RAJALAKSHMI ENGINEERING COLLEGE (Autonomous)

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

AI19341

PRINCIPLES OF ARTIFICIAL INTELLIGENCE LAB

THIRD YEAR

FIFTH SEMESTER

INDEX

S.NO	DATE	EXP NAME	VIVA MARK	SIGNATURE

EX.NO: **DATE:**

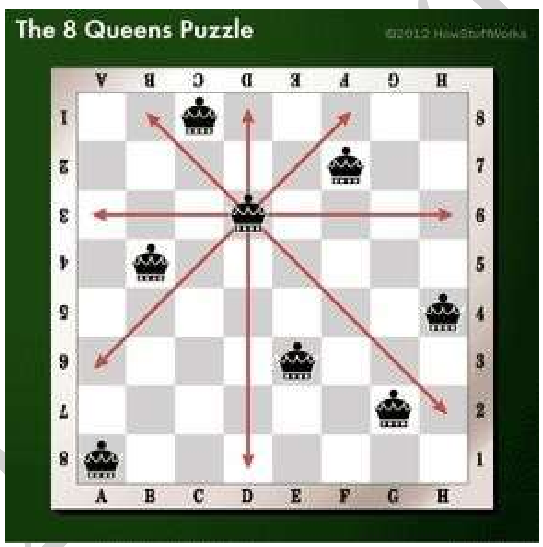
8- QUEENS PROBLEM

AIM :

To implement an 8-Queens problem using Python.

You are given an 8x8 board; find a way to place 8 queens such that no queen can attack any other queen on the chessboard. A queen can only be attacked if it lies on the same row, same column, or the same diagonal as any other queen. Print all the possible configurations.

To solve this problem, we will make use of the Backtracking algorithm. The backtracking algorithm, in general checks all possible configurations and test whether the required result is obtained or not. For the given problem, we will explore all possible positions the queens can be relatively placed at. The solution will be correct when the number of placed queens = 8.



CODE:

```
def is_safe(board, row, col):
    for i in range(row):
        if board[i] == col or \
           board[i] - i == col - row or \
           board[i] + i == col + row:
            return False
    return True

def solve_queens(board, row, solutions):
    if row == 8:
        solutions.append(board.copy())
        return

    for col in range(8):
        if is_safe(board, row, col):
            board[row] = col
            solve_queens(board, row + 1, solutions)
            board[row] = -1

def print_solutions(solutions):
    for solution in solutions:
        for row in range(8):
            board_row = ['Q' if col == solution[row] else '.' for col in range(8)]
            print(' '.join(board_row))
        print()

def eight_queens():
    solutions = []
    board = [-1] * 8

    solve_queens(board, 0, solutions)

    print_solutions(solutions)

eight_queens()
```

OUTPUT:

Enter the number of queens
8
[1, 0, 0, 0, 0, 0, 0, 0]
[0, 0, 0, 0, 1, 0, 0, 0]
[0, 0, 0, 0, 0, 0, 0, 1]
[0, 0, 0, 0, 0, 1, 0, 0]
[0, 0, 1, 0, 0, 0, 0, 0]
[0, 0, 0, 0, 0, 0, 1, 0]
[0, 1, 0, 0, 0, 0, 0, 0]
[0, 0, 0, 1, 0, 0, 0, 0]

RESULT:
Thus, the code has been successfully executed, and the output has been verified successfully.

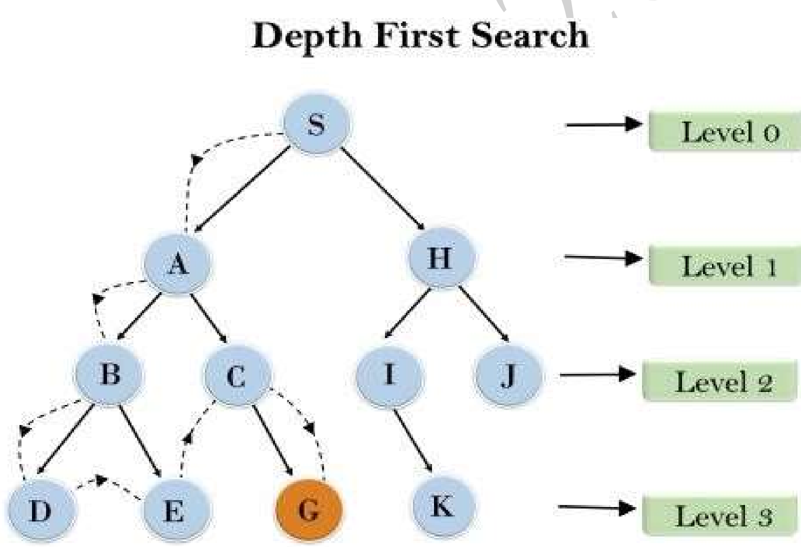
EX.NO: **DATE:**

DEPTH-FIRST SEARCH

AIM :

To implement a depth-first search problem using Python.

- Depth-first search (DFS) algorithm or searching technique starts with the root node of graph G, and then travel deeper and deeper until we find the goal node or the node which has no children by visiting different node of the tree.
- The algorithm, then backtracks or returns back from the dead end or last node towards the most recent node that is yet to be completely unexplored.
- The data structure (DS) which is being used in DFS Depth-first search is stack. The process is quite similar to the BFS algorithm.
- In DFS, the edges that go to an unvisited node are called discovery edges while the edges that go to an already visited node are called block edges.

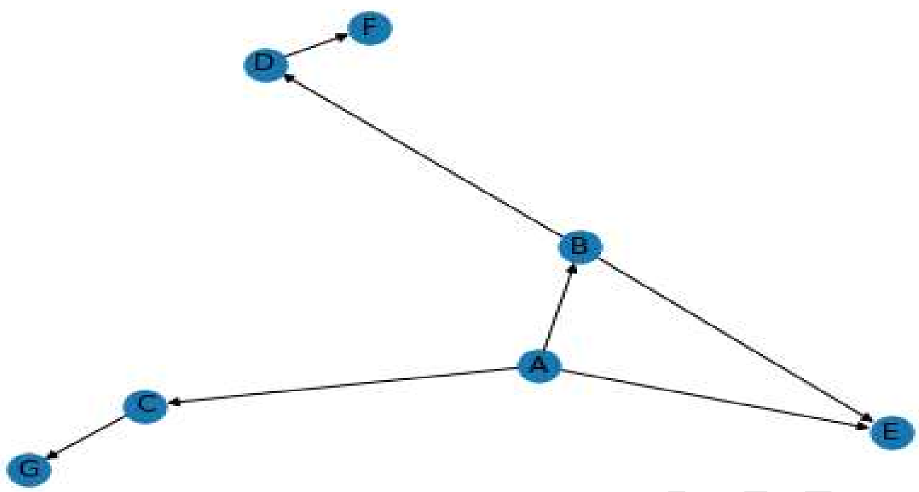


CODE:

```
class Graph:
    def __init__(self, vertices):
        self.vertices = vertices
        self.graph = {i: [] for i in range(vertices)}

    def add_edge(self, u, v):
        self.graph[u].append(v)

    def dfs(self, start):
        visited = [False] * self.vertices
        stack = []
        stack.append(start)

        while stack:
            node = stack.pop()

            if not visited[node]:
                print(node, end=" ")
                visited[node] = True

            for neighbor in reversed(self.graph[node]):
                if not visited[neighbor]:
                    stack.append(neighbor)

if __name__ == "__main__":
    g = Graph(5)
    g.add_edge(0, 1)
    g.add_edge(0, 2)
    g.add_edge(1, 3)
    g.add_edge(1, 4)

    print("DFS Traversal starting from vertex 0:")
    g.dfs(0)
```

OUTPUT:

```
Following is DFS from (starting from vertex A)
A B D F E C G
```

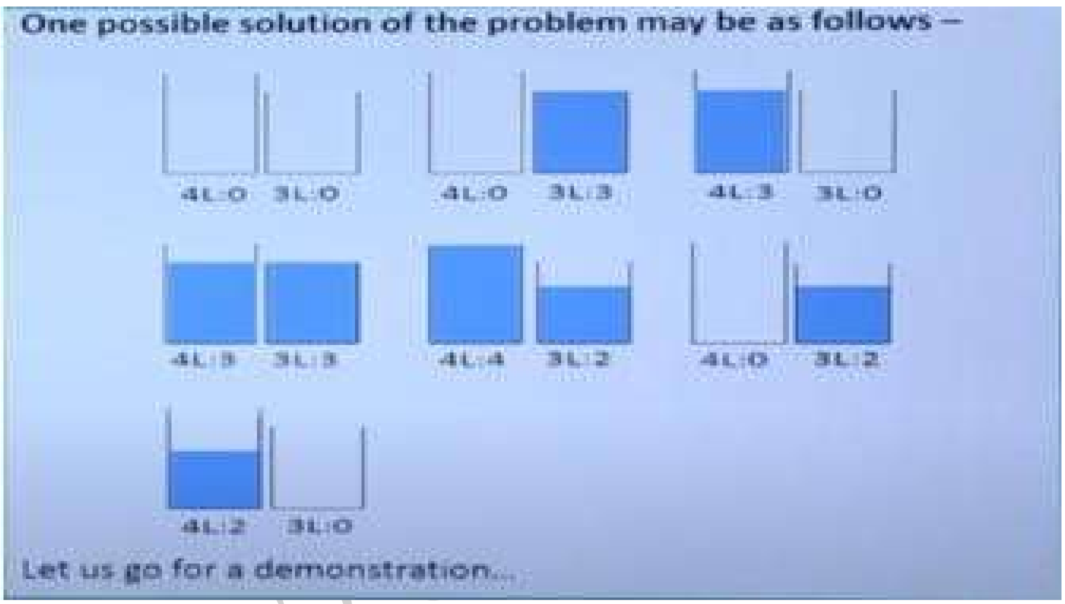


RESULT:
Thus, the code has been successfully executed, and the output has been verified successfully.

