

## Genetic Algorithm for Optimization Problem

Import random

POPULATION-SIZE = 100

GENES = " abcdefghijklmnopqrstuvwxyz ABCDEFHIJKLMNOPQRSTUVWXYZ

MNOPQRSTUVWXYZabcdefghijklmnopqrstuvwxyz 1234567890, .-:;!#\$%&/()=?@#\$%^&\*

TARGET = " BEST!!" : Individual must be

class Individual (object):

def \_\_init\_\_(self, chromosome):

self.chromosome = chromosome

def calculate\_fitness(self): = self.cal\_fitness()

@classmethod

def mutated\_gene(self):

global GENES

gene = random.choice(GENES)

return gene

@classmethod

def create\_gnome(self):

global TARGET

gnome = len(TARGET)

(chromosome, mutation(self, mutated\_gene(), for i in range(gnome - len))]

child\_chromosome = [None]

from zip(gp1, gp2) in zip(self.chromosome,

parent\_chromosome):

pmb = random.random()

if pmb < 0.15:

child = chromosome.append(gp1)

elif prob < 0.90:

child = chromosome.append(gp2)

else:

child = chromosome.append(self.mutated(gene1))

return Individual(child=chromosome)

def col\_fitness(self):

global TARGET

fitness = 0

for ga, gt in zip(self.chromosome, TARGET):

if ga == gt: fitness += 1

return fitness

def main():

global POPULATION\_SIZE

generation = 1

found = False

population = [I]

for i in range(POPULATION\_SIZE):

gnome = Individual.create(gnome)

population.append(Individual(gnome))

while not found:

population = sorted(population, key=lambda

x: x.fitness)

if population[0].fitness <= 0:

found = True

break

new generation =  $\text{r}(\text{int}(10 * \text{POPULATION\_SIZE} / 100))$

new generation =  $\text{extended}(\text{population}[0:\text{S}])$

$\text{S} = \text{int}(90 * \text{POPULATION\_SIZE}) / 100$

for  $i$  in range(S):  $\text{new}[\text{i}] = \text{parent1}$

parent1 = random.choice(population[1:S])

parent2 = random.choice(population[1:S])

child = parent1.mate(parent2)

new.append(child)

current\_population = new\_generation

print("Generation: 1 fit string: " + fit\_string)

format(generation, "", join(population[0].chromosome))

population[0].fitness)

generation += 1

format(generation, "", join(population[0].chromosome))

print("Generation: 1 fit string: " + fit\_string)

fit\_string = format(generation, "", join(population[0].chromosome))

population[0].fitness))

If ~~norm~~ = 1 - math.log(fit\_string) / max\_fitness

norm = math.log(fit\_string) / max\_fitness

output gen: 1 str: BR6CP fitness: 3

gen: 2 str: BR6CP fitness: 3

gen: 3 str: BR6CP fitness: 3

gen: 4 str: B9SCF fitness: 2

gen: 5 str: B9SCF fitness: 1

gen: 6 str: B#SCF fitness: 1

gen: 7 str: B#SCF fitness: 1

gen: 8 str: BHSCF fitness: 1

gen: 9 str: BMSCF fitness: 0

Practise 21. Swarm Optimization for function

### Optimization:

(a) Define objective function.

Import random module.

Import math module.

Import copy module.

Import sys module.

Define fitness function (position):

$$\text{fitnessVal} = 0.0$$

for i in range (len(position)):

$$x_i = \text{position}[i]$$

fitnessVal += ( $x_i^2 * x_i$ ) - (10 \* math.cos(2 \* pi \* x\_i))

return fitnessVal

def fitnessSphere (position):

fitnessVal = 0.0

for i in range (len(position)):

$$x_i = \text{position}[i]$$

$$\text{fitnessVal} += (x_i^2 + x_i)$$

return fitnessVal

~~class particle:~~

def \_\_init\_\_(self, fitness, dim, minx, maxx, seed):

self.dim = random.Random(seed)

self.position = [0.0 for i in range(dim)]

self.velocity = [0.0 for i in range(dim)]

self.best\_pos = [0.0 for i in range(dim)]

for i in range(dim):

$$\text{self.position}[i] = (\max - \min) *$$

i / (seed + self.dim - 1) + minx

self. velocity<sub>i</sub> = (maxx - minx) \* self. rand. random() / (maxx - minx).

self. fitness<sub>i</sub> = fitness<sub>i</sub>(self. position).

