

Keras Syntax Basics

```
In [1]: import pandas as pd
import numpy as np
```

```
In [2]: import seaborn as sns
%matplotlib inline
```

```
In [3]: df = pd.read_csv('fake_reg.csv') #Fake data but good for practice
```

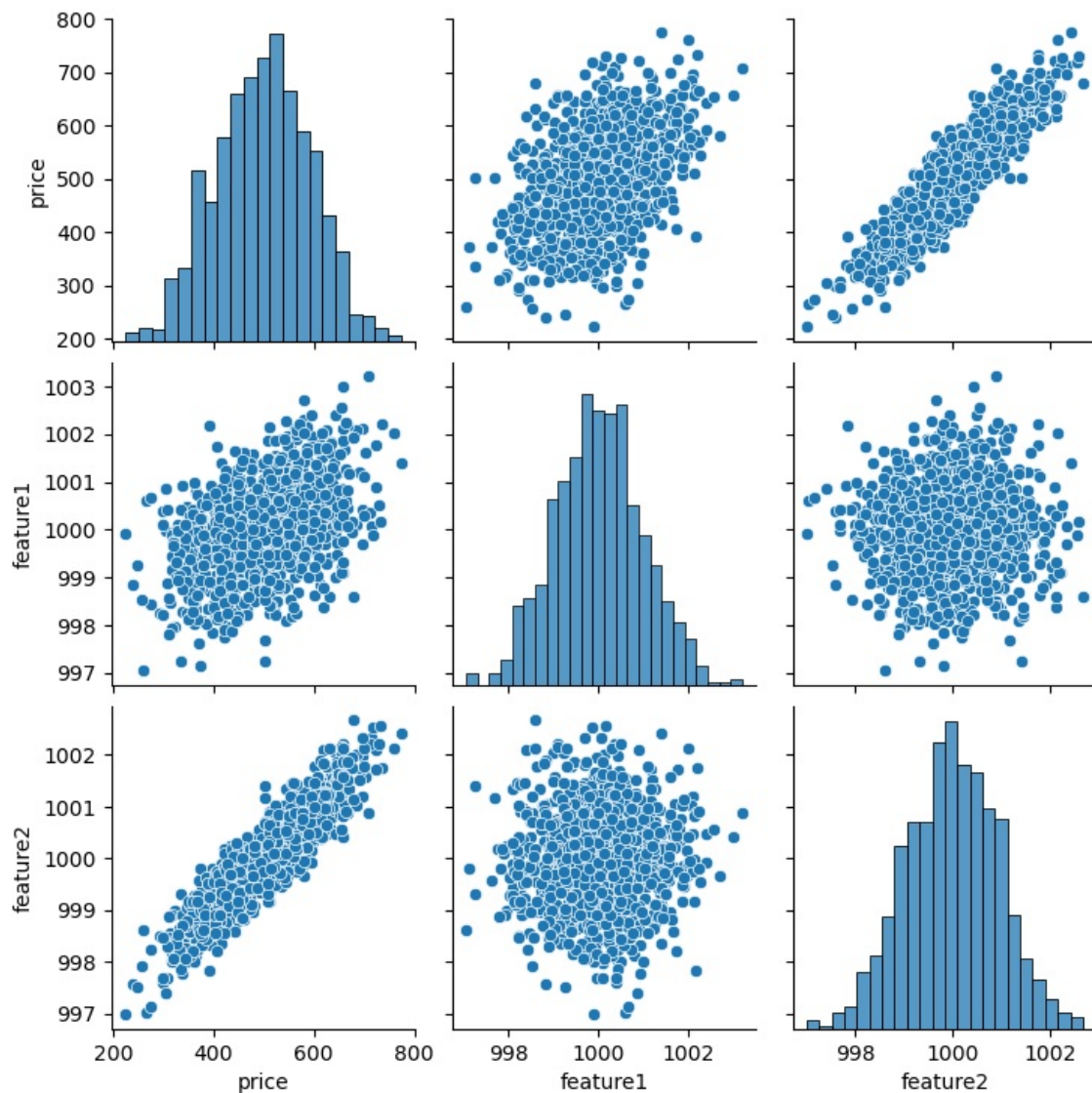
```
In [4]: df.head()
```

```
Out[4]:
```

	price	feature1	feature2
0	461.527929	999.787558	999.766096
1	548.130011	998.861615	1001.042403
2	410.297162	1000.070267	998.844015
3	540.382220	999.952251	1000.440940
4	546.024553	1000.446011	1000.338531

```
In [5]: sns.pairplot(df)
```

```
Out[5]: <seaborn.axisgrid.PairGrid at 0x1e82ee5a520>
```



```
In [6]: from sklearn.model_selection import train_test_split
```

```
In [7]: X = df[['feature1', 'feature2']].values
```

```
In [8]: y = df['price'].values
```

```
In [9]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

