



Observation

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Genetic Algorithm for Optimization

Algorithm

- 1) Randomly initialize populations p
- 2) Determine fitness of population
- 3) Until convergence repeat:
 - a) Select parents from population
 - b) Crossover and generate new population
 - c) perform mutation on new population
 - d) calculate fitness for new population

// Initialize population

population = initialize_population (N)

calculate_fitness (population)

while not converged:

// Select parents based on fitness

parents = select_parents (population, fitness)

// Create new population through

crossovers

new_population = []

while size (new_population) < size

(population)

parent1, parent2 = random_selection (parents)

(parents)

offspring1, offspring2 = crossover

(parent1, parent2)

new_population.append(offspring1)

new_population.append(offspring2)

// Mutate new population

for individual in new_population:

if random() < mutation_rate * probability:

mutate(individual)

1. calculate fitness for new population

new_fitness = calculate_fitness

(new_population)

// Optionally replace old population
with new population.

old_population = new_population

Code :

import random

def fitness_function(x):

return x**2

population_size = 500

mutation_rate = 0.01

crossover_rate = 0.7

generations = 5

lower_bound = -10

upper_bound = 10

def create_population():

population = [random.uniform

(lower_bound, upper_bound)]

for i in range (population_size)]

return population

e def evaluate_fitness (population):

$$\text{fitness_score} = [\text{fitness_function}(\text{individual})]$$

def select (population, fitness_scores):

$$\text{total_fitness} = \sum (\text{fitness_scores})$$

$$\text{selection_prob} = (\text{score} / \text{total_fitness})$$

for score in fitness_scores
Score

return selected

def crossover (parent 1, parent 2):

if random.random () < crossover_rate:

$$\text{child 1} = (\text{parent 1} + \text{parent 2}) / 2$$

$$\text{child 2} = (\text{parent 1} + \text{parent 2}) / 2$$

else:

$$\text{child 1, child 2} = \text{parent 1, parent 2}$$

return child 1, child 2

Output:

Generation 1: Best fitness = 99.8289...

Best

Individual = 9.99144

~~9.99144~~
2/10/25

particle Swarm Optimization

Algorithm

1) Initialize parameters:

- Define the no. of particles N
- Set the max. no. of iterations T
- choose the ~~problems~~ problem dimensions D
- Initialize the positions X and velocity V
- Initialize $p\text{Best}$ for each particle as its initial position
- Initialize $g\text{Best}$ as the ~~pa best~~ position among all $p\text{Best}$.

2) Evaluate Fitness:

- for each particle i ($1 \text{ to } N$):
 calculate the fitness $f(x_i)$
 using fitness function

3) Update $p\text{Best}$ & $g\text{Best}$:

- for each particle i :
 if $f(x_i) < f(p\text{Best}_i)$ update
 $p\text{Best}_i = x_i$
- Update $g\text{Best}$:
 if $f(p\text{Best}_i) < f(g\text{Best})$ set
 $g\text{Best} = p\text{Best}_i$ for the particle
 with the best fitness

4) Update Velocities & Positions for each particle i :

$$v_i = w v_i + c_1 s_1 (p\text{Best}_i - x_i) + c_2 s_2 (g\text{Best})$$

$$x_i = x_i + v_i$$

- 5) If max no. of iterations T is reached, stop else go back to step 2

Code :-

```
import numpy as np
```

```
class Particle:
```

```
    def __init__(self, bounds):  
        self.position = np.random.uniform  
            (bounds[0], bounds[1])  
        self.velocity = np.random.uniform(-1)  
        self.
```

```
def SphereFun(r):  
    return np.sum(r**2)
```

```
def particle = S = 0 (dim, bounds,  
n-particles, n-iter).
```

```
particle = np.random.uniform  
    (bound[0], bound[1],  
    (n-particles, dim))
```

```
velocities = np.random.uniform  
    (1 / (n-particles),  
    dim))
```

```
personal-best-pos = np.array  
    (SphereFun,  
    for p in particles))
```

global-bolt-pos = personal-b-s [np. array
(personal-b, v)]

for in range (n-iterations)