self. best. pos = copy. copy(self. position)

self. best. fitness<sub>old</sub> = self. fitness<sub>i</sub>.

def psn(fitness, max\_pos, n, dim, minx, maxx):

    w = 0.729

    c1 = 1.49445

    c2 = 1.49445

    wind = standard. Random(0)

    return [self. best. pos, self. best. fitness<sub>old</sub>]

swarm = [Particle(fitness, dim, minx, maxx, i) for i in range(n)]

best. swarm. pos = [0.0 for i in range(dim)]

best. swarm. fitness<sub>old</sub> = sys. float. info. max.

for i in range(n):

    if swarm[i]. fitness < best. swarm. fitness<sub>old</sub>:

        best. swarm. fitness<sub>old</sub> = swarm[i]. fitness

        best. swarm. pos = copy. copy(swarm[i]. position)

        print("Position: ", best. swarm. pos)

        print("Fitness: ", best. swarm. fitness)

iter = 0

while iter < max\_iter:

    if iter % 10 == 0 and iter > 1:

        point. (f, iter) = (iter, best. fitness)

        for i in range(n):

            for k in range(dim):

$\sigma_1 = \text{rand. standard}()$

$\sigma_2 = \text{rand. standard}()$

$\text{swarm}[i]. velocity[k] = ($

$c_1 * \sigma_1 + c_2 * \text{swarm}[i]. velocity[k] +$

$c_3 * \sigma_2 * (\text{best\_part\_pos}[k] -$

$\text{swarm}[i]. position[k]) +$

$(c_4 * \sigma_2 * (\text{best\_swarm\_pos}[k] - \text{swarm}[i].$

$.position[k]))$

)

If.  $\text{swarm}[i]. velocity[k] < \min x:$

$\text{swarm}[i]. velocity[k] = \min x$

elif.  $\text{swarm}[i]. velocity[k] > \max x:$

$\text{swarm}[i]. velocity[k] = \max x.$

End If. End For. End For Orange (if Pm):

For. I = 1 To N. Best +=  $\text{swarm}[i]. position[x] + \text{swarm}[i]. velocity[x]$

$\text{swarm}[i]. fitness = \text{fitness}(\text{swarm}[i]. position)$

End If. End For. Best =  $\text{swarm}[1]. position$

If.  $\text{swarm}[1]. fitness < \text{swarm}[1]. best\_part\_fitness:$

$\text{swarm}[1]. best\_part\_fitness = \text{swarm}[1]. fitness$

$\text{swarm}[1]. best\_part\_pos = \text{copy\_copy}(\text{swarm}[1].$

$.position)$

If.  $\text{swarm}[1]. fitness < \text{best\_swarm\_fitness}:$

$\text{best\_swarm\_fitness} = \text{swarm}[1]. fitness$

$\text{best\_swarm\_pos} = \text{copy\_copy}(\text{swarm}[1].$

$.position)$

$I + \alpha + 1$

$\text{swarm}[I + \alpha]. \text{swarm\_pos}$

point ("In Begin particle swarm optimization on Rastrigin function")

$\text{dim} = 3$  (Dimension of the search space)

$\text{fitnes} = \text{fitness}$  - Rastrigin

point ("Goal is to minimize Rastrigin's function in  $\text{dim}$  variables")

point ("function has known min = 0.0 at ", end = "")

point (".", ".join([""] \* (dim - 1)) + ", 0)")

$\text{num\_particle} = 50$

$\text{max\_iter} = 100$  (Number of iterations)

point ("Setting num\_particle = " + str(num\_particle) + ")

point ("Setting max\_iter = " + str(max\_iter) + ")

point ("In Starting PSO algorithm")

point ("best\_position = psd(fitnes, max\_iter, num\_particle, dim, -10.0, 10.0) found solution")

point ("In PSO completed")

point ("In Best Solution found : ")

point ("f" + best\_position[k] + ".6f") for  $k$  in range(dim)

~~fitnesglobal = fitness(best\_position)~~

~~point ("Fitness of best solution = " + fitnesglobal + ".6f")~~

point ("In End particle swarm for Rastrigin function")

point ("Goal is to minimize Sphere function in  $\text{dim}$  variables")

point ("function has known min = 0.0 at ", end = "")

point (".", ".join([""] \* (dim - 1)) + ", 0)")

