Deccan Education Society's Kirti M. Doongursee College of Arts, Science and Commerce [Autonomous], Dadar (West), Mumbai-400 028.



M.Sc. [Computer Science]

Practical journal

Seat Number [

Department of Computer Science and Information Technology

Department of Computer Science and Information Technology Deccan Education Society's

Kirti M. Doongursee College of Arts, Science and Commerce [Autonomous], Dadar (West), Mumbai-400 028.

CERTIFICATE

This is to certify that	
• • • • • • • • • • • • • • • • • • • •	No has completed Practical journal and Deep Learning under my supervision
Lecturer-In-Charge	H.O.D. Department of Computer Science & IT
Date: / /2024	Date:
Examined by: Date:	Remarks:

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$Practical \hbox{-} 1.1 \underline{\hspace{0.1cm}} linear \underline{\hspace{0.1cm}} regression \underline{\hspace{0.1cm}} study \underline{\hspace{0.1cm}} dataset$

```
[]: !pip install scikit-learn pandas numpy
[1]: import pandas as pd
     df = pd.read_csv("./dataset/Study.csv")
[1]:
         Hours
                Scores
           2.5
     0
                     21
     1
           5.1
                     47
           3.2
     2
                     27
     3
           8.5
                     75
     4
           3.5
                     30
     5
           1.5
                     20
           9.2
     6
                     88
     7
           5.5
                     60
     8
           8.3
                     81
           2.7
     9
                     25
     10
           7.7
                     85
           5.9
                     62
     11
     12
           4.5
                     41
           3.3
     13
                     42
     14
           1.1
                     17
     15
           8.9
                     95
           2.5
     16
                     30
     17
           1.9
                     24
           6.1
                     67
     18
           7.4
     19
                     69
     20
           2.7
                     30
     21
           4.8
                     54
     22
           3.8
                     35
     23
           6.9
                     76
     24
           7.8
                     86
[2]: df.info()
    <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 25 entries, 0 to 24
    Data columns (total 2 columns):
          Column Non-Null Count Dtype
```

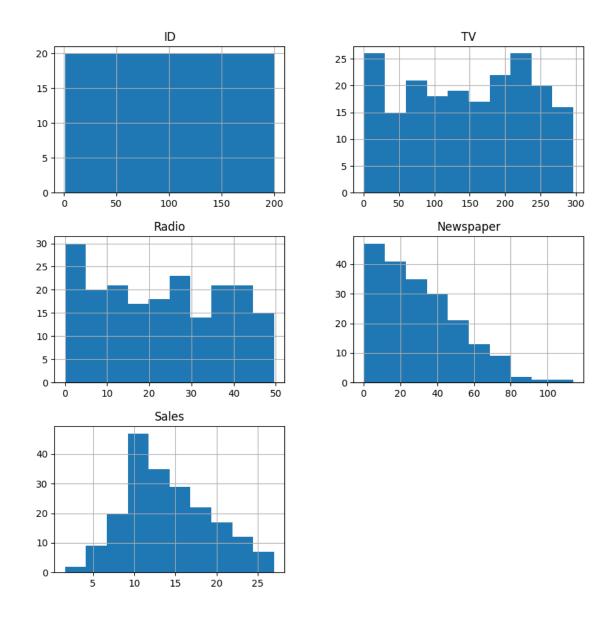
```
0
         Hours
                  25 non-null
                                   float64
         Scores 25 non-null
                                   int64
     1
    dtypes: float64(1), int64(1)
    memory usage: 532.0 bytes
[3]: x = df.iloc[:,:-1]
     y = df.iloc[:,-1]
[4]: x
[4]:
         Hours
           2.5
     0
           5.1
     1
     2
           3.2
     3
           8.5
     4
           3.5
     5
           1.5
           9.2
     6
     7
           5.5
     8
           8.3
     9
           2.7
     10
           7.7
           5.9
     11
     12
           4.5
           3.3
     13
     14
           1.1
           8.9
     15
           2.5
     16
     17
           1.9
     18
           6.1
           7.4
     19
     20
           2.7
     21
           4.8
     22
           3.8
     23
           6.9
     24
           7.8
[5]: y
[5]: 0
           21
           47
     1
           27
     2
     3
           75
     4
           30
     5
           20
     6
           88
           60
```

```
9
           25
           85
     10
     11
           62
           41
     12
           42
     13
     14
           17
     15
           95
     16
           30
     17
           24
     18
           67
     19
           69
     20
           30
           54
     21
     22
           35
     23
           76
     24
           86
     Name: Scores, dtype: int64
[6]: from sklearn.model_selection import train_test_split
[7]: xtrain, xtest, ytrain, ytest = train_test_split(x,y,test_size=0.
      →2,random_state=1)
[8]: ytrain
[8]: 10
           85
           67
     18
     19
           69
     4
           30
     2
           27
     20
           30
     6
           88
     7
           60
     22
           35
           47
     1
     16
           30
           21
     0
     15
           95
     24
           86
     23
           76
     9
           25
     8
           81
     12
           41
     11
           62
           20
     Name: Scores, dtype: int64
```

```
[9]: from sklearn.linear_model import LinearRegression
[10]: lr = LinearRegression()
[11]: lr.fit(xtrain, ytrain)
[11]: LinearRegression()
[12]: | predictions = lr.predict(xtest)
     Beta 0
[14]: lr.intercept_
[14]: -1.5369573315500702
     Beta 1
[15]: lr.coef_
[15]: array([10.46110829])
[16]: print(ytest)
      print(predictions)
     14
           17
     13
           42
     17
           24
     3
           75
     21
           54
     Name: Scores, dtype: int64
     [ 9.97026179 32.98470004 18.33914843 87.38246316 48.67636248]
[17]: from sklearn.metrics import mean_absolute_error,r2_score
[18]: mean_absolute_error(ytest,predictions)
[18]: 7.882398086270432
     R2 Score should be close to 1
[19]: r2_score(ytest, predictions)
[19]: 0.8421031525243527
```