$s_1, s_2 = np. random, rand(dim)$

np. random, rand(dim)

velocities = co.T * velocities + 1.0 *

(personal-b-p.
particle) *

α^1, α^2 as (global-b-p
particle)

particle+ = velocities

particle = np. clip (particles,
bounds(0))

values = np. array ([sphere-fns
(p) for
p in particles])

settlement = values < personal.v

personal-bolt-p = (better
values) =
particles

global-b-pos = personal-bolt
-p (np.array([
personal-b.v]))

return global-bolt robot pos

dim = 2

bounds = (-10, 10)

n-particle = 30

n-iterations = 30

bolt-pos,best-value = particle-
value

Prop (dim, bounds, n-particles,

n-iterations)

print ("Best position", best_pos)

print ("Best value = ", best_val)

Output

Best position = [0.002 - 0.001]

Best value = 0.00008

Ant colony optimization for the Traveling Salesperson Problem

Algorithm

- 1) initialize ~~pesonal~~ parameters:
no. of ants, pheromone, heuristic, evaporation rate, pheromone level
- 2) construct solution:
 - each ant starts at a random city.
 - Select the next city based on pheromone level, and heuristic
 - Repeat until all cities are visited forming a completed tour
- 3) Calculate the total distance for each ant tour. Trace the best tour found so far.
- 4) Update pheromones:
Evaporate pheromones globally
Deposit new pheromones on edges proportionally to the quality of each ant's tour.
Repeat for fixed iterations
- 5) output : The Best tour.

Code:-

```
import numpy as np  
import random
```

```
def aco_tsp(d, n, a, b, g):  
    c = np.ones((n, n)) / n  
    t = None  
    l = float('inf')  
    for i in range(g):  
        s = []  
        for u in range(n):  
            v = set()  
            u = [random.randint(0, n - 1)]  
  
            v.add(u[0])  
            while len(v) < n:  
                x = u[-1]  
                p = [0]  
                t = 0  
                for y in range(n):  
                    if y not in v:  
                        p.append(((x - y) ** a) *  
                                  ((1 / d[x - y]) ** b))  
                t += p[-1]  
                p = [2 / t for i in p]  
  
            np_u.append(np.random.choices(  
                                         range(n),  
                                         weights=p,  
                                         k=1)[0])
```

v.add($u[1]$)

s.append(u)

$$C^* = \{1-8\}$$

for u in S^* :

$$d-u = \text{sum}(a[u[:], u[i+1:]])$$

for i in range($n-1$): $d(u[-1], a[0])$

if $l-u < 1$:

$$l = l-u$$

$$t = u$$

for i in range($n-1$):

$$c[u[:], u[i+1:]] +=$$

$$1/d-u$$

$$c[u[-1], u[0]] +=$$

$$1/l-u$$

return t, l

$$d = [(0, 2, 9, 5), (2, 0, 6, 3),$$

$$(3, 6, 0, 8), (5, 8, 3, 2, 0)]$$

distance Matrix

$$t, l = \text{aco_tsp}(d, 10, 100, 12, 0.1)$$

Print("Best tour : ", t)

Print("Best distance : ", l)

Output:

Best tour : [0, 1, 3, 2, 0]

Best Distance : 16.0

Cuckoo Search

Algorithm

1) Initialization :

Start with a set of initial solutions (nests)

2) ~~as~~ cuckoo ~~is~~ egg laying!
generate new solutions by
slightly modifying existing
solutions through a random
walk called Levy flight.

3) ~~to~~ Solution Evaluation

Evaluate the quality of all
solutions (cuckoo eggs and host
nests)

4) Selection :

~~Keep~~ Keep the best solution
(nest) for the next generation

5) Iteration

Repeat steps 2 - 5 for a
specified number ~~of~~ of
iterations.

