## dl-1

## April 29, 2024

```
[]: import tensorflow as tf
    from tensorflow.keras.datasets import boston_housing
    from sklearn import preprocessing
     import plotly.graph_objects as go
     import matplotlib.pyplot as plt
[]: (train_x,train_y),(test_x,test_y)=boston_housing.load_data()
    Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
    datasets/boston_housing.npz
    57026/57026 [=========== ] - Os Ous/step
[]: print("Train Shape:",train_x.shape)
    print("Test Shape :",test_x.shape)
    print("Training Sample :",train_x[0])
    print("Training Target Sample :",train_y[0])
    Train Shape : (404, 13)
    Test Shape : (102, 13)
    Training Sample : [ 1.23247
                                                               0.538
                                            8.14
                                                      0.
                                                                          6.142
    91.7
       3.9769
                 4.
                        307.
                                   21.
                                            396.9
                                                       18.72
                                                               ]
    Training Target Sample: 15.2
[]: mean=train_x.mean(axis=0)
    std=train_x.std(axis=0)
[]: train_x=(train_x-mean)/std
    test_x=(test_x-mean)/std
[]: train_x[0]
[]: array([-0.27224633, -0.48361547, -0.43576161, -0.25683275, -0.1652266,
           -0.1764426 , 0.81306188, 0.1166983 , -0.62624905, -0.59517003,
            1.14850044, 0.44807713, 0.8252202 ])
[]: from tensorflow.keras.models import Sequential
    from tensorflow.keras.layers import Dense
```

```
[]: def HousePricePredictionModel():
    model=Sequential()
    model.add(Dense(128,activation='relu',input_shape=(train_x[0].

¬shape),name='dense_1')) #128 Neurons
    model.add(Dense(64,activation='relu',name='dense_2')) #64 Neurons
    model.add(Dense(1,activation='linear',name='dense_output')) #1 Neuron
    model.compile(optimizer='adam', loss='mse', metrics=['mae'])
    model.summary()
    return model
[]: model=HousePricePredictionModel()
   history=model.
    ⇒fit(x=train_x,y=train_y,epochs=100,batch_size=1,verbose=1,validation_data=(test_x,test_y))
  Model: "sequential"
   Layer (type)
                                     Param #
                Output Shape
  ______
   dense 1 (Dense)
                     (None, 128)
                                      1792
   dense 2 (Dense)
                     (None, 64)
                                      8256
   dense_output (Dense)
                                      65
                     (None, 1)
  _____
  Total params: 10113 (39.50 KB)
  Trainable params: 10113 (39.50 KB)
  Non-trainable params: 0 (0.00 Byte)
               -----
  Epoch 1/100
  6.8544 - val_loss: 26.4772 - val_mae: 3.8849
  Epoch 2/100
  2.8920 - val_loss: 19.2604 - val_mae: 3.1217
  Epoch 3/100
  2.5604 - val_loss: 24.2789 - val_mae: 3.4730
  Epoch 4/100
  2.6224 - val_loss: 20.7704 - val_mae: 3.0387
  Epoch 5/100
  2.4140 - val_loss: 29.3337 - val_mae: 3.4136
  Epoch 6/100
  2.3145 - val_loss: 22.0202 - val_mae: 3.0515
```

```
Epoch 7/100
2.2966 - val_loss: 24.7855 - val_mae: 3.2647
Epoch 8/100
2.3890 - val_loss: 25.4460 - val_mae: 3.3251
Epoch 9/100
2.4288 - val_loss: 18.5491 - val_mae: 2.8343
Epoch 10/100
2.2443 - val_loss: 18.2872 - val_mae: 2.6382
Epoch 11/100
2.1740 - val_loss: 18.5864 - val_mae: 2.8444
Epoch 12/100
2.2036 - val_loss: 28.1095 - val_mae: 3.1375
Epoch 13/100
2.1735 - val_loss: 22.1057 - val_mae: 3.0095
Epoch 14/100
2.0313 - val_loss: 24.7198 - val_mae: 3.4032
Epoch 15/100
2.1097 - val_loss: 15.9679 - val_mae: 2.5888
Epoch 16/100
