6th semester BCA Machine learning lab

manual

2)data exploration and preprocessing in ML

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

df = pd.read_csv("Lab1.csv")
df.head()

In [69]:

Out[69]:

| | country | age | salary | purchased |
|---|---------|------|--------|-----------|
| 0 | France | NaN | 7200 | no |
| 1 | Spain | 27.0 | 4800 | yes |
| 2 | Germany | 30.0 | 5400 | yes |
| 3 | UK | 49.0 | 98000 | no |

df.tail()

Out[70]:

In [70]:

| | country | age | salary | purchased |
|---|---------|------|--------|-----------|
| 0 | France | NaN | 7200 | no |
| 1 | Spain | 27.0 | 4800 | yes |
| 2 | Germany | 30.0 | 5400 | yes |
| 3 | UK | 49.0 | 98000 | no |

In [71]:

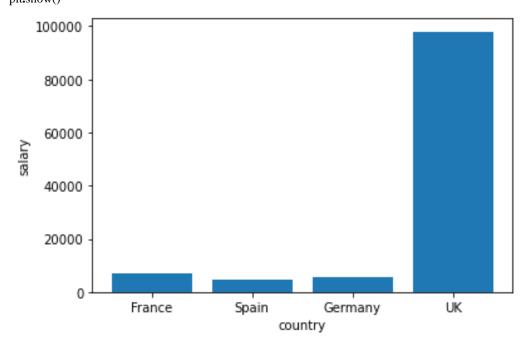
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4 entries, 0 to 3
Data columns (total 4 columns):
Column Non-Null Count Dtype

```
0 country 4 non-null object
           3 non-null float64
2 salary 4 non-null int64
3 purchased 4 non-null object
dtypes: float64(1), int64(1), object(2)
memory usage: 256.0+ bytes
                                                                                                  In [72]:
df.describe()
                                                                                                 Out[72]:
                           salary
               age
 count
          3.000000
                         4.000000
 mean
         35.333333
                    28850.000000
         11.930353
                    46111.278447
   std
         27.000000
                      4800.000000
  min
  25%
         28.500000
                      5250.000000
  50%
         30.000000
                      6300.000000
  75%
         39.500000
                    29900.000000
        49.000000
                    98000.000000
                                                                                                  In [73]:
df.isnull().sum()
                                                                                                 Out[73]:
country
age
         1
salary
purchased 0
dtype: int64
                                                                                                  In [74]:
df['age'].fillna(df['age'].mean(), inplace = True)
df['salary'].fillna(df['salary'].mean(), inplace=True)
                                                                                                  In [75]:
df.isnull().sum()
                                                                                                 Out[75]:
country
age
salary
purchased 0
dtype: int64
                                                                                                  In [76]:
```

```
from sklearn.impute import SimpleImputer
x = df.iloc[:,:-1].values
                                                                                                      Out[76]:
array([['France', 35.333333333333336, 7200],
    ['Spain', 27.0, 4800],
    ['Germany', 30.0, 5400],
    ['UK', 49.0, 98000]], dtype=object)
                                                                                                       In [77]:
y = df.iloc[:,3:].values
У
                                                                                                      Out[77]:
array([['no'],
    ['yes'],
    ['yes'],
    ['no']], dtype=object)
                                                                                                       In [78]:
imp = SimpleImputer(missing_values =np.nan, strategy = "mean")
x[:, 1:3] = imp_fit_transform(x[:, 1:3])
X
                                                                                                      Out[78]:
array([['France', 35.33333333333336, 7200.0],
    ['Spain', 27.0, 4800.0],
    ['Germany', 30.0, 5400.0],
    ['UK', 49.0, 98000.0]], dtype=object)
                                                                                                       In [79]:
from sklearn.preprocessing import LabelEncoder
                                                                                                       In [80]:
le = LabelEncoder()
h = le.fit_transform(x[:,0])
                                                                                                      Out[80]:
array([0, 2, 1, 3])
                                                                                                       In [81]:
y = le.fit_transform(y)
C:\Users\25LAB-2BCA\anaconda3\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for ex
ample using ravel().
 return f(*args, **kwargs)
                                                                                                      Out[81]:
array([0, 1, 1, 0])
                                                                                                       In [82]:
from sklearn.utils import column_or_1d
y = column_or_1d(y, warn = True)
y
                                                                                                      Out[82]:
array([0, 1, 1, 0])
                                                                                                       In [83]:
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
                                                                                                       In [84]:
transform = ColumnTransformer([('norm1', OneHotEncoder(), [0])], remainder = "passthrough")
x = transform.fit_transform(x)
```

```
Out[84]:
array([[1.0, 0.0, 0.0, 0.0, 35.33333333333333336, 7200.0],
    [0.0, 0.0, 1.0, 0.0, 27.0, 4800.0],
    [0.0, 1.0, 0.0, 0.0, 30.0, 5400.0],
    [0.0, 0.0, 0.0, 1.0, 49.0, 98000.0]], dtype=object)
                                                                                                           In [85]:
from sklearn.model_selection import train_test_split
x_train,x_test,y_train, y_test = train_test_split(x, y, test_size = 0.2, random_state = 0)
                                                                                                           In [86]:
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
                                                                                                           In [87]:
x_{train}[:,4:6] = sc.fit_{transform}(x_{train}[:,4:6])
x_train
                                                                                                          Out[87]:
array([[0.0,\,0.0,\,0.0,\,1.0,\,1.3109359202840398,\,1.4138527953056175],
    [0.0, 0.0, 1.0, 0.0, -1.1149081191200718, -0.7345887349522664],
    [1.0, 0.0, 0.0, 0.0, -0.1960278011639687, -0.679264060353351]],
   dtype=object)
                                                                                                           In [91]:
plt.bar(df['country '],df['salary'])
plt.xlabel('country')
plt.ylabel('salary')
plt.show()
```

