



||JAI SRI GURUDEV||



S J C INSTITUTE OF TECHNOLOGY

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING



ARTIFICIAL INTELLIGENCE & MACHINE LEARNING LABORATORY MANUAL [18CSL76] (VII SEM CSE-CBCS REVISED 2018 SCHEME)

Prepared By:

Prof. HARSHAVARDHAN DODDAMANI

Prof. JAGADISH N

Assistant Professors

Dept of CSE

SJCIT, Chickballapur

S.J.C.INSTITUTE OF TECHNOLOGY

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

CHICKBALLAPUR -562101

During the Year: 2021

COLLEGE VISION AND MISSION

VISION

SJCIT is committed to Quality Education, Training and Research.

MISSION

- Augmenting the supply of competent Engineers and Managers.
- Building Engineers and Managers with value, Vision and Versatility.
- Developing and Dissemination of new Knowledge and Insights.

DEPARTMENT VISION AND MISSION

Vision

To build competent professionals embedded with human values to meet the challenges in the field of Computer Science & Engineering.

Mission

- Empower the graduates with the fundamentals in design and implementation of computational systems through curriculum and research in collaboration with Industry and other organization.
- Imparting Center of Excellence in state-of-Art Infrastructure to make competent graduates by providing professionally committed Faculties.
- Inculcate Ethical values, Technical Capabilities & Leadership abilities for meeting the current and future demands of Industry and Society .

PEO's

1. PEO1 - Graduates shall have strong foundation in fundamentals to solve Engineering problems in different domains.
2. PEO2 - Graduates shall be professional in engineering practice and can demonstrate good problem solving and communication skills.
3. PEO3 - Graduates shall have successful careers as computer Science Engineers and be able to lead & manage teams.
4. PEO4 - Graduates shall be pursuing post graduation, research and engage in the process of life-long learning.

PSO's

PSO1:- Ability to adapt to a rapidly changing environment by learning and employing new programming skills and technologies.

PSO2:- Ability to use diverse knowledge across the domains with inter-personnel skills to deliver the Industry need

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING LABORATORY
(Effective from the academic year 2018 -2019)

SEMESTER – VII

CIE Marks 40

Number of Contact Hours/Week 0:0:2

Exam Hours 03

Course Code 18CSL76

SEE Marks 60

Total Number of Lab Contact Hours 36

Credits – 2

Course Learning Objectives: This course (18CSL76) will enable students to:

- Implement and evaluate AI and ML algorithms in and Python programming language.

Descriptions (if any):

Installation procedure of the required software must be demonstrated, carried out in groups and documented in the journal.

Programs List:

1. Implement A* Search algorithm.
2. Implement AO* Search algorithm.
3. For a given set of training data examples stored in a .CSV file, implement and demonstrate the Candidate-Elimination algorithm to output a description of the set of all hypotheses consistent with the training examples.
4. Write a program to demonstrate the working of the decision tree based ID3 algorithm. Use an Appropriate data set for building the decision tree and apply this knowledge to classify a new sample.
5. Build an Artificial Neural Network by implementing the Back propagation algorithm and test the Same using appropriate data sets.
6. Write a program to implement the naïve Bayesian classifier for a sample training data set stored as a .CSV file. Compute the accuracy of the classifier, considering few test data sets.
7. Apply EM algorithm to cluster a set of data stored in a .CSV file. Use the same data set for clustering using k-Means algorithm. Compare the results of these two algorithms and comment on the quality of clustering. You can add Java/Python ML library classes/API in the program.
8. Write a program to implement k-Nearest Neighbor algorithm to classify the iris data set. Print Both correct and wrong predictions. Java/Python ML library classes can be used for this problem.
9. Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs

Laboratory Course Outcomes: The student should be able to:

- Implement and demonstrate AI and ML algorithms.
- Evaluate different algorithms.

Conduct of Practical Examination:

- Experiment distribution for laboratories having only one part: Students are allowed to pick one experiment from the lot with equal opportunity.
- For laboratories having PART A and PART B: Students are allowed to pick one experiment from PART A and one experiment from PART B, with equal opportunity.
- Change of experiment is allowed only once and marks allotted for procedure to be made zero of the changed part only.
- Marks Distribution (*Coursed to change in accordance with university regulations*)
- For laboratories having only one part – Procedure + Execution + Viva-Voce: 15+70+15 = 100 Marks
- For laboratories having PART A and PART B

i. Part A – Procedure + Execution + Viva = $6 + 28 + 6 = 40$ Marks

ii. Part B – Procedure + Execution + Viva = $9 + 42 + 9 = 60$ Marks

Installing Anaconda on Windows

This tutorial will demonstrate how you can install Anaconda, a powerful package manager, on Microsoft Windows.

Anaconda is a package manager, an environment manager, and Python distribution that contains a collection of many open source packages. This is advantageous as when you are working on a data science project, you will find that you need many different packages (numpy, scikit-learn, scipy, pandas to name a few), which an installation of Anaconda comes preinstalled with. If you need additional packages after installing Anaconda, you can use Anaconda's package manager, conda, or pip to install those packages. This is highly advantageous as you don't have to manage dependencies between multiple packages yourself. Conda even makes it easy to switch between Python 2 and 3 (you can learn more [here](#)). In fact, an installation of Anaconda is also the [recommended way to install Jupyter Notebooks](#) which you can learn more about [here](#) on the DataCamp community.

This tutorial will include:

- [How to Install Anaconda on Windows](#)
- [How to test your installation and fix common installation issues](#)
- [What to do after installing Anaconda.](#)

With that, let's get started!

Download and Install Anaconda

1. Go to the [Anaconda Website](#) and choose a Python 3.x graphical installer (A) or a Python 2.x graphical installer (B). If you aren't sure which Python version you want to install, choose Python 3. Do not choose both.

Anaconda 5.1 For Windows Installer

A
Python 3.6 version *
[Download](#)
[64-Bit Graphical Installer \(537 MB\)](#) ⓘ
[32-Bit Graphical Installer \(436 MB\)](#)
B
Python 2.7 version *
[Download](#)
[64-Bit Graphical Installer \(523 MB\)](#) ⓘ
[32-Bit Graphical Installer \(420 MB\)](#)
[Behind a firewall?](#)
[How to get Python 3.5 or other Python versions](#)
[How to Install ANACONDA](#)

2. Locate your download and double click it.

Anaconda 5.1 For Windows Installer

Python 3.6 version *
[Download](#)
[64-Bit Graphical Installer \(537 MB\)](#) ⓘ
[32-Bit Graphical Installer \(436 MB\)](#)
Python 2.7 version *
[Download](#)
[64-Bit Graphical Installer \(523 MB\)](#) ⓘ
[32-Bit Graphical Installer \(420 MB\)](#)
[Behind a firewall?](#)
[How to get Python 3.5 or other Python versions](#)
[How to Install ANACONDA](#)

