

Import Libraries

```
1 !pip install deap
2
3 import array
4 import random
5 import numpy as np
6 import matplotlib.pyplot as plot
7 import matplotlib.cm as cm
8
9 from deap import base, creator, tools
10 from deap.benchmarks.tools import hypervolume
11 from sympy.combinatorics.graycode import random_bitstring, gray_to_bin, bin_to_gray
```

Collecting deap

Downloading deap-1.3.1-cp37-cp37m-manylinux_2_5_x86_64.manylinux1_x86_64.manylinux_2_12_x86_64.manylinux2010_x86_64.whl (160
|██| 160 kB 14.1 MB/s

Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from deap) (1.21.6)

Installing collected packages: deap

Successfully installed deap-1.3.1

Constants

```
1 # Binary length
2 BITS = 10
3 # -4.0 <= x1,x2,x3 <= 4.0
4 LOWER_BOUND, UPPER_BOUND = - 4, 4
5 # Number of genes (decision variables)
6 DECISION_VARIABLES = 3
7
8 POPULATION_SIZE = 25
9 NUMBER_OF_GENERATIONS = 30
10 OFFSPRING_SIZE = 25
```

```

11 CROSS_PROBABILITY = 0.9
12 MUTATION_PROBABILITY = 1/(BITS * DECISION_VARIABLES)
13
14 random.seed(10)

```

Functions

```

1 def gray_to_real(gray, lower, upper):
2     """ Converts between gray coding to a
3     real value in range [lower, upper] """
4     l = len(gray)
5     # Converts to binary, then integer
6     binary = gray_to_bin(gray)
7     integer = int(binary, 2)
8     # Converts to real-valued
9     x = lower + (upper - lower) * (1 / (2**l - 1)) * integer
10    return x

```

```

1 def evaluation(individual):
2     """ Evaluation function """
3     # An individual's genes
4     g1, g2, g3 = individual[0], individual[1], individual[2]
5     # Converts from gray code to real-valued
6     x1, x2, x3 = gray_to_real(g1, LOWER_BOUND, UPPER_BOUND), gray_to_real(g2, LOWER_BOUND, UPPER_BOUND), gray_to_real(g3, LOWER_BOUND, UPPER_BOUND)
7
8     f1 = ((x1/2)**2 + (x2/4)**2 + x3**2) / 3
9     f2 = (((x1/2) - 1)**2 + ((x2/4) - 1)**2 + (x3 - 1)**2) / 3
10    return f1, f2

```

```

1 def check_dominated(individual, current_front):
2     # Compare with individuals in current front starting from last
3     for compare_ind in current_front[::-1]:
4         if compare_ind.fitness.dominates(individual.fitness):

```

```
5     return True
6
1 def sequential_search(ind, fronts):
2     # Current front to check
3     front_index = 0
4     while True:
5         current_front = fronts[front_index]
6         dominated = check_dominated(ind, current_front)
7         if not dominated:
8             # Adds individual to current front
9             fronts[front_index].append(ind)
10        return fronts
11    front_index += 1
12    if front_index + 1 > len(fronts):
13        # Add individual to new front
14        new_front = [ind]
15        fronts.append(new_front)
16    return fronts
```

```
1 def efficient_ND_sort(population):
2     """ Efficient non-dominated sorting """
3     # Copies population to prevent population changing
4     copy_population = toolbox.clone(population)
5     # Sort population by f1, then by f2 if f1 is equal
6     copy_population.sort(key=lambda ind: (ind.fitness.values[0], ind.fitness.values[1]))
7     # Assigns best f1 to front 1
8     fronts = [[copy_population[0]]]
9     copy_population.remove(copy_population[0])
10    for ind in copy_population:
11        fronts = sequential_search(ind, fronts)
12    return fronts
```

```
1 def assignCrowdingDist(front):
2     """ Deap function to assign crowding distance to individuals in a front """
3     if len(front) == 0:
4         return
```

```

5  distances = [0.0] * len(front)
6  crowd = [(ind.fitness.values, i) for i, ind in enumerate(front)]
7
8  nobj = len(front[0].fitness.values)
9
10 for i in range(nobj):
11     crowd.sort(key=lambda element: element[0][i])
12     distances[crowd[0][1]] = float("inf")
13     distances[crowd[-1][1]] = float("inf")
14     if crowd[-1][0][i] == crowd[0][0][i]:
15         continue
16     norm = nobj * float(crowd[-1][0][i] - crowd[0][0][i])
17     for prev, cur, next in zip(crowd[:-2], crowd[1:-1], crowd[2:]):
18         distances[cur[1]] += (next[0][i] - prev[0][i]) / norm
19
20 for i, dist in enumerate(distances):
21     front[i].fitness.crowding_dist = dist

```

```

1 def compete(first, second):
2     # Comparision based on dominance
3     if first.fitness.dominates(second.fitness):
4         return first
5     elif second.fitness.dominates(first.fitness):
6         return second
7     # Comparision based on crowding distance
8     if first.fitness.crowding_dist > second.fitness.crowding_dist:
9         return first
10    elif first.fitness.crowding_dist < second.fitness.crowding_dist:
11        return second
12    # Random selection
13    if random.random() <= 0.5:
14        return first
15    return second

```

```

1 def binaryTournament(population, pair_number):

