bostonhouse

April 28, 2024

```
[]: import numpy as np
    import pandas as pd
    df = pd.read_csv("/content/drive/MyDrive/DL/1_boston_housing.csv")
    df.head()
[]:
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       0.00632 18.0
                       2.31
                                  0.538
                                         6.575
                                                65.2 4.0900
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                                                                   296
                                                                           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
                                                                2
                                                                   242
                                                                           17.8
    3 0.03237
                 0.0
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                                0 0.458
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                                                45.8 6.0622
                                                                3
                                                                   222
                                                                           18.7
    4 0.06905
                 0.0
                       2.18
                                0 0.458 7.147
                                                54.2 6.0622
                                                                3 222
                                                                           18.7
            b lstat
                      MEDV
       396.90
                4.98
                      24.0
    1 396.90
                9.14
                      21.6
    2 392.83
                4.03
                      34.7
    3 394.63
                2.94
                      33.4
    4 396.90
                5.33
                      36.2
[]: df.info()
```

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 506 entries, 0 to 505 Data columns (total 14 columns):

		•	•
#	Column	Non-Null Count	Dtype
0	crim	506 non-null	float64
1	zn	506 non-null	float64
2	indus	506 non-null	float64
3	chas	506 non-null	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	b	506 non-null	float64

```
12 lstat
                  506 non-null
                                   float64
     13 MEDV
                  506 non-null
                                   float64
    dtypes: float64(11), int64(3)
    memory usage: 55.5 KB
[]: from sklearn.model_selection import train_test_split
     X = df.loc[:, df.columns != 'MEDV']
     y = df.loc[:, df.columns == 'MEDV']
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,_
      →random_state=123)
[]: from sklearn.linear_model import LinearRegression
     from sklearn.metrics import mean_squared_error, mean_absolute_error
     # Assuming you have already split your data into training and testing sets \Box
      \hookrightarrow (X train, X test, y train, y test)
     # Linear Regression model
     regressor = LinearRegression()
     # Fitting the model
     regressor.fit(X_train, y_train)
[]: LinearRegression()
[]: # Predictions on the test set
     y_pred = regressor.predict(X_test)
     # Calculating mean squared error and mean absolute error
     mse_lr = mean_squared_error(y_test, y_pred)
     mae_lr = mean_absolute_error(y_test, y_pred)
     print('Mean squared error on test data: ', mse_lr)
