linear-regression-boston

April 23, 2024

```
import pandas as pd
      import matplotlib.pyplot as plt
     0.0.1 Load Dataset
 [8]: df = pd.read_csv("boston.csv")
      df.head(10)
 [8]:
             CRIM
                      ZN
                          INDUS
                                  CHAS
                                          NOX
                                                   RM
                                                          AGE
                                                                   DIS
                                                                        RAD
                                                                              TAX
                                                                                   PTRATIO
      0
         0.00632
                   18.0
                           2.31
                                     0
                                        0.538
                                                6.575
                                                         65.2
                                                               4.0900
                                                                           1
                                                                              296
                                                                                       15.3
      1
         0.02731
                    0.0
                           7.07
                                        0.469
                                                6.421
                                                         78.9
                                                               4.9671
                                                                              242
                                                                                       17.8
      2
         0.02729
                    0.0
                           7.07
                                     0
                                        0.469
                                                7.185
                                                         61.1
                                                               4.9671
                                                                           2
                                                                              242
                                                                                       17.8
         0.03237
                    0.0
                           2.18
                                        0.458
                                                6.998
                                                         45.8
                                                               6.0622
                                                                           3
                                                                              222
                                                                                       18.7
      3
                                     0
      4 0.06905
                    0.0
                           2.18
                                     0
                                        0.458
                                                7.147
                                                         54.2
                                                               6.0622
                                                                           3
                                                                              222
                                                                                       18.7
         0.02985
                    0.0
                           2.18
                                     0
                                        0.458
                                                6.430
                                                         58.7
                                                               6.0622
                                                                           3
                                                                              222
                                                                                       18.7
      5
         0.08829
                   12.5
                           7.87
                                     0
                                        0.524
                                                6.012
                                                         66.6
                                                               5.5605
                                                                           5
                                                                              311
                                                                                       15.2
      6
      7
         0.14455
                   12.5
                                        0.524
                                                                           5
                                                                              311
                           7.87
                                                6.172
                                                         96.1
                                                               5.9505
                                                                                       15.2
         0.21124
                   12.5
                           7.87
                                        0.524
                                                5.631
                                                                           5
                                                        100.0
                                                               6.0821
                                                                              311
                                                                                       15.2
         0.17004
                                        0.524
                                                6.004
                   12.5
                           7.87
                                                         85.9
                                                               6.5921
                                                                              311
                                                                                       15.2
               В
                  LSTAT
                          MEDV
                                CAT. MEDV
                                             Unnamed: 15
                                                           Unnamed: 16
      0
         396.90
                   4.98
                          24.0
                                         0
                                                      NaN
                                                                    NaN
         396.90
                   9.14
                          21.6
                                         0
      1
                                                      NaN
                                                                    NaN
                   4.03
      2
         392.83
                          34.7
                                         1
                                                      NaN
                                                                    NaN
      3
         394.63
                   2.94
                          33.4
                                         1
                                                      NaN
                                                                    NaN
         396.90
                   5.33
                          36.2
                                         1
                                                      NaN
                                                                    NaN
         394.12
      5
                   5.21
                          28.7
                                         0
                                                      NaN
                                                                    NaN
         395.60
                  12.43
                          22.9
                                         0
      6
                                                      NaN
                                                                    NaN
      7
         396.90
                  19.15
                          27.1
                                         0
                                                      NaN
                                                                    NaN
      8
         386.63
                  29.93
                          16.5
                                         0
                                                      NaN
                                                                    NaN
         386.71
                  17.10
                          18.9
                                         0
                                                      NaN
                                                                    NaN
 [9]: df.drop(columns=['Unnamed: 15', 'Unnamed: 16'], inplace=True)
[10]: df.drop(columns=['CAT. MEDV'],inplace=True)
