Genetic Algorithms

GeeksforGeeks

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Genetic Algorithms(GAs) are adaptive heuristic search algorithms that belong to the larger part of evolutionary algorithms. Genetic algorithms are based on the ideas of natural selection and genetics. These are intelligent exploitation of random searches provided with historical data to direct the search into the region of better performance in solution space. **They are commonly used to generate high-quality solutions for optimization problems and search problems.**

Genetic algorithms simulate the process of natural selection which means those species that can adapt to changes in their environment can survive and reproduce and go to the next generation. In simple words, they simulate "survival of the fittest" among individuals of consecutive generations to solve a problem. **Each generation consists of a population of individuals** and each individual represents a point in search space and possible solution. Each individual is represented as a string of character/integer/float/bits. This string is analogous to the Chromosome.

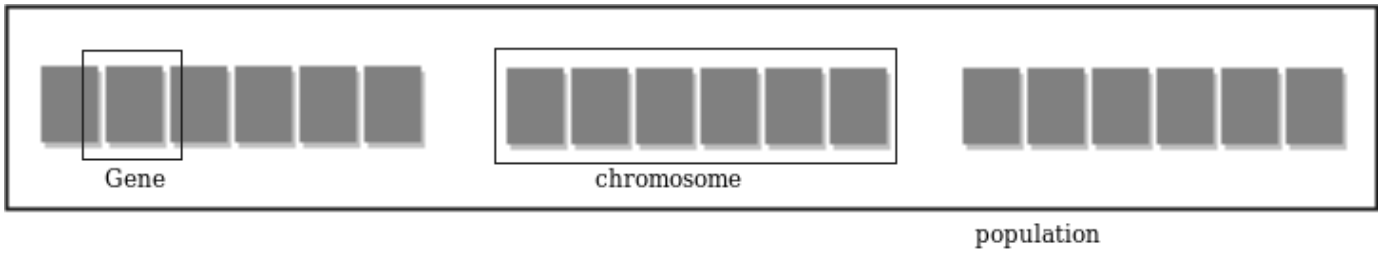
Foundation of Genetic Algorithms

Genetic algorithms are based on an analogy with the genetic structure and behavior of chromosomes of the population. Following is the foundation of GAs based on this analogy –

1. Individuals in the population compete for resources and mate
2. Those individuals who are successful (fittest) then mate to create more offspring than others
3. Genes from the "fittest" parent propagate throughout the generation, that is sometimes parents create offspring which is better than either parent.
4. Thus each successive generation is more suited for their environment.

Search space

The population of individuals are maintained within search space. Each individual represents a solution in search space for given problem. Each individual is coded as a finite length vector (analogous to chromosome) of components. These variable components are analogous to Genes. Thus a chromosome (individual) is composed of several genes (variable components).



Fitness Score

A Fitness Score is given to each individual which **shows the ability of an individual to "compete"**. The individual having optimal fitness score (or near optimal) are sought.

The GAs maintains the population of n individuals (chromosome/solutions) along with their fitness scores.The individuals having better fitness scores are given more chance to reproduce than others. The individuals with better fitness scores are selected who mate and produce **better offspring** by combining chromosomes of parents. The population size is static so the room has to be created for new arrivals. So, some individuals die and get replaced by new arrivals eventually creating new

generation when all the mating opportunity of the old population is exhausted. It is hoped that over successive generations better solutions will arrive while least fit die.

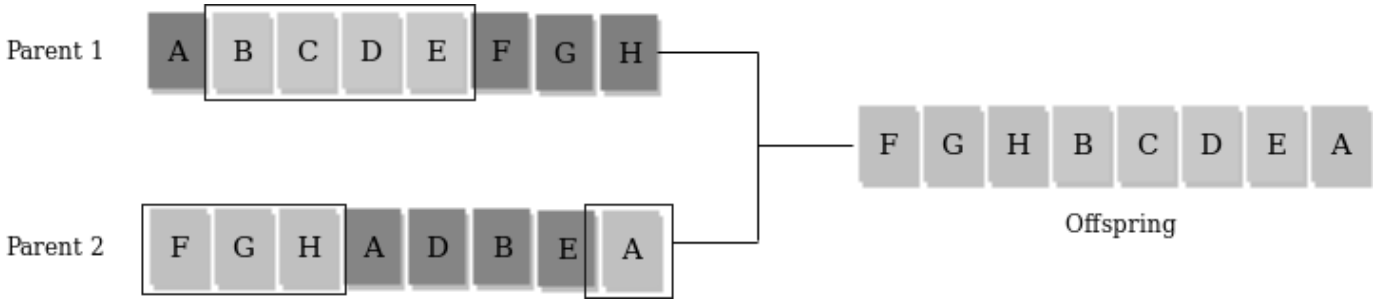
Each new generation has on average more "better genes" than the individual (solution) of previous generations. Thus each new generations have better **"partial solutions"** than previous generations. Once the offspring produced having no significant difference from offspring produced by previous populations, the population is converged. The algorithm is said to be converged to a set of solutions for the problem.

Operators of Genetic Algorithms

Once the initial generation is created, the algorithm evolves the generation using following operators –

1) Selection Operator: The idea is to give preference to the individuals with good fitness scores and allow them to pass their genes to successive generations.