```

```
2  """ Binary tournament selection
3  Prevents the same individuals being repeatedly selected """
4  # Pairs of selected individuals
5  selected = []
6  # Copies population
7  copy_pop = [ind for ind in population]
8
9  # Number of parent pairs
10 for i in range(pair_number):
11     # Randomly select two individuals
12     first = random.choice(copy_pop)
13     # Remove from population to prevent repeat selection
14     copy_pop.remove(first)
15     # Checks if all individuals selected
16     if (len(copy_pop) == 0):
17         # Adds more individuals for selection
18         copy_pop = [ind for ind in population]
19     second = random.choice(copy_pop)
20     copy_pop.remove(second)
21     if (len(copy_pop) == 0):
22         copy_pop = [ind for ind in population]
23     first_parent = compete(first, second)
24
25     # Randomly select two more individuals
26     first = random.choice(copy_pop)
27     copy_pop.remove(first)
28     if (len(copy_pop) == 0):
29         copy_pop = [ind for ind in population]
30     second = random.choice(copy_pop)
31     if (len(copy_pop) == 0):
32         copy_pop = [ind for ind in population]
33     copy_pop.remove(second)
34     second_parent = compete(first, second)
35     selected.append([first_parent, second_parent])
36
37 return selected
```

```
1 def flipMutation(individual, probability=0.1):
2     # Iterates through decision variables
3     for i in range(len(individual)):
4         # Creates updated decision variable
5         new_var = ""
6         # Iterates through bits in decision variable
7         for bit in individual[i]:
8             new_bit = bit
9             # Flip bit
10            if random.random() <= probability:
11                if bit == '0':
12                    new_bit = '1'
13                if bit == '1':
14                    new_bit = '0'
15            new_var += new_bit
16        # Updates mutated decision variable
17        individual[i] = new_var
18    return individual
```