```

Checking for null values

```
[11]: df.isnull().sum()
[11]: CRIM
                  0
      ZN
                  0
      INDUS
                  0
      CHAS
                  0
      NOX
                  0
      RM
                  0
      AGE
                  0
      DIS
                  0
      RAD
                  0
      TAX
                  0
      PTRATIO
                  0
      В
                  0
      LSTAT
      MF.DV
                  0
      dtype: int64
[12]: df.info()
     <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 506 entries, 0 to 505
     Data columns (total 14 columns):
                    Non-Null Count Dtype
           Column
      0
           CRIM
                    506 non-null
                                     float64
                    506 non-null
                                     float64
      1
           ZN
      2
           INDUS
                    506 non-null
                                     float64
                    506 non-null
      3
           CHAS
                                     int64
      4
          NOX
                    506 non-null
                                     float64
      5
          RM
                    506 non-null
                                     float64
      6
           AGE
                    506 non-null
                                     float64
      7
           DIS
                    506 non-null
                                     float64
      8
           RAD
                    506 non-null
                                     int64
      9
           TAX
                    506 non-null
                                     int64
      10
          PTRATIO
                    506 non-null
                                     float64
      11
          В
                    506 non-null
                                     float64
      12
          LSTAT
                    506 non-null
                                     float64
                    506 non-null
      13 MEDV
                                     float64
     dtypes: float64(11), int64(3)
     memory usage: 55.5 KB
[13]: df.describe()
「13]:
                    CRIM
                                   ZN
                                            INDUS
                                                          CHAS
                                                                        NOX
                                                                                      RM
      count
             506.000000
                          506.000000
                                       506.000000
                                                   506.000000
                                                                506.000000
                                                                             506.000000
                                        11.136779
                                                      0.069170
      mean
               3.613524
                           11.363636
                                                                   0.554695
                                                                               6.284634
```

```
std
         8.601545
                     23.322453
                                   6.860353
                                                0.253994
                                                             0.115878
                                                                         0.702617
         0.006320
                      0.000000
                                   0.460000
                                                0.000000
                                                             0.385000
                                                                          3.561000
min
25%
         0.082045
                      0.000000
                                   5.190000
                                                0.000000
                                                             0.449000
                                                                          5.885500
50%
         0.256510
                      0.000000
                                   9.690000
                                                0.000000
                                                             0.538000
                                                                         6.208500
75%
         3.677083
                     12.500000
                                  18.100000
                                                0.000000
                                                             0.624000
                                                                          6.623500
        88.976200
                    100.000000
                                  27.740000
                                                1.000000
                                                             0.871000
                                                                         8.780000
max
               AGE
                            DIS
                                        RAD
                                                     TAX
                                                              PTRATIO
                                                                                    \
                                                                                 В
       506.000000
                    506.000000
                                 506.000000
                                              506.000000
                                                          506.000000
                                                                       506.000000
count
        68.574901
                                   9.549407
                                                                       356.674032
mean
                      3.795043
                                              408.237154
                                                            18.455534
std
        28.148861
                      2.105710
                                   8.707259
                                              168.537116
                                                             2.164946
                                                                        91.294864
         2.900000
                      1.129600
                                   1.000000
                                              187.000000
                                                            12.600000
                                                                         0.320000
min
25%
        45.025000
                      2.100175
                                   4.000000
                                              279.000000
                                                            17.400000
                                                                       375.377500
50%
        77.500000
                      3.207450
                                   5.000000
                                              330.000000
                                                            19.050000
                                                                       391.440000
75%
        94.075000
                      5.188425
                                  24.000000
                                              666.000000
                                                            20.200000
                                                                       396.225000
max
       100.000000
                     12.126500
                                  24.000000
                                              711.000000
                                                            22.000000
                                                                       396.900000
             LSTAT
                           MEDV
       506.000000
                    506.000000
count
                     22.532806
mean
        12.653063
std
         7.141062
                      9.197104
         1.730000
                      5.000000
min
25%
         6.950000
                     17.025000
50%
        11.360000
                     21.200000
75%
        16.955000
                     25.000000
max
        37.970000
                     50.000000
```

Checking correlation with target variable MEDV

[14]: df.corr()['MEDV'].sort_values()

Name: MEDV, dtype: float64

```
[14]: LSTAT
                 -0.737663
      PTRATIO
                 -0.507787
      INDUS
                 -0.483725
      TAX
                 -0.468536
      NOX
                 -0.427321
      CRIM
                 -0.388305
      RAD
                 -0.381626
      AGE
                 -0.376955
      CHAS
                  0.175260
      DIS
                  0.249929
      В
                  0.333461
      ZN
                  0.360445
      RM
                  0.695360
      MEDV
                  1.000000
```

```
[15]: X = df.loc[:,['LSTAT','PTRATIO','RM']]
      Y = df.loc[:,"MEDV"]
      X.shape,Y.shape
[15]: ((506, 3), (506,))
     0.0.2 Preparing training and testing data set
[16]: from sklearn.model_selection import train_test_split
      x_train,x_test,y_train,y_test = train_test_split(X,Y,test_size=0.