Get Started

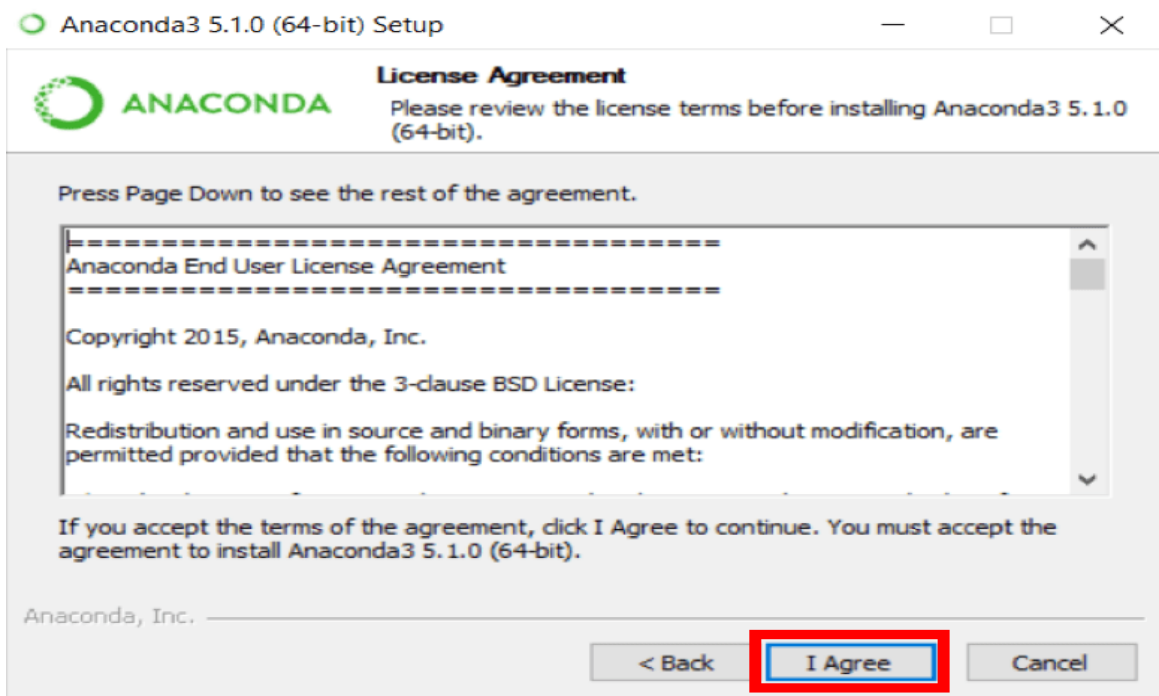
Anaconda3-5.1.0-...exe

Show all

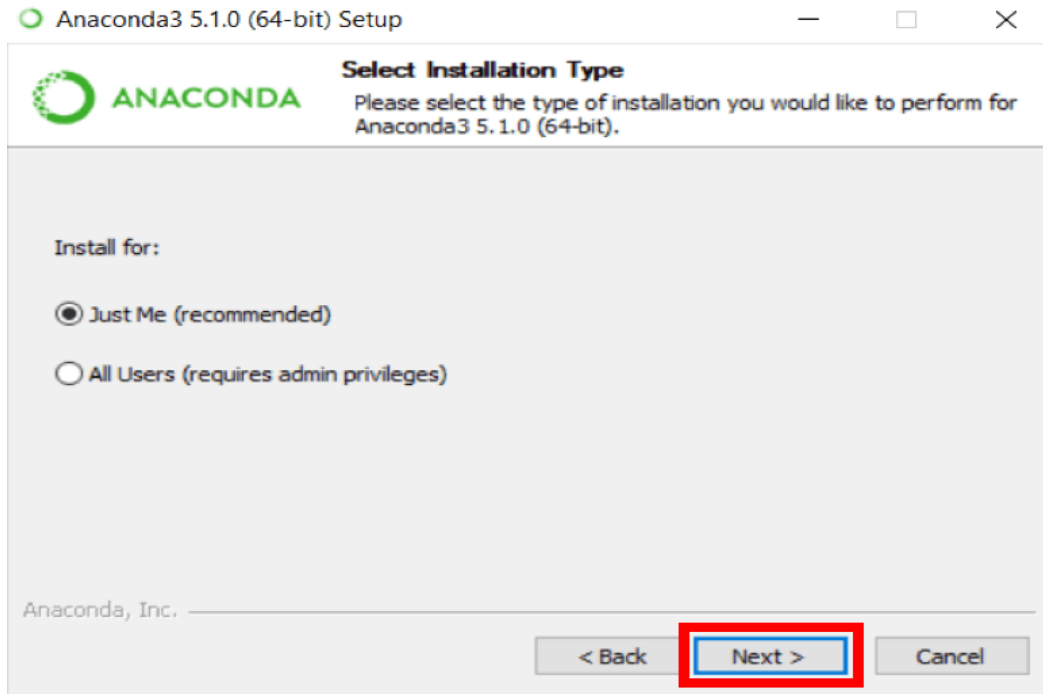
When the screen below appears, click on Next.



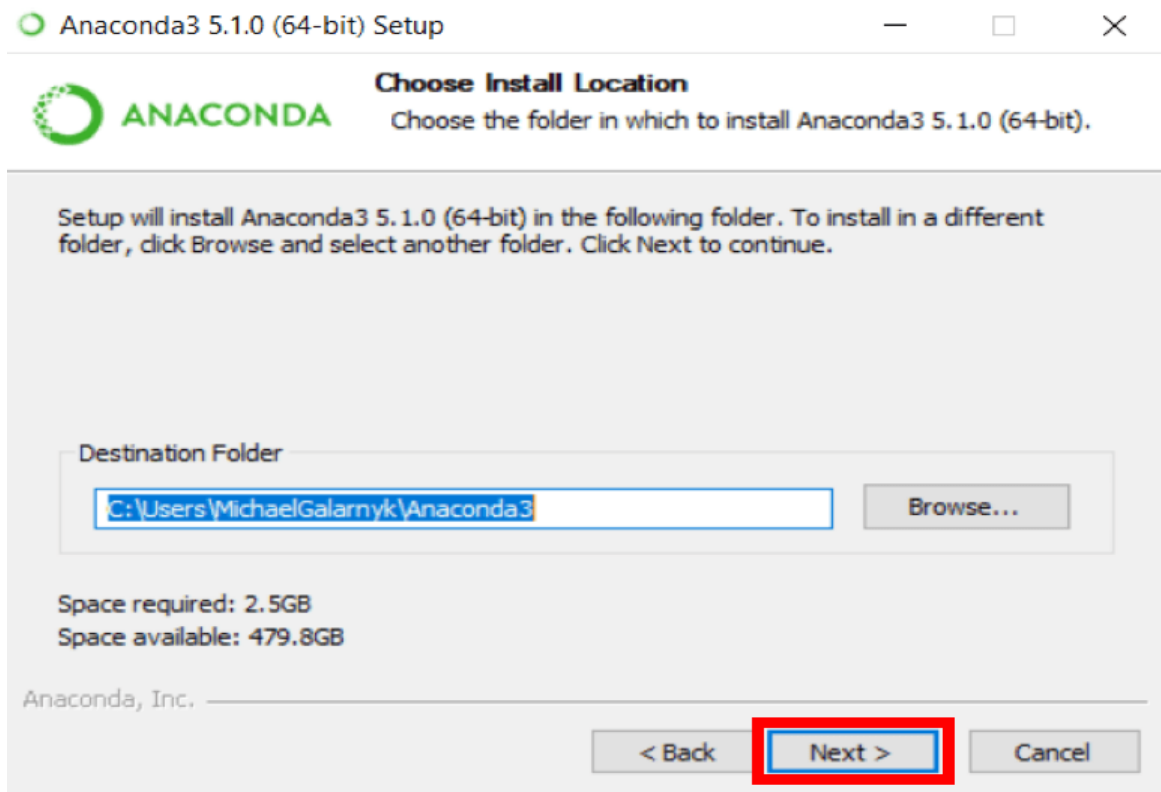
3. Read the license agreement and click on I Agree.