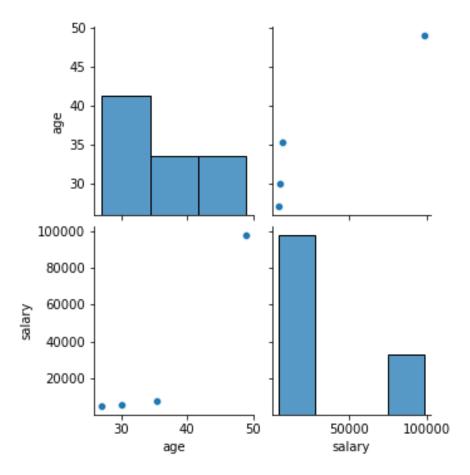


import seaborn as sns
sns.pairplot(df)

Out[92]:

In [92]:

<seaborn.axisgrid.PairGrid at 0x18b7dac21f0>



3) evaluate classifier using performance measures

```
from sklearn.datasets import load iris
from sklearn.model selection import train_test_split
from sklearn.linear model import LogisticRegression
from sklearn.metrics import
accuracy_score,precision_score,recall_score,fl_score,roc_auc_score,confusio
n matrix, classification report
iris=load iris()
x=iris.data
y=iris.target
                                                                         In [2]:
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_sta
te=42)
log_reg=LogisticRegression(max_iter=1000)
                                                                         In [3]:
log_reg.fit(x_train,y_train)
y_pred=log_reg.predict(x_test)
accuracy=round(accuracy_score(y_test,y_pred)*100,2)
print("Accuracy:",accuracy)
Accuracy: 100.0
                                                                         In [4]:
precision=precision_score(y_test,y_pred,average="weighted")
print("Precision:", precision)
Precision: 1.0
```

```
In [5]:
recall=recall score(y test,y pred,average="weighted")
print("Recall:", recall)
Recall: 1.0
                                                                        In [6]:
f1=f1 score(y test, y pred, average="weighted")
print("f1score:",f1)
f1score: 1.0
                                                                        In [7]:
roc_auc=roc_auc_score(y_test,log_reg.predict_proba(x_test),multi_class='ovr
print("ROC AUC score:",roc_auc)
ROC AUC score: 1.0
                                                                        In [8]:
conf matrix=confusion matrix(y test,y pred)
print("Confusion matrix:",conf matrix)
Confusion matrix: [[10 0 0]
[0 9 0]
 [ 0 0 11]]
                                                                        In [9]:
result1=classification_report(y_test,y_pred)
print("Classification report:", result1)
Classification report:
                                     precision
                                                  recall f1-score
                                                                      suppor
           0
                  1.00
                             1.00
                                       1.00
                                                   10
                  1.00
                             1.00
                                       1.00
           1
                                                    9
                  1.00
                             1.00
                                       1.00
                                                   11
                                       1.00
                                                    30
   accuracy
                                       1.00
  macro avg
                   1.00
                             1.00
                                                    30
weighted avg
                   1.00
                             1.00
                                       1.00
                                                    30
4)k nearest neighbour classification using python
import pandas as pd
import numpy as np
df=pd.read_csv("heart.csv")
df.head()
                                                                       Out[1]:
```