1.9993 - val_loss: 25.3262 - val_mae: 3.2867
Epoch 17/100
2.0479 - val_loss: 21.6699 - val_mae: 2.8441
Epoch 18/100
2.1155 - val_loss: 17.5582 - val_mae: 2.7240
Epoch 19/100
1.9698 - val_loss: 22.1726 - val_mae: 2.8663
Epoch 20/100
2.0140 - val_loss: 17.1870 - val_mae: 2.5850
Epoch 21/100
1.9163 - val_loss: 23.1554 - val_mae: 3.4150
Epoch 22/100
1.9605 - val_loss: 16.7647 - val_mae: 2.6188
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```
Epoch 23/100
1.9094 - val_loss: 16.2485 - val_mae: 2.5095
Epoch 24/100
1.9080 - val_loss: 15.7093 - val_mae: 2.4118
Epoch 25/100
1.9051 - val_loss: 18.5611 - val_mae: 2.8629
Epoch 26/100
1.8239 - val_loss: 26.4514 - val_mae: 3.6140
Epoch 27/100
1.8907 - val_loss: 15.0086 - val_mae: 2.5578
Epoch 28/100
1.8301 - val_loss: 13.2839 - val_mae: 2.4152
Epoch 29/100
1.7846 - val_loss: 15.3856 - val_mae: 2.6119
Epoch 30/100
1.7069 - val_loss: 18.0060 - val_mae: 2.8778
Epoch 31/100
1.8021 - val_loss: 16.6499 - val_mae: 2.6627
Epoch 32/100
1.7396 - val_loss: 17.2037 - val_mae: 2.6207
Epoch 33/100
1.6382 - val_loss: 14.1261 - val_mae: 2.5173
Epoch 34/100
1.6509 - val_loss: 15.4182 - val_mae: 2.7163
Epoch 35/100
1.6745 - val_loss: 12.3262 - val_mae: 2.4387
Epoch 36/100
1.6889 - val_loss: 14.7611 - val_mae: 2.5378
Epoch 37/100
1.6091 - val_loss: 16.0123 - val_mae: 2.8206
Epoch 38/100
1.6337 - val_loss: 12.4893 - val_mae: 2.4050
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Epoch 39/100
1.6248 - val_loss: 20.8809 - val_mae: 3.2139
Epoch 40/100
1.6796 - val_loss: 12.3559 - val_mae: 2.4427
Epoch 41/100
1.5859 - val_loss: 15.3846 - val_mae: 2.6266
Epoch 42/100
1.6122 - val_loss: 12.8935 - val_mae: 2.3894
Epoch 43/100
1.5401 - val_loss: 12.2845 - val_mae: 2.4129
Epoch 44/100
1.6177 - val_loss: 14.2689 - val_mae: 2.6281
Epoch 45/100
1.5842 - val_loss: 14.2848 - val_mae: 2.5043
Epoch 46/100
1.5611 - val_loss: 11.5462 - val_mae: 2.3556
Epoch 47/100
1.5434 - val_loss: 12.6742 - val_mae: 2.4254
Epoch 48/100
1.5248 - val_loss: 16.4655 - val_mae: 2.8389
Epoch 49/100
1.5938 - val_loss: 11.4510 - val_mae: 2.3695
Epoch 50/100
1.4866 - val_loss: 11.3599 - val_mae: 2.4598
Epoch 51/100
1.5247 - val_loss: 10.3315 - val_mae: 2.2088
Epoch 52/100
1.5065 - val_loss: 11.3532 - val_mae: 2.3254
1.4665 - val_loss: 11.8015 - val_mae: 2.3003
Epoch 54/100
1.3987 - val_loss: 13.9809 - val_mae: 2.7377
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Epoch 55/100
1.4272 - val_loss: 14.3588 - val_mae: 2.5282
Epoch 56/100
1.4167 - val_loss: 12.6394 - val_mae: 2.7418
Epoch 57/100
1.3750 - val_loss: 11.1096 - val_mae: 2.3214
Epoch 58/100
1.4757 - val_loss: 11.7369 - val_mae: 2.3626
Epoch 59/100
1.4427 - val_loss: 12.9964 - val_mae: 2.5940
Epoch 60/100
1.3758 - val_loss: 13.6081 - val_mae: 2.5208
Epoch 61/100
1.3755 - val_loss: 11.9123 - val_mae: 2.4916
Epoch 62/100
1.4140 - val_loss: 11.8553 - val_mae: 2.2961
Epoch 63/100
1.4459 - val_loss: 12.0564 - val_mae: 2.4176
Epoch 64/100
1.3715 - val_loss: 11.1579 - val_mae: 2.4052
Epoch 65/100
1.3710 - val_loss: 11.8275 - val_mae: 2.4355
Epoch 66/100
1.3386 - val_loss: 11.5528 - val_mae: 2.4786
Epoch 67/100
1.3936 - val_loss: 14.7788 - val_mae: 2.7532
Epoch 68/100
1.4673 - val_loss: 14.4449 - val_mae: 2.5285
Epoch 69/100
1.3702 - val_loss: 11.8227 - val_mae: 2.3093
Epoch 70/100
1.2939 - val_loss: 12.3480 - val_mae: 2.4865
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Epoch 71/100
1.2804 - val_loss: 14.4785 - val_mae: 2.7044
Epoch 72/100
1.2547 - val_loss: 14.0953 - val_mae: 2.8615
Epoch 73/100
1.2090 - val_loss: 11.4618 - val_mae: 2.4959
Epoch 74/100
1.4065 - val_loss: 10.6010 - val_mae: 2.2548
Epoch 75/100
1.3618 - val_loss: 10.2108 - val_mae: 2.2965
Epoch 76/100
1.3034 - val_loss: 12.3665 - val_mae: 2.5695
Epoch 77/100
