Local Search Algorithms

- In many optimization problems, ***path*** is irrelevant
- the goal state itself is the solution
- Ex: The 8-queen problem, the final configuration of the queens is the important not the order they were put
- Operates using only single current state, rather than multiple paths.
- Find Optimal Configuration (satisfies the constraints)
- Use ***iterative improvement algorithms***
- Good for Optimization problems: find the best state according to some objective function
- A **Complete** local search algorithm finds a goal if exists
- An **Optimal** algorithm finds the global minimum or maximum

Local Search Algorithms

- Search algorithms like BFS, DFS or A* explore all the search space systematically by keeping one or more paths in memory and by recording which alternatives have been explored.
- Local search algorithms operate using a single current state (rather than multiple paths)
- move only to neighbours of that state.
- Ignore paths
- Advantages:
  - Use very little memory
  - Can often find reasonable solutions in large or infinite (continuous) state spaces.

Local Search Algorithms

local search algorithms :

- are useful for solving pure **optimization problems,** in which the aim is to find the best state according to an **objective function.**

- operate using a **single current state** (rather than multiple paths) and generally move only to neighbors of that state.

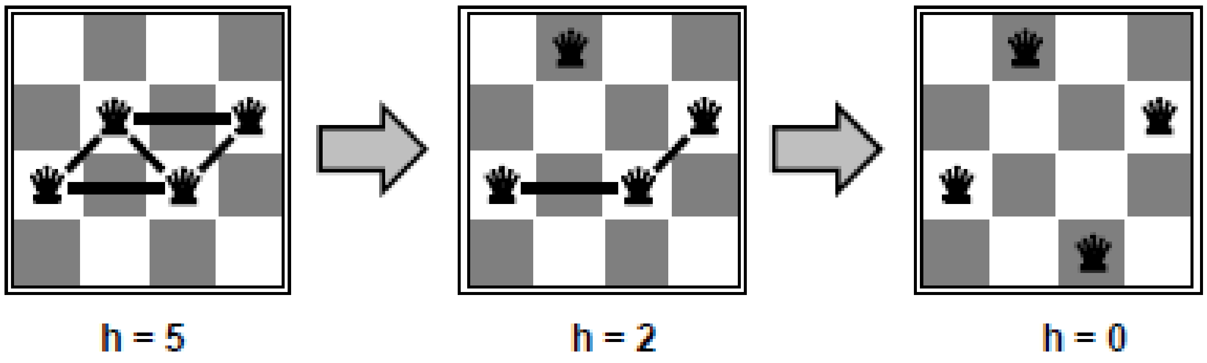
Local Search Algorithms

- Local Search Algorithms are used in:
  - Optimization problems
  - find the best state according to some objective function
  - All states have an objective function
  - Goal is to find state with max (or min) objective value
  - Local search can do very well on these problems.

Local Search Algorithms

Example n-queens

- Put n queens on an nxn board with no two queens on the same row, column, or diagonal
- Local search: start with all n, move a queen to reduce conflicts



Local Search Algorithms

- Hill Climbing
- Simulated annealing
- Genetic algorithms
- Local search in continuous spaces

Local beam search

- One Solution to improve hill Climbing.
- Keep track of *k* states instead of one
  - Initially: *k* randomly selected states
  - Next: determine all successors of *k* states
  - If any of successors is goal $\rightarrow$ finished
  - Else select *k* best from successors and repeat.
- Major difference with random-restart search
  - Information is used for *k* search branches.
- Also improved to stochastic beam search

Simulated Annealing

- Annealing is a process for obtaining low energy states of a solid in a heat bath.

- The process contains two steps:
  - Increase the temperature of the heat bath to a maximum value at which the solid melts.
  - Decrease carefully the temperature of the heat bath until the particles arrange themselves in the ground state of the solid. Ground state is a minimum energy state of the solid.

- The ground state of the solid is obtained only if the maximum temperature is high enough and the cooling is done slowly.

Simulated Annealing

```
function SIMULATED-ANNEALING( problem, schedule) return a solution state
    input: 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 ← 1 to ∞ do
      T ← schedule[t]
      if T = 0 then return current
      next ← a randomly selected successor of current
      $\Delta E$ ← VALUE[next] - VALUE[current]
      if $\Delta E > 0$ then current ← next
      else current ← next only with probability $e^{\Delta E / T}$
```

The cost of a solution is equivalent to the “energy” of a state.