Genetic Algorithm

```
1 # Creates a fitness for minimization of a problem with 2 objectives
2 creator.create("FitnessMin", base.Fitness, weights=(-1.0, -1.0))
3 # Creates class Individual with fitness set for minimization
4 creator.create("Individual", list, fitness=creator.FitnessMin)
5
6 toolbox = base.Toolbox()
7
8 # Generation function for decision variables using 10 bit gray coding
9 toolbox.register("gray_code", random_bitstring, BITS)
10 # Initializers for individual and population
11 toolbox.register("individual", tools.initRepeat, creator.Individual, toolbox.gray_code, DECISION_VARIABLES)
12 toolbox.register("population", tools.initRepeat, list, toolbox.individual)
13
14 # Genetic operators
15 toolbox.register("evaluate", evaluation) # Uses evaluation function
```

```
16 toolbox.register("sort", efficient_ND_sort) # Non-dominated sorting into fronts
17 toolbox.register("crowd", assignCrowdingDist) # Assign crowding distance to each individual of the list
18 toolbox.register("tournament", binaryTournament) # Tournament selection
19 toolbox.register("mate", tools.cxUniform, indpb=0.5) # Uniform crossover with 50% chance of exchange
20 toolbox.register("mutate", flipMutation, probability=MUTATION_PROBABILITY) # Flip mutation with chance = 1 / chromosome length

1 def main():
2     stats = tools.Statistics()
3     logbook = tools.Logbook()
4     logbook.header = "generation", "x1", "x2", "x3", "f1", "f2", "front_number", "crowding_distance"
5
6     # Initiate the population
7     pop = toolbox.population(POPULATION_SIZE)
8     print("Initial Population is \n",pop)
9     print("The Length of the initial Population", len(pop))
10    # Hypervolume over generations
11    hypervolumes = []
12
13    # Evaluate fitness of population
14    invalid_individuals = [ind for ind in pop if not ind.fitness.valid]
15    fitnesses = list(map(toolbox.evaluate, pop))
16    for ind, fit in zip(invalid_individuals, fitnesses):
17        ind.fitness.values = fit
18
19    # Find the worst f1 and f2 values
20    copy_pop = toolbox.clone(pop)
21    # Sort population by f1 and f2
22    copy_pop.sort(key=lambda x: x.fitness.values[0], reverse=True)
23    worst_f1 = copy_pop[0].fitness.values[0]
24    copy_pop.sort(key=lambda x: x.fitness.values[1], reverse=True)
25    worst_f2 = copy_pop[0].fitness.values[1]
26    # Sets reference point for hypervolume
27    reference = [worst_f1, worst_f2]
28    print("Worst f1: " + str(worst_f1))
29    print("Worst f2: " + str(worst_f2))
30    print("\n")
31
```

```
32 # Sort population into fronts
33 fronts = toolbox.sort(pop)
34 updated_pop = []
35 for i in range(len(fronts)):
36     front = fronts[i]
37     # Assign crowding distance to individuals in each front
38     toolbox.crowd(front)
39     for ind in front:
40         updated_pop.append(ind)
41         # Print out individuals and fitness
42         logbook.record(generation=0, x1=ind[0], x2=ind[1], x3=ind[2], f1=ind.fitness.values[0], f2=ind.fitness.values[1], front_num=
43         print(logbook.stream)
44 print("\n")
45 # Updates population so that individuals have crowding distance
46 pop = updated_pop
47
48 # Calculates hypervolume of generation 0
49 hv = hypervolume(fronts[0], reference)
50 hypervolumes.append(hv)
51
52 for generation in range(1, NUMBER_OF_GENERATIONS + 1):
53     # Selects parents through tournament selection
54     parent_pairs = toolbox.tournament(pop, len(pop))
55
56     parents = []
57     offspring = []
58     for pair in parent_pairs:
59         # Makes copies of parents to modify
60         parent1 = toolbox.clone(pair[0])
61         parent2 = toolbox.clone(pair[1])
62         offspring1 = toolbox.clone(parent1)
63         offspring2 = toolbox.clone(parent2)
64         # Cross over
65         if random.random() <= CROSS_PROBABILITY:
66             toolbox.mate(offspring1, offspring2)
67         # Mutate both offspring
68         toolbox.mutate(offspring1)
```



```
69     toolbox.mutate(offspring2)
70     parents.append(parent1)
71     offspring.append(offspring1)
72     parents.append(parent2)
73     offspring.append(offspring2)
74 # Caps to 25 offspring
75 offspring = offspring[:OFFSPRING_SIZE]
76 parents = parents[:OFFSPRING_SIZE]
77 print("\n")
78 print("The parents in the generation {} are {}".format(generation, parents))
79 print("The total count of parents in the generation {} are {}".format(generation, len(parents)))
80 print("The offspring in the generation {} are {}".format(generation, offspring))
81 print("The total count of offsprings in the generation {} are {}".format(generation, len(offspring)))
82 # Offspring still have parent's fitness
83 parent_f1 = [off.fitness.values[0] for off in offspring]
84 parent_f2 = [off.fitness.values[1] for off in offspring]
85 # Offspring fitness is updated
86 fitnesses = list(map(toolbox.evaluate, offspring))
87 for off, fit in zip(offspring, fitnesses):
88     off.fitness.values = fit
89 #if generation == 1 or generation == 10 or generation == 20 or generation == NUMBER_OF_GENERATIONS:
90
91 # Print graph
92 if generation == 1 or generation == 10 or generation == 20 or generation == NUMBER_OF_GENERATIONS:
93     offspring_f1 = [off.fitness.values[0] for off in offspring]
94     offspring_f2 = [off.fitness.values[1] for off in offspring]
95     # Plot parents and offspring fitness
96     plot.figure()
97     plot.title('Parents and Offspring Fitness for Generation ' + str(generation))
98     plot.plot(parent_f1, parent_f2, 'ro', alpha=0.5, label='Parents')
99     plot.plot(offspring_f1, offspring_f2, 'bo', alpha=0.5, label='Offspring')
100    plot.xlabel('f1')
101    plot.ylabel('f2')
102    plot.legend()
103
104 # Combine parents and offspring then sort
105 combined_pop = parents + offspring
```

```
106 fronts = toolbox.sort(combined_pop)
107 sorted_pop = []
108 for i in range(len(fronts)):
109     front = fronts[i]
110     # Assign crowding distance to individuals in each front
111     toolbox.crowd(front)
112     # Sort individual's in front by crowding distance in descending order
113     front.sort(key=lambda x: x.fitness.crowding_dist, reverse=True)
114     for ind in front:
115         # Ensures individual's are unique to improve diversity
116         duplicated = False
117         for ind2 in sorted_pop:
118             if ind == ind2:
119                 duplicated = True
120             if not duplicated:
121                 sorted_pop.append(ind)
122 # Select top individuals
123 pop = sorted_pop[:POPULATION_SIZE]
124
125 # Hypervolume using the worst objective values as the reference point
126 hv = hypervolume(fronts[0], reference)
127 hypervolumes.append(hv)
128
129 # Print graph
130 if generation == 1 or generation == 10 or generation == 20 or generation == NUMBER_OF_GENERATIONS:
131     # Worst individuals
132     rejected_pop = sorted_pop[POPULATION_SIZE:]
133     # Fitness of selected and rejected individuals
134     selected_f1 = [ind.fitness.values[0] for ind in pop]
135     selected_f2 = [ind.fitness.values[1] for ind in pop]
136     rejected_f1 = [ind.fitness.values[0] for ind in rejected_pop]
137     rejected_f2 = [ind.fitness.values[1] for ind in rejected_pop]
138
139 # Plot fronts
140 plot.figure()
141 plot.title('Fronts for Generation ' + str(generation))
142 # Iterable rainbow colour map
```

```

143     colours = iter(cm.hsv(np.linspace(0, 1, len(fronts))))
144     for f in range(len(fronts)-1, 0, -1):
145         front_f1s = [ind.fitness.values[0] for ind in fronts[f]]
146         front_f2s = [ind.fitness.values[1] for ind in fronts[f]]
147         plot.plot(front_f1s, front_f2s, 'o', color=next(colours), label='Front ' + str(f))
148     plot.xlabel('f1')
149     plot.ylabel('f2')
150     plot.legend(loc='upper left', bbox_to_anchor=(1.05, 1))
151
152     # Plot parents and offspring fitness
153     plot.figure()
154     plot.title('Selected Solutions Fitness for Generation ' + str(generation))
155     plot.plot(selected_f1, selected_f2, 'o', alpha=0.5, label='Selected')
156     plot.plot(rejected_f1, rejected_f2, 'o', alpha=0.5, label='Not selected')
157     plot.xlabel('f1')
158     plot.ylabel('f2')
159     plot.legend()
160
161     # Plot hypervolume over generations
162     hvs = np.array(hypervolumes)
163     # Makes list of generation numbers same shape as hypervolumes list
164     gens = np.zeros_like(hvs)
165     for i in range(0, len(gens)):
166         gens[i] = i
167     plot.figure()
168     plot.title('Hypervolume Over Generations')
169     plot.plot(gens, hvs, '-*', color='indigo')
170     plot.xlabel('Generation')
171     plot.ylabel('Hypervolume')
172     plot.show()
173
174     return pop

```

```

1 # Run the genetic algorithm
2 pop = main()
3 print("Population: \n" + str(pop))
4 print("\n")