EX.NO: **DATE:**

DEPTH-FIRST SEARCH – WATER JUG PROBLEM

In the **water jug problem in Artificial Intelligence**, we are provided with two jugs: one having the capacity to hold 3 gallons of water and the other has the capacity to hold 4 gallons of water. There is no other measuring equipment available and the jugs also do not have any kind of marking on them. So, the agent's task here is to fill the 4-gallon jug with 2 gallons of water by using only these two jugs and no other material. Initially, both our jugs are empty.



CODE:

```
from collections import deque

def DFS(a, b, target):

    m = {}
    isSolvable = False
    path = []
    q = deque()

    q.append((0, 0))

    while (len(q) > 0):
        u = q.popleft()
        if ((u[0], u[1]) in m):
            continue

        if ((u[0] > a or u[1] > b or
             u[0] < 0 or u[1] < 0)):
            continue

        path.append([u[0], u[1]])

        m[(u[0], u[1])] = 1

        if (u[0] == target or u[1] == target):
            isSolvable = True

            if (u[0] == target):
                if (u[1] != 0):

                    path.append([u[0], 0])
            else:
                if (u[0] != 0):
                 path.append([0, u[1]])
                sz = len(path)
               for i in range(sz):
                 print("(", path[i][0], ",",path[i][1], ")")
            break
        q.append([u[0], b])
        q.append([a, u[1]])
 for ap in range(max(a, b) + 1):
            c = u[0] + ap
            d = u[1] - ap

            if (c == a or (d == 0 and d >= 0)):
                q.append([c, d])
```

```
            c = u[0] - ap
            d = u[1] + ap

            if ((c == 0 and c >= 0) or d == b):
                q.append([c, d])

        q.append([a, 0])
        q.append([0, b])
    if (not isSolvable):
        print ("No solution")

Jug1, Jug2, target = 4, 3, 2
print("Path from initial state ""to solution state ::")
DFS(Jug1, Jug2, target)
```

OUTPUT:

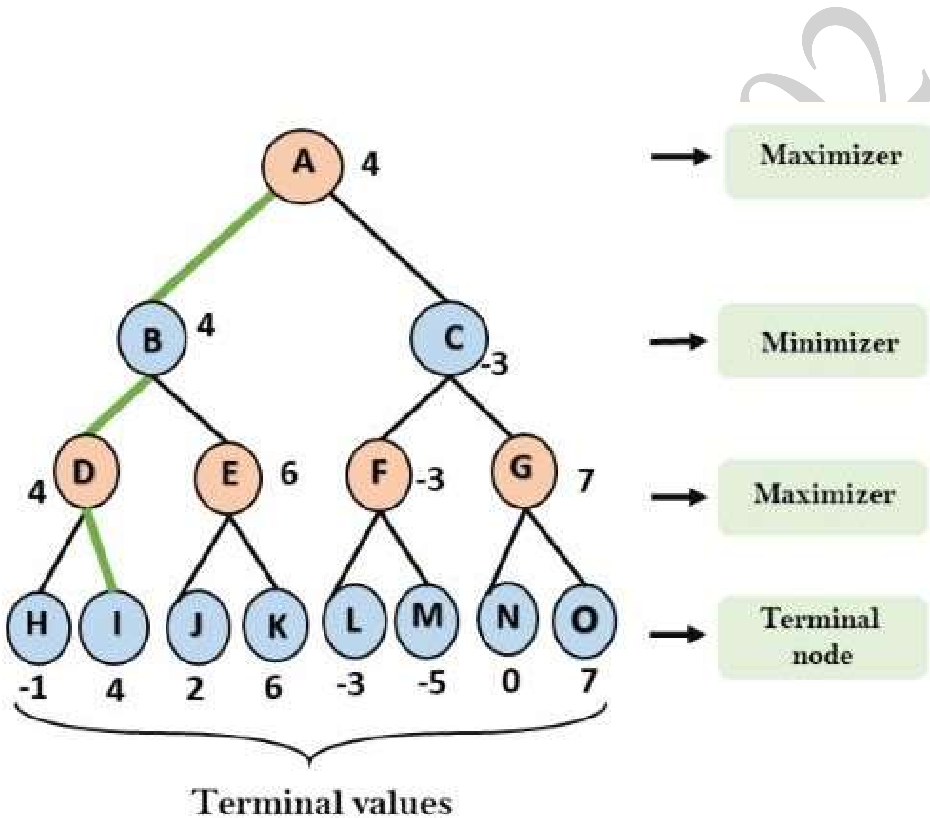
```
Path from initial state to solution state ::
( 0 , 0 )
( 0 , 3 )
( 4 , 0 )
( 4 , 3 )
( 3 , 0 )
( 1 , 3 )
( 3 , 3 )
( 4 , 2 )
( 0 , 2 )
```


RESULT:
Thus, the code has been successfully executed, and the output has been verified successfully.

EX.NO: **DATE:**

MINIMAX ALGORITHM

- A simple example can be used to explain how the minimax algorithm works. We've included an example of a game-tree below, which represents a two-player game.
- There are two players in this scenario, one named Maximizer and the other named Minimizer.
- Maximizer will strive for the highest possible score, while Minimizer will strive for the lowest possible score.
- Because this algorithm uses DFS, we must go all the way through the leaves to reach the terminal nodes in this game-tree.
- The terminal values are given at the terminal node, so we'll compare them and retrace the tree till we reach the original state.



CODE:

```
from math import inf as infinity
from random import choice
import platform
import time
from os import system
HUMAN = -1
COMP = +1
board = [
    [0, 0, 0],
    [0, 0, 0],
    [0, 0, 0],
]
def evaluate(state):
   if wins(state, COMP):
        score = +1
    elif wins(state, HUMAN):
        score = -1
    else:
        score = 0
return score

def wins(state, player):

    win_state = [
        [state[0][0], state[0][1], state[0][2]],
        [state[1][0], state[1][1], state[1][2]],
        [state[2][0], state[2][1], state[2][2]],
        [state[0][0], state[1][0], state[2][0]],
        [state[0][1], state[1][1], state[2][1]],
        [state[0][2], state[1][2], state[2][2]],
        [state[0][0], state[1][1], state[2][2]],
        [state[2][0], state[1][1], state[0][2]],
    ]
    if [player, player, player] in win_state:
        return True
    else:
        return False
def game_over(state):
return wins(state, HUMAN) or wins(state, COMP)
def empty_cells(state):
    cells = []
    for x, row in enumerate(state):
        for y, cell in enumerate(row):
            if cell == 0:
                cells.append([x, y])

  return cells
def valid_move(x, y):
```

```
    if [x, y] in empty_cells(board):
        return True
    else:
        return False
def set_move(x, y, player):

    if valid_move(x, y):
        board[x][y] = player
        return True
    else:
        return False
def minimax(state, depth, player):
    if player == COMP:
        best = [-1, -1, -infinity]
    else:
        best = [-1, -1, +infinity]

    if depth == 0 or game_over(state):
        score = evaluate(state)
        return [-1, -1, score]
    for cell in empty_cells(state):
        x, y = cell[0], cell[1]
        state[x][y] = player
        score = minimax(state, depth - 1, -player)
        state[x][y] = 0
        score[0], score[1] = x, y

        if player == COMP:
            if score[2] > best[2]:
                best = score  # max value
        else:
            if score[2] < best[2]:
                best = score  # min value

    return best

def clean():

    os_name = platform.system().lower()
    if 'windows' in os_name:
        system('cls')
    else:
        system('clear')

def render(state, c_choice, h_choice):
    chars = {
        -1: h_choice,
        +1: c_choice,
```

```
        0: ' '

    }
    str_line = '---------------'

    print('\n' + str_line)
    for row in state:
        for cell in row:
            symbol = chars[cell]
            print(f'| {symbol} |', end='')
        print('\n' + str_line)

def ai_turn(c_choice, h_choice):

    depth = len(empty_cells(board))
    if depth == 0 or game_over(board):
        return

    clean()
    print(f'Computer turn [{c_choice}]')
    render(board, c_choice, h_choice)

    if depth == 9:
        x = choice([0, 1, 2])
        y = choice([0, 1, 2])
    else:
        move = minimax(board, depth, COMP)
        x, y = move[0], move[1]

    set_move(x, y, COMP)
    time.sleep(1)

def human_turn(c_choice, h_choice):

    depth = len(empty_cells(board))
    if depth == 0 or game_over(board):
        return
    move = -1
    moves = {
        1: [0, 0], 2: [0, 1], 3: [0, 2],
        4: [1, 0], 5: [1, 1], 6: [1, 2],
        7: [2, 0], 8: [2, 1], 9: [2, 2],
    }

    clean()
    print(f'Human turn [{h_choice}]')
    render(board, c_choice, h_choice)
    while move < 1 or move > 9:
        try:
```

```
            move = int(input('Use numpad (1..9): '))
            coord = moves[move]

            can_move = set_move(coord[0], coord[1], HUMAN)
            if not can_move:
                print('Bad move')
                move = -1
        except (EOFError, KeyboardInterrupt):
            print('Bye')
            exit()
        except (KeyError, ValueError):
            print('Bad choice')

def main():

    clean()
    h_choice = ''  # X or O
    c_choice = ''  # X or O
    first = ''  # if human is the first

    while h_choice != 'O' and h_choice != 'X':
        try:
            print('')
            h_choice = input('Choose X or O\nChosen: ').upper()
        except (EOFError, KeyboardInterrupt):
            print('Bye')
            exit()
        except (KeyError, ValueError):
            print('Bad choice')


    if h_choice == 'X':
        c_choice = 'O'
    else:
        c_choice = 'X'

    clean()
    while first != 'Y' and first != 'N':
        try:
            first = input('First to start?[y/n]: ').upper()
        except (EOFError, KeyboardInterrupt):
            print('Bye')
            exit()
        except (KeyError, ValueError):
            print('Bad choice')
```

```
    while len(empty_cells(board)) > 0 and not game_over(board):
        if first == 'N':
            ai_turn(c_choice, h_choice)
            first = ''

        human_turn(c_choice, h_choice)
        ai_turn(c_choice, h_choice)

    if wins(board, HUMAN):
        clean()
        print(f'Human turn [{h_choice}]')
        render(board, c_choice, h_choice)
        print('YOU WIN!')
    elif wins(board, COMP):
        clean()
        print(f'Computer turn [{c_choice}]')
        render(board, c_choice, h_choice)
        print('YOU LOSE!')
    else:
        clean()
        render(board, c_choice, h_choice)
        print('DRAW!')

    exit()
if __name__ == '__main__':
    main()
```