4. Click on Next.



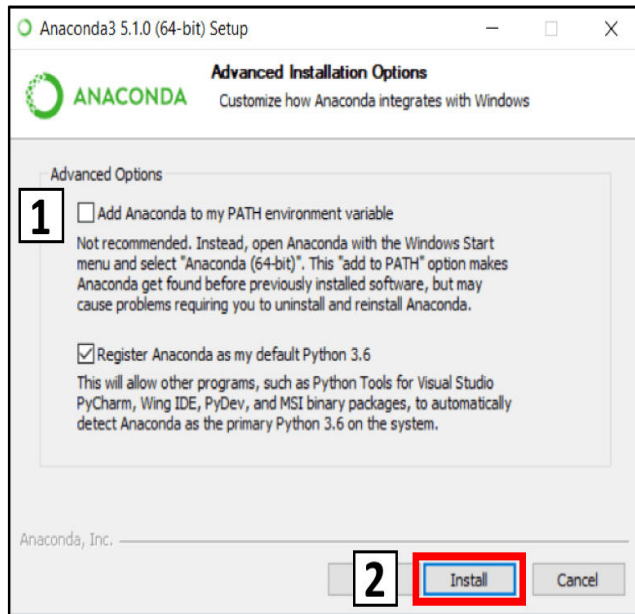
5. Note your installation location and then click Next.



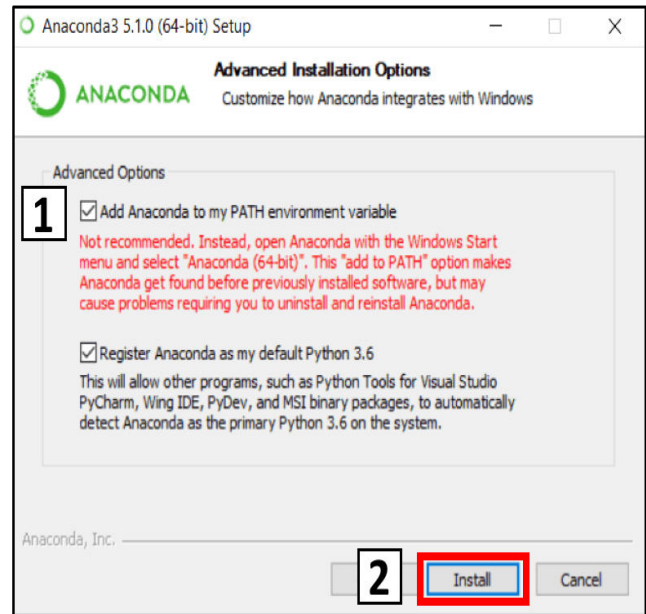
6. This is an important part of the installation process. The recommended approach is to not check the box to add Anaconda to your path. This means you will have to use Anaconda

Navigator or the Anaconda Command Prompt (located in the Start Menu under "Anaconda") when you wish to use Anaconda (you can always add Anaconda to your PATH later if you don't check the box). If you want to be able to use Anaconda in your command prompt (or git bash, cmder, powershell etc), please use the alternative approach and check the box.