$\text{num\_particle} = 50$

$\text{max\_iter} = 100$

point ("Setting num. particles = from particle")

point ("f" setting max\_iter = {max\_iter})

point ("In starting PSO algorithm")

best position = pso(fitneess, max\_iter, num\_particle, dim,  
-10.0, 10.0)

point ("In PSO completed")

point ("In best solution found")

point ("f" best position [k] : .6f 3" for k in range  
(dim))

fitnessVal = fitness(best\_position)

point ("Fitness of best solution = " + fitnessVal + "f")

point ("In End particles current from Sphere function")

O/P ("Algorithm has 0.0001 error after 100 iterations")

Best Solution found [0.0001, -0.0001, 0.0001]

Best solution: 0.0001

(After 100 iterations error is 0.0001)

(The best solution found is 0.0001)

After 100 iterations, the minimum value is 0.0001

Condition to exit loop is 0.0001

minimum value is found to be 0.0001

After 100 iterations, the minimum value is 0.0001

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Condition to exit loop is 0.0001

## Part 1) Colony Optimization for the Travelling Salesman Problem.

Import random

Import numpy as np

Import math

Import time

class City:

def \_\_init\_\_(self, x, y):

self.x = x

def \_\_init\_\_(self, city):

def distance(self, city):

return math.sqrt((self.x - city.x)\*\*2 + (self.y - city.y)\*\*2)

class ACO\_TSP:

def \_\_init\_\_(self, cities, num\_ants, num\_iterations, alpha = 1.0, beta = 2.0, rho = 0.5, q0 = 0.9):

self.cities = cities

self.num\_ants = num\_ants

self.num\_iterations = num\_iterations

self.alpha = alpha

self.beta = beta

self.rho = rho

self.q0 = q0

(self.init\_tour() for i in range(num\_ants))

self.pheromone = np.zeros((self.num\_cities, self.num\_cities))

self.how\_iter = np.zeros((self.num\_cities, self.num\_cities))

self.tour = None

adult

adult

$\text{self-best\_host\_length} = \text{host}('inf')$

for  $i$  in orange ( $\text{self.num\_cities}$ ):

for  $j$  in orange ( $i+1$ ,  $\text{self.num\_cities}$ ):

$\text{digit} = \text{city}(i), \text{digit}' = \text{city}(j)$

$\text{self.heuristic}[i][j] = 1.0 / \text{digit}$  if  $\text{digit} \neq 0$

edge:

$\text{self.heuristic}[j][i] = \text{self.heuristic}[i][j]$

def select\_next\_city ( $\text{self}, \text{current\_city}$ ,  
 $\text{visited\_cities}$ ):

$\text{probabilities} = \text{np.zeros}(\text{self.num\_cities})$

$\text{total\_pheromone} = 0.0$

for city in orange ( $\text{self.num\_cities}$ ):

if city not in visited\_cities:

$\text{pheromone} = \text{self.pheromone}[\text{current\_city}][\text{city}]$

$\text{self.alpha} = \alpha$  (constant value)

$\text{heuristic} = \text{self.heuristic}[\text{current\_city}][\text{city}]$

$\text{self.beta} = \beta$  (constant value)

$\text{probabilities}[\text{city}] = \text{pheromone} * \text{heuristic}$

$\text{total\_pheromone} + = \text{probabilities}[\text{city}]$

If  $\text{total\_pheromone} = 0$ :

return random.choice ([city for city in orange  
( $\text{self.num\_cities}$ ) if city not in visited\_cities])

$\text{probabilities} /= \text{total\_pheromone}$

If random.random() < self.g0:

next\_city = np.argmax (probabilities)

edge:

next\_city = np.random.choice ( $\text{self.num\_cities}$ , p=probabilities)

def update\_pheromone(self, ont):

$$\text{self.pheromone}^i = (1 - \text{self.who})$$

(0.1) initial function

for ant in ants: who = self.who

$$\text{pheromone}_i \cdot \text{deposit} = 1.0 / \text{ant.tour.length}$$

for i in range (self.num\_cities):

current\_i = ants[0].ont[i]

$$\text{next\_city} = \text{ont.down}[i+1] / \text{self.num\_cities}$$

$$\text{self.pheromone}[current\_city][next\_city] +=$$

pheromone\_deposit

$$\text{self.pheromone}[next\_city][current\_city] +=$$

pheromone\_deposit

def. tour(self):

for i in range (self.num\_iterations):

for j in range (self.num\_cities):