       →25,random_state=10)
     0.0.3 Normalizing training and testing dataset
[17]: from sklearn.preprocessing import StandardScaler
[18]: scaler = StandardScaler()
[19]: scaler.fit(x_train)
[19]: StandardScaler()
[20]: x_train = scaler.transform(x_train)
      x_test = scaler.transform(x_test)
     0.0.4 Preparing model
[21]: from keras.models import Sequential
      from keras.layers import Dense
                                                 Traceback (most recent call last)
      ModuleNotFoundError
      Cell In[21], line 1
       ----> 1 from keras.models import Sequential
             2 from keras.layers import Dense
      ModuleNotFoundError: No module named 'keras'
[22]: model = Sequential()
      NameError
                                                 Traceback (most recent call last)
      Cell In[22], line 1
       ----> 1 model = Sequential()
```

NameError: name 'Sequential' is not defined

```
[37]: model.add(Dense(128,input_shape=(3,),activation='relu',name='input'))
    model.add(Dense(64,activation='relu',name='layer_1'))
    model.add(Dense(1,activation='linear',name='output'))
    model.compile(optimizer='adam', loss='mse', metrics=['mae'])
    model.summary()
    Model: "sequential_1"
    Layer (type)
                          Output Shape
    ______
    input (Dense)
                          (None, 128)
                                              512
                          (None, 64)
    layer_1 (Dense)
                                              8256
    output (Dense)
                          (None, 1)
                                              65
    Total params: 8,833
    Trainable params: 8,833
    Non-trainable params: 0
[38]: model.fit(x_train,y_train,epochs=100,validation_split=0.05)
    /home/pratik/.local/lib/python3.8/site-
    packages/keras/engine/data_adapter.py:1699: FutureWarning: The behavior of
    `series[i:j]` with an integer-dtype index is deprecated. In a future version,
    this will be treated as *label-based* indexing, consistent with e.g. `series[i]`
    lookups. To retain the old behavior, use `series.iloc[i:j]`. To get the future
    behavior, use `series.loc[i:j]`.
