<u>Machine Learning Lab : Assignment 3</u>

Genetic Algorithm

Notebook authored by Sonaal P. Pradeep (B170163CS)

About the algorithm

Brute force applications of problems require a lot of time and processing power to find an optimal solution. The genetic algorithm is an approach which incorporates techniques **seen naturaly in nature**, in the form of evolution.

One iteration in a genetic algorithm consists of the following :

1. Parent Selection
2. Inter-Breeding
3. Mutation
4. Survivors Selection

Before implementing a problem for this algorithm, the problem **needs to be encoded**. The encoding can be of the following forms :

1. Binary Representation
2. Integer Representation
3. Real Value Representation
4. Permutation Representation

Constraints given

1. The **objective function** used is $f(x) = x^3 + 9$. The goal is to **maximize the objective fuction**.
2. The value of *x* is represented as a 6 **digit binary number**.
3. Binary encoding scheme
4. Size of the population is 10
5. Parent selection is based on the **Roulette Wheel selection** .
6. Mutation probability 0.01.
7. Survival selection criteria : Replace 20% worst population in offsprings with 20% best population from the parent.

Importing necessary modules

In [16]:
```
import numpy as np
import math
import random

import matplotlib.pyplot as plt
from pylab import rcParams

rcParams['figure.figsize'] = 15, 10
```

User defined functions

In [17]:
```
def f(x):
    '''
    The objective function is defined so that it can be used in the calculations involved in the roulette
    wheel selection and survivor selection.

    Input : Number
    Returns : The value wrt the objective function i.e x^3 + 9
    '''
    return pow(x, 3) + 9
```

In [18]:
```
def create_Parents(population_Size, bit_Length):
    '''
    The parents choosen initially are generated randomly based on the constraints / encoding of the probl
em

    Parameters : population_Size - The number of parents to choose
                 bit_Length - Problem specific encoding, acts as encoding

    Returns : bitStrings of required length and size. The string format for binary numbers are removed as
well
    and appended to the left with 0's, the corressponding list of numbers
    '''
    max_number = pow(2, bit_Length) - 1
    num_list = [np.random.randint(0, max_number) for _ in range(population_Size)]

    return [format(num, "#08b").lstrip('0b').zfill(6) for num in num_list]
```

In [19]:
```
def find_chance(parents):
    '''
    Finds the probabilities required for the roulette wheel selection

    Input : parents - The parents who's chances need to be calculated
    Returns : List of chances for corresponding parents
    '''
    num_list = [int(b, 2) for b in parents]
    list_sum = sum([f(x) for x in num_list])

    return [f(num) / list_sum for num in num_list]
```

In [20]:
```
def select_Succesors(parents, population):
    '''
    Choosing the successors which will propogate to the next generation

    Input : parents - The parents who have chances to go to the next generation
            population -
    Returns : The choosen children to go to the next generation
    '''
    selection_chance = find_chance(parents)
    return [np.random.choice(parents, p = selection_chance) for _ in range(population)]
```

In [21]:
```
def cross_breed(parent, cross_over_type, cross_breed_shuffle, bit_cross_over, bit_Length):
    '''
    Cross breeding deals with the swapping of characteristics of 2 parents. Its the first layer of proces
s what leads
    to generating new children. It happens at the phenotype level

    Input : parent - The genes that are going through cross breeding
            cross_over_type - Can be "uniform" or "single-point"
                        In "single-point", a index is selected and all the genes to the right of both par
ents
                        interchanged
                        In "uniform", all bits have an equivalent chance of being swapped
            shuffle - If True, the parent is shuffled before cross_breeding
            bit_cross_over - Used when cross_over_type is "uniform", governs the chance a bit will get ex
changed
            bit_Length - The length of the genes

    Returns : Children in which cross breeding is complete. Their size is the same size as that of the pa
rents
    '''
    partition_size = len(parent) // 2

    if cross_breed_shuffle:
        np.random.shuffle(parent)

    child_set_1, child_set_2 = parent[:partition_size], children[partition_size:]

    if cross_over_type == "uniform":

        for ind in range(partition_size):
            for b in range(bit_Length):
                rand_val = np.random.rand()

                if rand_val < cross_over_chance:

                    bit_1 = int(child_set_1[ind], 2) & pow(2, b)
                    bit_2 = int(child_set_2[ind], 2) & pow(2, b)

                    if bit_1 != bit_2:
                        child_set_1[ind] = format(int(child_set_1[ind], 2) ^ pow(2, b), "#08b").lstrip('0
b').zfill(6)
```

```
                        child_set_2[ind] = format(int(child_set_2[ind], 2) ^ pow(2, b), "#08b").lstrip('0
b').zfill(6)

        return np.append(child_set_1, child_set_2)

    elif cross_over_type == "single-point":

        for ind in range(partition_size):
            slice_index = np.random.randint(1, bit_Length - 2)

            r_child_1 = child_set_1[ind][slice_index:]
            r_child_2 = child_set_2[ind][slice_index:]

            child_set_1[ind] = child_set_1[ind][:slice_index] + r_child_2
            child_set_2[ind] = child_set_2[ind][:slice_index] + r_child_1

        return np.append(child_set_1, child_set_2)
```

