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

- In many optimization problems, path is irrelevant; the goal state itself is the solution
- 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.**
- In such cases, can use iterative improvement algorithms; keep a single “current" state, try to improve it

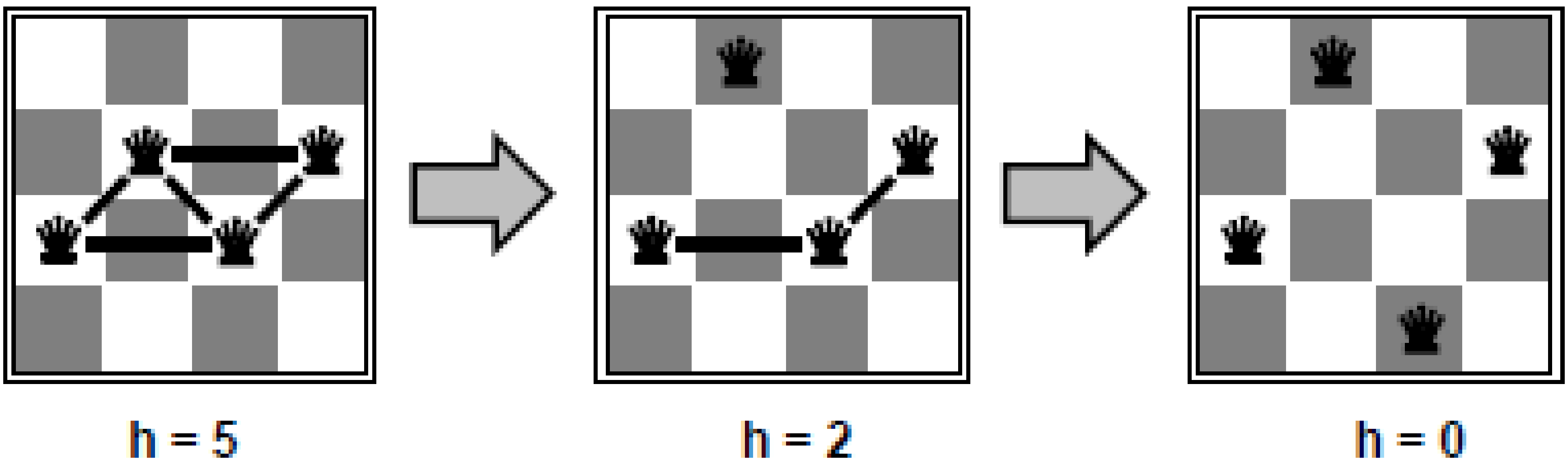
Local Search Algorithms

- **Local search algorithms operate using**
- a single **current state (rather than multiple paths) and generally move only to neighbors** of that state.
- Recall:
- A **complete,** local search algorithm always finds a goal if one exists;
- An **optimal algorithm** always finds a, global minimum/maximum.