     return t[start:end]
    Epoch 1/100
    21.1973 - val_loss: 684.2971 - val_mae: 23.4446
    Epoch 2/100
    20.2731 - val_loss: 630.4888 - val_mae: 22.2464
    Epoch 3/100
    18.9328 - val_loss: 557.4312 - val_mae: 20.5203
    Epoch 4/100
    16.9609 - val_loss: 464.9811 - val_mae: 18.3199
```

Epoch 5/100

```
14.3374 - val_loss: 361.5852 - val_mae: 15.6702
Epoch 6/100
11.2933 - val_loss: 259.4221 - val_mae: 12.6659
Epoch 7/100
8.0840 - val_loss: 184.6476 - val_mae: 10.3077
Epoch 8/100
12/12 [============== ] - Os 3ms/step - loss: 51.1009 - mae:
5.8868 - val_loss: 143.0784 - val_mae: 8.6210
Epoch 9/100
5.0207 - val_loss: 122.0487 - val_mae: 7.6780
Epoch 10/100
4.4855 - val_loss: 109.6800 - val_mae: 7.2366
Epoch 11/100
12/12 [============== ] - Os 3ms/step - loss: 29.9512 - mae:
4.0640 - val_loss: 102.8176 - val_mae: 7.0559
Epoch 12/100
3.8241 - val_loss: 98.0677 - val_mae: 6.8996
Epoch 13/100
12/12 [============== ] - Os 3ms/step - loss: 24.9706 - mae:
3.6743 - val_loss: 93.2265 - val_mae: 6.7188
Epoch 14/100
3.5606 - val_loss: 91.2786 - val_mae: 6.6632
Epoch 15/100
12/12 [=============== ] - Os 3ms/step - loss: 22.7392 - mae:
3.4870 - val_loss: 89.9420 - val_mae: 6.5950
Epoch 16/100
12/12 [============== ] - Os 3ms/step - loss: 21.9554 - mae:
3.4222 - val loss: 87.4618 - val mae: 6.5106
Epoch 17/100
3.3762 - val_loss: 86.6438 - val_mae: 6.4625
Epoch 18/100
3.3364 - val_loss: 86.2997 - val_mae: 6.4570
Epoch 19/100
12/12 [=============== ] - Os 3ms/step - loss: 20.3429 - mae:
3.3059 - val_loss: 87.6115 - val_mae: 6.5001
Epoch 20/100
12/12 [=============== ] - Os 3ms/step - loss: 19.7910 - mae:
3.2573 - val_loss: 86.8414 - val_mae: 6.4395
Epoch 21/100
```

```
12/12 [=============== ] - Os 3ms/step - loss: 19.3040 - mae:
3.2172 - val_loss: 85.3897 - val_mae: 6.3410
Epoch 22/100
3.1857 - val_loss: 83.8950 - val_mae: 6.2748
Epoch 23/100
3.1427 - val_loss: 85.9416 - val_mae: 6.2838
Epoch 24/100
12/12 [============== ] - Os 3ms/step - loss: 17.9731 - mae:
3.0871 - val_loss: 85.2962 - val_mae: 6.2192
Epoch 25/100
3.0524 - val_loss: 84.0756 - val_mae: 6.1301
Epoch 26/100
12/12 [============== ] - Os 3ms/step - loss: 17.2496 - mae:
3.0313 - val_loss: 83.8474 - val_mae: 6.0809
Epoch 27/100
12/12 [============== ] - Os 3ms/step - loss: 16.8987 - mae:
3.0019 - val_loss: 82.9085 - val_mae: 6.0096
Epoch 28/100
2.9855 - val_loss: 82.4742 - val_mae: 5.9599
Epoch 29/100
12/12 [============== ] - Os 3ms/step - loss: 16.3804 - mae:
2.9552 - val_loss: 84.0461 - val_mae: 5.9848
Epoch 30/100
2.9228 - val_loss: 82.8573 - val_mae: 5.8955
Epoch 31/100
12/12 [=============== ] - Os 3ms/step - loss: 15.8775 - mae:
2.9189 - val_loss: 82.3173 - val_mae: 5.8456
Epoch 32/100
12/12 [============== ] - Os 3ms/step - loss: 15.7003 - mae:
2.9055 - val loss: 82.2009 - val mae: 5.8318
Epoch 33/100
2.8817 - val_loss: 81.1925 - val_mae: 5.7864
Epoch 34/100
2.8577 - val_loss: 82.7803 - val_mae: 5.8049
Epoch 35/100
12/12 [================ ] - Os 3ms/step - loss: 15.1625 - mae:
2.8552 - val_loss: 82.5307 - val_mae: 5.7775
Epoch 36/100
12/12 [=============== ] - Os 3ms/step - loss: 14.9914 - mae:
2.8294 - val_loss: 82.5536 - val_mae: 5.7522
Epoch 37/100
```

```
12/12 [=============== ] - Os 3ms/step - loss: 14.7915 - mae:
2.8238 - val_loss: 81.7447 - val_mae: 5.7054
Epoch 38/100
2.8152 - val_loss: 80.9904 - val_mae: 5.6606
Epoch 39/100
12/12 [================= ] - Os 3ms/step - loss: 14.5984 - mae:
2.7850 - val_loss: 83.0082 - val_mae: 5.7130
Epoch 40/100
12/12 [============== ] - Os 3ms/step - loss: 14.4250 - mae:
2.7908 - val_loss: 79.6669 - val_mae: 5.6064
Epoch 41/100
2.8150 - val_loss: 84.1153 - val_mae: 5.7513
Epoch 42/100
2.7555 - val_loss: 81.3843 - val_mae: 5.6236
Epoch 43/100
12/12 [============== ] - Os 3ms/step - loss: 14.0879 - mae:
2.7372 - val_loss: 79.7218 - val_mae: 5.5161
Epoch 44/100
2.7283 - val_loss: 82.5691 - val_mae: 5.5710
Epoch 45/100
12/12 [============== ] - Os 3ms/step - loss: 13.8294 - mae:
2.7071 - val_loss: 83.5797 - val_mae: 5.5885
Epoch 46/100
2.6897 - val_loss: 81.4584 - val_mae: 5.5139
Epoch 47/100
12/12 [=============== ] - Os 3ms/step - loss: 13.6327 - mae:
2.6876 - val_loss: 81.5313 - val_mae: 5.5337
Epoch 48/100
12/12 [============== ] - Os 3ms/step - loss: 13.4871 - mae:
2.6831 - val_loss: 81.8829 - val_mae: 5.5197
Epoch 49/100
2.6598 - val_loss: 81.6146 - val_mae: 5.5109
Epoch 50/100
2.6507 - val_loss: 82.3006 - val_mae: 5.5114
Epoch 51/100
12/12 [=============== ] - Os 3ms/step - loss: 13.3731 - mae:
2.6582 - val_loss: 79.2186 - val_mae: 5.4195
Epoch 52/100
12/12 [================ ] - Os 3ms/step - loss: 13.0755 - mae:
2.6232 - val_loss: 82.1192 - val_mae: 5.4674
Epoch 53/100
```

```
2.6301 - val_loss: 82.2511 - val_mae: 5.4621
Epoch 54/100
2.6066 - val_loss: 80.3709 - val_mae: 5.3996
Epoch 55/100
2.5896 - val_loss: 80.9426 - val_mae: 5.3828
Epoch 56/100
12/12 [============== ] - Os 3ms/step - loss: 12.9274 - mae:
2.5858 - val_loss: 80.2519 - val_mae: 5.3328
Epoch 57/100
2.5847 - val_loss: 82.8984 - val_mae: 5.3706
Epoch 58/100
12/12 [============== ] - Os 3ms/step - loss: 12.7283 - mae:
2.5830 - val_loss: 80.4384 - val_mae: 5.3213
Epoch 59/100
12/12 [============== ] - Os 3ms/step - loss: 12.5721 - mae:
2.5648 - val_loss: 81.8696 - val_mae: 5.3709
Epoch 60/100
2.5413 - val_loss: 80.1730 - val_mae: 5.3064
Epoch 61/100
12/12 [============== ] - Os 3ms/step - loss: 12.3504 - mae:
2.5372 - val_loss: 82.3537 - val_mae: 5.3312
Epoch 62/100
2.5263 - val_loss: 81.8209 - val_mae: 5.3155
Epoch 63/100
12/12 [=============== ] - Os 3ms/step - loss: 12.1914 - mae:
2.5186 - val_loss: 81.0043 - val_mae: 5.2819
Epoch 64/100
12/12 [============== ] - Os 3ms/step - loss: 12.0838 - mae:
2.5141 - val loss: 82.2268 - val mae: 5.2991
Epoch 65/100
2.5192 - val_loss: 80.9062 - val_mae: 5.2588
Epoch 66/100
2.4995 - val_loss: 81.0292 - val_mae: 5.2457
Epoch 67/100
12/12 [=============== ] - Os 3ms/step - loss: 11.9510 - mae:
2.4905 - val_loss: 81.9456 - val_mae: 5.2709
Epoch 68/100