```
In [10]: X_train.shape
```

```
Out[10]: (700, 2)
```

```
In [11]: X_test.shape
```

```
Out[11]: (300, 2)
```

```
In [12]: from sklearn.preprocessing import MinMaxScaler
```

```
In [13]: #help(MinMaxScaler)
```

```
In [14]: scaler = MinMaxScaler()
```

```
In [15]: scaler.fit(X_train)
```

```
Out[15]: MinMaxScaler()
```

```
In [16]: X_train = scaler.transform(X_train)
```

```
In [17]: X_test = scaler.transform(X_test)
```

```
In [18]: X_train.min()
```

```
Out[18]: 0.0
```

```
In [19]: from tensorflow.keras.models import Sequential  
from tensorflow.keras.layers import Dense
```

```
In [20]: #1st method  
#model = Sequential([Dense(4,activation='relu'),  
                    #Dense(2,activation='relu'),  
                    #Dense(1)])
```

```
In [21]: #2nd method - preferred and more convenient. Adding 1 by 1
```

```
model = Sequential()  
  
model.add(Dense(4,activation='relu'))  
model.add(Dense(4,activation='relu'))  
model.add(Dense(4,activation='relu'))  
  
model.add(Dense(1)) #Last layer so we don't want activation  
  
model.compile(optimizer='rmsprop',loss='mse')
```

```
In [22]: model.fit(x=X_train,y=y_train,epochs=250)
```

```
Epoch 1/250  
22/22 [=====] - 1s 2ms/step - loss: 256630.6250  
Epoch 2/250  
22/22 [=====] - 0s 2ms/step - loss: 256520.9219  
Epoch 3/250  
22/22 [=====] - 0s 2ms/step - loss: 256404.5312  
Epoch 4/250  
22/22 [=====] - 0s 3ms/step - loss: 256264.5312  
Epoch 5/250  
22/22 [=====] - 0s 3ms/step - loss: 256100.6562  
Epoch 6/250  
22/22 [=====] - 0s 2ms/step - loss: 255909.8125  
Epoch 7/250  
22/22 [=====] - 0s 2ms/step - loss: 255687.9844  
Epoch 8/250  
22/22 [=====] - 0s 2ms/step - loss: 255431.0156  
Epoch 9/250  
22/22 [=====] - 0s 2ms/step - loss: 255136.5938  
Epoch 10/250  
22/22 [=====] - 0s 2ms/step - loss: 254801.8750  
Epoch 11/250  
22/22 [=====] - 0s 2ms/step - loss: 254422.8125  
Epoch 12/250  
22/22 [=====] - 0s 2ms/step - loss: 253994.6719  
Epoch 13/250  
22/22 [=====] - 0s 2ms/step - loss: 253519.7500  
Epoch 14/250  
22/22 [=====] - 0s 2ms/step - loss: 252987.1094  
Epoch 15/250  
22/22 [=====] - 0s 2ms/step - loss: 252395.0000  
Epoch 16/250  
22/22 [=====] - 0s 2ms/step - loss: 251737.2188  
Epoch 17/250  
22/22 [=====] - 0s 2ms/step - loss: 251014.6562  
Epoch 18/250
```

22/22 [=====] - 0s 2ms/step - loss: 250227.4531
Epoch 19/250
22/22 [=====] - 0s 2ms/step - loss: 249362.4531
Epoch 20/250
22/22 [=====] - 0s 2ms/step - loss: 248417.7344
Epoch 21/250
22/22 [=====] - 0s 3ms/step - loss: 247383.6562
Epoch 22/250
22/22 [=====] - 0s 2ms/step - loss: 246268.5000
Epoch 23/250
22/22 [=====] - 0s 2ms/step - loss: 245053.5781
Epoch 24/250
22/22 [=====] - 0s 2ms/step - loss: 243743.8594
Epoch 25/250
22/22 [=====] - 0s 2ms/step - loss: 242332.6094
Epoch 26/250
22/22 [=====] - 0s 2ms/step - loss: 240822.6719
Epoch 27/250
22/22 [=====] - 0s 2ms/step - loss: 239196.1875
Epoch 28/250
22/22 [=====] - 0s 2ms/step - loss: 237450.6719
Epoch 29/250
22/22 [=====] - 0s 2ms/step - loss: 235585.5938
Epoch 30/250
22/22 [=====] - 0s 2ms/step - loss: 233593.5938
Epoch 31/250
22/22 [=====] - 0s 2ms/step - loss: 231479.8594
Epoch 32/250
22/22 [=====] - 0s 3ms/step - loss: 229226.3125
Epoch 33/250