| | age | sex | ср | trtbps | chol | fbs | restecg | thalachh | exng | oldpeak | slp | caa | thall | output | • |
|---|-----|-----|----|--------|------|-----|---------|----------|------|---------|-----|-----|-------|--------|---|
| 0 | 60 | 1 | 3 | 145 | 233 | 1 | 0 | 150 | 0 | 2.3 | 0 | 0 | 1 | 1 | |
| 1 | 35 | 1 | 2 | 130 | 250 | 0 | 1 | 187 | 0 | 3.5 | 0 | 0 | 2 | 1 | |
| 2 | 41 | 0 | 1 | 130 | 204 | 0 | 0 | 172 | 0 | 1.4 | 2 | 0 | 2 | 1 | |

| | age | sex | сp | trtbps | chol | fbs | restecg | thal | achh | exng | oldpeak | slp | caa | thall (| output |
|---------------|-------------------|------|------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------|--------------------|--------------------|---------------------------------------|--------------------|
| 3 | 55 | 1 | 1 | 120 | 236 | 0 | 1 | | 178 | 0 | 0.8 | 2 | 0 | 2 | 1 |
| 4 | 56 | 0 | 0 | 120 | 354 | 0 | 1 | | 163 | 1 | 0.6 | 2 | 0 | 2 | 1 |
| df. | desc | ribe | : () | | | | | | | | | | | | In [2]: |
| | ag | e | sex | ср | trtb | chol | fbs | reste | thal | exng | oldp | slp | caa | thall | Out[2]: |
| | 8 | | Sen | СP | ps | CHOI | 105 | cg | achh | vang. | eak | ыр | cuu | · · · · · · · · · · · · · · · · · · · | ut |
| co u nt | 289 0000 00 | 0 0 | 89. 000 00 | 289. 0000 00 | 0000 | 289. 0000 00 | 289. 0000 00 | 289. 0000 00 | 289. 0000 00 |
| m ea n | 54.0 1038 | R U |).67 201 | 1.02 0761 | 131. 3771 63 | 247. 9619 38 | 0.14 5329 | 0.51 5571 | 150. 2318 34 | 0.31 8339 | 1.00 7612 | 1.41 8685 | 0.71 2803 | 2.31 4879 | 0.57 0934 |
| st d | 9.13 2310 | |).46 977 | 1.02 7192 | 17.5 1843 2 | 51.5 9620 8 | 0.35 3043 | 0.51 4309 | 22.8 9965 0 | 0.46 6640 | | 0.61 3333 | 1.02 2596 | 0.59 6128 | 0.49 5801 |
| m in | 29.0 0000 | n U | 0.00 | 0.00 0000 | 94.0 0000 0 | 126. 0000 00 | 0.00 0000 | 0.00 | 71.0 0000 0 | 0.00 0000 | | 0.00 | 0.00 | 0.00 0000 | 0.00 0000 |
| 25 % | 47.0 0000 | n U | 0.00 | 0.00 0000 | 120. 0000 00 | 212. 0000 00 | 0.00 0000 | 0.00 | 136. 0000 00 | 0.00 0000 | | 1.00 0000 | 0.00 0000 | 2.00 0000 | 0.00 0000 |
| 50 % | 54.0 0000 | n 1 | .00 | 1.00 0000 | 130. 0000 00 | 243. 0000 00 | 0.00 | 1.00 0000 | 154. 0000 00 | 0.00 0000 | | 1.00 0000 | 0.00 0000 | 2.00 0000 | 1.00 0000 |
| 75 % | 60.0 0000 | 0 0 | .00 | 2.00 0000 | 140. 0000 00 | 276. 0000 00 | 0.00 | 1.00 0000 | 168. 0000 00 | 1.00 0000 | | 2.00 0000 | 1.00 0000 | 3.00 0000 | 1.00 0000 |
| m ax | 77.0 0000 | 0 0 | .00 | 3.00 0000 | 200. 0000 00 | 564. 0000 00 | 1.00 0000 | 2.00 0000 | 202. 0000 00 | 1.00 0000 | | 2.00 0000 | 4.00 0000 | 3.00 0000 | 1.00 0000 |
| a e | i - 6 - | () | | | | | | | | | | | | | In [3]: |

