INDEX Subject:- CA LAB-VII(A): LAB on Machine Learning

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Roll No. :- 140
Practical No. :- 1

Practical Name :- Introduction to pycharm , Pandas Library, DataFrames, And

Loading CSV File in DataFrame

```
import pandas as pd
"pd. version "
df1 = pd.DataFrame({"A": [1, 2, 3], "B": [2, 3, 4]}, index=[0, 1, 2])
print("df1:\n", df1)
df2 = pd.DataFrame({"B": [4, 5, 7], "C": ["x", "y", "z"]}, index=[4, 5, 6])
print("\ndf2:\n", df2)
df3 = df1.combine first(df2)
print("\n combination of df1 and df2:\n", df3)
classes = pd.Series(["mathematics", "chemistry", "physics", "history", "geography", "german"])
grades = pd.Series([90, 54, 77, 22, 25, 40])
year = pd. Series([2015, 2016, 2017, 2018, 2019, 2020])
df4 = pd. DataFrame({"Classes": classes, "Grades": grades, "Year": year})
print("\n", df4)
# upload a csv file in sample data section
# load the .csv in data frame
data frame = pd.read csv("C:/Users/nilesh/PycharmProjects/dataset.csv")
print("\n", data frame)
OUTPUT:
C:\Users\nilesh\MCA-I ML\Scripts\python.exe C:/Users/nilesh/PycharmProjects/MCA-
I ML/1 prat.py
df1:
  A B
0 1 2
1 2 3
2 3 4
df2:
  ВС
4 4 x
5 5 y
6 7 z
```

combination of df1 and df2:

A В С

0 1.0 2 NaN

1 2.0 3 NaN

2 3.0 4 NaN

4 NaN 4 x

5 NaN 5 y

6 NaN 7 z

Classes Grades Year

0 mathematics 90 2015

1 chemistry 54 2016

2 physics 77 2017

3 history 22 2018

4 geography 25 2019

5 german 40 2020

sky temp humidity water wind forcast enjoy-sport

0 sunny warm high cool strong same yes 1 sunny warm high warm strong same yes low warm weak change 2 rainy cold no 3 rainy cold high warm weak change no 4 sunny warm high warm strong same yes 5 sunny cold high warm strong same no 6 sunny warm high cool strong change no 7 rainy cold low warm strong same yes

Process finished with exit code 0

```
Name :- Nilesh Vijay Patil
Roll No :- 140
Practical No :- 2
Practical Name :- Implement the Find-S Inductive Learning algorithm.
```

```
import pandas as pd
import numpy as np
data=pd.read csv("C:/Users/comp/PycharmProjects/dataset2.csv")
print("Given data set")
print(data)
#making an array of all the attributes
d=np.array(data)[:,:-1]
print("The attributes are:\n",d)
#segrating the target that has positive and negative example
target=np.array(data)[:,-1]
print("The target is:",target)
#traing function to implement find s algoritham
def train(c,t):
  for i,val in enumerate(t):
     if val == "Yes":
       specific hypothesis=c[i].copy()
       break
  for i,val in enumerate(c):
     if t[i] == "Yes":
       for x in range(len(specific hypothesis)):
          if val[x] != specific hypothesis[x]:
            specific hypothesis[x] = '?'
          else:
            pass
  return specific hypothesis
#obtaining the final hypothesis
print("The final hypothesis is:",train(d,target))
```

OUTPUT:-

C:\Users\comp\PycharmProjects\Mlpract\venv\Scripts\python.exe C:/Users/comp/PycharmProjects/Mlpract/mlfirst.py

Given data set

| | sky | air temp | humidity | wind | water | forcast | enjoy_sport |
|---|-------|----------|----------|--------|-------|---------|-------------|
| 0 | sunny | warm | normal | strong | warm | same | Yes |
| 1 | sunny | warm | hight | strong | warm | same | Yes |
| 2 | rainy | cold | hight | strong | warm | change | No |
| 3 | sunny | warm | hight | strong | cool | change | Yes |
| 4 | sunny | warm | normal | strong | cool | same | Yes |
| 5 | rainy | cold | hight | strong | warm | change | No |

The attributes are:

```
[['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
```

['sunny' 'warm' 'hight' 'strong' 'warm' 'same']

['rainy' 'cold' 'hight' 'strong' 'warm' 'change']

['sunny' 'warm' 'hight' 'strong' 'cool' 'change']

['sunny' 'warm' 'normal' 'strong' 'cool' 'same']

['rainy' 'cold' 'hight' 'strong' 'warm' 'change']]

The target is: ['Yes' 'Yes' 'No' 'Yes' 'Yes' 'No']

The final hypothesis is: ['sunny' 'warm' '?' 'strong' '?' '?']