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

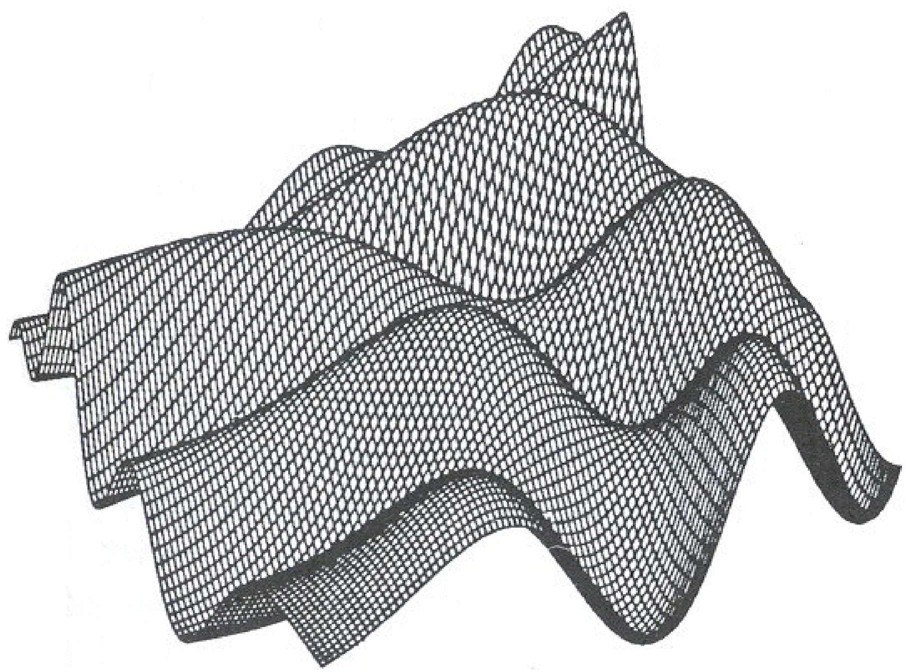


Local Search Algorithms

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

Simulated annealing search

- **Idea:** escape local maxima by allowing some “bad” moves but gradually decrease their size and frequency
- At fixed temperature T, state occupation probability reaches Boltzman distribution
- T decreases slowly enough and guarantees to reach best state x
- “Ping-pong ball example”



Simulated annealing search

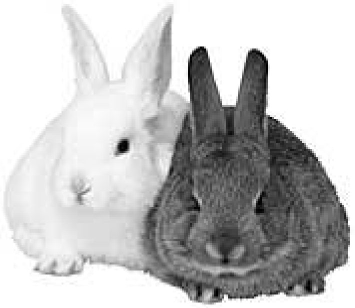
- *Algorithm:*
  - *From current state, pick a random successor state;*
  - *If it is better than current state, then use it as current state;*
  - *Otherwise, -Instead of restarting from a random point- we can allow the search to take some downhill steps to try to escape local maxima.*

Simulated annealing search

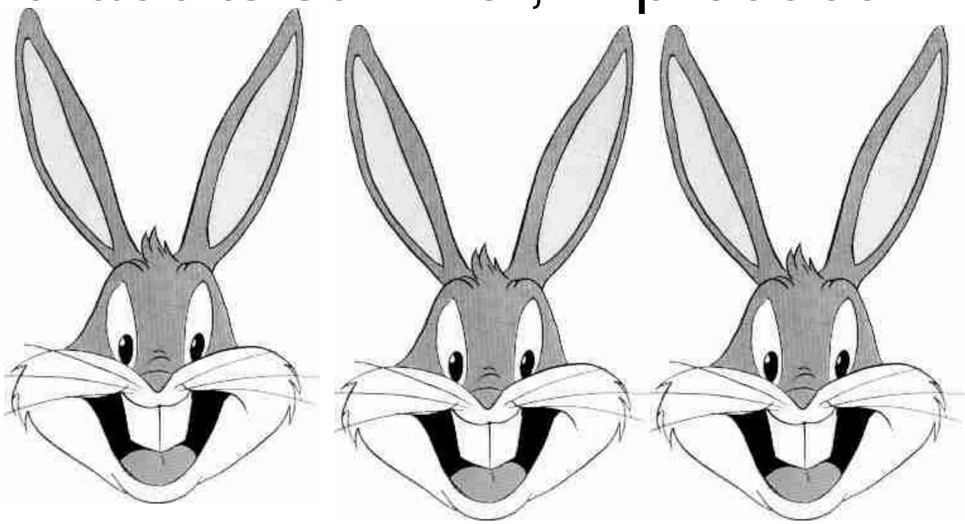
- *Probability of downward steps is controlled by **temperature parameter.***
- High temperature implies high chance of trying locally "bad" moves, allowing nondeterministic exploration.
- Low temperature makes search more deterministic (like hill-climbing).
- Temperature begins high and gradually decreases according to a predetermined **annealing schedule.**
- Initially we are willing to try out lots of possible paths, but over time we gradually settle in on the most promising path.
- If temperature is lowered slowly enough, an optimal solution will be found. In practice, this schedule is often too slow

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

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;