In [22]:
```python
def mutation(children, mutation_type, bit_mutation, bit_Length):
    '''
    Mutation happens at the genotype level, and it happens inherently in the children, and doesn't requir
e a
    pair.

    Input : children - The genes that will undergo mutation
            mutation_type - The method in which mutation would happen. It can be "scan-all" or "random"
                    In "scan-all", each bit has to chance to get switched
                    In "random", a random bit is choosen to get swapped
            bit_mutation - The likelihood a bit would interchange, and is necessary if mutation_type is
 "scan-all"
            bit_Length - The length of the genes

    Returns : The mutated children
    '''
    population_size = len(children)

    if mutation_type == "scan-all":
        for ind in range(population_size):
            for b in range(bit_Length):
                rand_val = np.random.ranf()

                if rand_val < bit_mutation:
                    children[ind] = format(int(children[ind], 2) ^ pow(2, b), "#08b").lstrip('0b').zfill(
6)

        return children

    elif mutation_type == "random":
        for ind in range(population_size):

            b_ind = np.random.randint(0, bit_Length - 1)

            children[ind] = format(int(children[ind], 2) ^ pow(2, b_ind), "#08b").lstrip('0b').zfill(6)

        return children
```

In [23]:
```
def evolution(parents, children, population_Size, survival_death_rate):
    '''
    The evolution function decides which amongst the 2 * population_Size of parents and children go throu
gh to
    the next generation. This functions picks the best x% of parents and the best (100 - x)% of children

    Input - parents - The array of parents
            children - The array of parents after cross breeding and mutation
            population_Size - The number of genes in a generation
            survival_death_rate - Decides the percent of parents that survive

    Returns - Array of children that progress to the next generation
    '''
    parent_partition = int(math.floor(population_Size * survival_death_rate))
    children_partition = population_Size - parent_partition

    fitted_parents = [f(int(x, 2)) for x in parents]
    fitted_children = [f(int(x, 2)) for x in children]

    sorted_parents = np.sort(parents)[::-1]
    sorted_children = np.sort(children)[::-1]

    progressors = np.append(sorted_parents[:parent_partition], sorted_children[:children_partition])

    return progressors
```

In [24]:
```
def plot_generation_graph(lines, generations, num_of_lines, opti_fn_y):
    '''
    The function is used to plot how well the children are working in each generation.

    Input : lines - A multi-dimensional list consisting of the history of each child
            generations - The life of the children
            num_of_lines - The number of children that needs to be plotted
            opti_fn_y - Plot the y-axis based of the optimisation function
    '''
    col_list = {0 : 'maroon', 1 : 'green', 2 : 'cornflowerblue', 3 : 'olive', 4 : 'black',
                5 : 'blue', 6 : 'silver', 7 : 'purple', 8 : 'slateblue', 9 : 'hotpink'}

    line_list = [[] for _ in range(num_of_lines)]

    for l in range(len(lines)):
        for i in range(min(num_of_lines, 10)):
            if opti_fn_y == False:
                line_list[i].append(int(lines[l][i], 2))
            else:
                line_list[i].append(f(int(lines[l][i], 2)))

    x = range(generations)

    fig = plt.figure()
    ax = fig.add_subplot(111)

    for i in range(min(num_of_lines, 10)):
        if i == 0:
            ax.plot(x, line_list[i], c = col_list[i], linestyle = "--", marker = 'o', label = "Child " +
str(i+1))
        else:
            ax.plot(x, line_list[i], c = col_list[i], label = "Child " + str(i+1))

    plt.title("Graph")
    plt.xlabel("Number of Generations")

    if opti_fn_y == False:
        plt.ylabel("Bit String Value")
    elif opti_fn_y == True:
        plt.ylabel("Optm. Function Value")
```