([self.ant[j].ont[i]] / self.num\_cities)]

for ante in ants:

ont.computant\_solutions()

self.update\_pheromone(onte)

for ont in ants: ont = 0.0

(0.1) if ont.tour.length < self.best\_tour\_length:

self.best\_tour\_length = ont.tour.length

self.best\_tour = ont.tour

point (f"1 iteration of iteration + 1) / (self.num\_iterations):

Best Tour Length = self.best\_tour\_length

return self.best\_tour, self.best\_tour\_length

Best Tour Length

Celogg Ant:

def init (self, num\_cities, size\_top):

self.size\_top = size\_top

self.tour = []

`self.tour = length = 0; q = deque();`

`def construct_solution(self):`

`start_city = random.randint(0, self.num_cities - 1)`

`self.tour = [start_city]; visited = set()`

`self.tour_length = 0; q.append(start_city)`

`visited.add(start_city); current_city = start_city`

`for i in range(self.num_cities - 1):`

`next_city = self.qs_dsp.select_next_city(q=q, n=q[0])`

`self.tour.append(next_city); q.append(next_city)`

`visited.add(next_city); current_city = next_city`

`self.tour_length += self.qs_dsp.get_tour_length(city=q[-1], cities=q[:-1])`

`current_city = next_city; visited.add(next_city)`

`self.tour_length += self.qs_dsp.get_tour_length(city=q[-1], cities=q[:-1])`

`if len(visited) == self.num_cities - 1:`

`city_q = City([0, 2, 1, 3, 4, 5, 6, 7, 8, 9])`

`q10 = ArcTSP(city_q, num_cities=10, num_iterations=100)`

`alpha1 = 1.0, beta1 = 2.0, rho1 = 0.51, q10 = 0.9)`

~~`alpha1 = 1.0, beta1 = 2.0, rho1 = 0.51, q10 = 0.9)`~~

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# Lab - 4

Manual

Date 21/11/24

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## Cuckoo Search (CS):

Import numpy as np  
from scipy.special import gamma

```
def objective(x):
    return np.sum(x**2)
```

(constant)  $\alpha = \gamma(1 + \beta) + \beta^2$

```
def levy_flight(beta, dim):
    sigma = (gamma(1 + beta) + np.sin(np.pi * beta / 2) /
            gamma((1 + beta) / 2)) * beta ** np.power(2, (beta + 1) / 2) * np.sqrt(1 / beta)
```

$\sigma = \sqrt{\alpha}$

$v = np.random.normal(0, sigma, dim)$

$u = np.random.normal(0, 1, dim)$

$w = v / np.abs(v) * (1 / beta) - 1$

```
def cuckoo_search(obj_func, dim, bounds, N=20, p=0.1,
                  max_iter=100):
```

$negt = np.random.uniform(bounds[0], bounds[1], (N, dim))$

$fitnegt = np.array([obj_func(neqt) for neqt in negt])$

$begt = negt[negt == np.argmin(fitnegt)]$

~~$begt = fitnegt = np.mean(fitnegt)$~~

for i in range(max\_iter):

$newt = negt = np.copy(negt)$

for i in range(N):

$step = levy_flight(1.5, dim)$

$newt[negt[i]] = negt[i] + 0.01 * step$

$newt[negt[i]] = np.clip(newt[negt[i]], bounds[0], bounds[1])$

$new_fitnegt = np.array([obj_func(neqt) for neqt in newt])$

for  $i \in [0, \text{range}(n))$ :

If  $\text{np.random} < \text{prob}$  and new-fitness( $i$ )  
 $>$  fitness( $i$ ): narrow trap of length  $n$  to segment.

$$\text{negt}[i] = \text{new\_negt}[i]$$

$$\text{fitness}[i] = \text{new\_fitness}[i]$$

( $\text{begt}$ ,  $\text{negt}$ ,  $\text{fitness}$ ,  $\text{idx}$ )

$$\text{begt} = \text{negt}[\text{idx}]$$

$$\text{begt}[\text{negt}[\text{idx}]] = \text{negt}[\text{begt}[\text{negt}[\text{idx}]]]$$

$$\text{begt}[\text{fitness}[\text{idx}]] = \text{fitness}[\text{begt}[\text{fitness}[\text{idx}]]]$$

