Topic: Neural Network for Simple Linear Regression

Objective for this template:

- 1. Introduce participants to fundamental concepts of simple linear regression
- 2. Use tensorflow to build a simple sequential neural network regression model
- 3. Demonstrate the process of training the model and evaluating its performance
- 4. Allow participants to practice normalizing the dataset to improve the performance of the dataset

Designed By: Rodolfo C. Raga Jr. Copyright @2021

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Step 1: load the tensorflow library and other helper libraries using the import keyword

```
import tensorflow as tf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score

print("Done with library declaration. Current version of Tensorflow is :", tf.__version__)

Done with library declaration. Current version of Tensorflow is : 2.7.0
```

Step 2: Load a sample data into a numpy array. Here, the market_budget attribute serves as the feature attribute while the subscribers_gained attribute serves as the target attribute.

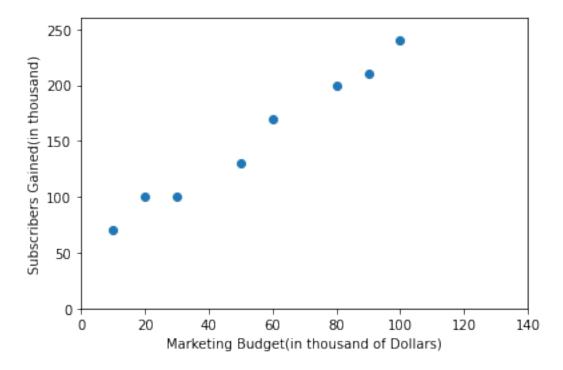
```
market_budget = np.array([60,80,100,30,50,20,90,10,], dtype=float)
subscribers_gained = np.array([170,200,240,100,130,100,210,70],
dtype=float)
#market_budget = np.array([50, 69, 85 , 83, 74, 81, 97, 92, 114,
85], dtype=float)
#subscribers_gained = np.array([90, 125, 140, 160, 130, 180, 150, 140,
200, 130], dtype=float)

print("marketing budget data :", market_budget)
print("# of subscribers gained :", subscribers_gained)
print("Done with loading data to dataframes...")
```

```
marketing budget data : [ 60. 80. 100. 30. 50. 20. 90. 10.] # of subscribers gained : [170. 200. 240. 100. 130. 100. 210. 70.] Done with loading data to dataframes...
```

Step 3: Analyze the relationship between the two attributes by visualizing the correlation using a scatter chart.

```
plt.scatter(market_budget, subscribers_gained)
plt.xlim(0,140)
plt.ylim(0,260)
plt.xlabel('Marketing Budget(in thousand of Dollars)')
plt.ylabel('Subscribers Gained(in thousand)')
plt.show()
print("Done with displaying scatter chart...")
```



Done with displaying scatter chart...

Step 3.1: Optionally, apply Normalization to the dataset using MinMaxScaler

```
from sklearn.preprocessing import MinMaxScaler
import pandas as pd
scaler = MinMaxScaler(feature_range=(0, 1))
rescaledMB = scaler.fit_transform(market_budget.reshape(-1, 1))
rescaledMBDF = pd.DataFrame(rescaledMB)

rescaledSG = scaler.fit_transform(subscribers_gained.reshape(-1, 1))
rescaledSGDF = pd.DataFrame(rescaledSG)

print("marketing budget data :", rescaledMBDF.head())
print("\n# of subscribers gained :", rescaledSGDF.head())
```

```
marketing budget data: 0
0 0.555556
1 0.777778
2 1.000000
3 0.222222
4 0.444444

# of subscribers gained: 0
0 0.588235
1 0.764706
2 1.000000
3 0.176471
4 0.352941
```

Step 4: Separate the data into distinct training and testing datasets. Separating the dataset returns four NumPy arrays:

- 1. The X_train and y_train_labels arrays are the training set—the data the model uses to learn.
- 2. The X_test and y_test labels arrays are the data used to test the model performance.

```
#X_train, X_test, y_train, y_test =
train_test_split(rescaledMBDF, rescaledSGDF, random_state=42,
test_size=0.3)
X_train, X_test, y_train, y_test =
train_test_split(market_budget, subscribers_gained, random_state=42,
test_size=0.3)
print("Done with data separation...") #rescaledMBDF, rescaledSGDF
Done with data separation...
```

Step 5: We start building the neural network by using the Sequential API to define a Sequential model object named model. This type of model takes a list of layers (Input, Hidden, Output) as arguments and implicitly assumes the order of the calculation from the input layer to the output layer based on the sequence of layer definitions.

```
model = tf.keras.Sequential()
print("Done with declaring Sequential model object...")
```

Done with declaring Sequential model object...

Step 6: Then we start defining the layers using the Dense class. Dense implements the operation: output = activation(dot(input, kernel) + bias) where activation is the elementwise activation function passed as the activation argument, kernel is a weights matrix created by the layer, and bias is a bias vector created by the layer (only applicable if use_bias is True)

```
layer_0 = tf.keras.layers.Dense(units=40, input_shape=[1])
layer_1 = tf.keras.layers.Dense(units=20)
layer_2 = tf.keras.layers.Dense(units=10)
layer_3 = tf.keras.layers.Dense(units=1)
```

```
print("Done with defining layer properties...")
Done with defining layer properties...

Step 7: After that, we insert the dense layer into our sequential model.

#model = tf.keras.Sequential([layer_0, layer_1, layer_2, layer_3])
model.add(layer_0)
model.add(layer_1)
model.add(layer_2)
model.add(layer_3)
```

#print the model architecture for inspection
model.summary()

Model: "sequential_5"

Layer (type)	Output Shape	Param #
dense_20 (Dense)	(None, 40)	80
dense_21 (Dense)	(None, 20)	820
dense_22 (Dense)	(None, 10)	210
dense_23 (Dense)	(None, 1)	11

Total params: 1,121 Trainable params: 1,121 Non-trainable params: 0

Step 8: Compile the built model architecture. The compilation configures the learning process by defining an optimizer, a loss function, and other useful training parameters.