12/12 [================ ] - Os 3ms/step - loss: 11.9244 - mae:
2.5124 - val_loss: 80.4283 - val_mae: 5.2259
Epoch 69/100
```

```
12/12 [=============== ] - Os 3ms/step - loss: 11.8111 - mae:
2.4702 - val_loss: 80.2744 - val_mae: 5.2222
Epoch 70/100
2.4784 - val_loss: 82.1776 - val_mae: 5.2416
Epoch 71/100
2.4718 - val_loss: 79.9181 - val_mae: 5.1496
Epoch 72/100
12/12 [============== ] - Os 3ms/step - loss: 11.6516 - mae:
2.4528 - val_loss: 81.3688 - val_mae: 5.1745
Epoch 73/100
2.4364 - val_loss: 81.5457 - val_mae: 5.1724
Epoch 74/100
12/12 [============== ] - Os 3ms/step - loss: 11.6022 - mae:
2.4720 - val_loss: 82.5531 - val_mae: 5.1809
Epoch 75/100
12/12 [============== ] - Os 3ms/step - loss: 11.3654 - mae:
2.4368 - val_loss: 81.2617 - val_mae: 5.1176
Epoch 76/100
2.4344 - val_loss: 82.1688 - val_mae: 5.1470
Epoch 77/100
12/12 [============== ] - Os 3ms/step - loss: 11.4002 - mae:
2.4252 - val_loss: 81.4868 - val_mae: 5.1287
Epoch 78/100
2.4045 - val_loss: 80.9666 - val_mae: 5.1395
Epoch 79/100
12/12 [=============== ] - Os 3ms/step - loss: 11.1954 - mae:
2.3919 - val_loss: 81.4386 - val_mae: 5.0960
Epoch 80/100
12/12 [============== ] - Os 3ms/step - loss: 11.2026 - mae:
2.4224 - val_loss: 80.0435 - val_mae: 5.1421
Epoch 81/100
2.4191 - val_loss: 81.8591 - val_mae: 5.1589
Epoch 82/100
2.3819 - val_loss: 81.2953 - val_mae: 5.0771
Epoch 83/100
12/12 [=============== ] - Os 3ms/step - loss: 11.0476 - mae:
2.3804 - val_loss: 81.5968 - val_mae: 5.0807
Epoch 84/100
12/12 [================ ] - Os 3ms/step - loss: 11.0166 - mae:
2.3936 - val_loss: 83.5097 - val_mae: 5.1785
Epoch 85/100
```

```
12/12 [============== ] - Os 3ms/step - loss: 10.9730 - mae:
2.3777 - val_loss: 81.7998 - val_mae: 5.1038
Epoch 86/100
2.3799 - val_loss: 82.7827 - val_mae: 5.1333
Epoch 87/100
2.3697 - val_loss: 83.3495 - val_mae: 5.1081
Epoch 88/100
2.3782 - val_loss: 84.2799 - val_mae: 5.2340
Epoch 89/100
12/12 [=============== ] - Os 3ms/step - loss: 10.8551 - mae:
2.3657 - val_loss: 82.8966 - val_mae: 5.1426
Epoch 90/100
12/12 [=============== ] - Os 3ms/step - loss: 10.7487 - mae:
2.3737 - val_loss: 82.9162 - val_mae: 5.1396
Epoch 91/100
12/12 [============== ] - Os 3ms/step - loss: 10.7692 - mae:
2.3567 - val_loss: 81.7738 - val_mae: 5.0534
Epoch 92/100
2.3858 - val_loss: 83.4745 - val_mae: 5.1617
Epoch 93/100
12/12 [============== ] - Os 3ms/step - loss: 10.7417 - mae:
2.3593 - val_loss: 80.3109 - val_mae: 5.0397
Epoch 94/100
2.3462 - val_loss: 83.9402 - val_mae: 5.1520
Epoch 95/100
12/12 [=============== ] - Os 3ms/step - loss: 10.5802 - mae:
2.3409 - val_loss: 83.6694 - val_mae: 5.1339
Epoch 96/100
12/12 [============== ] - Os 3ms/step - loss: 10.6581 - mae:
2.3396 - val_loss: 82.1335 - val_mae: 5.0487
Epoch 97/100
2.3562 - val_loss: 83.7102 - val_mae: 5.1258
Epoch 98/100
2.3370 - val_loss: 81.2809 - val_mae: 5.0286
Epoch 99/100
12/12 [=============== ] - Os 3ms/step - loss: 10.5333 - mae:
2.3380 - val_loss: 83.6725 - val_mae: 5.1323
Epoch 100/100