OUTPUT:

```
varun@Varuns-MacBook-Air CN % python3 minimax.py

Choose X or O
Chosen: x
First to start?[y/n]: y
Human turn [X]

---------------
|   ||   ||   |
---------------
|   ||   ||   |
---------------
|   ||   ||   |
---------------
Use numpad (1..9): 4
Computer turn [O]

---------------
|   ||   ||   |
---------------
| X ||   ||   |
---------------
|   ||   ||   |
---------------
Human turn [X]

---------------
| O ||   ||   |
---------------
| X ||   ||   |
---------------
|   ||   ||   |
---------------
Use numpad (1..9): 2
Computer turn [O]

---------------
| O || X ||   |
---------------
| X ||   ||   |
---------------
|   ||   ||   |
---------------
Human turn [X]

---------------
| O || X ||   |
---------------
| X || O ||   |
---------------
|   ||   ||   |
---------------
Use numpad (1..9): 3
Computer turn [O]

---------------
| O || X || X |
---------------
| X || O ||   |
---------------
|   ||   ||   |
---------------
Computer turn [O]

---------------
| O || X || X |
---------------
| X || O ||   |
---------------
|   ||   || O |
---------------
YOU LOSE!
varun@Varuns-MacBook-Air CN %
```

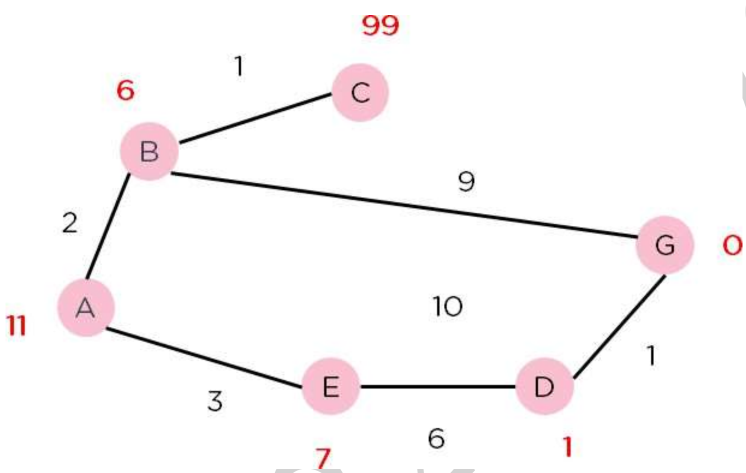
RESULT:

Thus, the code has been successfully executed, and the output has been verified successfully.

EX.No : **DATE :**

A* SEARCH ALGORITHM

A heuristic algorithm sacrifices optimality, with precision and accuracy for speed, to solve problems faster and more efficiently.
All graphs have different nodes or points which the algorithm has to take, to reach the final node. The paths between these nodes all have a numerical value, which is considered as the weight of the path. The total of all paths transverse gives you the cost of that route.
Initially, the Algorithm calculates the cost to all its immediate neighboring nodes,n, and chooses the one incurring the least cost. This process repeats until no new nodes can be chosen and all paths have been traversed. Then, you should consider the best path among them. If f(n) represents the final cost, then it can be denoted as :
$f(n) = g(n) + h(n)$, where :
$g(n)$ = cost of traversing from one node to another. This will vary from node to node
$h(n)$ = heuristic approximation of the node's value. This is not a real value but an approximation cost.



CODE:

```
from collections import deque

class Graph:
    def __init__(self, adjac_lis):
        self.adjac_lis = adjac_lis

    def get_neighbors(self, v):
        return self.adjac_lis[v]

    def h(self, n):
        H = {
            'A': 1,
            'B': 1,
            'C': 1,
            'D': 1
        }
        return H[n]

    def a_star_algorithm(self, start, stop):
        open_lst = set([start])
        closed_lst = set([])
        poo = {}
        poo[start] = 0
        par = {}
        par[start] = start

        while len(open_lst) > 0:
            n = None
            for v in open_lst:
                if n == None or poo[v] + self.h(v) < poo[n] + self.h(n):
                    n = v;

            if n == None:
                print('Path does not exist!')
                return None

            if n == stop:
                reconst_path = []

                while par[n] != n:
                    reconst_path.append(n)
                    n = par[n]

                reconst_path.append(start)

                reconst_path.reverse()
```

```
                print('Path found: {}'.format(reconst_path))
                return reconst_path


            for (m, weight) in self.get_neighbors(n):
                if m not in open_lst and m not in closed_lst:
                    open_lst.add(m)
                    par[m] = n
                    poo[m] = poo[n] + weight
                else:
                    if poo[m] > poo[n] + weight:
                        poo[m] = poo[n] + weight
                        par[m] = n

                        if m in closed_lst:
                            closed_lst.remove(m)
                            open_lst.add(m)
            open_lst.remove(n)
            closed_lst.add(n)

        print('Path does not exist!')
        return None

adjac_lis = {
    'A': [('B', 1), ('C', 3), ('D', 7)],
    'B': [('D', 5)],
    'C': [('D', 12)]
}
graph1 = Graph(adjac_lis)
graph1.a_star_algorithm('A', 'D')
```

OUTPUT:

```
Path found: ['A', 'B', 'D']
```

RESULT:

Thus, the code has been successfully executed, and the output has been verified successfully.

EX.NO : **DATE:**

INTRODUCTION TO PROLOG

AIM

To learn PROLOG terminologies and write basic programs.

TERMINOLOGIES

1. Atomic Terms: -

    Atomic terms are usually strings made up of lower- and uppercase letters, digits, and the underscore, starting with a lowercase letter.

    Ex:

        dog
        ab_c_321

2. Variables: -

    Variables are strings of letters, digits, and the underscore, starting with a capital letter or an underscore.

    Ex:

        Dog
        Apple_420

3. Compound Terms: -

    Compound terms are made up of a PROLOG atom and a number of arguments (PROLOG terms, i.e., atoms, numbers, variables, or other compound terms) enclosed in parentheses and separated by commas.

    Ex:

        is_bigger(elephant,X)
        f(g(X,_),7)

4. Facts: -

    A fact is a predicate followed by a dot.

    Ex:

        bigger_animal(whale).
        life_is_beautiful.

5. Rules: -

    A rule consists of a head (a predicate) and a body (a sequence of predicates separated by commas).

    Ex:

        is_smaller(X,Y):-is_bigger(Y,X).
        aunt(Aunt,Child):-sister(Aunt,Parent),parent(Parent,Child).

SOURCE CODE:

KB1:

```
woman(mia).
woman(jody).
woman(yolanda).
```

playsAirGuitar(jody).
party.
Query 1: ?-woman(mia).
Query 2: ?-playsAirGuitar(mia).
Query 3: ?-party.
Query 4: ?-concert.

OUTPUT: -

```
?- woman(mia).
true.

?- playsAirGuitar(mia).
false.

?- party.
true.

?- concert.
ERROR: Unknown procedure: concert/0 (DWIM could not correct goal)
?-
```

KB2:
happy(yolanda).
listens2music(mia).
Listens2music(yolanda):-happy(yolanda).
playsAirGuitar(mia):-listens2music(mia).
playsAirGuitar(Yolanda):-listens2music(yolanda).

OUTPUT: -

```
?- playsAirGuitar(mia).
true .

?- playsAirGuitar(yolanda).
true.

?-
```

KB3:
likes(dan,sally).
likes(sally,dan).
likes(john,brittney).
married(X,Y) :- likes(X,Y) , likes(Y,X).
friends(X,Y) :- likes(X,Y) ; likes(Y,X).

OUTPUT: -

```
?- likes(dan,X).
X = sally.

?- married(dan,sally).
true.

?- married(john,brittney).
false.
```

KB4:

food(burger).
food(sandwich).
food(pizza).
lunch(sandwich).
dinner(pizza).
meal(X):-food(X).