Step 9: Train the model by using the set training data

```
trained model = model.fit(X train, y train, epochs=500, batch size=32,
verbose=1)
print("Done with model training")
Epoch 1/500
33250.1016 - mse: 33250.1016
Epoch 2/500
- mse: 32133.1602
Epoch 3/500
1/1 [============= ] - Os 19ms/step - loss: 31042.8633
- mse: 31042.8633
Epoch 4/500
- mse: 29978.0566
Epoch 5/500
- mse: 28937.2500
Epoch 6/500
- mse: 27918.9883
Epoch 7/500
- mse: 26921.8281
Epoch 8/500
- mse: 25944.2852
Epoch 9/500
- mse: 24984.8848
Epoch 10/500
- mse: 24042.3320
Epoch 11/500
- mse: 23115.5215
Epoch 12/500
- mse: 22203.5273
Epoch 13/500
- mse: 21305.5645
Epoch 14/500
- mse: 20421.0059
Epoch 15/500
- mse: 19549.3945
Epoch 16/500
```

```
- mse: 18690.4102
Epoch 17/500
- mse: 17843.8867
Epoch 18/500
- mse: 17009.7695
Epoch 19/500
- mse: 16188.1328
Epoch 20/500
- mse: 15379.1484
Epoch 21/500
- mse: 14583.0938
Epoch 22/500
- mse: 13800.3379
Epoch 23/500
- mse: 13031.3506
Epoch 24/500
- mse: 12276.6953
Epoch 25/500
- mse: 11537.0225
Epoch 26/500
- mse: 10813.0732
Epoch 27/500
- mse: 10105.6699
Epoch 28/500
- mse: 9415.7197
Epoch 29/500
- mse: 8744.2051
Epoch 30/500
mse: 8092.1772
Epoch 31/500
mse: 7460.7515
Epoch 32/500
- mse: 6851.0889
```

```
Epoch 33/500
mse: 6264.3965
Epoch 34/500
1/1 [============= ] - Os 6ms/step - loss: 5701.8994 -
mse: 5701.8994
Epoch 35/500
mse: 5164.8213
Epoch 36/500
mse: 4654.3804
Epoch 37/500
mse: 4171.7490
Epoch 38/500
mse: 3718.0317
Epoch 39/500
mse: 3294.2422
Epoch 40/500
mse: 2901.2703
Epoch 41/500
mse: 2539.8464
Epoch 42/500
- mse: 2210.5110
Epoch 43/500
mse: 1913.5778
Epoch 44/500
- mse: 1649.1000
Epoch 45/500
- mse: 1416.8418
Epoch 46/500
mse: 1216.2419
Epoch 47/500
mse: 1046.4001
Epoch 48/500
mse: 906.0581
Epoch 49/500
```

```
mse: 793.5976
Epoch 50/500
mse: 707.0497
Epoch 51/500
mse: 644.1174
Epoch 52/500
mse: 602.2180
Epoch 53/500
mse: 578.5372
Epoch 54/500
mse: 570.1015
Epoch 55/500
mse: 573.8622
Epoch 56/500
mse: 586.7892
Epoch 57/500
mse: 605.9681
Epoch 58/500
mse: 628.6969
Epoch 59/500
mse: 652.5670
Epoch 60/500
mse: 675.5366
Epoch 61/500
mse: 695.9764
Epoch 62/500
mse: 712.6917
Epoch 63/500
mse: 724.9162
Epoch 64/500
mse: 732.2888
Epoch 65/500
mse: 734.8013
Epoch 66/500
```

```
mse: 732.7421
Epoch 67/500
mse: 726.6248
Epoch 68/500
mse: 717.1198
Epoch 69/500
mse: 704.9871
Epoch 70/500
1/1 [============= ] - Os 7ms/step - loss: 691.0145 -
mse: 691.0145
Epoch 71/500
mse: 675.9698
Epoch 72/500
mse: 660.5606
Epoch 73/500
mse: 645.4027
Epoch 74/500
mse: 631.0065
Epoch 75/500
mse: 617.7659
Epoch 76/500
mse: 605.9598
Epoch 77/500
mse: 595.7565
Epoch 78/500
mse: 587.2275
Epoch 79/500
mse: 580.3586
Epoch 80/500
mse: 575.0679
Epoch 81/500
mse: 571.2201
Epoch 82/500
```