Practical-1.2_linear_regression_Advertising_dataset

```
[]: !pip install numpy pandas scikit-learn matplotlib
[2]: import pandas as pd
[3]: df = pd.read_csv('./dataset/Advertising.csv')
[4]: df
[4]:
                             Newspaper
                                         Sales
                      Radio
               230.1
                       37.8
                                   69.2
                                          22.1
     0
            1
                                   45.1
     1
            2
                44.5
                       39.3
                                          10.4
     2
            3
                17.2
                       45.9
                                   69.3
                                           9.3
     3
              151.5
                       41.3
                                   58.5
                                          18.5
     4
              180.8
                       10.8
                                   58.4
                                          12.9
     195
         196
                38.2
                        3.7
                                   13.8
                                           7.6
     196
         197
                94.2
                        4.9
                                    8.1
                                           9.7
     197
          198
              177.0
                        9.3
                                    6.4
                                          12.8
     198
         199
               283.6
                       42.0
                                   66.2
                                          25.5
     199
         200 232.1
                                    8.7
                                          13.4
                        8.6
     [200 rows x 5 columns]
[5]: df.hist(figsize = (10,10))
[5]: array([[<Axes: title={'center': 'ID'}>, <Axes: title={'center': 'TV'}>],
            [<Axes: title={'center': 'Radio'}>,
             <Axes: title={'center': 'Newspaper'}>],
            [<Axes: title={'center': 'Sales'}>, <Axes: >]], dtype=object)
```



```
66.2
      198
          199
                283.6
                        42.0
      199
          200
                232.1
                         8.6
                                    8.7
      [200 rows x 4 columns]
 [7]: y = df.iloc[:,-1]
      у
             22.1
 [7]: 0
      1
             10.4
      2
              9.3
      3
             18.5
             12.9
      195
              7.6
      196
              9.7
      197
             12.8
      198
             25.5
      199
             13.4
      Name: Sales, Length: 200, dtype: float64
 [8]: from sklearn.model selection import train test split
      xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size=0.3,random_state=2)
 [9]: from sklearn.linear_model import LinearRegression
      lr = LinearRegression()
[10]: lr.fit(xtrain,ytrain)
[10]: LinearRegression()
[11]: predict1 = lr.predict(xtest)
[12]: predict1
[12]: array([13.9532874, 9.66868515, 6.8184482, 15.17477774, 18.17445759,
             15.71712804, 7.57102926, 20.49761622, 13.19168021, 17.33321225,
             11.14787534, 19.48405747, 9.21291503, 10.79916797, 13.87449153,
             12.82277648, 9.32688188, 18.03502362, 16.4741683, 18.82432455,
             16.92036691, 16.04687481, 12.02316254, 12.14339122, 14.87243899,
             12.08358743, 15.49759505, 8.08839314, 16.76959963, 13.87908137,
             16.20151428, 17.08595853, 13.05758661, 13.02632284, 8.91762832,
             11.01315087, 21.97837505, 19.89971271, 15.98938391, 20.23559933,
             21.12563546, 17.17066585, 21.13093152, 15.04421578, 19.66106778,
             18.74322737, 17.58850441, 10.34247317, 9.60222257, 13.00297864,
             12.59823575, 14.39336676, 17.46356839, 16.99371718, 8.55587416,
             17.10336367, 9.13263193, 4.15865759, 7.67835429, 24.67819442])
```

197 198 177.0

9.3

6.4

1.5264827355298254

Practical-2.1_Logistic_Regression_placement_dataset

```
[1]: import pandas as pd
[2]: df = pd.read_csv("./dataset/placement.csv")
[3]: df
[3]:
          cgpa
                placement_exam_marks
          7.19
                                 26.0
                                             1
     1
          7.46
                                 38.0
                                             1
     2
          7.54
                                 40.0
                                             1
     3
          6.42
                                  8.0
                                             1
     4
          7.23
                                 17.0
                                             0
           •••
     995 8.87
                                             1
                                 44.0
     996
         9.12
                                 65.0
                                             1
     997 4.89
                                 34.0
                                             0
     998 8.62
                                 46.0
                                             1
     999 4.90
                                 10.0
                                             1
     [1000 rows x 3 columns]
[4]: df.info()
    <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 1000 entries, 0 to 999
    Data columns (total 3 columns):
         Column
                                Non-Null Count
                                                 Dtype
         ----
                                                 float64
     0
                                 1000 non-null
         cgpa
     1
         placement_exam_marks
                                1000 non-null
                                                 float64
                                 1000 non-null
                                                 int64
         placed
    dtypes: float64(2), int64(1)
    memory usage: 23.6 KB
[5]: df.shape
[5]: (1000, 3)
[6]: df.head()
```

```
[6]:
        cgpa placement_exam_marks placed
     0 7.19
                             26.0
                                       1
     1 7.46
                             38.0
                                       1
     2 7.54
                             40.0
                                       1
     3 6.42
                                       1
                             8.0
     4 7.23
                             17.0
[7]: df['placed'].unique()
[7]: array([1, 0])
[8]: X = df.iloc[:,:-1]
[9]: y = df.iloc[:,-1]
[10]: from sklearn.model_selection import train_test_split
[11]: xtrain, xtest, ytrain, ytest = train_test_split(X, y, test_size=0.25, random_state=1)
[12]: from sklearn.linear_model import LogisticRegression
[13]: classifier = LogisticRegression()
[14]: classifier.fit(xtrain, ytrain)
[14]: LogisticRegression()
[15]: predictions = classifier.predict(xtest)
[16]: probability = classifier.predict_proba(xtest)
[17]: probability[:10]
[17]: array([[0.57188237, 0.42811763],
            [0.58207783, 0.41792217],
            [0.54254942, 0.45745058],
            [0.52320624, 0.47679376],
            [0.55570161, 0.44429839],
            [0.51994635, 0.48005365],
            [0.49926819, 0.50073181],
            [0.51124366, 0.48875634],
            [0.55763857, 0.44236143],
            [0.497788 , 0.502212 ]])
[18]: predictions
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0,
```

```
[19]: from sklearn.metrics import accuracy_score
```

[20]: accuracy_score(ytest, predictions)

[20]: 0.48

Practical-2.2_Logistic_Regression_iris_cv_kfold

```
[1]: from sklearn.datasets import load_iris
[2]: from sklearn.model_selection import cross_val_score, KFold
[3]: from sklearn.linear_model import LogisticRegression
   iris = load_iris()
   x = iris.data
[14]: x[:10]
[14]: array([[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],
        [5.4, 3.9, 1.7, 0.4],
        [4.6, 3.4, 1.4, 0.3],
        [5., 3.4, 1.5, 0.2],
        [4.4, 2.9, 1.4, 0.2],
        [4.9, 3.1, 1.5, 0.1]
[7]: y = iris.target
[8]: y
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
        [9]: | lr = LogisticRegression()
[10]: k_fold = KFold(n_splits=7)
```