Process finished with exit code 0

Roll No :- 140 Practical No :- 3

Practical Name :- Implement the Candidate-Elimination Inductive Learning algorithm.

```
import numpy as np
import pandas as pd
data=pd.read csv('C:/Users/comp/PycharmProjects/dataset2.csv')
concepts=np.array(data.iloc[:,0:-1])
print("\nInstance are:\n",concepts)
target=np.array(data.iloc[:,-1])
print("\nTarget values are:\n",target)
def learn(cocepts,target):
  specific h=concepts[0].copy()
  print("\nInitialization of specific h and general h")
  print("\nSpecific boundary:",specific h)
  general_h=[["?" for i in range(len(specific_h))]for i in range(len(specific_h))]
  print("\nGeneric boundaries:".general h)
  for i, h in enumerate(concepts):
     print("\nInstance",i+1, "is", h)
     if target[i]=="Yes":
       print("Instance is positive")
       for x in range(len(specific h)):
          if h[x] != specific h[x]:
            specific h[x]="?"
            general h[x][x]='?'
     else:
       print("Instance is negative")
       for x in range(len(specific h)):
          if h[x] != specific h[x] and specific h[x] !='?':
            general h[x][x] = \text{specific } h[x]
          else:
            general h[x][x]="?"
            specific h[x]='?'
     print("Specific boundary after",i+1,"Instance is",specific h)
     print("Generic boundary after",i+1, "Instance is",general h)
     print("\n")
  indices=[i for i, val in enumerate(general h) if val == ['?','?','?','?','?','?']]
  for i in indices:
     general h.remove(['?','?','?','?','?'])
  return specific h, general h
s final, g final=learn(concepts, target)
print("Final specific h:", s final, sep="\n")
print("Final general h:", g final, sep="\n")
```

OUTPUT:-

C:\Users\comp\PycharmProjects\Mlpract\venv\Scripts\python.exe C:\Users\comp\PycharmProjects\Mlpract/mlsecond.py

Instance are:

[['sunny' 'warm' 'normal' 'strong' 'warm' 'same']

['sunny' 'warm' 'hight' 'strong' 'warm' 'same']

['rainy' 'cold' 'hight' 'strong' 'warm' 'change']

['sunny' 'warm' 'hight' 'strong' 'cool' 'change']

['sunny' 'warm' 'normal' 'strong' 'cool' 'same']

['rainy' 'cold' 'hight' 'strong' 'warm' 'change']]

Target values are:

['Yes' 'Yes' 'No' 'Yes' 'Yes' 'No']

Initialization of specific h and general h

Specific boundary: ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']

Generic boundaries: [['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?'], ['?', '?'], ['?', '?', '?'], ['?', '?', '?'], ['?', '?', '?']

Instance 1 is ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']

Instance is positive

Specific boundary after 1 Instance is ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']

Instance 2 is ['sunny' 'warm' 'hight' 'strong' 'warm' 'same']

Instance is positive

Specific boundary after 2 Instance is ['sunny' 'warm' '?' 'strong' 'warm' 'same']

Instance 3 is ['rainy' 'cold' 'hight' 'strong' 'warm' 'change']

Instance is negative

Specific boundary after 3 Instance is ['sunny' 'warm' '?' '?' '?' 'same']

Instance 4 is ['sunny' 'warm' 'hight' 'strong' 'cool' 'change']

Instance is positive

Specific boundary after 4 Instance is ['sunny' 'warm' '?' '?' '?' '?']

Instance 5 is ['sunny' 'warm' 'normal' 'strong' 'cool' 'same']

Instance is positive

Specific boundary after 5 Instance is ['sunny' 'warm' '?' '?' '?' '?']

Generic boundary after 5 Instance is [['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?'], ['?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?', '?']

Instance 6 is ['rainy' 'cold' 'hight' 'strong' 'warm' 'change']

Instance is negative

Specific boundary after 6 Instance is ['sunny' 'warm' '?' '?' '?' '?']

Final specific h:

['sunny' 'warm' '?' '?' '?']

Final general h:

[['sunny', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?']]

Process finished with exit code 0

Roll No :- 140 Practical No :- 4

Practical Name :- Write a program to implement Decision tree using python programming.

```
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.datasets import load iris
data b= load iris()
df = pd.DataFrame(data b.data,columns = data b.feature names)
df['target'] = data b.target
#df['target']
print(df)
#print(data b)
print("Dataset Labels=",data b.target names)
from sklearn.tree import DecisionTreeClassifier
from sklearn import metrics
from sklearn import tree
from sklearn.model selection import train test split
x train, x test, y train, y test = train test split(df[data b.feature names],
df['target'])
#print(x train)
#print(x test)
#print(y train)
#print(v test)
clf = DecisionTreeClassifier(max depth = 2,random state= 1, criterion='gini')
#'gini'
clf = clf.fit(x train, y train)
y pred = clf.predict(x test)
#print(y test, y pred)
print("Accuracy:",metrics.accuracy score(y test,y pred))
fn = ['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']
cn=['setosa','versicolor','virginica']
fig. axes = plt.subplots(nrows = 1, ncols = 1, figsize = (4.4), dpi = 300)
tree.plot tree(clf, feature names = fn, class names = cn, filled = True)
fig.savefig('dstimg.png')
```

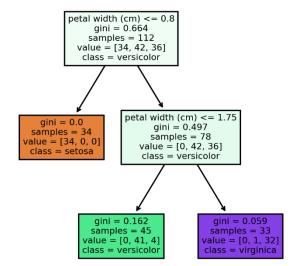
Output:-

| sepal lei | ngth (cm) | sepal width (cm) | petal | width (cm) | target |
|-----------|-----------|------------------|-------|------------|--------|
| 0 | 5.1 | 3.5 | 0.2 | 0 | |
| 1 | 4.9 | 3.0 | 0.2 | 0 | |
| 2 | 4.7 | 3.2 | 0.2 | 0 | |
| 3 | 4.6 | 3.1 | 0.2 | 0 | |
| 4 | 5.0 | 3.6 | 0.2 | 0 | |
| | ••• | ••• | | | |
| 145 | 6.7 | 3.0 | 2.3 | 2 | |
| 146 | 6.3 | 2.5 | 1.9 | 2 | |
| 147 | 6.5 | 3.0 | 2.0 | 2 | |
| 148 | 6.2 | 3.4 | 2.3 | 2 | |
| 149 | 5.9 | 3.0 | 1.8 | 2 | |

