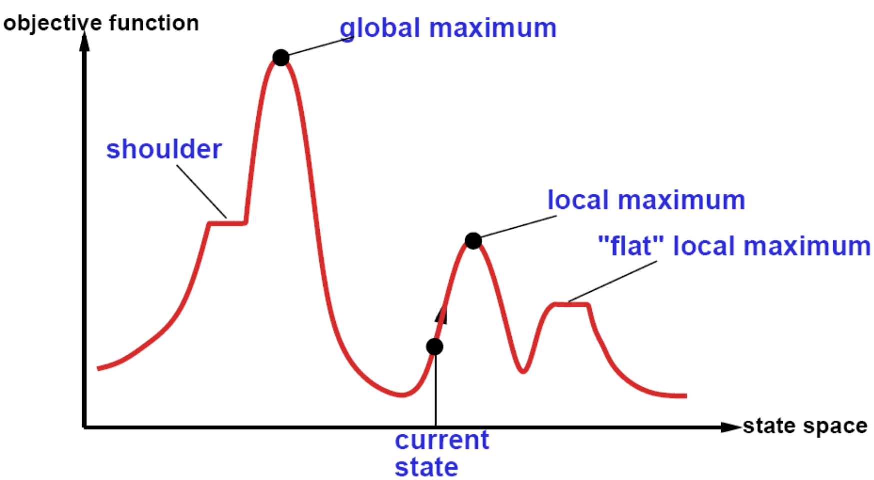

Many local optima → hard

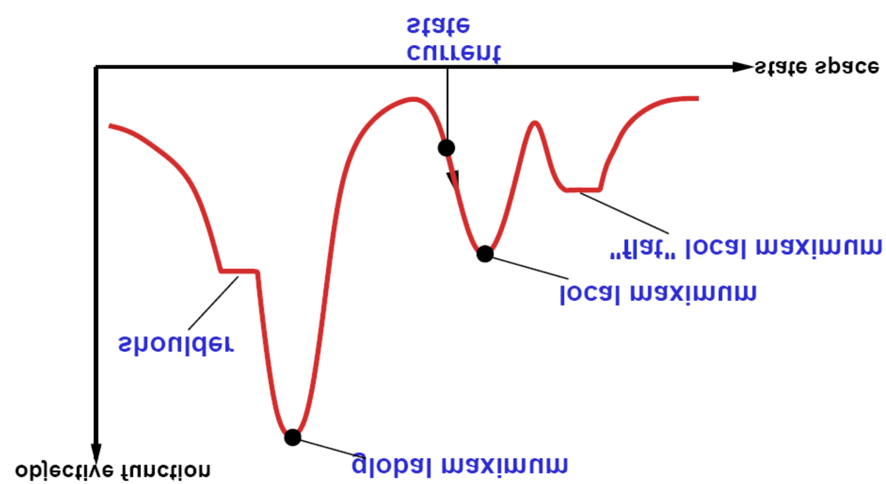
Many discrete optimization problems are like this.

# Minimization vs. Maximization

- The name hill climbing implies **maximizing a function**.
- Optimizers like to state problems as **minimization problems** (and call hill climbing gradient descent instead).
- Both types of problems are equivalent:

