So far, we have considered methods that systematically explore the full search space, possibly using **principled** pruning (A* etc.).

The current best such algorithms (RBFS / SMA*) can handle search spaces of up to 10^{100} states.

But search spaces for some real-world problems might be much bigger — e.g. $10^{30,000}$ states.

Local Search Methods

Local Search Methods

Applicable when we're interested in the Goal State — not in how to get there.

E.g. N-Queens, VLSI layout, or map coloring.

Basic idea:

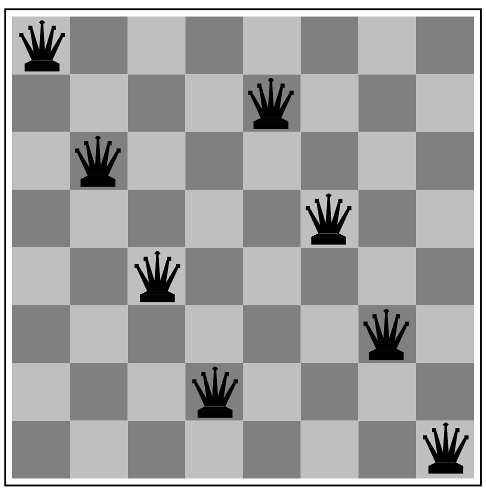
use a single **current state**

don't save paths followed

generally move only to successors/neighbors of that state

Generally require a **complete state description**.