OUTPUT:

```
?-
|    food(pizza).
true.

?- meal(X),lunch(X).
X = sandwich ,

?- dinner(sandwich).
false.

?-
```

KB5:

owns(jack,car(bmw)).
owns(john,car(chevy)).
owns(olivia,car(civic)).
owns(jane,car(chevy)).
sedan(car(bmw)).
sedan(car(civic)).
truck(car(chevy)).

OUTPUT:

```
?-
|    owns(john,X).
X = car(chevy).

?- owns(john,_).
true.

?- owns(Who,car(chevy)).
Who = john ,

?- owns(jane,X),sedan(X).
false.

?- owns(jane,X),truck(X).
X = car(chevy).
```

RESULT:

Thus, the code has been successfully executed, and the output has been verified successfully.

EX.NO **DATE :**

PROLOG- FAMILY TREE

AIM :

To develop a family tree program using PROLOG with all possible facts, rules, and queries.

SOURCE CODE:
KNOWLEDGE BASE:

```
/*FACTS :: */
male(peter).
male(john).
male(chris).
male(kevin).

female(betty).
female(jeny).
female(lisa).
female(helen).

parentOf(chris,peter).
parentOf(chris,betty).
parentOf(helen,peter).
parentOf(helen,betty).
parentOf(kevin,chris).
parentOf(kevin,lisa).
parentOf(jeny,john).
parentOf(jeny,helen).

/*RULES :: */
/* son,parent
* son,grandparent*/

father(X,Y):- male(Y), parentOf(X,Y).

mother(X,Y):- female(Y), parentOf(X,Y).

grandfather(X,Y):- male(Y),parentOf(X,Z),parentOf(Z,Y).

grandmother(X,Y):- female(Y),parentOf(X,Z),parentOf(Z,Y).

brother(X,Y):- male(Y), father(X,Z), father(Y,W),Z==W.

sister(X,Y):- female(Y), father(X,Z),father(Y,W),Z==W.
```

OUTPUT:

RESULT:
Thus, the code has been successfully executed, and the output has been verified successfully.

EX.NO : **DATE :**

UNIFICATION AND RESOLUTION

AIM:

To execute programs based on Unification and Resolution.

Deduction in prolog is based on the Unification and Instantiation. Let's understand these terminologies by examples rather than by definitions. Remember one thing, matching terms are unified and variables get instantiated. In other words, Unification leads to Instantiation

Example 1: Let s see for below the prolog program - how unification and instantiation take place after querying.

Facts :

likes(john, jane).
likes(jane, john).

Query :

?- likes(john, X).
Answer : X = jane.

Here upon asking the query first prolog start to search matching terms in Facts in top-down manner for likes predicate with two arguments and it can match likes(john, ...) i.e. Unification. Then it looks for the value of X asked in query and it returns answer X = jane i.e. Instantiation - X is instantiated to jane .

Example 2 : At the prolog query prompt, when you write below query,

?- owns(X, car(bmw)) = owns(Y, car(C)).

You will get Answer : X = Y, C = bmw.

Here owns(X, car(bmw)) and owns(Y, car(C)) unifies -- because (i) predicate names owns are same on both side (ii) number of arguments for that predicate, i.e. 2, are equal both side. (iii) 2nd argument with car predicate inside the brackets are same both side and even in that predicate again number of arguments are same. So, here terms unify in which X=Y. So, Y is substituted with X -- i.e. written as {X | Y} and C is instantiated to bmw, -- written as {bmw | C} and this is called Unification with Instantiation.

But when you write ?- owns(X, car(bmw)) = likes(Y, car(C)). then prolog will return false since it can not match the owns and likes predicates.

Resolution is one kind of proof technique that works this way - (i) select two clauses that contain conflicting terms (ii) combine those two clauses and (iii) cancel out the conflicting terms.

For example we have following statements,

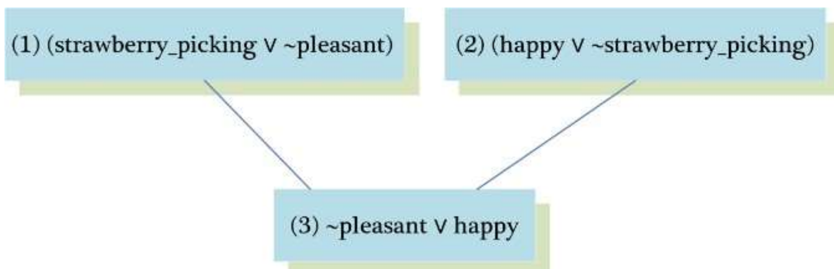
(1) If it is a pleasant day you will do strawberry picking
(2) If you are doing strawberry picking you are happy.

Above statements can be written in propositional logic like this -

(1) strawberry_picking ← pleasant
(2) happy ← strawberry_picking

And again these statements can be written in CNF like this -

(1) (strawberry_picking ∨~pleasant) ∧
(2) (happy ∨~strawberry_picking)
By resolving these two clauses and cancelling out the conflicting terms strawberry_picking and ~strawberry_picking , we can have one new clause,
(3) ~pleasant ∨ happy
How ? See the figure on right.
When we write above new clause in infer or implies form, we have
pleasant → happy or happy ← pleasant
i.e. If it is a pleasant day you are happy.

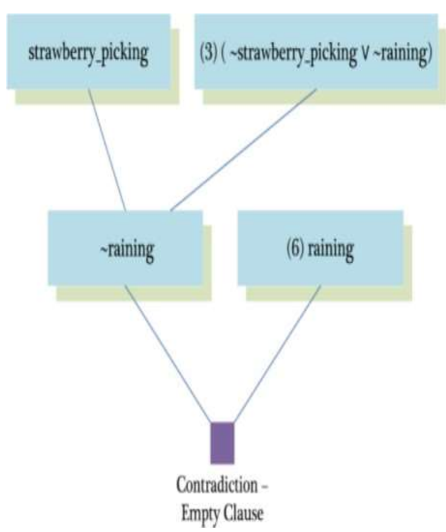


But sometimes from the collection of the statements we have, we want to know the answer of this question - "Is it possible to prove some other statements from what we actually know?" In order to prove this we need to make some inferences and those other statements can be shown true using Refutation proof method i.e. proof by contradiction using Resolution. So for the asked goal we will negate the goal and will add it to the given statements to prove the contradiction.
Let s see an example to understand how Resolution and Refutation work. In below example, Part(I) represents the English meanings for the clauses, Part(II) represents the propositional logic statements for given english sentences, Part(III) represents the Conjunctive Normal Form (CNF) of Part(II) and Part(IV) shows some other statements we want to prove using Refutation proof method.
Part(I) : English Sentences
(1) If it is sunny and warm day you will enjoy.
(2) If it is warm and pleasant day you will do strawberry picking

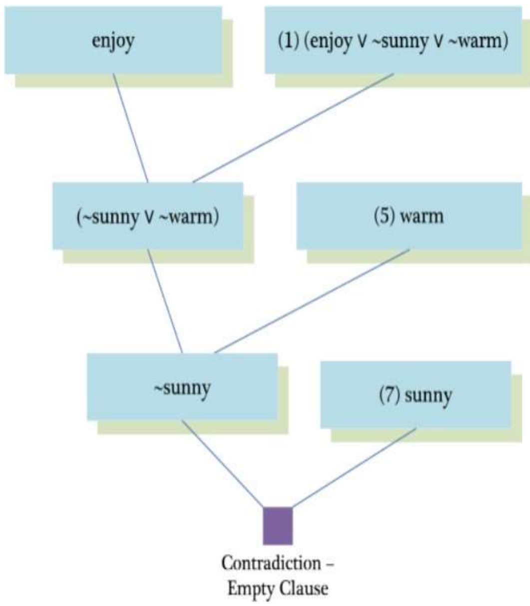
(3) If it is raining then no strawberry picking.
(4) If it is raining you will get wet.
(5) It is warm day
(6) It is raining
(7) It is sunny
Part(II) : Propositional Statements
(1) enjoy ← sunny ∧ warm
(2) strawberry_picking ← warm ∧ pleasant
(3) ~strawberry_picking ← raining
(4) wet ← raining

(5) warm
(6) raining
(7) sunny
Part(III) : CNF of Part(II)
(1) (enjoy ∨~sunny∨~warm) ∧
(2) (strawberry_picking ∨~warm∨~pleasant) ∧
(3) (~strawberry_picking ∨~raining) ∧
(4) (wet ∨~raining) ∧
(5) (warm) ∧
(6) (raining) ∧
(7) (sunny)

Part(IV) : Other statements we want to prove by Refutation
(Goal 1) You are not doing strawberry picking.
(Goal 2) You will enjoy.
(Goal 3) Try it yourself : You will get wet.
Goal 1 : You are not doing strawberry picking.
Prove : ~strawberry_picking
Assume : strawberry_picking (negate the goal and add it to given clauses).



Goal 2 : You will enjoy.
Prove : enjoy
Assume : ~enjoy (negate the goal and add it to given clauses)



SOURCE CODE:

```
enjoy:-sunny,warm.
strawberrry_picking:-warm,plesant.
notstrawberry_picking:-raining.
wet:-raining.
warm.
raining.
sunny.
```

OUTPUT:

```
?- notstrawberry_picking.
true.

?- enjoy.
true.

?- wet.
true.
```

RESULT:

Thus, the code has been successfully executed, and the output has been verified successfully.