mse: 568.6442 Epoch 83/500

```
mse: 567.1464
Epoch 84/500
mse: 566.5245
Epoch 85/500
mse: 566.5774
Epoch 86/500
mse: 567.1149
Epoch 87/500
mse: 567.9626
Epoch 88/500
1/1 [============ ] - Os 8ms/step - loss: 568.9698 -
mse: 568.9698
Epoch 89/500
mse: 570.0083
Epoch 90/500
mse: 570.9765
Epoch 91/500
mse: 571.7980
Epoch 92/500
mse: 572.4203
Epoch 93/500
mse: 572.8134
Epoch 94/500
mse: 572.9658
Epoch 95/500
mse: 572.8832
Epoch 96/500
mse: 572.5831
Epoch 97/500
1/1 [============ ] - Os 8ms/step - loss: 572.0936 -
mse: 572.0936
Epoch 98/500
mse: 571.4486
```

```
Epoch 99/500
mse: 570.6857
Epoch 100/500
mse: 569.8429
Epoch 101/500
mse: 568.9581
Epoch 102/500
mse: 568.0653
Epoch 103/500
mse: 567.1940
Epoch 104/500
mse: 566.3693
Epoch 105/500
1/1 [============ ] - Os 8ms/step - loss: 565.6099 -
mse: 565.6099
Epoch 106/500
mse: 564.9289
Epoch 107/500
mse: 564.3336
Epoch 108/500
mse: 563.8265
Epoch 109/500
mse: 563.4053
Epoch 110/500
mse: 563.0640
Epoch 111/500
mse: 562.7936
Epoch 112/500
mse: 562.5845
Epoch 113/500
mse: 562.4237
Epoch 114/500
mse: 562.2998
Epoch 115/500
```

```
mse: 562.2009
Epoch 116/500
mse: 562.1166
Epoch 117/500
mse: 562.0370
Epoch 118/500
mse: 561.9547
Epoch 119/500
mse: 561.8633
Epoch 120/500
mse: 561.7592
Epoch 121/500
mse: 561.6390
Epoch 122/500
mse: 561.5021
Epoch 123/500
mse: 561.3489
Epoch 124/500
mse: 561.1802
Epoch 125/500
mse: 560.9987
Epoch 126/500
mse: 560.8068
Epoch 127/500
mse: 560.6073
Epoch 128/500
mse: 560.4031
Epoch 129/500
mse: 560.1970
Epoch 130/500
mse: 559.9911
Epoch 131/500
mse: 559.7877
Epoch 132/500
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```
mse: 559.5884
Epoch 133/500
mse: 559.3938
Epoch 134/500
mse: 559.2049
Epoch 135/500
mse: 559.0215
Epoch 136/500
mse: 558.8439
Epoch 137/500
mse: 558.6712
Epoch 138/500
mse: 558.5027
Epoch 139/500
mse: 558.3376
Epoch 140/500
mse: 558.1749
Epoch 141/500
mse: 558.0140
Epoch 142/500
mse: 557.8537
Epoch 143/500
mse: 557.6933
Epoch 144/500
mse: 557.5323
Epoch 145/500
mse: 557.3704
Epoch 146/500
mse: 557.2072
Epoch 147/500
mse: 557.0419
Epoch 148/500
mse: 556.8754
```

```
Epoch 149/500
mse: 556.7066
Epoch 150/500
mse: 556.5367
Epoch 151/500
mse: 556.3652
Epoch 152/500
mse: 556.1926
Epoch 153/500
mse: 556.0193
Epoch 154/500
mse: 555.8452
Epoch 155/500
1/1 [============ ] - Os 6ms/step - loss: 555.6705 -
mse: 555.6705
Epoch 156/500
mse: 555.4955
Epoch 157/500
mse: 555.3204
Epoch 158/500
mse: 555.1452
Epoch 159/500
mse: 554.9703
Epoch 160/500
mse: 554.7953
Epoch 161/500
mse: 554.6201
Epoch 162/500
mse: 554.4452
Epoch 163/500
mse: 554.2701
Epoch 164/500
mse: 554.0951
Epoch 165/500
```

