

# Problem Solving by Search 3

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# Outline

Introduction

Formulation of the Problem

Basic Idea Behind Local Search

Hill Climbing

Simulated Annealing

Genetic Algorithms

# Overview

**Search:** very important technique in CS and AI

Different kinds of search:

- ▶ **Deterministic search**
  - ▶ Uninformed (“blind”) search strategies ✓
  - ▶ Informed or heuristic search strategies: ✓  
use information about problem structure
- ▶ **Local search**
- ▶ **Search in game trees** (not covered in this course)

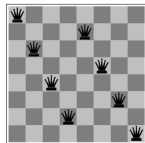
In this lecture: **Local search**

# What is the Problem?

- ▶ Search methods mentioned so far are often too expensive
- ▶ They systematically explore the state space (state space = set of "complete" configurations)
- ▶ Solution was a **path** from the start to a goal
- ▶ From now on:
  - ▶ **path** to goal is **irrelevant** (**goal state** itself is the **solution**)
  - ▶ Each state  $n$  has a **score** (or objective function)  $f(n)$
  - ▶ Goal: Find a goal state with **best** (or reasonable) score
- ▶ The focus is therefore on optimization problems

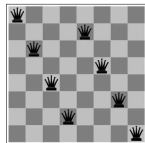
# Examples

- ▶ N-queens problem:
  - ▶ Put  $N$  queens on the board **without** conflicts
  - ▶ Let  $f(n)$  be the number of conflicting queens in state  $n$
  - ▶ Search  $s$  with lowest score  $f(s)$

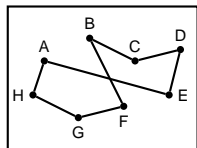


# Examples

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- ▶ Traveling Salesperson problem (TSP)
  - ▶ Start at, e.g., A and make a tour
  - ▶ Visit each city ones and return to A
  - ▶ State: order of cities,  $f(s)$ : total kms
  - ▶ Problem is NP-hard

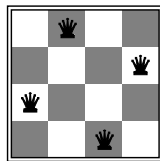
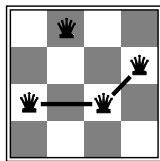
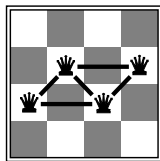


# Basic Idea Behind Local Search

- ▶ **Basic Idea:** Perform an iterative improvement
  - ▶ Keep a **single "current" state** (rather than multiple paths)
  - ▶ Try to improve it
- ▶ Move iteratively to neighbors of the current state
- ▶ Do **not** retain search path
- ▶ Constant space, often rather fast, but **incomplete**
- ▶ What is a **neighbor**?
  - ▶ **Neighborhood** has to be defined application-dependent

## 4-queens

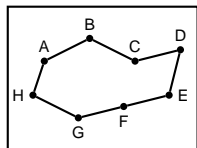
- ▶ Take leftmost state  $s$  with  $h(s) = 5$  and try to improve
- ▶ Generate neighbor by moving a queen in the column
- ▶ For the state  $t$  in the middle,  $h(t) < h(s)$
- ▶ Again, generate neighbor by moving a queen in the column
- ▶ Resulting state has score 0 and is a solution





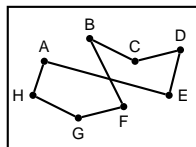
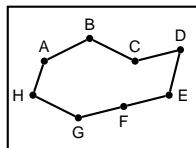
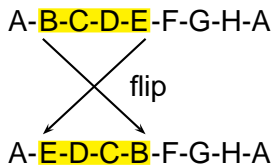
# TSP

- ▶ State  $s$ : A-B-C-D-E-F-G-H-A
- ▶  $f(s)$ : length of the tour
- ▶ One possibility: 2-change



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# Hill Climbing (or Gradient Ascent/Descent)