22/22 [=====] - 0s 3ms/step - loss: 226840.8281
Epoch 34/250
22/22 [=====] - 0s 2ms/step - loss: 224323.0469
Epoch 35/250
22/22 [=====] - 0s 2ms/step - loss: 221648.8281
Epoch 36/250
22/22 [=====] - 0s 2ms/step - loss: 218834.5625
Epoch 37/250
22/22 [=====] - 0s 2ms/step - loss: 215876.3906
Epoch 38/250
22/22 [=====] - 0s 2ms/step - loss: 212757.9219
Epoch 39/250
22/22 [=====] - 0s 2ms/step - loss: 209462.5312
Epoch 40/250
22/22 [=====] - 0s 2ms/step - loss: 206019.6094
Epoch 41/250
22/22 [=====] - 0s 2ms/step - loss: 202418.4062
Epoch 42/250
22/22 [=====] - 0s 2ms/step - loss: 198671.5156
Epoch 43/250
22/22 [=====] - 0s 2ms/step - loss: 194737.4844
Epoch 44/250
22/22 [=====] - 0s 2ms/step - loss: 190662.8906
Epoch 45/250
22/22 [=====] - 0s 2ms/step - loss: 186401.8438
Epoch 46/250
22/22 [=====] - 0s 2ms/step - loss: 181983.0469
Epoch 47/250
22/22 [=====] - 0s 2ms/step - loss: 177384.2500
Epoch 48/250
22/22 [=====] - 0s 2ms/step - loss: 172659.2969
Epoch 49/250
22/22 [=====] - 0s 2ms/step - loss: 167734.7031
Epoch 50/250
22/22 [=====] - 0s 2ms/step - loss: 162679.6719
Epoch 51/250
22/22 [=====] - 0s 3ms/step - loss: 157473.2969
Epoch 52/250
22/22 [=====] - 0s 2ms/step - loss: 152121.8594
Epoch 53/250
22/22 [=====] - 0s 3ms/step - loss: 146617.8438
Epoch 54/250
22/22 [=====] - 0s 2ms/step - loss: 140981.0156
Epoch 55/250
22/22 [=====] - 0s 2ms/step - loss: 135218.2500
Epoch 56/250
22/22 [=====] - 0s 2ms/step - loss: 129341.9297
Epoch 57/250
22/22 [=====] - 0s 2ms/step - loss: 123362.8438
Epoch 58/250
22/22 [=====] - 0s 2ms/step - loss: 117274.0781
Epoch 59/250
22/22 [=====] - 0s 2ms/step - loss: 111109.7031
Epoch 60/250
22/22 [=====] - 0s 2ms/step - loss: 104900.0312
Epoch 61/250
22/22 [=====] - 0s 2ms/step - loss: 98652.3672
Epoch 62/250
22/22 [=====] - 0s 2ms/step - loss: 92351.1797

Epoch 63/250
22/22 [=====] - 0s 2ms/step - loss: 86029.0703
Epoch 64/250
22/22 [=====] - 0s 1ms/step - loss: 79706.6172
Epoch 65/250
22/22 [=====] - 0s 1ms/step - loss: 73423.9141
Epoch 66/250
22/22 [=====] - 0s 1ms/step - loss: 67181.1328
Epoch 67/250
22/22 [=====] - 0s 1ms/step - loss: 61044.7617
Epoch 68/250
22/22 [=====] - 0s 1ms/step - loss: 55075.1484
Epoch 69/250
22/22 [=====] - 0s 1ms/step - loss: 49174.9531
Epoch 70/250
22/22 [=====] - 0s 2ms/step - loss: 43468.8984
Epoch 71/250
22/22 [=====] - 0s 2ms/step - loss: 37978.7578
Epoch 72/250
22/22 [=====] - 0s 2ms/step - loss: 32708.5020
Epoch 73/250
22/22 [=====] - 0s 2ms/step - loss: 27773.6738
Epoch 74/250
22/22 [=====] - 0s 2ms/step - loss: 23131.3320
Epoch 75/250
22/22 [=====] - 0s 2ms/step - loss: 18868.4844
Epoch 76/250
22/22 [=====] - 0s 2ms/step - loss: 15066.8232
Epoch 77/250
22/22 [=====] - 0s 2ms/step - loss: 11730.9014
Epoch 78/250
22/22 [=====] - 0s 2ms/step - loss: 8834.3154
Epoch 79/250
22/22 [=====] - 0s 2ms/step - loss: 6509.7163
Epoch 80/250
22/22 [=====] - 0s 2ms/step - loss: 4762.8599
Epoch 81/250
22/22 [=====] - 0s 2ms/step - loss: 3635.6643
Epoch 82/250
22/22 [=====] - 0s 2ms/step - loss: 3035.9058
Epoch 83/250
22/22 [=====] - 0s 2ms/step - loss: 2849.3743
Epoch 84/250
22/22 [=====] - 0s 2ms/step - loss: 2803.8464
Epoch 85/250
22/22 [=====] - 0s 2ms/step - loss: 2769.5430
Epoch 86/250
22/22 [=====] - 0s 2ms/step - loss: 2730.9304
Epoch 87/250
