Genetic Algorithms

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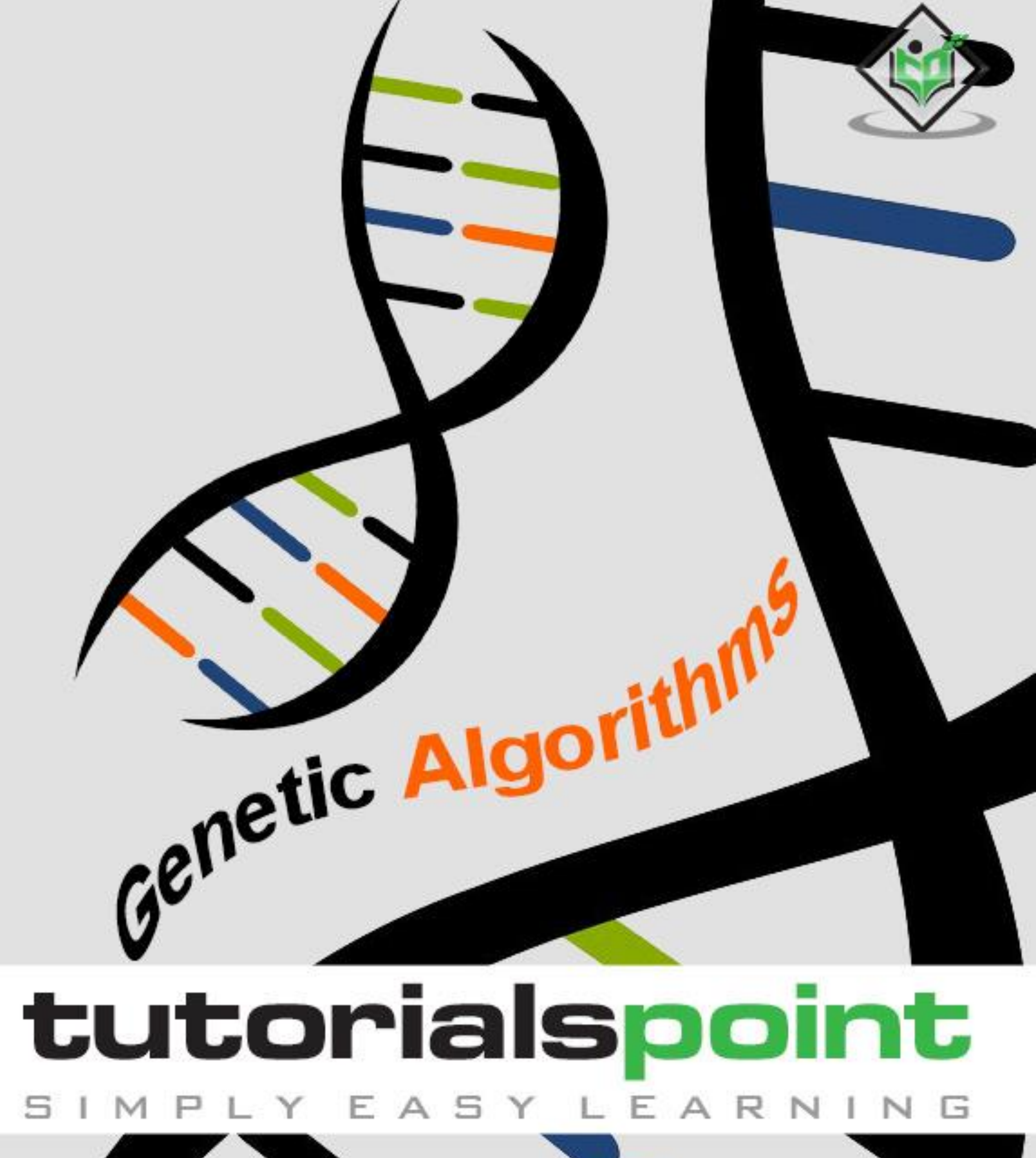

About the Tutorial

This tutorial covers the topic of Genetic Algorithms. From this tutorial, you will be able to understand the basic concepts and terminology involved in Genetic Algorithms. We will also discuss the various crossover and mutation operators, survivor selection, and other components as well.

