University of Guilan

Computational Intelligence

Subject10: Evolutionary Computation

Instructor: Ali Tourani

A.Tourani1991@gmail.Com

Agenda

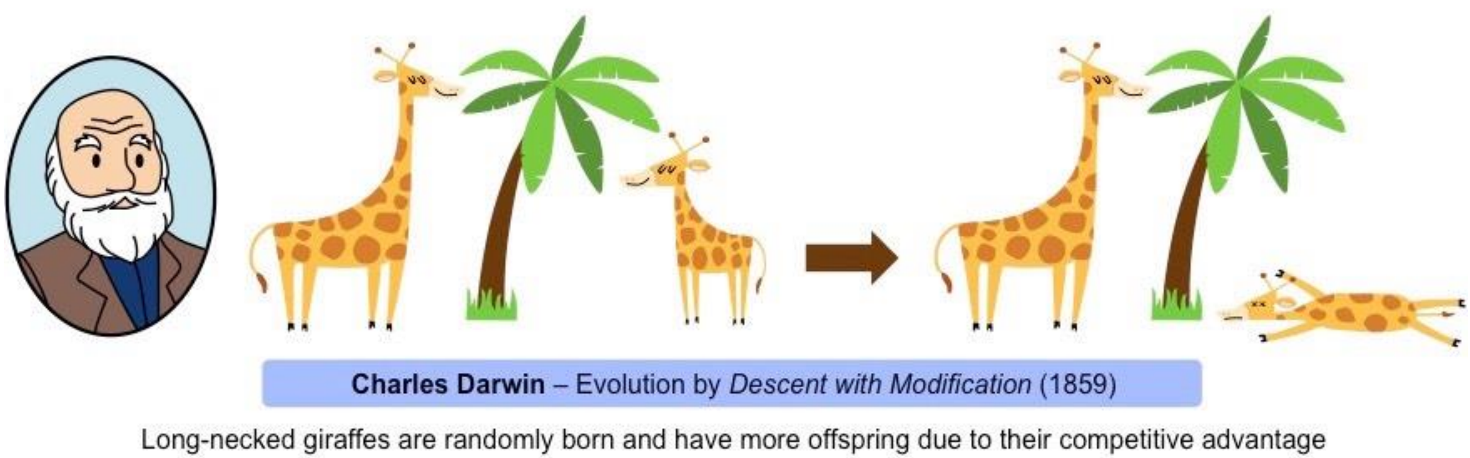
- A brief review
- Main concepts
- Evolutionary algorithms

A Brief Review

Darwin's Theory of Evolution

- Species living today had been changed over time
- Organisms better suited to conditions ➔ more likely to reproduce

Image from ib.bioninja.com.au



University of Guilan

A Brief Review

Applying theory of evolution to Computer Science

- Novel technologies/methods/approaches/data structures/solutions/etc form from combinations of existing ones
- **Evolutionary Computation**: a family of algorithms for global optimization
- Generally:
  - Generating and iteratively updating an initial set of candidate solutions
  - Producing new items by removing less desired solutions and small random changes
  - Applying a simulation of Natural Selection
  - Evolving to increase the fitness factors
- We need **Searching Algorithms**

A Brief Review

Search algorithms and methods

Informed Search

- Have information on the goal state
- More efficient searching
- Decision-making based on a heuristic function (how close a state is to the goal state)
- Samples: **Greedy, A***

Uninformed Search

- AKA Blind search
- No additional information on the goal node
- Samples: **BFS, DFS, Uniform Cost**

Analytical Methods

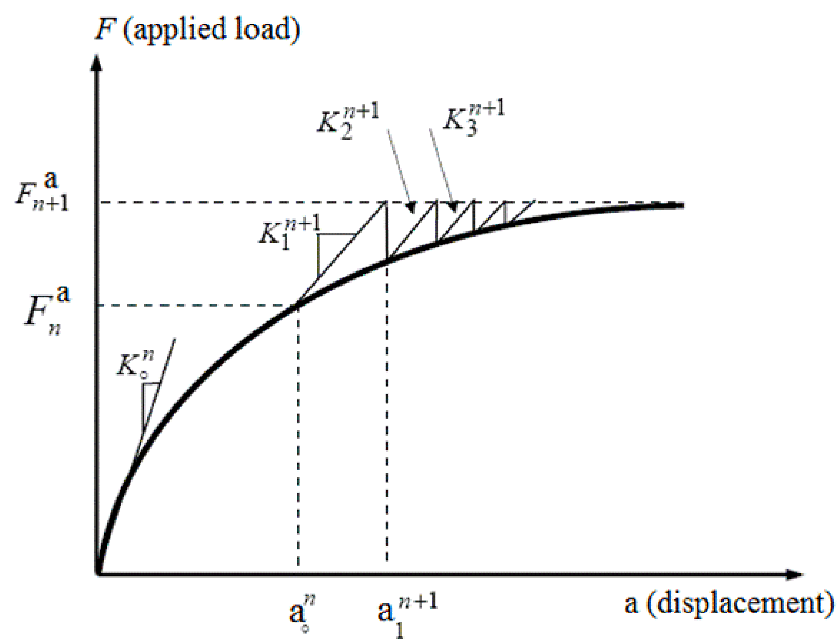
- Based on mathematics
- Generally used for numerical analysis and root-finding purposes
- Sample: **Newton's method**

A Brief Review

Search algorithms and methods – Analytical methods

Newton's method (Newton–Raphson)

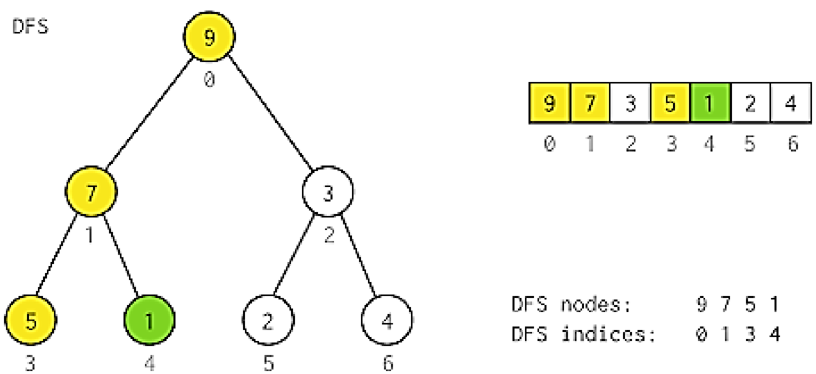
A root-finding algorithm to produce successively better approximations to the roots of a real-valued function