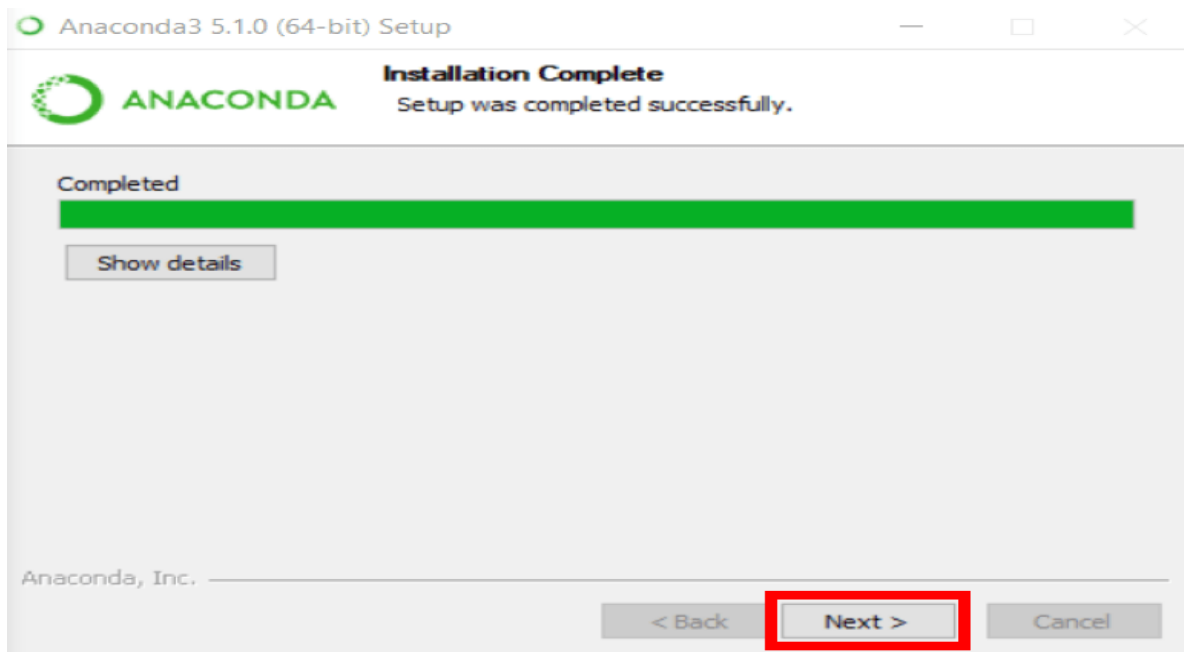
Recommended Approach



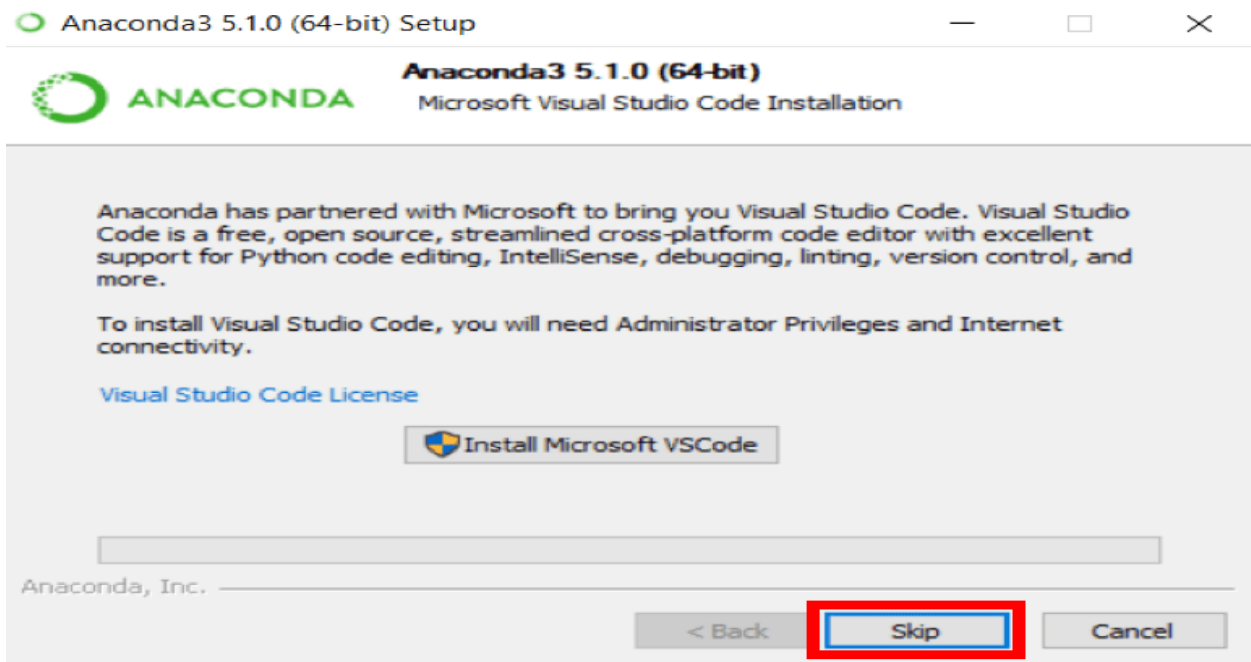
Alternative Approach



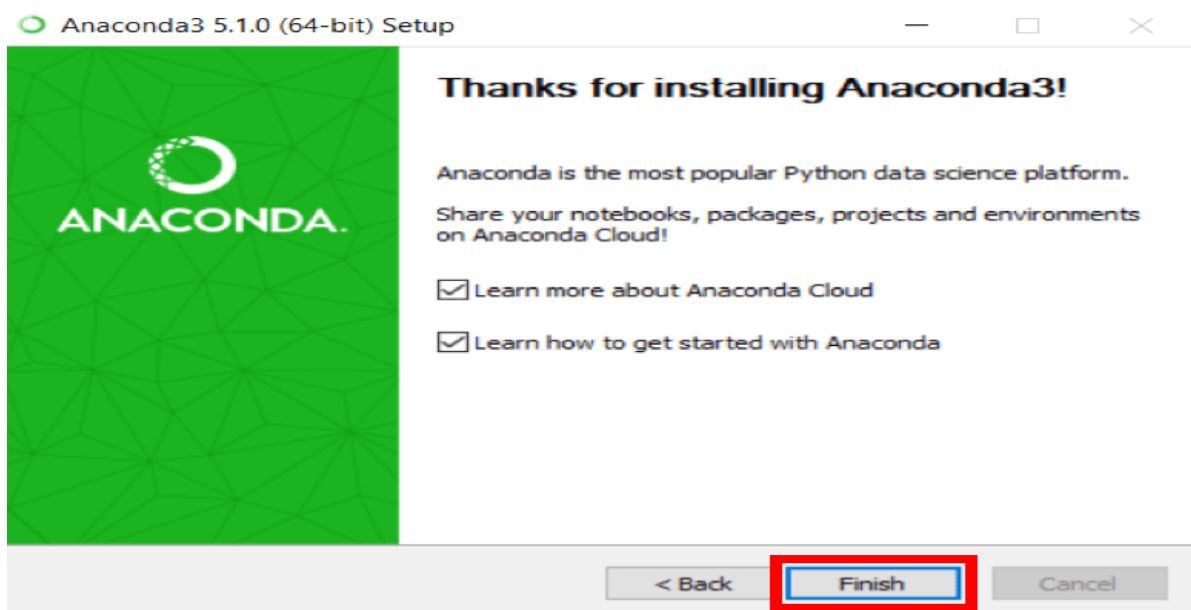
7. Click on Next.



8. You can install Microsoft VSCode if you wish, but it is optional.



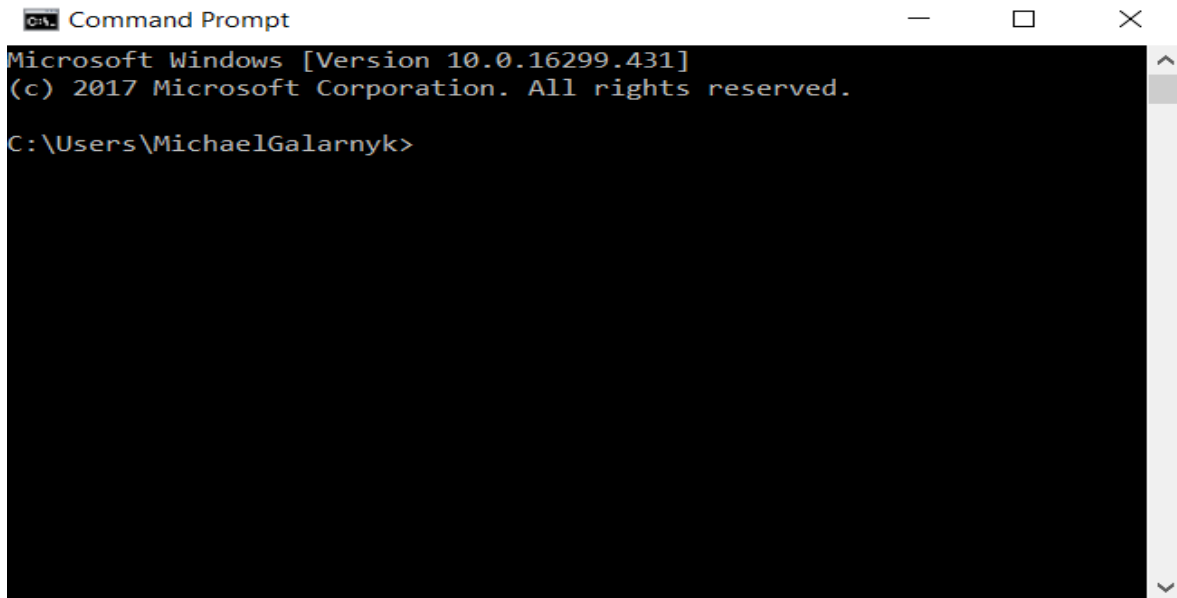
9. Click on Finish.



Add Anaconda to Path (Optional)

This is an **optional** step. This is for the case where you didn't check the box in step 6 and now want to add Anaconda to your Path. The advantage of this is that you will be able to use Anaconda in your Command Prompt, Git Bash, cmd etc.

1. Open a Command Prompt.



2. Check if you already have Anaconda added to your path. Enter the commands below into your Command Prompt. This is checking if you already have Anaconda added to your path. If you get a command **not recognized** error like in the left side of the image below, proceed to step 3. If you get an output similar to the right side of the image below, you have already added Anaconda to your path.

conda --version

python --version

Proceed to Step 3

```
Select Command Prompt
Microsoft Windows [Version 10.0.16299.431]
(c) 2017 Microsoft Corporation. All rights reserved.

C:\Users\MichaelGalarnyk>conda --version
'conda' is not recognized as an internal or external command,
operable program or batch file.

C:\Users\MichaelGalarnyk>python --version
'python' is not recognized as an internal or external command,
operable program or batch file.

C:\Users\MichaelGalarnyk>
```

Anaconda Already Added to Path

```
Select Command Prompt
Microsoft Windows [Version 10.0.16299.431]
(c) 2017 Microsoft Corporation. All rights reserved.

C:\Users\MichaelGalarnyk>conda --version
conda 4.4.10

C:\Users\MichaelGalarnyk>python --version
Python 3.6.4 :: Anaconda, Inc.

C:\Users\MichaelGalarnyk>
```

3. If you don't know where your conda and/or python is, open an **Anaconda Prompt** and type in the following commands. This is telling you where conda and python are located on your computer.