```

```
[[['0110011100', '1100101011', '111011010'], ['1100000110', '1111010010', '0011000110'], ['0010011110', '1000111000', '1111010010']],
The Length of the initial Population 25
Worst f1: 6.087783202058105
Worst f2: 11.195310083778537
```

generation	x1	x2	x3	f1	f2	front_number	crowding_distance
0	0010011010	1101011111	0100111111	0.438074	2.23899	1	inf
0	1010001110	1101001001	0101100001	0.468535	0.964787	1	1
0	1110010000	1111111100	1111110001	0.824706	0.177916	1	inf
0	0010010111	0011110111	1100100001	0.639304	2.50147	2	inf
0	0110011100	1100101011	1111011010	0.722229	1.49349	2	0.455462
0	0010011110	1000111000	1111000110	1.02239	1.44696	2	0.688963
0	1001100000	0100111010	1110100000	1.77846	0.666369	2	inf
0	0110011011	0111011001	0101000001	0.640634	3.10886	3	inf
0	0011111011	1111111111	1101101010	0.74027	2.00159	3	0.484633
0	0011111011	1011101111	1101000011	1.04417	1.8415	3	0.386424
0	1101110001	0000101010	1010001110	1.77435	1.73362	3	0.515367
0	1001100111	0011110110	1110011001	2.31126	1.3673	3	inf
0	0110110000	0000110010	1111000101	0.912611	2.41505	4	inf
0	0111011011	1001110111	1010100100	2.32643	1.52976	4	inf
0	1010001111	0011110011	0010010100	2.12146	4.34465	5	inf
0	1010110100	0100111101	1000111001	4.86439	2.72135	5	1
0	1000110111	1111100100	1001101000	5.0039	2.27174	5	inf
0	1100010000	1010110101	0011100010	2.24888	4.46947	6	inf
0	1011110100	0101000101	1000110010	5.25205	3.0282	6	inf
0	1100000110	1111010010	0011000110	2.96714	5.72993	7	inf
0	0111000100	0001100001	1000001110	5.45397	4.77981	7	inf
0	1101000000	0111111001	0001011011	3.42411	6.4176	8	inf
0	1001000111	0100010110	0000110101	5.34444	7.83352	9	inf
0	1010001111	0010001011	0000011000	5.45937	8.69919	10	inf
0	0011001110	0001000110	0000000100	6.08778	11.1953	11	inf

```
[[ '1010001111', '0011110011', '0010010100'], [ '1010001110', '1101001001', '0101100001'], [ '0110110000', '0000110010', '1111001001'], [ '1010001111', '0011110011', '0010010100'], [ '1010001110', '1101001001', '0101100001'], [ '0110110000', '0000110010', '1111001001']]
The total count of parents in the generation 1 are 25
The offspring in the generation 1 are
```

```
[[ '0010000111', '0011110011', '0101100001'], ['1010001110', '1101001000', '0010010100'], ['1101110001', '0010110010', '1010001110']]
The total count of offsprings in the generation 1 are 25
```

The parents in the generation 2 are

```
[[ '1110010000', '1100101011', '1111010001'], ['1001100000', '0100111010', '0100111111'], ['0010011011', '0110111010', '0100111010']]
The total count of parents in the generation 2 are 25
```

The offspring in the generation 2 are

```
[[ '1001100000', '0100111010', '1111010001'], ['1110000000', '1100101011', '0100111111'], ['0010000111', '0110111010', '0100111010']]
The total count of offsprings in the generation 2 are 25
```

The parents in the generation 3 are

```
[[ '0010000111', '0110111010', '0100111111'], ['1110010000', '1100001011', '1100100001'], ['1101110001', '0010110010', '0101101010']]
The total count of parents in the generation 3 are 25
```

The offspring in the generation 3 are

```
[[ '0010000111', '0110111010', '0100111111'], ['1110010000', '1101001011', '1100000001'], ['1010011010', '1000111000', '1111001010']]
The total count of offsprings in the generation 3 are 25
```

The parents in the generation 4 are

```
[[ '1110010000', '1111011101', '1100111001'], ['1110010000', '1101001011', '1100000001'], ['1101000000', '1101011111', '0100111010']]
The total count of parents in the generation 4 are 25
```

The offspring in the generation 4 are

```
[[ '1110010000', '1111011101', '1100000001'], ['1110010000', '1101001111', '1100111001'], ['1101000000', '1100001011', '0100111010']]
The total count of offsprings in the generation 4 are 25
```

The parents in the generation 5 are

```
[[ '1110010000', '1100001011', '1100100001'], ['1110010000', '1111011101', '1100000001'], ['1110010000', '1001110111', '1100111010']]
The total count of parents in the generation 5 are 25
```

The offspring in the generation 5 are

```
[[ '1110010000', '1111011101', '1100100001'], ['1110010000', '1100001011', '0100000001'], ['1110010000', '1000111000', '1100111010']]
The total count of offsprings in the generation 5 are 25
```

The parents in the generation 6 are

```
[[ '1100010000', '0101001011', '1100000001'], ['1100100000', '1101001001', '1111000110'], ['1110011000', '1001110111', '1101101010']]
The total count of parents in the generation 6 are 25
```

The offspring in the generation 6 are

```
[[ '1100010100', '0101001011', '1111000110'], ['1100100000', '1101001001', '1100000001'], ['1110011000', '1000111000', '1111001010']]
```


The parents in the generation 17 are

```
[['0100100000', '1100000011', '1100110001'], ['1100000000', '1010111000', '1111000110'], ['1100000000', '1100000011', '1101000000']]
```

The total count of parents in the generation 17 are 25

The offspring in the generation 17 are

```
[['0101100000', '1100000011', '1100110001'], ['1100000000', '1010101000', '1111000110'], ['0110010000', '1111011101', '1100110000']]
```

The total count of offsprings in the generation 17 are 25

The parents in the generation 18 are

```
[['11110000000', '1000111000', '1111000010'], ['1110010001', '1010010101', '1111000010'], ['1100100011', '1000111010', '110011
```