Also, there will be other advanced topics that deal with topics like Schema Theorem, GAs in Machine Learning, etc. which are also covered in this tutorial.

After going through this tutorial, the reader is expected to gain sufficient knowledge to come up with his/her own genetic algorithms for a given problem.

Audience

This tutorial is prepared for the students and researchers at the undergraduate/graduate level who wish to get "good solutions" for optimization problems "fast enough" which cannot be solved using the traditional algorithmic approaches.

Prerequisites

Genetic Algorithms is an advanced topic. Even though the content has been prepared keeping in mind the requirements of a beginner, the reader should be familiar with the fundamentals of Programming and Basic Algorithms before starting with this tutorial.

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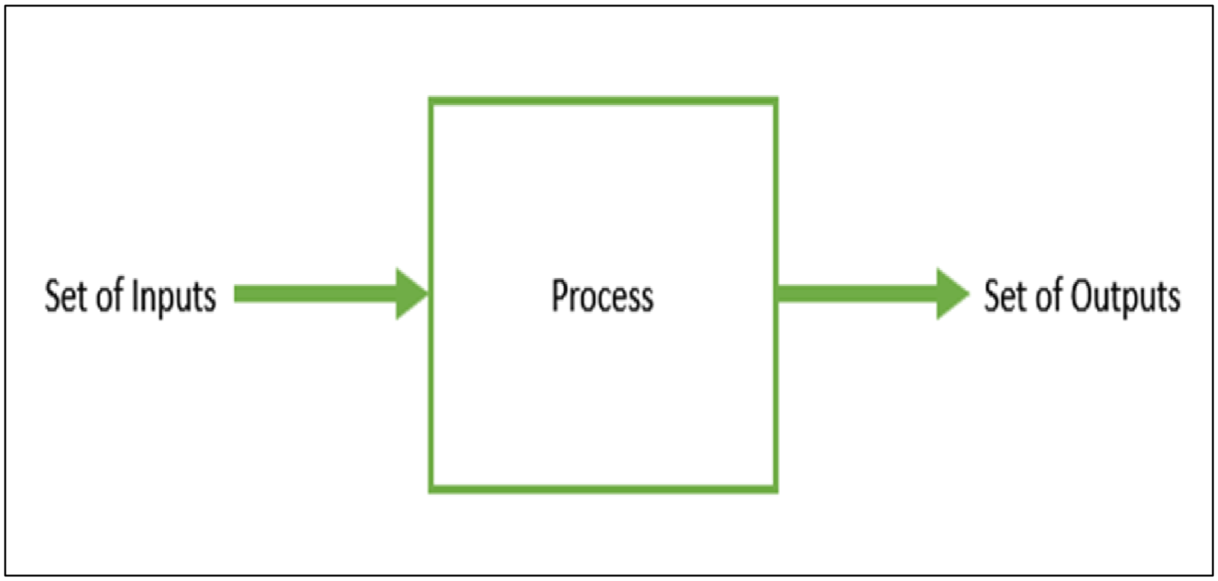
Table of Contents

1. Genetic Algorithms – Introduction

Genetic Algorithm (GA) is a search-based optimization technique based on the principles of **Genetics and Natural Selection**. It is frequently used to find optimal or near-optimal solutions to difficult problems which otherwise would take a lifetime to solve. It is frequently used to solve optimization problems, in research, and in machine learning.

Introduction to Optimization

Optimization is the process of **making something better**. In any process, we have a set of inputs and a set of outputs as shown in the following figure.



Optimization refers to finding the values of inputs in such a way that we get the "best" output values. The definition of "best" varies from problem to problem, but in mathematical terms, it refers to maximizing or minimizing one or more objective functions, by varying the input parameters.

The set of all possible solutions or values which the inputs can take make up the search space. In this search space, lies a point or a set of points which gives the optimal solution. The aim of optimization is to find that point or set of points in the search space.

What are Genetic Algorithms?

Nature has always been a great source of inspiration to all mankind. Genetic Algorithms (GAs) are search based algorithms based on the concepts of natural selection and genetics. GAs are a subset of a much larger branch of computation known as **Evolutionary Computation**.