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 289 entries, 0 to 288

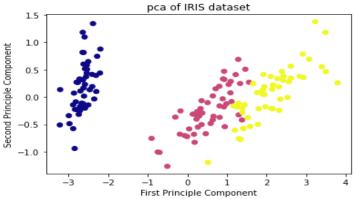
```
# Column Non-Null Count Dtype
___
     -----
 0 age 289 non-null int64
1 sex 289 non-null int64
 2 cp 289 non-null int64
3 trtbps 289 non-null int64
4 chol 289 non-null int64
5 fbs 289 non-null int64
 6 restecg 289 non-null int64
 7 thalachh 289 non-null int64
 8 exng 289 non-null int64
9 oldpeak 289 non-null float64
10 slp 289 non-null int64
11 caa 289 non-null int64
12 thall 289 non-null int64
13 output 289 non-null int64
dtypes: float64(1), int64(13)
memory usage: 31.7 KB
                                                                               In [4]:
df.isnull().sum()
                                                                              Out[4]:
         0
age
           0
sex
cp
trtbps
           0
           0
fbs
            0
restecg
           0
thalachh 0
exng 0 oldpeak 0 slp 0
caa
thall
output 0
dtype: int64
                                                                               In [5]:
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
                                                                               In [6]:
y=df.iloc[:,13]
x=df.iloc[:,:-1]
                                                                               In [7]:
from sklearn.model selection import train test split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_sta
te=0)
                                                                               In [8]:
x_train_scaled=scaler.fit_transform(x_train)
x_test_scaled=scaler.fit_transform(x_test)
                                                                               In [9]:
from sklearn.neighbors import KNeighborsClassifier
lr=KNeighborsClassifier(n neighbors=5)
lr.fit(x train scaled, y train)
```

Data columns (total 14 columns):

```
y_pred=lr.predict(x_test_scaled)
                                                                       In [10]:
from sklearn.metrics import
classification_report,confusion_matrix,accuracy_score
result=confusion matrix(y test,y pred)
print("Confusion Matrix: ")
print(result)
Confusion Matrix:
[[19 8]
[ 5 26]]
                                                                       In [11]:
result1=classification_report(y_test,y_pred)
print("Classification Report :",)
print(result1)
Classification Report :
              precision recall f1-score
                                               support
                  0.79
                           0.70
                                       0.75
                                                    27
           1
                   0.76
                                       0.80
                             0.84
                                                    31
                                        0.78
                                                    58
   accuracy
                                        0.77
                   0.78
                             0.77
                                                    58
   macro avg
                                        0.77
weighted avg
                   0.78
                             0.78
                                                    58
                                                                       In [12]:
result2=round(accuracy score(y test,y pred)*100,2)
print("Acccuracy: ",result2)
Acccuracy: 77.59
5) dimensionality reduction using pca
import numpy as np
import pandas as pd
from sklearn.datasets import load iris
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
                                                                        In [3]:
iris = load iris()
x = iris.data
y = iris.target
print(x)
print(y)
s = x.shape
print(s)
[[5.1 3.5 1.4 0.2]
[4.9 3. 1.4 0.2]
 [4.7 3.2 1.3 0.2]
 [4.6 3.1 1.5 0.2]
[5. 3.6 1.4 0.2]
 [5.8 2.8 5.1 2.4]
 [6.4 3.2 5.3 2.3]
 [6.5 3. 5.5 1.8]
 [7.7 3.8 6.7 2.2]
```

