VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB RECORD

Bio Inspired Systems (23CS5BSBIS)

Submitted by

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in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING
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B.M.S. College of Engineering,

Bull Temple Road, Bangalore 560019

(Affiliated To Visvesvaraya Technological University, Belgaum)

Department of Computer Science and Engineering

<u>CERTIFICATE</u>

This is to certify that the Lab work entitled " Bio Inspired Systems (23CS5BSBIS)" carried out by **Jayashree Tarai (1BM24CS407),** who is bonafide student of **B.M.S. College of Engineering.** It is in partial fulfillment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum. The Lab report has been approved as it satisfies the academic requirements of the above mentioned subject and the work prescribed for the said degree.

Soumya T Assistant Professor Department of CSE, BMSCE	Dr. Kavitha Sooda Professor & HOD Department of CSE, BMSCE

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Github Link:

https://github.com/Jayashreecse/Bio-Inspired-System-Lab

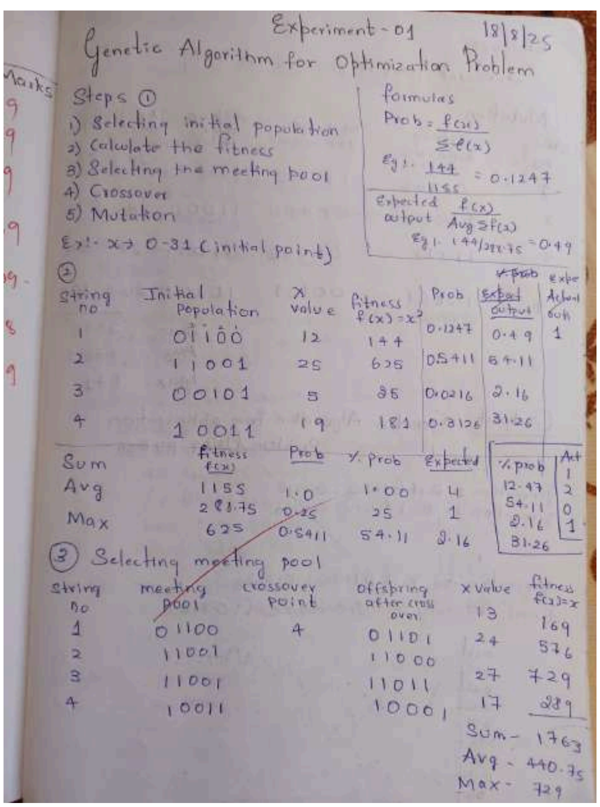
Program 1

Genetic Algorithm for Optimization Problems:

Genetic Algorithms (GA) are inspired by the process of natural selection and genetics, where the fittest individuals are selected for reproduction to produce the next generation. GAs are widely used for solving optimization and search problems. Implement a Genetic Algorithm using Python to solve a basic optimization problem, such as finding the maximum value of a mathematical function.

Implementation Steps:
1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the population size, mutation rate, crossover rate, and number of generations.
3. Create Initial Population: Generate an initial population of potential solutions.
4. Evaluate Fitness: Evaluate the fitness of each individual in the population.
5. Selection: Select individuals based on their fitness to reproduce.
6. Crossover: Perform crossover between selected individuals to produce offspring.
7. Mutation: Apply mutation to the offspring to maintain genetic diversity.
8. Iteration: Repeat the evaluation, selection, crossover, and mutation processes for a fixed number of generations or until convergence criteria are met.
9. Output the Best Solution: Track and output the best solution found during the generations.

Algorithm: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Genetic Algorithm for Optimization Problem

Steps ①
1) Selecting initial population
2) Calculate the fitness
3) Selecting the meeting pool
4) Crossover
5) Mutation

Formulas

Prob = $\frac{f(x)}{\sum f(x)}$

Eg:- $\frac{144}{1155} = 0.1247$

Expected output $\frac{f(x)}{Avg \sum f(x)}$

Eg:- 144/288.75 = 0.49

Ex:- x → 0-31 (initial point)

②

String no	Initial Population	x value	fitness $f(x) = x^2$	Prob	Expected output	Actual count
1	01100	12	144	0.1247	0.49	1
2	11001	25	625	0.5411	54.11	
3	00101	5	25	0.0216	2.16	
4	10011	19	181	0.3126	31.26	

	fitness f(x)	Prob	% prob	Expected
Sum	1155	1.0	1.00	4
Avg	288.75	0.25	25	1
Max	625	0.5411	54.11	2.16

% prob	Act
12.47	1
54.11	2
2.16	0
31.26	1

③ Selecting meeting pool

String no	meeting pool	crossover point	offspring after cross over	x value	fitness $f(x) = x^2$
1	01100	4	01101	13	169
2	11001		11000	24	576
3	11001		11011	27	729
4	10011		10001	17	289

Sum - 1763
Avg - 440.75
Max - 729

Crossover

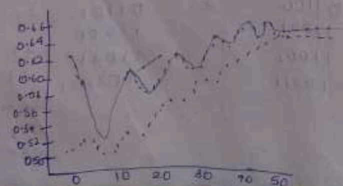
Crossover point is choosen randomly

Mutation

String no	offspring after cross over	Mutation chromosome	offspring after mutation	x value	fitness
1	01101	10000	11101	29	841
2	11000	00000	11000	24	576
3	11011	00000	11011	27	728
4	10001	00101	10100	20	400
				Sum	2546
				Avg	686.5
				Max	841

Output Genetic Algorithm for optimization Problem Using python

Generation 1, Best fitness : 0.6235
generation 2, Best fitney : 0.6100
⋮
generation 50, Best fitness : 0.6550
final Accuracy on Validation set : 0.6700



Pseudocode:

Note : chromosome : set of binary numbers
M Mutation : change in genetic of offspring

```
Function fitness(x)
  Return x* x
function decode (chromosome)
  Convert the binary list to decimal number
  Return decimal_value
function create_population ()
  population = []
  for i = 1 to 10
  chromosome = random. list of 5 bits (0 or 1)
  Add chromosomes to population
  Return population
Function evaluate population (population)
  fitness_list = []
  for each chromosome in population
    x = decode (chromosome)
    f = fitness (x)
    Add f to fitness list
  Return fitness_list
function select_parents (population, fitness_lists)
  Use roulette, wheel selection based on fitness value
  Return selected parents
function Crossover (parent 1, parent 2)
  If random < 0.7
  choose a random crossover point
  child1 = first part of parent1 + second part of parent2
  Child2 = first part of parent 2 + second part of part 1
Else :
  child 1 = copy of parent1
  child 2 = copy of parent2
  Return child 1, child2
function mutate (chromosome)
  for each bit in chromosome
    if random < 0.1:
      flip the bit (0 becomes 1, 1 becomes 0)
  Return chromosome
function genetic algorithm ()
  population = create_population()
  best chromosome = None
  best_fitness = infinity
  for generation = 1 to 10
    fitness_list = Evaluate_population (population)
    find chromosome with highest fitness
    If this fitness > best_fitness
      best_chromosome = that chromosome
      best_fitness = its fitness
    Print generation number, best x & best fitness
    Selected = select_parents (population, fitness_list)
    next_generation = []
    for i = 0 to population_size
      parent 1 = selected [i]
      parent 2 = selected [i+1]
      Child 1, child2 = crossover (parent1, parent2)
      Child 1 = mutate (child1)
      child 2 = mutate (child2)
      Add child and child2 next generation
  population = next generation
  Return decode (best_chromosome, best fitness)
Call genetic algorithm ()
```

(4)

Code:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# Creating a sample dataset
X, y = make_classification(n_samples=500, n_features=10, n_informative=8, n_classes=2)
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2)