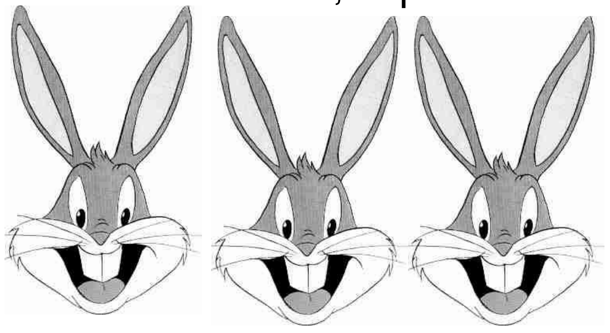
Simulated Annealing

- The search is started with a randomized state. loop we will move to neighboring states always accepting the moves that decrease the energy while only accepting bad moves accordingly to a probability distribution dependent on the “temperature” of the system.
- Decrease the temperature slowly, accepting less bad moves at each temperature level until at very low temperatures the algorithm becomes a greedy hill-climbing algorithm.

The Genetic Algorithm (Evolutionary Analogy)

- Consider a population of rabbits:
  - some individuals are faster and smarter than others
  - Slower, dumper rabbits are likely to be caught and eaten by foxes

  - Fast, smart rabbits survive ,… produce more rabbits.



Evolutionary Analogy

- The rabbits that survive generate offspring, which start to mix up their genetic material
- Furthermore, nature occasionally throws in a wild properties because genes can mutate
- In this analogy, an individual rabbit represents a solution to the problem(i.e. Single point in the space)
- The foxes represent the problem constraints (solutions that do more well are likely to survive)

Evolutionary Analogy

- Evolution Fundamental Laws: Survival of the fittest.

➢ Change in species is due to change in genes over reproduction or/and due to mutation.

➢ For selection, we use a fitness function to rank individuals of the population

➢ For reproduction, we define a crossover operator which takes state descriptions of individuals and combine them to create new ones

➢ For mutation, we can choose individuals in the population and alter part of its state.

The Genetic Algorithm

- Directed search algorithms based on the mechanics of biological evolution
- Developed by John Holland, University of Michigan (1970's)
- To design artificial systems software that retains the robustness of natural systems
- Provide efficient, effective techniques for search problems, optimization and machine learning applications
- Widely-used today in business, scientific and engineering circles

Terminology

- ***Evolutionary Computation (EC)*** refers to computer-based problem solving systems that use computational models of evolutionary process.
- ***Chromosome*** – It is an individual representing a candidate solution of the optimization problem.
- ***Population*** – A set of chromosomes.
- ***gene*** – It is the fundamental building block of the chromosome, each gene in a chromosome represents each variable to be optimized. It is the smallest unit of information.
- **Objective**: To find "a" best possible chromosome for a given problem.