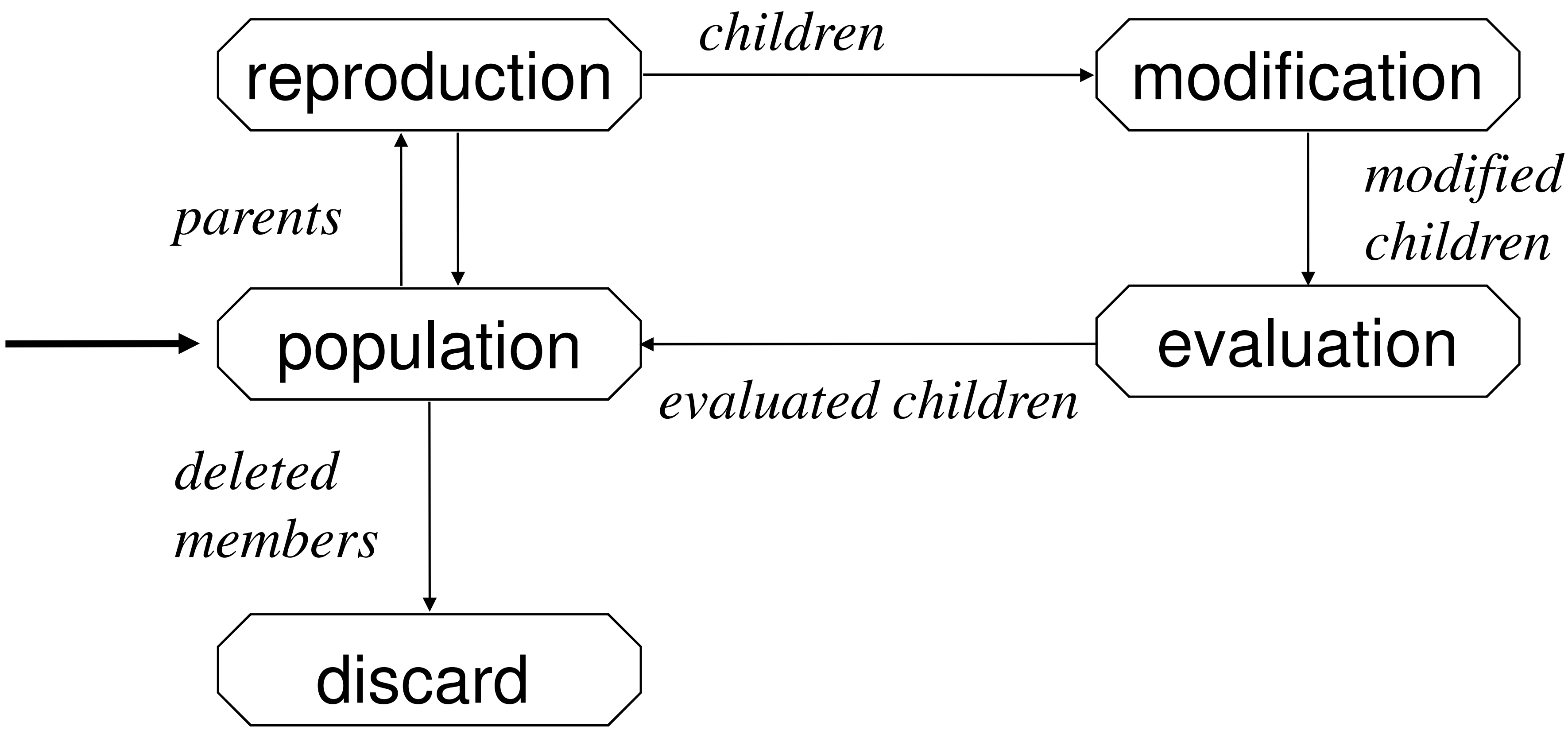
  Perform mutation on offspring;

  Select population *P(t+1)* of new generation;

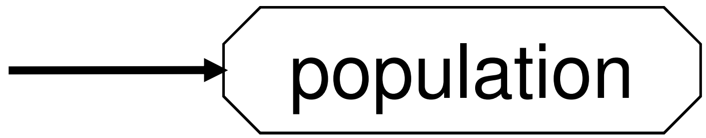
  Advance to the new generation, *i.e.,* $t = t+1$;