$$\max(f(x)) \quad \Longleftrightarrow \quad \min(-f(x))$$



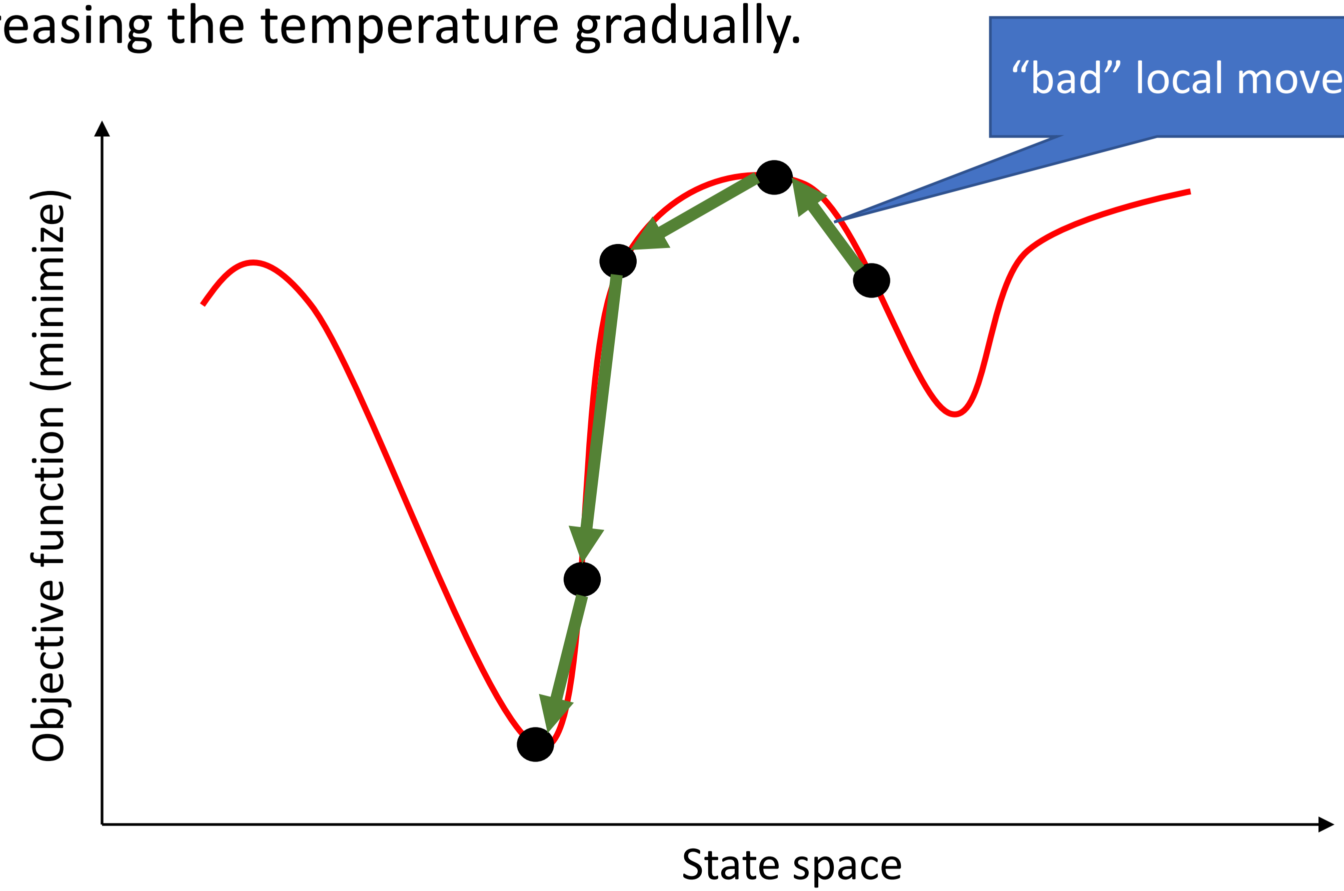



# Simulated Annealing

Use heat to escape local optima…

# Simulated Annealing

- **Idea**: First-choice stochastic hill climbing + escape local minima by **allowing some "bad" moves** but gradually decrease their frequency.
- Inspired by the process of tempering or hardening metals by decreasing the temperature gradually.



# Simulated Annealing

- **Idea**: First-choice stochastic hill climbing + escape local minima by allowing some "bad" moves but gradually decreasing their frequency as we get closer to the solution.
- The probability of accepting "bad" moves follows **an annealing schedule** that reduces the temperature $T$ over time $t$.

```
function SIMULATED-ANNEALING(problem, schedule) returns a solution state
    current ← problem.INITIAL
    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^(−ΔE/T)
```