12/12 [=============== ] - Os 3ms/step - loss: 10.3605 - mae:
2.3148 - val_loss: 83.1757 - val_mae: 5.0693
```

```
[38]: <keras.callbacks.History at 0x7fbddc67a490>
[39]: output = model.evaluate(x_test,y_test)
     [44]: print(f"Mean Squared Error: {output[0]}"
            ,f"Mean Absolute Error: {output[1]}",sep="\n")
     Mean Squared Error: 22.26400375366211
     Mean Absolute Error: 3.1030352115631104
[45]: | y_pred = model.predict(x=x_test)
     4/4 [======== ] - 0s 4ms/step
[46]: print(*zip(y_pred,y_test))
     (array([24.506329], dtype=float32), 28.4) (array([30.56254], dtype=float32),
     31.1) (array([25.646534], dtype=float32), 23.5) (array([27.445961],
     dtype=float32), 26.6) (array([19.707462], dtype=float32), 19.6)
     (array([16.464933], dtype=float32), 14.3) (array([42.08562], dtype=float32),
     50.0) (array([14.898803], dtype=float32), 14.3) (array([20.1403],
     dtype=float32), 20.7) (array([43.237473], dtype=float32), 37.6)
     (array([17.841496], dtype=float32), 20.4) (array([26.564915], dtype=float32),
     27.5) (array([22.473684], dtype=float32), 36.2) (array([32.409435],
     dtype=float32), 32.0) (array([31.079502], dtype=float32), 33.1)
     (array([51.951847], dtype=float32), 48.8) (array([25.474497], dtype=float32),
     24.6) (array([19.781612], dtype=float32), 26.4) (array([21.237524],
     dtype=float32), 23.2) (array([19.808071], dtype=float32), 17.0)
     (array([33.196445], dtype=float32), 41.3) (array([15.7997875], dtype=float32),
     14.9) (array([22.308857], dtype=float32), 18.5) (array([24.506542],
     dtype=float32), 25.0) (array([36.95174], dtype=float32), 36.4)
     (array([21.02158], dtype=float32), 19.5) (array([19.072449], dtype=float32),
     27.1) (array([16.65482], dtype=float32), 14.9) (array([42.864365],
     dtype=float32), 46.0) (array([11.255093], dtype=float32), 17.9)
     (array([34.67793], dtype=float32), 30.3) (array([32.396557], dtype=float32),
     31.6) (array([26.159986], dtype=float32), 23.1) (array([23.886639],
     dtype=float32), 24.7) (array([15.139406], dtype=float32), 16.7)
     (array([19.983408], dtype=float32), 18.3) (array([8.552556], dtype=float32),
     8.4) (array([32.28726], dtype=float32), 37.3) (array([24.598032],
     dtype=float32), 22.1) (array([24.136978], dtype=float32), 22.0)
     (array([39.275646], dtype=float32), 46.7) (array([25.97865], dtype=float32),
     30.1) (array([13.960388], dtype=float32), 12.1) (array([29.030474],
     dtype=float32), 29.1) (array([17.66833], dtype=float32), 16.6)
     (array([27.10108], dtype=float32), 23.9) (array([17.861822], dtype=float32),
     19.9) (array([18.575834], dtype=float32), 21.4) (array([44.4922],
     dtype=float32), 45.4) (array([16.563892], dtype=float32), 15.6)
```

```
(array([20.46928], dtype=float32), 22.7) (array([14.620689], dtype=float32),
12.5) (array([20.612724], dtype=float32), 24.3) (array([39.50388],
dtype=float32), 43.8) (array([24.186283], dtype=float32), 22.0)
