Computational Intelligence Optimisation

Lab 2: Introduction to GAs using Deap

For this exercise we are going to simulation/solve the Moth scenario discussed in the Venables et al. paper shared earlier using the DEAP libraries. The process to do so is as follows:

- 1. Import libraries and define evolutionary parameters
- 2. Set up the toolbox
- 3. Define fitness, individual and population creators
- 4. Create the fitness function
- 5. Set up the genetic operators
- 6. Run the algorithm

Step 1: Import libraries and define evolutionary parameters:

```
2 # import libraries
3∘from deap import base
4 from deap import creator
5 from deap import tools
 6 from deap import algorithms
8∘import random
 9 import numpy as np
10
11 import matplotlib.pyplot as plt
12
13 ##************
14
15 ## parameters
16 \text{ chrom\_size} = 100
17 population_size = 200
18 P CROSSOVER = 0.9
19 M MUTATION = 0.1
20 MAX GENERATIONS = 200
21 \text{ RANDOM\_SEED} = 42
22
```

Step 2: Set up the toolbox

```
23 ## set up the toolbox
24 toolbox = base.Toolbox()
```

Step 3: Define fitness, individual and population creators

```
## define the structure of the <a href="chromosome">chromosome</a> and register the funct
27 toolbox.register("binary", random.randint, 0,1)
28
29
       ## create a function to evaluate the individual and providing on
30 creator.create("FitnessMax", base.Fitness, weights=(1.0,))
31
32
       ## create a function to create an individual
933 creator.create("Individual", list, fitness=creator.FitnessMax)
       ## define/register a function to create an individual
36 toolbox.register("IndividualCreator", tools.initRepeat,
937
                     creator.Individual, toolbox.binary, chrom_size)
38
39
       ## define/register a function to generate a population of indivi
40 toolbox.register("PopulationCreator", tools.initRepeat,
41
                     list, toolbox.IndividualCreator)
42
```

Step 4: Create the fitness function

```
## set up a fitness/evaluation function [0
460 def fitnessFunction(individual):
    return sum(individual), ## return the ind:
48
```

Step 5: Set up the genetic operators

```
toolbox.register("evaluate", fitnessFunction)
toolbox.register("select", tools.selTournament, tournsize=3)
toolbox.register("mate", tools.cxTwoPoint)
toolbox.register("mutate", tools.mutFlipBit, indpb=1/population_size)
```

Step 6: Run the algorithm

```
57 ## run the algorithm
58edef main():
59
      population = toolbox.PopulationCreator(n=population_size)
50
51
52
      stats = tools.Statistics(lambda ind: ind.fitness.values)
53
      stats.register("max", np.max)
54
      stats.register("avg", np.mean)
55
56
      population, logbook= algorithms.eaSimple(population,
                                                 toolbox, cxpb=P_CROSSOVER,
57
58
                                                  mutpb=M_MUTATION,
59
                                                  ngen= MAX_GENERATIONS,
70
                                                  stats=stats, verbose=True)
71
72
      maxFitnessValues, meanFitnessValues = logbook.select("max", "avg")
73
74
      plt.plot(maxFitnessValues, color='red')
75
      plt.plot(meanFitnessValues, color='green')
76
      plt.xlabel('Max/average fitness')
77
      plt.ylabel('Max/average fitness over generations')
78
      plt.show()
79
30 if __name__ == "__main__":
31
      main()
```

Exercise 2:

Implement a GA to solve the Guard Scheduling Problem