6) Termination

The algorithm stops when a
stopping criterion is met

code

import numpy as np

def V(b=1.5):

$$S = \frac{(\text{gamma}(1+b))^{\frac{1}{2}} \cdot \text{np.sin}(\text{np.pi}^{\frac{1}{b}} \cdot 2)}{\text{gamma}((1+b)/2)^{\frac{1}{2}}} \cdot \text{np.sin}(\text{np.pi}^{\frac{b}{2}})$$
$$(1/b)$$

$$u, v = \text{np.random.randn}(2)$$
$$\text{return } S^* u / \text{abs}(v)^{\frac{1}{b}} \cdot (1/b)$$

def f(b, n, p, i):

$$d = \text{exp}(b(\cdot, 0))$$

$$S = \text{np.random.randn}(n, d)^{\frac{1}{2}} (b(:, 1) - b(:, 0)) + b(:, 0)$$

$$t = \delta(\text{np.argmax}(f(x) \text{ for } x \text{ in } S)])$$

$$t-f = f(t)$$

for i in range(i):

for j in range(n):

$$x = S(j) + 10^{\frac{1}{2}}(d(j) - t)$$

$$x_g = \text{np.clip}(x, b(:, 1), b(:, 1))$$

$$x - f = f(x)$$

$$\text{if } x - f < f(S(j)) \\ S[j] = x$$

if np.random.rand() < p:

$$S[j] = \text{np.random.}$$

$$\text{rand}(d)^{\frac{1}{2}} \\ (b(:, 1) - S[:, 0])$$

```
for j in range(n):
    if f(s[j]) < f(t):
        t = s[j]
    f_t = f(t)
return t, f_t
print(f"Best Solution : {best_solution}")
print(f"Best fitness : {best_fitness}")
```

Output:

Best Solution: [1.95581557,
-1.27762143,
0.59020481
3.72681103,
0.79926703,
-0.5427445,
-0.96002716,
-0.36068296,
3.18591725
1.31872125]

Best Fitness : 33.45259804 - 839685

GREY WOLF OPTIMIZER

Algorithm

1. input : Define parameters
num_wolves, dimension, bounds,
max_iter, objective function

2. initialization :

$$x_{ij} = \text{min_bound} + \text{rand}() * (\text{max_bound} - \text{min_bound})$$

Compute the fitness values

$$f(x) = \sum x_i^2$$

alpha_pos : Best wolf

beta_pos : Second Best

delta_pos : Third Best

3. ~~for t = 1 to max_iter:~~

$$\text{update } a = 2 - (2 * t) / \text{max_iter}$$

for each wolf::

$$A = 2 * a * \text{rand}() - a$$

$$C = 2 * \text{rand}()$$

compute the distance b/w the
wolf and the three leaders

4. Evaluate fitness : compute fitness
of updated pop.

5. Output : alpha_pos and alpha_beta

code:-

import numpy as np

```
def gws(f, lb, ub, n=5, i=500):
    d = len(lb)
    a = lambda l: 2 - l**2 * (2 / i)
    X = np.random.rand(n, d) *
        (ub - lb) + lb
```

a, b, d = X [np.argmax(f(x)) for x in X], X [np.argmin(f(x)) for x in X], X [np.argmax(f(x)) for x in X]

for i in range(i):
 for j in range(n):
 f(X[i]) < f(a) and
 (a, f(a)) := (x[j], f(x[j]))
 f(x[i]) > f(b) and
 f(x[j]) > f(b) and f(x[j]) <

for j in range(max - ite)
a = 2 - t**2 * (2 * max - ite)

population = update_pop

(pop - old pop),
fitness = eval_fitness(pop,
obj - func)

for i in range(num_wolves):

if fitness[i] < a - score:
a - score = fitness[i]

a-pop = pop[n]

diff_fitness(f) & b-select

b-select = fitness(f)

b-pop = pop[f]

return a-pop, a-select

num_values = 30

dim = 5

bound = (-10, 10)

max_iter = 50

printf("Best Solution: {best solution}")

printf("Best score: {best score}")

output:

iteration 1150, best fitness : 46.87190

Best Solution: [2.51916187 -1.8335
41]