until *stopping condition is true;*

The GA Cycle of Reproduction



Chromosomes

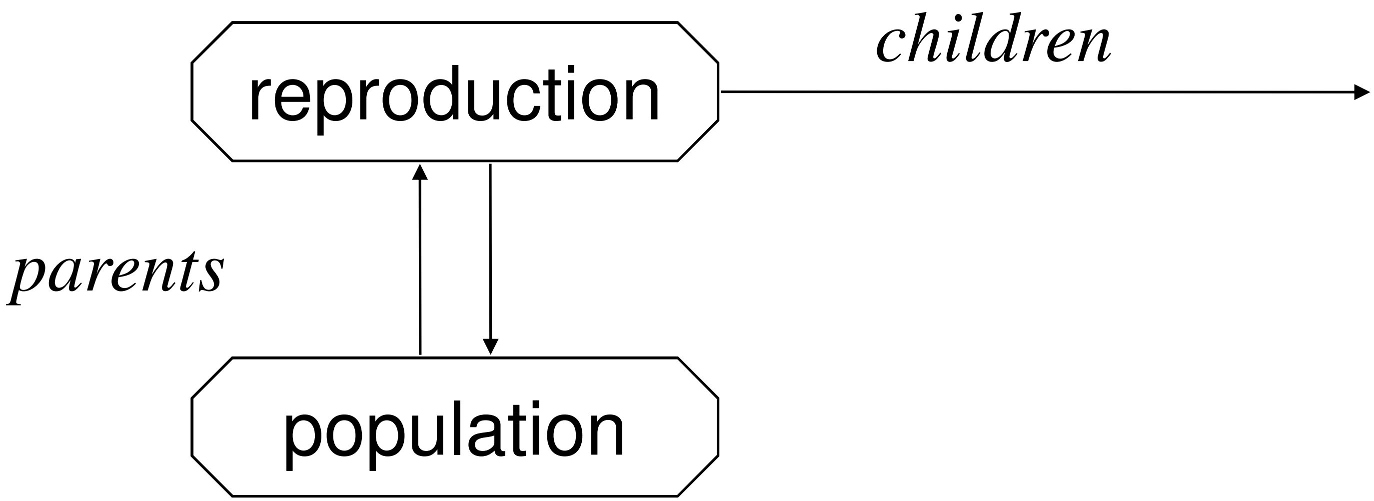


Chromosomes could be:

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



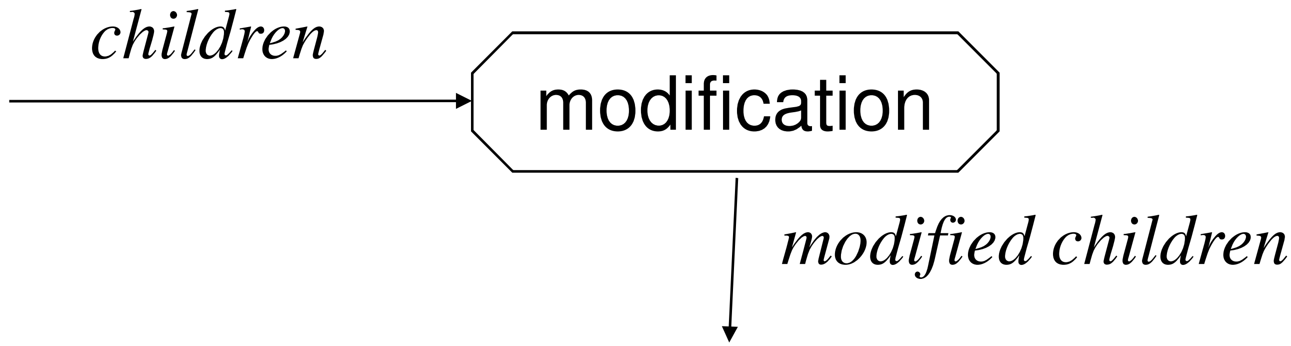
Reproduction is a processes of creating new chromosomes out of chromosomes in the population. Parents are ”selected” at each iteration.