22/22 [=====] - 0s 2ms/step - loss: 2689.9502
Epoch 88/250
22/22 [=====] - 0s 2ms/step - loss: 2651.8040
Epoch 89/250
22/22 [=====] - 0s 2ms/step - loss: 2615.8093
Epoch 90/250
22/22 [=====] - 0s 2ms/step - loss: 2573.8435
Epoch 91/250
22/22 [=====] - 0s 2ms/step - loss: 2533.2053
Epoch 92/250
22/22 [=====] - 0s 2ms/step - loss: 2491.5415
Epoch 93/250
22/22 [=====] - 0s 2ms/step - loss: 2453.9858
Epoch 94/250
22/22 [=====] - 0s 2ms/step - loss: 2412.9771
Epoch 95/250
22/22 [=====] - 0s 2ms/step - loss: 2370.6987
Epoch 96/250
22/22 [=====] - 0s 2ms/step - loss: 2330.8494
Epoch 97/250
22/22 [=====] - 0s 2ms/step - loss: 2293.1206
Epoch 98/250
22/22 [=====] - 0s 2ms/step - loss: 2254.5349
Epoch 99/250
22/22 [=====] - 0s 2ms/step - loss: 2217.7583
Epoch 100/250
22/22 [=====] - 0s 2ms/step - loss: 2180.5461
Epoch 101/250
22/22 [=====] - 0s 2ms/step - loss: 2141.7825
Epoch 102/250
22/22 [=====] - 0s 2ms/step - loss: 2101.5088
Epoch 103/250
22/22 [=====] - 0s 2ms/step - loss: 2063.1221
Epoch 104/250
22/22 [=====] - 0s 2ms/step - loss: 2034.8225
Epoch 105/250
22/22 [=====] - 0s 2ms/step - loss: 1997.9510
Epoch 106/250
22/22 [=====] - 0s 2ms/step - loss: 1962.2644
Epoch 107/250

22/22 [=====] - 0s 1ms/step - loss: 1928.8392
Epoch 108/250
22/22 [=====] - 0s 1ms/step - loss: 1894.0985
Epoch 109/250
22/22 [=====] - 0s 2ms/step - loss: 1856.9039
Epoch 110/250
22/22 [=====] - 0s 2ms/step - loss: 1821.2643
Epoch 111/250
22/22 [=====] - 0s 2ms/step - loss: 1787.5177
Epoch 112/250
22/22 [=====] - 0s 2ms/step - loss: 1751.9626
Epoch 113/250
22/22 [=====] - 0s 2ms/step - loss: 1723.6821
Epoch 114/250
22/22 [=====] - 0s 1ms/step - loss: 1690.2601
Epoch 115/250
22/22 [=====] - 0s 2ms/step - loss: 1659.8728
Epoch 116/250
22/22 [=====] - 0s 2ms/step - loss: 1625.2550
Epoch 117/250
22/22 [=====] - 0s 1ms/step - loss: 1590.1779
Epoch 118/250
22/22 [=====] - 0s 2ms/step - loss: 1555.1262
Epoch 119/250
22/22 [=====] - 0s 2ms/step - loss: 1527.1045
Epoch 120/250
22/22 [=====] - 0s 2ms/step - loss: 1493.3951
Epoch 121/250
22/22 [=====] - 0s 2ms/step - loss: 1456.8392
Epoch 122/250
22/22 [=====] - 0s 2ms/step - loss: 1424.6793
Epoch 123/250
22/22 [=====] - 0s 2ms/step - loss: 1391.5946
Epoch 124/250
22/22 [=====] - 0s 2ms/step - loss: 1361.7054
Epoch 125/250
22/22 [=====] - 0s 1ms/step - loss: 1331.8073
Epoch 126/250
22/22 [=====] - 0s 1ms/step - loss: 1298.2312
Epoch 127/250
22/22 [=====] - 0s 1ms/step - loss: 1268.4208
Epoch 128/250
22/22 [=====] - 0s 2ms/step - loss: 1236.8861
Epoch 129/250
22/22 [=====] - 0s 2ms/step - loss: 1207.6373
Epoch 130/250
22/22 [=====] - 0s 2ms/step - loss: 1176.4358
Epoch 131/250
22/22 [=====] - 0s 2ms/step - loss: 1148.1315
Epoch 132/250
22/22 [=====] - 0s 2ms/step - loss: 1119.1160
Epoch 133/250
22/22 [=====] - 0s 2ms/step - loss: 1086.8479
Epoch 134/250
22/22 [=====] - 0s 2ms/step - loss: 1059.7987
Epoch 135/250
22/22 [=====] - 0s 2ms/step - loss: 1032.5806
Epoch 136/250
22/22 [=====] - 0s 2ms/step - loss: 1004.7205
Epoch 137/250
22/22 [=====] - 0s 2ms/step - loss: 978.8600
Epoch 138/250
22/22 [=====] - 0s 2ms/step - loss: 951.5021
Epoch 139/250
22/22 [=====] - 0s 2ms/step - loss: 925.9261
Epoch 140/250
22/22 [=====] - 0s 2ms/step - loss: 896.9711
Epoch 141/250