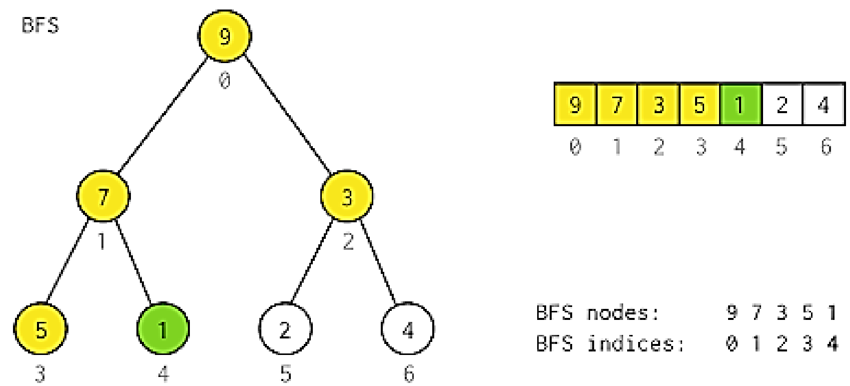


A Brief Review

Search algorithms and methods – Uninformed Search

Depth-first search (DFS) and Breadth-first search (BFS)

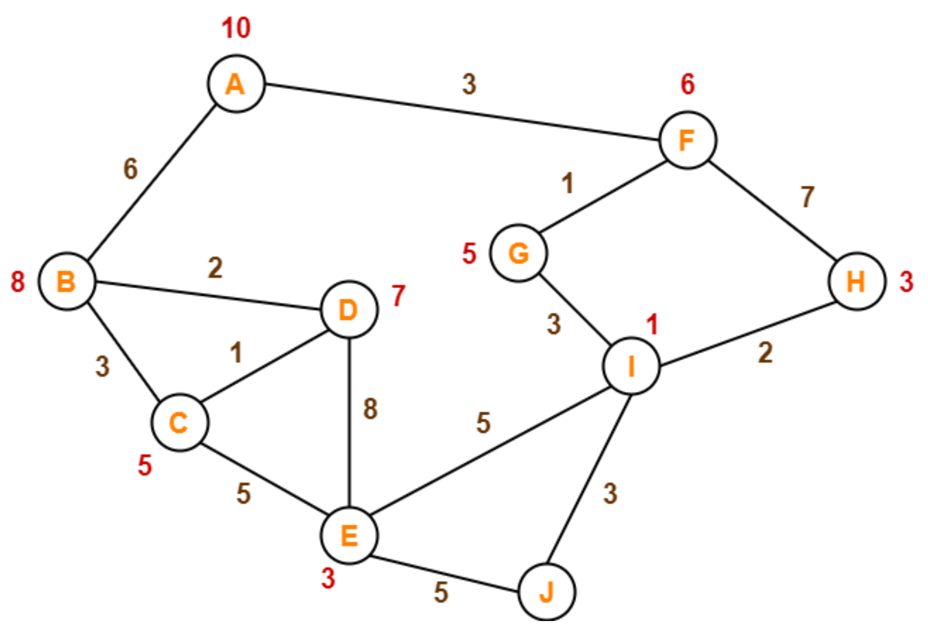




A Brief Review

Search algorithms and methods – Informed Search

Greedy and A* algorithms



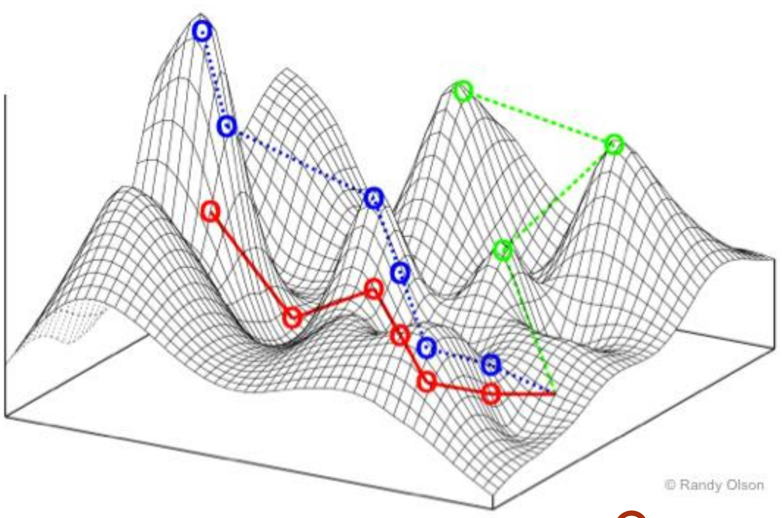
Main Concepts

Search space

- The set or domain through which an algorithm searches

Fitness landscapes (adaptive landscapes)

- Visualizing the distribution of fitness values as a kind of landscape
  - Peaks and valleys
- Height: a visual metaphor for fitness

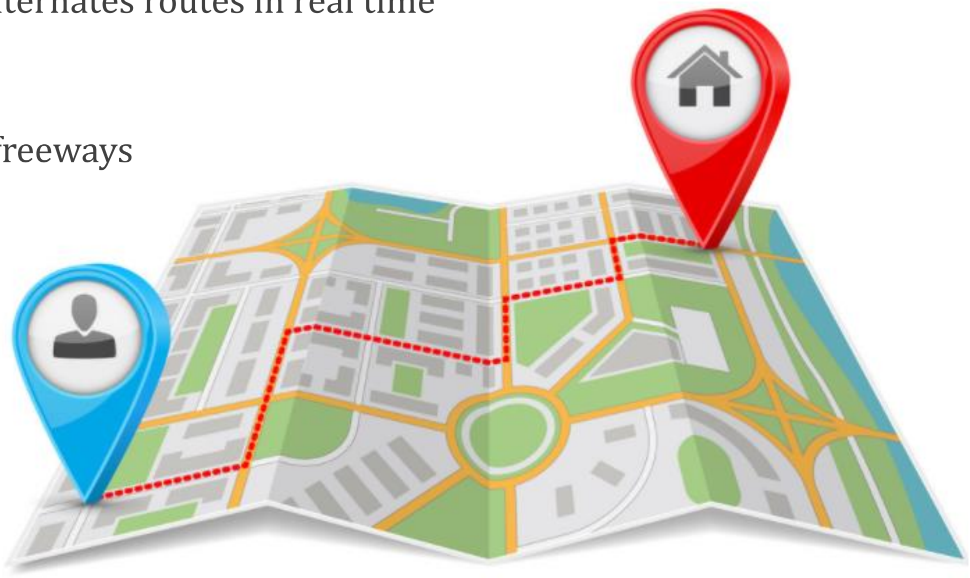


Main Concepts

Fitness landscapes – Application in a routing system

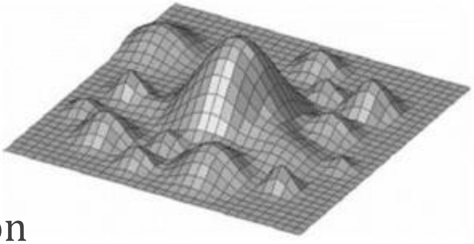
- Lowest cost (faster)
  - Finding the shortest path and alternates routes in real time
- Optimal route
  - Guiding through highways and freeways