1.3291 - val_loss: 11.5152 - val_mae: 2.3948
Epoch 78/100
1.2086 - val_loss: 12.7598 - val_mae: 2.4383
Epoch 79/100
1.3143 - val_loss: 11.6451 - val_mae: 2.4104
Epoch 80/100
1.2924 - val_loss: 11.0637 - val_mae: 2.3769
Epoch 81/100
1.2066 - val_loss: 11.1246 - val_mae: 2.5179
Epoch 82/100
1.2301 - val_loss: 11.0412 - val_mae: 2.4354
Epoch 83/100
1.2953 - val_loss: 13.1144 - val_mae: 2.5434
Epoch 84/100
1.2476 - val_loss: 10.3407 - val_mae: 2.3168
1.1455 - val_loss: 12.0468 - val_mae: 2.3457
Epoch 86/100
1.2196 - val_loss: 11.7692 - val_mae: 2.4890
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Epoch 87/100
  1.1963 - val_loss: 12.1750 - val_mae: 2.3008
  Epoch 88/100
  1.3137 - val_loss: 10.8993 - val_mae: 2.3241
  Epoch 89/100
  1.0989 - val_loss: 11.0223 - val_mae: 2.3422
  Epoch 90/100
  1.1902 - val_loss: 11.3606 - val_mae: 2.4105
  Epoch 91/100
  1.1642 - val_loss: 10.3123 - val_mae: 2.3654
  Epoch 92/100
  1.1181 - val_loss: 10.1262 - val_mae: 2.2096
  Epoch 93/100
  1.1905 - val_loss: 12.5619 - val_mae: 2.4429
  Epoch 94/100
  1.2653 - val_loss: 9.8133 - val_mae: 2.2528
  Epoch 95/100
  1.1561 - val_loss: 10.3101 - val_mae: 2.2520
  Epoch 96/100
  1.1551 - val_loss: 11.7081 - val_mae: 2.3610
  Epoch 97/100
  1.1241 - val_loss: 11.3845 - val_mae: 2.3941
  Epoch 98/100
  1.1368 - val_loss: 9.9193 - val_mae: 2.2567
  Epoch 99/100
  1.2102 - val_loss: 10.0739 - val_mae: 2.2588
  Epoch 100/100
  1.1355 - val_loss: 10.3713 - val_mae: 2.3987
[]: test_x[8]
[]: array([-0.39570978, -0.48361547, 2.13815109, -0.25683275, 0.20183093,
     -0.43176465, 0.85606329, -0.81539201, -0.85646254, -1.31131055,
```

```
0.28394328, 0.24795926, 0.71618792])
[]: test_input=[[-0.39570978, -0.48361547, 2.13815109, -0.25683275, 0.20183093,
           -0.43176465, 0.85606329, -0.81539201, -0.85646254, -1.31131055,
           0.28394328, 0.24795926, 0.71618792]]
    print("Actual Output :",test_y[8])
    print("Predicted Output :",model.predict(test_input))
   Actual Output : 20.5
    1/1 [======] - Os 112ms/step
   Predicted Output : [[17.897112]]
[]: fig = go.Figure()
    fig.add_trace(go.Scattergl(y=history.history['loss'],name='Train'))
    fig.add_trace(go.Scattergl(y=history.history['val_loss'],name='Valid'))
    fig.update layout(height=500, width=700, xaxis title='Epoch', yaxis title='Loss')
    fig.show()
[]: fig = go.Figure()
    fig.add_trace(go.Scattergl(y=history.history['mae'],name='Train'))
    fig.add_trace(go.Scattergl(y=history.history['val_mae'],name='Valid'))
    fig.update_layout(height=500, width=700,xaxis_title='Epoch',yaxis_title='Mean_

→Absolute Error')
    fig.show()
[]: mse_nn,mae_nn=model.evaluate(test_x,test_y)
   []: print('Mean squared error on test data :',mse_nn)
    print('Mean absolute error on test data :',mae_nn)
   Mean squared error on test data: 10.371269226074219
   Mean absolute error on test data: 2.398691415786743
[]: from sklearn.metrics import r2_score
    y_dl=model.predict(test_x)
    r2=r2_score(test_y,y_dl)
    print('R2 Score :',r2)
    4/4 [======= ] - Os 6ms/step
   R2 Score: 0.87541098462976
[]: from sklearn.linear_model import LinearRegression
    from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
```

[]: lr\_model=LinearRegression()

lr\_model.fit(train\_x,train\_y)

```
[]: LinearRegression()
```

```
[]: y_pred=lr_model.predict(test_x)
```

```
[]: mse_lr=mean_squared_error(test_y,y_pred)
mae_lr=mean_absolute_error(test_y,y_pred)
r2=r2_score(test_y,y_pred)
print('Mean squared error on test data :',mse_lr)
print('Mean absolute error on test data :',mae_lr)
print('R2 Score :',r2)
```

Mean squared error on test data : 23.19559925642298 Mean absolute error on test data : 3.4641858124067175

R2 Score : 0.7213535934621552