[150 rows x 5 columns]

Dataset Labels= ['setosa' 'versicolor' 'virginica']

Accuracy: 0.9736842105263158



```
Name :- Nilesh Vijay Patil
```

Roll No :- 140 Practical No :- 5.1

Practical Name :- Write a program to implement Decision tree using python programming.

```
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.datasets import load_iris
data b= load iris()
df = pd.DataFrame(data_b.data,columns = data_b.feature_names)
df['target'] = data b.target
#df['target']
print(df)
#print(data_b)
print("Dataset Labels=",data b.target names)
from sklearn.tree import DecisionTreeClassifier
from sklearn import metrics
from sklearn import tree
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(df[data_b.feature_names],
df['target'])
\#print(x_train)
\#print(x\_test)
#print(y_train)
#print(y_test)
clf = DecisionTreeClassifier(max depth = 2,random state= 1, criterion='gini')
#'gini'
clf = clf.fit(x_train,y_train)
y_pred = clf.predict(x_test)
#print(y test, y pred)
print("Accuracy:",metrics.accuracy_score(y_test,y_pred))
fn = ['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']
cn=['setosa','versicolor','virginica']
fig. axes = plt.subplots(nrows = 1, ncols = 1, figsize = (4,4), dpi = 300)
tree.plot_tree(clf, feature_names = fn, class_names = cn, filled = True)
fig.savefig('dstimg.png')
```

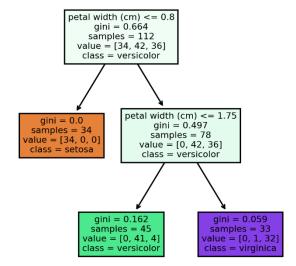
Output:-

| ; | sepal length (cm) | sepal width (cm) | petal | width (| (cm) | target |
|----|-------------------|------------------|-------|---------|------|--------|
| 0 | 5.1 | 3.5 | 0.2 | 0 | | |
| 1 | 4.9 | 3.0 | 0.2 | 0 | | |
| 2 | 4.7 | 3.2 | 0.2 | 0 | | |
| 3 | 4.6 | 3.1 | 0.2 | 0 | | |
| 4 | 5.0 | 3.6 | 0.2 | 0 | | |
| | | | | | | |
| 14 | 6.7 | 3.0 | 2.3 | 2 | | |
| 14 | 6.3 | 2.5 | 1.9 | 2 | | |
| 14 | 6.5 | 3.0 | 2.0 | 2 | | |
| 14 | 18 6.2 | 3.4 | 2.3 | 2 | | |
| 14 | 5.9 | 3.0 | 1.8 | 2 | | |

[150 rows x 5 columns]

Dataset Labels= ['setosa' 'versicolor' 'virginica']

Accuracy: 0.9736842105263158



Roll No :- 140 Practical No:- 5.2

Practical Name:- Write a program implement to decision tree to popular attribute selection measure like information gain, gini index etc. for decision tree.

```
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.datasets import load_iris
data b = load iris()
df=pd.DataFrame(data b.data,columns=data b.feature names)
df['target'] = data_b.target
#df['target']
print(df)
#print(data_b)
print("Dataset Labels=",data_b.target_names)
from sklearn.tree import DecisionTreeClassifier
from sklearn import metrics
from sklearn import tree
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(df[data_b.feature_names], df['target'])
print(x train)
print(x_test)
print(y_train)
print(y test)
clf = DecisionTreeClassifier(max_depth = 5,random_state =1, criterion='gini') #'gini'
clf = clf.fit(x_train, y_train)
y_pred = clf.predict(x_test)
print(y test, y pred)
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
fn=['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']
cn=['setosa', 'versicolor', 'virginica']
fig, axes = plt.subplots(nrows = 1, ncols = 1, figsize = (4, 4), dpi = 300)
tree.plot tree(clf, feature names = fn, class names = cn, filled = True); fig.savefig('dstimg.png')
output:-
C:\Users\patil\PycharmProjects\ml\venv\Scripts\python.exe
C:\Users\patil\PycharmProjects\ml\ml4.py
  sepal length (cm) sepal width (cm) ... petal width (cm) target
0
           5.1
                      3.5 ...
                                     0.2
                                            0
                      3.0 ...
1
           4.9
                                     0.2
                                            0
2
                      3.2 ...
           4.7
                                     0.2
                                            0
3
                      3.1 ...
           4.6
                                     0.2
                                            0
```

| 4 | 5.0 | 3.6 | 0.2 | 0 |
|-----|-----|-----|-----|---|
| | ••• | | | |
| 145 | 6.7 | 3.0 | 2.3 | 2 |
| 146 | 6.3 | 2.5 | 1.9 | 2 |
| 147 | 6.5 | 3.0 | 2.0 | 2 |
| 148 | 6.2 | 3.4 | 2.3 | 2 |
| 149 | 5.9 | 3.0 | 1.8 | 2 |

[150 rows x 5 columns]