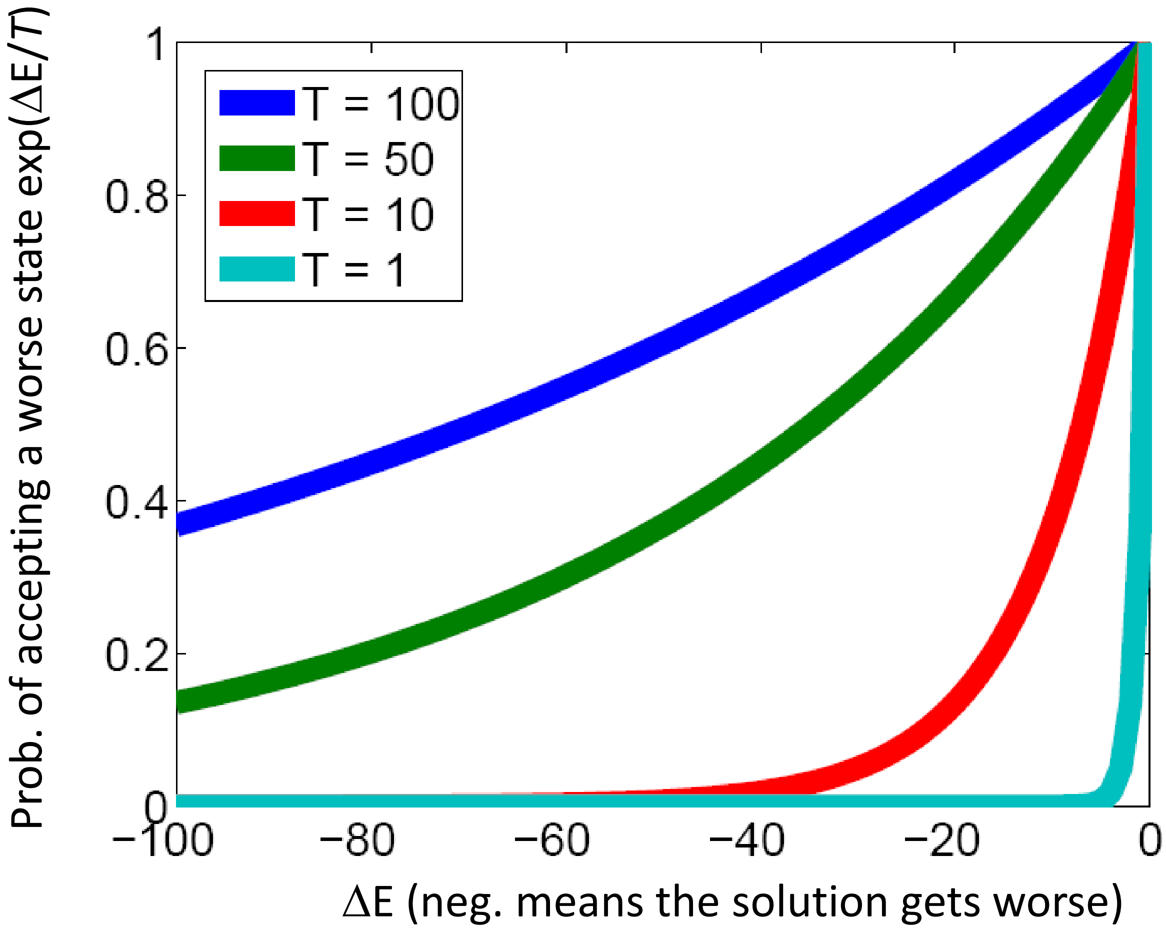
Typically, we start with a random state

Always do good moves

Uses the Metropolis acceptance criterion to accept "bad" moves

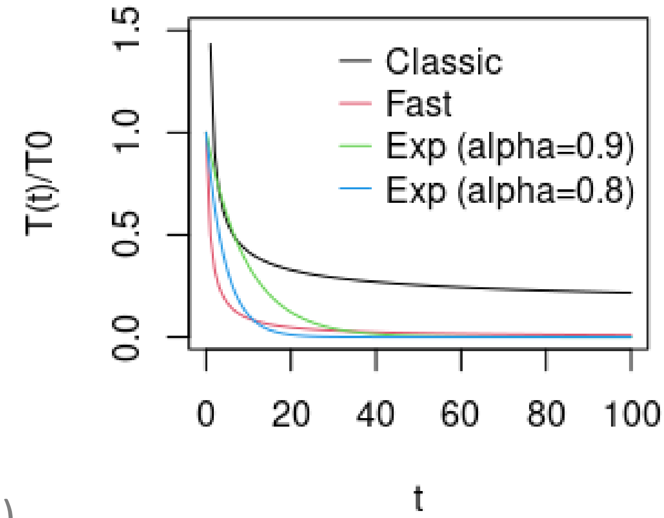
Note: Use VALUE(current) – VALUE(next) for minimization

# The Effect of Temperature




The lower the temperature, the less likely the algorithm will accept a worse state.