where conda

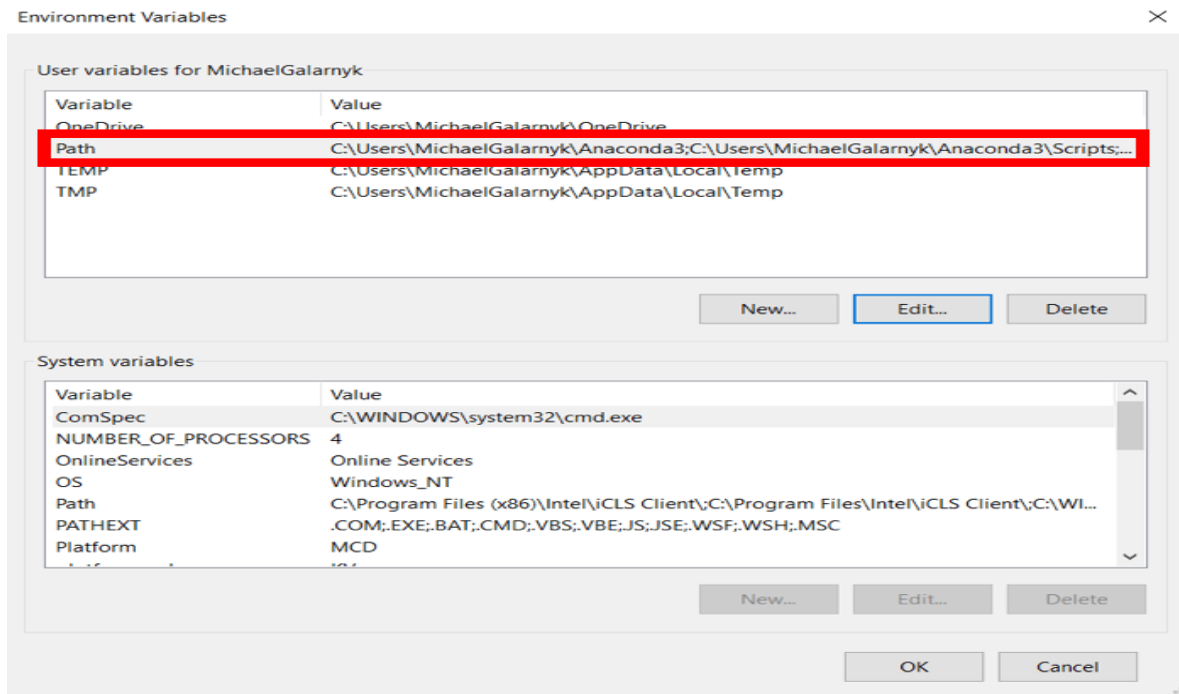
where python

```
Anaconda Prompt
(base) C:\Users\MichaelGalarnyk>where conda
C:\Users\MichaelGalarnyk\Anaconda3\Library\bin\conda.bat
C:\Users\MichaelGalarnyk\Anaconda3\Scripts conda.exe

(base) C:\Users\MichaelGalarnyk>where python
C:\Users\MichaelGalarnyk\Anaconda3 python.exe

(base) C:\Users\MichaelGalarnyk>
```

4. Add conda and python to your PATH. You can do this by going to your Environment Variables and adding the output of step 3 (enclosed in the red rectangle) to your path. If you are having issues, here is a short [video](#) on adding conda and python to your PATH.



5. Open a **new Command Prompt**. Try typing `conda --version` and `python --version` into the **Command Prompt** to check to see if everything went well.



Select Command Prompt



Microsoft Windows [Version 10.0.16299.431]
(c) 2017 Microsoft Corporation. All rights reserved.

C:\Users\MichaelGalarnyk>conda --version
conda 4.4.10

C:\Users\MichaelGalarnyk>python --version
Python 3.6.4 :: Anaconda, Inc.

C:\Users\MichaelGalarnyk>

PROGRAM.NO.1

Implement A* Search algorithm.

```
def A_star(start_node, stop_node):
```

```
    open_set = set(start_node)
```

```
    closed_set = set()
```

```
    g = { } #store distance from starting node
```

```
    parents = { } # parents contains an adjacency map of all nodes
```

```
    #distance of starting node from itself is zero
```

```
    g[start_node] = 0
```

```
    #start_node is root node i.e it has no parent nodes
```

```
    #so start_node is set to its own parent node
```

```
    parents[start_node] = start_node
```

```
    while len(open_set) > 0:
```

```
        n = None
```

```
        #node with lowest f() is found
```

```
        for v in open_set:
```

```
            if n == None or g[v] + heuristic(v) < g[n] + heuristic(n):
```

```
                n = v
```

```
    if n == stop_node or Graph_nodes[n] == None:
```

```
        pass
```

```
    else:
```

```
        for (m, weight) in get_neighbors(n):
```

```
            #nodes 'm' not in first and last set are added to first
```

```
            if m not in open_set and m not in closed_set:
```

```
                open_set.add(m)
```

```
                #n is set its parent
```

```
                parents[m] = n
```

```
                g[m] = g[n] + weight
```

```
    #for each node m,compare its distance from start i.e g(m) to the
```

```
    #from start through n node
```

```
    else:
```

```
        if g[m] > g[n] + weight: # if better cost found, then update the existing cost g(m)
            g[m] = g[n] + weight
            #change parent of m to n
            parents[m] = n

        #if m in closed set,remove and add to open
        if m in closed_set:
            closed_set.remove(m)
            open_set.add(m)

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

    # if the current node is the stop_node
    # then we begin reconstructin the path from it to the start_node
    if n == stop_node:
        path = []

        while parents[n] != n:
            path.append(n)
            n = parents[n]

        path.append(start_node)

        path.reverse()

        print('Optimal Path :')
        return path

    # remove n from the open_list, and add it to closed_list
    # because all of his neighbors were inspected
    open_set.remove(n)
    closed_set.add(n)

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

#define fuction to return neighbor and its distance
#from the passed node
```

```
def get_neighbors(v):
    if v in Graph_nodes:
        return Graph_nodes[v]
    else:
        return None
#for simplicity we ll consider heuristic distances given
#and this function returns heuristic distance for all nodes
def heuristic(n):
    H_dist = {
        'S': 8,
        'A': 8,
        'B': 4,
        'C': 3,
        'D': 1000,
        'E': 1000,
        'G': 0,
    }

    return H_dist[n]

#Describe your graph here
Graph_nodes = {'S': [['A', 1], ['B', 5], ['C', 8]],
               'A': [['D', 3], ['E', 7], ['G', 9]],
               'B': [['G', 4]],
               'C': [['G', 5]],
               'D': None,
               'E': None}

A_star('S', 'G')
```

OUTPUT:- (Note:-better to Run in Jupyter Note book of Anaconda for correct output)

Optimal Path :
['S', 'B', 'G']

PROGRAM.Mo.2(AO* Algorithm)

Implement AO* Search algorithm.

Function to implement recursive AO Algorithm*

def recAOStar(n):

global finalPath

print("Expanding Node : ", n)

and_nodes = []

or_nodes = []

#Segregation of AND and OR nodes

if (n in allNodes):

if 'AND' in allNodes[n]:

and_nodes = allNodes[n]['AND']

if 'OR' in allNodes[n]:

or_nodes = allNodes[n]['OR']

If leaf node then return

if len(and_nodes) == 0 and len(or_nodes) == 0:

return

solvable = False

marked = {}

while not solvable:

If all the child nodes are visited and expanded, take the least cost of all the child nodes

if len(marked) == len(and_nodes) + len(or_nodes):

min_cost_least, min_cost_group_least = least_cost_group(and_nodes, or_nodes, {})

solvable = True

change_heuristic(n, min_cost_least)

optimal_child_group[n] = min_cost_group_least

continue

Least cost of the unmarked child nodes

min_cost, min_cost_group = least_cost_group(and_nodes, or_nodes, marked)

is_expanded = False

If the child nodes have sub trees then recursively visit them to recalculate the heuristic of the child node

```
if len(min_cost_group) > 1:
    if (min_cost_group[0] in allNodes):
        is_expanded = True
        recAOStar(min_cost_group[0])
    if (min_cost_group[1] in allNodes):
        is_expanded = True
        recAOStar(min_cost_group[1])
else:
    if (min_cost_group in allNodes):
        is_expanded = True
        recAOStar(min_cost_group)
```

If the child node had any subtree and expanded, verify if the new heuristic value is still the least among all nodes

```
if is_expanded:
    min_cost_verify, min_cost_group_verify = least_cost_group(and_nodes, or_nodes, {})

    if min_cost_group == min_cost_group_verify:
        solvable = True
        change_heuristic(n, min_cost_verify)
        optimal_child_group[n] = min_cost_group
```

If the child node does not have any subtrees then no change in heuristic, so update the min cost of the current node

```
else:
    solvable = True
    change_heuristic(n, min_cost)
    optimal_child_group[n] = min_cost_group
```