Dataset Labels= ['setosa' 'versicolor' 'virginica']

sepal length (cm) sepal width (cm) petal length (cm) petal width (cm)

| 15 | 5.7 | 4.4 | 1.5 | 0.4 |
|-----|-----|-----|-----|-----|
| 73 | 6.1 | 2.8 | 4.7 | 1.2 |
| 53 | 5.5 | 2.3 | 4.0 | 1.3 |
| 104 | 6.5 | 3.0 | 5.8 | 2.2 |
| 69 | 5.6 | 2.5 | 3.9 | 1.1 |
| | | | | |
| 96 | 5.7 | 2.9 | 4.2 | 1.3 |
| 18 | 5.7 | 3.8 | 1.7 | 0.3 |
| 77 | 6.7 | 3.0 | 5.0 | 1.7 |
| 88 | 5.6 | 3.0 | 4.1 | 1.3 |
| 24 | 4.8 | 3.4 | 1.9 | 0.2 |

[112 rows x 4 columns]

sepal length (cm) sepal width (cm) petal length (cm) petal width (cm)

| 148 | 6.2 | 3.4 | 5.4 | 2.3 |
|-----|-----|-----|-----|-----|
| 1 | 4.9 | 3.0 | 1.4 | 0.2 |
| 30 | 4.8 | 3.1 | 1.6 | 0.2 |
| 107 | 7.3 | 2.9 | 6.3 | 1.8 |
| 123 | 6.3 | 2.7 | 4.9 | 1.8 |
| 149 | 5.9 | 3.0 | 5.1 | 1.8 |

| 132 | 6.4 | 2.8 | 5.6 | 2.2 |
|-----|-----|-----|-----|-----|
| 9 | 4.9 | 3.1 | 1.5 | 0.1 |
| 112 | 6.8 | 3.0 | 5.5 | 2.1 |
| 117 | 7.7 | 3.8 | 6.7 | 2.2 |
| 75 | 6.6 | 3.0 | 4.4 | 1.4 |
| 102 | 7.1 | 3.0 | 5.9 | 2.1 |
| 89 | 5.5 | 2.5 | 4.0 | 1.3 |
| 127 | 6.1 | 3.0 | 4.9 | 1.8 |
| 37 | 4.9 | 3.6 | 1.4 | 0.1 |
| 16 | 5.4 | 3.9 | 1.3 | 0.4 |
| 29 | 4.7 | 3.2 | 1.6 | 0.2 |
| 83 | 6.0 | 2.7 | 5.1 | 1.6 |
| 133 | 6.3 | 2.8 | 5.1 | 1.5 |
| 135 | 7.7 | 3.0 | 6.1 | 2.3 |
| 40 | 5.0 | 3.5 | 1.3 | 0.3 |
| 59 | 5.2 | 2.7 | 3.9 | 1.4 |
| 43 | 5.0 | 3.5 | 1.6 | 0.6 |
| 106 | 4.9 | 2.5 | 4.5 | 1.7 |
| 131 | 7.9 | 3.8 | 6.4 | 2.0 |
| 23 | 5.1 | 3.3 | 1.7 | 0.5 |
| 26 | 5.0 | 3.4 | 1.6 | 0.4 |
| 74 | 6.4 | 2.9 | 4.3 | 1.3 |
| 70 | 5.9 | 3.2 | 4.8 | 1.8 |
| 109 | 7.2 | 3.6 | 6.1 | 2.5 |
| 90 | 5.5 | 2.6 | 4.4 | 1.2 |
| 99 | 5.7 | 2.8 | 4.1 | 1.3 |
| 139 | 6.9 | 3.1 | 5.4 | 2.1 |
| 20 | 5.4 | 3.4 | 1.7 | 0.2 |
| 62 | 6.0 | 2.2 | 4.0 | 1.0 |
| 147 | 6.5 | 3.0 | 5.2 | 2.0 |
| 116 | 6.5 | 3.0 | 5.5 | 1.8 |

```
118 7.7 2.6 6.9 2.3
```

15 0

73 1

53 1

104 2

69 1

..

96 1

18 0

77 1

88 1

24 0

Name: target, Length: 112, dtype: int32

148 2

1 0

30 0

107 2

123 2

149 2

132 2

9 0

112 2

117 2

75 1

102 2

89 1

127 2

37 0

16 0

29 0

83 1

- 133 2
- 135 2
- 40 0
- 59 1
- 43 0
- 106 2
- 131 2
- 23 0
- 26 0
- 74 1
- 70 1
- 109 2
- 90 1
- 99 1
- 139 2
- 20 0
- 62 1
- 147 2
- 116 2
- 118 2

Name: target, dtype: int32

- 148 2
- 1 0
- 30 0
- 107 2
- 123 2
- 149 2
- 132 2
- 9 0
- 112 2
- 117 2

```
75 1
```