Best score: 2.0959372052319
e-09

Parallel Cellular

Algorithm

1. initialize parameters:
num-cells, grid-size, iterations,
neighbor-size, convergence
2. Initialize population:
generate a population of num-cell
with random position within field
place each position in $\text{cells} = 10^8$
3. evaluate fitness:
for each cell, calculate fitness
using optima optimization function
 $f(x) = x^2$
4. Update state:
for each cell, find the
neighboring cells, and update
the cells position based on
the best of neighbour
5. iterate:
for $i = 1$ to max-iter
6. output:
Best solution and Best value

Code:

import numpy as np

def opti(n):

return x**2

num_cells = 100

grid_size = 10

iter = 100

neig_size = 3

conver_thres = 0.0001

np.random.seed(111)

popn = np.random.uniform(-10, 10,
num_cells)

def eval_f(popn):

return np.array([opti(cell) for
each cell in popn])

fitness_val = eval_f(popn)

for i in range(iter):

fitness_val = eval_f(popn)

min_ida = np.argmin(fitness_val)

min_fitness = fitness_val[min_ida]

better_sol = pop[min_ida]

if iter > 0:

improvement = prev_f - min_fitness

pop = update(pop, fitness_val)

prev_f = min_fitness

loop.

if improvement < convergence:
print(f "Converged at : f_top
Iteration")

break

print(f "Best solution : f_top.sol")
print(f "Best fitness : f_min.fitness")

output

Iteration 1: Best fitness : 0.00930
0487

Best Solution : -0.09641797777

Converged at iteration 20 with
fitness , 2.20521162205187e-05
Best solution : 0.008695968087
Best fitness : 2.205241622051e-05

Gene Expression Algorithm

Algorithm

1. Initialize parameters:
pop-size, num-genes, mutation-rate,
Cross-rate, num-gen
2. Generate an initial population of individual with genes with initial values.
3. Evaluate fitness of each individual using objective function $f(x) = 10x \cdot n + \sum (x_i^2 - 10x_i \cos(2\pi x_i))$
4. Use roulette wheel selection to choose parent
5. Consider: apply 2 point crossover offspring
6. Apply mutation: Randomly change one of the gene by adding random values.
7. Iterate for set no. of generations
8. Return Best solution & fitness value.

Code:

import numpy as np

def obj(x):

return $10 * \text{len}(x) + \sum(x^2)$
 $10 * \text{np.}$

$\cos(2 * \pi * x)$
for $n \in \mathbb{N}$)

pop_size = 100

muting = 10

c_r = 0.7

n_gen = 100

m_v = 0.01

popn = np. random. uniform

(-5. - 5, 5, n)

def eval(popn):

return np. array([(obj(ind) for
ind in popn)])

def sel(popn, fit):

f_sum = np. sum(fit)

prob / = np. sum(probs)

s_indices = np. random.

choice(np.

arrange(len
(popn))

return popn(sel_indices)

def mutation(popn):

for i in range(len(popn)): # popn[i] is a list of genes

if np.random.rand() < m_m:

m_p = np.random.randint(0, num_genes)

popn[i][m_p] = np.random.uniform(-0.5, 0.5)

return population

for generation in range(num_gen):

fit = eval(popn)

pop = selection(popn, fit)

pop = crossover(pop)

pop = mutation(popn)

best_sol = popn[np.argmax(fit)]

print(f"generation {generation} + {best_sol}")

Best Solution : [best_solution]
fitness = [min(fit)]

final_f = eval(pop)

Best_sol = popn[np.argmax(fit)]

print(f"final Best solution")

{ Best_sol }
fitness : [min(fit)]

Output

Generation 1: Best Solution!

(-0.01980868

-4.81178370

-3.83458543

3.54614127

1.04950891)

Final Best Solution is (p: 8997071

2.212.74312465

1.8437788 -2.0993

2.34789789

2.6442209)