GAs were developed by John Holland and his students and colleagues at the University of Michigan, most notably David E. Goldberg and has since been tried on various optimization problems with a high degree of success.

In GAs, we have **a pool or a population of possible solutions** to the given problem. These solutions then undergo recombination and mutation (like in natural genetics), producing new children, and the process is repeated over various generations. Each individual (or candidate solution) is assigned a fitness value (based on its objective function value) and the fitter individuals are given a higher chance to mate and yield more "fitter" individuals. This is in line with the Darwinian Theory of "Survival of the Fittest".

In this way we keep "evolving" better individuals or solutions over generations, till we reach a stopping criterion.

Genetic Algorithms are sufficiently randomized in nature, but they perform much better than random local search (in which we just try various random solutions, keeping track of the best so far), as they exploit historical information as well.

Advantages of GAs

GAs have various advantages which have made them immensely popular. These include –

- Does not require any derivative information (which may not be available for many real-world problems).
- Is faster and more efficient as compared to the traditional methods.
- Has very good parallel capabilities.
- Optimizes both continuous and discrete functions and also multi-objective problems.
- Provides a list of "good" solutions and not just a single solution.
- Always gets an answer to the problem, which gets better over the time.
- Useful when the search space is very large and there are a large number of parameters involved.

Limitations of GAs

Like any technique, GAs also suffer from a few limitations. These include –

- GAs are not suited for all problems, especially problems which are simple and for which derivative information is available.
- Fitness value is calculated repeatedly which might be computationally expensive for some problems.

- Being stochastic, there are no guarantees on the optimality or the quality of the solution.

- If not implemented properly, the GA may not converge to the optimal solution.

GA – Motivation

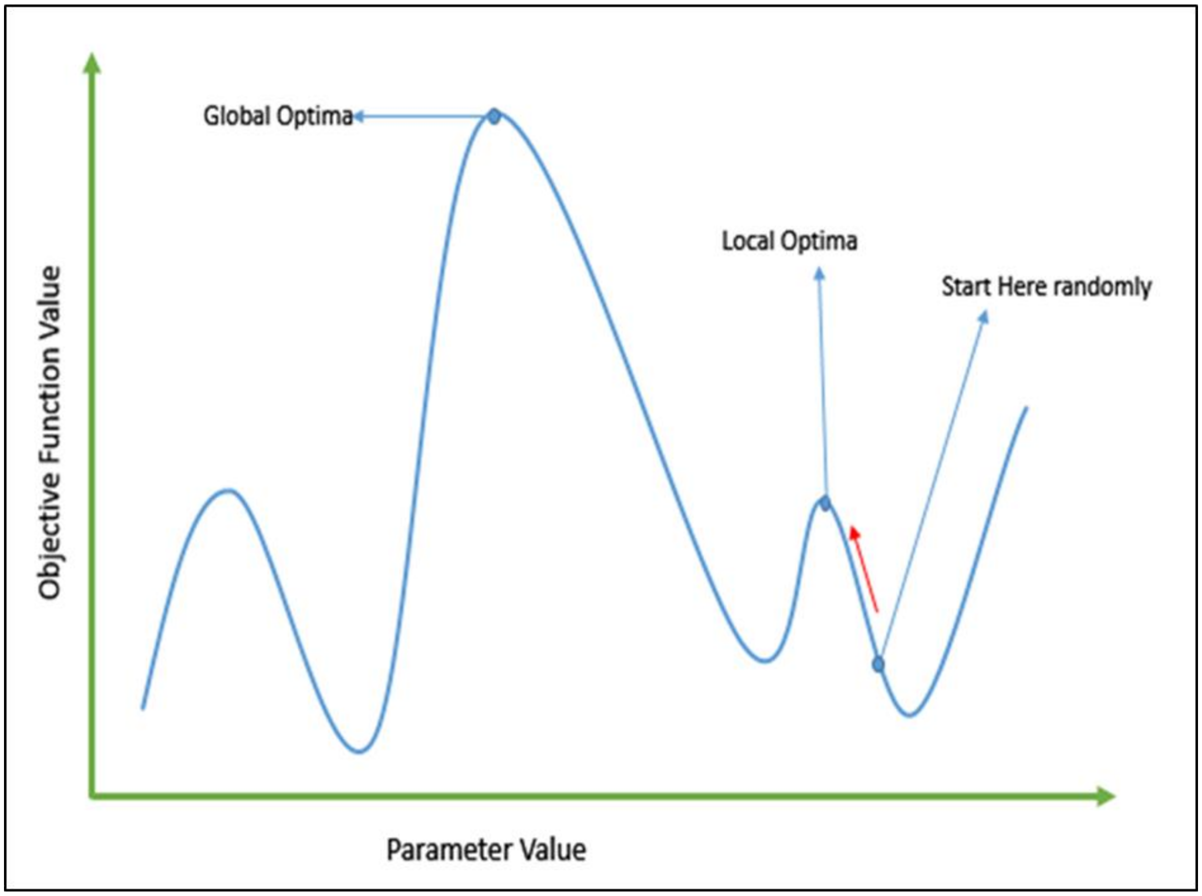
Genetic Algorithms have the ability to deliver a "good-enough" solution "fast-enough". This makes genetic algorithms attractive for use in solving optimization problems. The reasons why GAs are needed are as follows:

Solving Difficult Problems

In computer science, there is a large set of problems, which are **NP-Hard**. What this essentially means is that, even the most powerful computing systems take a very long time (even years!) to solve that problem. In such a scenario, GAs prove to be an efficient tool to provide **usable near-optimal solutions** in a short amount of time.

Failure of Gradient Based Methods

Traditional calculus based methods work by starting at a random point and by moving in the direction of the gradient, till we reach the top of the hill. This technique is efficient and works very well for single-peaked objective functions like the cost function in linear regression. But, in most real-world situations, we have a very complex problem called as landscapes, which are made of many peaks and many valleys, which causes such methods to fail, as they suffer from an inherent tendency of getting stuck at the local optima as shown in the following figure.



Getting a Good Solution Fast

Some difficult problems like the Travelling Salesperson Problem (TSP), have real-world applications like path finding and VLSI Design. Now imagine that you are using your GPS Navigation system, and it takes a few minutes (or even a few hours) to compute the "optimal" path from the source to destination. Delay in such real world applications is not acceptable and therefore a "good-enough" solution, which is delivered "fast" is what is required.

2. Genetic Algorithms – Fundamentals

This section introduces the basic terminology required to understand GAs. Also, a generic structure of GAs is presented in both **pseudo-code and graphical forms**. The reader is advised to properly understand all the concepts introduced in this section and keep them in mind when reading other sections of this tutorial as well.