     print('Mean absolute error on test data: ', mae_lr)
    Mean squared error on test data: 28.405854810508146
    Mean absolute error on test data: 3.6913626771162664
[]: from sklearn.preprocessing import StandardScaler
    mms = StandardScaler()
     mms.fit(X train)
     X_train = mms.transform(X_train)
     X_test = mms.transform(X_test)
[]: from tensorflow.keras.models import Sequential
     from tensorflow.keras.layers import Dense
```

```
model = Sequential()

model.add(Dense(128, input_shape=(13, ), activation='relu', name='dense_1'))
model.add(Dense(64, activation='relu', name='dense_2'))
model.add(Dense(32, activation='relu', name='dense_3'))
model.add(Dense(16, activation='relu', name='dense_4'))
model.add(Dense(1, activation='relu', name='dense_output'))

model.compile(optimizer='adam', loss='mse', metrics=['mae'])
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 128)	1792
dense_2 (Dense)	(None, 64)	8256
dense_3 (Dense)	(None, 32)	2080
dense_4 (Dense)	(None, 16)	528
dense_output (Dense)	(None, 1)	17

Total params: 12673 (49.50 KB)
Trainable params: 12673 (49.50 KB)
Non-trainable params: 0 (0.00 Byte)

```
6.2678 - val_loss: 29.0603 - val_mae: 4.2359
Epoch 6/100
4.5157 - val_loss: 24.8668 - val_mae: 3.8740
Epoch 7/100
3.7044 - val_loss: 13.4622 - val_mae: 2.6501
Epoch 8/100
3.5865 - val_loss: 11.8256 - val_mae: 2.4234
Epoch 9/100
3.2447 - val_loss: 11.9806 - val_mae: 2.5500
Epoch 10/100
3.0898 - val_loss: 11.3341 - val_mae: 2.6661
Epoch 11/100
3.0028 - val_loss: 10.3772 - val_mae: 2.5477
Epoch 12/100
2.8680 - val_loss: 9.4586 - val_mae: 2.4696
Epoch 13/100
11/11 [============== ] - Os 7ms/step - loss: 15.2510 - mae:
2.8649 - val_loss: 8.7481 - val_mae: 2.3798
Epoch 14/100
2.7309 - val_loss: 7.9584 - val_mae: 2.1728
Epoch 15/100
2.6289 - val_loss: 7.6652 - val_mae: 2.0998
Epoch 16/100
2.6358 - val loss: 7.3439 - val mae: 2.0469
Epoch 17/100
2.5150 - val_loss: 7.4387 - val_mae: 2.0482
Epoch 18/100
2.4696 - val_loss: 7.0743 - val_mae: 1.9703
Epoch 19/100
2.4199 - val_loss: 7.2182 - val_mae: 2.0069
Epoch 20/100
2.3653 - val_loss: 7.4251 - val_mae: 2.0441
Epoch 21/100
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2.3783 - val_loss: 7.6012 - val_mae: 2.0459
Epoch 22/100
2.3320 - val_loss: 7.9825 - val_mae: 2.0880
Epoch 23/100
2.2560 - val_loss: 7.3414 - val_mae: 2.0100
Epoch 24/100
2.2720 - val_loss: 8.7596 - val_mae: 2.1805
Epoch 25/100
2.2422 - val_loss: 8.3408 - val_mae: 2.0807
Epoch 26/100
2.2135 - val_loss: 9.0558 - val_mae: 2.2543
Epoch 27/100
2.2084 - val_loss: 8.4129 - val_mae: 2.0596
Epoch 28/100
2.1948 - val_loss: 9.2000 - val_mae: 2.1455
Epoch 29/100
2.1112 - val_loss: 9.1660 - val_mae: 2.0979
Epoch 30/100
2.1203 - val_loss: 9.2944 - val_mae: 2.1207
Epoch 31/100
2.1513 - val_loss: 9.3776 - val_mae: 2.1199
Epoch 32/100
2.0662 - val_loss: 10.6675 - val_mae: 2.3048
Epoch 33/100
2.0680 - val_loss: 10.7615 - val_mae: 2.2569
Epoch 34/100
2.0804 - val_loss: 8.9162 - val_mae: 1.9760
Epoch 35/100
2.0279 - val_loss: 10.5830 - val_mae: 2.2423
Epoch 36/100
2.0223 - val_loss: 9.6021 - val_mae: 2.1441
Epoch 37/100
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1.9900 - val_loss: 9.7770 - val_mae: 2.1223
Epoch 38/100
1.9792 - val_loss: 10.1151 - val_mae: 2.1829
Epoch 39/100
1.9872 - val_loss: 9.7837 - val_mae: 2.1473
Epoch 40/100
1.9536 - val_loss: 10.7361 - val_mae: 2.2084
Epoch 41/100
1.9143 - val_loss: 10.2387 - val_mae: 2.1447
Epoch 42/100
1.9076 - val_loss: 10.7103 - val_mae: 2.1416
Epoch 43/100