Google maps is using Dijkstra's Shortest Path Algorithm

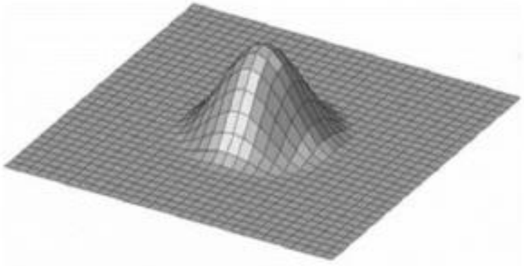


Main Concepts

Two important concepts



- *Exploration*
  - **Discovery** of new opportunities through experimentation
  - Associated with random behavior (solutions that are yet to be refined)
  - For instance, Random Search Algorithm
- *Exploitation*
  - Refinement of existing products through **local search**
  - Associated with systematic behavior (the hope of improving a promising solution)
  - For instance, Hill-Climb Algorithm



Main Concepts

University of Guilan

Concepts inspired by the process of Natural Selection

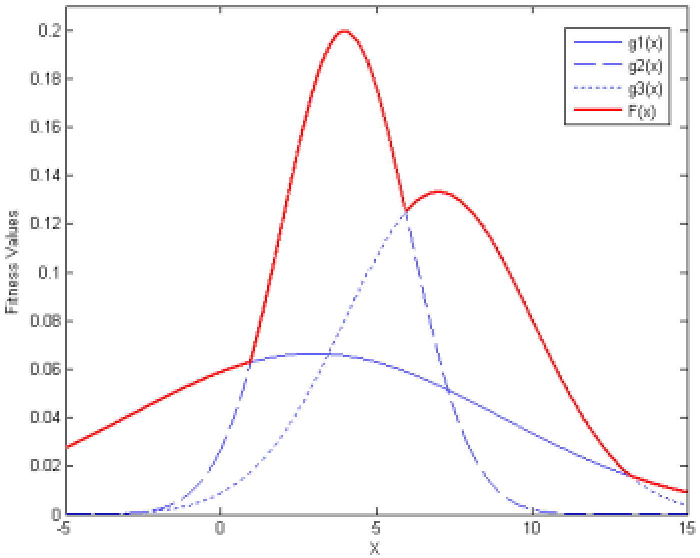
- Gene
  - The functional unit to store data and inheritance
  - One parameter of the optimization problem
- Chromosome (genome)
  - Characteristics of individuals (represents candidate solutions)
    - All solutions ➔ Population
  - Contains at least one Gene
  - A set of parameters/properties to define a proposed solution
  - **Genotype**: the genetic <u>composition</u> of an individual inherited from its parents
  - **Phenotype**: expressed <u>behavioral</u> traits of an individual in an environment

Main Concepts

University of Guilan

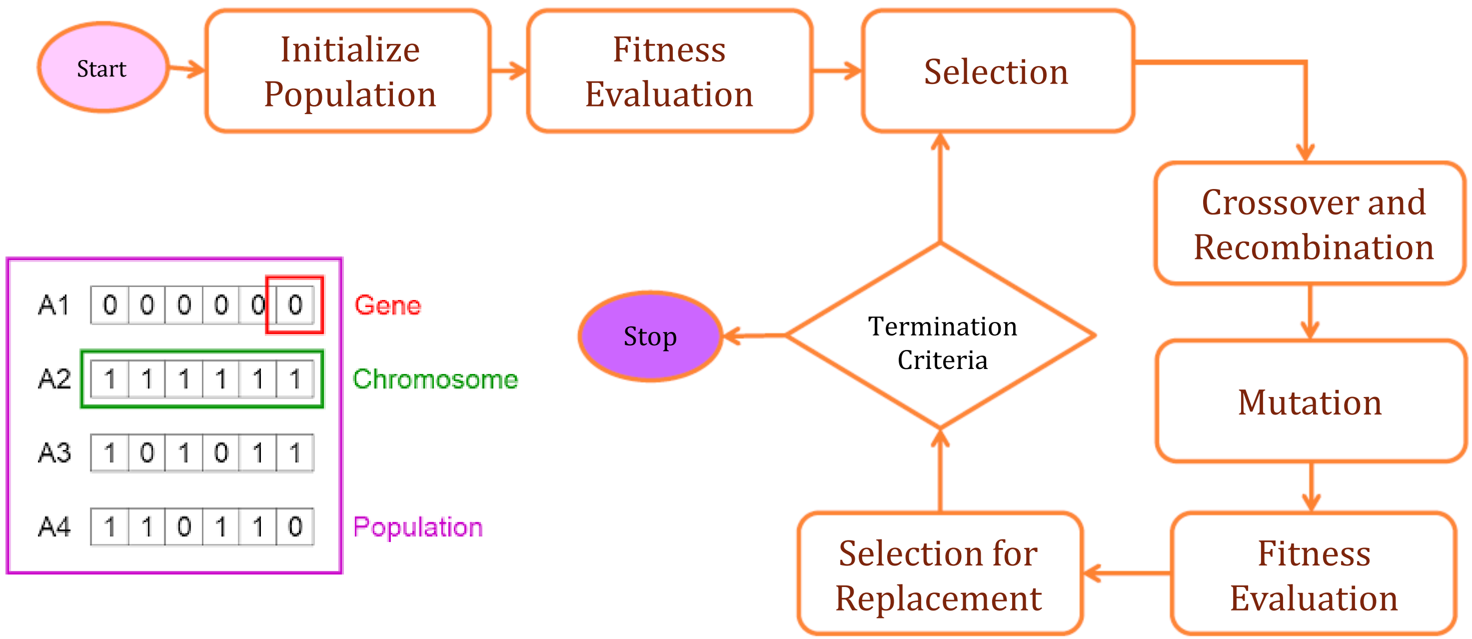
Concepts inspired by the process of Natural Selection

- Fitness Function
  - The most important component of an Evolutionary Algorithm
  - Quantifies the quality of a chromosome
    - How close the solution is to the optimal solution?
    - Who are the best parents to reproduce new solution?



Evolutionary Algorithms

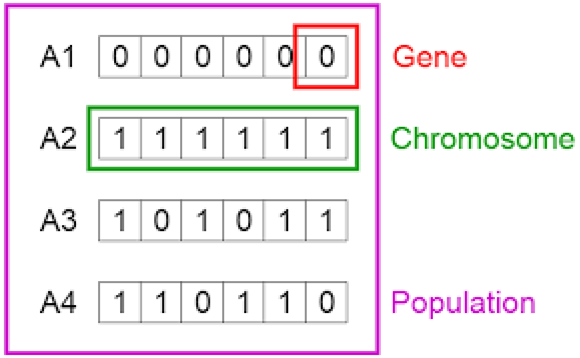
Generic diagram of EC algorithms



Evolutionary Algorithms

Methodology – Chromosome (Genome) definition

- A standard representation of each candidate solution
  - A point in search space
- Has a huge impact on the final result
- Some of the most common Chromosomes
  - A binary vector ➔ Genes: 0s and 1s
  - A range of numbers ➔ Genes: real numbers
  - A set or structure ➔ Genes: objects
  - A tree or graph ➔ Genes: nodes and relations