$\text{begt}[\text{negt}[\text{idx}]] = \text{begt}[\text{fitness}[\text{idx}]]$

return  $\text{begt}$ ,  $\text{negt}$ ,  $\text{fitness}$ ,  $\text{idx}$

dimensions:  $\text{np.random} \in [0, 1)$ ,  $\text{minmax}.q1 = r$ ,

$\text{minmax}.q3$  or  $\text{maxmin}.q3 = r$

$\text{begt}$ ,  $\text{negt}$ ,  $\text{fitness}$  =  $\text{random}_\text{search}(\text{Objective}, \text{dim}, \text{lower}, \text{upper}, \text{bound})$ .

shared with  $\text{random}_\text{search}$  function.  $\text{idx}$

$\text{o/p}$  :  $\text{begt}$ ,  $\text{negt}$ ,  $\text{fitness}$ ,  $\text{idx}$  ( $\text{idx} = \text{negt}[\text{idx}]$ )

$\text{begt}$ ,  $\text{negt}$ ,  $\text{fitness}$ ,  $\text{idx}$  ( $\text{idx} = \text{fitness}[\text{idx}]$ )

$\text{begt}$ ,  $\text{negt}$ ,  $\text{fitness}$ ,  $\text{idx}$  ( $\text{idx} = \text{begt}[\text{idx}]$ )

$\text{begt}$ ,  $\text{negt}$ ,  $\text{fitness}$ ,  $\text{idx}$  ( $\text{idx} = \text{negt}[\text{idx}]$ )

$\text{begt}$ ,  $\text{negt}$ ,  $\text{fitness}$ ,  $\text{idx}$  ( $\text{idx} = \text{fitness}[\text{idx}]$ )

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$\text{begt}$ ,  $\text{negt}$ ,  $\text{fitness}$ ,  $\text{idx}$  ( $\text{idx} = \text{fitness}[\text{idx}]$ )

## Gorey wolf optimization (Gwo)

Import numpy as np

```
def gwo(obj=functions.dim, dim=ScoutAgents, maxIter=1000,
```

```
Alpha_pos = np.zeros(dim)
```

```
Beta_pos = np.zeros(dim)
```

```
Delta_pos = np.zeros(dim)
```

```
Alpha_score = float("inf")
```

```
Beta_score = float("inf")
```

```
Delta_score = float("inf")
```

```
positions = np.random.uniform(lb, ub, (ScoutAgents), dim)
```

for iteration in range(maxIter):

for i in range(ScoutAgents):

```
fitness[i] = obj.function(positions[i].copy())
```

```
fitneg[i] = obj.function(positions[i].copy())
```

if fitneg[i] < Alpha\_score:

```
Alpha_score, Alpha_pos = fitness, positions[i].copy()
```

else if fitneg[i] < Beta\_score:

```
Beta_score, Beta_pos = fitness, positions[i].copy()
```

elif fitneg[i] < Delta\_score:

```
Delta_score, Delta_pos = fitness, positions[i].copy()
```

```
point(f"Iteration {iteration + 1}/{maxIter}, Best point:
```

({Alpha\_pos[0]}, {Alpha\_pos[1]}, {Alpha\_pos[2]})")

(Alpha\_pos[0], Alpha\_pos[1], Alpha\_pos[2])

Iteration {iteration + 1}/{maxIter}, Best:

for i in range(ScoutAgents):

for  $j \in \text{range(dim)}:$  then

$a_1, a_2 = \text{np.random.rand}()$  np. random, rand

$$A_1, C_1 = 2 * a + p_1 - 0.5 * p_2 + 0.5$$

$D_{\text{alpha}} = abp(C_1 + \text{Alpha.pop}[j] - \text{position}_i)$

$$x_1 = \text{Alpha.pop}[j] - A_1 * D_{\text{alpha}}$$

$a_1, a_2 = \text{np.random.rand}()$  np. random, rand

$$A_2, C_2 = (2 * b) + p_1 - 0.5 * p_2 + 0.5$$

$D_{\text{beta}} = abp(C_2 + \text{Beta.pop}[j] - \text{position}_i)$

$$x_2 = \text{Beta.pop}[j] - A_2 * D_{\text{beta}}$$

( $\alpha$  and  $\beta$  found) -  $x_1, x_2, x_3$

$a_1, a_2 = \text{np.random.rand}()$  np. random, rand

$$A_3, C_3 = (2 * b) + p_1 - 0.5 * p_2 + 0.5$$

$D_{\text{delta}} = abp(C_3 + \text{Delta.pop}[j] - \text{position}_i)$

$$x_3 = \text{Delta.pop}[j] - A_3 * D_{\text{delta}}$$

( $\alpha, \beta, \delta$  found) under  $\alpha, \beta, \delta$  condition

$$\text{position}_i[i, j] = (x_1 + x_2 + x_3) / 3$$

if  $i > \text{max\_dim}$ , then  $j = \text{max\_dim}$

. distribution, Alpha.pop, Alpha.score

def sphere\_function(x):