Basic Terminology

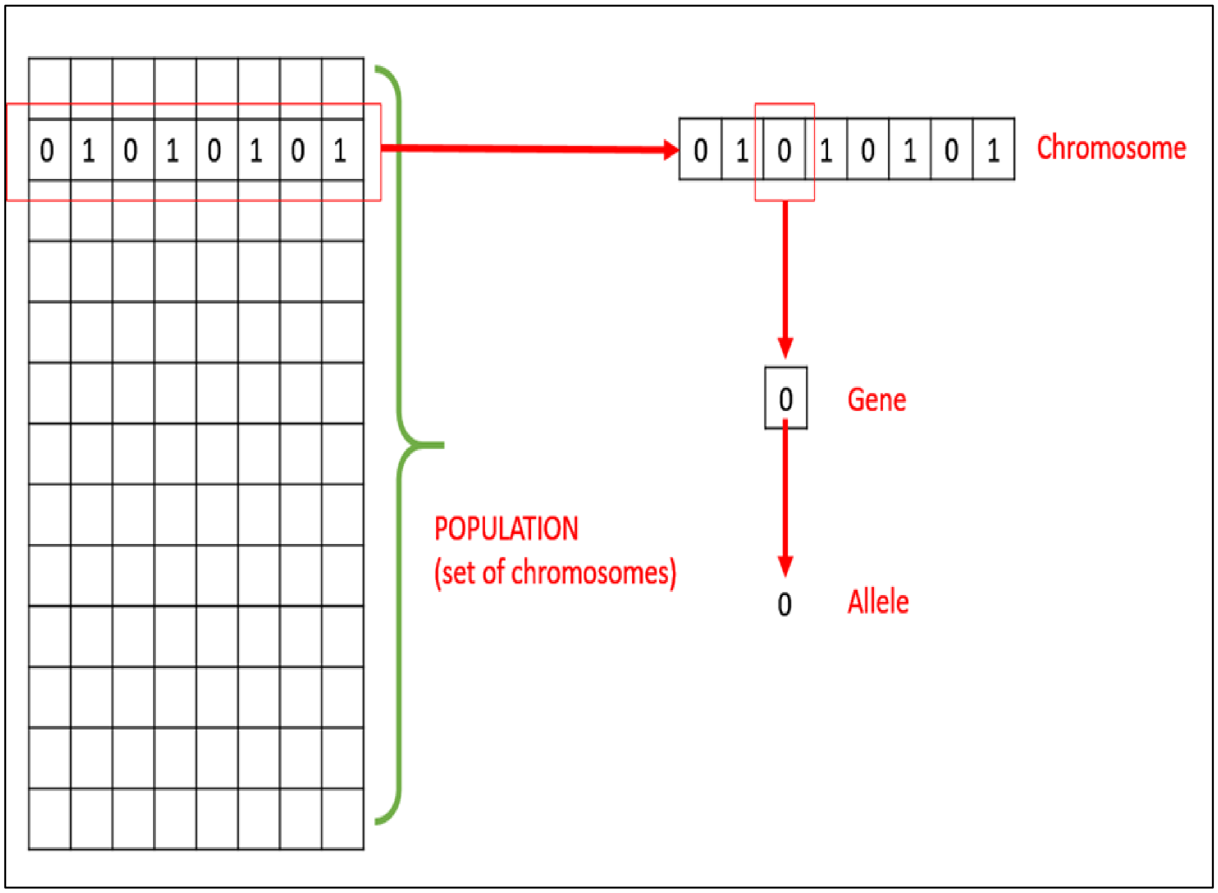
Before beginning a discussion on Genetic Algorithms, it is essential to be familiar with some basic terminology which will be used throughout this tutorial.

- **Population** – It is a subset of all the possible (encoded) solutions to the given problem. The population for a GA is analogous to the population for human beings except that instead of human beings, we have **Candidate Solutions** representing human beings.

- **Chromosomes** – A chromosome is one such solution to the given problem.

- **Gene** – A gene is one element position of a chromosome.

- **Allele** – It is the value a gene takes for a particular chromosome.