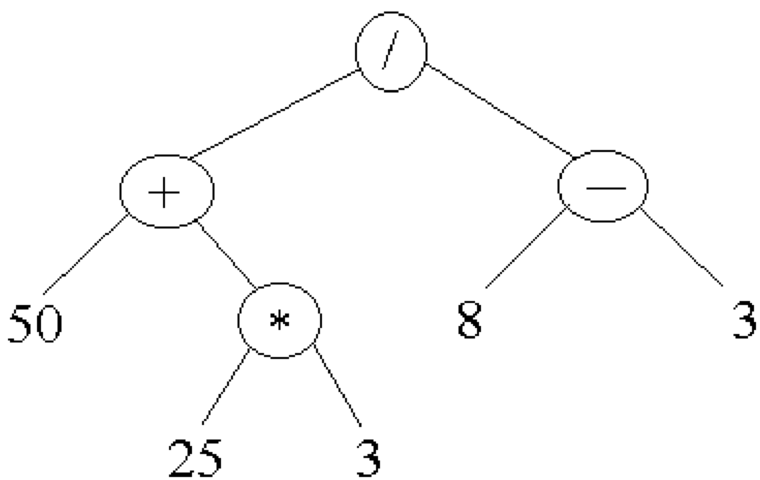


Evolutionary Algorithms

Methodology – Chromosome (Genome) definition

- Sample chromosomes

0	1	1	1	0	1



2.51	-3.8	12.9	0.01	9.83	-99

5	2	4	1	6	3

Evolutionary Algorithms

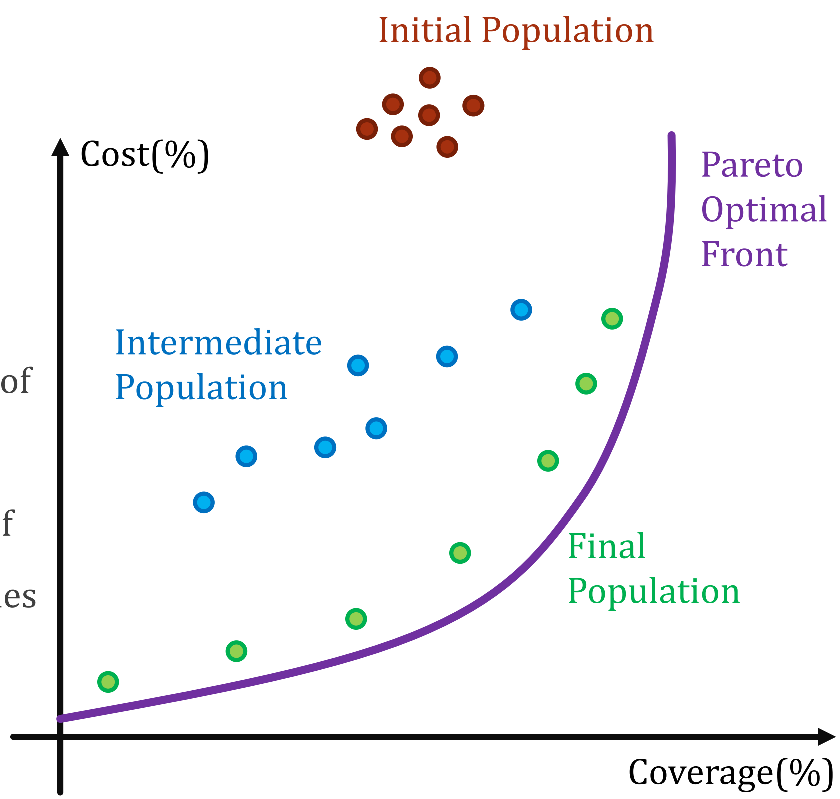
University of Guilan

Methodology – Initial Population

- The first step of an EA
- Different method to generate an

Initial population:

  - **Random**: a uniform representation of the entire search space
  - **Intelligent**: generate a population of Chromosomes with highest fitness values

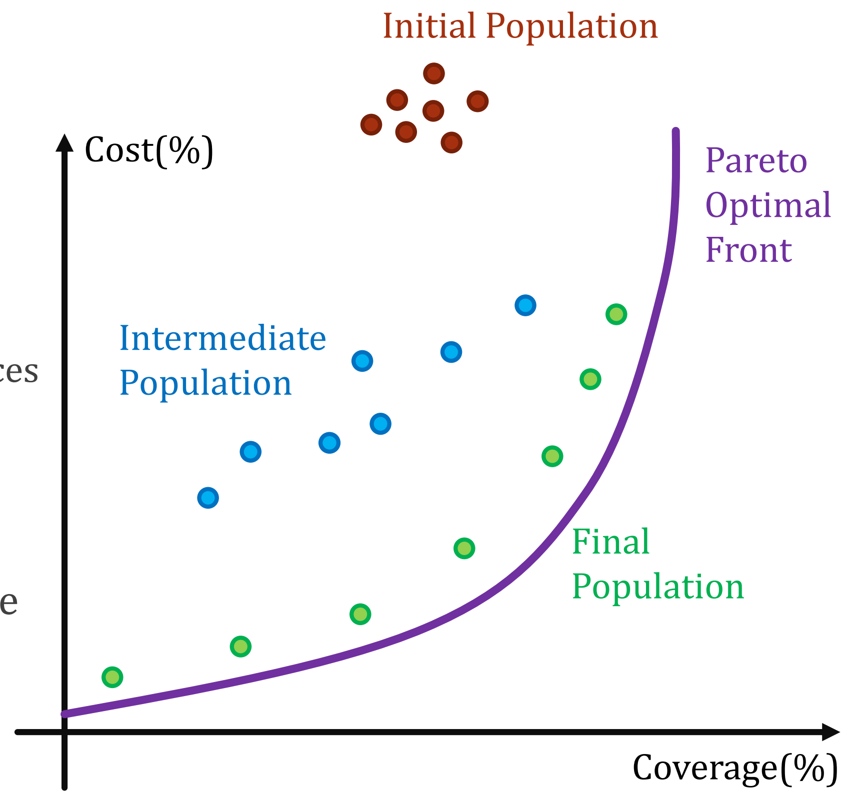


Evolutionary Algorithms

Methodology – Initial Population

- The size of an initial population is extremely important:
  - Small: does not cover all data
  - Large: needs more time and resources

- Increasing the size of population during the process leads to an increase in exploration value

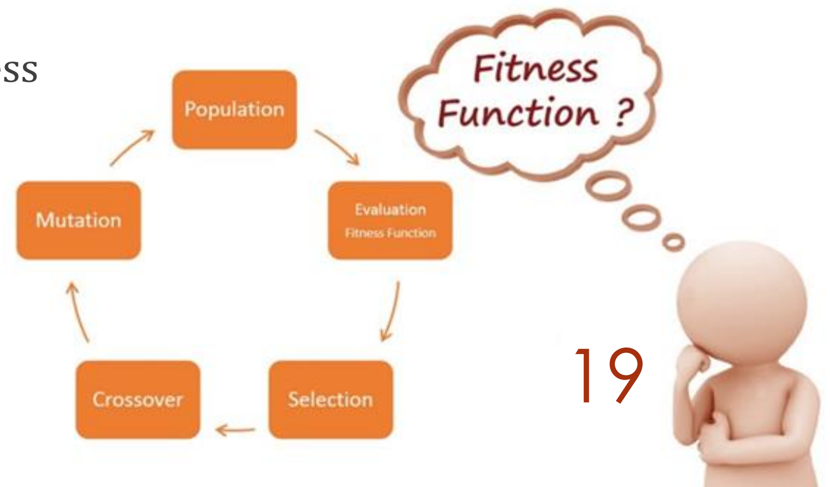


University of Guilan

Evolutionary Algorithms

Methodology – Fitness function

- The heart of an EA 
- How well each individual can solve the problem?
  - How well it fulfills whatever criteria the algorithm is optimizing for
- Must be calculated for all chromosomes
  - Usually represented by a **real number**
- Sometimes it is hard to calculate the fitness
- Main application: in the **Selection** phase