EX.NO : **DATE :**

FUZZY LOGIC – IMAGE PROCESSING

An edge is a boundary between two uniform regions. You can detect an edge by comparing the intensity of neighbouring pixels. However, because uniform regions are not crisply defined, small intensity differences between two neighbouring pixels do not always represent an edge. Instead, the intensity difference might represent a shading effect. The fuzzy logic approach for image processing allows you to use membership functions to define the degree to which a pixel belongs to an edge or a uniform region.
Import RGB Image and Convert to Grayscale

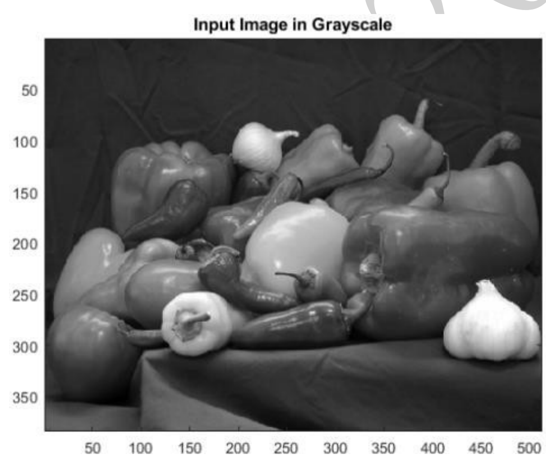
Import the image.

```
Irgb = imread('peppers.png');
```

Irgb is a 384 x 512 x 3 uint8 array. The three channels of Irgb (third array dimension) represent the red, green, and blue intensities of the image.

Convert Irgb to grayscale so that you can work with a 2-D array instead of a 3-D array. To do so, use the rgb2gray function.

```
Igray = rgb2gray(Irgb);
figure
image(Igray,'CDataMapping','scaled')
colormap('gray')
title('Input Image in Grayscale')
```



Convert Image to Double-Precision Data

The evalfis function for evaluating fuzzy inference systems supports only single-precision and double-precision data.
Therefore, convert Igray to a double array using the im2double function.

```
I = im2double(Igray);
```

Obtain Image Gradient

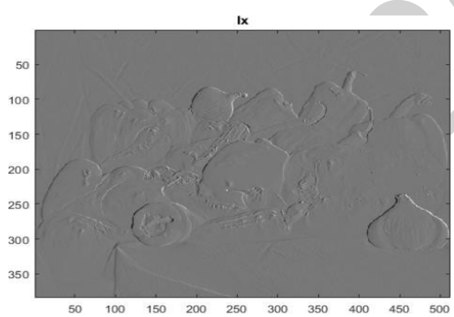
The fuzzy logic edge-detection algorithm for this example relies on the image gradient to locate breaks in uniform regions. Calculate the image gradient along the x-axis and y-axis.

Gx and Gy are simple gradient filters. To obtain a matrix containing the x-axis gradients of I, you convolve I with Gx using the conv2 function. The gradient values are in the [-1 1] range. Similarly, to obtain the y-axis gradients of I, convolve I with
Gy.

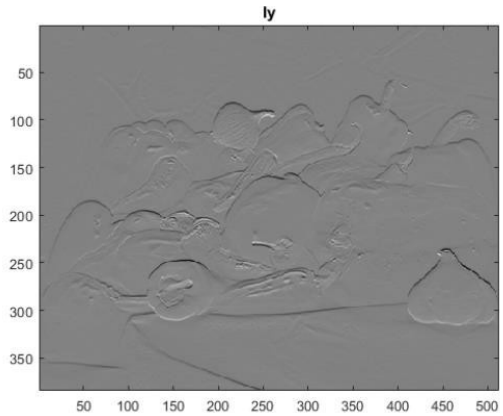
```
Gx = [-1 1];
Gy = Gx';
Ix = conv2(I,Gx,'same');
Iy = conv2(I,Gy,'same');
```

Plot the image gradients.

```
figure
image(Ix,'CDataMapping','scaled')
colormap('gray')
title('Ix')
```




```
figure
image(Iy,'CDataMapping','scaled')
colormap('gray')
title('Iy')
```



Define Fuzzy Inference System (FIS) for Edge Detection
Create a fuzzy inference system (FIS) for edge detection, edgeFIS.

edgeFIS = mamfis('Name','edgeDetection');
Specify the image gradients, Ix and Iy, as the inputs of edgeFIS.
edgeFIS = addInput(edgeFIS,[-1 1],'Name','Ix');
edgeFIS = addInput(edgeFIS,[-1 1],'Name','Iy');

Specify a zero-mean Gaussian membership function for each input. If the gradient value for a pixel is 0, then it belongs to
the zero membership function with a degree of 1.
sx = 0.1;
sy = 0.1;
edgeFIS = addMF(edgeFIS,'Ix','gaussmf',[sx 0],'Name','zero');
edgeFIS = addMF(edgeFIS,'Iy','gaussmf',[sy 0],'Name','zero');
sx and sy specify the standard deviation for the zero membership function for the Ix and Iy inputs.

To adjust the edge detector performance, you can change the values of sx and sy. Increasing the values makes the algorithm less sensitive to the edges in the image and decreases the intensity of the detected edges.

Specify the intensity of the edge-detected image as an output of edgeFIS.
edgeFIS = addOutput(edgeFIS,[0 1],'Name','Iout');

Specify the triangular membership functions, white and black, for Iout.
wa = 0.1;
wb = 1;
wc = 1;
ba = 0;
bb = 0;
bc = 0.7;

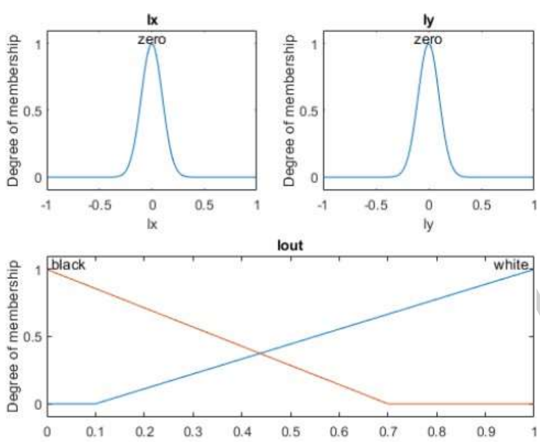
edgeFIS = addMF(edgeFIS,'Iout','trimf',[wa wb wc],'Name','white');

edgeFIS = addMF(edgeFIS,'Iout','trimf',[ba bb bc],'Name','black');

As you can with sx and sy, you can change the values of wa, wb, wc, ba, bb, and bc to adjust the edge detector performance. The triplets specify the start, peak, and end of the triangles of the membership functions. These parameters influence the intensity of the detected edges.

Plot the membership functions of the inputs and outputs of edgeFIS.

```
figure
subplot(2,2,1)
plotmf(edgeFIS,'input',1)
title('Ix')
subplot(2,2,2)
plotmf(edgeFIS,'input',2)
title('Iy')
subplot(2,2,[3 4])
plotmf(edgeFIS,'output',1)
title('Iout')
```



Specify FIS Rules

Add rules to make a pixel white if it belongs to a uniform region and black otherwise. A pixel is in a uniform region when the image gradient is zero in both directions. If either direction has a nonzero gradient, then the pixel is on an edge.

```
r1 = "If Ix is zero and Iy is zero then Iout is white";
r2 = "If Ix is not zero or Iy is not zero then Iout is black";
edgeFIS = addRule(edgeFIS,[r1 r2]);
edgeFIS.Rules
ans =
1x2 fisrule array with properties:
```

Description
Antecedent
Consequent
Weight
Connection
Details:
Description

---

1 "Ix==zero & Iy==zero => Iout=white (1)"
2 "Ix~=zero | Iy~=zero => Iout=black (1)"

Evaluate FIS

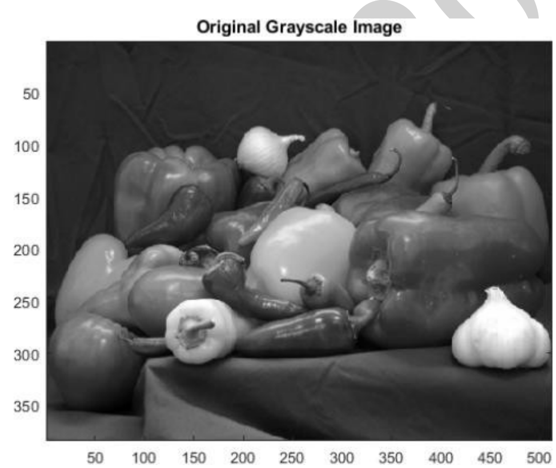
Evaluate the output of the edge detector for each row of pixels in I using corresponding rows of Ix and Iy as inputs.

```
Ieval = zeros(size(I));
for ii = 1:size(I,1)
Ieval(ii,:) = evalfis(edgeFIS,[(Ix(ii,:));(Iy(ii,:))]');
end
```

Plot Results

Plot the original grayscale image.