return  $\text{np.sum}(x * x)$

example of  $x$  is generated by  $\text{np.random}$

import  $\text{np}$   
 $x = \text{np.random.rand}(5)$  - 5 is dimension of  $x$

Search-agent =  $\text{SearchAgent}(x, \text{popsize})$

agent.best\_position =  $\text{np.array}([0, 0, 0, 0, 0])$

$$lb, ub = -10, 10$$

and this, agent must have function "fitness"

best\_position, best\_score, sigma (sphere function, dim)

Search-agent, max\_iter, lb, ub)

period ("BestPosition": 4, "BestPosition")

point ("BestScore": 4, "BestScore")

o/p

Rept position :  $[-3.1825e-05, 3.455e-05, 3.125e-05]$

Rept : Scale :  $1.0726e-09$ ,  $1.0726e-09$

~~initializing latent variable~~

latent variable initial value

latent variable final value

## Parallel cellular Algorithms and Programs.

Import numpy as np and initialize it.

```
def optimization_function(position):
    return position[0]**2 + position[1]**2
```

```
def initialize_parameters():
    grid_size = (10, 10)
```

```
    num_iterations = 100
```

```
    neighbourhood_size = 1
```

```
return grid_size, num_iterations, neighbourhood_size
```

```
def initialize_population(grid_size):
    population = np.random.uniform(-10, 10 (grid_size))
```

```
grid_size[0], 2))
```

```
return population
```

```
def evaluate_fitness(population):
    fitness = np.zeros((population.shape[0], population.
```

```
.shape[1]))
```

```
for i in range(population.shape[0]):
```

```
    for j in range(population.shape[1]):
```

```
        fitness[i, j] = optimization_function
            (population[i, j])
```

```
return fitness
```

```
def update_state(population, fitness, neighbourhood_size):
    updated_population = np.copy(population)
```

```
for i in range(population.shape[0]):
```

```
    for j in range(population.shape[1]):
```

```
        x_min = max(i - neighbourhood_size, 0)
```

```
        x_max = min(i + neighbourhood_size, p
```

$y_{\max} = \min(y + \text{neighbourhood\_size}, \text{population\_size})$

$\text{best\_neighbour} = \text{population}[i, j]$

$\text{best\_fitness} = \text{fitness}[i, j]$

for  $x$  in range ( $x_{\min}, x_{\max}$ ):

for  $y$  in range ( $y_{\min}, y_{\max}$ ):

if  $\text{fitness}[x, y] < \text{best\_fitness}$ ,

$\text{best\_neighbour} = \text{population}[x, y]$

$\text{best\_fitness} = \text{fitness}[x, y]$

updated\_population[i, j] = (population[i, j] + best\_neighbour) / 2

return updated\_population.

~~def parallel\_cellular\_algorithm():~~

~~grid\_size, num\_iterations, neighbourhood\_size =~~

~~initialize\_parameters()~~

$\text{population} = \text{initialize_population(grid\_size)}$

$\text{best\_solution} = \text{None}$

$\text{best\_fitness} = \text{float('inf')}$

for iteration in range(num\_iterations):

$\text{fitness} = \text{evaluate_fitness}(\text{population})$

$\min\_fitness < \text{np}. \min(\text{fitness})$

$\text{best\_fitness} = \min\_fitness$ :

$\text{best\_solution} = \text{population}[\text{np}. \text{argmin}(\text{fitness}), \text{fitness}. \text{shape}]$ .

$\text{population} = \text{update\_state}(\text{population}, \text{fitness},$   
 $\text{neighbourhood\_size})$

point (f" Best Solution : Best solution 3, Best  
Fitness : best\_fitness").

return best\_solution, best\_fitness.

If name == "main":

parallel\_cellular\_algorithm()

Output: best\_fitness = 0.0000000000000002

best\_solution = [ -8.02149781 -7.04216626 ]

Best Solution : [-8.02149781 -7.04216626].