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)	→	(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 or 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	00110110 11011011	00110110 11011011
Off-spring1 Off-spring2	01110111 10011010	00111011 11010110	01011010 10110111

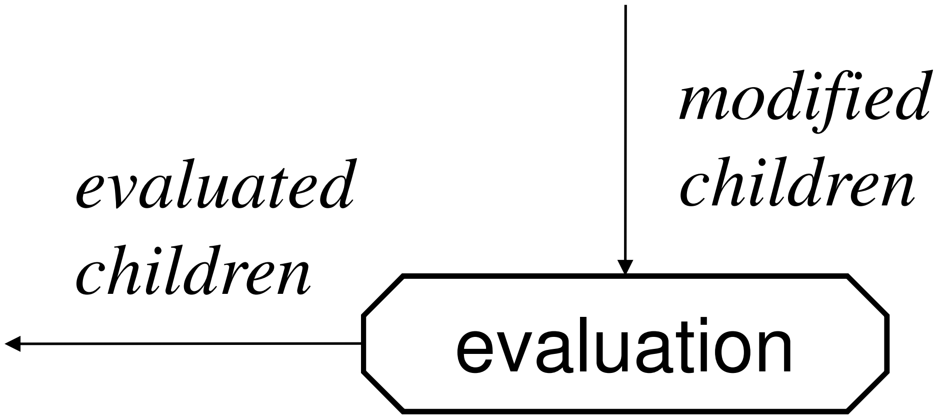
Mutation: Local Modification

Before:	(1	0	1	1	$\boxed{0}$	1	1	0)
After:	(1	0	1	1	$\boxed{1}$	1	1	0)

Before:	(1.38	$\boxed{-69.4}$	326.44	0.1)
After:	(1.38	$\boxed{-67.5}$	326.44	0.1)

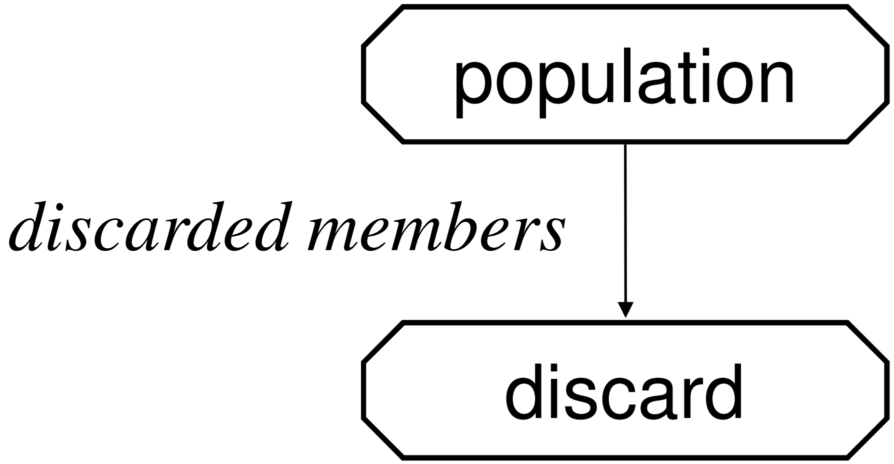
- Causes movement in the search space (local or global)
- Restores lost information to the population
- Prevents falling all solutions in population into a local optimum.