# Cooling Schedule




The cooling schedule is very important.
Popular schedules for the temperature at time $t$:

- **Classic simulated annealing:** $T_t = T_0 \frac{1}{\log(1+t)}$
- **Fast simulated annealing** (Szy and Hartley; 1987)
$$T_t = T_0 \frac{1}{1+t}$$
- **Exponential cooling** (Kirkpatrick, Gelatt and Vecchi; 1983)
$$T_t = T_0 \alpha^t \quad \text{for} \quad 0.8 < \alpha < 1$$

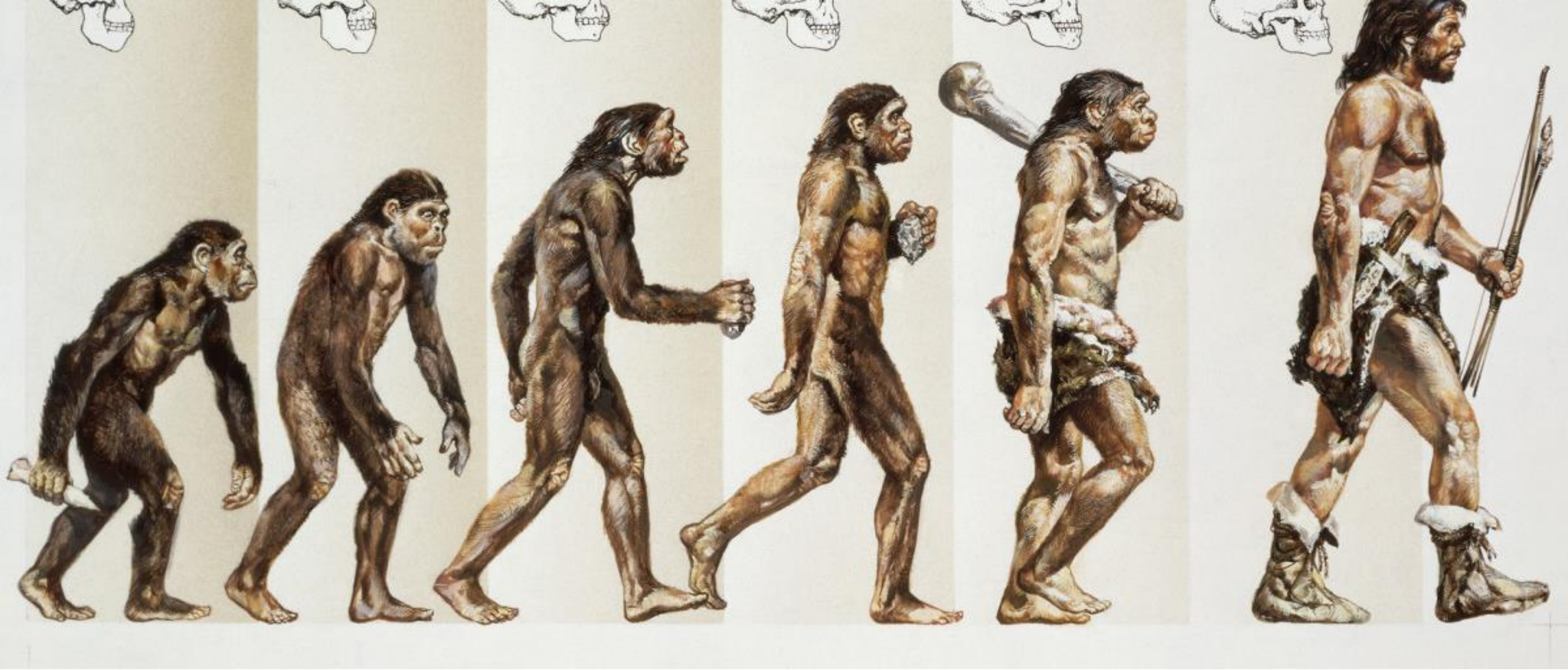
Notes:

- The best schedule is typically determined by trial-and-error.
- Choose $T_0$ to provide a high probability that any move will be accepted at time $t = 0$.
- $T_t$ will not become 0 but very small. Stop when $T < \epsilon$ ($\epsilon$ is a very small constant).