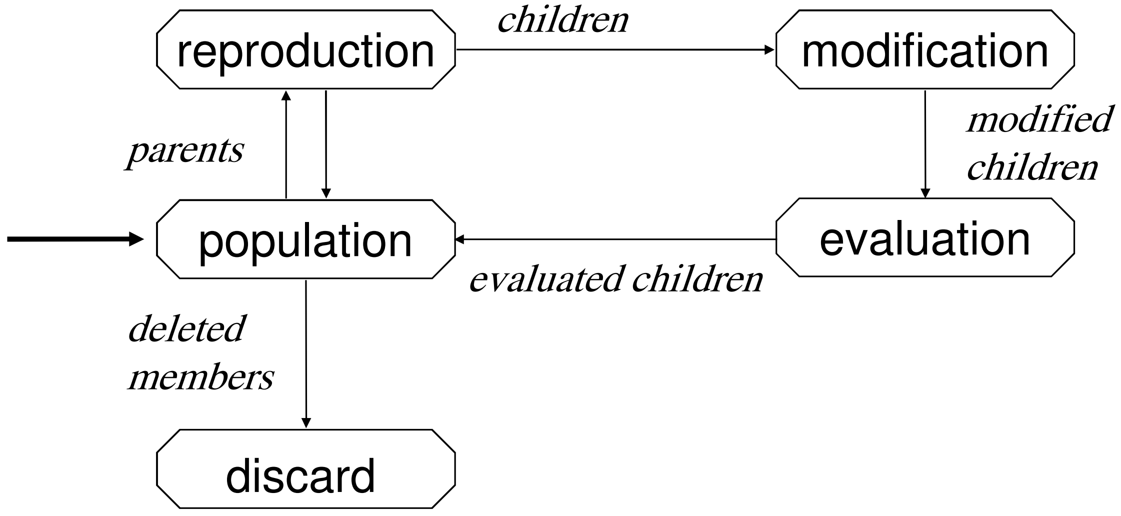
Overview of GAs

- GA emulates genetic evolution.
- A GA has distinct features:
  - A string representation of chromosomes.
  - A selection procedure for initial population and for off-spring creation.
  - A cross-over method and a mutation method.
  - A fitness function.
  - A replacement procedure.

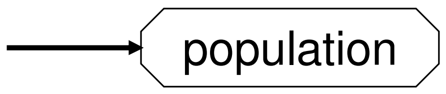
Overview of GAs

- Parameters that affect GA are:
  - initial population
  - size of the population
  - selection process and
  - fitness function

The GA Cycle of Reproduction



Chromosomes

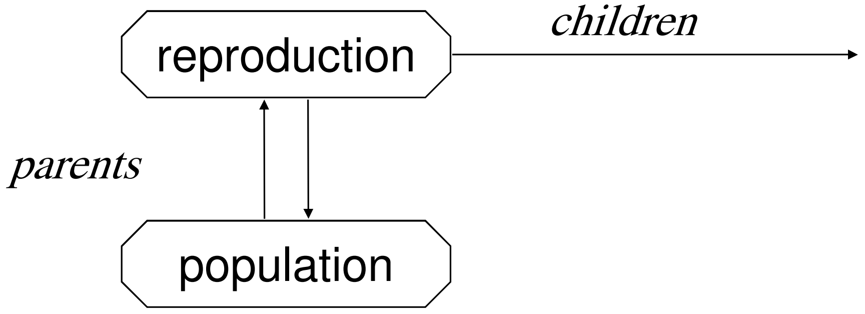


Chromosomes could be:

Bit strings	(0101 ... 1100)
Real numbers	(43.2 -33.1 ... 0.0 89.2)
Permutations of element	(E11 E3 E7 ... E1 E15)
Lists of rules	(R1 R2 R3 ... R22 R23)
Program elements	(genetic programming)

... any data structure ...

Reproduction



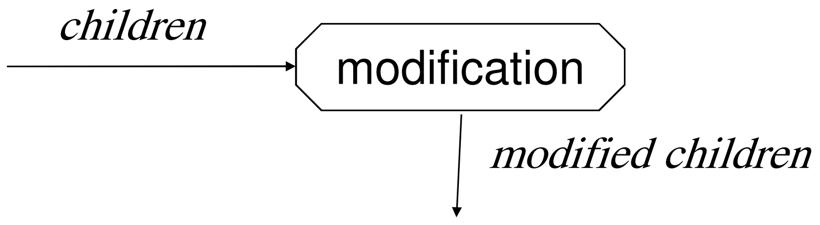
Reproduction is a processes of creating new chromosomes out of chromosomes in the population. Parents are ”selected” at each iteration.

Selection Process

- Selection is a procedure of picking parent chromosome to produce off-spring.
- Types of selection:
  - Random Selection – Parents are selected randomly from the population.
  - Proportional Selection – probabilities for picking each chromosome is calculated as:

$$P(\mathbf{x}_i) = f(\mathbf{x}_i)/\Sigma f(\mathbf{x}_j) \quad \text{for all } j$$

Chromosome Modification



- Operator types are:
  - Mutation
  - Crossover (recombination)

Crossover

P1 (0 1 1 0 1 0 0 0) $\longrightarrow$ (1 1 0 1 1 0 0 0) C1

P2 (1 1 0 1 1 0 1 0) (0 1 1 0 1 0 1 0) C2

Cross-over : It is a process of creating one or more new individuals through the combination of genetic material randomly selected from two parents.

