Lab-07
To implement Genetic Algorithms with Artificial Intelligence

Objectives:

- To studyGenetic Algorithms.
- To study about how to Use GA for Optimization Problems.
- To learn stages of GA mechanism for optimization process

Apparatus:

- Hardware Requirement
  Personal computer.
- Software Requirement
  Anaconda.

Theory:

Genetic Algorithms (GAs):

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. It has since been tried on various optimization problems with a high degree of success.

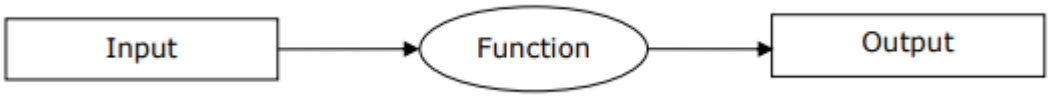
In GAs, we have a pool of possible solutions to the given problem. These solutions then undergo recombination and mutation (like in natural genetics), produces new children, and the process is repeated for various generations. Each individual (or candidate solution) is assigned a fitness value (based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

Thus, it keeps evolving better individuals or solutions over generations, till it reaches a stopping criterion.

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

How to Use GA for Optimization Problems?

Optimization is an action of making design, situation, resource and system, as effective as possible. The following block diagram shows the optimization process:



Stages of GA mechanism for optimization process

The following is a sequence of steps of GA mechanism when used for optimization of problems.
Step 1: Generate the initial population randomly.
Step 2: Select the initial solution with best fitness values.
Step 3: Recombine the selected solutions using mutation and crossover operators.
Step 4: Insert an offspring into the population.
Step 5: Now, if the stop condition is met, return the solution with their best fitness value. Else go to step 2.

Installing Necessary Packages

For solving the problem by using Genetic Algorithms in Python, we are going to use a powerful package for GA called DEAP. It is a library of novel evolutionary computation framework for rapid prototyping and testing of ideas. We can install this package with the help of the following command on command prompt:

```
pip install deap
```

If you are using anaconda environment, then following command can be used to install deap:
conda install -c conda-forge deap

Implementing Solutions using Genetic Algorithms

This section explains the implementation of solutions using Genetic Algorithms.

Generating bit patterns

The following example shows you how to generate a bit string that would contain 15 ones,

based on the One Max problem. Import the necessary packages as shown:

```
import random
from deap import base, creator, tools
```

Define the evaluation function. It is the first step to create a genetic algorithm.

```
def eval_func(individual):
    target_sum = 15
    return len(individual) - abs(sum(individual) - target_sum),
```

Now, create the toolbox with the right parameters:

```
def create_toolbox(num_bits):
    creator.create("FitnessMax", base.Fitness, weights=(1.0,))
    creator.create("Individual", list, fitness=creator.FitnessMax)
```

Initialize the toolbox:

```
    toolbox = base.Toolbox()
toolbox.register("attr_bool", random.randint, 0, 1)
```

```
toolbox.register("individual", tools.initRepeat, creator.Individual,
        toolbox.attr_bool, num_bits)
  toolbox.register("population", tools.initRepeat, list, toolbox.individual)
```

Register the evaluation operator:

```
    toolbox.register("evaluate", eval_func)
```

Now, register the crossover operator:

```
    toolbox.register("mate", tools.cxTwoPoint)
```

Register a mutation operator:

```
    toolbox.register("mutate", tools.mutFlipBit, indpb=0.05)
```

Define the operator for breeding:

```
    toolbox.register("select", tools.selTournament, tournsize=3)
    return toolbox
if __name__ == "__main__":
    num_bits = 45
    toolbox = create_toolbox(num_bits)
    random.seed(7)
    population = toolbox.population(n=500)
    probab_crossing, probab_mutating  = 0.5, 0.2
    num_generations = 10
    print('\nEvolution process starts')
```

Evaluate the entire population:

```
    fitnesses = list(map(toolbox.evaluate, population))
    for ind, fit in zip(population, fitnesses):
        ind.fitness.values = fit
    print('\nEvaluated', len(population), 'individuals')
```

Create and iterate through generations:

```
    for g in range(num_generations):
        print("\n- Generation", g)
```

Selecting the next generation individuals:

```
offspring = toolbox.select(population, len(population))
```

Now, clone the selected individuals:

```
offspring = list(map(toolbox.clone, offspring))
```

Apply crossover and mutation on the offspring:

```
for child1, child2 in zip(offspring[::2], offspring[1::2]):
        if random.random() < probab_crossing:
        toolbox.mate(child1, child2)
```

Delete the fitness value of child:

```
        del child1.fitness.values
        del child2.fitness.values
```

Now, apply mutation:

```
        for mutant in offspring:
                if random.random() < probab_mutating:
                toolbox.mutate(mutant)
                del mutant.fitness.values
```

Evaluate the individuals with an invalid fitness:

```
        invalid_ind = [ind for ind in offspring if not ind.fitness.valid]
        fitnesses = map(toolbox.evaluate, invalid_ind)
        for ind, fit in zip(invalid_ind, fitnesses):
            ind.fitness.values = fit
        print('Evaluated', len(invalid_ind), 'individuals')
```

Now, replace population with next generation individual:

```
        population[:] = offspring
```

Print the statistics for the current generations:

```
        fits = [ind.fitness.values[0] for ind in population]
        length = len(population)
        mean = sum(fits) / length
```

```
        sum2 = sum(x*x for x in fits)
        std = abs(sum2 / length - mean**2)**0.5
        print('Min =', min(fits), ', Max =', max(fits))
        print('Average =', round(mean, 2), ', Standard deviation =',
                round(std, 2))
    print("\n- Evolution ends")
```

Print the final output:

```
best_ind = tools.selBest(population, 1)[0]
print('\nBest individual:\n', best_ind)
print('\nNumber of ones:', sum(best_ind))
```

Following would be the output:

```
Evolution process starts
Evaluated 500 individuals
    - Generation 0
Evaluated 295 individuals
Min = 32.0 , Max = 45.0
Average = 40.29 , Standard deviation = 2.61
    - Generation 1
Evaluated 292 individuals
Min = 34.0 , Max = 45.0
Average = 42.35 , Standard deviation = 1.91
    - Generation 2
Evaluated 277 individuals
Min = 37.0 , Max = 45.0
Average = 43.39 , Standard deviation = 1.46
… … … …
    - Generation 9
Evaluated 299 individuals
Min = 40.0 , Max = 45.0
Average = 44.12 , Standard deviation = 1.11
- Evolution ends
```

Best individual:

[0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1,
1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1]

Number of ones: 15

Lab task:

It is one of the best known problems in genetic programming. All symbolic regression problems use an arbitrary data distribution, and try to fit the most accurate data with a symbolic formula. Usually, a measure like the RMSE (Root Mean Square Error) is used to measure an individual's fitness. It is a classic regressor problem and here we are using the equation $\mathbf{5}\boldsymbol{X}\ \mathbf{3} - \mathbf{6}\boldsymbol{X}\mathbf{2} + \mathbf{8}\boldsymbol{X} = \mathbf{1}$. We need to follow all the steps as followed in the above example, but the main part would be to create the primitive sets because they are the building blocks for the individuals so the evaluation can start. Here you will be using the classic set of primitives.

Implement it in python