# Neural Network Structure
input_size = X.shape[1]
hidden_size = 5
output_size = 1

# Helper functions for the Neural Network
def sigmoid(x):
    return 1 / (1 + np.exp(-x))
def forward_pass(X, weights1, weights2):
    hidden_input = np.dot(X, weights1)
    hidden_output = sigmoid(hidden_input)
    output_input = np.dot(hidden_output, weights2)
    output = sigmoid(output_input)
    return output
def compute_fitness(weights):
    predictions = forward_pass(X_train, weights['w1'], weights['w2'])
    predictions = (predictions > 0.5).astype(int)
    accuracy = accuracy_score(y_train, predictions)
    return accuracy
# Genetic Algorithm Parameters
population_size = 20
generations = 10
mutation_rate = 0.1

# Initialize Population
population = []
for _ in range(population_size):
    individual = {
        'w1': np.random.randn(input_size, hidden_size),
        'w2': np.random.randn(hidden_size, output_size)
    }
    population.append(individual)

# Tracking performance
best_fitness_history = []
```

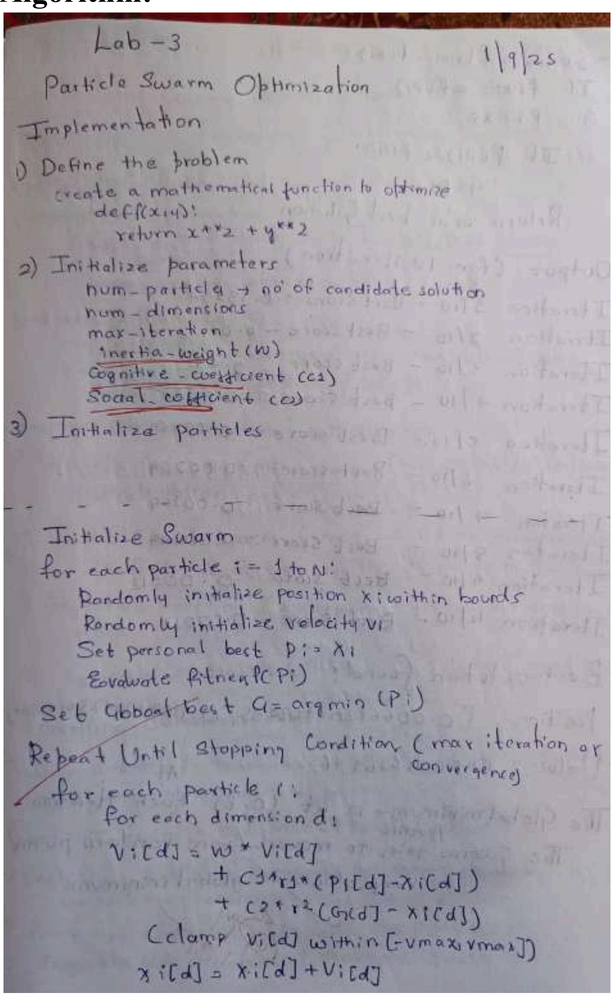
```
average_fitness_history = []

# Main Genetic Algorithm Loop
for generation in range(generations):
    # Evaluate Fitness of each Individual
    fitness_scores = np.array([compute_fitness(individual) for individual in population])
    best_fitness = np.max(fitness_scores)
    average_fitness = np.mean(fitness_scores)
    best_fitness_history.append(best_fitness)
    average_fitness_history.append(average_fitness)

    # Selection: Select top half of the population
    sorted_indices = np.argsort(fitness_scores)[::-1]
    population = [population[i] for i in sorted_indices[:population_size//2]]
   # Crossover and Mutation
    new_population = []
    while len(new_population) < population_size:
        parents = np.random.choice(population, 2, replace=False)
        child = {
            'w1': (parents[0]['w1'] + parents[1]['w1']) / 2,
            'w2': (parents[0]['w2'] + parents[1]['w2']) / 2
        }
       # Mutation
        if np.random.rand() < mutation_rate:
            child['w1'] += np.random.randn(*child['w1'].shape) * 0.1
            child['w2'] += np.random.randn(*child['w2'].shape) * 0.1
       new_population.append(child)
    population = new_population
 print(f"Generation {generation+1}, Best Fitness: {best_fitness:.4f}")

# Evaluate the best individual on validation set
best_individual = population[np.argmax(fitness_scores)]
predictions = forward_pass(X_val, best_individual['w1'], best_individual['w2'])
predictions = (predictions > 0.5).astype(int)
final_accuracy = accuracy_score(y_val, predictions)
print(f"Final Accuracy on Validation Set: {final_accuracy:.4f}")
# Plotting the results
plt.figure(figsize=(10, 5))
plt.plot(best_fitness_history, label='Best Fitness')
plt.plot(average_fitness_history, label='Average Fitness')
plt.title('Fitness Over Generations')
plt.xlabel('Generation')
plt.ylabel('Fitness')
plt.legend()
plt.grid(True)
plt.show()
```

Program 2

Particle Swarm Optimization for Function Optimization:

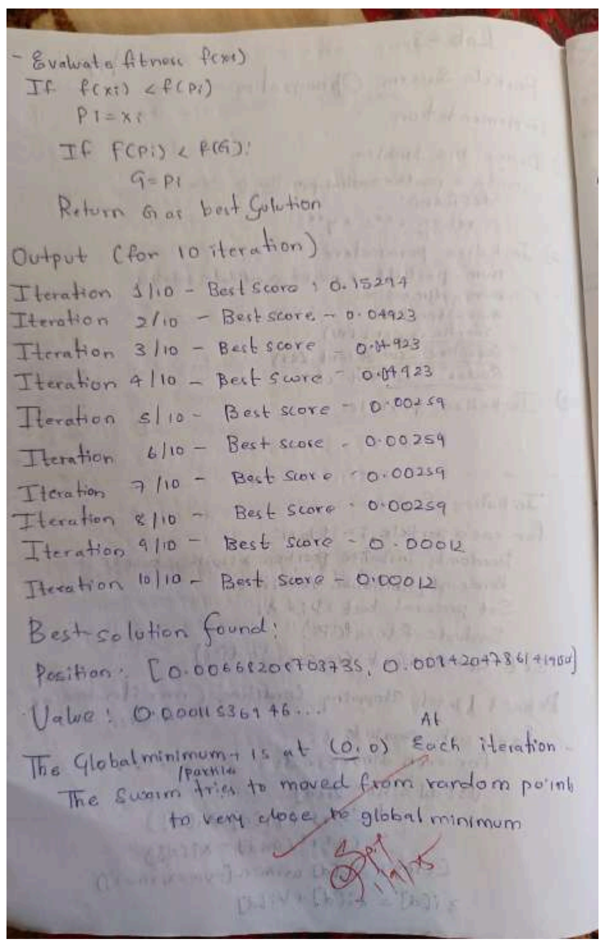
Particle Swarm Optimization (PSO) is inspired by the social behavior of birds flocking or fish schooling. PSO is used to find optimal solutions by iteratively improving a candidate solution with regard to a given measure of quality. Implement the PSO algorithm using Python to optimize a mathematical function.
Implementation Steps:
1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the number of particles, inertia weight, cognitive and social coefficients.
3. Initialize Particles: Generate an initial population of particles with random positions and velocities.
4. Evaluate Fitness: Evaluate the fitness of each particle based on the optimization function.
5. Update Velocities and Positions: Update the velocity and position of each particle based on its own best position and the global best position.
6. Iterate: Repeat the evaluation, updating, and position adjustment for a fixed number of iterations or until convergence criteria are met.
7. Output the Best Solution: Track and output the best solution found during the iterations.

Algorithm:



Lab - 3 1/9/25
Particle Swarm Optimization
Implementation
1) Define the problem
create a mathematical function to optimize
def f(x,y):
return x**2 + y**2
2) Initialize parameters
num_particle → no of candidate solution
num_dimensions
max_iteration
inertia_weight (w)
Cognitive_coefficient (c1)
Social_cofficient (c2)
3) Initialize particles

Initialize Swarm
for each particle i = 1 to N:
Randomly initialize position xi within bounds
Randomly initialize velocity vi
Set personal best pi = xi
Evaluate fitness f(pi)
Set Global best G = argmin (Pi)
Repeat Until stopping Condition (max iteration or convergence)
for each particle i:
for each dimension d:
vi[d] = w * vi[d]
+ c1*r1*(pi[d]-xi[d])
+ c2*r2(G[d] - xi[d])
(clamp vi[d] within [-vmax, vmax])
xi[d] = xi[d] + vi[d]



- Evaluate fitness f(xi)
If f(xi) < f(pi)
pi = xi
If f(pi) < f(G):
G = pi
Return G as best solution
Output (for 10 iteration)
Iteration 1/10 - Best score : 0.15294
Iteration 2/10 - Best score - 0.04923
Iteration 3/10 - Best score - 0.04923
Iteration 4/10 - Best score - 0.04923
Iteration 5/10 - Best score - 0.00259
Iteration 6/10 - Best score - 0.00259
Iteration 7/10 - Best score - 0.00259
Iteration 8/10 - Best score - 0.00259
Iteration 9/10 - Best score - 0.00012
Iteration 10/10 - Best score - 0.00012
Best solution found:
Position: [0.0066820670373S, 0.0014204786141950]
Value: 0.000115361 46...
The Global minimum is at (0, 0) At Each iteration
The swarm /particle tries to moved from random point to very close to global minimum

Code:

```
import random

# Define the function to optimize
def objective_function(position):
    x, y = position
    return x**2 + y**2

# PSO parameters
num_particles = 30
num_dimensions = 2
max_iterations = 10   # Changed from 100 to 10

w = 0.5
c1 = 1.5
c2 = 1.5

# Initialize particles
particles = []
velocities = []
personal_best_positions = []
personal_best_scores = []

for _ in range(num_particles):
    position = [random.uniform(-10, 10) for _ in range(num_dimensions)]
    velocity = [random.uniform(-1, 1) for _ in range(num_dimensions)]
    particles.append(position)
    velocities.append(velocity)
    personal_best_positions.append(position[:])
    personal_best_scores.append(objective_function(position))

global_best_index = personal_best_scores.index(min(personal_best_scores))
global_best_position = personal_best_positions[global_best_index][:]
global_best_score = personal_best_scores[global_best_index]

for iteration in range(max_iterations):
    for i in range(num_particles):
        for d in range(num_dimensions):
            r1 = random.random()
            r2 = random.random()

            velocities[i][d] = (w * velocities[i][d] +
                                c1 * r1 * (personal_best_positions[i][d] - particles[i][d]) +
                                c2 * r2 * (global_best_position[d] - particles[i][d]))

            particles[i][d] += velocities[i][d]
```

```
        fitness = objective_function(particles[i])

        if fitness < personal_best_scores[i]:
            personal_best_positions[i] = particles[i][:]
            personal_best_scores[i] = fitness

            if fitness < global_best_score:
                global_best_position = particles[i][:]
                global_best_score = fitness

    print(f"Iteration {iteration+1}/{max_iterations} — Best Score: {global_best_score:.5f}")

print("\nBest solution found:")
print(f"Position: {global_best_position}")
print(f"Value: {global_best_score}")
```

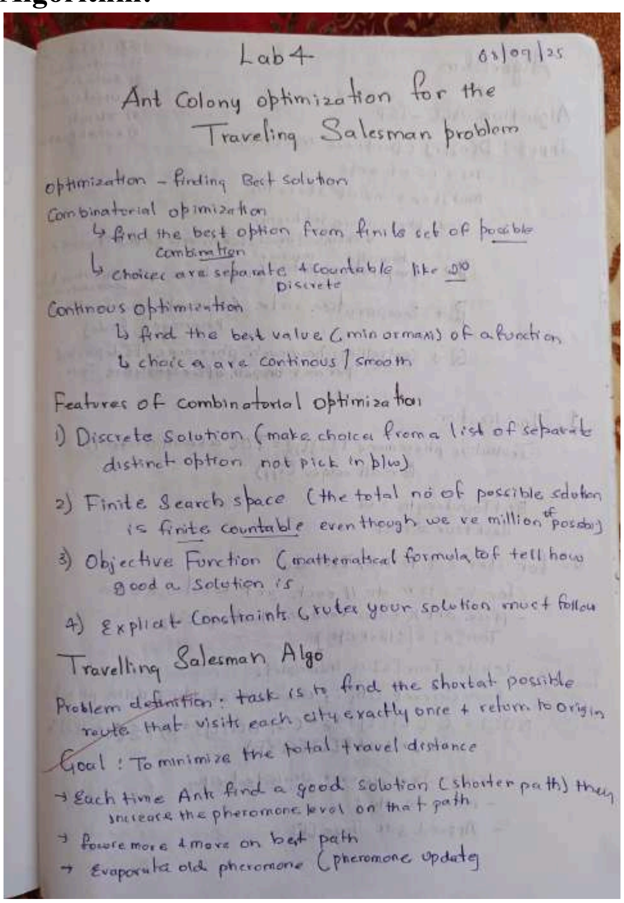
Program 3:

Ant Colony Optimization for the Traveling Salesman Problem:

The foraging behavior of ants has inspired the development of optimization algorithms that can solve complex problems such as the Traveling Salesman Problem (TSP). Ant Colony Optimization (ACO) simulates the way ants find the shortest path between food sources and their nest. Implement the ACO algorithm using Python to solve the TSP, where the objective is to find the shortest possible route that visits a list of cities and returns to the origin city.

Implementation Steps:
1. Define the Problem: Create a set of cities with their coordinates.
2. Initialize Parameters: Set the number of ants, the importance of pheromone (alpha), the importance of heuristic information (beta), the evaporation rate (rho), and the initial pheromone value.
3. Construct Solutions: Each ant constructs a solution by probabilistically choosing the next city based on pheromone trails and heuristic information.
4. Update Pheromones: After all ants have constructed their solutions, update the pheromone trails based on the quality of the solutions found.
5. Iterate: Repeat the construction and updating process for a fixed number of iterations or until convergence criteria are met.
6. Output the Best Solution: Keep track of and output the best solution found during the iterations.

Algorithm:



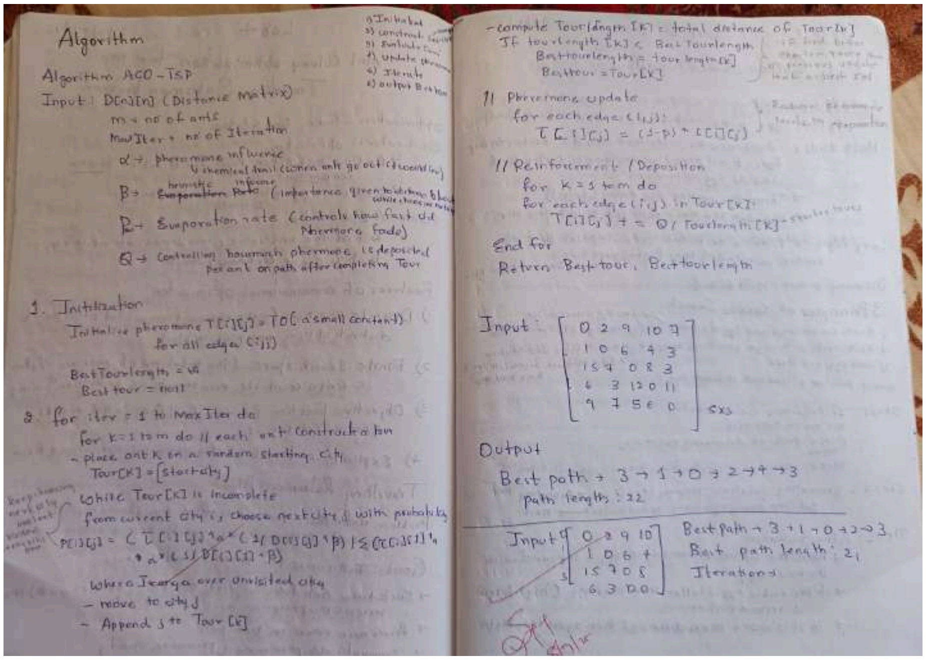
Lab4 03/09/25

Ant Colony optimization for the Traveling Salesman problem

optimization - finding Best solution
Combinatorial opimization
↳ find the best option from finite set of possible combination
↳ choices are separate + countable like 0/1
Discrete
Continous optimization
↳ find the best value (min or max) of a function
↳ choice are continous / smooth

Features of combinatorial optimization
1) Discrete Solution (make choice from a list of separate distinct option not pick in b/w)
2) Finite Search space (the total no of possible solution is finite countable even though we've million of possibility)
3) Objective Function (mathematical formula to tell how good a solution is
4) Explicit Constraints (rules your solution must follow

Travelling Salesman Algo
Problem definition: task is to find the shortest possible route that visits each city exactly once + return to origin
Goal : To minimize the total travel distance
→ Each time Ant find a good solution (shorter path) then increase the pheromone level on that path
→ Follow more + more on best path
→ Evaporate old pheromone (pheromone update)



Algorithm

Algorithm ACO-TSP

Input: D[n][n] (Distance Matrix)

m → no of ants

MaxIter → no of Iteration

α → pheromone influence

β → heuristic influence (importance given to distance)

ρ → Evaporation rate (controls how fast old pheromone fade)

Q → Controlling how much pheromone is deposited per ant on path after completing Tour

1. Initialization

Initialize pheromone τ[i][j] = τ0 (a small constant) for all edges (i,j)

BestTourlength = ∞

Best tour = null

2. for iter = 1 to MaxIter do

for k = 1 to m do // each ant construct a tour

- place ant k on a random starting city

Tour[k] = [startcity]

while Tour[k] is incomplete

from current city i, choose next city j with probability

P[i][j] = (τ[i][j]^α × (1/D[i][j])^β) / Σ(τ[i][l]^α × (1/D[i][l])^β)

where l ranges over unvisited city

- move to city j

- Append j to Tour[k]

- compute Tourlength[k] = total distance of Tour[k]

If tourlength[k] < Best Tourlength

Besttourlength = tour length[k]

Besttour = Tour[k]

// Pheromone update

for each edge (i,j):

τ[i][j] = (1-ρ) * τ[i][j]

// Reinforcement / Deposition

for k = 1 to m do

for each edge (i,j) in Tour[k]:

τ[i][j] += Q / Tourlength[k]

End for

Return Best tour, Besttourlength

Input:

$$\begin{bmatrix} 0 & 2 & 9 & 10 & 7 \\ 1 & 0 & 6 & 4 & 3 \\ 15 & 7 & 0 & 8 & 3 \\ 6 & 3 & 12 & 0 & 11 \\ 9 & 7 & 5 & 6 & 0 \end{bmatrix}_{5\times5}$$

Output

Best path → 3 → 1 → 0 → 2 → 4 → 3

path length: 22

Code:

```
import random
import math

class ACO_TSP:
    def __init__(self, distances, n_ants=10, n_iterations=100, alpha=1, beta=5, rho=0.5, Q=100):
        self.distances = distances
        self.n = len(distances)
        self.n_ants = n_ants
        self.n_iterations = n_iterations
        self.alpha = alpha
        self.beta = beta
        self.rho = rho
        self.Q = Q
        self.pheromone = [[1 for _ in range(self.n)] for _ in range(self.n)]

        self.best_length = float("inf")
        self.best_tour = None

    def run(self):
        for it in range(self.n_iterations):
            all_tours = []
            all_lengths = []

            for ant in range(self.n_ants):
                tour = self.construct_solution()
                length = self.compute_length(tour)
```

```
            all_tours.append(tour)
            all_lengths.append(length)

            if length < self.best_length:
                self.best_length = length
                self.best_tour = tour

        self.update_pheromones(all_tours, all_lengths)

    return self.best_tour, self.best_length

def construct_solution(self):
    start = random.randint(0, self.n - 1)
    tour = [start]
    unvisited = set(range(self.n))
    unvisited.remove(start)

    current = start
    while unvisited:
        next_city = self.choose_next_city(current, unvisited)
        tour.append(next_city)
        unvisited.remove(next_city)
        current = next_city

    return tour

def choose_next_city(self, current, unvisited):
    probs = []
    total = 0
    for city in unvisited:
        tau = self.pheromone[current][city] ** self.alpha
        eta = (1.0 / self.distances[current][city]) ** self.beta
        value = tau * eta
        probs.append((city, value))
        total += value

    r = random.random() * total
    cumulative = 0
    for city, value in probs:
        cumulative += value
        if cumulative >= r:
            return city
    return probs[-1][0]

def compute_length(self, tour):
    length = 0
    for i in range(len(tour) - 1):
```

```
            length += self.distances[tour[i]][tour[i+1]]
        length += self.distances[tour[-1]][tour[0]]
        return length

    def update_pheromones(self, all_tours, all_lengths):
        for i in range(self.n):
            for j in range(self.n):
                self.pheromone[i][j] *= (1 - self.rho)

        for tour, length in zip(all_tours, all_lengths):
            for i in range(len(tour) - 1):
                a, b = tour[i], tour[i+1]
                self.pheromone[a][b] += self.Q / length
                self.pheromone[b][a] += self.Q / length
            a, b = tour[-1], tour[0]
            self.pheromone[a][b] += self.Q / length
            self.pheromone[b][a] += self.Q / length


# Example usage
if __name__ == "__main__":
    distances = [
        [0, 2, 9, 10, 7],
        [1, 0, 6, 4, 3],
        [15, 7, 0, 8, 3],
        [6, 3, 12, 0, 11],
        [9, 7, 5, 6, 0]
    ]

    aco = ACO_TSP(distances, n_ants=10, n_iterations=50, alpha=1, beta=5, rho=0.5, Q=100)
    best_tour, best_length = aco.run()