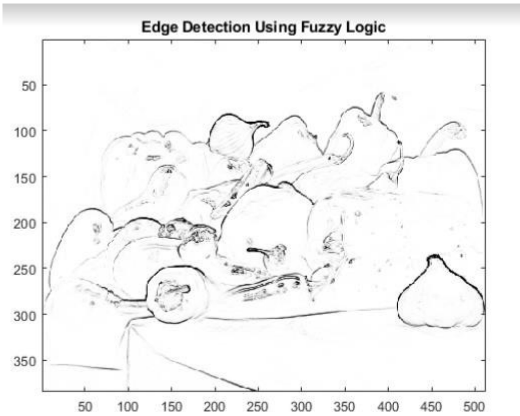
```
figure
image(I,'CDataMapping','scaled')
colormap('gray')
title('Original Grayscale Image')
```



Plot the detected edges.

```
figure
image(Ieval,'CDataMapping','scaled')
colormap('gray')
```

title('Edge Detection Using Fuzzy Logic')



RESULT:
Thus, the code has been successfully executed, and the output has been verified successfully.

EX.NO : **DATE :**

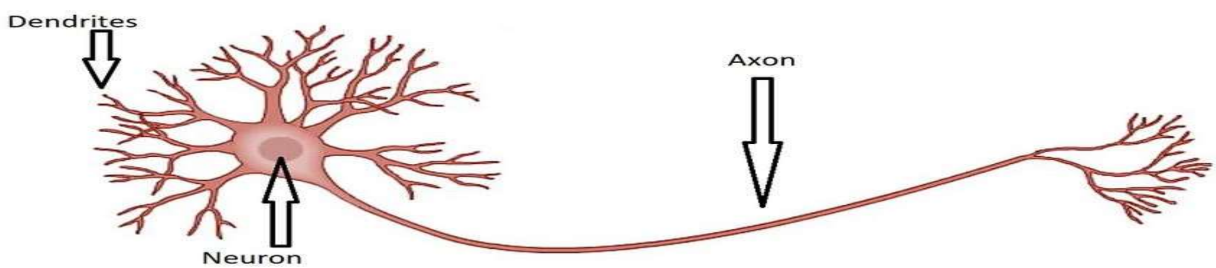
IMPLEMENTING ARTIFICIAL NEURAL NETWORKS FOR AN APPLICATION USING PYTHON - CLASSIFICATION

AIM :

To implementing artificial neural networks for an application in classification using python.

What is an Artificial Neural Network?

Artificial Neural Network is much similar to the human brain. The human Brain consist of **neurons**. These neurons are connected. In the human brain, neuron looks something like this…

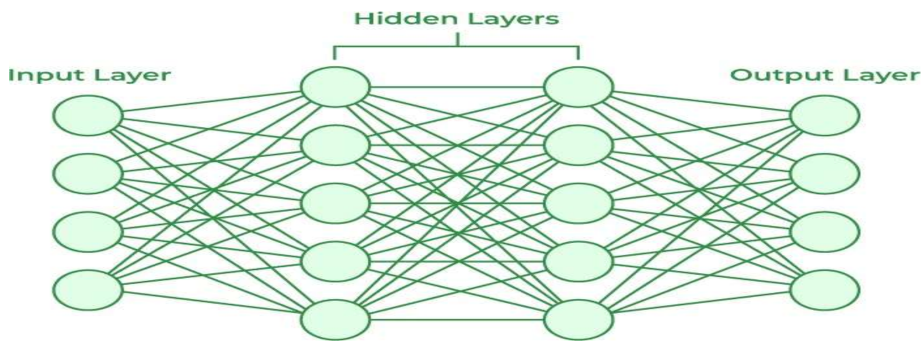


As you can see in this image, There are **neurons, Dendrites, and axons.**
What do you think?
When you touch the hot surface, how you suddenly remove your hand?. This is the procedure that happens inside you.When you touch some hot surface. Then automatically your skin sends a signal to the neuron. And then the neuron takes a decision, **"Remove your hand"**. So that's all about the **Human Brain.** In the same way, **Artificial Neural Network works.**

Artificial Neural Networks

Artificial Neural Networks contain artificial neurons which are called **units**. These units are arranged in a series of layers that together constitute the whole Artificial Neural Network in a system. A layer can have only a dozen units or millions of units as this depends on how the complex neural networks will be required to learn the hidden patterns in the dataset. Commonly, Artificial Neural Network has an input layer, an output layer as well as hidden layers. The input layer receives data from the outside world which the neural network needs to analyze or learn about. Then this data passes through one or multiple hidden layers that transform the input into data that is valuable for the output layer. Finally, the output layer provides an output in the form of a response of the Artificial Neural Networks to input data provided.

The structures and operations of human neurons serve as the basis for artificial neural networks. It is also known as neural networks or neural nets. The input layer of an artificial neural network is the first layer, and it receives input from external sources and releases it to the hidden layer, which is the second layer. In the hidden layer, each neuron receives input from the previous layer neurons, computes the weighted sum, and sends it to the neurons in the next layer. These connections are weighted means effects of the inputs from the previous layer are optimized more or less by assigning different-different weights to each input and it is adjusted during the training process by optimizing these weights for improved model performance.

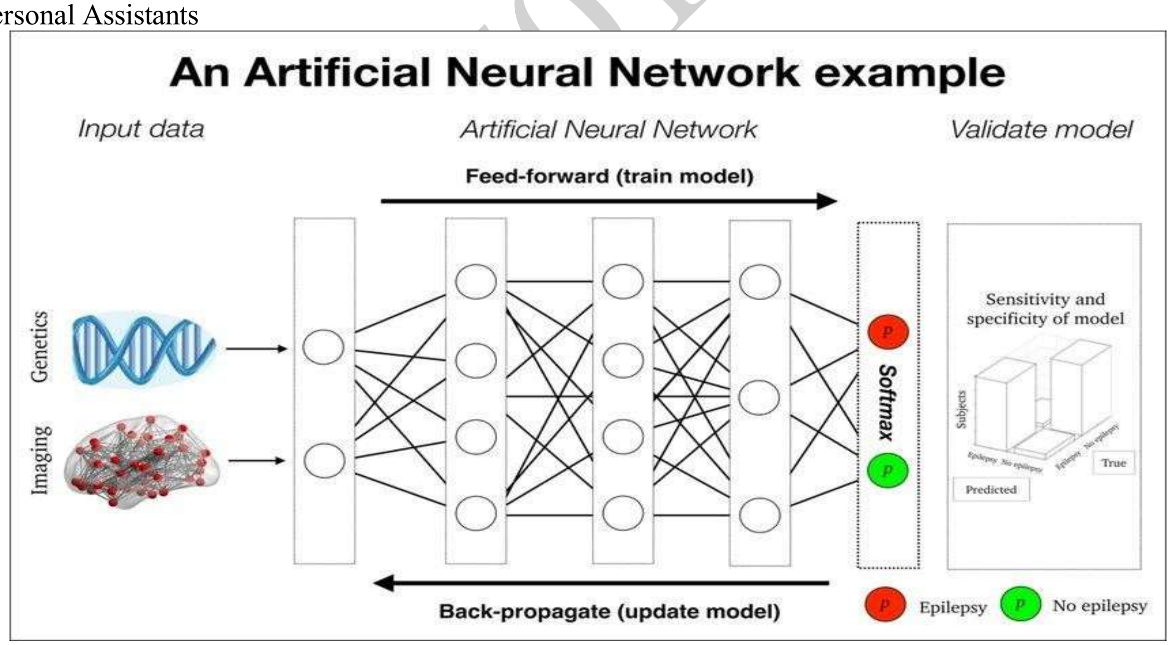


What are the types of Artificial Neural Networks?

1. Feedforward Neural Network
2. Convolutional Neural Network
3. Modular Neural Network
4. Radial basis function Neural Network
5. Recurrent Neural Network

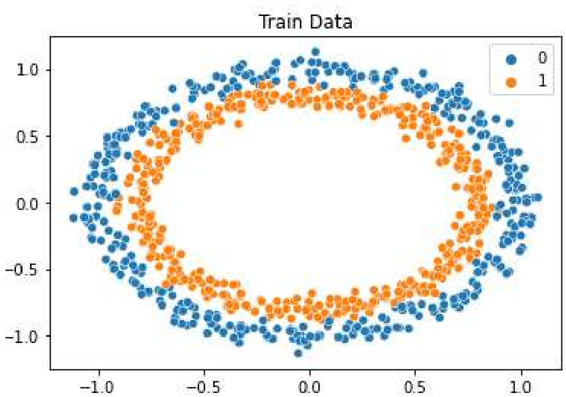
Applications of Artificial Neural Networks

1. Social Media
2. Marketing and Sales
3. Healthcare
4. Personal Assistants



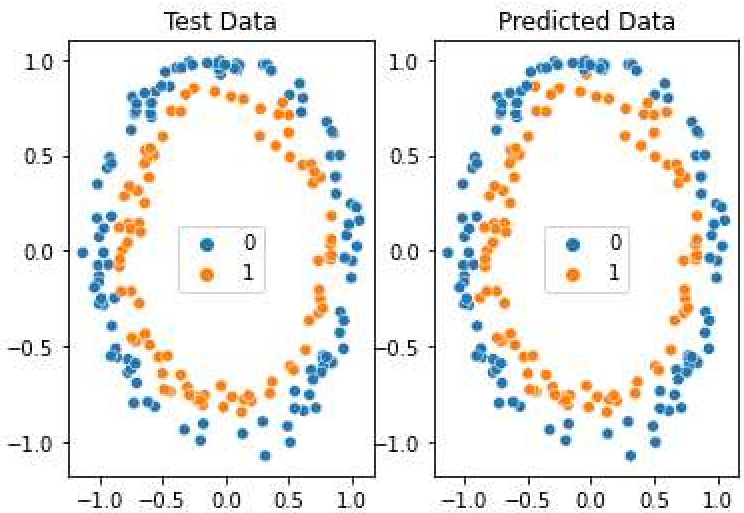
SOURCE CODE:

```
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import train_test_split
from sklearn.datasets import make_circles
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

X, y = make_circles(n_samples=1000, noise=0.05)

ns.scatterplot(X_train[:,0], X_train[:,1], hue=y_train)
plt.title("Train Data")
plt.show()
```




```
clf = MLPClassifier(max_iter=1000)
clf.fit(X_train, y_train)
print(f"R2 Score for Training Data = {clf.score(X_train, y_train)}")

print(f"R2 Score for Test Data = {clf.score(X_test, y_test)}")

y_pred = clf.predict(X_test)

fig, ax =plt.subplots(1,2)
sns.scatterplot(X_test[:,0], X_test[:,1], hue=y_pred, ax=ax[0])
ax[1].title.set_text("Predicted Data")
sns.scatterplot(X_test[:,0], X_test[:,1], hue=y_test, ax=ax[1])
ax[0].title.set_text("Test Data")
plt.show()
```

OUTPUT :



RESULT:
Thus, the code has been successfully executed, and the output has been verified successfully.