The total count of parents in the generation 18 are 25

The offspring in the generation 18 are

```
[['11110000100', '10001111001', '1011000010'], ['11100000001', '1010010101', '11111000010'], ['1100100011', '10001111010', '110011
```

The total count of offsprings in the generation 18 are 25

The parents in the generation 19 are

```
[['11110011000', '1000010000', '1111000010'], ['11100000000', '1000111000', '11111000010'], ['0100100000', '11000000011', '110011
```

The total count of parents in the generation 19 are 25

The offspring in the generation 19 are

```
[['11110011000', '1000010000', '1111000010'], ['11100000000', '1000111000', '11111000010'], ['0111010000', '1100000011', '110011
```

The total count of offsprings in the generation 19 are 25

The parents in the generation 20 are

```
[['11110001000', '1000010000', '1111000111'], ['1101001000', '1111011010', '1100111001'], ['1110011000', '1000010000', '111100
```

The total count of parents in the generation 20 are 25

The offspring in the generation 20 are

```
[['11101001000', '11111011010', '11110001111'], ['1110001000', '1000010010', '1100111001'], ['1110011000', '1100000011', '110011
```

The total count of offsprings in the generation 20 are 25

The parents in the generation 21 are

[['1101001000', '1110010110', '1101000010'], ['1110011001', '1000010000', '1111000010'], ['1100111000', '1000111000', '110001

The total count of parents in the generation 21 are 25

The offspring in the generation 21 are

```
[['11110011001', '1000010000', '1111010011'], ['1101001000', '1110010110', '1101000110'], ['1100000000', '1100100011', '110001
```

The total count of offsprings in the generation 21 are 25

The parents in the generation 22 are


```

[['0100000000', '1000010000', '1101011011'], ['1110011101', '1110010110', '1111000110'], ['1110011001', '1000010000', '1111000110'],
The total count of parents in the generation 22 are 25
The offspring in the generation 22 are
[['1100000000', '1000010000', '1101011011'], ['1110011101', '1110010110', '1111000110'], ['1110011000', '1000010000', '1011000110'],
The total count of offsprings in the generation 22 are 25

```

```

The parents in the generation 23 are
[['0100000000', '1010111000', '1100010010'], ['1101001000', '1110010110', '1101000110'], ['1110011000', '1110010110', '1111000110'],
The total count of parents in the generation 23 are 25
The offspring in the generation 23 are
[['0100000000', '1010111000', '1100111010'], ['1101001000', '0110010110', '1101000110'], ['1110011001', '1000010000', '0111000110'],
The total count of offsprings in the generation 23 are 25

```

```

The parents in the generation 24 are
[['1110011001', '1000010100', '1100011011'], ['1101000000', '1000010000', '1101010010'], ['1101001000', '1111011010', '1111000110'],
The total count of parents in the generation 24 are 25
The offspring in the generation 24 are
[['1101000000', '1000010000', '1100011111'], ['1110101001', '1001010100', '1101010010'], ['1101001000', '1111011010', '1100110100'],
The total count of offsprings in the generation 24 are 25

```

```

The parents in the generation 25 are
[['1100000000', '1100000011', '1100011011'], ['1110011000', '1000010100', '1111000110'], ['1101001000', '1110010110', '1101000110'],
The total count of parents in the generation 25 are 25
The offspring in the generation 25 are
[['0100000000', '1000010100', '1111000110'], ['1110011000', '1100000011', '1100011011'], ['1101001000', '1110010110', '1101000110'],
The total count of offsprings in the generation 25 are 25