    # Format tour as edges
    path_str = " -> ".join(map(str, best_tour)) + f" -> {best_tour[0]}"
    print("\n=== Final Best Solution ===")
    print("Best path:", path_str)
    print("Best path length:", best_length)
```

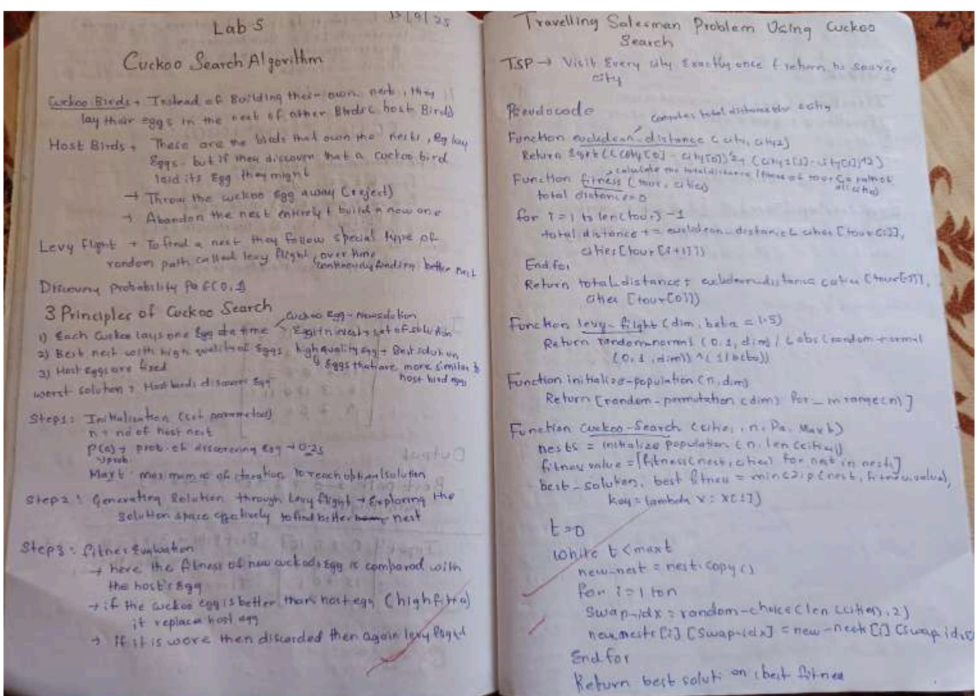
Program 4:

Cuckoo Search (CS):

Cuckoo Search (CS) is a nature-inspired optimization algorithm based on the brood parasitism of some cuckoo species. This behavior involves laying eggs in the nests of other birds, leading to the optimization of survival strategies. CS uses Lévy flights to generate new solutions, promoting global search capabilities and avoiding local minima. The algorithm is widely used for solving continuous optimization problems and has applications in various domains, including engineering design, machine learning, and data mining.

Implementation Steps:
1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the number of nests, the probability of discovery, and the number of iterations.
3. Initialize Population: Generate an initial population of nests with random positions.
4. Evaluate Fitness: Evaluate the fitness of each nest based on the optimization function.
5. Generate New Solutions: Create new solutions via Lévy flights.
6. Abandon Worst Nests: Abandon a fraction of the worst nests and replace them with new random positions.
7. Iterate: Repeat the evaluation, updating, and replacement process for a fixed number of iterations or until convergence criteria are met.
8. Output the Best Solution: Track and output the best solution found during the iterations.

Algorithm:


Lab 5

Cuckoo Search Algorithm

Cuckoo Birds → Instead of building their own nest, they lay their eggs in the nest of other Birds (host Birds)

Host Birds → These are the birds that own the nests, Eg lay Eggs but if they discover that a cuckoo bird laid its Egg they might
→ Throw the cuckoo egg away (reject)
→ Abandon the nest entirely & build a new one

Levy Flight → To find a nest they follow special type of random path called levy flight, over time continuously finding better nest

Discovery Probability Pa ∈ (0,1)

3 Principles of Cuckoo Search
1) Each Cuckoo lays one Egg at a time
2) Best nest with high quality of Eggs
3) Host Eggs are fixed

Cuckoo Egg = New solution
Egg in nests = set of solution
high quality Egg → Best solution
Eggs that are more similar to host bird eggs

worst solution → Host birds discover Egg

Step 1: Initialization (set parameters)
n → no of host nest
P(a) → prob. of discovering Egg → 0.25
Max t = maximum no of iteration to reach optimal solution

Step 2: Generating Solution through Levy flight → Exploring the solution space effectively to find better nest

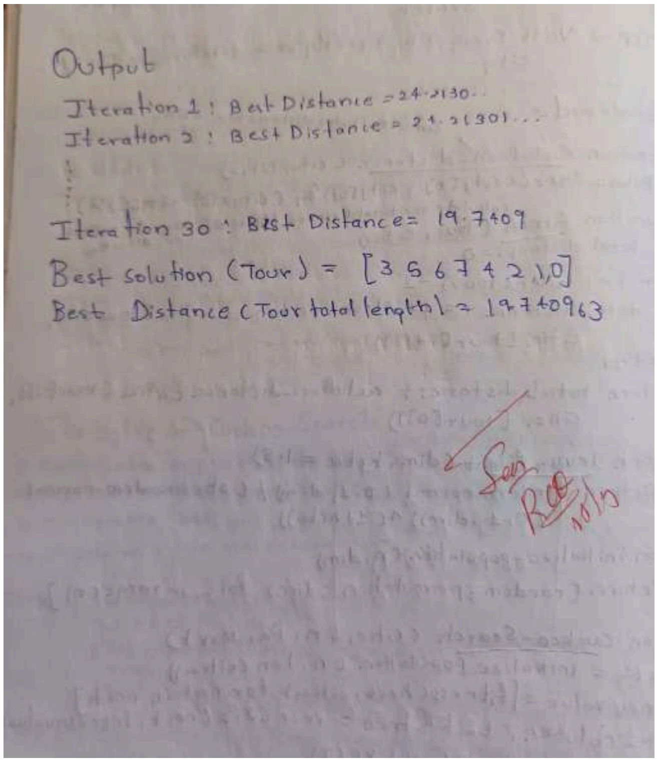
Step 3: Fitness Evaluation
→ here the fitness of new cuckoo's Egg is compared with the host's Egg
→ if the cuckoo egg is better than host egg (high fitness) it replaces host egg
→ If it is worse then discarded then again levy flight

Travelling Salesman Problem Using Cuckoo Search

TSP → Visit Every city Exactly once & return to source city

Pseudocode

```
Function euclidean_distance (city, city2)
    Return sqrt((city[0] - city[0])^2 + (city1[1] - city[1])^2)
Function fitness (tour, cities)
    total distance = 0
    for i = 1 to len(tour) - 1
        total distance += euclidean_distance(cities[tour[i]],
            cities[tour[i+1]])
    End for
    Return total_distance + euclidean_distance(cities[tour[-1]],
        cities[tour[0]])
Function levy_flight (dim, beta = 1.5)
    Return random.normal(0, 1, dim) / (abs(random.normal
        (0, 1, dim)) ^ (1/beta))
Function initialize_population (n, dim)
    Return [random_permutation(dim) for _ in range(n)]
Function Cuckoo_Search (cities, n, Pa, Max t)
    nests = initialize population (n, len(cities))
    fitness value = [fitness(nest, cities) for nest in nests]
    best_solution, best fitness = min(zip(nest, fitness_value),
        key = lambda x: x[1])
    t = 0
    While t < max t
        new_nest = nest.copy()
        for i = 1 to n
            swap_idx = random_choice(len(cities), 2)
            new_nests[i][swap_idx] = new_nests[i][swap_idx
        End for
    Return best solution, best fitness
```



Output

Iteration 1 : Best Distance = 24.2130..

Iteration 2 : Best Distance = 24.2130...

⋮

Iteration 30 : Best Distance = 19.7409

Best solution (Tour) = [3 5 6 7 4 2 1,0]

Best Distance (Tour total length) = 19.740963

Code:

```
import numpy as np

# Problem data (same as before)
weights = np.array([12, 7, 11, 8, 9])
values = np.array([24, 13, 23, 15, 16])
capacity = 26

n = 10       # Number of nests
Pa = 0.25    # Probability of abandoning worst nests
max_iter = 100

def fitness(solution):
    total_weight = np.sum(solution * weights)
    if total_weight > capacity:
        return 0
    else:
        return np.sum(solution * values)

def initial_nests(n, dim):
    return np.random.randint(0, 2, (n, dim))

def levy_flight(Lambda=1.5):
    sigma = (np.math.gamma(1 + Lambda) * np.sin(np.pi * Lambda / 2) /
            (np.math.gamma((1 + Lambda) / 2) * Lambda * 2 ** ((Lambda - 1) / 2))) ** (1 /
Lambda)
```

```
    u = np.random.normal(0, sigma, size=weights.shape[0])
    v = np.random.normal(0, 1, size=weights.shape[0])
    step = u / np.abs(v) ** (1 / Lambda)
    return step

def get_new_solution(nest):
    step_size = levy_flight()
    new_sol_cont = nest + 0.01 * step_size * (nest - np.mean(nest))
    s = 1 / (1 + np.exp(-new_sol_cont))
    new_sol = np.array([1 if x > 0.5 else 0 for x in s])
    return new_sol

def abandon_worst_nests(nests, fitnesses, Pa):
    num_abandon = int(Pa * len(nests))
    worst_indices = np.argsort(fitnesses)[:num_abandon]
    for i in worst_indices:
        nests[i] = np.random.randint(0, 2, nests.shape[1])
        fitnesses[i] = fitness(nests[i])
    return nests, fitnesses

def cuckoo_search():
    dim = weights.shape[0]
    t = 0

    # Step 4 and 5: Initialize population and evaluate fitness
    nests = initial_nests(n, dim)
    fitnesses = np.array([fitness(nest) for nest in nests])

    while t < max_iter:
        for i in range(n):
            # Step 7 and 8: Generate cuckoo and evaluate fitness
            cuckoo = get_new_solution(nests[i])
            cuckoo_fit = fitness(cuckoo)