1.9026 - val_loss: 10.0700 - val_mae: 2.1940
Epoch 44/100
1.9100 - val_loss: 10.1638 - val_mae: 2.1425
Epoch 45/100
1.8672 - val_loss: 10.9349 - val_mae: 2.2297
Epoch 46/100
1.8691 - val_loss: 9.6392 - val_mae: 2.0353
Epoch 47/100
1.8489 - val_loss: 10.3861 - val_mae: 2.1083
Epoch 48/100
1.8468 - val_loss: 11.3101 - val_mae: 2.2088
Epoch 49/100
1.8130 - val_loss: 10.1045 - val_mae: 2.1258
Epoch 50/100
1.8268 - val_loss: 10.6866 - val_mae: 2.1276
Epoch 51/100
1.8339 - val_loss: 10.3599 - val_mae: 2.0862
Epoch 52/100
1.8440 - val_loss: 10.7999 - val_mae: 2.1365
Epoch 53/100
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1.7827 - val_loss: 11.2738 - val_mae: 2.0973
Epoch 54/100
1.8115 - val_loss: 10.1321 - val_mae: 2.0261
Epoch 55/100
1.7849 - val_loss: 9.7666 - val_mae: 1.9875
Epoch 56/100
1.7605 - val_loss: 9.6525 - val_mae: 1.9901
Epoch 57/100
1.7179 - val_loss: 10.3535 - val_mae: 2.0041
Epoch 58/100
1.7317 - val_loss: 9.8177 - val_mae: 1.9761
Epoch 59/100
1.7148 - val_loss: 10.8562 - val_mae: 2.0966
Epoch 60/100
1.7391 - val_loss: 9.1167 - val_mae: 1.9043
Epoch 61/100
1.7187 - val_loss: 10.9807 - val_mae: 2.1239
Epoch 62/100
1.6960 - val_loss: 9.5215 - val_mae: 1.9513
Epoch 63/100
1.6771 - val_loss: 11.7740 - val_mae: 2.2756
Epoch 64/100
1.7411 - val loss: 9.6136 - val mae: 1.9935
Epoch 65/100
1.7117 - val_loss: 9.1349 - val_mae: 1.8898
Epoch 66/100
1.6527 - val_loss: 10.4305 - val_mae: 2.0992
Epoch 67/100
1.6257 - val_loss: 8.2997 - val_mae: 1.9269
Epoch 68/100
1.6331 - val_loss: 8.8860 - val_mae: 1.9678
Epoch 69/100
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1.6124 - val_loss: 9.1836 - val_mae: 1.9825
Epoch 70/100
1.5919 - val_loss: 11.0205 - val_mae: 2.1775
Epoch 71/100
1.6281 - val_loss: 8.5903 - val_mae: 1.9352
Epoch 72/100
1.5735 - val_loss: 9.7532 - val_mae: 2.0531
Epoch 73/100
1.5683 - val_loss: 7.8694 - val_mae: 1.9178
Epoch 74/100
1.6631 - val_loss: 11.5396 - val_mae: 2.2655
Epoch 75/100
1.6270 - val_loss: 9.2957 - val_mae: 1.9973
Epoch 76/100
1.5688 - val_loss: 12.2088 - val_mae: 2.4134
Epoch 77/100
1.7409 - val_loss: 8.8129 - val_mae: 1.9120
Epoch 78/100
1.5567 - val_loss: 8.9943 - val_mae: 2.0436
Epoch 79/100
1.5516 - val_loss: 9.9061 - val_mae: 2.0723
Epoch 80/100
1.5463 - val_loss: 9.4317 - val_mae: 1.9966
Epoch 81/100
1.5455 - val_loss: 10.0888 - val_mae: 2.0971
Epoch 82/100
1.5229 - val_loss: 10.3211 - val_mae: 2.0763
Epoch 83/100
1.5045 - val_loss: 8.2224 - val_mae: 2.0125
Epoch 84/100
1.4808 - val_loss: 10.8078 - val_mae: 2.2010
Epoch 85/100
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1.4978 - val_loss: 9.5990 - val_mae: 2.0491
Epoch 86/100
1.5214 - val_loss: 10.4532 - val_mae: 2.0968
Epoch 87/100
1.4686 - val_loss: 9.9915 - val_mae: 2.0324
Epoch 88/100
1.5333 - val_loss: 8.3806 - val_mae: 2.1140
Epoch 89/100
1.5181 - val_loss: 9.6633 - val_mae: 2.2019
Epoch 90/100
1.4646 - val_loss: 8.6010 - val_mae: 1.9789
Epoch 91/100
1.4193 - val_loss: 11.4210 - val_mae: 2.2112
Epoch 92/100
1.4288 - val_loss: 9.6377 - val_mae: 2.0078
Epoch 93/100
1.3804 - val_loss: 9.0980 - val_mae: 1.9980
Epoch 94/100
1.4435 - val_loss: 7.5765 - val_mae: 1.9845
Epoch 95/100
1.3981 - val_loss: 9.5147 - val_mae: 2.1248
Epoch 96/100
1.3856 - val loss: 8.1894 - val mae: 2.0050
Epoch 97/100
1.3896 - val_loss: 9.2924 - val_mae: 2.1421
Epoch 98/100
1.3844 - val_loss: 8.4724 - val_mae: 1.9684
Epoch 99/100
1.3200 - val_loss: 9.7832 - val_mae: 1.9984
Epoch 100/100
1.3539 - val_loss: 10.9911 - val_mae: 2.1160
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