102 2

89 1

127 2

37 0

16 0

29 0

83 1

133 2

135 2

40 0

59 1

43 0

106 2

131 2

23 0

26 0

74 1

70 1

109 2

90 1

99 1

139 2

20 0

62 1

147 2

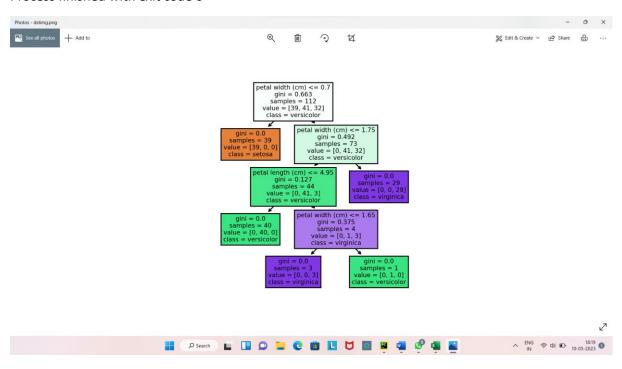
116 2

118 2

21

Accuracy: 0.9210526315789473

Process finished with exit code 0



Roll No: 140 Practical No: 6

Practical Name: Implement simple KNN using Euclidean distance in Python.

```
Code: KNN using Euclidean distance.
from pandas import DataFrame
from sklearn.datasets import load_iris
data_b = load_iris()
df= DataFrame(data_b.data, columns=data_b.feature_names)
df['target'] = data_b.target
#print(df)
#print(data_b.DESCR)
print("Dataset Labels=",data_b.target_names)
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, y_test = train_test_split(df[data_b.feature_names], df['target'],
random_state=1)
print(X_train.head(6))
print(Y_train.head(6))
print(X_test.head())
clf = KNeighborsClassifier(n_neighbors=6)
clf.fit(X_train, Y_train) # model is trained
y_pred=clf.predict(X_test)
#print(y_test, y_pred)
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(cm)
```

OUTPUT:

C:\Users\nilesh\MCA-I_ML\Scripts\python.exe
C:/Users/nilesh/PycharmProjects/MCA-I_ML/KNN.py
Dataset Labels= ['setosa' 'versicolor' 'virginica']
sepal length (cm) sepal width (cm) petal length (cm) petal width (cm)
54 6.5 2.8 4.6 1.5

```
108
           6.7
                     2.5
                                5.8
                                          1.8
112
           6.8
                     3.0
                                5.5
                                          2.1
17
          5.1
                     3.5
                                          0.3
                                1.4
119
           6.0
                     2.2
                                5.0
                                          1.5
103
           6.3
                     2.9
                                5.6
                                          1.8
54 1
108 2
112 2
17 0
119 2
103 2
```

Name: target, dtype: int32

sepal length (cm) sepal width (cm) petal length (cm) petal width (cm)

| 14 | 5.8 | 4.0 | 1.2 | 0.2 |
|-----|-----|-----|-----|-----|
| 98 | 5.1 | 2.5 | 3.0 | 1.1 |
| 75 | 6.6 | 3.0 | 4.4 | 1.4 |
| 16 | 5.4 | 3.9 | 1.3 | 0.4 |
| 131 | 7.9 | 3.8 | 6.4 | 2.0 |

Accuracy: 1.0 Confusion Matrix:

[[13 0 0] [0160] [0 0 9]]

Process finished with exit code 0

Code: For Breast Cancer Data Set

```
from pandas import DataFrame
#from sklearn.datasets import load iris
from sklearn.datasets import load_breast_cancer
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
\#data b = load iris()
data_b = load_breast_cancer()
df = DataFrame(data_b.data, columns=data_b.feature_names)
df['target'] = data_b.target
# print(df)
# print(data b.DESCR)
print("Dataset Labels=", data_b.target_names)
X train, X test, Y train, y test = train test split(df[data b.feature names], df['target'],
random_state=1)
print(X_train.head(6))
print(Y_train.head(6))
print(X test.head())
clf = KNeighborsClassifier(n_neighbors=6)
clf.fit(X_train, Y_train) # model is trained
y_pred = clf.predict(X_test)
# print(y_test, y_pred)
print("Accuracy:", metrics.accuracy_score(y_test, y_pred))
cm = confusion_matrix(y_test, y_pred)
```

OUTPUT:

C:\Users\nilesh\MCA-I_ML\Scripts\python.exe C:/Users/nilesh/PycharmProjects/MCA-I_ML/KNN.py Dataset Labels= ['malignant' 'benign'] mean radius mean texture ... worst symmetry worst fractal dimension 562 15.22 30.62 ... 0.14090 0.4089 291 14.96 19.10 ... 0.2962 0.08472 16 14.68 20.13 ... 0.3029 0.08216 546 10.32 16.35 ... 0.2681 0.07399 293 17.46 ... 11.85 0.3101 0.07007 350 17.07 ... 11.66 0.2731 0.06825

[6 rows x 30 columns] 562 0 291 1 16 0

Name: target, dtype: int32

mean radius mean texture ... worst symmetry worst fractal dimension

| 421 | 14.69 | 13.98 | 0.2827 | 0.09208 |
|-----|-------|-------|--------|---------|
| 47 | 13.17 | 18.66 | 0.3900 | 0.11790 |
| 292 | 12.95 | 16.02 | 0.3380 | 0.09584 |
| 186 | 18.31 | 18.58 | 0.3206 | 0.06938 |
| 414 | 15.13 | 29.81 | 0.3233 | 0.06165 |

[5 rows x 30 columns]

Accuracy: 0.9370629370629371

Confusion Matrix:

[[51 4] [583]]

Number of correct predictions= 134 Number of wrong predictions = 9

Process finished with exit code 0

Roll No :- 140

Practical No 7: Write a program to implement k-Nearest Neighbour algorithm to classify the iris dataset. Print both correct and wrong predictions. Java/Python ML library classes can be used for this problem.