Average Cross Validation score:0.9319727891156463

Practical-3.1_Lasso_Regression_housing-dataset

```
[]: !pip install numpy pandas scikit-learn
[1]: import pandas as pd
     df = pd.read_csv("./dataset/boston-housing-dataset.csv")
     # First 3
     df.head(3)
     # Random 3
     df.sample(3)
     # Last 3
     df.tail(3)
[1]:
            CRIM
                    ZN
                       INDUS CHAS
                                        NX
                                               RM
                                                    AGE
                                                            DIS RAD
                                                                        TAX \
                                            6.976 91.0
     503 0.06076 0.0
                       11.93
                                    0.573
                                                        2.1675
                                                                      273.0
                                  0
                                                                   1
     504 0.10959
                  0.0
                       11.93
                                  0
                                    0.573
                                            6.794 89.3
                                                        2.3889
                                                                      273.0
                                                                   1
     505 0.04741
                  0.0
                       11.93
                                    0.573
                                           6.030 80.8 2.5050
                                                                      273.0
         PTRATIO
                       B LSTAT MEDV
     503
            21.0
                  396.90
                           5.64
                                 23.9
     504
            21.0 393.45
                            6.48 22.0
     505
            21.0 396.90
                           7.88 11.9
[2]: x = df.iloc[:,:-1]
     x.shape
[2]: (506, 13)
[3]: y = df.iloc[:,-1]
     У
[3]: 0
            24.0
            21.6
     1
           34.7
     2
     3
           33.4
           36.2
```

```
22.4
      501
      502
             20.6
      503
             23.9
      504
             22.0
      505
             11.9
      Name: MEDV, Length: 506, dtype: float64
 [4]: from sklearn.linear_model import Lasso
      model = Lasso()
 [5]: from sklearn.model_selection import train_test_split
 [6]: xtrain, xtest, ytrain, ytest = train_test_split(x,y,test_size = 0.25,_u
       →random_state = 1)
      model.fit(xtrain, ytrain)
 [6]: Lasso()
 [7]: from sklearn.model_selection import RepeatedKFold
      cv = RepeatedKFold(n_splits = 10, n_repeats=3, random_state=1)
 [8]: from sklearn.metrics import r2_score
      ypred = model.predict(xtest)
      r2_score(ytest, ypred)
 [8]: 0.662198077052326
 [9]: from sklearn.preprocessing import StandardScaler
      sc = StandardScaler()
      x_sc = sc.fit_transform(x)
      xtrain, xtest, ytrain, ytest = train_test_split(x_sc,y,test_size = 0.25,__
      →random state=1)
      model1 = Lasso()
      params = {'alpha':[0.00001,0.0001,0.001,0.01]}
[10]: from sklearn.model_selection import GridSearchCV
      search = GridSearchCV(model1, params, cv=cv)
      result = search.fit(x_sc,y)
      result.best_params_
[10]: {'alpha': 0.01}
[11]: model2 = Lasso(alpha=0.01)
      model2.fit(xtrain,ytrain)
[11]: Lasso(alpha=0.01)
```

```
[12]: ypred2 = model2.predict(xtest)
    r2_score(ytest, ypred2)
```

[12]: 0.7787372388293925

Practical-

3.2 Linear Regression standard scalar california housing

```
!pip install numpy pandas scikit-learn
[1]: import pandas as pd
     from sklearn.datasets import fetch_california_housing
[2]: boston = fetch_california_housing()
     boston_df = pd.DataFrame(boston.data, columns=boston.feature_names)
     boston_df["Price_House"]=boston.target
     boston_df
[2]:
            MedInc
                    HouseAge
                              AveRooms
                                         AveBedrms
                                                     Population
                                                                  AveOccup
                                                                            Latitude
     0
            8.3252
                         41.0
                               6.984127
                                           1.023810
                                                          322.0
                                                                  2.555556
                                                                               37.88
            8.3014
     1
                         21.0
                              6.238137
                                           0.971880
                                                         2401.0
                                                                  2.109842
                                                                               37.86
     2
            7.2574
                         52.0 8.288136
                                           1.073446
                                                          496.0
                                                                  2.802260
                                                                               37.85
     3
            5.6431
                         52.0 5.817352
                                           1.073059
                                                          558.0
                                                                  2.547945
                                                                               37.85
     4
            3.8462
                         52.0 6.281853
                                           1.081081
                                                          565.0
                                                                 2.181467
                                                                               37.85
     20635
            1.5603
                         25.0 5.045455
                                           1.133333
                                                          845.0
                                                                  2.560606
                                                                               39.48
     20636
            2.5568
                         18.0 6.114035
                                           1.315789
                                                          356.0
                                                                  3.122807
                                                                               39.49
     20637
            1.7000
                         17.0 5.205543
                                           1.120092
                                                         1007.0
                                                                  2.325635
                                                                               39.43
     20638
            1.8672
                         18.0 5.329513
                                           1.171920
                                                          741.0
                                                                  2.123209
                                                                               39.43
     20639
            2.3886
                         16.0 5.254717
                                           1.162264
                                                         1387.0
                                                                 2.616981
                                                                               39.37
                       Price_House
            Longitude
     0
              -122.23
                              4.526
     1
              -122.22
                              3.585
     2
              -122.24
                              3.521
              -122.25
                              3.413
              -122.25
                              3.422
     20635
              -121.09
                              0.781
              -121.21
                              0.771
     20636
              -121.22
                              0.923
     20637
              -121.32
                              0.847
     20638
     20639
              -121.24
                              0.894
```