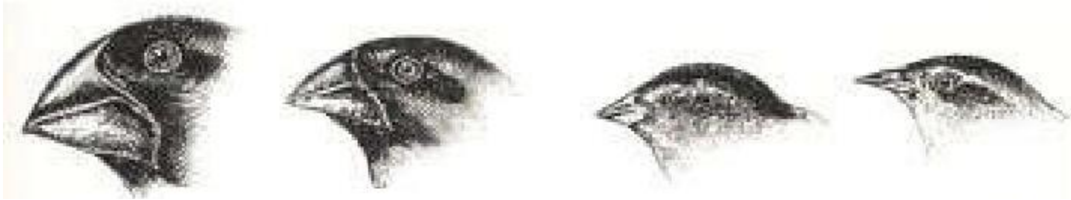


Evolutionary Algorithms

University of Guilan

Methodology – Selection

- One of the most important phases in an EA
- Goal: selecting the fittest element for reproduction
- **Evolutionary/Selection Pressure**:
  - Usually expressed as a **selection coefficient**
  - The more EP we apply, the more concentration on the Fitness function
  - Too much EP will cause:
    - Concentration on a **limited population** + Decrease in the **variety** of elements

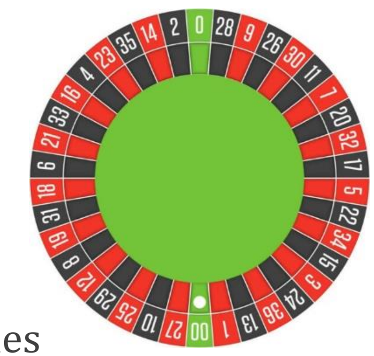


Evolutionary Algorithms

Methodology – Selection

- Selection methods – Random
  - Chromosomes with equal chances to be selected
  - No need to Fitness Function
  - The lowest Selection Pressure

Evolutionary Algorithms



Methodology – Selection

- Selection methods - Fitness proportionate selection
  - AKA Roulette Wheel Selection
  - A proportion of the wheel is assigned to each of the chromosomes
    - Based on their fitness value
    - Optimized chromosomes → More chance of selection

$$P_i = \frac{f_i}{\sum f_i}$$

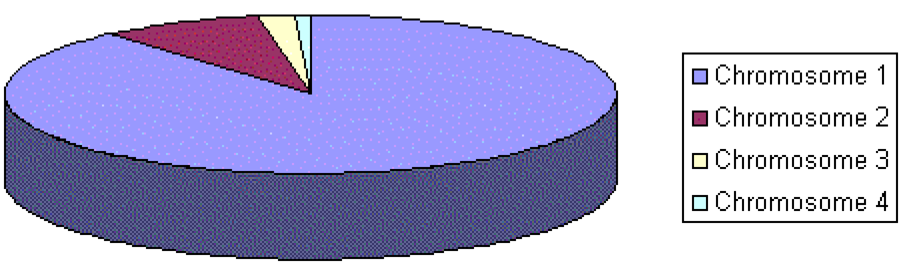
No.	Chromosome	Fitness	Chance
1	01101	169	14.4
2	11000	576	49.2
3	01000	64	5.5
4	10011	361	30.9

Evolutionary Algorithms

Methodology – Selection

- Selection methods – Rank Selection
  - Choosing the of individuals in descending fitness value order
    - Fittest solution first, then other solutions with lower fitness values
  - A loss in the selection pressure towards fitter individuals
  - Also works with negative fitness values

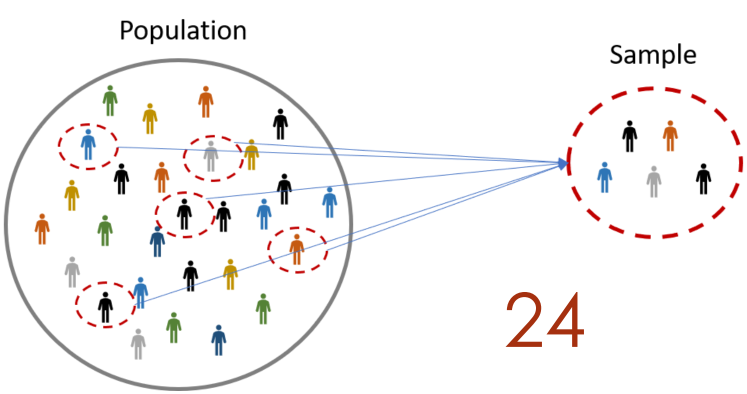
$$P_i = \frac{f_i}{\sum f_i}$$



Evolutionary Algorithms

Methodology – Selection

- Selection methods - Tournament selection
  - Running several **tournaments** among a few randomly chosen individuals
    - Randomly select a group of elements and then, find the fittest
  - Very large groups?
    - Getting closer to the main population with a high Selection Pressure
  - Very small groups?
    - Getting closer to the Random Selection method

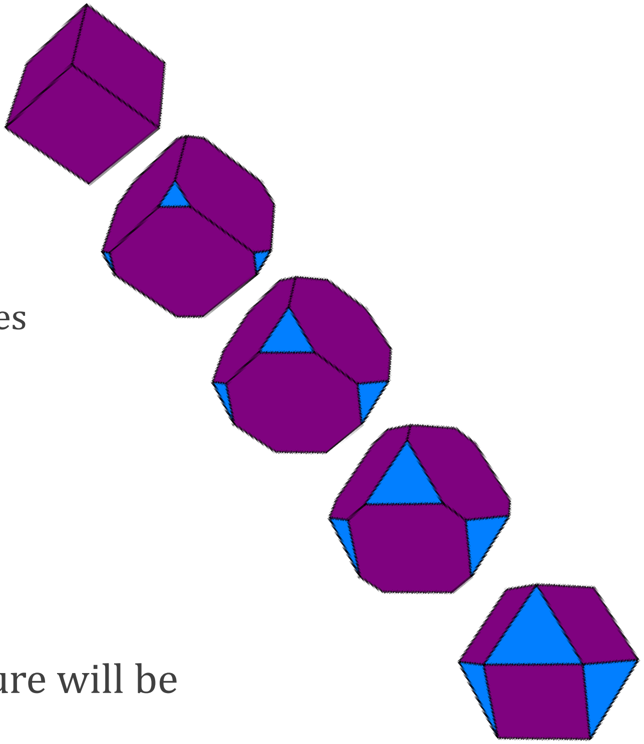


Evolutionary Algorithms

University of Guilan

Methodology – Selection

- Selection methods – Truncation selection
  - Here is the process:
    1. Order chromosomes based on their Fitness values
    2. Select the best T-percent
    3. Choose N elements from them
    4. Repeat until reaching the goal
  - T=100 ➔ the same as Random Selection
  - The bigger T is, the lower the Selection Pressure will be