#Mark the child node which was expanded

```
marked[min_cost_group] = 1
return heuristic(n)
```

```
# Function to calculate the min cost among all the child nodes
def least_cost_group(and_nodes, or_nodes, marked):
    node_wise_cost = {}

    for node_pair in and_nodes:
        if not node_pair[0] + node_pair[1] in marked:
            cost = 0
            cost = cost + heuristic(node_pair[0]) + heuristic(node_pair[1]) + 2
            node_wise_cost[node_pair[0] + node_pair[1]] = cost

    for node in or_nodes:
        if not node in marked:
            cost = 0
            cost = cost + heuristic(node) + 1
            node_wise_cost[node] = cost

    min_cost = 999999
    min_cost_group = None

    # Calculates the min heuristic
    for costKey in node_wise_cost:
        if node_wise_cost[costKey] < min_cost:
            min_cost = node_wise_cost[costKey]
            min_cost_group = costKey

    return [min_cost, min_cost_group]

# Returns heuristic of a node
def heuristic(n):
    return H_dist[n]

# Updates the heuristic of a node
def change_heuristic(n, cost):
    H_dist[n] = cost
    return
```

Function to print the optimal cost nodes

def print_path(node):

print(optimal_child_group[node], end="")

node = optimal_child_group[node]

if len(node) > 1:

if node[0] in optimal_child_group:

print("->", end="")

print_path(node[0])

if node[1] in optimal_child_group:

print("->", end="")

print_path(node[1])

else:

if node in optimal_child_group:

print("->", end="")

print_path(node)

#Describe the heuristic here

H_dist = { 'A': -1, 'B': 4, 'C': 2, 'D': 3, 'E': 6, 'F': 8, 'G': 2, 'H': 0, 'I': 0, 'J': 0 }

#Describe your graph here

allNodes = {

'A': {'AND': [('C', 'D')], 'OR': ['B']},

'B': {'OR': ['E', 'F']},

'C': {'OR': ['G'], 'AND': [('H', 'I')]},

'D': {'OR': ['J']}

}

optimal_child_group = {}

optimal_cost = recAOStar('A')

print('Nodes which gives optimal cost are')

print_path('A')

print('\nOptimal Cost is :: ', optimal_cost)

OUTPUT:-

Expanding Node : A

Expanding Node : B

Expanding Node : C

Expanding Node : D

Nodes which gives optimal cost are

CD->HI->J

Optimal Cost is :: 5

Program.No.3(Candidate Elimination Algorithm)

For a given set of training data examples stored in a .CSV file, implement and demonstrate the Candidate-Elimination algorithm to output a description of the set of all hypotheses consistent with the training examples.

```
dataarr=[]
with open('data/enjoysport.csv') as f:
    for line in f:
        dataarr.append(line.strip().split(','))

rows = len(dataarr)
cols = len(dataarr[0])
shypo = ['0']*(cols-1)
ghypo = ['?']*(cols-1)
print("Initial Specific Hypothesis is ", shypo)
print("Initial General Hypothesis is ", ghypo)

for x in range(1, rows):
    lst = dataarr[x]

    if lst[cols-1] == "1":
        for i in range(0, cols-1):
            if shypo[i] == lst[i]:
                continue
            shypo[i] = '?' if shypo[i] != '0' else lst[i]
        for g in ghypo:
            if g[i] != '?' and shypo[i] == '?':
                ghypo.remove(g)

    elif lst[cols-1] == "0":
        ghypo.clear()
        for i in range(0, cols-1):
            if lst[i] != shypo[i] and shypo[i] != '?':
                temp_list = ['?']*i + [shypo[i]] + ['?']*(cols-2-i)
                if temp_list not in ghypo:
                    ghypo.append(temp_list)

    print("S Hypothesis after row ", x, " = ", shypo)
    print("G Hypothesis after row ", x, " = ", ghypo)
print("Final SHypothesis ", shypo)
```

```
print("Final GHypothesis ", ghypo)
```

OUTPUT:- (Note:-Use Enjoysport csv file)

Initial Specific Hypothesis is = ['0', '0', '0', '0', '0', '0']

Initial General Hypothesis is = [['?', '?', '?', '?', '?', '?']]

S Hypothesis after row 1 = ['Sunny', 'Warm', 'Normal', 'Strong', 'Warm', 'Same']

G Hypothesis after row 1 = [['?', '?', '?', '?', '?', '?']]

S Hypothesis after row 2 = ['Sunny', 'Warm', '?', 'Strong', 'Warm', 'Same']

G Hypothesis after row 2 = [['?', '?', '?', '?', '?', '?']]

S Hypothesis after row 3 = ['Sunny', 'Warm', '?', 'Strong', 'Warm', 'Same']

G Hypothesis after row 3 = [['Sunny', '?', '?', '?', '?', '?'], ['?', 'Warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', 'Same']]

S Hypothesis after row 4 = ['Sunny', 'Warm', '?', 'Strong', '?', '?']

G Hypothesis after row 4 = [['Sunny', '?', '?', '?', '?', '?'], ['?', 'Warm', '?', '?', '?', '?']]

Final SHypothesis ['Sunny', 'Warm', '?', 'Strong', '?', '?']

Final GHypothesis [['Sunny', '?', '?', '?', '?', '?'], ['?', 'Warm', '?', '?', '?', '?']]

PROGRAM.NO.4(Decision trees)

Write a program to demonstrate the working of the decision tree based ID3 algorithm. Use an appropriate data set for building the decision tree and apply this knowledge to classify a new sample.

```
import math

def dataset_split(data, arc, val):
    newData = []
    # iterate through every record in the data-set and split the data-set
    for rec in data:
        if rec[arc] == val:
            reducedSet = list(rec[:arc])
            reducedSet.extend(rec[arc+1:])
            newData.append(reducedSet)
    return newData

def calc_entropy(data):
    # Calculate the length of the data-set
    entries = len(data)
    labels = { }
    # Read the class labels from the data-set file into the dict object "labels"
    for rec in data:
        label = rec[-1]
        if label not in labels.keys():
            labels[label] = 0
        labels[label] += 1
    entropy = 0.0
    # For every class label (x) calculate the probability p(x)
    for key in labels:
        prob = float(labels[key])/entries
        # Entropy formula calculation
        entropy -= prob * math.log(prob, 2)
    # Return the entropy of the data-set
    return entropy

def attribute_selection(data):
    features = len(data[0]) - 1
    baseEntropy = calc_entropy(data)
    max_InfoGain = 0.0
    bestAttr = -1

    for i in range(features):
        # store the values of the features in a variable
        AttrList = [rec[i] for rec in data]
```

```
# get the unique values from the feature values
uniqueVals = set(AttrList)
newEntropy = 0.0
attrEntropy = 0.0
for value in uniqueVals:
    # function call to split the data-set
    newData = dataset_split(data, i, value)

    # probability calculation
    prob = len(newData)/float(len(data))

    # entropy calculation for the attributes
    newEntropy = prob * calc_entropy(newData)
    attrEntropy += newEntropy

    # calculation of Information Gain
    infoGain = baseEntropy - attrEntropy
    # identify the attribute with max info-gain
    if infoGain > max_InfoGain:
        max_InfoGain = infoGain
        bestAttr = i

# return the attribute identified
return bestAttr

def decision_tree(data, labels):
    # list variable to store the class-labels (terminal nodes of decision tree)
    classList = [rec[-1] for rec in data]

    if classList.count(classList[0]) == len(classList):
        return classList[0]

    maxGainNode = attribute_selection(data)
    treeLabel = labels[maxGainNode]

    theTree = {treeLabel: {}}
    del(labels[maxGainNode])

    # get the unique values of the attribute identified
    nodeValues = [rec[maxGainNode] for rec in data]
    uniqueVals = set(nodeValues)
    for value in uniqueVals:
        subLabels = labels[:]

        # update the non-terminal node values of the decision tree
        theTree[treeLabel][value] = decision_tree(dataset_split(data, maxGainNode, value), subLabels)
```

```
return theTree

def print_tree(tree, level):
    if tree == 'yes' or tree == 'no':
        print(' '*level, 'd =', tree)
        return
    for key,value in tree.items():
        print(' '*level, key)
        print_tree(value, level * 2)

with open('data/tennis.csv', 'r') as csvfile:
    fdata = [line.strip() for line in csvfile]
    metadata = fdata[0].split(',')
    train_data = [x.split(',') for x in fdata[1:]]

tree = decision_tree(train_data, metadata)
print_tree(tree, 1)
print(tree)
```

