```
from numpy.random import randint
import math
# The objective function is a two-dimensional inverted Gaussian function, centred at (7, 9)
def objective(x):
 y = math.exp(((x[0]-7)**2) + (x[1]-9)**2)
 return y
# The decode function decodes binary bitstrings to numbers for each input and scales the value to fall within defined bounds
def decode(bounds, n_bits, bitstring):
 for i in range(len(bounds)):
    # Extract the substring for the current value
    start, end = i * n_bits, (i * n_bits) + n_bits # Define the start and end indices of the substring
   substring = bitstring[start:end] # Extract the substring
    # Convert the substring to a string of characters
             '.join([str(s) for s in substring]) # Join the values in the substring together into a string of characters
    # Convert the string of characters to an integer
   integer = int(chars, 2) # Convert the binary number string into an integer
   # Scale the integer to the desired range
   value = bounds[i][0] + (integer/largest) * (bounds[i][1] - bounds[i][0]) # Scale the integer to a value within the defined bounds
    # Store the decoded value
   decoded.append(value)
 return decoded
#Let us understand the decoding part first that takes the bounds as input along with the
#number of bits and the actual bitstring itself and decodes the bitstring back
#to original values that fall within the test bounds.
test_bounds=[[-10.0, 10.0], [-10.0, 10.0]]
test n bits = 16
#test_n_pop = 100
#Generate a random bit string (of values 0 and 1) of length n_bits*len(bounds). In our case 16*2 = 32
test_bit_string = randint(0, 2, test_n_bits*len(test_bounds)).tolist()
decoded_values = decode(test_bounds, test_n_bits, test_bit_string)
print(test bit string)
print(decoded values)
      [0,\,0,\,1,\,0,\,0,\,0,\,0,\,1,\,1,\,0,\,0,\,0,\,0,\,1,\,0,\,0,\,1,\,0,\,1,\,1,\,0,\,1,\,1,\,0,\,1,\,0,\,0,\,0,\,0,\,1,\,1] \\ [-7.381591796875,\,-2.87017822265625] 
def selection(pop, scores, k=3):
    # Randomly select one index from the population as the initial selection
   selection_ix = randint(len(pop))
    \# Perform a tournament among k randomly selected individuals
    for ix in randint(0, len(pop), k-1):
        # Check if the current individual has a better score than the selected one
       if scores[ix] < scores[selection_ix]:</pre>
            # Update the selected individual if a better one is found
           selection_ix = ix
   # Return the best individual from the tournament
   return pop[selection_ix]
#Let us understand the selection process.
#Create a test population
test_bounds=[[-10.0, 10.0], [-10.0, 10.0]]
test_n_bits = 16
test_n_pop = 100
#Create a random population from which we will select based on the scores (from the objective function)
pop = [randint(0, 2, test_n_bits*len(test_bounds)).tolist() for _ in range(test_n_pop)]
# decode population
test_decoded = [decode(test_bounds, test_n_bits, p) for p in pop]
# evaluate all candidates in the population using our objective function
test scores = [objective(d) for d in test decoded]
#Run the selection to pick the selected ones from our population
test_selection = selection(pop, test_scores, k=3)
print("From a population of :", len(pop), " the selected pop is: ")
print(test_selection)
     From a population of : 100 the selected pop is: [1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0]
```

```
https://colab.research.google.com/drive/1oy0uMkgHbxOlsg5WssoYeWSyhYOhwoCW#scrollTo=cLP_qMWeKsXN&printMode=true
```

```
5/4/24, 11:15 PM
                                                                              EXP-10 genetic_algorithm_in_python.ipynb - Colab
    def crossover(p1, p2, r_cross):
          # Children are copies of the parents by default
         c1, c2 = p1.copy(), p2.copy()
          # Check if recombination should occur
          if rand() < r_cross:
              # Select a crossover point (not at the end of the string)
              pt = randint(1, len(p1)-2)
              # Perform crossover in the children
              c1 = p1[:pt] + p2[pt:]
c2 = p2[:pt] + p1[pt:]
          # Return the two children
         return [c1, c2]
    #Let us understand the Crossover .
    test_r_cross = 0.9 #Crossover rate
    test_bounds=[[-10.0, 10.0], [-10.0, 10.0]]
    test n bits = 16
    test_p1 = randint(0, 2, test_n_bits*len(test_bounds)).tolist()
    test_p2 = randint(0, 2, test_n_bits*len(test_bounds)).tolist()
    test_c1, test_c2 = crossover(test_p1, test_p2, test_r_cross)
    print("Parent 1 is: ", test_p1)
print("Child 1 is: ", test_c1)
print("Parent 2 is: ", test_p2)
print("Child 2 is: ", test_c2)
          Parent 1 is: [1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1]
Child 1 is: [1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1]
Parent 2 is: [1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0]
Child 2 is: [1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0]
    #The crossover process can generate offsprings that are very similar to the parents. This might cause a new generation with low diversity.