EX.NO : **DATE :**

IMPLEMENTING ARTIFICIAL NEURAL NETWORKS FOR AN APPLICATION USING PYTHON - REGRESSION

Regression using Artificial Neural Networks

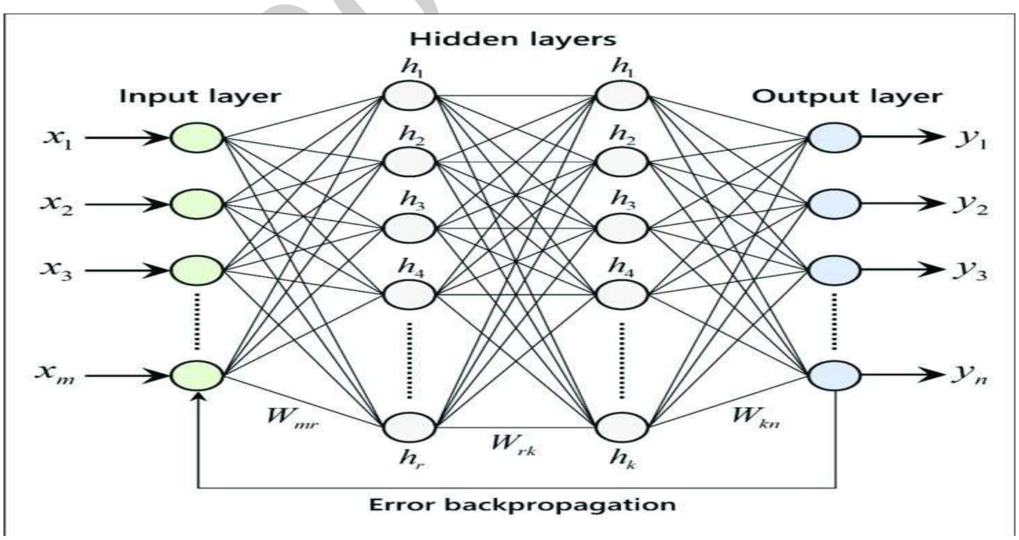
Why do we need to use Artificial Neural Networks for Regression instead of simply using Linear Regression?

The purpose of using Artificial Neural Networks for Regression over Linear Regression is that the linear regression can only learn the linear relationship between the features and target and therefore cannot learn the complex non-linear relationship. In order to learn the complex non-linear relationship between the features and target, we are in need of other techniques. One of those techniques is to use Artificial Neural Networks. Artificial Neural Networks have the ability to learn the complex relationship between the features and target due to the presence of activation function in each layer. Let's look at what are Artificial Neural Networks and how do they work.

Artificial Neural Networks

Artificial Neural Networks are one of the deep learning algorithms that simulate the workings of neurons in the human brain. There are many types of Artificial Neural Networks, Vanilla Neural Networks, Recurrent Neural Networks, and Convolutional Neural Networks. The Vanilla Neural Networks have the ability to handle structured data only, whereas the Recurrent Neural Networks and Convolutional Neural Networks have the ability to handle unstructured data very well. In this post, we are going to use Vanilla Neural Networks to perform the Regression Analysis.

Structure of Artificial Neural Networks



The Artificial Neural Networks consists of the Input layer, Hidden layers, Output layer. The hidden layer can be more than one in number. Each layer consists of n number of neurons. Each layer will be having an Activation Function associated with each of the neurons. The activation function is the function that is responsible for introducing non-linearity in the relationship. In our case, the output layer must contain a linear activation function. Each layer can also have regularizers associated with it. Regularizers are responsible for preventing overfitting.

Artificial Neural Networks consists of two phases,

- Forward Propagation
- Backward Propagation

Forward propagation is the process of multiplying weights with each feature and adding them. The bias is also added to the result. Backward propagation is the process of updating the weights in the model. Backward propagation requires an optimization function and a loss function.

AIM :

To implementing artificial neural networks for an application in Regression using python.

SOURCE CODE :

```
from sklearn.neural_network import MLPRegressor
from sklearn.model_selection import train_test_split
from sklearn.datasets import make_regression
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
X, y = make_regression(n_samples=1000, noise=0.05, n_features=100)
X.shape, y.shape // ((1000, 100), (1000,))
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, shuffle=True, random_state=42)
clf = MLPRegressor(max_iter=1000)
clf.fit(X_train, y_train)
print(f"R2 Score for Training Data = {clf.score(X_train, y_train)}")
print(f"R2 Score for Test Data = {clf.score(X_test, y_test)}")
```

OUTPUT :

R2 Score for Test Data = 0.9686558466621529

RESULT:

Thus, the code has been successfully executed, and the output has been verified successfully

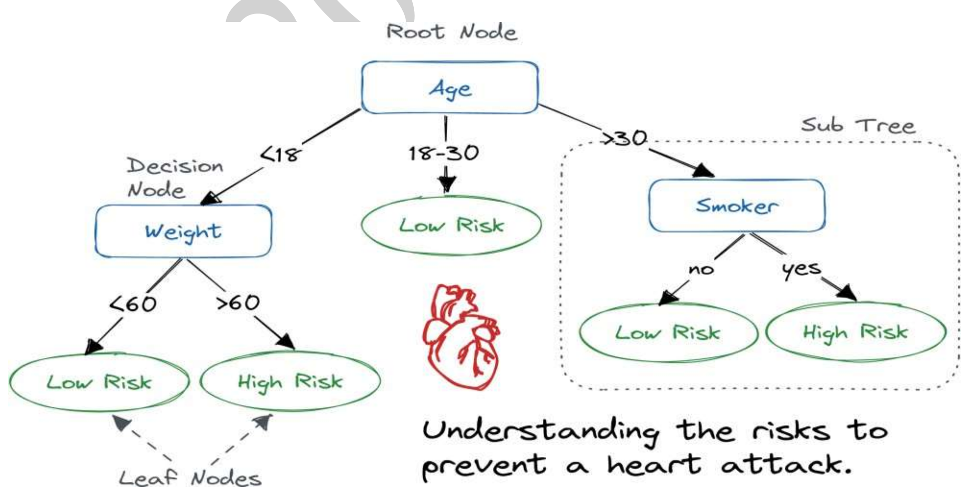
EX.NO : **DATE :**

DECISION TREE CLASSIFICATION

Classification is a two-step process; a learning step and a prediction step. In the learning step, the model is developed based on given training data. In the prediction step, the model is used to predict the response to given data. A Decision tree is one of the easiest and most popular classification algorithms used to understand and interpret data. It can be utilized for both classification and regression problems.

The Decision Tree Algorithm

A decision tree is a flowchart-like tree structure where an internal node represents a feature(or attribute), the branch represents a decision rule, and each leaf node represents the outcome.
The topmost node in a decision tree is known as the root node. It learns to partition on the basis of the attribute value. It partitions the tree in a recursive manner called recursive partitioning. This flowchart-like structure helps you in decision-making. It's visualization like a flowchart diagram which easily mimics the human level thinking. That is why decision trees are easy to understand and interpret.



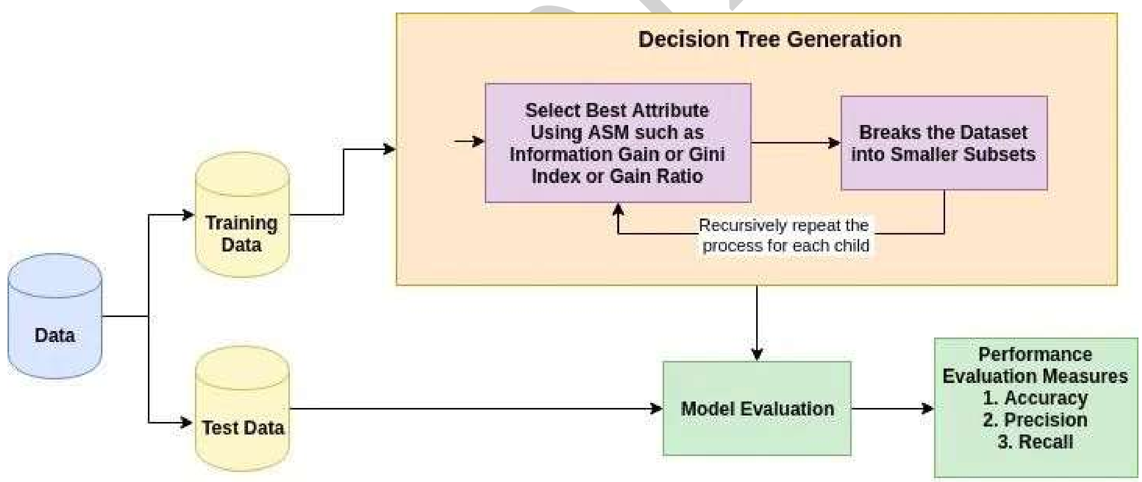
A decision tree is a white box type of ML algorithm. It shares internal decision-making logic, which is not available in the black box type of algorithms such as with a neural network. Its training time is faster compared to the neural network algorithm.