Evaluation

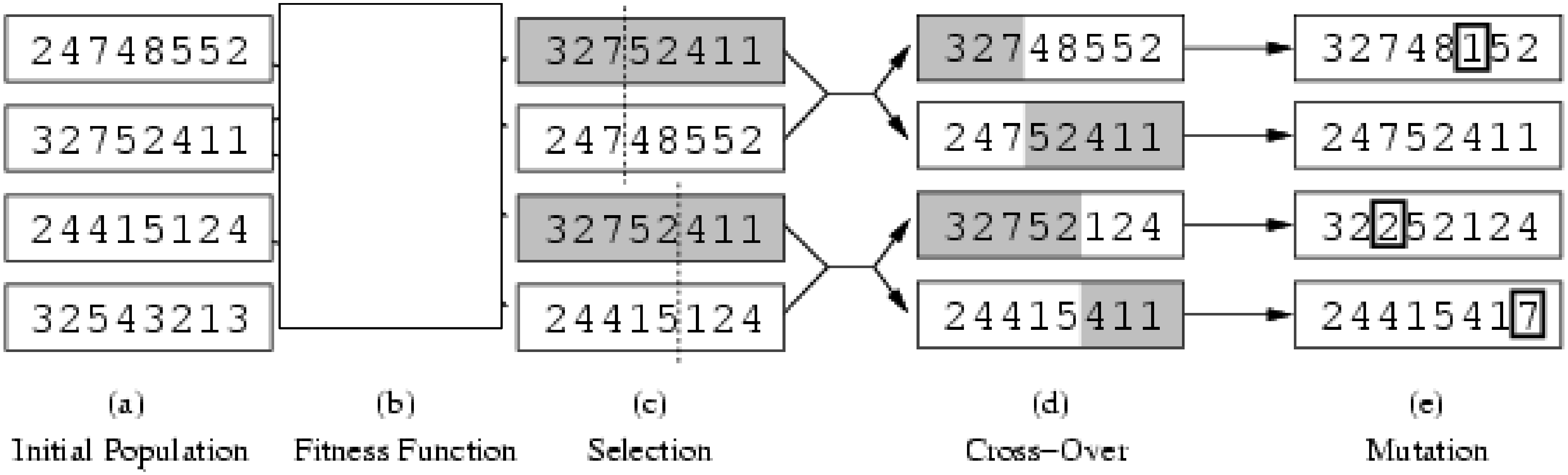


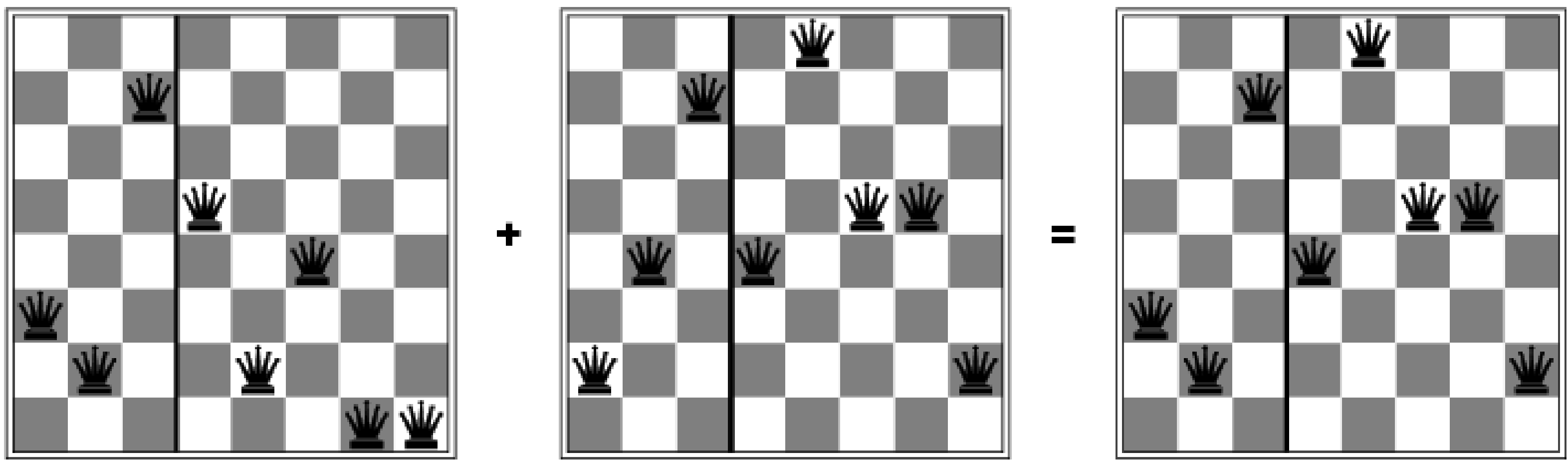
- The evaluator decodes a chromosome and assigns it a fitness measure