```

```

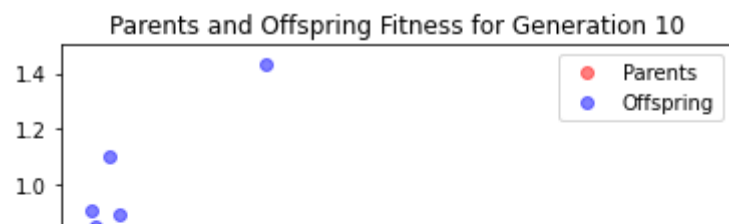
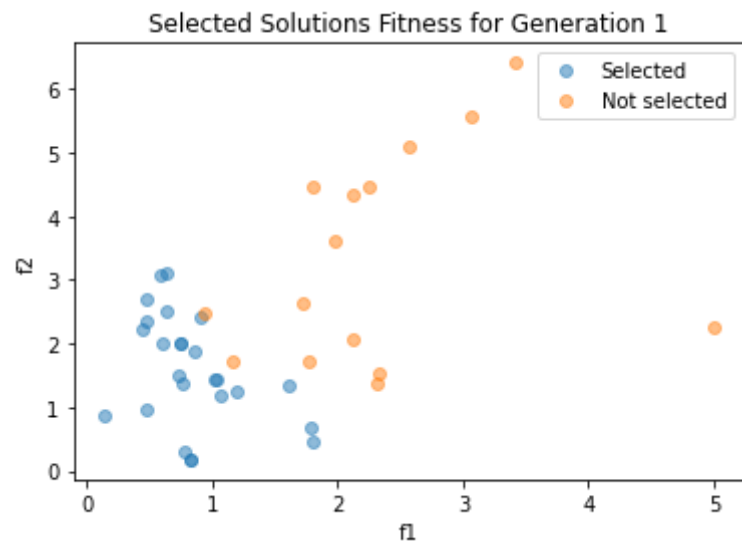
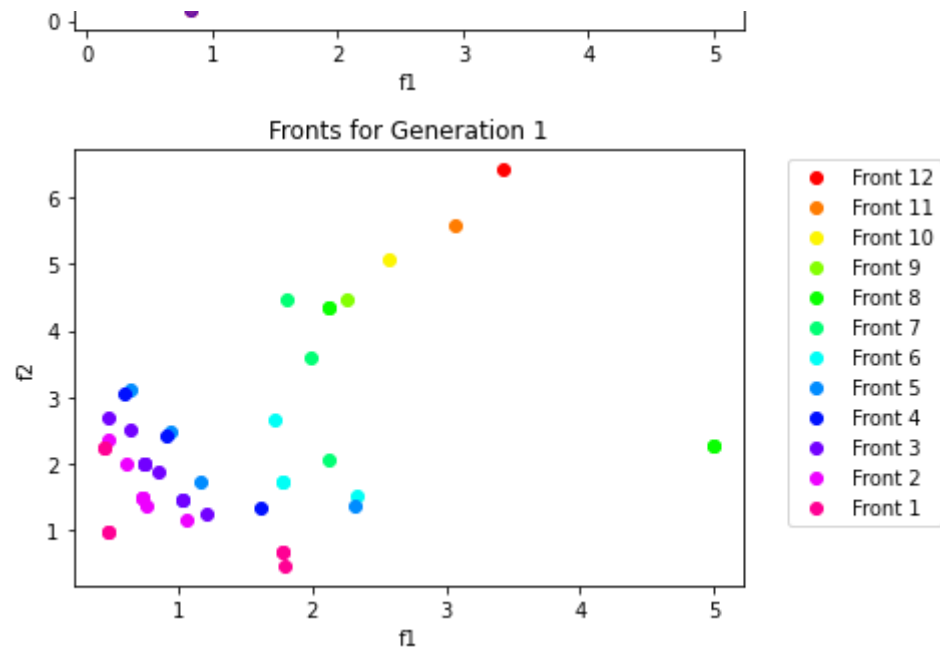
The parents in the generation 26 are
[['1111001010', '1011011010', '1111000110'], ['1101001010', '1110010110', '1100010010'], ['1110101001', '1001010100', '1101000110'],
The total count of parents in the generation 26 are 25
The offspring in the generation 26 are
[['1111001010', '1011011010', '1111000110'], ['1100001010', '1110010110', '1100010010'], ['1110101001', '1000010100', '1111000110'],
The total count of offsprings in the generation 26 are 25

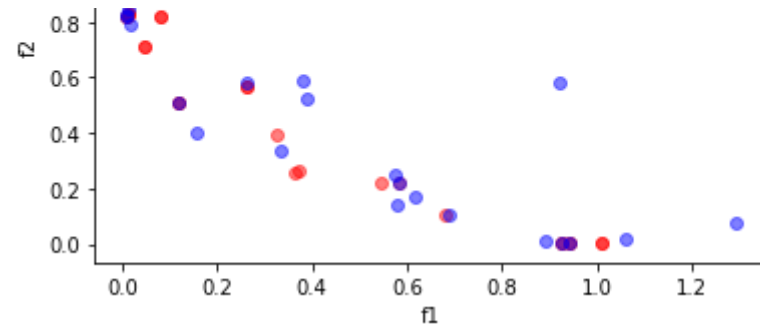
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```

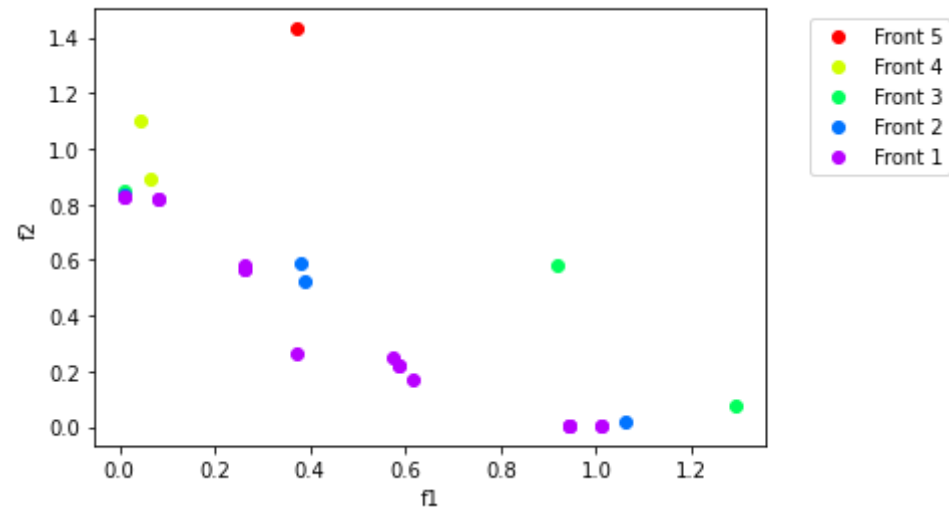
The parents in the generation 27 are
[['1110011000', '1000010101', '1111000110'], ['1110011000', '1000010100', '1111000110'], ['1111000001', '1110010110', '1101000110'],

