HW3 AI

genetic algorithm, hill climbing, simulated annealing

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```
import math
import random
```

definition of Ackley function, it takes a chromosome as a list of x and y and returns f(x,y).

```
def fitness(chromosome):
    x, y = chromosome
    return -20 * math.exp(-0.2 * math.sqrt(0.5 * (x ** 2 + y ** 2))) -
math.exp(
        0.5 * (math.cos(math.pi * 2 * x) + math.cos(math.pi * 2 * y))) +
math.exp(1) + 20
```

genetic algorithm :

(each step has been shown in the code)

1. making our initial population by constructing pop_size of random nodes.
2. sort our population using the fitness function defined above in order to choose our parents.
3. we take the half best of our population and choose the parent_size number of it randomly.
4. using crossover function to generate children using alpha. it produces parent_size * parent_size children.
5. using mutation function on every child with the probability of beta.
6. we replace the half bad part of the population by randomly selecting childs from half good part of them.
7. if iterator reaches the "iterations" then the program ends.
8. the graph of the best answer in each iteration has been drawn and the final answer has been printed.

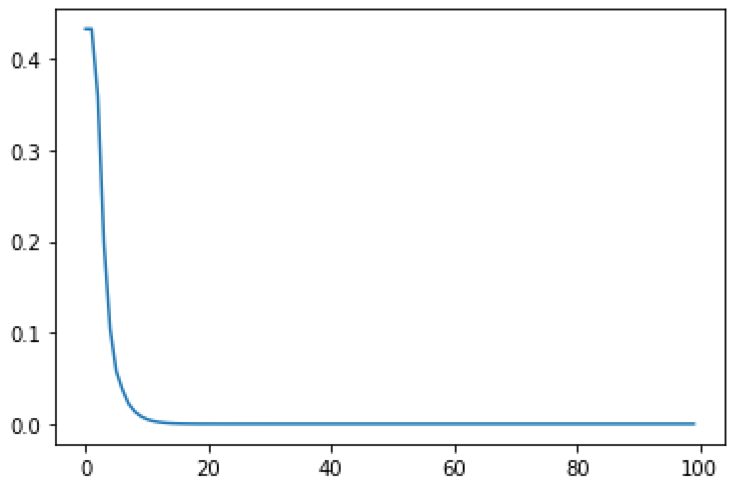
```
alpha = 0.7
beta = 0.1
iterations = 100
pop_size = 100
```

```python
parent_size = 10

#5
def mutation(chromosome):
    if random.random() < beta:
        chromosome[random.choice([0, 1])] = random.random() * 10 - 5

#4
def crossover(parent1,parent2):
    x1, y1 = parent1
    x2, y2 = parent2
    child1 = [(x1 + x2) * alpha, (y1 + y2) * alpha]
    child2 = [(x1 + x2) * (1 - alpha), (y1 + y2) * (1- alpha)]
    return child1, child2

# 1
population = list()
for _ in range(pop_size):
    population.append([random.random() * 10 - 5, random.random() * 10 - 5])

bests = []
population.sort(key=fitness)  #2

for _ in range(iterations): #6
    parents = random.choices(population[:int(100//2)], k = parent_size)  #3
    children = []
    for p1 in parents:
        for p2 in parents:
            c1, c2 = crossover(p1, p2)  #4
            mutation(c1)  #5
            mutation(c2)
            children.append(c1)
            children.append(c2)
    #7
    children.sort(key=fitness)
    population  = population[:int(pop_size//2)] +
random.choices(children[:pop_size], k = int(pop_size//2))
    population.sort(key=fitness)
    bests.append(fitness(population[0]))

#8
print("x:",round(population[0][0],3),
      "y:",round(population[0][1],3),"f(x,y):",
round(fitness(population[0]),3))
```

```python
import matplotlib.pyplot as plt
x = list(range(iterations))

plt.plot(x, bests)
plt.show()
```

output:

x: 0.0 y: 0.0 f(x,y): 0.0



hill climbing algorithm:

we start from the root defined as [-5,-5]. At each step root is replaced by its best successor.

we calculate the best successor by this method:

1. we divide the continuous space by 0.01 to make discrete space.
2. we calculate the value of three ahead neighbors of each node and return the best. (and if there wasn't any better one but there was one that was the same we return that.)
3. if there isn't any better or same neighbor then the algorithm executes.

the final answer has been returned.

```python
def best_succesor(node):
    x, y = node
    x2,y2 = node
    best = fitness(node)
```

```
    for I in range(0,100):
        for J in range(0,100):
            i = I/100
            j = J/100
            if abs(x+i) <= 5 and abs(y+j) <= 5:
                temp = fitness([x+i,y+j])
                if temp <= best:
                    best = temp
                    x2 = x+i
                    y2 = y+j
    if x == x2 and y == y2:
        return False, [x,y]
    else:
        return True, [x2,y2]


root = [-5,-5]
iterate = True

while iterate:
    iterate, root = best_succesor(root)

root
```

Output:

[6.245004513516506e-16, 6.245004513516506e-16]

simulated annealing algorithm:

1. function schedule decreases T by multiplying it with alpha.
2. define initial root
3. At each step we produce a random successor,if it was better than our root, we replace the root.
4. else we replace if with a probability calculated using T which decreases as the algorithm goes long.
5. when T decreases enough until it reaches to almost zero.
6. the final result has been printed.

```python
def random_succesor(node):
    x, y = node
    x2,y2 = random.choice([(0.01,0), (0,0.01), (0.01,0.01)])
    return [x+x2, y+y2]

def schedule(T):
    alpha = 0.995
    return T * alpha

t = 0
T = 400
current = [-5,-5]
while True:

    t += 1
    T = schedule(T)
    if T < 0.0001:
        print()
        break
    else:
        next_ = random_succesor(current)
        delta_E = fitness(current) - fitness(next_)
        if delta_E >= 0:
            current = next_
        else:
            if random.random() <= math.exp(delta_E * 500 / T):
                current = next_

current
```

Output:

[0.009999999999937692, 0.009999999999937692]