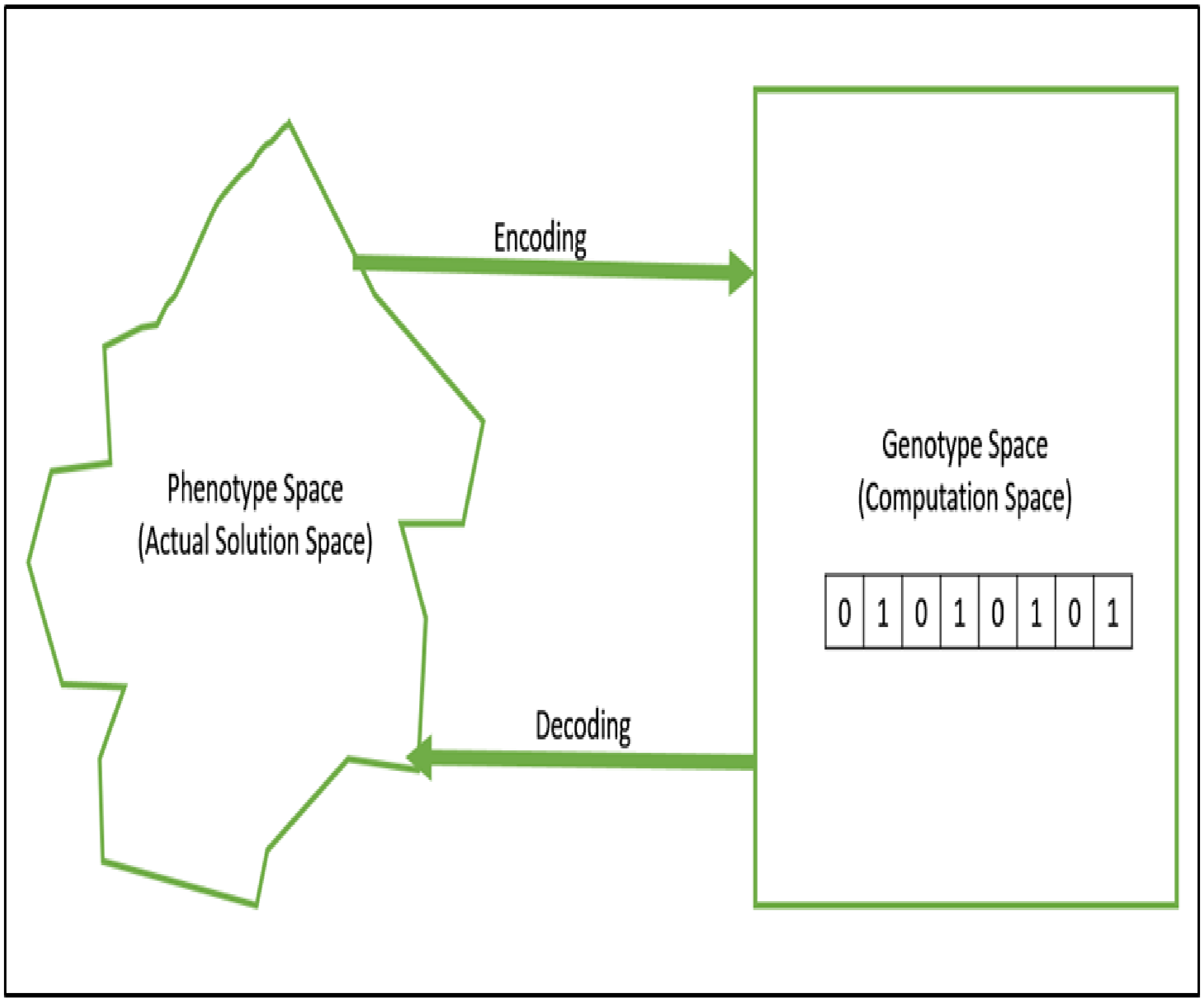
- **Genotype** – Genotype is the population in the computation space. In the computation space, the solutions are represented in a way which can be easily understood and manipulated using a computing system.

- **Phenotype** – Phenotype is the population in the actual real world solution space in which solutions are represented in a way they are represented in real world situations.

- **Decoding and Encoding** – For simple problems, the **phenotype and genotype** spaces are the same. However, in most of the cases, the phenotype and genotype spaces are different. Decoding is a process of transforming a solution from the genotype to the phenotype space, while encoding is a process of transforming from the phenotype to genotype space. Decoding should be fast as it is carried out repeatedly in a GA during the fitness value calculation.

  For example, consider the 0/1 Knapsack Problem. The Phenotype space consists of solutions which just contain the item numbers of the items to be picked.

  However, in the genotype space it can be represented as a binary string of length n (where n is the number of items). A **0 at position x** represents that **x**$^{\mathbf{th}}$ item is picked while a 1 represents the reverse. This is a case where genotype and phenotype spaces are different.



- **Fitness Function –** A fitness function simply defined is a function which takes the solution as input and produces the suitability of the solution as the output. In some cases, the fitness function and the objective function may be the same, while in others it might be different based on the problem.