[20640 rows x 9 columns]

```
[3]: x = boston_df.iloc[:,:-1]
[4]: x
[4]:
            MedInc
                    HouseAge
                              AveRooms
                                          AveBedrms
                                                     Population
                                                                 AveOccup
                                                                            Latitude
     0
            8.3252
                         41.0
                               6.984127
                                           1.023810
                                                          322.0
                                                                  2.555556
                                                                                37.88
                                           0.971880
     1
            8.3014
                         21.0
                               6.238137
                                                         2401.0
                                                                  2.109842
                                                                                37.86
     2
            7.2574
                         52.0
                              8.288136
                                           1.073446
                                                          496.0
                                                                  2.802260
                                                                                37.85
     3
            5.6431
                         52.0
                              5.817352
                                           1.073059
                                                          558.0
                                                                  2.547945
                                                                                37.85
     4
            3.8462
                         52.0 6.281853
                                                          565.0
                                                                                37.85
                                           1.081081
                                                                  2.181467
             •••
                                                                   ...
     20635
            1.5603
                         25.0 5.045455
                                           1.133333
                                                          845.0
                                                                  2.560606
                                                                                39.48
                                                                                39.49
     20636
            2.5568
                         18.0 6.114035
                                           1.315789
                                                          356.0
                                                                 3.122807
     20637
            1.7000
                         17.0 5.205543
                                           1.120092
                                                         1007.0
                                                                 2.325635
                                                                               39.43
     20638
            1.8672
                         18.0 5.329513
                                                          741.0
                                                                  2.123209
                                                                                39.43
                                           1.171920
            2.3886
                         16.0 5.254717
                                                                 2.616981
                                                                                39.37
     20639
                                           1.162264
                                                         1387.0
            Longitude
     0
              -122.23
              -122.22
     1
     2
              -122.24
     3
              -122.25
     4
              -122.25
                ...
     20635
              -121.09
     20636
              -121.21
     20637
              -121.22
     20638
              -121.32
     20639
              -121.24
     [20640 rows x 8 columns]
[5]: y = boston_df.iloc[:,-1]
[6]: y
[6]: 0
              4.526
     1
              3.585
     2
              3.521
     3
              3.413
              3.422
     20635
              0.781
     20636
              0.771
     20637
              0.923
```

```
20638
               0.847
               0.894
      20639
      Name: Price_House, Length: 20640, dtype: float64
 [7]: from sklearn.preprocessing import StandardScaler
      sc = StandardScaler()
      x sc= sc.fit transform(x)
 [8]: x_sc
 [8]: array([[ 2.34476576, 0.98214266, 0.62855945, ..., -0.04959654,
               1.05254828, -1.32783522],
             [ 2.33223796, -0.60701891, 0.32704136, ..., -0.09251223,
               1.04318455, -1.32284391],
             [ 1.7826994 , 1.85618152, 1.15562047, ..., -0.02584253,
               1.03850269, -1.33282653],
             [-1.14259331, -0.92485123, -0.09031802, ..., -0.0717345,
               1.77823747, -0.8237132 ],
             [-1.05458292, -0.84539315, -0.04021111, ..., -0.09122515,
               1.77823747, -0.87362627],
             [-0.78012947, -1.00430931, -0.07044252, ..., -0.04368215,
               1.75014627, -0.83369581]])
 [9]: from sklearn.model_selection import train_test_split
      xtrain,xtest,ytrain,ytest = train_test_split(x_sc,y,test_size=0.
       →3,random_state=2)
[10]: from sklearn.linear_model import LinearRegression
      lr = LinearRegression()
[11]: lr.fit(xtrain,ytrain)
[11]: LinearRegression()
[12]: predict1 = lr.predict(xtest)
[13]: from sklearn.metrics import r2_score,mean_absolute_error
[14]: print(r2_score(ytest,predict1))
     0.6015507891610434
[15]: print(mean_absolute_error(ytest,predict1))
     0.5362588391493065
```

Practical-

3.3_ridge_Regression_standard_scalar_california_housing

```
[]: !pip install numpy pandas scikit-learn
[1]: import pandas as pd
     from sklearn.datasets import fetch_california_housing
     ds = fetch california housing()
     df = pd.DataFrame(ds.data, columns=ds.feature_names)
     df.head(3)
[1]:
       MedInc HouseAge
                          AveRooms AveBedrms
                                              Population AveOccup
                                                                     Latitude \
     0 8.3252
                    41.0
                                                    322.0
                                                                        37.88
                          6.984127
                                     1.023810
                                                           2.555556
     1 8.3014
                    21.0 6.238137
                                     0.971880
                                                   2401.0 2.109842
                                                                        37.86
     2 7.2574
                    52.0 8.288136
                                     1.073446
                                                    496.0 2.802260
                                                                        37.85
       Longitude
     0
          -122.23
         -122.22
     1
     2
          -122.24
[2]: df["HousePrice"]=ds.target
     df.head(3)
[2]:
       MedInc HouseAge
                          AveRooms
                                    AveBedrms
                                               Population AveOccup
                                                                     Latitude \
     0 8.3252
                    41.0
                                     1.023810
                                                    322.0
                                                           2.555556
                                                                        37.88
                          6.984127
     1 8.3014
                    21.0
                          6.238137
                                     0.971880
                                                   2401.0 2.109842
                                                                        37.86
     2 7.2574
                    52.0
                          8.288136
                                     1.073446
                                                    496.0 2.802260
                                                                        37.85
       Longitude HousePrice
     0
          -122.23
                        4.526
          -122.22
                        3.585
     1
     2
         -122.24
                        3.521
[3]: X = df.iloc[:,:-1]
     y = df.iloc[:,-1]
[4]: X.head(3)
```

```
[4]:
        MedInc HouseAge AveRooms AveBedrms Population AveOccup Latitude \
     0 8.3252
                                                                          37.88
                     41.0 6.984127
                                    1.023810
                                                     322.0 2.555556
      1 8.3014
                     21.0 6.238137
                                      0.971880
                                                    2401.0 2.109842
                                                                          37.86
      2 7.2574
                     52.0 8.288136
                                      1.073446
                                                     496.0 2.802260
                                                                         37.85
         Longitude
      0
           -122.23
           -122.22
      1
      2
           -122.24
 [5]: y.head(3)
 [5]: 0
           4.526
           3.585
      1
      2
           3.521
      Name: HousePrice, dtype: float64
 [6]: from sklearn.preprocessing import StandardScaler
      sc = StandardScaler()
      x_sc = sc.fit_transform(X)
      x_sc
 [6]: array([[ 2.34476576, 0.98214266, 0.62855945, ..., -0.04959654,
               1.05254828, -1.32783522],
             [ 2.33223796, -0.60701891, 0.32704136, ..., -0.09251223,
               1.04318455, -1.32284391],
             [ 1.7826994 , 1.85618152, 1.15562047, ..., -0.02584253,
               1.03850269, -1.33282653],
             [-1.14259331, -0.92485123, -0.09031802, ..., -0.0717345,
               1.77823747, -0.8237132 ],
             [-1.05458292, -0.84539315, -0.04021111, ..., -0.09122515,
               1.77823747, -0.87362627],
             [-0.78012947, -1.00430931, -0.07044252, ..., -0.04368215,
               1.75014627, -0.83369581]])
 [7]: from sklearn.model_selection import train_test_split
      xtrain, xtest, ytrain, ytest = train_test_split(x_sc, y, test_size = 0.3,__
       →random_state=2)
 [8]: from sklearn.linear_model import Ridge
      rr = Ridge(alpha = 10)
 [9]: rr.fit(xtrain,ytrain)
 [9]: Ridge(alpha=10)
[10]: predict = rr.predict(xtest)
```

```
[11]: from sklearn.metrics import r2_score, mean_absolute_error r2_score(ytest,predict)
```