22/22 [=====] - 0s 2ms/step - loss: 869.2953
Epoch 142/250
22/22 [=====] - 0s 2ms/step - loss: 843.1307
Epoch 143/250
22/22 [=====] - 0s 1ms/step - loss: 813.8500
Epoch 144/250
22/22 [=====] - 0s 2ms/step - loss: 786.9199
Epoch 145/250
22/22 [=====] - 0s 2ms/step - loss: 758.3617
Epoch 146/250
22/22 [=====] - 0s 2ms/step - loss: 732.9052
Epoch 147/250
22/22 [=====] - 0s 2ms/step - loss: 707.1234
Epoch 148/250
22/22 [=====] - 0s 2ms/step - loss: 681.0797
Epoch 149/250
22/22 [=====] - 0s 2ms/step - loss: 654.6371
Epoch 150/250
22/22 [=====] - 0s 3ms/step - loss: 631.7554
Epoch 151/250
22/22 [=====] - 0s 2ms/step - loss: 610.2105

Epoch 152/250
22/22 [=====] - 0s 2ms/step - loss: 589.0707
Epoch 153/250
22/22 [=====] - 0s 2ms/step - loss: 568.1700
Epoch 154/250
22/22 [=====] - 0s 1ms/step - loss: 544.5796
Epoch 155/250
22/22 [=====] - 0s 2ms/step - loss: 523.6497
Epoch 156/250
22/22 [=====] - 0s 2ms/step - loss: 501.7621
Epoch 157/250
22/22 [=====] - 0s 2ms/step - loss: 480.6465
Epoch 158/250
22/22 [=====] - 0s 2ms/step - loss: 459.2298
Epoch 159/250
22/22 [=====] - 0s 2ms/step - loss: 437.6848
Epoch 160/250
22/22 [=====] - 0s 2ms/step - loss: 418.3203
Epoch 161/250
22/22 [=====] - 0s 2ms/step - loss: 399.8095
Epoch 162/250
22/22 [=====] - 0s 2ms/step - loss: 382.4026
Epoch 163/250
22/22 [=====] - 0s 2ms/step - loss: 363.8797
Epoch 164/250
22/22 [=====] - 0s 1ms/step - loss: 344.5782
Epoch 165/250
22/22 [=====] - 0s 2ms/step - loss: 326.4766
Epoch 166/250
22/22 [=====] - 0s 2ms/step - loss: 309.0964
Epoch 167/250
22/22 [=====] - 0s 2ms/step - loss: 292.2574
Epoch 168/250
22/22 [=====] - 0s 2ms/step - loss: 276.0246
Epoch 169/250
22/22 [=====] - 0s 2ms/step - loss: 259.3790
Epoch 170/250
22/22 [=====] - 0s 2ms/step - loss: 243.5462
Epoch 171/250
22/22 [=====] - 0s 2ms/step - loss: 228.9668
Epoch 172/250
22/22 [=====] - 0s 2ms/step - loss: 213.3387
Epoch 173/250
22/22 [=====] - 0s 2ms/step - loss: 201.9413
Epoch 174/250
22/22 [=====] - 0s 2ms/step - loss: 188.8056
Epoch 175/250
22/22 [=====] - 0s 2ms/step - loss: 176.9319
Epoch 176/250
22/22 [=====] - 0s 2ms/step - loss: 163.7818
Epoch 177/250
22/22 [=====] - 0s 2ms/step - loss: 153.8987
Epoch 178/250
22/22 [=====] - 0s 1ms/step - loss: 143.1696
Epoch 179/250
22/22 [=====] - 0s 1ms/step - loss: 132.2054
Epoch 180/250
22/22 [=====] - 0s 2ms/step - loss: 122.6939
Epoch 181/250
22/22 [=====] - 0s 2ms/step - loss: 112.7238
Epoch 182/250
22/22 [=====] - 0s 2ms/step - loss: 104.3776
Epoch 183/250
22/22 [=====] - 0s 2ms/step - loss: 96.5934
Epoch 184/250
22/22 [=====] - 0s 2ms/step - loss: 88.8860
Epoch 185/250
22/22 [=====] - 0s 2ms/step - loss: 82.8837
Epoch 186/250
22/22 [=====] - 0s 2ms/step - loss: 76.0315
Epoch 187/250
22/22 [=====] - 0s 2ms/step - loss: 70.2759
Epoch 188/250
22/22 [=====] - 0s 2ms/step - loss: 64.5379
Epoch 189/250
22/22 [=====] - 0s 2ms/step - loss: 59.1233
Epoch 190/250
22/22 [=====] - 0s 2ms/step - loss: 53.8740
Epoch 191/250
22/22 [=====] - 0s 2ms/step - loss: 50.0658
Epoch 192/250
22/22 [=====] - 0s 2ms/step - loss: 46.2637
Epoch 193/250
22/22 [=====] - 0s 3ms/step - loss: 43.3418
Epoch 194/250
22/22 [=====] - 0s 3ms/step - loss: 40.2520
Epoch 195/250
22/22 [=====] - 0s 3ms/step - loss: 38.1849
Epoch 196/250