[7.7 2.6 6.9 2.3]

```
[6.8 3.2 5.9 2.3]
[6.7 3.3 5.7 2.5]
[6.7 3. 5.2 2.3]
[6.3 2.5 5. 1.9]
[6.5 3. 5.2 2. ]
[6.2 3.4 5.4 2.3]
[5.9 3. 5.1 1.8]]
2 21
(150, 4)
                                                           In [4]:
target names = iris.target names
print(target_names)
['setosa' 'versicolor' 'virginica']
                                                           In [5]:
scaler =StandardScaler()
x scaled =scaler.fit transform(x)
print(x scaled)
[[-9.00681170e-01 1.01900435e+00 -1.34022653e+00 -1.31544430e+00]
[-1.14301691e+00 -1.31979479e-01 -1.34022653e+00 -1.31544430e+00]
[-1.38535265e+00 \quad 3.28414053e-01 \quad -1.39706395e+00 \quad -1.31544430e+00]
[-1.50652052e+00 9.82172869e-02 -1.28338910e+00 -1.31544430e+00]
[-1.02184904e+00 1.24920112e+00 -1.34022653e+00 -1.31544430e+00]
[-5.37177559e-01 1.93979142e+00 -1.16971425e+00 -1.05217993e+00]
                                                          In [6]:
pca = PCA(n components = 2)
x pca = pca.fit transform(x)
print(x pca)
print(x_pca.shape)
[[-2.68412563 0.31939725]
[-2.71414169 -0.17700123]
[-2.88899057 -0.14494943]
[-2.74534286 -0.31829898]
[-2.72871654 0.32675451]
[-2.28085963 0.74133045]
 [-2.82053775 -0.08946138]
(150, 2)
                                                           In [7]:
plt.scatter(x pca[:, 0], x pca[:, 1], c=y, cmap='plasma')
plt.xlabel('First Principle Component')
plt.ylabel('Second Principle Component')
plt.title('pca of IRIS dataset')
plt.show()
```



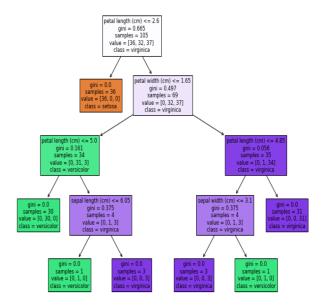
y_pred = lr.predict(X_test)

6) regression analysis using linear regression #linear regression import numpy as np import pandas as pd from sklearn.model selection import train test split from sklearn.metrics import mean squared error, mean absolute error, from sklearn.datasets import load iris In [3]: iris = load iris() In [4]: X = iris.data In [5]: y = iris.target In [6]: X_train, X_test, y_train, y_test = train_test_split(X, y, train_size = 0.7, test_size = 0.3, random_state=100) In [14]: X_train Out[14]: [array([[4.6, 3.4, 1.4, 0.3], [5., 3., 1.6, 0.2], [5.1, 3.7, 1.5, 0.4], [5.8, 2.6, 4., 1.2], [4.9, 3.1, 1.5, 0.1], [5.1, 3.3, 1.7, 0.5], [5., 3.2, 1.2, 0.2], from sklearn.linear model import LinearRegression lr = LinearRegression() In [18]: lr.fit(X_train,y_train) Out[18]: LinearRegression() In [19]:

In [20]:

```
mse = mean_squared_error(y_test, y_pred)
                                                                         In [21]:
y pred = lr.predict(X test)
                                                                         In [22]:
mse = mean squared error(y test, y pred)
print(mse)
0.035170909783059694
r2 = r2\_score(v\_test, v\_pred) print(r2)
                                                                         In [23]:
mae = mean absolute error(y test, y pred)
print(mae)
0.13682917742580056
7) classification using logistic regression
from sklearn.datasets import load iris
from sklearn.model selection import train test split
from sklearn.linear model import LogisticRegression
from sklearn.metrics import
accuracy score, precision score, recall score, fl score, roc auc score, confusio
n matrix, classification report
iris=load iris()
x=iris.data
y=iris.target
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_sta
te=42)
log reg=LogisticRegression(max iter=1000)
                                                                           In [3]:
log_reg.fit(x_train,y_train)
y_pred=log_reg.predict(x test)
accuracy=round(accuracy_score(y_test,y_pred)*100,2)
print("Accuracy:",accuracy)
Accuracy: 100.0
                                                                           In [4]:
precision=precision score(y test,y pred,average="weighted")
print("Precision:",precision)
Precision: 1.0
                                                                           In [5]:
recall=recall_score(y_test,y_pred,average="weighted")
print("Recall:", recall)
Recall: 1.0
                                                                           In [6]:
f1=f1 score(y test, y pred, average="weighted")
print("f1score:",f1)
f1score: 1.0
                                                                           In [7]:
roc auc=roc auc score(y test,log reg.predict proba(x test),multi class='ovr
```

```
print("ROC AUC score:", roc auc)
ROC AUC score: 1.0
                                                                        In [8]:
Confusion _matrix=confusion matrix(y_test,y_pred)
print("Confusion matrix:",conf matrix)
Confusion matrix: [[10 0 0]
[ 0 9 0]
[ 0 0 11]]
                                                                        In [9]:
result1=classification report(y test, y pred)
print("Classification report:", result1)
Classification report:
                                    precision recall f1-score
                                                                      suppor
           0
                  1.00
                            1.00
                                       1.00
                                                   10
           1
                  1.00
                            1.00
                                       1.00
                                                    9
                  1.00
                             1.00
                                       1.00
                                                   11
                                       1.00
                                                    30
   accuracy
                  1.00
                             1.00
                                       1.00
                                                    30
  macro avg
weighted avg
                  1.00
                             1.00
                                       1.00
                                                    30
8) DECISION TREE
import pandas as pd
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.model selection import train test split
from sklearn import metrics
                                                                        In [2]:
from sklearn.datasets import load iris
iris = load iris()
x = iris.data
y = iris.target
                                                                        In [3]:
dtc = DecisionTreeClassifier()
                                                                        In [6]:
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3,
random state=1)
dtc.fit(x train, y train)
                                                                       Out[6]:
DecisionTreeClassifier()
                                                                        In [7]:
iris.target names
                                                                       Out[7]:
array(['setosa', 'versicolor', 'virginica'], dtype='<U10')</pre>
                                                                       In [10]:
import matplotlib.pyplot as plt
plt.figure(figsize=(12,8))
plot_tree(dtc, feature_names = iris.feature_names, class_names =
list(iris.target_names), filled=True)
plt.show()
```