[11]: 0.6014258698314037

```
[12]: mean_absolute_error(ytest,predict)
```

[12]: np.float64(0.536239634635214)

Practical-

3.4_Lasso_Regression_standard_scalar_california_housing

```
[]: !pip install numpy pandas scikit-learn
[1]: import pandas as pd
     from sklearn.datasets import fetch_california_housing
[2]: ds = fetch_california_housing()
     df = pd.DataFrame(ds.data, columns = ds.feature_names)
     df["HousePrice"] = ds.target
     df.head(3)
[2]:
       MedInc HouseAge
                         AveRooms AveBedrms Population AveOccup Latitude \
     0 8.3252
                    41.0
                                                           2.555556
                                                                        37.88
                          6.984127
                                     1.023810
                                                    322.0
     1 8.3014
                    21.0
                          6.238137
                                     0.971880
                                                   2401.0 2.109842
                                                                        37.86
     2 7.2574
                    52.0 8.288136
                                     1.073446
                                                    496.0 2.802260
                                                                        37.85
       Longitude HousePrice
     0
          -122.23
                        4.526
         -122.22
                        3.585
     1
         -122.24
                        3.521
[3]: X = df.iloc[:,:-1]
     y = df.iloc[:,-1]
[4]: X.head(3)
[4]:
       MedInc
               HouseAge
                                    AveBedrms
                                              Population AveOccup
                          AveRooms
                                                                     Latitude \
     0 8.3252
                    41.0
                                                           2.555556
                                                                        37.88
                          6.984127
                                     1.023810
                                                    322.0
     1 8.3014
                    21.0
                                                   2401.0 2.109842
                                                                        37.86
                          6.238137
                                     0.971880
     2 7.2574
                    52.0 8.288136
                                     1.073446
                                                    496.0 2.802260
                                                                        37.85
       Longitude
          -122.23
     0
         -122.22
     1
     2
         -122.24
[5]: y.head(3)
```

```
[5]: 0
           4.526
           3.585
      1
      2
           3.521
      Name: HousePrice, dtype: float64
 [6]: from sklearn.preprocessing import StandardScaler
      sc = StandardScaler()
      x_sc = sc.fit_transform(X)
      x_sc
 [6]: array([[ 2.34476576, 0.98214266, 0.62855945, ..., -0.04959654,
               1.05254828, -1.32783522],
             [2.33223796, -0.60701891, 0.32704136, ..., -0.09251223,
               1.04318455, -1.32284391],
             [ 1.7826994 , 1.85618152, 1.15562047, ..., -0.02584253,
               1.03850269, -1.33282653],
             [-1.14259331, -0.92485123, -0.09031802, ..., -0.0717345,
               1.77823747, -0.8237132 ],
             [-1.05458292, -0.84539315, -0.04021111, ..., -0.09122515,
               1.77823747, -0.87362627],
             [-0.78012947, -1.00430931, -0.07044252, ..., -0.04368215,
               1.75014627, -0.83369581]])
 [7]: from sklearn.model_selection import train_test_split
      xtrain, xtest, ytrain, ytest = train_test_split(x_sc, y, test_size=0.3,__
       →random_state=2)
 [8]: from sklearn.linear model import Lasso
      lr = Lasso(alpha=10)
 [9]: lr.fit(xtrain, ytrain)
 [9]: Lasso(alpha=10)
[10]: predict = lr.predict(xtest)
[11]: from sklearn.metrics import r2_score, mean_absolute_error
      r2_score(ytest, predict)
[11]: -0.00033321189864432554
[12]: mean_absolute_error(ytest,predict)
[12]: np.float64(0.9147942692371251)
```

Practical-4_KNN_Regressor-assignment-done

```
[1]: import pandas as pd
     data = pd.read_csv("./dataset/BostonHousing.csv")
     data.head(3)
[1]:
                      indus
                              chas
           crim
                                      nox
                                                   age
                                                           dis rad
                                                                     tax
                                                                         ptratio \
                   zn
                                              rm
     0 0.00632 18.0
                        2.31
                                 0 0.538 6.575
                                                                     296
                                                  65.2 4.0900
                                                                  1
                                                                              15.3
     1 0.02731
                  0.0
                        7.07
                                 0 0.469
                                           6.421
                                                 78.9 4.9671
                                                                  2
                                                                     242
                                                                              17.8
     2 0.02729
                  0.0
                        7.07
                                 0 0.469 7.185 61.1 4.9671
                                                                     242
                                                                              17.8
              lstat
                       medv
       396.90
                 4.98
                       24.0
     1 396.90
                 9.14
                       21.6
     2 392.83
                 4.03 34.7
[2]: from sklearn.preprocessing import MinMaxScaler
     sc = MinMaxScaler(feature_range=(0,1))
[3]: x_{og} = data.iloc[:,:-1]
[4]: x = sc.fit_transform(x_og)
[4]: array([[0.00000000e+00, 1.80000000e-01, 6.78152493e-02, ...,
             2.87234043e-01, 1.00000000e+00, 8.96799117e-02],
            [2.35922539e-04, 0.00000000e+00, 2.42302053e-01, ...,
             5.53191489e-01, 1.00000000e+00, 2.04470199e-01],
            [2.35697744e-04, 0.00000000e+00, 2.42302053e-01, ...,
             5.53191489e-01, 9.89737254e-01, 6.34657837e-02],
            [6.11892474e-04, 0.00000000e+00, 4.20454545e-01, ...,
             8.93617021e-01, 1.00000000e+00, 1.07891832e-01],
            [1.16072990e-03, 0.00000000e+00, 4.20454545e-01, ...,
             8.93617021e-01, 9.91300620e-01, 1.31070640e-01],
            [4.61841693e-04, 0.00000000e+00, 4.20454545e-01, ...,
             8.93617021e-01, 1.00000000e+00, 1.69701987e-01]])
[5]: x.shape
```

```
[5]: (506, 13)
 [6]: y = data.iloc[:,-1]
      y.shape
 [6]: (506,)
 [7]: from sklearn.model_selection import train_test_split
      xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size=0.25,__
       →random_state = 1)
 [8]: from sklearn.neighbors import KNeighborsRegressor
      model = KNeighborsRegressor(n_neighbors=3)
      model.fit(xtrain,ytrain)
 [8]: KNeighborsRegressor(n_neighbors=3)
 [9]: predictions = model.predict(xtest)
[10]: from sklearn.metrics import r2_score
      r2_score(ytest, predictions)
[10]: 0.8069614057252134
     0.1 Testing with StandardScaler
[11]: from sklearn.preprocessing import StandardScaler
      ss = StandardScaler()
[12]: ss.fit(x_og)
      x = ss.transform(x_og)
[13]: xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size=0.25,__
       →random state = 1)
          Find best number of neighbors using gridSearchCV
[14]: from sklearn.model_selection import GridSearchCV
[15]: model2 = KNeighborsRegressor()
[16]: param = {"n_neighbors": [1,3,5,7,9,11],
               "weights": ["uniform", "distance"]}
      scoring = "neg_mean_squared_error"
[17]: search = GridSearchCV(model2, param, scoring = scoring, cv = 5)
      search.fit(xtrain, ytrain)
```

```
print(f"Best Params: {search.best_params_}")

Best Params: {'n_neighbors': 3, 'weights': 'distance'}

[18]: final_model = search.best_estimator_

[19]: predictions2 = final_model.predict(xtest)

from sklearn.metrics import r2_score
    r2_score(ytest, predictions2)
```