Crossover is a critical feature of genetic algorithms:

- It greatly accelerates search early in evolution of a population
- It leads to effective combination of schemata (subsolutions on different chromosomes)

Cross-over

- Uniform cross-over : where corresponding bit positions are randomly exchanged between two parents.
- One point : random bit is selected and entire sub-string after the bit is swapped.
- Two point : two bits are selected and the sub-string between the bits is swapped.

	Uniform Cross-over	One point Cross-over	Two point Cross-over
Parent1 Parent2	00110110 11011011	001|10110 110|11011	0|01101|10 1|10110|11
Off-spring1 Off-spring2	01110111 10011010	001|11011 11010110	0|10110|10 10110111

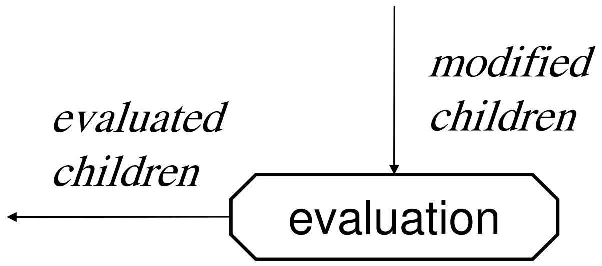
Mutation: Local Modification

Before:	(1 0 1 1 **0** 1 1 0)
After:	(1 0 1 1 **1** 1 1 0)

Before:	(1.38 **-69.4** 326.44 0.1)
After:	(1.38 **-67.5** 326.44 0.1)

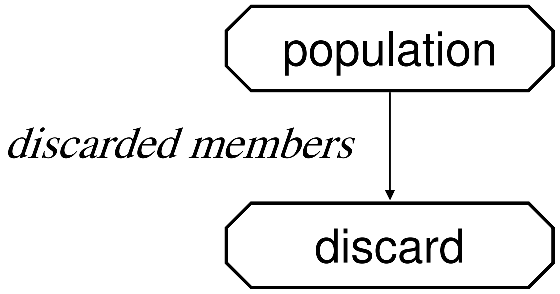
- Causes movement in the search space (local or global)
- Restores lost information to the population
- Prevents falling all solutions in population into a local optimum.

Evaluation



- The evaluator decodes a chromosome and assigns it a fitness measure

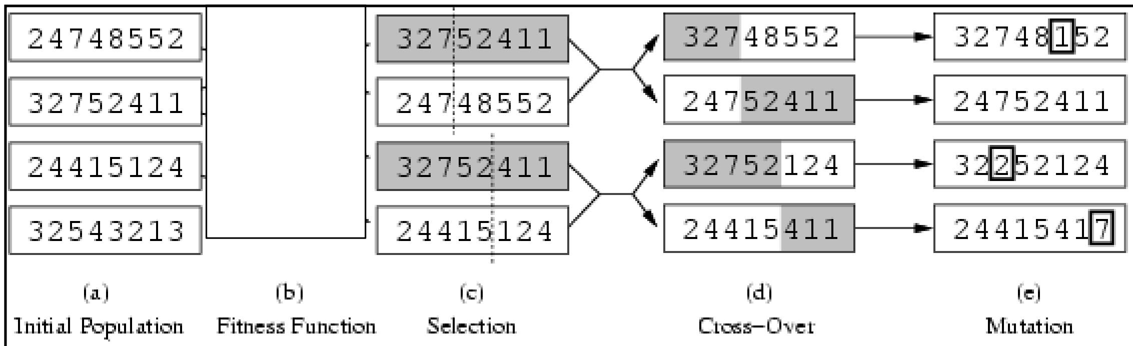
Deletion

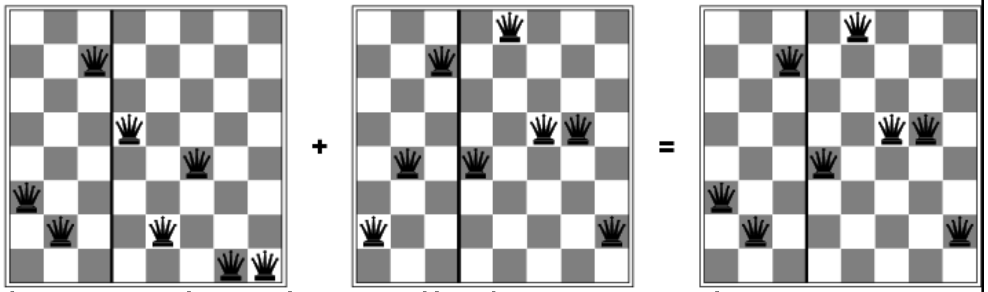


- ***Generational*** GA:
  entire populations replaced with each iteration
- ***Steady-state*** GA:
  a few members replaced each generation