Code:

```
from pandas import DataFrame
from sklearn.datasets import load iris
data b=load iris()
df=DataFrame(data b.data,columns=data b.feature names)
df['target']=data b.target
print("Dataset Labels=",data b.target names)
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
from sklearn.metrics import confusion matrix
from sklearn.model selection import train test split
x train,x test,y train,y test=train test split(df]data b.feature names],df['target'],random sta
te=1)
print(x train)
print(x test)
clf=KNeighborsClassifier(n neighbors=6)
clf.fit(x train,y train)
y pred=clf.predict(x test)
print("Accurancy:",metrics.accuracy_score(y_test,y_pred))
cm=confusion matrix(y test,y pred)
print("Confussion Matrix:")
print(cm)
Output:-
```

```
Dataset Labels= ['setosa' 'versicolor' 'virginica']
Accurancy: 1.0
Confussion Matrix:
[[13 0 0]
[0160]
[0 \ 0 \ 9]]
Process finished with exit code 0
```

Roll No.: 140
Practical No.: 8

Practical Name: Write a Program for Confusion Matrix and calculate Precision, Recall, F-

Measure

```
from sklearn.datasets import load iris, load breast cancer
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion matrix, precision score, recall score, f1 score
# Load the Irish dataset
iris = load iris()
X_iris = iris.data
y_iris = iris.target
# Split the Irish dataset into training and testing sets
X_train_iris, X_test_iris, y_train_iris, y_test_iris = train_test_split(X_iris, y_iris, test_size=0.2,
random state=42)
# Train the KNN classifier on the Irish d3ataset
knn iris = KNeighborsClassifier()
knn_iris.fit(X_train_iris, y_train_iris)
# Make predictions on the Irish testing set
y_pred_iris = knn_iris.predict(X_test_iris)
# Calculate the confusion matrix for Irish dataset
cm_iris = confusion_matrix(y_test_iris, y_pred_iris)
print("Confusion Matrix (Irish Dataset):")
print(cm_iris)
# Calculate precision, recall, and F-measure for Irish dataset
precision_iris = precision_score(y_test_iris, y_pred_iris, average='macro')
recall_iris = recall_score(y_test_iris, y_pred_iris, average='macro')
f1_iris = f1_score(y_test_iris, y_pred_iris, average='macro')
print("Precision (Irish Dataset):", precision iris)
print("Recall (Irish Dataset):", recall_iris)
print("F-measure (Irish Dataset):", f1_iris)
# Load the Breast Cancer dataset
cancer = load_breast_cancer()
X cancer = cancer.data
y_cancer = cancer.target
```

```
# Split the Breast Cancer dataset into training and testing sets
X_train_cancer, X_test_cancer, y_train_cancer, y_test_cancer = train_test_split(X_cancer, y_cancer,
                                            test_size=0.2, random_state=42)
# Train the KNN classifier on the Breast Cancer dataset
knn cancer = KNeighborsClassifier()
knn_cancer.fit(X_train_cancer, y_train_cancer)
# Make predictions on the Breast Cancer testing set
y_pred_cancer = knn_cancer.predict(X_test_cancer)
# Calculate the confusion matrix for Breast Cancer dataset
cm_cancer = confusion_matrix(y_test_cancer, y_pred_cancer)
print("\nConfusion Matrix (Breast Cancer Dataset):")
print(cm_cancer)
# Calculate precision, recall, and F-measure for Breast Cancer dataset
precision cancer = precision score(y test cancer, y pred cancer)
recall_cancer = recall_score(y_test_cancer, y_pred_cancer)
f1_cancer = f1_score(y_test_cancer, y_pred_cancer)
print("Precision (Breast Cancer Dataset):", precision_cancer)
print("Recall (Irish Dataset):", recall_cancer)
print("F-measure (Irish Dataset):", f1_cancer)
OUTPUT:
        Confusion Matrix (Irish Dataset):
        [[10 0 0]
        [0 \ 9 \ 0]
        [0\ 0\ 11]]
        Precision (Irish Dataset): 1.0
        Recall (Irish Dataset): 1.0
        F-measure (Irish Dataset): 1.0
        Confusion Matrix (Breast Cancer Dataset):
```

Precision (Breast Cancer Dataset): 0.9342105263157895

F-measure (Irish Dataset): 0.9659863945578232

[[38 5] [071]]

Recall (Irish Dataset): 1.0

Roll No.: 140 Practical No.: 9

Practical NameWrite a program for linear regression and find parameters like Sum of

Squared Errors (SSE), Total Sum of Squares (SST), R2, Adjusted R2, etc.

```
import numpy as np
from sklearn.linear model import LinearRegression
from sklearn.metrics import r2_score
# Input data
X = np.array([[1, 1], [1, 2], [2, 2], [2, 3]])
y = np.array([3, 4, 5, 6])
model = LinearRegression() # Create a linear regression model
model.fit(X, y) # Fit the model to the data
y_pred = model.predict(X) # Predict the output
sse = np.sum((y_pred - y) ** 2) # Calculate SSE (Sum of Squared Errors)
sst = np.sum((y - np.mean(y)) ** 2) # Calculate SST (Total Sum of Squares)
r2 = r2_score(y, y_pred) # Calculate R2 score
# Calculate adjusted R2
n = X.shape[0] # Number of samples
p = X.shape[1] # Number of predictors
adjusted_r2 = 1 - (1 - r2) * (n - 1) / (n - p - 1)
# Print the results
print("Sum of Squared Errors(SSE):- ", sse)
print("Total Sum of Squares(SST):- ", sst)
print("R Square(R2):- ", r2)
print("Adjusted Square(R2):- ", adjusted_r2 )
OUTPUT:
```