[19]: 0.8638489106891928

Practical-5_KNN_Classifier_assignment_done

```
[1]: from sklearn.datasets import load_iris
     df = load_iris()
     x = df.data
     y = df.target
[2]: x
[2]: array([[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],
            [5.4, 3.9, 1.7, 0.4],
            [4.6, 3.4, 1.4, 0.3],
            [5., 3.4, 1.5, 0.2],
            [4.4, 2.9, 1.4, 0.2],
            [4.9, 3.1, 1.5, 0.1],
            [5.4, 3.7, 1.5, 0.2],
            [4.8, 3.4, 1.6, 0.2],
            [4.8, 3., 1.4, 0.1],
            [4.3, 3., 1.1, 0.1],
            [5.8, 4., 1.2, 0.2],
            [5.7, 4.4, 1.5, 0.4],
            [5.4, 3.9, 1.3, 0.4],
            [5.1, 3.5, 1.4, 0.3],
            [5.7, 3.8, 1.7, 0.3],
            [5.1, 3.8, 1.5, 0.3],
            [5.4, 3.4, 1.7, 0.2],
            [5.1, 3.7, 1.5, 0.4],
            [4.6, 3.6, 1., 0.2],
            [5.1, 3.3, 1.7, 0.5],
            [4.8, 3.4, 1.9, 0.2],
            [5., 3., 1.6, 0.2],
            [5., 3.4, 1.6, 0.4],
            [5.2, 3.5, 1.5, 0.2],
            [5.2, 3.4, 1.4, 0.2],
            [4.7, 3.2, 1.6, 0.2],
            [4.8, 3.1, 1.6, 0.2],
```

```
[5.4, 3.4, 1.5, 0.4],
[5.2, 4.1, 1.5, 0.1],
[5.5, 4.2, 1.4, 0.2],
[4.9, 3.1, 1.5, 0.2],
[5., 3.2, 1.2, 0.2],
[5.5, 3.5, 1.3, 0.2],
[4.9, 3.6, 1.4, 0.1],
[4.4, 3., 1.3, 0.2],
[5.1, 3.4, 1.5, 0.2],
[5., 3.5, 1.3, 0.3],
[4.5, 2.3, 1.3, 0.3],
[4.4, 3.2, 1.3, 0.2],
[5., 3.5, 1.6, 0.6],
[5.1, 3.8, 1.9, 0.4],
[4.8, 3., 1.4, 0.3],
[5.1, 3.8, 1.6, 0.2],
[4.6, 3.2, 1.4, 0.2],
[5.3, 3.7, 1.5, 0.2],
[5., 3.3, 1.4, 0.2],
[7., 3.2, 4.7, 1.4],
[6.4, 3.2, 4.5, 1.5],
[6.9, 3.1, 4.9, 1.5],
[5.5, 2.3, 4., 1.3],
[6.5, 2.8, 4.6, 1.5],
[5.7, 2.8, 4.5, 1.3],
[6.3, 3.3, 4.7, 1.6],
[4.9, 2.4, 3.3, 1.],
[6.6, 2.9, 4.6, 1.3],
[5.2, 2.7, 3.9, 1.4],
[5., 2., 3.5, 1.],
[5.9, 3., 4.2, 1.5],
[6., 2.2, 4., 1.],
[6.1, 2.9, 4.7, 1.4],
[5.6, 2.9, 3.6, 1.3],
[6.7, 3.1, 4.4, 1.4],
[5.6, 3., 4.5, 1.5],
[5.8, 2.7, 4.1, 1.],
[6.2, 2.2, 4.5, 1.5],
[5.6, 2.5, 3.9, 1.1],
[5.9, 3.2, 4.8, 1.8],
[6.1, 2.8, 4., 1.3],
[6.3, 2.5, 4.9, 1.5],
[6.1, 2.8, 4.7, 1.2],
[6.4, 2.9, 4.3, 1.3],
[6.6, 3., 4.4, 1.4],
[6.8, 2.8, 4.8, 1.4],
[6.7, 3., 5., 1.7],
```

```
[6., 2.9, 4.5, 1.5],
[5.7, 2.6, 3.5, 1.],
[5.5, 2.4, 3.8, 1.1],
[5.5, 2.4, 3.7, 1.],
[5.8, 2.7, 3.9, 1.2],
[6., 2.7, 5.1, 1.6],
[5.4, 3., 4.5, 1.5],
[6., 3.4, 4.5, 1.6],
[6.7, 3.1, 4.7, 1.5],
[6.3, 2.3, 4.4, 1.3],
[5.6, 3., 4.1, 1.3],
[5.5, 2.5, 4., 1.3],
[5.5, 2.6, 4.4, 1.2],
[6.1, 3., 4.6, 1.4],
[5.8, 2.6, 4., 1.2],
[5., 2.3, 3.3, 1.],
[5.6, 2.7, 4.2, 1.3],
[5.7, 3., 4.2, 1.2],
[5.7, 2.9, 4.2, 1.3],
[6.2, 2.9, 4.3, 1.3],
[5.1, 2.5, 3., 1.1],
[5.7, 2.8, 4.1, 1.3],
[6.3, 3.3, 6., 2.5],
[5.8, 2.7, 5.1, 1.9],
[7.1, 3., 5.9, 2.1],
[6.3, 2.9, 5.6, 1.8],
[6.5, 3., 5.8, 2.2],
[7.6, 3., 6.6, 2.1],
[4.9, 2.5, 4.5, 1.7],
[7.3, 2.9, 6.3, 1.8],
[6.7, 2.5, 5.8, 1.8],
[7.2, 3.6, 6.1, 2.5],
[6.5, 3.2, 5.1, 2.],
[6.4, 2.7, 5.3, 1.9],
[6.8, 3., 5.5, 2.1],
[5.7, 2.5, 5., 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., 2.2, 5., 1.5],
[6.9, 3.2, 5.7, 2.3],
[5.6, 2.8, 4.9, 2.],
[7.7, 2.8, 6.7, 2.],
[6.3, 2.7, 4.9, 1.8],
[6.7, 3.3, 5.7, 2.1],
```

```
[7.2, 3.2, 6., 1.8],
        [6.2, 2.8, 4.8, 1.8],
        [6.1, 3., 4.9, 1.8],
        [6.4, 2.8, 5.6, 2.1],
        [7.2, 3., 5.8, 1.6],
        [7.4, 2.8, 6.1, 1.9],
        [7.9, 3.8, 6.4, 2.],
        [6.4, 2.8, 5.6, 2.2],
        [6.3, 2.8, 5.1, 1.5],
        [6.1, 2.6, 5.6, 1.4],
        [7.7, 3., 6.1, 2.3],
        [6.3, 3.4, 5.6, 2.4],
        [6.4, 3.1, 5.5, 1.8],
        [6., 3., 4.8, 1.8],
        [6.9, 3.1, 5.4, 2.1],
        [6.7, 3.1, 5.6, 2.4],
        [6.9, 3.1, 5.1, 2.3],
        [5.8, 2.7, 5.1, 1.9],
        [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]])
[3]: y
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
        [4]: from sklearn.model_selection import train_test_split
   xtrain, xtest, ytrain, ytest = train_test_split(x,y,test_size=0.2, random_state_
    \Rightarrow= 1)
[5]: from sklearn.neighbors import KNeighborsClassifier
   model = KNeighborsClassifier()
   model.fit(xtrain,ytrain)
[5]: KNeighborsClassifier()
[6]: predictions = model.predict(xtest)
```

```
[7]: from sklearn.metrics import accuracy_score
     accuracy_score(ytest, predictions)
```