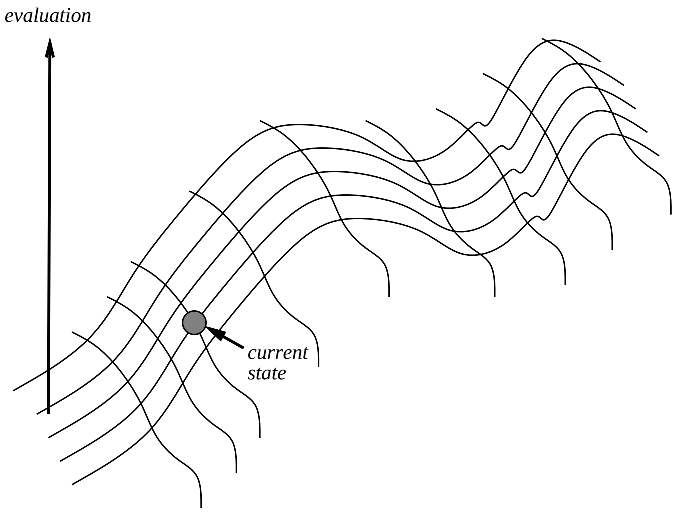
Example



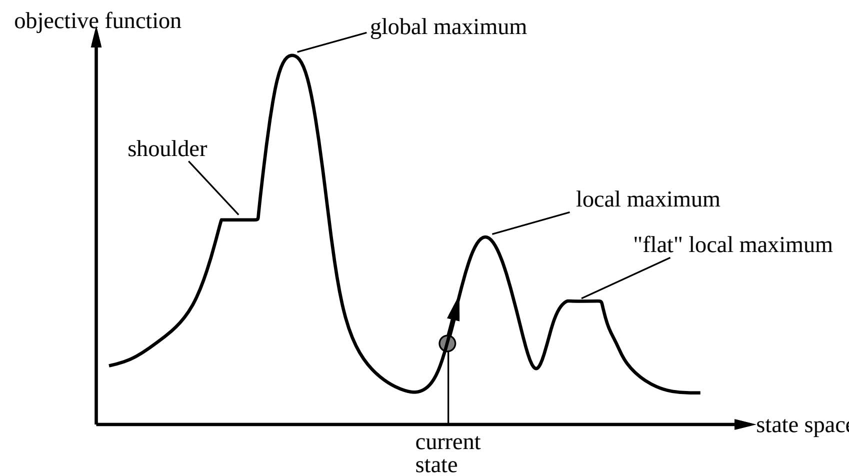
Hill-Climbing Search

```
function HILL-CLIMBING(problem) returns a solution state
  inputs: problem, a problem
  static: 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 Pathologies



Improvements to Basic Local Search

Issue: How to move more quickly to successively higher plateaus and avoid getting “stuck” / **local minima**.

Idea: Introduce uphill moves (“noise”) to escape from long plateaus (or true local minima).

Strategies:

- Multiple runs from randomly generated initial states
- Random-restart hill-climbing
- Tabu search
- Simulated Annealing
- Genetic Algorithms

Variations on Hill-Climbing

1. **random restarts:** simply restart at a new random state after a pre-defined number of local steps.
2. **tabu:** prevent returning quickly to same state. Implementation: Keep fixed length queue (“tabu list”): add most recent step to queue; drop “oldest” step. Never make step that’s currently on the tabu list.

Simulated Annealing

Idea:
Use conventional hill-climbing techniques, but occasionally take a step in a direction other than that in which the rate of change is maximal.

As time passes, the probability that a down-hill step is taken is gradually reduced and the size of any down-hill step taken is decreased.

Kirkpatrick *et al.* 1982; Metropolis *et al.* 1953.

SA Algorithm

current, next: nodes/states

T: "temperature" controlling probability of downward steps

schedule: mapping from time to "temperature"

h: heuristic evaluation function

current $\leftarrow$ initial state
for $t \leftarrow 1$ to inf do

  $T \leftarrow schedule[t]$
  if $T = 0$ then return *current*
  next $\leftarrow$ randomly selected successor of *current*
  $\Delta E \leftarrow h(next)$ - $h(current)$
  if $\Delta E > 0$ then *current* $\leftarrow$ *next*
  else *current* $\leftarrow$ *next* only with probability $e^{\Delta E/T}$

Genetic Algorithms

- Approach mimics *evolution.*
- Usually presented using a rich (and different) vocabulary:
  - fitness, populations, individuals, genes, crossover, mutations, etc.
- Still, can be viewed quite directly in terms of standard **local search**.

Features of evolution

- High degree of parallelism
- New individuals ("next state / neighboring states"):
  - derived from "parents" ("crossover operation")
  - genetic mutations
- Selection of next generation:
  - based on survival of the fittest

Genetic Algorithms

Inspired by biological processes that produce genetic change in populations of individuals.

Genetic algorithms (GAs) are local search procedures that usually the following basic elements:

- A Darwinian notion of **fitness**: the most fit individuals have the best chance of survival and reproduction.
- Mating operators:
  - Parents are selected.
  - Parents contribute their genetic material to their children.
  - Mutation: individuals are subject to random changes in their genetic material.

General Idea

- Maintain a population of individuals (states / strings / candidate solutions)
- Each individual is evaluated using a **fitness function**, i.e. an evaluation function. The fitness scores force individuals to compete for the privilege of survival and reproduction.
- Generate a sequence of generations:
  - From the current generation, select **pairs** of individuals (based on fitness) to generate new individuals, using **crossover**.
- Introduce some noise through random **mutations**.
- Hope that average and maximum fitness (i.e. value to be optimized) increases over time.

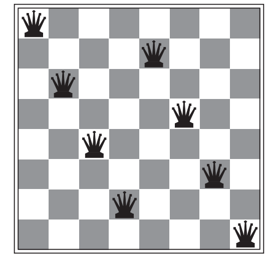
Genetic algorithms as search

- Genetic algorithms are local heuristic search algorithms.
- Especially good for problems that have large and poorly understood search spaces.
- Genetic algorithms use a randomized parallel beam search to explore the state space.
- You must be able to define a good fitness function, and of course, a good state representation.

Binary string representations

- Individuals are usually represented as a string over a finite alphabet, usually bit strings.
- Individuals represented can be arbitrarily complex.
- E.g. each component of the state description is allocated a specific portion of the string, which encodes the values that are acceptable.
- Bit string representation allows crossover operation to change multiple values in the state description. Crossover and mutation can also produce previously unseen values.

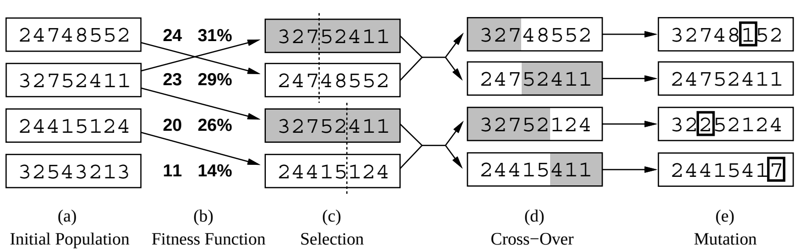
8-queens State Representation



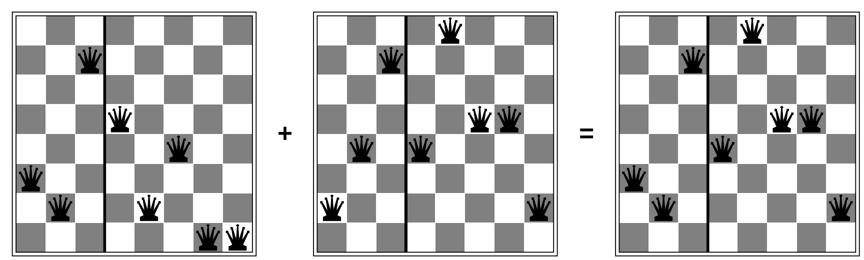
option 1: 86427531

option 2: 111 101 011 001 110 100 010 000

GA: High-level Algorithm



Crossover Example



Another Example