(array([34.64388], dtype=float32), 33.8) (array([19.930775], dtype=float32),
19.3) (array([18.89568], dtype=float32), 22.6) (array([21.176815],
dtype=float32), 16.1) (array([21.034569], dtype=float32), 15.0)
(array([18.339993], dtype=float32), 19.6) (array([21.137554], dtype=float32),
21.2) (array([51.624172], dtype=float32), 50.0) (array([56.14203],
dtype=float32), 50.0) (array([27.36555], dtype=float32), 29.4)
(array([15.268709], dtype=float32), 17.8) (array([24.735828], dtype=float32),
22.8) (array([12.591748], dtype=float32), 8.8) (array([27.126993],
dtype=float32), 32.5) (array([40.339428], dtype=float32), 42.8)
(array([16.689852], dtype=float32), 12.6) (array([27.98465], dtype=float32),
28.6) (array([17.789898], dtype=float32), 19.1) (array([21.564999],
dtype=float32), 50.0) (array([21.122467], dtype=float32), 27.5)
(array([12.93322], dtype=float32), 23.7) (array([48.340298], dtype=float32),
50.0) (array([10.2400875], dtype=float32), 7.2) (array([20.198032],
dtype=float32), 18.7) (array([32.495087], dtype=float32), 37.0)
(array([20.165474], dtype=float32), 22.9) (array([24.815548], dtype=float32),
22.9) (array([20.013338], dtype=float32), 17.1) (array([24.288055],
dtype=float32), 22.0) (array([31.427582], dtype=float32), 23.6)
(array([25.81147], dtype=float32), 23.9) (array([25.682194], dtype=float32),
27.1) (array([34.150513], dtype=float32), 29.0) (array([23.863184],
dtype=float32), 22.2) (array([11.1325245], dtype=float32), 7.0)
(array([23.009584], dtype=float32), 20.7) (array([21.158339], dtype=float32),
18.5) (array([23.660124], dtype=float32), 21.6) (array([24.155087],
dtype=float32), 23.0) (array([18.824171], dtype=float32), 16.0)
(array([19.678234], dtype=float32), 15.0) (array([25.252113], dtype=float32),
23.9) (array([19.542976], dtype=float32), 24.4) (array([21.263361],
dtype=float32), 22.6) (array([18.398333], dtype=float32), 19.8)
(array([21.704134], dtype=float32), 22.2) (array([19.568924], dtype=float32),
18.6) (array([19.732323], dtype=float32), 19.7) (array([23.8418],
dtype=float32), 23.1) (array([13.837982], dtype=float32), 13.5)
(array([21.036032], dtype=float32), 21.2) (array([19.110723], dtype=float32),
23.1) (array([15.809771], dtype=float32), 13.6) (array([28.556469],
dtype=float32), 22.8) (array([23.521175], dtype=float32), 18.2)
(array([11.745223], dtype=float32), 13.1) (array([17.627365], dtype=float32),
23.2) (array([24.611477], dtype=float32), 22.8) (array([24.487736],
dtype=float32), 25.1) (array([21.870634], dtype=float32), 18.9)
(array([13.559553], dtype=float32), 10.9) (array([14.871121], dtype=float32),
19.3) (array([20.880054], dtype=float32), 17.4) (array([18.778835],
dtype=float32), 15.6) (array([20.01767], dtype=float32), 20.6)
(array([30.024704], dtype=float32), 50.0) (array([35.32085], dtype=float32),
32.7) (array([21.411596], dtype=float32), 21.8) (array([16.723742],
dtype=float32), 13.4) (array([17.538132], dtype=float32), 16.6)
(array([23.341366], dtype=float32), 23.6) (array([13.014972], dtype=float32),
11.0)
```

[]:[