# Simulated Annealing Search

- **Guarantee:** If temperature decreases slowly enough, then simulated annealing search will find a global optimum with probability approaching one.
- However:
  - This usually takes impractically long.
  - The more downhill/uphill steps you need to escape a local optimum, the less likely you are to make all of them in a row.

- The related **Markov Chain Monte Carlo (MCMC)** method is a general family of randomized algorithms for exploring complicated state spaces.

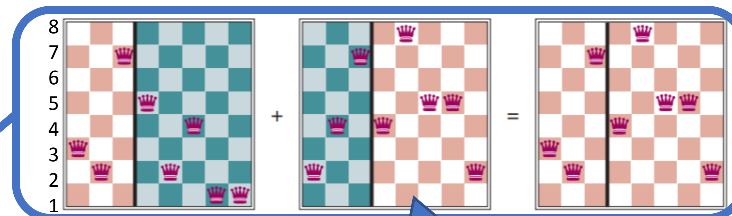


# Evolutionary Algorithms

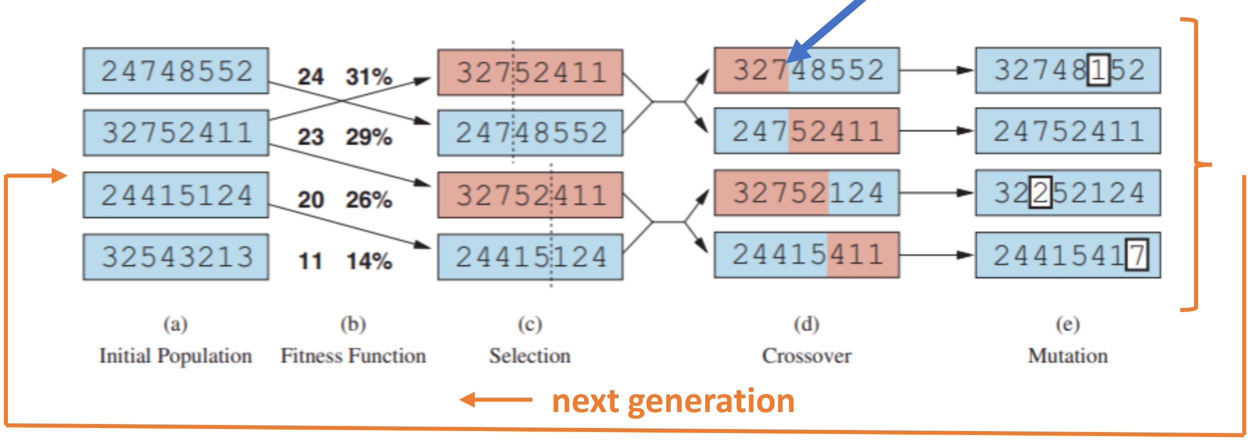
A Population-based Metaheuristics

# Evolutionary Algorithms / Genetic Algorithms

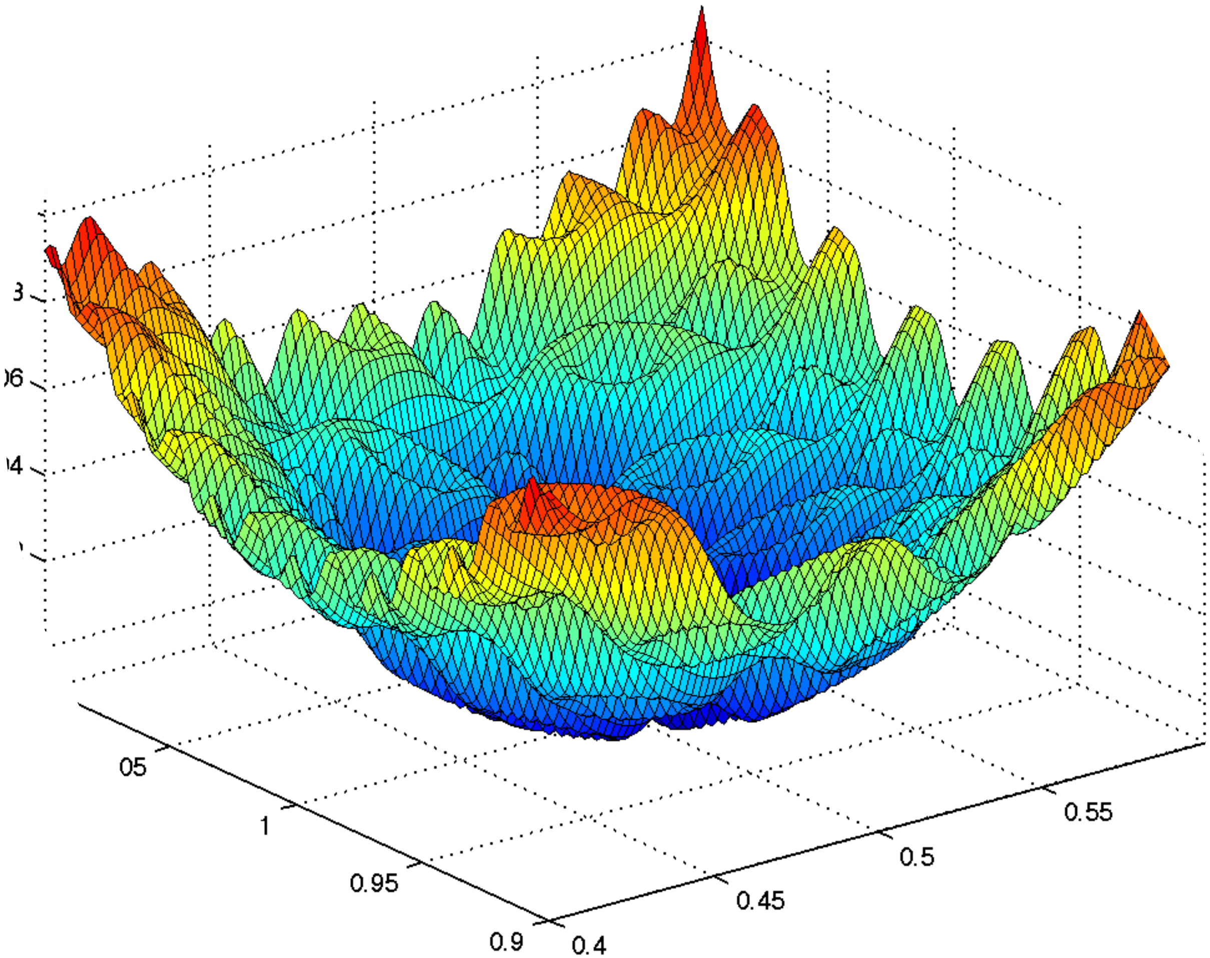
- A metaheuristic for **population-**based optimization.
- Uses mechanisms inspired by biological evolution (genetics):
  - Reproduction: Random selection with probability based on a **fitness** function.
  - Random recombination (crossover)
  - Random mutation
  - Repeated for many generations