    # The mutation process solves this problem by changing the value of some features in the offspring at random.
    import random
    \  \, \text{def mutation(bitstring, r\_mut):}
          rand = random.random
          for i in range(len(bitstring)):
               # Check for a mutation
              \quad \text{if rand() < r\_mut:} \\
                   # Flip the bit
                   bitstring[i] = 1 - bitstring[i]
          return bitstring
    #Run the cell a few times to see random mutations
    #Let us understand the mutation.
    # define range for input
    test_bounds = [[-10.0, 10.0], [-10.0, 10.0]]
test_n_bits = 16
    # mutation rate
    r_mut = 1.0 / (float(test_n_bits) * len(test_bounds))
    test_bitstring = randint(0, 2, test_n_bits*len(test_bounds)).tolist()
print("String before mutation is ", test_bitstring)
    mutation(test_bitstring, r_mut)
    print("String after mutation is ", test_bitstring)
           String before mutation is [1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0]
           String after mutation is [1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0]
```

4

```
### Putting all together into our Genetic algorithm that runs until it finds the best
#The whole fitness assignment, selection, recombination, and mutation process is #repeated until a stopping criterion is satisfied.
#Each generation is likely to be more adapted to the environment than the old one.
# genetic algorithm implementation
\label{lem:condition} \mbox{def genetic\_algorithm(objective, bounds, n\_bits, n\_iter, n\_pop, r\_cross, r\_mut):}
      # initialize the population with random bitstrings
      pop = [randint(0, 2, n_bits * len(bounds)).tolist() for _ in range(n_pop)]
      # track the best solution found so far
      best, best_eval = 0, objective(decode(bounds, n_bits, pop[0]))
      # iterate over generations
# define range for input
bounds = [[-10.0, 10.0], [-10.0, 10.0]]
# define the total iterations
n_iter = 100
# bits per variable
n bits = 16
# define the population size
n pop = 100
# crossover rate
r_{cross} = 0.9
# mutation rate
r_mut = 1.0 / (float(n_bits) * len(bounds))
# perform the genetic algorithm search
best, score = genetic_algorithm(objective, bounds, n_bits, n_iter, n_pop, r_cross, r_mut)
decoded = decode(bounds, n_bits, best)
print('The result is (%s) with a score of %f' \% (decoded, score))
        >0, new best f([6.59576416015625, -4.91668701171875]) = 15226255570032929632811703095627561406785600829184526631384854884011445909140610
        >0, new best f([6.66107177734375, -2.20306396484375]) = 3610764485693253965191136431791075775003425704442331136.000000 >0, new best f([5.64239501953125, 3.71673583984375]) = 8372481809677.679688
       >0, new best f([7.9803466796875, 6.5802001953125]) = 912.794440

>0, new best f([7.2625732421875, 9.986572265625]) = 912.835645

>0, new best f([7.00775146484375, 9.33441162109375]) = 1.118391

>2, new best f([7.00775146484375, 9.2803955078125]) = 1.081860

>4, new best f([7.16339111328125, 9.195556640625]) = 1.067094
       >4, new best f([7.16339111328125, 9.195556640625]) = 1.067094

>5, new best f([7.00714111328125, 9.1986083984375]) = 1.040287

>5, new best f([6.9500732421875, 9.1497802734375]) = 1.025240

>6, new best f([6.8939208984375, 9.07196044921875]) = 1.016567

>7, new best f([6.96868896484375, 9.0716552734375]) = 1.006134

>9, new best f([7.07550048828125, 8.992919921875]) = 1.0008767

>9, new best f([7.01889322265625, 9.0008544921875]) = 1.000817
        >14, new best f([6.990966796875, 9.0032958984375]) = 1.000092
>16, new best f([6.99127197265625, 9.0008544921875]) = 1.000077
>17, new best f([6.99798583984375, 8.99749755859375]) = 1.000010
        >28, new best f([7.003173828125, 8.99993896484375]) = 1.000010
>28, new best f([6.99951171875, 8.997802734375]) = 1.000005
        >32, new best f([7.0001220703125, 8.9984130859375]) = 1.000003

>33, new best f([7.0001220703125, 9.00146484375]) = 1.000002

>40, new best f([6.99951171875, 8.9996337890625]) = 1.000000
        >41, new best f([7.0001220703125, 8.9996337890625]) = 1.000000
>43, new best f([7.0001220703125, 8.99993896484375]) = 1.000000
        The result is ([7.0001220703125, 8.99993896484375]) with a score of 1.000000
```