Sum of Squared Errors(SSE):- 0.0 Total Sum of Squares(SST):- 5.0 R Square(R2):- 1.0 Adjusted Square(R2):- 1.0

Roll No. :- 140 Practical No :- 10

Practical Name: Write the program to implement the naive Bayesian Classifier for a sample training dataset stored as a .CSV file. Compute the accuracy of the classifier considering a few test dataset.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn import datasets
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix
iris = datasets.load_iris() #load dataset
x = iris.data #input
y = iris.target #traget
print("Features:", iris['feature_names'])
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25, random_state = 0)
NB = GaussianNB()
NB.fit(x_train, y_train)
y_pred = NB.predict(x_test)
cm = confusion_matrix(y_test,y_pred)
print("Confusion Matrix")
print(cm)
```

OUTPUT:

```
Features: ['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']
Confusion Matrix
[ [13 0 0]
  [0 16 0]
  [0 0 9]]
```

Roll No :- 140

Program No. :- 11.2

Practical Name :- Write a Program for Fuzzy c-means clustering in python.

```
import numpy as np
import skfuzzy as fuzz
from skfuzzy import control as ctrl
# Generate some example data
np.random.seed(0)
data = np.random.rand(100, 2)
# Define the number of clusters
n clusters = 3
# Apply fuzzy c-means clustering
cntr, u, u0, d, jm, p, fpc = fuzz.cluster.cmeans(
data.T, n clusters, 2, error=0.005, maxiter=1000, init=None)
# Predict cluster membership for each data point
cluster membership = np.argmax(u, axis=0)
# Print the cluster centers
print('Cluster Centers:', cntr)
# Print the cluster membership for each data point
print('Cluster Membership:', cluster membership)
```

Output :-

Cluster Centers: [[0.22645397 0.71840176]

[0.52083891 0.18668653]

[0.76252289 0.60239021]]

Cluster Membership: [2 2 0 0 2 2 2 1 0 2 2 0 0 0 1 0

 $0\ 0\ 2\ 2\ 1\ 1\ 2\ 1\ 1\ 2\ 1\ 1\ 1\ 1\ 1\ 1\ 0\ 1\ 1\ 2\ 2$

 $1 \; 1 \; 1 \; 1 \; 0 \; 1 \; 1 \; 2 \; 0 \; 0 \; 1 \; 1 \; 1 \; 1 \; 2 \; 0 \; 2 \; 0 \; 0 \; 1 \; 2 \; 2 \; 2 \; 2 \; 2 \; 0$

0 1 2 1 2 2 2 2 0 2 0

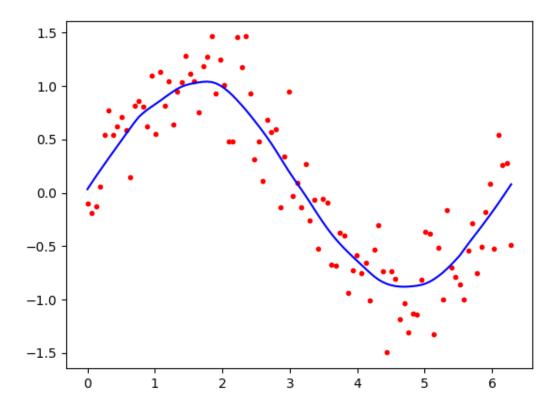
 $2\;0\;0\;0\;2\;1\;2\;2\;2\;0\;1\;1\;1\;1\;0\;1\;0\;1\;2\;2\;1\;1\;0\;2\;1\;0]$

Roll No :- 140 Practical No. :- 12

Practical Name: Implement the non-parametric locally weighted regression algorithm in order to fit data points. select the 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, iterations):
  n = len(x)
  r = int(ceil(f * n))
  h = [np.sort(np.abs(x - x[i]))[r] \text{ for } i \text{ 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(iterations):
     for i in range(n):
        weights = delta * w[:, i]
        b = np.array([np.sum(weights * y), np.sum(weights * y * x)])
        A = \text{np.array}([[\text{np.sum}(\text{weights}), \text{np.sum}(\text{weights * x})], [\text{np.sum}(\text{weights * x}), \text{np.sum}(\text{weights * x})]
* 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
import math
n = 100
x = np.linspace(0, 2 * math.pi, n)
y = np.sin(x) + 0.3 * np.random.randn(n)
f = 0.25
iterations = 3
yest = lowess(x, y, f, iterations)
import matplotlib.pyplot as plt
plt.plot(x, y, "r.")
plt.plot(x, yest, "b-")
plt.show()
```

OUTPUT:



Roll No. :- 140 Practical No. :- 13.1

Practical Name :- Construction Of simple Neural Network using Python

Code:-

```
import numpy as np
from scipy.special import expit as activation function
from scipy.stats import truncnorm
# define the network
# generate numbers within a truncated (bounded)
# normal Distribution
def truncated normal(mean=0, sd=1, low=0, upp=10):
  return truncnorm((low - mean) / sd, (upp - mean) / sd, loc=mean, scale=sd)
# creat the Network class and define the arguments:
# set the no. of neurons/nodes for each layer
# and initialize the weight matrices
class Nnetwork:
  def init (self, no of in nodes, no of out nodes, no of hidden nodes, learning rate):
    self.no of in nodes = no of in nodes
    self.no of out nodes = no of out nodes
    self.no of hidden nodes = no of hidden nodes
    self.learning rate = learning rate
    self.create weight matrices()
  def create weight matrices(self):
     """A method to initialize the weight matrices of the neural network"""
    rad = 1 / np.sqrt(self.no of in nodes) # rad = 0.2707
    x = truncated normal(mean=0, sd=1, low=-rad, upp=rad)
    self.weight in hidden = x.rvs((self.no of hidden nodes, self.no of in nodes))
    print("weights in hidden = ", self.weight in hidden)
    rad = 1/np.sqrt(self.no of hidden nodes)
    x = truncated normal(mean=0, sd=1, low=-rad, upp=rad)
    self.weight in hidden out = x.rvs((self.no of out nodes, self.no of hidden nodes))
    print("weights in hidden out = ", self.weight in hidden out)
  def train(self, input vector, target vector):
    pass
  def run(self, input vector):
    input vector = np.array(input vector, ndmin=2).T
    print("Input = ", input_vector)
    input hidden = activation function(self.weight in hidden @ input vector)
```

```
print("Hidden = ", input_hidden)

output_vector = activation_function(self.weight_in_hidden_out @ input_hidden)
print("Output = ", output_vector)
return output_vector

simple_network = Nnetwork(no_of_in_nodes=2, no_of_out_nodes=2, no_of_hidden_nodes=4, learning_rate=0.6)

#run simple network for arrays, lists and tuples with shape (2):

y = simple_network.run([2,3])
print("Y = ", y)
```

OUTPUT":

```
weights in hidden = [[-0.68798443 \ 0.29428266]]
[ 0.57363879 -0.64646032]
[-0.38809421 0.07104818]
[-0.23288421 0.26427463]]
weights in hidden out = [[0.12718945 - 0.15067287 - 0.36574728 0.3725497]
[-0.09102931 -0.22077172 0.40025881 -0.32163589]]
Input = [[2]]
[3]]
Hidden = [[0.37915865]]
[0.31171721]
[0.36284346]
[0.58104275]]
Output = [[0.52124119]]
[0.46381691]]
Y = [[0.52124119]]
[0.46381691]]
```

Roll No:- 140 Practical No:- 13.2

Practical Name: Classification Of Iris Dataset By Applying Artificial Neural Network

With Back-Propogation Algorithm

```
# classification of iris data set by aplying artificial neural network using Back-propagation
algorithm
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model selection import train test split
import matplotlib.pyplot as plt
# load dataset
data = load_iris()
# Get features and target
x = data.data
y = data.target
print("Y=", y)
y = pd.get_dummies(y).values
print(y[:3])
# split data into train and test data
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=20, random_state=4)
# initialize variable
learning rate = 0.1
iteration = 6000
N = y_{train.size}
# number of input features
input\_size = 4
# number of hidden layers neurons
hidden_size = 2
# mo. of neurons at output layers
output size = 3
results = pd.DataFrame(columns=["mse", "accuracy"])
# initialize weights
np.random.seed(10)
# initialiizing weight for the hidden layers
W1 = np.random.normal(scale=0.5, size=(input_size, hidden_size))
print("weight 1", W1)
# initializing weight for the output layers
```

```
W2 = np.random.normal(scale=0.5, size=(hidden_size, output_size))
print("weight 2", W2)
def sigmoid(x):
  return 1/(1 + np.exp(-x))
def mean_squared_error(y_pred, y_true):
  return (((y_pred - y_true) ** 2).sum()) / (2 * y_pred.size)
def accuracy(y_pred, y_true):
  acc = y_pred.argmax(axis=1) == y_true.argmax(axis=1)
  return acc.mean()
for itr in range(iteration):
  # feedforward propagation
  # on hidden layer
  Z1 = np.dot(x_train, W1)
  A1 = sigmoid(Z1)
# on output layer
  Z2 = np.dot(A1, W2)
  A2 = sigmoid(Z2)
# calculating error
  mse = mean_squared_error(A2, y_train)
  acc = accuracy(A2, y train)
  results = results._append({"mse": mse, "accuracy": acc}, ignore_index=True)
# backpropagation
  E1 = A2 - y_train
  dw1 = E1 * A2 * (1 - A2)
  E2 = np.dot(dw1, W2.T)
  dw2 = E2 * A1 * (1 - A1)
# weight updates
  W2\_update = np.dot(A1.T, dw1) / N
  W1_update = np.dot(x_train.T, dw2) / N
  W2 = W2 - learning_rate * W2_update
  W1 = W1 - learning_rate * W1_update
results.mse.plot(title="Mean squared Error")
results.accuracy.plot(title="Accuracy")
```

```
# feedforward
Z1 = np.dot(x_test, W1)
A1 = sigmoid(Z1)
Z2 = np.dot(A1, W2)
A2 = sigmoid(Z2)
acc = accuracy(A2, y_test)
print("Accuracy: {}".format(acc))
OUTPUT:
C:\Users\nilesh\MCA-I ML\Scripts\python.exe C:/Users/nilesh/PycharmProjects/MCA-
I ML/nural network Backpropa algo.py
2 2]
[[ True False False]
[ True False False]
[ True False False]]
weight 1 [[ 0.66579325  0.35763949]
[-0.77270015 -0.00419192]
[ 0.31066799 -0.36004278]
[ 0.13275579  0.05427426]]
```

weight 2 [[0.00214572 -0.08730011 0.21651309]

[0.60151869 -0.48253284 0.51413704]]