OUTPUT :- (Note:-Use tennis.csv as dataset)

Outlook

overcast

d = yes

rain

Wind

weak

d = yes

strong

d = no

sunny

Humidity

high

d = no

normal

d = yes

```
{'Outlook': {'overcast': 'yes', 'rain': {'Wind': {'weak': 'yes', 'strong': 'no'}}, 'sunny': {'Humidity': {'high': 'no', 'normal': 'yes'}}}}
```

PROGRAM.No.5 (Backpropagation Algorithm)

Build an Artificial Neural Network by implementing the Backpropagation algorithm and test the same using appropriate data sets.

```
import numpy as np
X = np.array([[2, 9], [1, 5], [3, 6]], dtype=float)
y = np.array([.92], [.86], [.89]), dtype=float)
X = X/np.amax(X, axis=0)

def sigmoid(x):
    return 1 / (1 + np.exp(-x))

def der_sigmoid(x):
    return x * (1 - x)

epoch = 5000
lr = 0.01
neurons_i = 2
neurons_h = 3
neurons_o = 1

weight_h = np.random.uniform(size=(neurons_i, neurons_h))
bias_h = np.random.uniform(size=(1, neurons_h))
weight_o = np.random.uniform(size=(neurons_h, neurons_o))
bias_o = np.random.uniform(size=(1, neurons_o))

for i in range(epoch):
    inp_h = np.dot(X, weight_h) + bias_h
    out_h = sigmoid(inp_h)

    inp_o = np.dot(out_h, weight_o) + bias_o
    out_o = sigmoid(inp_o)

    err_o = y - out_o
    grad_o = der_sigmoid(out_o)
    delta_o = err_o * grad_o

    err_h = delta_o.dot(weight_o.T)
    grad_h = der_sigmoid(out_h)
    delta_h = err_h * grad_h

    weight_o += out_h.T.dot(delta_o) * lr
    weight_h += X.T.dot(delta_h) * lr

print('Input: ', X)
print('Actual: ', y)
print('Predicted: ', out_o)
```

OUTPUT:-

Input: [[0.66666667 1.]
[0.33333333 0.55555556]
[1. 0.66666667]]
Actual: [[0.92]
[0.86]
[0.89]]
Predicted: [[0.89371021]
[0.87852765]
[0.89052431]]

PROGRAM.NO.6 (Naive bayes Classifier)

Write a program to implement the naïve Bayesian classifier for a sample training data set stored as a .CSV file. Compute the accuracy of the classifier, considering few test data sets.

```
import pandas as pd
import numpy as np
mush = pd.read_csv("data/mushrooms.csv")
mush = mush.replace('?', np.nan)
mush.dropna(axis=1, inplace=True)
target = 'class'
features = mush.columns[mush.columns != target]
target_classes = mush[target].unique()
test = mush.sample(frac=.3)
mush = mush.drop(test.index)
cond_probs = {}
target_class_prob = {}
for t in target_classes:
    mush_t = mush[mush[target] == t][features]
    target_class_prob[t] = float(len(mush_t) / len(mush))
    class_prob = {}

    for col in mush_t.columns:
        col_prob = {}
        for val, cnt in mush_t[col].value_counts().iteritems():
            pr = cnt/len(mush_t)
            col_prob[val] = pr
        class_prob[col] = col_prob
    cond_probs[t] = class_prob
def calc_probs(x):
    probs = {}
    for t in target_classes:
        p = target_class_prob[t]
        for col, val in x.iteritems():
            try:
                p *= cond_probs[t][col][val]
            except:
                p = 0
        probs[t] = p
    return probs
def classify(x):
    probs = calc_probs(x)
    max = 0
    max_class = ""
    for cl, pr in probs.items():
        if pr > max:
            max = pr
            max_class = cl
```



```
    return max_class
b = []
for i in mush.index:
    b.append(classify(mush.loc[i, features]) == mush.loc[i, target])
print(sum(b), "correct of", len(mush))
print("Accuracy:", sum(b)/len(mush))
# Test data
b = []
for i in test.index:
    b.append(classify(test.loc[i, features]) == test.loc[i, target])
print(sum(b), "correct of", len(test))
print("Accuracy:", sum(b)/len(test))
```

OUTPUT :- (NOTE:-Use Mushroom.csv as dataset)

5671 correct of 5687
Accuracy: 0.997186565851943

2435 correct of 2437
Accuracy: 0.9991793188346327

5674 correct of 5687
Accuracy: 0.9977140847547037

2433 correct of 2437
Accuracy: 0.9983586376692655

5671 correct of 5687
Accuracy: 0.997186565851943

2434 correct of 2437
Accuracy: 0.9987689782519491

PROGRAM.No.7(K-Means and EM algorithm)

Apply EM algorithm to cluster a set of data stored in a .CSV file. Use the same data set for clustering using k-Means algorithm. Compare the results of these two algorithms and comment on the quality of clustering. You can add Java/Python ML library classes/API in the program.

```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
from sklearn.mixture import GaussianMixture
from sklearn.cluster import KMeans

data = pd.read_csv('data/ex.csv')

f1 = data['V1'].values
f2 = data['V2'].values
X = np.array(list(zip(f1, f2)))
print("x: ", X)

print('Graph for whole dataset')
plt.scatter(f1, f2, c='black') # size can be set by adding s=size as param
plt.show()

kmeans = KMeans(2)
labels = kmeans.fit(X).predict(X)
print("labels for kmeans:", labels)

print('Graph using Kmeans Algorithm')
plt.scatter(f1, f2, c=labels)

centroids = kmeans.cluster_centers_
print("centroids:", centroids)
plt.scatter(centroids[:, 0], centroids[:, 1], marker='*', c='red')

plt.show()

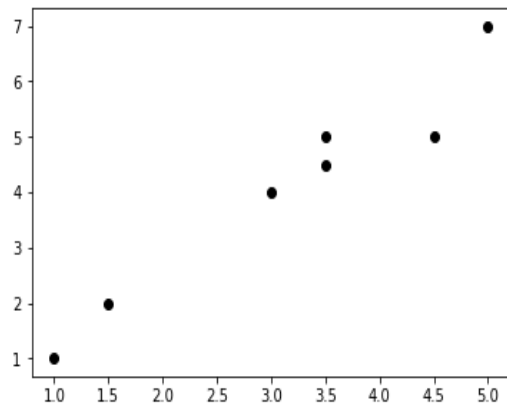
gmm = GaussianMixture(2)
labels = gmm.fit(X).predict(X)
print("Labels for GMM: ", labels)

print('Graph using EM Algorithm')
plt.scatter(f1, f2, c=labels)
plt.show()
```

OUTPUT:- (NOTE:-USE ex.csv)

x: [[1. 1.] [1.5 2.] [3. 4.] [5. 7.] [3.5 5.] [4.5 5.] [3.5 4.5]]

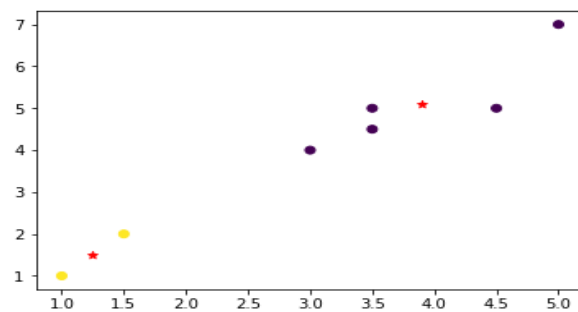
Graph for whole dataset



labels for kmeans: [1 1 0 0 0 0 0]