22/22 [=====] - 0s 2ms/step - loss: 36.3574
Epoch 197/250
22/22 [=====] - 0s 2ms/step - loss: 34.6796
Epoch 198/250
22/22 [=====] - 0s 2ms/step - loss: 32.6454
Epoch 199/250
22/22 [=====] - 0s 2ms/step - loss: 30.9656
Epoch 200/250
22/22 [=====] - 0s 2ms/step - loss: 29.9599
Epoch 201/250
22/22 [=====] - 0s 2ms/step - loss: 28.6788
Epoch 202/250
22/22 [=====] - 0s 2ms/step - loss: 28.1178
Epoch 203/250
22/22 [=====] - 0s 2ms/step - loss: 27.1385
Epoch 204/250
22/22 [=====] - 0s 2ms/step - loss: 26.5626
Epoch 205/250
22/22 [=====] - 0s 2ms/step - loss: 26.5577
Epoch 206/250
22/22 [=====] - 0s 2ms/step - loss: 26.0140
Epoch 207/250
22/22 [=====] - 0s 2ms/step - loss: 25.7898
Epoch 208/250
22/22 [=====] - 0s 2ms/step - loss: 25.5897
Epoch 209/250
22/22 [=====] - 0s 2ms/step - loss: 25.4914
Epoch 210/250
22/22 [=====] - 0s 2ms/step - loss: 25.1518
Epoch 211/250
22/22 [=====] - 0s 2ms/step - loss: 24.6354
Epoch 212/250
22/22 [=====] - 0s 2ms/step - loss: 24.5487
Epoch 213/250
22/22 [=====] - 0s 2ms/step - loss: 24.7406
Epoch 214/250
22/22 [=====] - 0s 2ms/step - loss: 24.6489
Epoch 215/250
22/22 [=====] - 0s 2ms/step - loss: 24.5997
Epoch 216/250
22/22 [=====] - 0s 2ms/step - loss: 24.1524
Epoch 217/250
22/22 [=====] - 0s 2ms/step - loss: 24.6055
Epoch 218/250
22/22 [=====] - 0s 1ms/step - loss: 24.5279
Epoch 219/250
22/22 [=====] - 0s 2ms/step - loss: 24.3975
Epoch 220/250
22/22 [=====] - 0s 2ms/step - loss: 24.8585
Epoch 221/250
22/22 [=====] - 0s 2ms/step - loss: 24.0338
Epoch 222/250
22/22 [=====] - 0s 2ms/step - loss: 24.4526
Epoch 223/250
22/22 [=====] - 0s 2ms/step - loss: 24.6730
Epoch 224/250
22/22 [=====] - 0s 2ms/step - loss: 23.9849
Epoch 225/250
22/22 [=====] - 0s 2ms/step - loss: 24.6794
Epoch 226/250
22/22 [=====] - 0s 2ms/step - loss: 24.1641
Epoch 227/250
22/22 [=====] - 0s 2ms/step - loss: 24.4464
Epoch 228/250
22/22 [=====] - 0s 2ms/step - loss: 24.2313
Epoch 229/250
22/22 [=====] - 0s 2ms/step - loss: 24.8725
Epoch 230/250
22/22 [=====] - 0s 1ms/step - loss: 23.9024
Epoch 231/250
22/22 [=====] - 0s 2ms/step - loss: 24.2521
Epoch 232/250
22/22 [=====] - 0s 2ms/step - loss: 24.5347
Epoch 233/250
22/22 [=====] - 0s 1ms/step - loss: 24.1900
Epoch 234/250
22/22 [=====] - 0s 2ms/step - loss: 24.0409
Epoch 235/250
22/22 [=====] - 0s 2ms/step - loss: 24.4561
Epoch 236/250
22/22 [=====] - 0s 2ms/step - loss: 24.3707
Epoch 237/250
22/22 [=====] - 0s 2ms/step - loss: 24.3323
Epoch 238/250
22/22 [=====] - 0s 2ms/step - loss: 24.2052
Epoch 239/250
22/22 [=====] - 0s 2ms/step - loss: 24.3102
Epoch 240/250
22/22 [=====] - 0s 2ms/step - loss: 24.2863

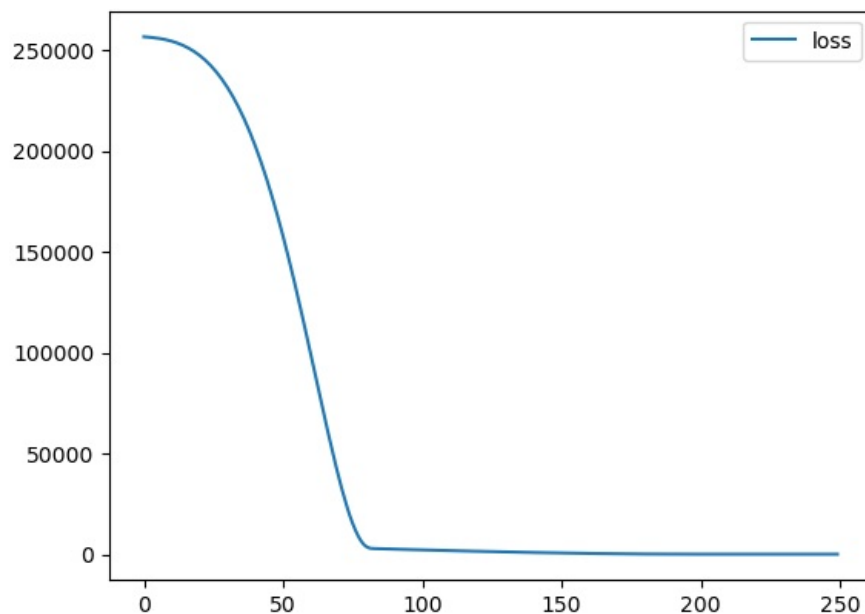
```
Epoch 241/250
22/22 [=====] - 0s 2ms/step - loss: 24.5386
Epoch 242/250
22/22 [=====] - 0s 2ms/step - loss: 24.2278
Epoch 243/250
22/22 [=====] - 0s 2ms/step - loss: 24.0992
Epoch 244/250
22/22 [=====] - 0s 2ms/step - loss: 24.1523
Epoch 245/250
22/22 [=====] - 0s 2ms/step - loss: 24.3276
Epoch 246/250
22/22 [=====] - 0s 2ms/step - loss: 24.2567
Epoch 247/250
22/22 [=====] - 0s 2ms/step - loss: 24.3360
Epoch 248/250
22/22 [=====] - 0s 2ms/step - loss: 24.7745
Epoch 249/250
22/22 [=====] - 0s 1ms/step - loss: 24.0316
Epoch 250/250
22/22 [=====] - 0s 1ms/step - loss: 23.8411
```