Best Fitness: -3012732754.660046.

parallel\_cellular\_algorithm, best\_fitness, solution

(parallel\_cellular\_algorithm, best

fitness, solution)

parallel\_cellular\_algorithm, best\_fitness,

parallel\_cellular\_algorithm, best\_fitness,

parallel\_cellular\_algorithm,

parallel\_cellular\_algorithm,

parallel\_cellular\_algorithm, best\_fitness,

## Optimization via Genetic Expression Algorithm

Import numpy as np

```
def optimization_function(solution):
    return solution[0]**2 + solution[1]**2.
```

```
def initialize_parameters():
    population_size = 50
    num_genes = 2
    mutation_rate = 0.1
    crossover_rate = 0.8.
```

```
num_generation = 100
```

~~return population, size, num\_genes, mutation\_rate,~~

```
def initialize_population(population_size, num_genes):
    np.random.uniform(-10, 10, (population_size, num_genes))
```

~~initialization function as np.~~

```
def evaluate_fitness(population):
    return np.array([optimization_function(ind)
        for ind in population])
```

```
def select_parents(population, fitness):
    probabilities = 1 / (fitness + 1e-6)
```

~~probabilities / sum(probabilities) .~~

~~indices = np.random.choice(range(len(population)), size=len(population), p=probabilities)~~

return population[indices]

~~for i in range(len(indices)):~~

```

def crossover(parent1, parent2, rate):
    offspring = []
    for i in range(0, len(parent1), 2):
        if random.random() < parent1[i] and np.random.rand() < rate:
            offspring.append(np.concatenate((parent1[i], parent2[i], parent1[i+1], parent2[i+1])))
        else:
            offspring.append(np.concatenate((parent1[i], parent2[i], parent1[i+1], parent2[i+1])))
    return np.array(offspring)

```

edge:

```

offspring.extend([parent1[i], parent2[i]])
if i + 1 < len(parent1) and i + 1 < len(parent2):
    offspring.append(np.array(crossover(parent1[i+1], parent2[i+1])))

```

```

def mutate(offspring, mutation_rate):
    for individual in offspring:
        if np.random.rand() < mutation_rate:
            gene = np.random.randint(individual.size)
            individual[gene] = np.random.normal()
    return offspring

```

```

def genetic_algorithm():
    population_size, num_genes, mutation_rate = input("Population size, number of genes, mutation rate: ")
    Initialize_population = Initialize_population(population_size, num_genes)
    best_solution = Initialize_population[0]
    best_fitness = float('inf')
    for generation in range(num_generations):
        population = Initialize_population
        for individual in population:
            fitness = calculate_fitness(individual)
            if fitness < best_fitness:
                best_fitness = fitness
                best_solution = individual
        print(f"Generation {generation}: Best fitness = {best_fitness}, Best solution = {best_solution}")
        population = crossover(population, mutation_rate)
        population = mutate(population, mutation_rate)

```

$\text{fitness} = \text{calculate\_fitness}(\text{population})$

$\min \text{fitness}, \text{idx} = \text{np.argmax}(\text{fitness})$

If  $\text{fitness}[\min \text{fitness\_idx}] < \text{best\_fitness}$ :

$\text{best\_fitness} = \text{fitness}[\min \text{fitness\_idx}]$

$\text{best\_solution} = \text{population}[\min \text{fitness\_idx}]$ ,

$\text{parents} = \text{select\_parents}(\text{population}, \text{fitness})$

$\text{offspring} = \text{crossover}(\text{parents}, \text{crossover\_rate})$

$\text{population} = \text{mutate}(\text{offspring}, \text{mutation\_rate})$

$\text{population} = \text{gene\_expression}(\text{population})$

$\text{print}("f^{\text{th}} \text{ Generation Solution}: \text{Best}$

$\text{Fitness} = \text{best\_fitness}")$

$\text{points} (" \text{Best Solution: } \text{best\_solution}, \text{ Best}$

$\text{Fitness: } \text{best\_fitness}")$

$\text{return best\_solution, best\_fitness.}$

~~def~~

$\text{f\_name} = " \text{main}"$

$\text{gene\_expression\_algorithm}()$

~~output~~

$\text{Best Solution: } [0.00434829 0.00143412]$

$\text{Best Fitness: } 2.096871137428934 \times 10^{-5}$ .