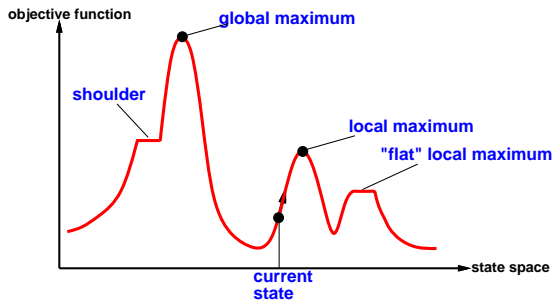
1. Choose an initial state  $n$
2. Compute all neighbors  $m$  of  $n$  with largest  $f(m)$
3. If  $f(m) \leq f(n)$  then return  $n$  and stop
4. Otherwise, let  $n = m$  and continue with 2

## Problems

- ▶ Very simple algorithm, get easily stuck in **local optima**
- ▶ How to get the neighbors?
  - ▶ By **small changes** of the state
  - ▶ Must be **easy to compute**
- ▶ Choose how to generate the neighbors crucial

## Hill Climbing cont'd

How does  $f$  (the objective function) evolve for varying states?



- ▶ **Random-restart** hill climbing overcomes local maxima
- ▶ **Random sideways moves**
  - ▶ **Escape** from shoulders
  - ▶ **Loop** on flat maxima

# Simulated Annealing

## Basic Idea

- ▶ Escape local optima by allowing some “bad” moves
- ▶ But gradually increase their size and frequency

1. Choose an initial state  $n$
2. Randomly pick  $m$  from the neighbors of  $n$
3. If  $f(m)$  is better than  $f(n)$  then set  $n = m$
4. Otherwise /\* if  $m$  is worse than  $n$  \*/  
With a small probability  $p$ , set  $n = m$
5. Continue with 2. until time limit is reached

- ▶  $p$  decreases over time and when  $|f(n) - f(m)|$  increases

## Simulated Annealing Cont'd

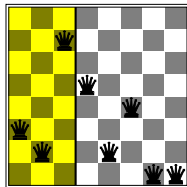
- ▶ If  $f(m)$  better than  $f(n)$ , then always continue with  $m$
- ▶ Otherwise, take  $m$  with probability

$$\exp\left(-\frac{|f(n) - f(m)|}{T}\right)$$

- ▶ Probability decreases exponentially with the badness  $|f(n) - f(m)|$
- ▶ The temperature parameter  $T$  is decreased over time (“cooling” or “annealing”)
- ▶ If badness is large, the probability is small

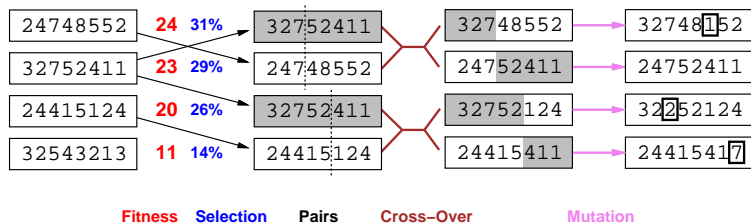
# Genetic Algorithms (GAs)

- ▶ GAs: heuristic stochastic search algos
- ▶ GAs require **states** encoded as **strings**
- ▶ State (right) encodes as **(3 2 7 5 2 4 1 1)**  
(places of the queens from bottom)
- ▶  $f(n)$  is called the **fitness** of  $n$   
**Goal:** Find **fittest**  $n$ , i.e., find **global optimum**
- ▶ Keep a **fixed number** of states  
(They are called the **population**)



# Genetic Algorithms Cont'd

- ▶ GAs generate neighbors by **crossover**, **mutation** and **natural selection**





# Genetic Algorithms Cont'd

- ▶ GAs generate neighbors by **crossover**, **mutation** and **natural selection**
- ▶ Crossover helps iff substrings are meaningful components
- ▶ **GAs  $\neq$  evolution**: e.g., real genes encode replication machinery