```
Out[22]: <keras.callbacks.History at 0x1e83900d610>
```

```
In [23]: loss_df = pd.DataFrame(model.history.history)
```

```
In [24]: loss_df.plot()
```

```
Out[24]: <AxesSubplot:>
```



```
In [ ]:
```

```
In [25]: model.evaluate(X_test,y_test,verbose=0) #This is our MSE
```

```
Out[25]: 24.962244033813477
```

```
In [26]: model.evaluate(X_train,y_train,verbose=0)
```

```
Out[26]: 24.01017951965332
```

```
In [27]: test_predictions = model.predict(X_test)
```

```
10/10 [=====] - 0s 1ms/step
```

```
In [28]: test_predictions
```

```
Out[28]: array([[405.072 ],
 [623.343 ],
 [591.9248 ],
 [572.0415 ],
 [366.42746],
 [578.9833 ],
 [514.87695],
 [458.88254],
 [549.0577 ],
 [447.29108],
 [611.5873 ],
 [548.7101 ],
 [418.88608],
 [408.66006],
 [651.01447],
 [437.07574],
```


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[550.4714],
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[502.95462],
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[350.29504],

```
[450.26443],
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[611.62305],
[387.99173],
[449.22232],
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[598.1345 ],
[499.20602],
[321.23425],
[554.9518 ],
[444.4207 ],
[528.85364],
[515.177 ],
[609.4501 ],
[416.7233 ],
[410.67102]], dtype=float32)
```