```

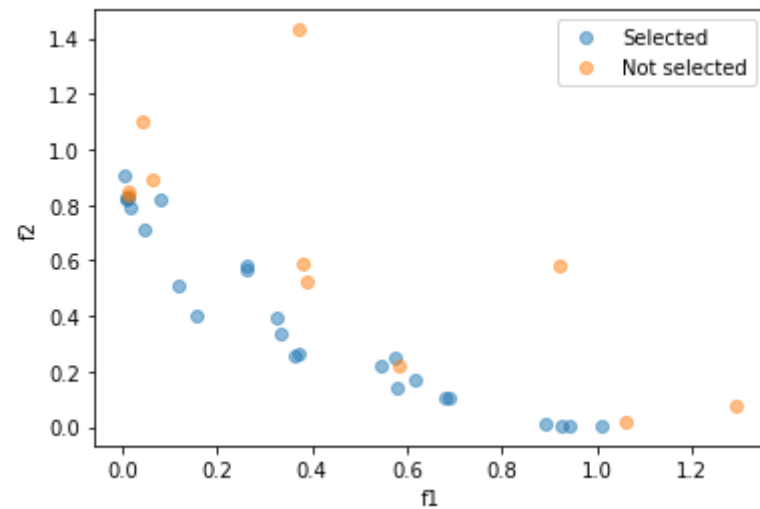



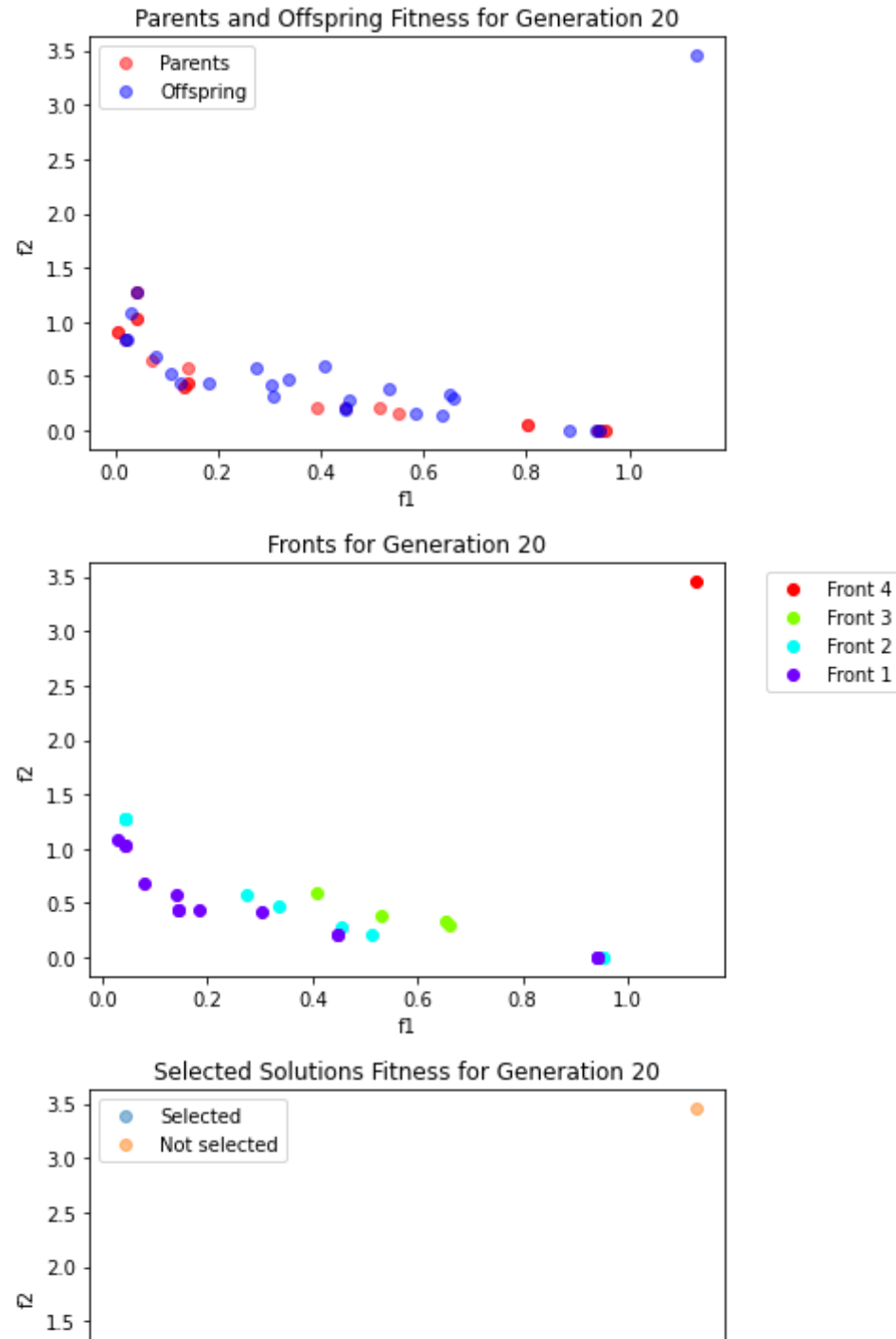


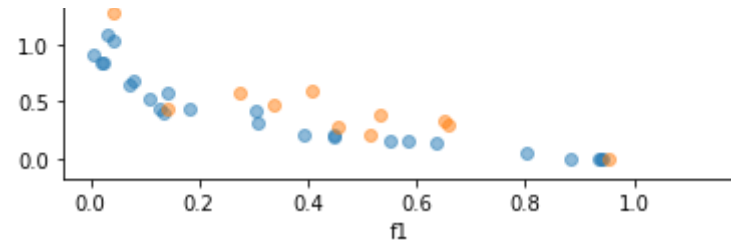
Fronts for Generation 10



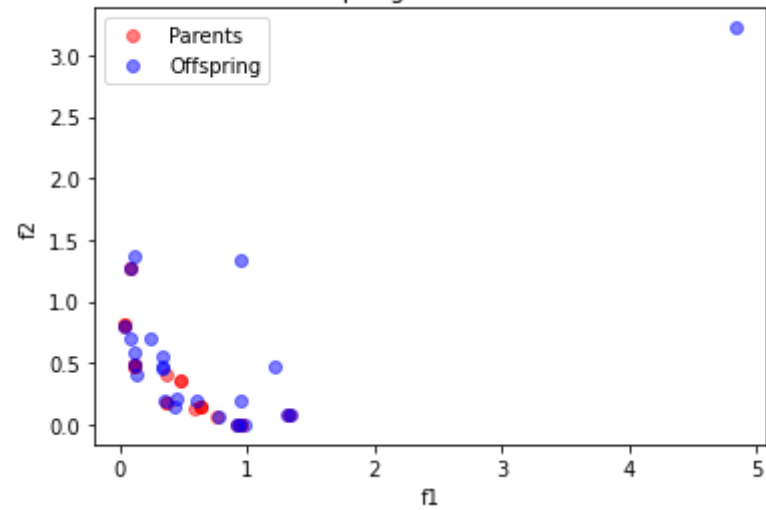
Selected Solutions Fitness for Generation 10



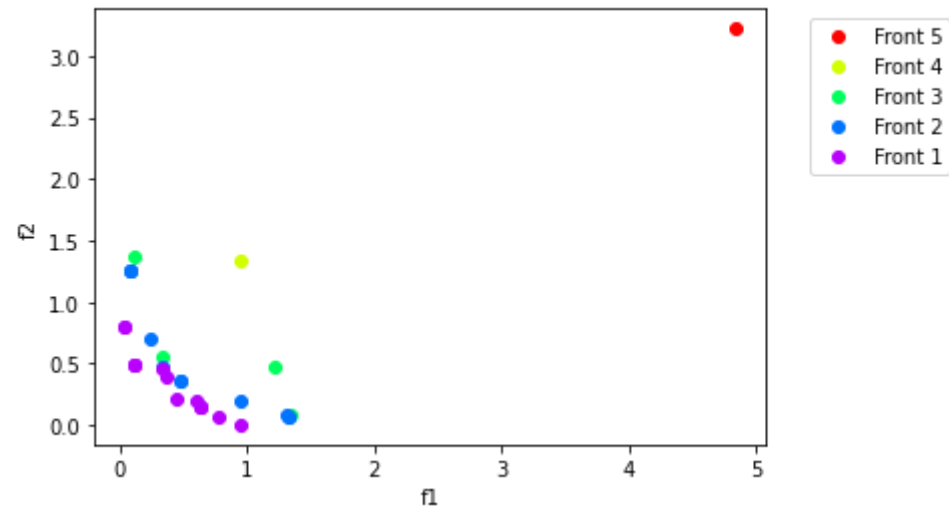




Parents and Offspring Fitness for Generation 30