9) SVM support vector machine

#classification using SVM

import pandas as pd
.

import numpy as np

dataset = pd.read_csv('titanic2.csv')

print(dataset.shape)

(891, 12)

dataset.head()

In [2]:

| | | | | | | | | | | | | Out[2]: |
|---|-----------------|------------|--|------------|----------|-----------|-----------|-------------------------|------------|-----------|--------------|--------------|
| | Passenge rId | Pcla ss | Name | Sex | Ag e | SibS p | Parc h | Ticket | Fare | Cabi n | Embark ed | Surviv ed |
| 0 | 1 | 3 | Braund, Mr. Owen Harris | male | 22. 0 | 1 | 0 | A/5 21171 | 7.250 | NaN | S | 0 |
| 1 | 2 | 1 | Cuming s, Mrs. John Bradley (Florenc e Briggs Th | fema le | 38. 0 | 1 | 0 | PC 17599 | 71.28 | C85 | С | 1 |
| 2 | 3 | 3 | Heikkin en, Miss. Laina | fema le | 26. 0 | 0 | 0 | STON/ O2. 3101282 | 7.925 0 | NaN | S | 1 |

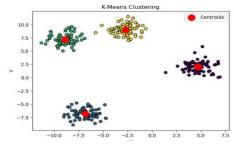
| | Passenge rId | Pcla ss | Name | Sex | Ag S | SibS p | Parc h | Ticket | Fare | Cabi n | Embark ed | Surviv ed |
|-------------|-----------------|------------|--|------------|----------|-----------|-----------|--------------|------------|-----------|--------------|--------------|
| 3 | 4 | 1 | Futrelle, Mrs. Jacques Heath (Lily May Peel) | fema le | 35. 0 | 1 | 0 | 113803 | 53.10 | C12 3 | S | 1 |
| 4 | 5 | 3 | Allen, Mr. William Henry | male | 35. 0 | 0 | 0 | 373450 | 8.050 0 | NaN | S | 0 |
| from | ı sklear | n.imp | ute impo | rt Si | mpleIı | mpute | er | | | | | In [3]: |
| | set.isn | | | | | | | | | | | |
| Pass | engerId | | 0 | | | | | | | | | Out[3]: |
| Pcla | | | 0 | | | | | | | | | |
| Name |) | | 0 | | | | | | | | | |
| Sex | | 1 | 0 | | | | | | | | | |
| Age SibS | 'n | Τ | 77 0 | | | | | | | | | |
| Parc | | | 0 | | | | | | | | | |
| Tick | | | 0 | | | | | | | | | |
| Fare | | | 0 | | | | | | | | | |
| Cabi | .n | 6 | 87 | | | | | | | | | |
| | ırked | | 2 | | | | | | | | | |
| | rived | | 0 | | | | | | | | | |
| dtyp | e: int6 | 4 | | | | | | | | | | |
| data | ıset = d | atase | t.drop(c | olumn | s=['Na | ame', | , 'C | abin', 'E | Embarl | ked']) | | In [4]: |
| data | ıset.hea | d() | | | | | | | | | | In [5]: |
| | | | | | | | | | | | | Out[5]: |
| | PassengerIo | d Pcla | ss Sex | Age | SibSp | Par | ch | T | icket | Fare | Survived | |
| 0 | : | 1 | 3 male | 22.0 | 1 | | 0 | A/5 2 | 21171 | 7.2500 | 0 | |
| 1 | 2 | 2 | 1 female | 38.0 | 1 | | 0 | PC 1 | 17599 | 71.2833 | 1 | |
| 2 | 3 | 3 | 3 female | 26.0 | 0 | | 0 | STON/O2. 310 | 01282 | 7.9250 | 1 | |
| 3 | 4 | 4 | 1 female | 35.0 | 1 | | 0 | 11 | 13803 | 53.1000 | 1 | |

```
PassengerId Pclass
                     Sex Age SibSp Parch
                                                   Ticket
                                                            Fare Survived
                 3
                     male
                          35.0
                                  0
                                        0
                                                   373450
                                                           8.0500
                                                                         In [6]:
dataset.isnull().sum()
                                                                        Out[6]:
PassengerId
                 0
Pclass
                 0
Sex
               177
Age
SibSp
                0
Parch
Ticket
                 0
Fare
Survived
dtype: int64
                                                                         In [7]:
imp = SimpleImputer(missing values=np.nan, strategy='mean')
x = dataset.iloc[:,:-1].values
y = dataset.iloc[:,8].values
Х
У
                                                                        Out[7]:
array([0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1,
       1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1,
       1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1,
       1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0,
       0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1,
       1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1,
       1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0], dtype=int64)
                                                                         In [8]:
x[:,3:4]=imp.fit transform(x[:,3:4])
                                                                         In [9]:
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
x[:,6] = le.fit transform(x[:,6])
x[:,2] = le.fit transform(x[:,2])
                                                                        Out[9]:
array([[1, 3, 1, ..., 0, 523, 7.25],
       [2, 1, 0, \ldots, 0, 596, 71.2833],
       [3, 3, 0, ..., 0, 669, 7.925],
       [889, 3, 0, \ldots, 2, 675, 23.45],
       [890, 1, 1, \ldots, 0, 8, 30.0],
       [891, 3, 1, ..., 0, 466, 7.75]], dtype=object)
                                                                        In [10]:
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
```

```
transform = ColumnTransformer([('norm1',
OneHotEncoder(),[2])],remainder='passthrough')
x =transform.fit transform(x)
print(x)
[[0.0 1.0 1 ... 0 523 7.25]
 [1.0 0.0 2 ... 0 596 71.2833]
 [1.0 0.0 3 ... 0 669 7.925]
[1.0 0.0 889 ... 2 675 23.45]
 [0.0 1.0 890 ... 0 8 30.0]
 [0.0 1.0 891 ... 0 466 7.75]]
                                                                        In [11]:
from sklearn.model selection import train test split
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size = 0.2,
random_state=0)
                                                                        In [12]:
from sklearn import svm
lr = svm.SVC()
lr.fit(x train, y train)
y pred = lr.predict(x test)
from sklearn.metrics import classification report, confusion matrix,
accuracy_score
result = confusion matrix(y test, y pred)
print("Confusion Matrix : ")
print(result)
Confusion Matrix :
[[102 8]
[ 50 19]]
                                                                          In [ ]:
10) NAVIE BAYES
# classification techniques - Naive Bayes
import pandas as pd
import numpy as np
from sklearn.model selection import train test split
                                                                         In [2]:
from sklearn.metrics import accuracy_score
df = pd.read csv("heart.csv")
df.head()
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
y = df.iloc[:,13]
x = df.iloc[:,:-1]
from sklearn.model selection import train test split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3,
random state=0)
x train scaled = scaler.fit transform(x train)
x test scaled = scaler.transform(x test)
                                                                         In [7]:
```

```
from sklearn.naive bayes import GaussianNB
gnb = GaussianNB()
gnb.fit(x train scaled, y train)
y pred = gnb.predict(x test scaled)
                                                                                  In [8]:
from sklearn.metrics import classification report, confusion matrix,
accuracy_score
result2 = round(accuracy score(y test, y pred)*100,2)
print("Accuracy : ",result2)
Accuracy: 79.31
                                                                                  In [9]:
result = confusion_matrix(y_test, y_pred)
print("Confusion Matrix : ")
print(result)
Confusion Matrix :
[[32 11]
 [ 7 37]]
                                                                                 In [10]:
result1 = classification_report(y_t
                                     est, y pred)
print("Classification Report : ")
print(result1)
Classification Report :
                precision recall f1-score
                                                     support
                    0.82 0.74
0.77 0.84
            0
                                             0.78
                                                           43
            1
                                             0.80
                                                           44
                                             0.79
                                                           87
    accuracy
                    0.80 0.79
                                           0.79
                                                           87
   macro avg
                     0.80
                                 0.79
                                            0.79
                                                           87
weighted avg
11) K MEANS CLUSTERING
import matplotlib.pyplot as plt
from sklearn.datasets
import make_blobs
from sklearn.cluster
import KMeans
# Generating synthetic data
X, _ = make_blobs(n_samples=300, centers=4, cluster_std=1.0, random_state=42)
# Initialize K-Means with the number of clusters
kmeans = KMeans(n_clusters=4)
# Fit the K-Means model to the data
kmeans.fit(X)
# Predict cluster
labels cluster_labels = kmeans.predict(X)
# Visualize the clusters
plt.figure(figsize=(7,5))
plt.scatter(X[:, 0], X[:, 1], c=cluster_labels, cmap='viridis', edgecolors='k')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1],
marker='o', s=200, color='red', label='Centroids')
plt.title('K-Means Clustering')
```

```
plt.xlabel('X')
plt.ylabel('Y')
plt.legend()
plt.show()
```