Deletion

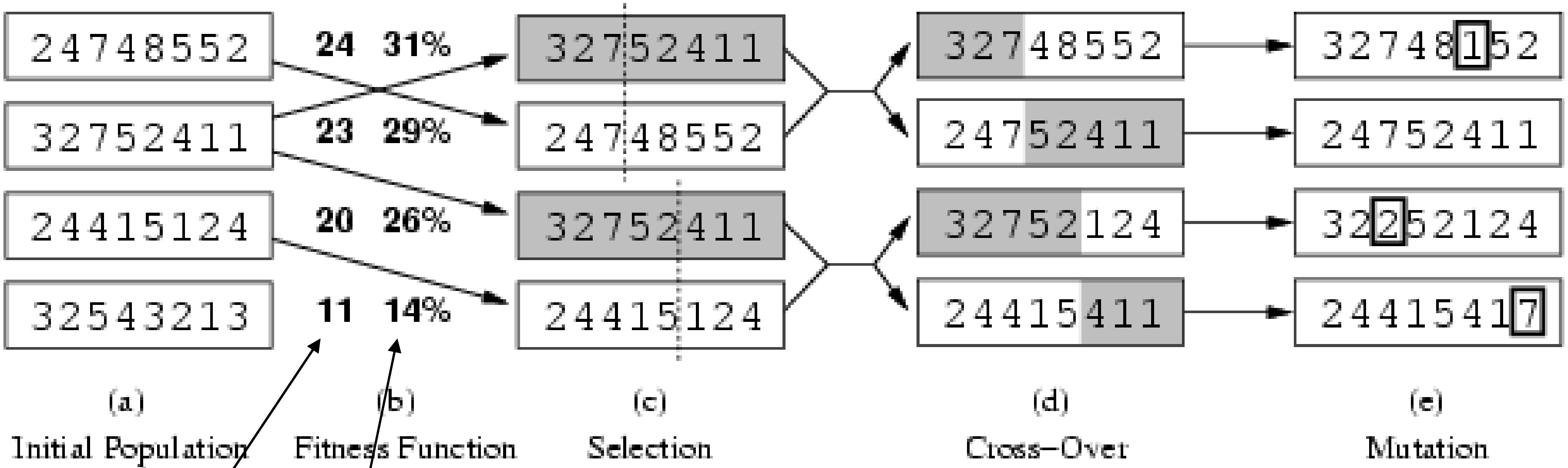


- *Generational* GA:
  entire populations replaced with each iteration
- *Steady-state* GA:
  a few members replaced each generation



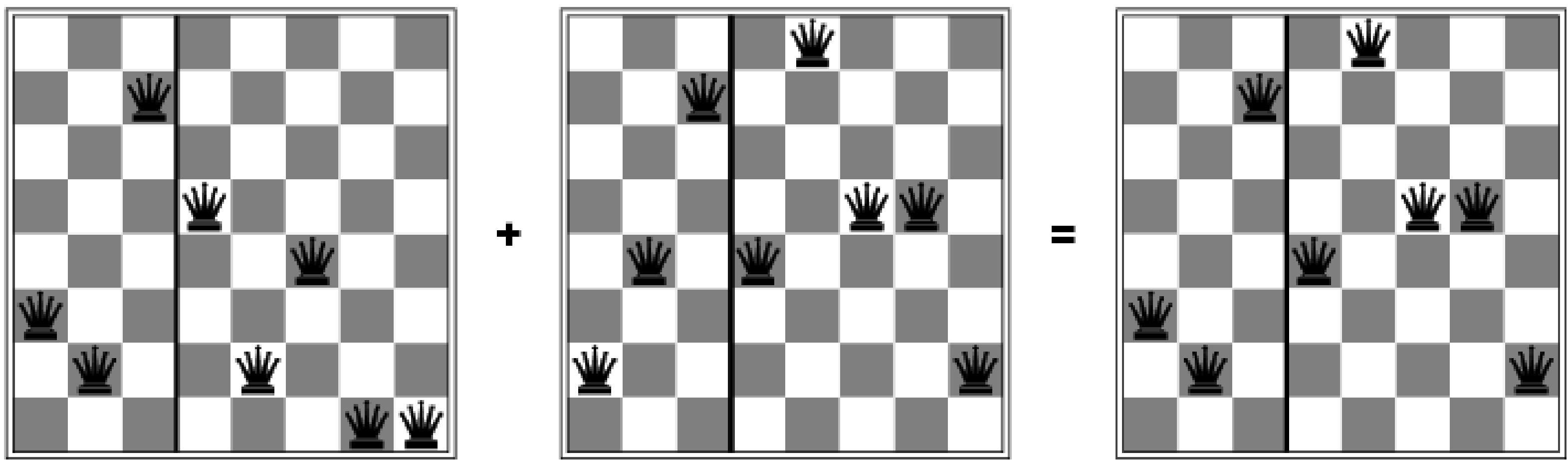


- Fitness function: number of non-attacking pairs of queens (min = 0, max = 8 × 7/2 = 28)



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