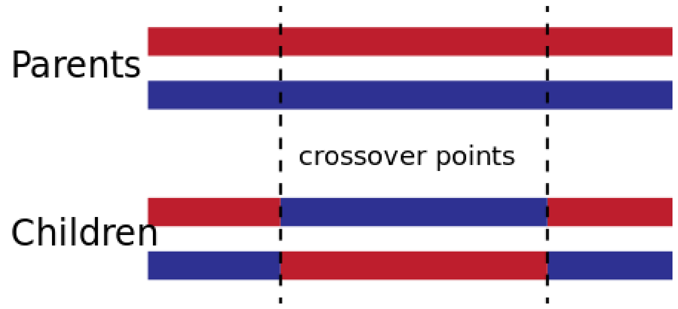


Evolutionary Algorithms

University of Guilan

Methodology – Reproduction

- Recombination/Crossover
  - Combining the genetic information of two parents
  - Generating new solutions from an existing population
  - **Outcome**: new offspring
  - More Crossover operator ➔ more cautious behavior



Evolutionary Algorithms

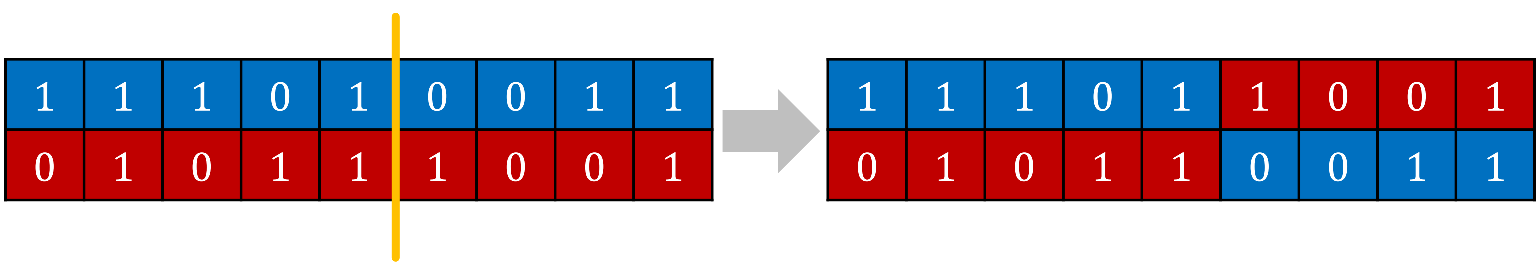
University of Guilan

Methodology – Reproduction

- Recombination/Crossover

  Single-point crossover

  - A random point (Crossover Point) is picked
  - Swapping items from the selected point
  - **Outcome**: two offspring, each with some data from both parents



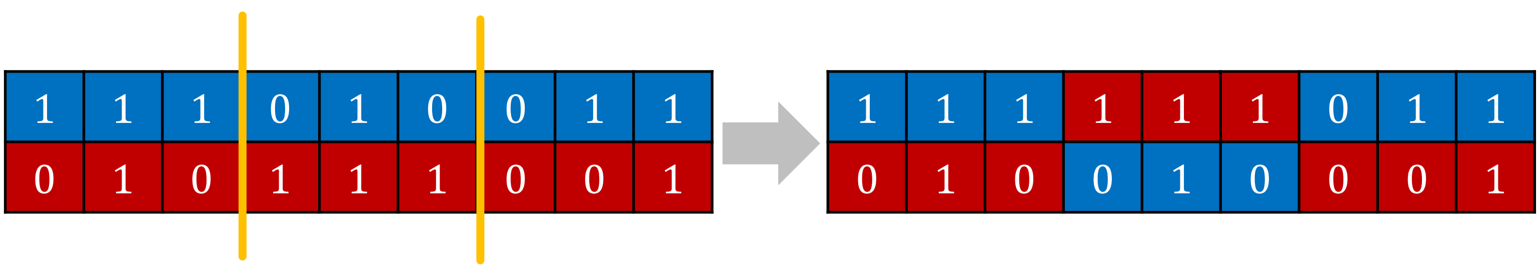
University of Guilan

Methodology – Reproduction

- Recombination/Crossover

  Two-point crossover

  - Two random points (Crossover Points) are picked
  - Swapping items between the two points
  - **Outcome**: two offspring, each with some data from both parents



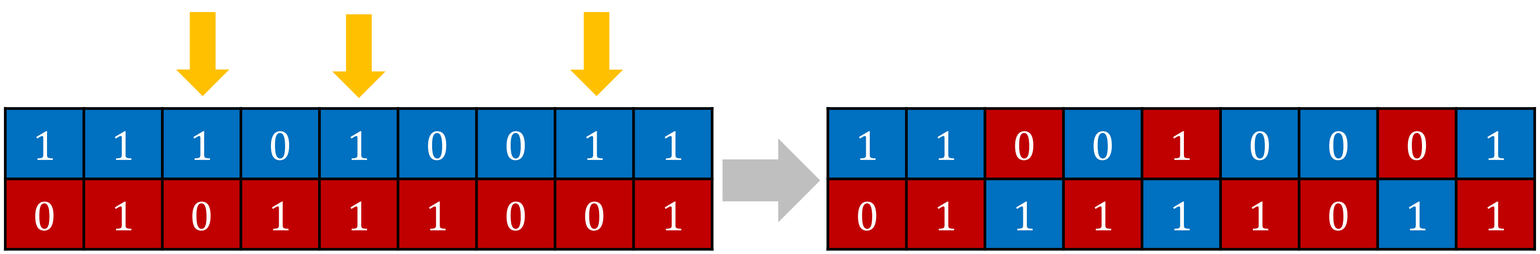
Evolutionary Algorithms

Methodology – Reproduction

- Recombination/Crossover

  Uniform crossover

  - Requires a random distribution to choose offspring genes
  - Each bit is chosen from either parent with equal probability



Evolutionary Algorithms

Methodology – Reproduction

- Recombination/Crossover

Simple arithmetic recombination (real numbers)

  - Choose a single gene and define a proper coefficient α
  - For chromosomes A and B:

$$C_1 = (A_i + B_i) * \alpha \text{ and } C_2 = (A_i + B_i) * (1 - \alpha)$$

0.1	0.2	0.4	0.5	0.8	0.3	0.7	0	0.2
0.3	0.7	0.5	0.6	0.2	0.1	0	0.2	0.3

0.1	0.2	0.4	0.5	0.8	0.2	0.7	0	0.2
0.3	0.7	0.5	0.6	0.2	0.2	0	0.2	0.3

$$\alpha = 0.5$$

Evolutionary Algorithms

University of Guilan

Methodology – Reproduction

- Recombination/Crossover

Whole arithmetic recombination (real numbers)