12) baaging

```
import pandas as pd
import numpy as np
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy score
```

```
# Load the Iris dataset
iris=load_iris()
X=iris.data
```

y=iris.target

```
# Split the dataset into training and testing sets
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=42)
```

```
from sklearn.ensemble import RandomForestClassifier
dt= RandomForestClassifier(n_estimators= 10, criterion="entropy")
dt.fit(X train,y train)
y_pred=dt.predict(X_test)
from sklearn.metrics import classification report,
confusion_matrix,accuracy_score
result1 = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(result1)
result2 = classification_report(y_test, y_pred)
print("Classification Report:",)
print (result2)
result3 = accuracy_score(y_test,y_pred)
print("Accuracy:",result3)
```

13. Ensemble method- Boosting

```
from sklearn.datasets import load_iris
from sklearn.model selection import train test split
from sklearn.metrics import accuracy_score
# Load Iris dataset
iris=load_iris()
X=iris.data
y=iris.target
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random state=42)
from sklearn.ensemble import GradientBoostingClassifier
gb=GradientBoostingClassifier()
gb.fit(x train,y train)
y_pred=gb.predict(x_test)
```

from sklearn.metrics import classification_report, confusion_matrix,

accuracy_score

```
result = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(result)
result1 = classification_report(y_test, y_pred)
print("Classification Report:",)
print (result1)
14. Ensemble method- Stacking
#Stacking
from sklearn.datasets import load iris
from sklearn.ensemble import StackingClassifier
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
# Load the Iris dataset
iris=load_iris()
X=iris.data
y=iris.target
```

```
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=42)
# Define base learners
base_learners = [
    ('decision_tree', DecisionTreeClassifier(max_depth=1)),
  ('Ir', LogisticRegression()) ]
# Define the meta-learner
meta_learner = SVC(probability=True, random_state=42)
# Initialize the Stacking Classifier with the base learners and the meta-learner
stack_clf = StackingClassifier(estimators=base_learners,
final_estimator=meta_learner)
# Train the stacking classifier
stack_clf.fit(X_train, y_train)
# Make predictions on the test set
```

```
y_pred = stack_clf.predict(X_test)
# Evaluate and print the accuracy of the model
print("Stacking Model Accuracy:", accuracy_score(y_test, y_pred))
from sklearn.metrics import classification report, confusion matrix,
Result2 = confusion matrix(y test, y pred)
print("Confusion Matrix:")
print(result2)
Result3 = classification report(y test, y pred)
print("Classification Report:",)
print (result3)
```