- Example: 8-queens problem



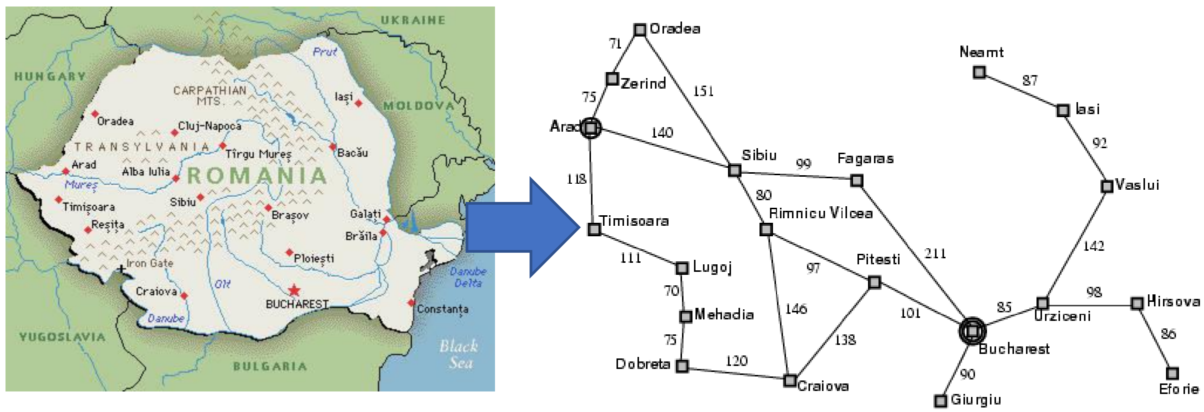

Individual = state
**Encoding** as a chromosome: row of the queen in each column




# Search in Continuous Spaces

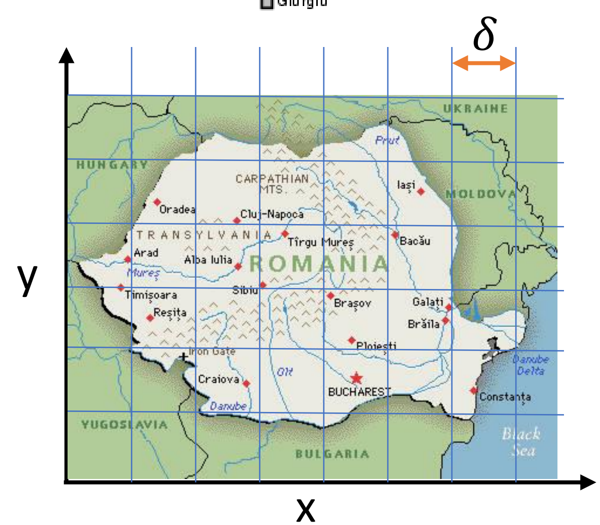
# Discretization of Continuous Space

- Use atomic states and create a graph as the transition function.



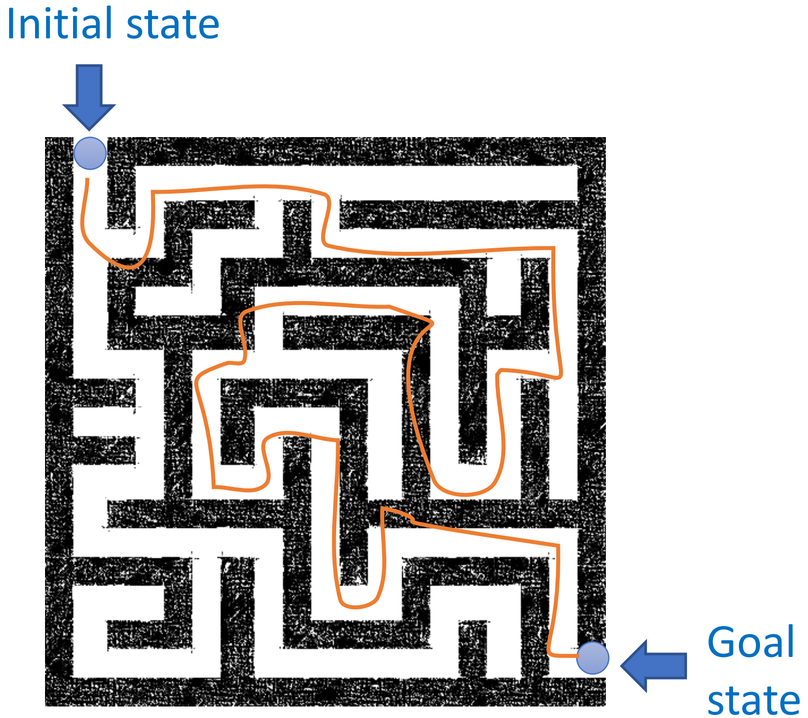

- Use a grid with spacing of size $\delta$

  Note: You probably need a way finer grid!