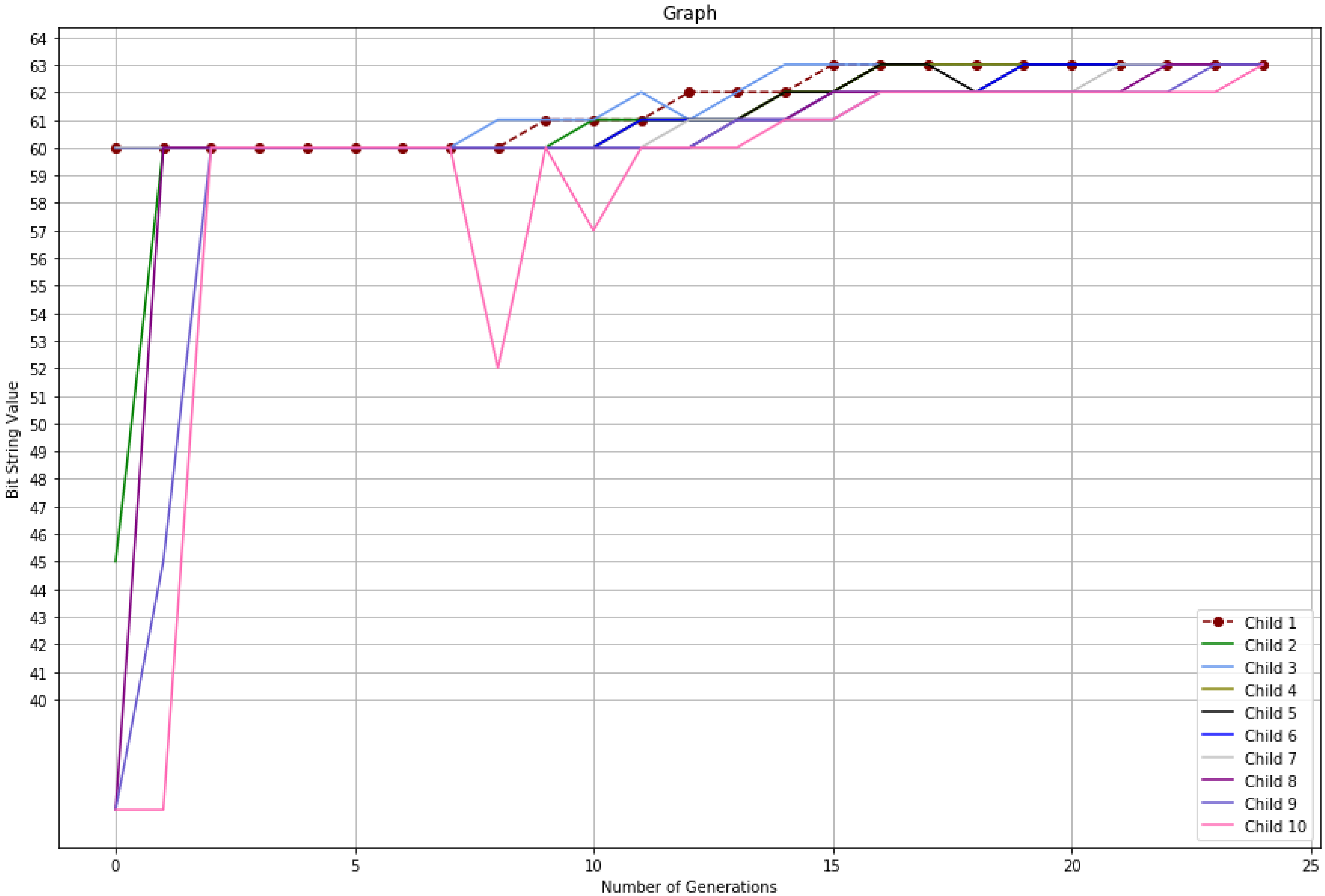
```
    if opti_fn_y == False:
        plt.yticks(range(40, 65, 1))

    plt.grid(True)
    plt.legend()
    plt.show()
```

Hyper Parameters

In [28]:
```
bit_Length = 6
population_Size = 10
max_num_of_generations = 25

inter_breeding_chance = 1
mutation_chance = 1

cross_breed_shuffle = True
bit_cross_over = 0.5
cross_over_type = "single-point"
bit_mutation = 0.01
mutation_type = "random"

survival_death = 0.2
```

Main Function

In [27]:
```
if __name__ == "__main__":
    parents = create_Parents(population_Size, bit_Length)
    plotting_elements = []

    num_of_generations = 0

    for _ in range(max_num_of_generations):
        children = select_Succesors(parents, population_Size)

        if np.random.rand() < inter_breeding_chance:
            bred_children = cross_breed(children, cross_over_type, cross_breed_shuffle, bit_cross_over, b
it_Length)

        if np.random.rand() < mutation_chance:
            mutant_children = mutation(children, mutation_type, bit_mutation, bit_Length)

        survivors = evolution(parents, mutant_children, population_Size, survival_death)
        parents = survivors

        plotting_elements.append(survivors)
        num_of_generations = num_of_generations + 1


    plot_generation_graph(plotting_elements, num_of_generations, num_of_lines = 10, opti_fn_y = False)
```



Graph
Bit String Value
Number of Generations
64
63
62
61
60
59
58
57
56
55
54
53
52
51
50
49
48
47
46
45
44
43
42
41
40
0
5
10
15
20
25
Child 1
Child 2
Child 3
Child 4
Child 5
Child 6
Child 7
Child 8
Child 9
Child 10


```
In [ ]:
```