            # Step 9: Choose a nest randomly
            j = np.random.randint(n)

            # Step 10-12: Replace if cuckoo is better
            if cuckoo_fit > fitnesses[j]:
                nests[j] = cuckoo
                fitnesses[j] = cuckoo_fit

        # Step 13 and 14: Abandon fraction Pa of worst nests and build new ones
        nests, fitnesses = abandon_worst_nests(nests, fitnesses, Pa)

        # Step 15 and 16: Keep and rank the best solution
        best_index = np.argmax(fitnesses)
```

```
        best_nest = nests[best_index].copy()
        best_fitness = fitnesses[best_index]

        print(f"Iteration {t+1}: Best fitness = {best_fitness}")

        t += 1

    # Step 19: Output the best solution
    return best_nest, best_fitness

best_solution, best_val = cuckoo_search()

print("\nBest solution found:")
print("Items selected:", best_solution)
print("Total value:", best_val)
print("Total weight:", np.sum(best_solution * weights))
```

Program 5:

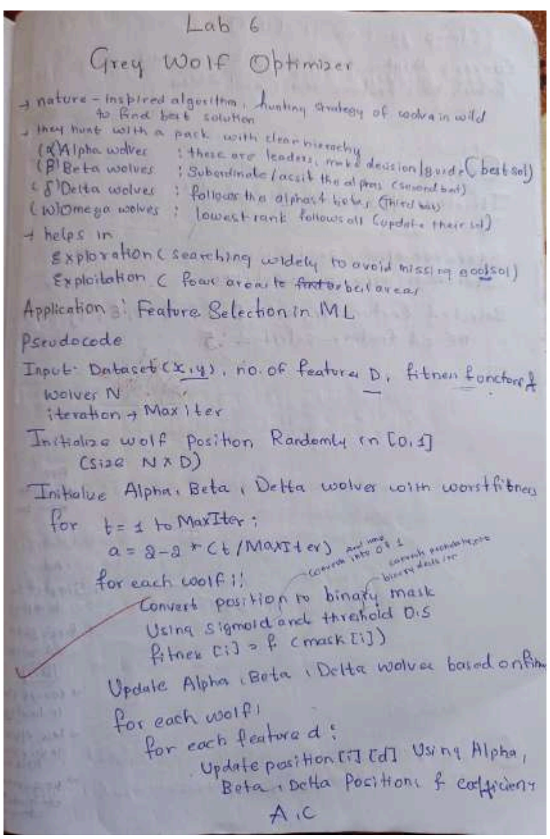
Grey Wolf Optimizer (GWO):

The Grey Wolf Optimizer (GWO) algorithm is a swarm intelligence algorithm inspired by the social hierarchy and hunting behavior of grey wolves. It mimics the leadership structure of alpha, beta, delta, and omega wolves and their collaborative hunting strategies. The GWO algorithm uses these social hierarchies to model the optimization process, where the alpha wolves guide the search process while beta and delta wolves assist in refining the search direction. This algorithm is effective for continuous optimization problems and has applications in engineering, data analysis, and machine learning.

Implementation Steps:

1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the number of wolves and the number of iterations.
3. Initialize Population: Generate an initial population of wolves with random positions.
4. Evaluate Fitness: Evaluate the fitness of each wolf based on the optimization function.
5. Update Positions: Update the positions of the wolves based on the positions of alpha, beta, and delta wolves.
6. Iterate: Repeat the evaluation and position updating process for a fixed number of iterations or until convergence criteria are met.
7. Output the Best Solution: Track and output the best solution found during the iterations

Algorithm:



Lab 6

Grey Wolf Optimizer

→ nature-inspired algorithm, hunting strategy of wolves in wild to find best solution

→ they hunt with a pack with clear hierarchy

(α) Alpha wolves : these are leaders, make decision/guide (best sol)

(β) Beta wolves : Subordinate/assist the alphas (second best)

(δ) Delta wolves : follows the alphas & betas (third best)

(ω) Omega wolves : lowest rank follows all (update their sol)

→ helps in

Exploration (searching widely to avoid missing good sol)

Exploitation (focus around the ~~first~~ best areas)

Application : Feature Selection in ML

Pseudocode

Input: Dataset (x, y), no. of features D, fitness function f

wolves N

iteration → Max iter

Initialize wolf position Randomly in [0, 1] (size N × D)

Initialize Alpha, Beta, Delta wolves with worst fitness

for t = 1 to MaxIter :

a = 2 - 2 * (t / MaxIter)

for each wolf i:

Convert position to binary mask Using sigmoid and threshold 0.5

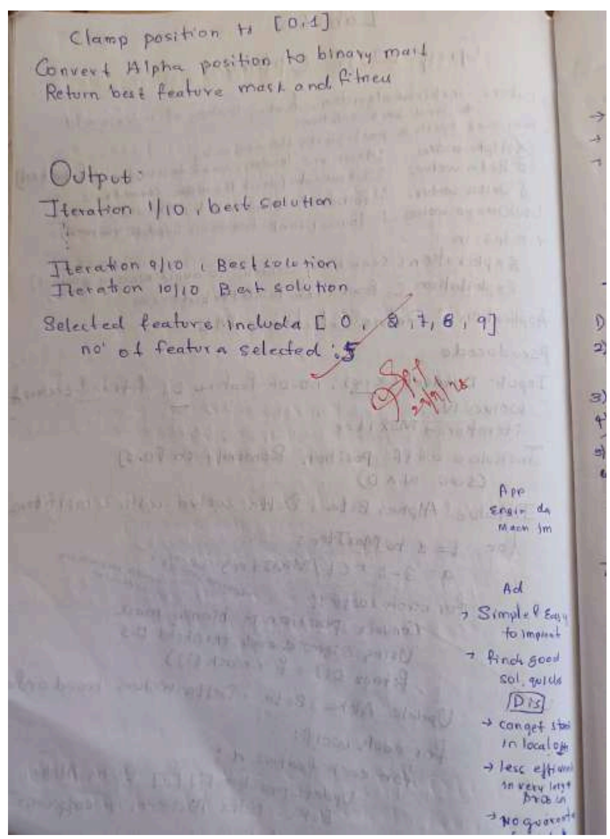
fitness [i] = f (mask [i])

Update Alpha, Beta, Delta wolves based on fitness

for each wolf i

for each feature d :

Update position [i] [d] Using Alpha, Beta, Delta Positions & coefficients A, C



Clamp position to [0, 1]

Convert Alpha position to binary mask

Return best feature mask and fitness

Output:

Iteration 1/10, best solution

Iteration 9/10, Best solution

Iteration 10/10 Best solution

Selected features include [0, 2, 7, 8, 9]

no. of features selected : 5

App

Engin da

Mach lm

Ad

→ Simple & Easy to implement

→ finds good sol. quick

Dis

→ can get stuck in local opt

→ less efficient in very large prob

→ No guarantee

Code:

```
import numpy as np
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier

# Load dataset
data = load_breast_cancer()
X = data.data
y = data.target
num_features = X.shape[1]

# Gray Wolf Optimizer parameters
num_wolves = 10  # Population size
max_iter = 10    # Number of iterations

# Binary GWO helper functions
def sigmoid(x):
    return 1 / (1 + np.exp(-x))

def binary_transform(x):
    return np.where(sigmoid(x) > np.random.rand(len(x)), 1, 0)