[7]: 1.0

```
0.1 Find best number of neighbors using gridSearchCV
 [8]: from sklearn.model_selection import GridSearchCV
 [9]: model2 = KNeighborsClassifier()
[10]: param = {"n_neighbors" : [1,3,5],
               "weights" : ["uniform", "distance"]}
      scoring = "neg_mean_squared_error"
[11]: search = GridSearchCV(model2, param, scoring = scoring, cv = 5)
      search.fit(xtrain, ytrain)
      print(f"Best Params: {search.best_params_}")
     Best Params: {'n_neighbors': 3, 'weights': 'uniform'}
[12]: final_model = search.best_estimator_
[13]: predictions2 = final_model.predict(xtest)
[14]: from sklearn.metrics import r2_score
      r2_score(ytest, predictions2)
```

[14]: 1.0

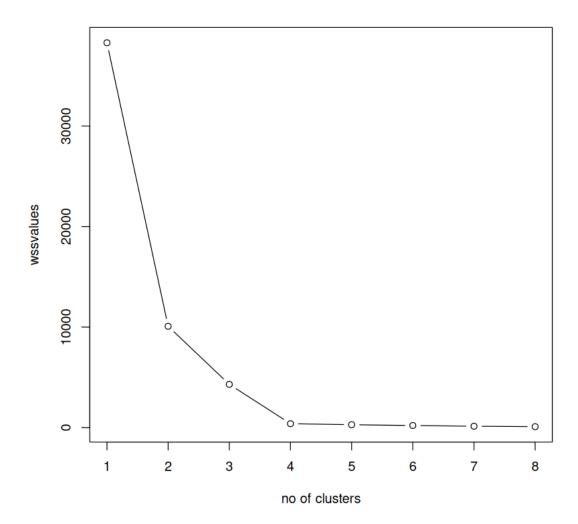
$Practical \hbox{-} 6_K \hbox{-} means \hbox{-} R$

```
[1]: library(ggplot2)
     library(cluster)
[3]: df = as.data.frame(read.csv("./dataset/marks.csv"))
     df
                           Roll\_no
                                     English
                                               Maths
                                                        Science
                            <int>
                                               <int>
                                      <int>
                                                        <int>
                           1
                                      99
                                               100
                                                        100
                           2
                                      98
                                               99
                                                        97
                           3
                                      92
                                               9
                                                        96
                           4
                                      95
                                               92
                                                        94
                           5
                                      90
                                               100
                                                        96
                           6
                                      80
                                               75
                                                        82
                                      75
                                               83
                                                        80
    A data.frame: 17 \times 4
                                      72
                                               73
                                                        74
                                      71
                                               82
                                                        76
                           10
                                      73
                                               74
                                                        76
                                               32
                           11
                                      34
                                                        28
                           12
                                      26
                                               28
                                                        30
                                      32
                           13
                                               30
                                                        31
                                      98
                                               97
                           14
                                                        98
                                      30
                           15
                                               29
                                                        29
                           16
                                      78
                                               75
                                                        78
                           17
                                      100
                                               99
                                                        100
[4]: kmdata = df[,2:4]
```

kmdata

	English	Maths	Science
	<int $>$	<int $>$	<int $>$
	99	100	100
	98	99	97
	92	9	96
	95	92	94
	90	100	96
	80	75	82
	75	83	80
A data.frame: 17×3	72	73	74
	71	82	76
	73	74	76
	34	32	28
	26	28	30
	32	30	31
	98	97	98
	30	29	29
	78	75	78
	100	99	100

```
[5]: wss = numeric(8)
for (k in 1:8) wss[k] = sum(kmeans(kmdata,centers = k, nstart = 25)$withinss)
plot(1:8,wss,type="b",xlab="no of clusters", ylab = "wssvalues")
```



K-means clustering with 3 clusters of sizes 4, 1, 12

Cluster means:

```
English Maths Science
```

- 1 30.50 29.75000 29.50000
- 2 92.00 9.00000 96.00000
- 3 85.75 87.41667 87.58333

Clustering vector:

[1] 3 3 2 3 3 3 3 3 3 1 1 1 3 1 3 3

Within cluster sum of squares by cluster: [1] 48.750 0.000 4254.083

(between_SS / total_SS = 88.8 %)

Available components:

[1] "cluster" "centers" "totss" "withinss" "tot.withinss"

[6] "betweenss" "size" "iter" "ifault"

Practical-7 SVM classifier

```
[1]: import pandas as pd
[4]: df = pd.read_csv("./dataset/diabetes.csv")
[5]: df.head(3)
[5]:
        Pregnancies
                     Glucose
                               BloodPressure
                                               SkinThickness
                                                               Insulin
                                                                         BMI
                                                                        33.6
                  6
                          148
                                           72
                                                          35
                                                                        26.6
     1
                  1
                           85
                                           66
                                                          29
                                                                     0
     2
                  8
                          183
                                           64
                                                           0
                                                                     0
                                                                        23.3
        DiabetesPedigreeFunction
                                   Age
                                        Outcome
     0
                            0.627
                                    50
     1
                            0.351
                                    31
                                               0
     2
                            0.672
                                    32
[6]: df.sample(2)
[6]:
                        Glucose
                                 BloodPressure
                                                 SkinThickness
                                                                 Insulin
          Pregnancies
                                                                           BMI
     442
                     4
                            117
                                             64
                                                            27
                                                                     120
                                                                          33.2
     311
                     0
                                             70
                            106
                                                            37
                                                                     148 39.4
          DiabetesPedigreeFunction Age
                                          Outcome
     442
                              0.230
                                       24
     311
                              0.605
                                      22
                                                 0
[7]: df.shape
[7]: (768, 9)
[8]: df["Outcome"].value_counts()
[8]: Outcome
     0
          500
          268
     1
     Name: count, dtype: int64
```

```
[9]: X = df.iloc[:,:-1]
      X.shape
 [9]: (768, 8)
[10]: y = df.iloc[:,-1]
      y.shape
[10]: (768,)
[11]: X
[11]:
           Pregnancies
                         Glucose
                                  BloodPressure
                                                  SkinThickness
                                                                  Insulin
                                                                             BMI
                                                                                 \
                             148
                                              72
                                                              35
                                                                         0 33.6
      0
                      6
      1
                      1
                              85
                                              66
                                                              29
                                                                         0
                                                                            26.6
      2
                      8
                                              64
                                                               0
                                                                            23.3
                             183
                                                                         0
      3
                      1
                              89
                                              66
                                                              23
                                                                        94
                                                                            28.1
      4
                      0
                             137
                                              40
                                                              35
                                                                       168 43.1
      763
                                              76
                                                              48
                                                                       180 32.9
                     10
                             101
      764
                      2
                             122
                                              70
                                                              27
                                                                         0 36.8
      765
                      5
                             121
                                              72
                                                              23
                                                                       112 26.2
      766
                      1
                             126
                                              60
                                                               0
                                                                         0 30.1
      767
                                                              31
                                                                         0 30.4
                      1
                              93
                                              70
           DiabetesPedigreeFunction
                                      Age
      0
                               0.627
                                        50
      1
                               0.351
                                        31
      2
                               0.672
                                        32
      3
                               0.167
                                        21
      4
                               2.288
                                        33
                                 ... ...
      763
                               0.171
                                        63
      764
                               0.340
                                        27
      765
                               0.245
                                        30
      766
                               0.349
                                        47
      767
                               0.315
                                        23
      [768 rows x 8 columns]
[12]: y
[12]: 0
             1
      1
             0
      2
             1
      3
             0
      4
             1
```

```
763
             0
      764
             0
      765
             0
      766
      767
     Name: Outcome, Length: 768, dtype: int64
[13]: from sklearn.model_selection import train_test_split
      xtrain, xtest, ytrain, ytest = train_test_split(X, y, test_size = 0.25, __
       →random_state=1)
[14]: xtrain.shape, xtest.shape, ytrain.shape, ytest.shape
[14]: ((576, 8), (192, 8), (576,), (192,))
[15]: from sklearn.svm import SVC
      model1 = SVC(kernel="linear", degree=2, coef0=1.5)
      # default will be linear kernal
      model1.fit(xtrain, ytrain)
[15]: SVC(coef0=1.5, degree=2, kernel='linear')
[16]: predictions = model1.predict(xtest)
[17]: from sklearn.metrics import accuracy_score, r2_score, confusion_matrix
      accuracy_score(ytest, predictions)
[17]: 0.78125
[18]: confusion_matrix(ytest, predictions)
[18]: array([[108, 15],
             [ 27, 42]])
[19]: model2 = SVC(kernel="poly", degree=2, coef0=1.5)
      model2.fit(xtrain, ytrain)
[19]: SVC(coef0=1.5, degree=2, kernel='poly')
[20]: predictions2 = model2.predict(xtest)
      accuracy_score(ytest, predictions2)
[20]: 0.796875
[21]: confusion_matrix(ytest, predictions2)
```

Practical-8 Ensemble Bagging

```
[1]: import numpy as np
     from sklearn.datasets import load_breast_cancer
     from sklearn.model_selection import train_test_split
[2]: from sklearn.preprocessing import StandardScaler
     from sklearn.linear_model import LogisticRegression
     from sklearn.pipeline import make pipeline
     from sklearn.ensemble import BaggingClassifier
[3]: df = load_breast_cancer()
     x=df.data
     y=df.target
[4]: xtrain, xtest, ytrain, ytest = train_test_split(x,y,test_size=0.
      →25,random_state=1)
[5]: pipeline= make pipeline(StandardScaler(), LogisticRegression(random_state=1))
[6]: pipeline.fit(xtrain,ytrain)
[6]: Pipeline(steps=[('standardscaler', StandardScaler()),
                     ('logisticregression', LogisticRegression(random_state=1))])
[7]: print("Score:",pipeline.score(xtest,ytest))
     pred1=pipeline.predict(xtest)
     from sklearn.metrics import accuracy_score
     print("Accuracy Score:",accuracy_score(ytest,pred1))
    Score: 0.9790209790209791
    Accuracy Score: 0.9790209790209791
[8]: bgclassifier=
      →BaggingClassifier(estimator=pipeline,n_estimators=100,max_features=10,max_samples=100,__
      →random_state=1)
[9]: bgclassifier.fit(xtrain,ytrain)
[9]: BaggingClassifier(estimator=Pipeline(steps=[('standardscaler',
                                                  StandardScaler()),
```