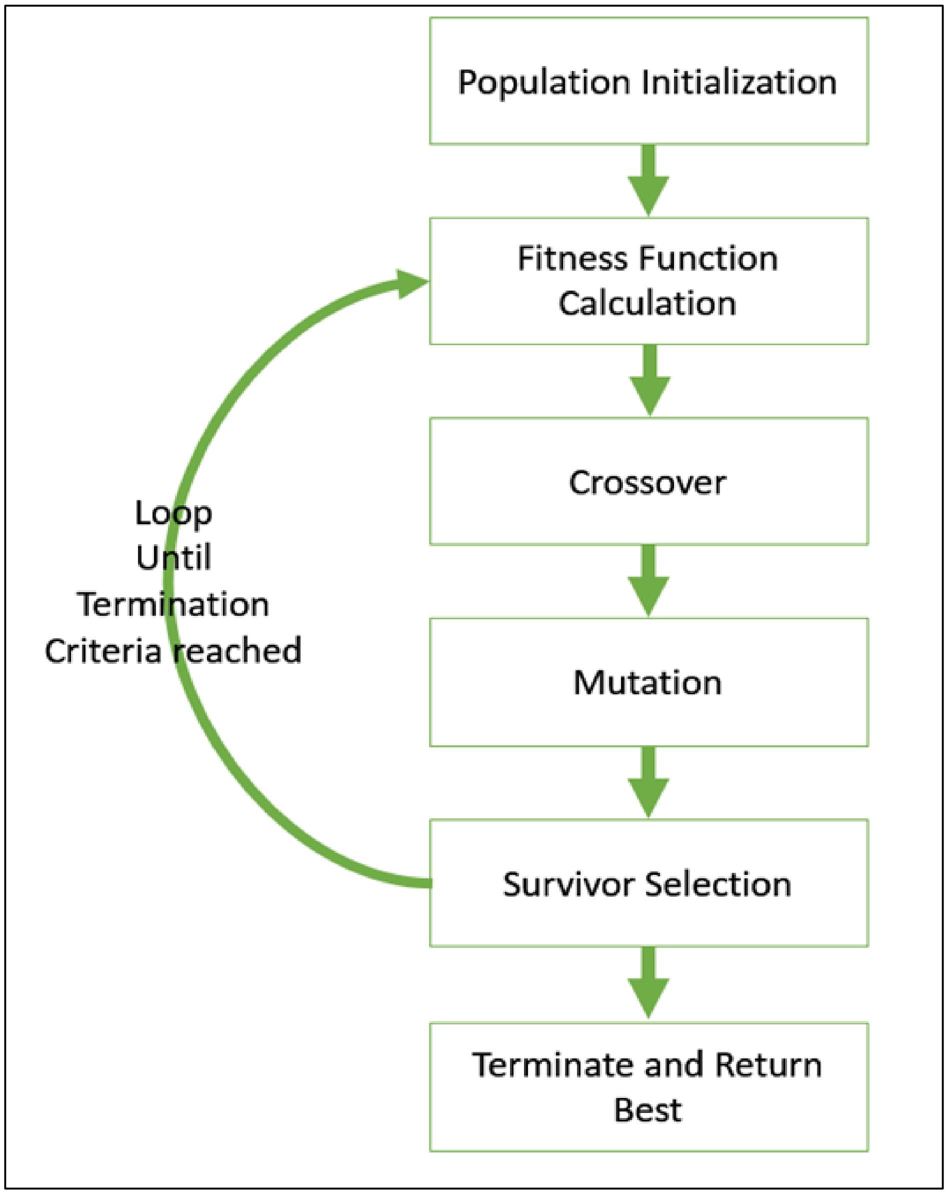
- **Genetic Operators –** These alter the genetic composition of the offspring. These include crossover, mutation, selection, etc.

Basic Structure

The basic structure of a GA is as follows –

We start with an initial population (which may be generated at random or seeded by other heuristics), select parents from this population for mating. Apply crossover and mutation operators on the parents to generate new off-springs. And finally these off-springs replace the existing individuals in the population and the process repeats. In this way genetic algorithms actually try to mimic the human evolution to some extent.

Each of the following steps are covered as a separate chapter later in this tutorial.


Population Initialization
Fitness Function Calculation
Crossover
Mutation
Survivor Selection
Terminate and Return Best
Loop Until Termination Criteria reached

A generalized pseudo-code for a GA is explained in the following program:

```
GA()
   initialize population
   find fitness of population
   while (termination criteria is reached) do
      parent selection
      crossover with probability pc
      mutation with probability pm
      decode and fitness calculation
      survivor selection
      find best
   return best
```