World championship chocolate chip cookie recipe.

	flour	sugar	salt	chips	vanilla	fitness
1	4	1	2	16	1	
2	4.5	3	1	14	2	
3	2	1	1	8	1	
4	2.2	2.5	2.5	16	2	
5	4.1	2.5	1.5	10	1	
6	8	1.5	2	8	2	
7	3	1.5	1.5	8	2	

generation 1

GA$(Fitness, Fitness\_threshold, p, r, m)$

- $P \leftarrow$ randomly generate p individuals
- For each i in P, compute $Fitness(i)$
- While $[\max_i Fitness(i)] < Fitness\_threshold$
  1. Probabilistically **select** $(1-r)p$ members of P to add to P_S.
  2. Probabilistically choose $\frac{r \cdot p}{2}$ pairs of individuals from P. For each pair, $\langle i_1, i_2 \rangle$, apply **crossover** and add the offspring to P_s
  3. **Mutate** $m \cdot p$ random members of P_s
  4. $P \leftarrow P_s$
  5. For each i in P, compute $Fitness(i)$
- Return the individual in P with the highest fitness.

Selecting Most Fit Individuals

Individuals are chosen probabilistically for survival and crossover based on **fitness proportionate selection**:

$$\Pr(i) = \frac{Fitness(i)}{\sum_{j=1}^{p} Fitness(i_j)}$$

Other selection methods include:

- **Tournament Selection:** 2 individuals selected at random. With probability p, the more fit of the two is selected. With probability $(1-p)$, the less fit is selected.

- **Rank Selection:** The individuals are sorted by fitness and the probability of selecting an individual is proportional to its rank in the list.

Crossover Operators

Single-point crossover:

Parent A:	**1**	**0**	**0**	**1**	**0**	**1**	**1**	**1**	**0**	**1**
Parent B:	0	1	0	1	1	1	0	1	1	0
Child AB:	**1**	**0**	**0**	**1**	**0**	1	0	1	1	0
Child BA:	0	1	0	1	1	**1**	**1**	**1**	**0**	**1**

Two-point crossover:

Parent A:	**1**	**0**	**0**	**1**	**0**	**1**	**1**	**1**	**0**	**1**
Parent B:	0	1	0	1	1	1	0	1	1	0
Child AB:	**1**	**0**	**0**	**1**	1	1	0	**1**	**0**	**1**
Child BA:	0	1	0	1	**0**	**1**	**1**	1	1	0

Uniform Crossover

Uniform crossover:

Parent A:	**1**	**0**	**0**	**1**	**0**	**1**	**1**	**1**	**0**	**1**
Parent B:	0	1	0	1	1	1	0	1	1	0
Child AB:	**1**	1	**0**	**1**	1	1	**1**	1	**0**	**1**
Child BA:	0	**0**	0	1	**0**	**1**	0	**1**	1	0

Mutation

Mutation: randomly toggle one bit

Individual A:	1	0	0	1	0	1	1	1	0	1
Individual A':	1	0	0	**0**	0	1	1	1	0	1

Mutation

- The **mutation** operator introduces random variations, allowing solutions to jump to different parts of the search space.
- What happens if the mutation rate is too low?
- What happens if the mutation rate is too high?
- A common strategy is to use a high mutation rate when search begins but to decrease the mutation rate as the search progresses.

Deriving illegal structures

Consider the traveling salesperson problem, where an individual represents a potential solution. The standard crossover operator can produce illegal children:

Parent A:	ITH	Pitt	Chicago	Denver	Boise
Parent B:	Boise	Chicago	ITH	Phila	Pitt
Child AB:	ITH	Pitt	Chicago	Phila	Pitt
Child BA:	Boise	Chicago	ITH	Denver	Boise

Two solutions:

1. define special genetic operators that only produce syntactically and semantically legal solutions.
2. ensure that the fitness function returns extremely low fitness values to illegal solutions.

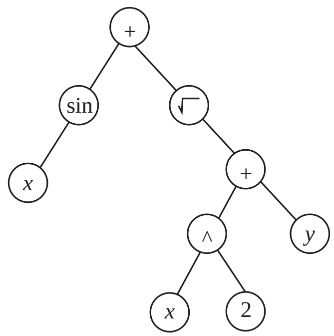
Applications: Parameter Optimization

- Parameter optimization problems are well-suited for GAs. Each individual represents a set of parameter values and the GA tries to find the set of parameter values that achieves the best performance.
- Crossover: creates new combinations of parameter values and, using a binary representation, both the crossover and mutation operators can produce new values.
- Many learning systems can be recast as parameter optimization problems. For example, most neural networks use a fixed architecture so learning consists entirely of adjusting weights and thresholds.

Genetic Programming

In **Genetic Programming**, programs are evolved instead of bit strings. Programs are represented by trees. For example:

$$\sin(x) + \sqrt{x^2 + y}$$



Remarks on GA's

- In practice, several 100 to 1000's of strings. Value of crossover difficult to determine (so far).
- **Crowding** can occur when an individual that is much more fit than others reproduces like crazy, which reduces diversity in the population.
- In general, GA's are highly sensitive to the representation.
- Given enough compute time, it's the best search algorithm in some domains.

Local Search — Summary

Surprisingly efficient search method.

Wide range of applications.
    any type of optimization / search task
Handles search spaces that are too large
    (e.g., 10^{1000}) for systematic search
Often best available algorithm when
    lack of global information.
Formal properties remain largely elusive.
Research area will most likely continue to thrive.