```
In [29]: test_predictions = pd.Series(test_predictions.reshape(300,))
```

```
In [30]: pred_df = pd.DataFrame(y_test,columns=['Test True Y'])
```

```
In [31]: pred_df = pd.concat([pred_df,test_predictions],axis=1)
```

```
In [32]: pred_df.columns = ['Test True Y','Model Predictions']
```

```
In [33]: pred_df
```

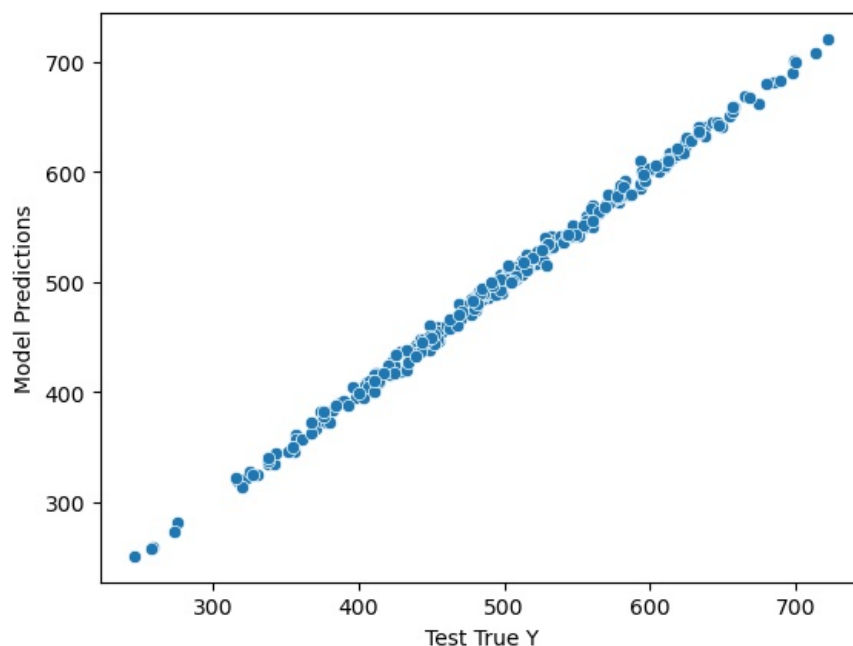
```
Out[33]:
```

	Test True Y	Model Predictions
0	402.296319	405.071991
1	624.156198	623.343018
2	582.455066	591.924805
3	578.588606	572.041504
4	371.224104	366.427460
...
295	525.704657	528.853638
296	502.909473	515.177002
297	612.727910	609.450073
298	417.569725	416.723297
299	410.538250	410.671021

300 rows × 2 columns

```
In [34]: #Let's plot these
sns.scatterplot(x='Test True Y',y='Model Predictions',data=pred_df) #Very good model
```

```
Out[34]: <AxesSubplot:xlabel='Test True Y', ylabel='Model Predictions'>
```



```
In [35]: from sklearn.metrics import mean_absolute_error,mean_squared_error
```

```
In [36]: mean absolute error(pred df['Test True Y'],pred df['Model Predictions'])
```

```
Out[36]: 3.9993414200148063
```

```
In [ ]: #MAE is good beacuse it means our model is only off 4 dollars
```

```
In [37]: df.describe()
```

```
Out[37]:
```

	price	feature1	feature2
count	1000.000000	1000.000000	1000.000000
mean	498.673029	1000.014171	999.979847
std	93.785431	0.974018	0.948330
min	223.346793	997.058347	996.995651
25%	433.025732	999.332068	999.316106
50%	502.382117	1000.009915	1000.002243
75%	564.921588	1000.637580	1000.645380
max	774.407854	1003.207934	1002.666308

```
In [38]: mean_squared_error(pred_df['Test True Y'],pred_df['Model Predictions'])
```

```
Out[38]: 24.962247126657825
```

```
In [39]: #Root mean squared error **0.5  
mean_squared_error(pred_df['Test True Y'],pred_df['Model Predictions'])**0.5
```

```
Out[39]: 4.996223286309152
```

```
In [40]: new_gem = [[998,1000]] #We wanna ask our model what is the price point for these features
```

```
In [41]: new_gem = scaler.transform(new_gem) #We gotta scale them first
```

```
In [42]: model.predict(new_gem) #Price is 419.40115
```

```
1/1 [=====] - 0s 203ms/step  
Out[42]: array([[419.50034]], dtype=float32)
```

```
In [43]: from tensorflow.keras.models import load_model
```

```
In [44]: model.save('my_gem_model.h5')
```

```
In [45]: later_model = load_model('my_gem_model.h5')
```

```
In [46]: later_model.predict(new_gem)
```

```
1/1 [=====] - 0s 484ms/step  
Out[46]: array([[419.50034]], dtype=float32)
```

```
In [ ]:
```