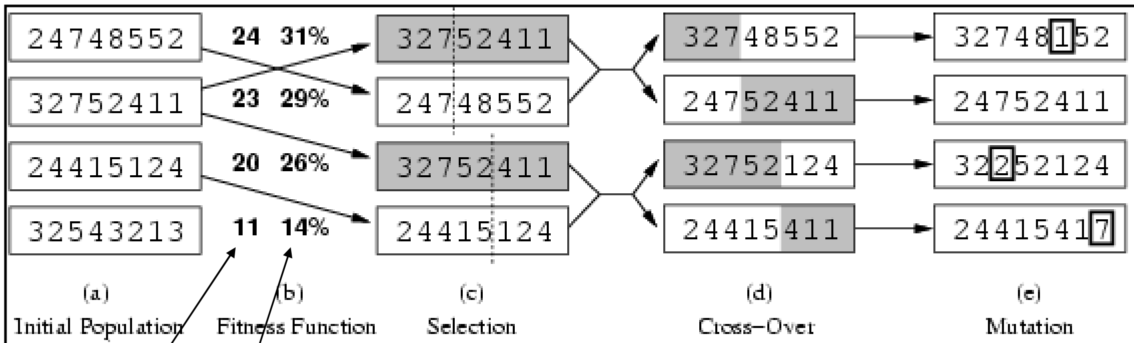
Evolutionary Algorithm

```
Let t = 0 be the generation counter;
create and initialize a population *P(0)*;
**repeat**
    Evaluate the fitness, $f(\mathbf{x}_i)$, for all $\mathbf{x}_i$ belonging to $P(t)$;
    Perform cross-over to produce offspring;
    Perform mutation on offspring;
    Select population $P(t+1)$ of new generation;
    Advance to the new generation, i.e., $t = t+1$;
**until** *stopping condition is true;*
```



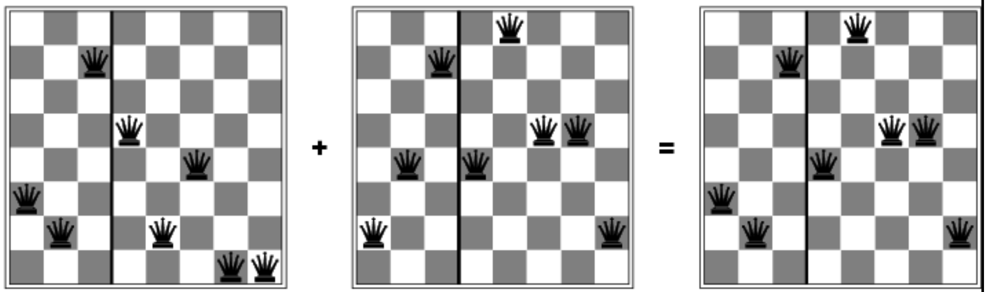


- Fitness function: number of non-attacking pairs of queens (min = 0, max = 8 × 7/2 = 28)



fitness:
#non-attacking queens

probability of being
regenerated
in next generation



- Fitness function: number of non-attacking pairs of queens (min = 0, max = 8 × 7/2 = 28)
- P(child) = 24/(24+23+20+11) = 31%
- P(child) = 23/(24+23+20+11) = 29% etc

Creativity in GA

- ✓ GAs can be thought of as a simultaneous, parallel hill climbing search --- The population as a whole is trying to converge to an optimal solution
- ✓ Because solutions can evolve from a variety of factors, very novel solutions can be discovered

A list of AI Search Algorithms

Systematic Search algorithms

- BFS, DFS,...
- A*
    - AO*
    - IDA* (Iterative Deepening)

Local Search Algorithms

- Minimax Search on Game Trees
- Viterbi Search on Probabilistic FSA
- Hill Climbing
- Simulated Annealing
- Gradient Descent
- Stack Based Search
- Genetic Algorithms
- Memetic Algorithms