- Define a proper coefficient α
- For all chromosomes A and B:

$$C_1 = (A_i + B_i) * \alpha \text{ and } C_2 = (A_i + B_i) * (1 - \alpha)$$

0.1	0.2	0.4	0.5	0.8	0.3	0.7	0	0.2
0.3	0.7	0.5	0.6	0.2	0.1	0	0.2	0.3

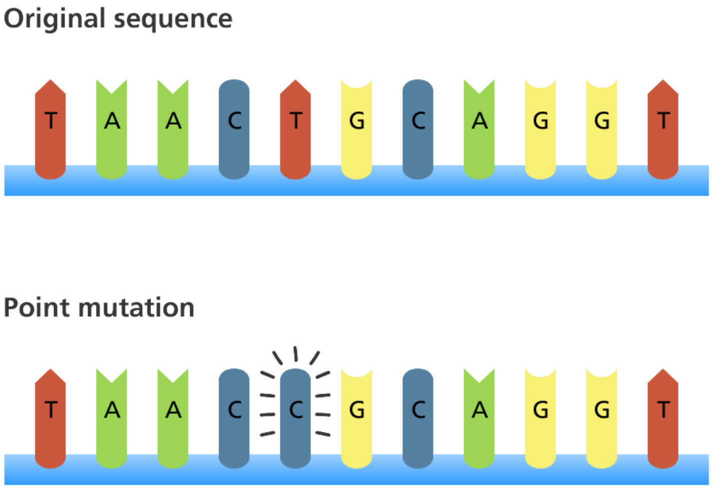
0.2	0.45	0.45	0.65	0.5	0.2	0.35	0.1	0.25
0.2	0.45	0.45	0.65	0.5	0.2	0.35	0.1	0.25

$\alpha = 0.5$

Evolutionary Algorithms

Methodology – Reproduction

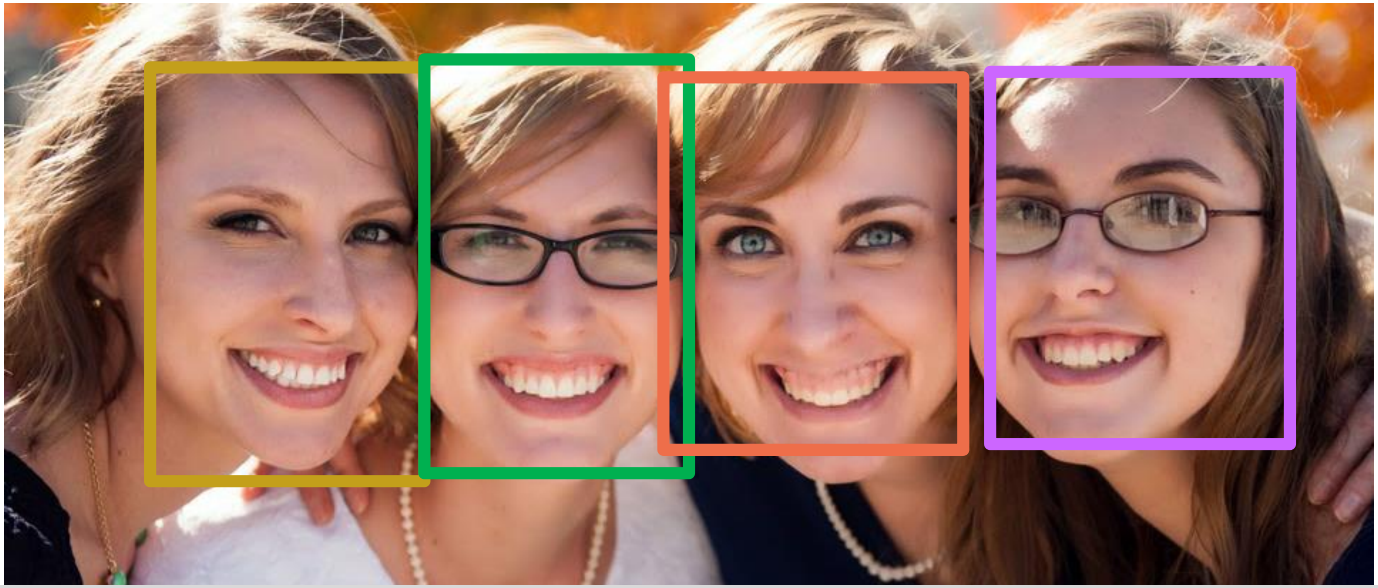
- Mutation
  - Used to maintain genetic diversity from one generation to the next
  - Alters one or more gene values in a chromosome from its initial state



Evolutionary Algorithms

Methodology – Reproduction

Family resemblance: Crossover

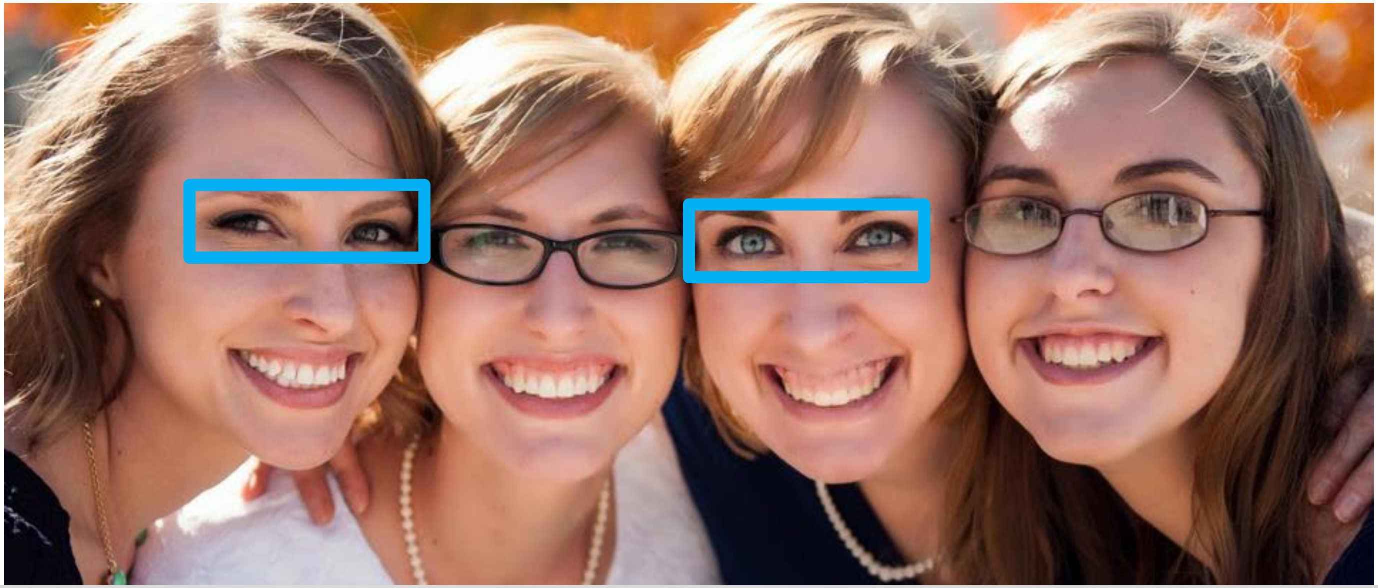


We can use other operators such as regrouping, colonization-extinction, or migration besides Mutation and Crossover