# Fitness function: classification accuracy
def fitness(position):
    selected_features = np.where(position == 1)[0]
    if len(selected_features) == 0:
        return 0
    X_selected = X[:, selected_features]
    clf = RandomForestClassifier(n_estimators=50)
    score = cross_val_score(clf, X_selected, y, cv=5).mean()
    return score

# Initialize wolves
wolves = np.random.uniform(-1, 1, (num_wolves, num_features))
binary_wolves = np.array([binary_transform(w) for w in wolves])
fitness_vals = np.array([fitness(w) for w in binary_wolves])

# Initialize alpha, beta, delta
alpha_idx = np.argmax(fitness_vals)
alpha = wolves[alpha_idx].copy()
alpha_score = fitness_vals[alpha_idx]

beta_idx = np.argsort(fitness_vals)[-2]
beta = wolves[beta_idx].copy()
beta_score = fitness_vals[beta_idx]
```

```
delta_idx = np.argsort(fitness_vals)[-3]
delta = wolves[delta_idx].copy()
delta_score = fitness_vals[delta_idx]

# Main loop
for t in range(max_iter):
    a = 2 - t * (2 / max_iter)  # Linearly decreasing a

    for i in range(num_wolves):
        for j in range(num_features):
            r1, r2 = np.random.rand(), np.random.rand()
            A1 = 2 * a * r1 - a
            C1 = 2 * r2
            D_alpha = abs(C1 * alpha[j] - wolves[i][j])
            X1 = alpha[j] - A1 * D_alpha

            r1, r2 = np.random.rand(), np.random.rand()
            A2 = 2 * a * r1 - a
            C2 = 2 * r2
            D_beta = abs(C2 * beta[j] - wolves[i][j])
            X2 = beta[j] - A2 * D_beta

            r1, r2 = np.random.rand(), np.random.rand()
            A3 = 2 * a * r1 - a
            C3 = 2 * r2
            D_delta = abs(C3 * delta[j] - wolves[i][j])
            X3 = delta[j] - A3 * D_delta

            wolves[i][j] = (X1 + X2 + X3) / 3

 # Update binary positions
    binary_wolves = np.array([binary_transform(w) for w in wolves])
    fitness_vals = np.array([fitness(w) for w in binary_wolves])

    # Update alpha, beta, delta
    sorted_idx = np.argsort(fitness_vals)[::-1]
    alpha, alpha_score = wolves[sorted_idx[0]].copy(), fitness_vals[sorted_idx[0]]
    beta, beta_score = wolves[sorted_idx[1]].copy(), fitness_vals[sorted_idx[1]]
    delta, delta_score = wolves[sorted_idx[2]].copy(), fitness_vals[sorted_idx[2]]

    print(f"Iteration {t+1}/{max_iter}, Best fitness: {alpha_score:.4f}")

# Best feature subset
best_features = np.where(binary_transform(alpha) == 1)[0]
print("Selected feature indices:", best_features)
print("Number of features selected:", len(best_features))
```

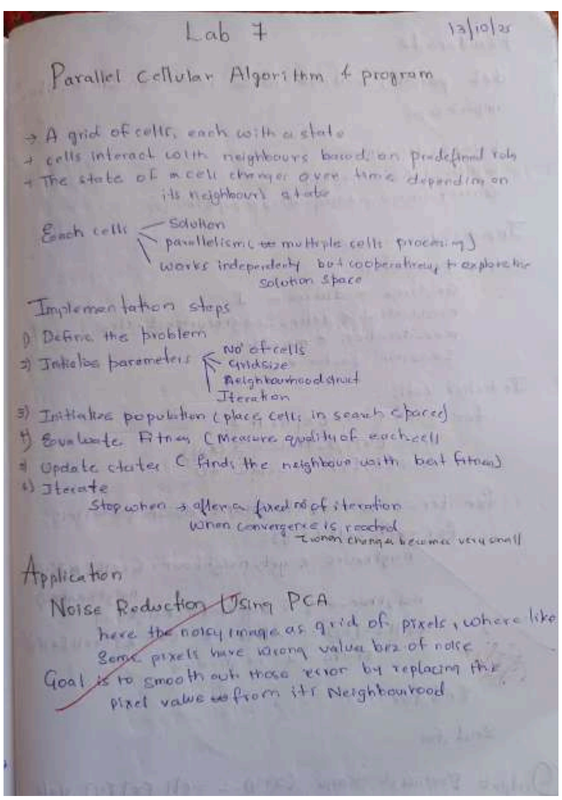
Program 6:

Parallel Cellular Algorithms and Programs:

Parallel Cellular Algorithms are inspired by the functioning of biological cells that operate in a highly parallel and distributed manner. These algorithms leverage the principles of cellular automata and parallel computing to solve complex optimization problems efficiently. Each cell represents a potential solution and interacts with its neighbors to update its state based on predefined rules. This interaction models the diffusion of information across the cellular grid, enabling the algorithm to explore the search space effectively. Parallel Cellular Algorithms are particularly suitable for large-scale optimization problems and can be implemented on parallel computing architectures for enhanced performance.

Implementation Steps:
1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the number of cells, grid size, neighborhood structure, and number of iterations. 3. Initialize Population: Generate an initial population of cells with random positions in the solution space.
4. Evaluate Fitness: Evaluate the fitness of each cell based on the optimization function.
5. Update States: Update the state of each cell based on the states of its neighboring cells and predefined update rules.
6. Iterate: Repeat the evaluation and state updating process for a fixed number of iterations or until convergence criteria are met.
7. Output the Best Solution: Track and output the best solution found during the iterations.

Algorithm:



Lab 7 13/10/25

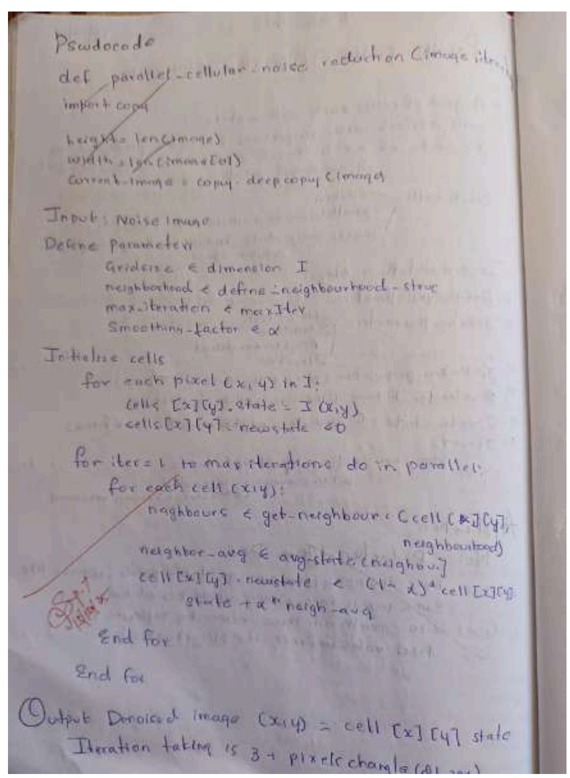
Parallel Cellular Algorithm & program

→ A grid of cells, each with a state
→ cells interact with neighbours based on predefined rules
→ The state of a cell changes over time depending on its neighbours' state

Each cells — Solution
— parallelism (multiple cells processing)
— works independently but cooperatively to explore the solution space

Implementation steps
1) Define the problem
2) Initialise parameters — No. of cells, Gridsize, Neighbourhood struct, Iteration
3) Initialize population (place cells in search space)
4) Evaluate fitness (Measure quality of each cell)
5) Update states (finds the neighbour with best fitness)
6) Iterate
Stop when → after a fixed no. of iteration
when convergence is reached
(when change becomes very small)

Application
Noise Reduction Using PCA
here the noisy image as grid of pixels, where like some pixels have wrong value bcz of noise
Goal is to smooth out those error by replacing the pixel value from its Neighbourhood



Pseudocode
def parallel_cellular_noise_reduction(image, ite...
import copy

height = len(image)
width = len(image[0])
current_image = copy.deepcopy(image)

Input: Noise Image
Define Parameter
Gridsize ← dimension I
neighborhood ← define_neighbourhood_struc
max_iteration ← maxIter
Smoothing_factor ← α

Initialise cells
for each pixel (x, y) in I:
cells[x][y].state = I(x,y)
cells[x][y].newstate ← 0

for iter = 1 to max iterations do in parallel:
for each cell (x,y):
neighbours ← get_neighbours(cell[x][y], neighbourhood)
neighbor_avg ← avg_state(neighbours)
cell[x][y].newstate ← (1 − α) * cell[x][y].state + α * neigh_avg
End for
End for

Output Denoised image (x,y) = cell[x][y].state
Iteration taking is 3 + pixels changed (...)

Code:

```
import numpy as np
import matplotlib.pyplot as plt
from skimage import data, util

def get_neighbors_indices(row, col, max_row, max_col):
    neighbors = []
    for dr in [-1, 0, 1]:
        for dc in [-1, 0, 1]:
            if dr == 0 and dc == 0:
                continue
            nr, nc = row + dr, col + dc
            if 0 <= nr < max_row and 0 <= nc < max_col:
                neighbors.append((nr, nc))
    return neighbors

def pca_noise_reduction(image, max_iterations=10, sigma=15):
    rows, cols = image.shape
    denoised_image = image.copy().astype(float)

    for iteration in range(max_iterations):
        new_image = denoised_image.copy()

        for i in range(rows):
            for j in range(cols):
                neighbors = get_neighbors_indices(i, j, rows, cols)

                weights = []
                intensities = []

                for nr, nc in neighbors:
                    diff = abs(denoised_image[nr, nc] - denoised_image[i, j])
                    weight = np.exp(-diff / sigma)
                    weights.append(weight)
                    intensities.append(denoised_image[nr, nc])

                weights = np.array(weights)
                intensities = np.array(intensities)

                if weights.sum() > 0:
                    new_value = np.sum(weights * intensities) / np.sum(weights)
                    new_image[i, j] = new_value

        denoised_image = new_image

    return denoised_image.astype(np.uint8)
```

```
# Load sample grayscale image: "camera"
image = data.camera()  # shape: (512, 512)

# Add salt & pepper noise
noisy_image = util.random_noise(image, mode='s&p', amount=0.05)
noisy_image = (noisy_image * 255).astype(np.uint8)

# Apply PCA-based denoising
denoised = pca_noise_reduction(noisy_image, max_iterations=10, sigma=20)

# 📌 Print only the 5×5 pixel values for comparison
print("\nOriginal Image 5x5 patch:")
print(image[100:105, 100:105])

print("\nNoisy Image 5x5 patch:")
print(noisy_image[100:105, 100:105])

print("\nDenoised Image 5x5 patch:")
print(denoised[100:105, 100:105])
```

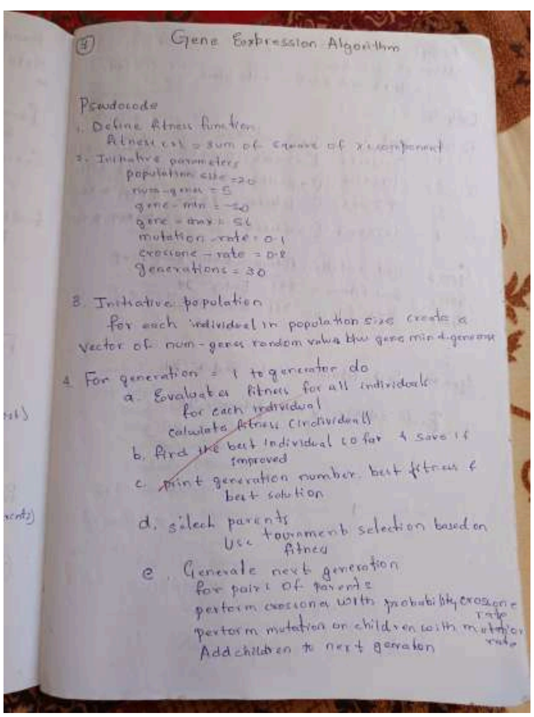
Program 7:

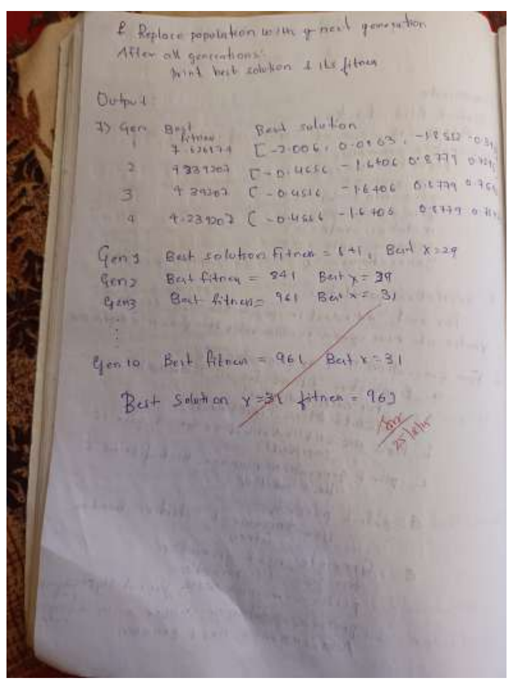
Optimization via Gene Expression Algorithms:

Gene Expression Algorithms (GEA) are inspired by the biological process of gene expression in living organisms. This process involves the translation of genetic information encoded in DNA into functional proteins. In GEA, solutions to optimization problems are encoded in a manner similar to genetic sequences. The algorithm evolves these solutions through selection, crossover, mutation, and gene expression to find optimal or near-optimal solutions. GEA is effective for solving complex optimization problems in various domains, including engineering, data analysis, and machine learning.

Implementation Steps:
1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the population size, number of genes, mutation rate, crossover rate, and number of generations.
3. Initialize Population: Generate an initial population of random genetic sequences.
4. Evaluate Fitness: Evaluate the fitness of each genetic sequence based on the optimization function.
5. Selection: Select genetic sequences based on their fitness for reproduction.
6. Crossover: Perform crossover between selected sequences to produce offspring.
7. Mutation: Apply mutation to the offspring to introduce variability.
8. Gene Expression: Translate genetic sequences into functional solutions.
9. Iterate: Repeat the selection, crossover, mutation, and gene expression processes for a fixed number of generations or until convergence criteria are met.
10. Output the Best Solution: Track and output the best solution found during the iterations.

Algorithm:





Code:

```
import numpy as np
import matplotlib.pyplot as plt
from gplearn.genetic import SymbolicRegressor
from gplearn.functions import make_function
from gplearn.fitness import make_fitness

# Generate training data
X = np.linspace(-10, 10, 100).reshape(-1, 1)
y = X**2 + np.sin(X)  # True function to approximate

# Define symbolic regressor
est_gp = SymbolicRegressor(
    population_size=500,
    generations=20,
    stopping_criteria=0.01,
    p_crossover=0.7,
    p_subtree_mutation=0.1,
    p_hoist_mutation=0.05,
    p_point_mutation=0.1,
    max_samples=0.9,
    verbose=1,
    parsimony_coefficient=0.001,
    random_state=42
)

# Fit model
est_gp.fit(X, y)

# Predict on training data
y_pred = est_gp.predict(X)

# Print discovered expression
print("\nDiscovered expression:")
print(est_gp._program)

# Plot the results
plt.figure(figsize=(10, 6))
plt.plot(X, y, label='True Function', color='blue')
plt.plot(X, y_pred, label='GEP Prediction', color='red', linestyle='--')
plt.legend()
plt.title("Gene Expression Programming (Symbolic Regression)")
plt.xlabel("X")
plt.ylabel("y")
plt.grid(True)
plt.show()
```