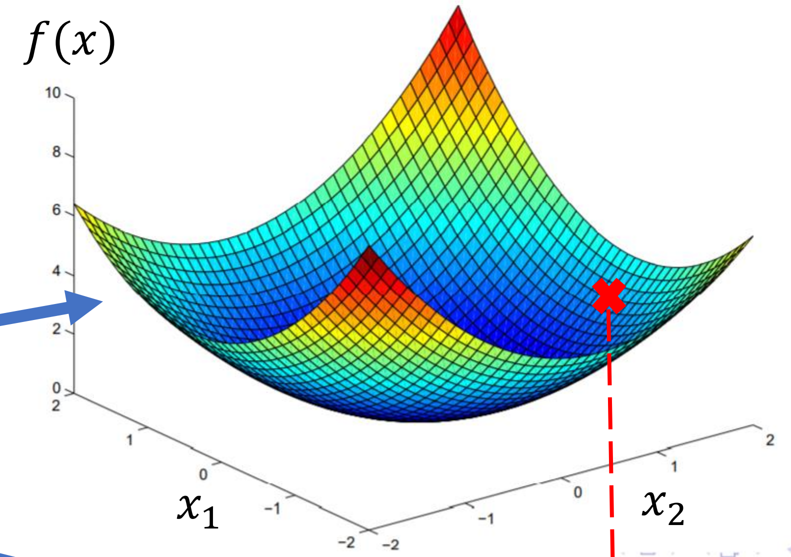


# Discretization of Continuous Space

How did we discretize this space?



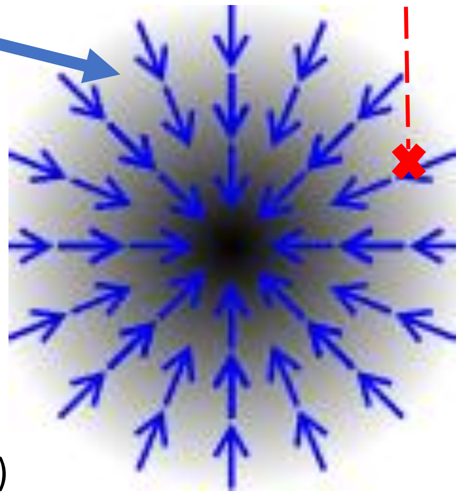
# Search in Continuous Spaces: Gradient




Minimize $f(\boldsymbol{x}) = f(x_1, x_2, \dots, x_k)$

Gradient at point $\boldsymbol{x}$: $\nabla f(\boldsymbol{x}) = \left(\frac{\partial f(x)}{\partial x_1}, \frac{\partial f(x)}{\partial x_1}, \dots, \frac{\partial f(x)}{\partial x_1}\right)$
(=evaluation of the Jacobian matrix at x)

Find optimum by solving: $\nabla f(\boldsymbol{x}) = 0$



- **Gradient descent (= Steepest-ascend hill climbing for minimization)** with step size $\alpha$

$$\boldsymbol{x} \leftarrow \boldsymbol{x} - \alpha \nabla f(\boldsymbol{x})$$

- **Newton-Raphson method** uses the inverse of the Hessian matrix (second-order partial derivative) $H_{ij} = \frac{\partial^2 f}{\partial x_i \partial x_j}$ for the step size $\alpha$

$$\boldsymbol{x} \leftarrow \boldsymbol{x} - \boldsymbol{H}_f^{-1}(\boldsymbol{x}) \nabla f(\boldsymbol{x})$$

Note: May get stuck in a local optima if the search space is non-convex! Use simulated annealing, momentum or other methods.

# Search in Continuous Spaces: Empirical Gradient Methods

- What if the mathematical formulation of the objective function is not known?
- We may have objective values at fixed points, called the training data.
- In this case, we can use **empirical gradient search.** This is related to steepest ascend hill climbing in the discretized state space.

→ We will talk more about search in continuous spaces with loss functions using gradient descend when we talk about **parameter learning for machine learning.**