Evolutionary Algorithms

Methodology – Reproduction

Different eye colors: Mutation



We can use other operators such as regrouping, colonization-extinction, or migration besides Mutation and Crossover

Evolutionary Algorithms

Methodology – Reproduction

- Mutation

Bit Flip (binary)

- Reverse the values of some genes

0	1	0	0	0	1	0	0	0

0	1	0	0	1	1	0	1	0

Evolutionary Algorithms

University of Guilan

Methodology – Reproduction

- Mutation

Complementary mutation (real number)

- Choose one or more genes and subtract them from the Max value

0.2	0.3	0.4	0.3	0.9	1	0.2	0	0.1

0.2	0.3	0.4	0.3	0.1	1	0.2	1	0.1

University of Guilan

Evolutionary Algorithms

Methodology – Reproduction

- Mutation

Relocation

- Choose some genes and replace them

0.2	0.3	0.4	0.3	0.9	1	0.2	0	0.1

0.2	0.3	0.4	0.3	0	1	0.2	0.9	0.1

Evolutionary Algorithms

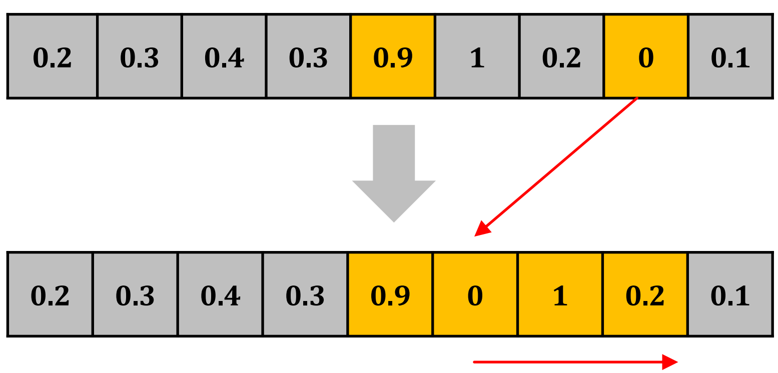
University of Guilan

Methodology – Reproduction

- Mutation

Insertion

- Randomly select two genes and shift the items between



Evolutionary Algorithms

Methodology – Reproduction

- Mutation

Hashing

- Randomly select two genes and hash the items between

0.2	0.3	0.4	0.3	0.9	1	0.2	0	0.1

0.2	0.3	0.4	0.3	0.2	0	0.9	1	0.1

Evolutionary Algorithms

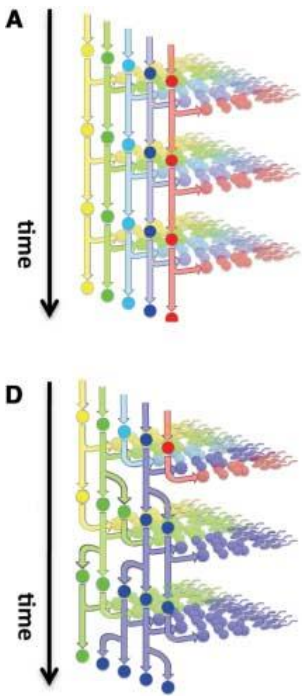
Methodology – Selection from the new generation

- Calculation based on the current and new generation
- Two common methods:
  - Steady-State Replacement
  - Generational Replacement

Evolutionary Algorithms

Methodology – Selection from the new generation

- Steady-State Replacement
  - Keep a large portion of the parents chromosomes
  - Replace **some** of the offspring set with parents
  - Maintaining the overall variation of items
  - Some methods:
    - Worst
    - Best
    - Oldest
    - Conservative

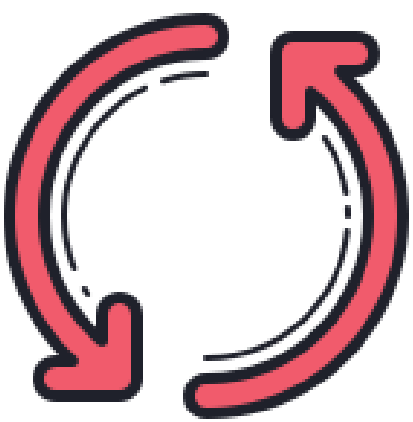


University of Guilan

Evolutionary Algorithms

Methodology – Selection from the new generation

- Generational Replacement
  - Replace **all** of the offspring set with parents
  - Example: replacing the best items with the worst ones
  - Fast convergence of the algorithm



Evolutionary Algorithms

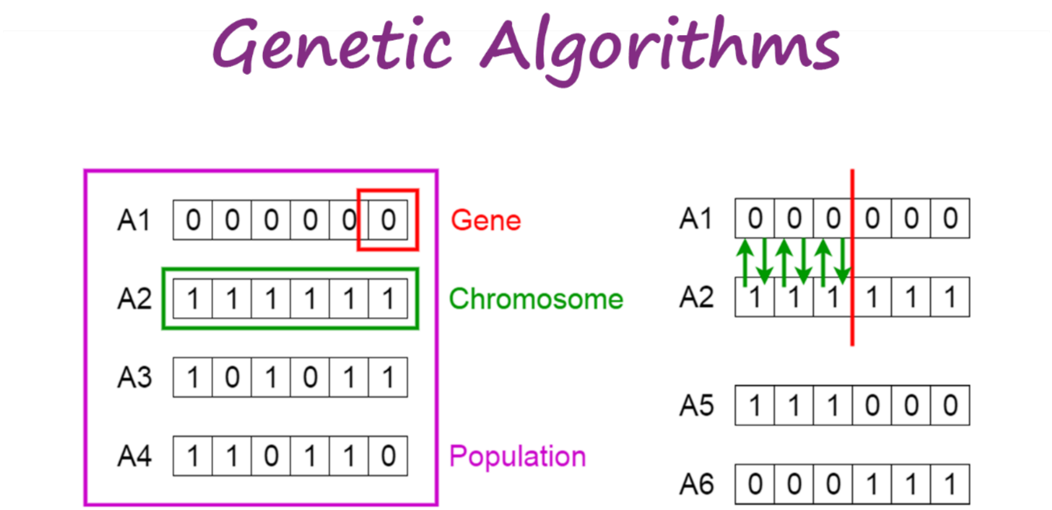
University of Guilan

Methodology – Termination condition

- Important in determining when a EA run will end
- We **may** find the best (fittest) solution (not always)
- Some common termination conditions:
  - No improvement in the population for X iterations
  - Reaching an absolute number of generations
  - The objective function value has reached a pre-defined value

What's Next?

- Common Evolutionary Algorithms



Questions?