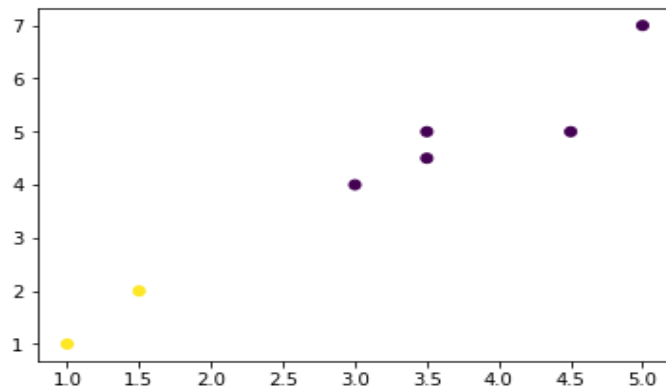
Graph using Kmeans Algorithm

centroids: [[3.9 5.1] [1.25 1.5]]



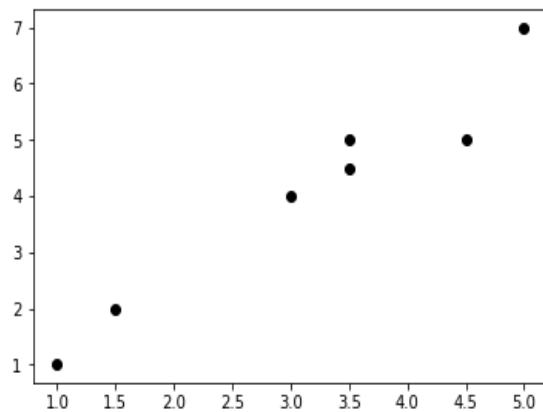
Labels for GMM: [1 1 0 0 0 0 0]

Graph using EM Algorithm



x: [[1. 1.] [1.5 2.] [3. 4.] [5. 7.] [3.5 5.] [4.5 5.] [3.5 4.5]]

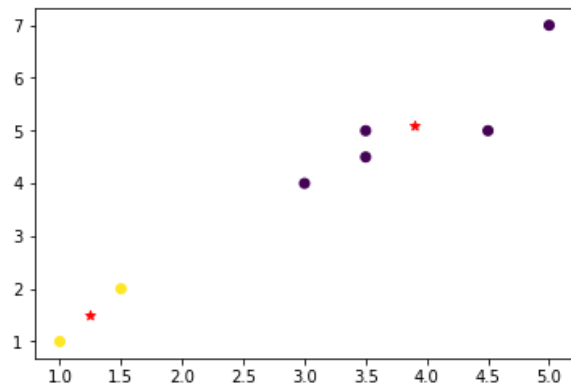
Graph for whole dataset



labels for kmeans: [1 1 0 0 0 0 0]

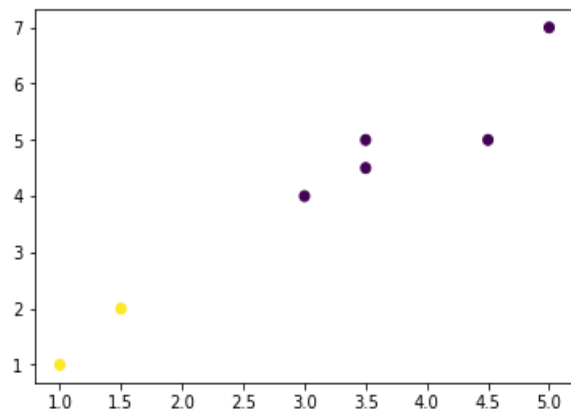
Graph using Kmeans Algorithm

centroids: [[3.9 5.1] [1.25 1.5]]



Labels for GMM: [1 1 0 0 0 0]

Graph using EM Algorithm



PROGRAM.NO.8(KNN)

Write a program to implement k-Nearest Neighbor algorithm to classify the iris data set. Print both correct and wrong predictions. Java/Python ML library classes can be used for this problem.

```
from sklearn.datasets import load_iris
from sklearn.neighbors import KNeighborsClassifier
import numpy as np
from sklearn.model_selection import train_test_split

iris_dataset = load_iris()
targets = iris_dataset.target_names

print("Class : number")
for i in range(len(targets)):
    print(targets[i], ': ', i)

X_train, X_test, y_train, y_test = train_test_split(iris_dataset["data"], iris_dataset["target"])
kn = KNeighborsClassifier(1)
kn.fit(X_train, y_train)

for i in range(len(X_test)):
    x_new = np.array([X_test[i]])
    prediction = kn.predict(x_new)
    print("Actual:[{0}] [{1}], Predicted:{2} {3}".format(y_test[i], targets[y_test[i]], prediction,
    targets[prediction]))

print("\nAccuracy: ", kn.score(X_test, y_test))
```

OUTPUT:-

```
Class : number
setosa : 0
versicolor : 1
virginica : 2
Actual:[2] [virginica], Predicted:[2] ['virginica']
Actual:[2] [virginica], Predicted:[2] ['virginica']
Actual:[2] [virginica], Predicted:[2] ['virginica']
Actual:[1] [versicolor], Predicted:[1] ['versicolor']
Actual:[1] [versicolor], Predicted:[1] ['versicolor']
Actual:[2] [virginica], Predicted:[2] ['virginica']
Actual:[1] [versicolor], Predicted:[1] ['versicolor']
Actual:[2] [virginica], Predicted:[2] ['virginica']
Actual:[1] [versicolor], Predicted:[1] ['versicolor']
Actual:[0] [setosa], Predicted:[0] ['setosa']
Actual:[1] [versicolor], Predicted:[1] ['versicolor']
```

Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[1] [versicolor],Predicted:[2] ['virginica']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[0] [setosa],Predicted:[0] ['setosa']

Accuracy: 0.973684210526

PROGRAM.NO.9(Locally Weighted Regression Algorithm)

Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs

```
from math import ceil
import numpy as np
from scipy import linalg

def lowess(x, y, f=2. / 3., iter=3):
    n = len(x)
    r = int(ceil(f * n))
    h = [np.sort(np.abs(x - x[i]))[r] for i in range(n)]
    w = np.clip(np.abs((x[:, None] - x[None, :]) / h), 0.0, 1.0)
    w = (1 - w ** 3) ** 3
    yest = np.zeros(n)
    delta = np.ones(n)
    for iteration in range(iter):
        for i in range(n):
            weights = delta * w[:, i]
            b = np.array([np.sum(weights * y), np.sum(weights * x)])
            A = np.array([[np.sum(weights), np.sum(weights * x)],
                          [np.sum(weights * x), np.sum(weights * x * x)]])
            beta = linalg.solve(A, b)
            yest[i] = beta[0] + beta[1] * x[i]

        residuals = y - yest
        s = np.median(np.abs(residuals))
        delta = np.clip(residuals / (6.0 * s), -1, 1)
        delta = (1 - delta ** 2) ** 2

    return yest

if __name__ == '__main__':
    import math
    n = 100
    x = np.linspace(0, 2 * math.pi, n)
    y = np.sin(x) + 0.3 * np.random.randn(n)

    # Straight Line Fitting
    # x=np.linspace(0,2.5,n) # For Linear
    # y= 1 + 0.25*np.random.randn(n) # For Linear

    f = 0.25
    yest = lowess(x, y, f, 3)
```



```
import pylab as pl
pl.clf()
pl.plot(x, y, label='y noisy')
pl.plot(x, yest, label='y predicted')
pl.legend()
pl.show()
```

OUTPUT:-