The time complexity of decision trees is a function of the number of records and attributes in the given data. The decision tree is a distribution-free or non-parametric method that does not depend upon probability distribution assumptions. Decision trees can handle high-dimensional data with good accuracy.

How Does the Decision Tree Algorithm Work?

The basic idea behind any decision tree algorithm is as follows:

1. Select the best attribute using Attribute Selection Measures (ASM) to split the records.
2. Make that attribute a decision node and breaks the dataset into smaller subsets.
3. Start tree building by repeating this process recursively for each child until one of the conditions will match:
    - All the tuples belong to the same attribute value.
    - There are no more remaining attributes.
    - There are no more instances.



AIM:

To classify the Social Network dataset using Decision tree analysis

Source Code :

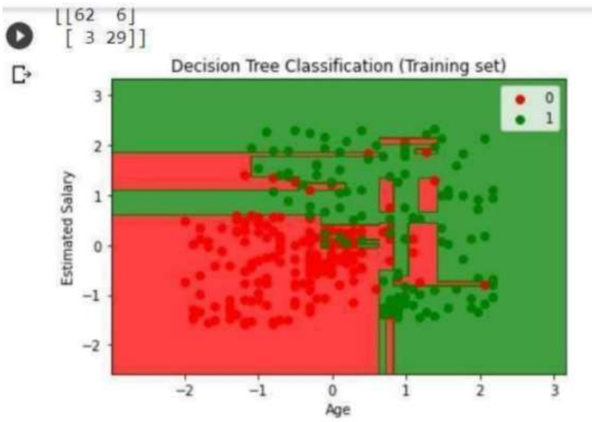
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

dataset = pd.read_csv('Social_Network_Ads.csv')
X = dataset.iloc[:, [2, 3]].values
y = dataset.iloc[:, -1].values

importtrain_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

import DecisionTreeClassifier
classifier = DecisionTreeClassifier(criterion = 'entropy', random_state = 0)

classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
import ListedColormap
X_set, y_set = X_train, y_train
```

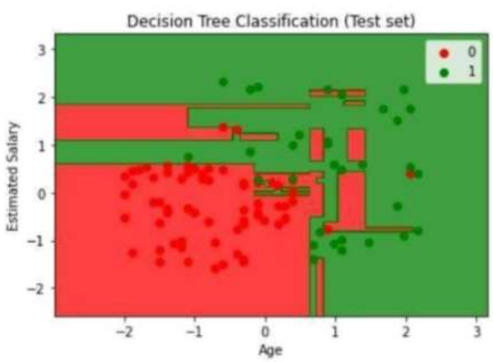
```
X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 1, stop = X_set[:, 0].max() + 1, step =
0.01), np.arange(start = X_set[:, 1].min() - 1, stop = X_set[:, 1].max() + 1, step = 0.01))
plt.contourf(X1, X2, classifier.predict(np.array([X1.ravel(),
X2.ravel()]).T).reshape(X1.shape), alpha = 0.75, cmap = ListedColormap(('red',
'green')))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())
for i, j in enumerate(np.unique(y_set)):
plt.scatter(X_set[y_set == j, 0], X_set[y_set == j,
1],
c = ListedColormap(('red', 'green'))(i), label =
j) plt.title('Decision Tree Classification
(Training set)') plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()
import ListedColormap
X_set, y_set = X_test, y_test
X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 1, stop = X_set[:, 0].max() + 1, step =
0.01), np.arange(start = X_set[:, 1].min() - 1, stop = X_set[:, 1].max() + 1, step = 0.01))
plt.contourf(X1, X2, classifier.predict(np.array([X1.ravel(),
X2.ravel()]).T).reshape(X1.shape), alpha = 0.75, cmap = ListedColormap(('red',
'green')))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())
for i, j in enumerate(np.unique(y_set)):
plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1],
c = ListedColormap(('red', 'green'))(i), label = j)
plt.title('Decision Tree Classification (Test set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
```

plt.legend()

plt.show()

OUTPUT :



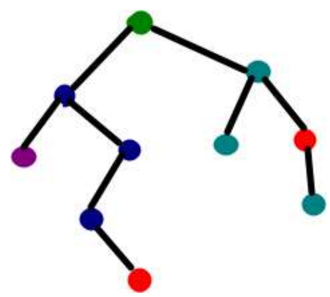


RESULT:
Thus, the code has been successfully executed, and the output has been verified successfully

EX.NO : **DATE :**

IMPLEMENTATION OF DECISION TREE CLASSIFICATION TECHNIQUES

Decision Tree is one of the most powerful and popular algorithm. Decision-tree algorithm falls under the category of supervised learning algorithms. It works for both continuous as well as categorical output variables.



AIM:

To implement a decision tree classification technique for gender classification using python.

EXPLANATION:

- Import tree from sklearn.
- Call the function DecisionTreeClassifier() from tree
- Assign values for X and Y.
- Call the function predict for Predicting on the basis of given random values for each given feature.
- Display the output.

SOURCE CODE:

```
from sklearn import tree
#Using DecisionTree classifier for prediction
clf = tree.DecisionTreeClassifier()

#Here the array contains three values which are height,weight and shoe size
X = [[181, 80, 91], [182, 90, 92], [183, 100, 92], [184, 200, 93], [185, 300, 94], [186, 400, 95], [187, 500, 96], [189, 600, 97], [190, 700, 98], [191, 800, 99], [192, 900, 100], [193, 1000, 101]]
Y = ['male', 'male', 'female', 'male' , 'female', 'male', 'female' , 'male' , 'female', 'male' , 'female' , 'male' ]
clf = clf.fit(X, Y)

#Predicting on basis of given random values for each given feature
predictionf = clf.predict([[181, 80, 91]])
predictionm = clf.predict([[183, 100, 92]])

#Printing final prediction
print(predictionf)
print(predictionm)
```

OUTPUT:

[‘male’]
[‘female’]

RESULT:

Thus, the code has been successfully executed, and the output has been verified successfully

EX NO : **DATE :**

IMPLEMENTATION OF CLUSTERING TECHNIQUES K - MEANS

The ***k*-means clustering** method is an unsupervised machine learning technique used to identify clusters of data objects in a dataset. There are many different types of clustering methods, but *k*-means is one of the oldest and most approachable. These traits make implementing *k*-means clustering in Python reasonably straightforward, even for novice programmers and data scientists.

If you're interested in learning how and when to implement *k*-means clustering in Python, then this is the right place. You'll walk through an end-to-end example of *k*-means clustering using Python, from preprocessing the data to evaluating results.

How does it work?

First, each data point is randomly assigned to one of the K clusters. Then, we compute the centroid (functionally the center) of each cluster, and reassign each data point to the cluster with the closest centroid. We repeat this process until the cluster assignments for each data point are no longer changing.

K-means clustering requires us to select K, the number of clusters we want to group the data into. The elbow method lets us graph the inertia (a distance-based metric) and visualize the point at which it starts decreasing linearly. This point is referred to as the "eblow" and is a good estimate for the best value for K based on our data.

AIM:

To implement a K - Means clustering technique using python language.

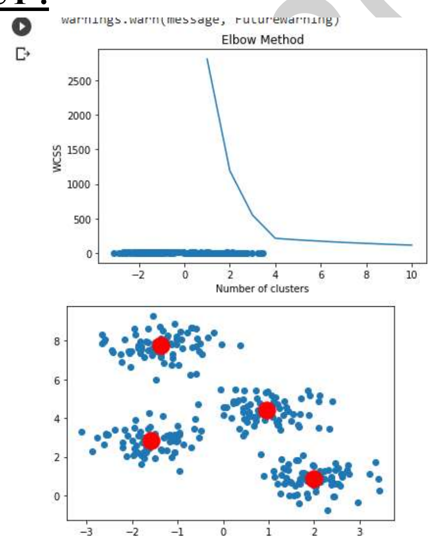
EXPLANATION:

- Import KMeans from sklearn.cluster
- Assign X and Y.
- Call the function KMeans().
- Perform scatter operation and display the output.

SOURCE CODE:

```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
from sklearn.datasets.samples_generator import make_blobs
from sklearn.cluster import KMeans
X, y = make_blobs(n_samples=300, centers=4, cluster_std=0.60, random_state=0)
plt.scatter(X[:,0], X[:,1])
wcss = []
for i in range(1, 11):
kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10, random_state=0)
kmeans.fit(X)
wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
kmeans = KMeans(n_clusters=4, init='k-means++', max_iter=300, n_init=10, random_state=0)
pred_y = kmeans.fit_predict(X)
plt.scatter(X[:,0], X[:,1])
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s=300, c='red')
plt.show()
```

OUTPUT :



RESULT:

Thus, the code has been successfully executed, and the output has been verified successfully