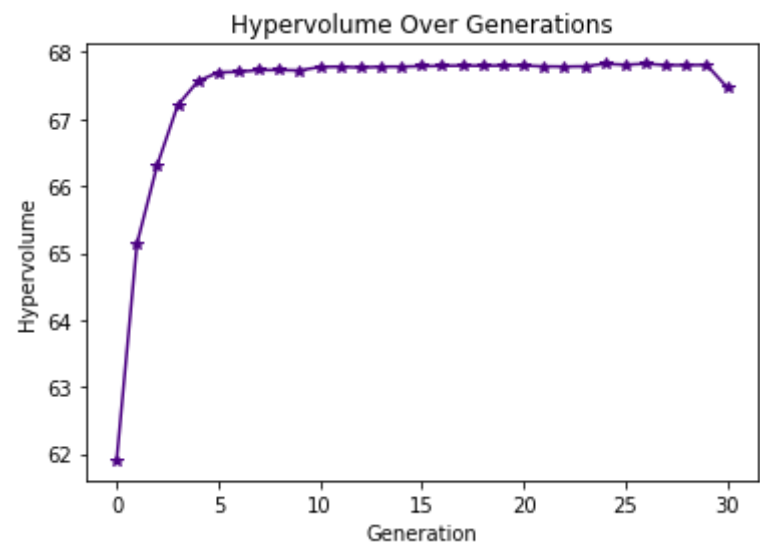
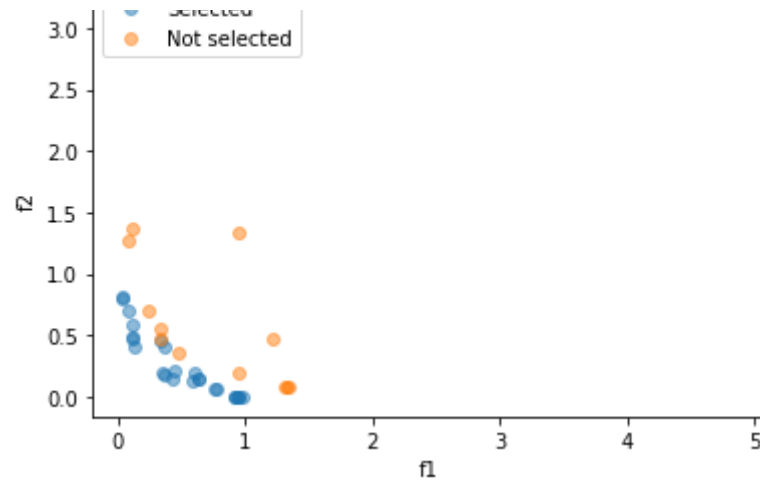


Fronts for Generation 30



Selected Solutions Fitness for Generation 30





Population:

`[['110000000', '1100000011', '1100111010'], ['1110000001', '1000011000', '1111000000'], ['1101001010', '1111011010', '1100111010']]`

✓ 0s completed at 11:13 PM