2) Crossover Operator: This represents mating between individuals. Two individuals are selected using selection operator and crossover sites are chosen randomly. Then the genes at these crossover sites are exchanged thus creating a completely new individual (offspring). For example –



3) Mutation Operator: The key idea is to insert random genes in offspring to maintain the diversity in the population to avoid premature convergence. For example –

The whole algorithm can be summarized as –

```
1) Randomly initialize populations p
2) Determine fitness of population
3) Until convergence repeat:
      a) Select parents from population
      b) Crossover and generate new population
      c) Perform mutation on new population
      d) Calculate fitness for new population
```

Example problem and solution using Genetic Algorithms

Given a target string, the goal is to produce target string starting from a random string of the same length. In the following implementation, following analogies are made –

- Characters A-Z, a-z, 0-9, and other special symbols are considered as genes
- A string generated by these characters is considered as chromosome/solution/Individual

Fitness score is the number of characters which differ from characters in target string at a particular index. So individual having lower fitness value is given more preference.

- C++
- Java
- Python3
- C#
- Javascript

C++

Java

Python3

```
import random

POPULATION_SIZE = 100

GENES =

TARGET = "I love GeeksforGeeks"

class Individual(object):

    def __init__(self, chromosome):

        self.chromosome = chromosome

        self.fitness = self.cal_fitness()

    @classmethod

    def mutated_genes(self):

        global GENES

        gene = random.choice(GENES)

        return gene

    @classmethod

    def create_gnome(self):

        global TARGET

        gnome_len = len(TARGET)

        return [self.mutated_genes() for _ in range(gnome_len)]

    def mate(self, par2):

        child_chromosome = []

        for gp1, gp2 in zip(self.chromosome, par2.chromosome):

            prob = random.random()

            if prob < 0.45:

                child_chromosome.append(gp1)

            elif prob < 0.90:
```

```
                child_chromosome.append(gp2)
            else:
                child_chromosome.append(self.mutated_genes())
        return Individual(child_chromosome)
    def cal_fitness(self):
        global TARGET
        fitness = 0
        for gs, gt in zip(self.chromosome, TARGET):
            if gs != gt: fitness+= 1
        return fitness
def main():
    global POPULATION_SIZE
    generation = 1
    found = False
    population = []
    for _ in range(POPULATION_SIZE):
                gnome = Individual.create_gnome()
                population.append(Individual(gnome))
    while not found:
        population = sorted(population, key = lambda x:x.fitness)
        if population[0].fitness <= 0:
            found = True
            break
        new_generation = []
        s = int((10*POPULATION_SIZE)/100)
        new_generation.extend(population[:s])
        s = int((90*POPULATION_SIZE)/100)
        for _ in range(s):
            parent1 = random.choice(population[:50])
            parent2 = random.choice(population[:50])
            child = parent1.mate(parent2)
            new_generation.append(child)
```

```
        population = new_generation

        print("Generation: {}\tString: {}\tFitness: {}".\

              format(generation,

              "".join(population[0].chromosome),

              population[0].fitness))

        generation += 1

    print("Generation: {}\tString: {}\tFitness: {}".\

          format(generation,

          "".join(population[0].chromosome),

          population[0].fitness))

if __name__ == '__main__':

    main()
```

C#

Javascript

Output:

```
Generation: 1    String: tO{"-?=jH[k8=B4]Oe@}    Fitness: 18
Generation: 2    String: tO{"-?=jH[k8=B4]Oe@}    Fitness: 18
Generation: 3    String: .#lRWf9k_Ifslw #O$k_    Fitness: 17
Generation: 4    String: .-1Rq?9mHqk3Wo]3rek_    Fitness: 16
Generation: 5    String: .-1Rq?9mHqk3Wo]3rek_    Fitness: 16
Generation: 6    String: A#ldW) #lIkslw cVek)    Fitness: 14
Generation: 7    String: A#ldW) #lIkslw cVek)    Fitness: 14
Generation: 8    String: (, o x _x%Rs=, 6Peek3   Fitness: 13
                           .
                           .
                           .
Generation: 29    String: I lope Geeks#o, Geeks   Fitness: 3
Generation: 30    String: I loMe GeeksfoBGeeks    Fitness: 2
Generation: 31    String: I love Geeksfo0Geeks    Fitness: 1
Generation: 32    String: I love Geeksfo0Geeks    Fitness: 1
Generation: 33    String: I love Geeksfo0Geeks    Fitness: 1
Generation: 34    String: I love GeeksforGeeks    Fitness: 0
```

Note: Every-time algorithm start with random strings, so output may differ

As we can see from the output, our algorithm sometimes stuck at a local optimum solution, this can be further improved by updating fitness score calculation algorithm or by tweaking mutation and crossover operators.

Why use Genetic Algorithms

- They are Robust
- Provide optimisation over large space state.
- Unlike traditional AI, they do not break on slight change in input or presence of noise

Application of Genetic Algorithms

Genetic algorithms have many applications, some of them are –

- Recurrent Neural Network
- Mutation testing
- Code breaking
- Filtering and signal processing
- Learning fuzzy rule base etc

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