mse: 553.9198 Epoch 166/500

```
mse: 553.7440
Epoch 167/500
mse: 553.5682
Epoch 168/500
mse: 553.3917
Epoch 169/500
mse: 553.2150
Epoch 170/500
mse: 553.0377
Epoch 171/500
1/1 [============ ] - Os 7ms/step - loss: 552.8597 -
mse: 552.8597
Epoch 172/500
mse: 552.6816
Epoch 173/500
mse: 552.5028
Epoch 174/500
1/1 [============ ] - Os 8ms/step - loss: 552.3234 -
mse: 552.3234
Epoch 175/500
mse: 552.1434
Epoch 176/500
mse: 551.9633
Epoch 177/500
mse: 551.7825
Epoch 178/500
mse: 551.6010
Epoch 179/500
mse: 551.4195
Epoch 180/500
mse: 551.2373
Epoch 181/500
mse: 551.0552
```

```
Epoch 182/500
mse: 550.8723
Epoch 183/500
mse: 550.6893
Epoch 184/500
mse: 550.5057
Epoch 185/500
mse: 550.3217
Epoch 186/500
mse: 550.1377
Epoch 187/500
mse: 549.9531
Epoch 188/500
mse: 549.7682
Epoch 189/500
mse: 549.5832
Epoch 190/500
mse: 549.3973
Epoch 191/500
mse: 549.2112
Epoch 192/500
mse: 549.0250
Epoch 193/500
mse: 548.8382
Epoch 194/500
1/1 [============ ] - Os 4ms/step - loss: 548.6509 -
mse: 548.6509
Epoch 195/500
mse: 548.4633
Epoch 196/500
mse: 548.2754
Epoch 197/500
mse: 548.0870
Epoch 198/500
```

```
mse: 547.8983
Epoch 199/500
mse: 547.7093
Epoch 200/500
mse: 547.5198
Epoch 201/500
mse: 547.3302
Epoch 202/500
mse: 547.1396
Epoch 203/500
mse: 546.9491
Epoch 204/500
mse: 546.7581
Epoch 205/500
mse: 546.5667
Epoch 206/500
mse: 546.3751
Epoch 207/500
mse: 546.1831
Epoch 208/500
mse: 545.9910
Epoch 209/500
mse: 545.7982
Epoch 210/500
mse: 545.6052
Epoch 211/500
mse: 545.4117
Epoch 212/500
mse: 545.2179
Epoch 213/500
mse: 545.0238
Epoch 214/500
mse: 544.8292
Epoch 215/500
```

```
mse: 544.6344
Epoch 216/500
mse: 544.4393
Epoch 217/500
- mse: 544.2437
Epoch 218/500
mse: 544.0478
Epoch 219/500
mse: 543.8516
Epoch 220/500
mse: 543.6550
Epoch 221/500
mse: 543.4581
Epoch 222/500
mse: 543.2610
Epoch 223/500
mse: 543.0634
Epoch 224/500
mse: 542.8656
Epoch 225/500
mse: 542.6670
Epoch 226/500
mse: 542.4684
Epoch 227/500
mse: 542.2695
Epoch 228/500
mse: 542.0704
Epoch 229/500
mse: 541.8706
Epoch 230/500
mse: 541.6705
Epoch 231/500
mse: 541.4704
```

```
Epoch 232/500
mse: 541.2698
Epoch 233/500
mse: 541.0690
Epoch 234/500
mse: 540.8677
Epoch 235/500
mse: 540.6659
Epoch 236/500
mse: 540.4642
Epoch 237/500
mse: 540.2617
Epoch 238/500
1/1 [============= ] - Os 9ms/step - loss: 540.0593 -
mse: 540.0593
Epoch 239/500
mse: 539.8563
Epoch 240/500
mse: 539.6532
Epoch 241/500
mse: 539.4496
Epoch 242/500
mse: 539.2460
Epoch 243/500
mse: 539.0416
Epoch 244/500
mse: 538.8372
Epoch 245/500
mse: 538.6324
Epoch 246/500
mse: 538.4271
Epoch 247/500
mse: 538.2219
Epoch 248/500
```

mse: 538.0160 Epoch 249/500

```
mse: 537.8099
Epoch 250/500
mse: 537.6034
Epoch 251/500
mse: 537.3969
Epoch 252/500
mse: 537.1898
Epoch 253/500
mse: 536.9824
Epoch 254/500
1/1 [============= ] - Os 6ms/step - loss: 536.7746 -
mse: 536.7746
Epoch 255/500
mse: 536.5670
Epoch 256/500
mse: 536.3588
Epoch 257/500
mse: 536.1498
Epoch 258/500
mse: 535.9410
Epoch 259/500
mse: 535.7321
Epoch 260/500
mse: 535.5225
Epoch 261/500
mse: 535.3127
Epoch 262/500
mse: 535.1027
Epoch 263/500
mse: 534.8923
Epoch 264/500
mse: 534.6817
```

```
Epoch 265/500
mse: 534.4706
Epoch 266/500
mse: 534.2593
Epoch 267/500
mse: 534.0479
Epoch 268/500
mse: 533.8359
Epoch 269/500
mse: 533.6237
Epoch 270/500
mse: 533.4108
Epoch 271/500
1/1 [============ ] - Os 6ms/step - loss: 533.1984 -
mse: 533.1984
Epoch 272/500
mse: 532.9854
Epoch 273/500
mse: 532.7721
Epoch 274/500
mse: 532.5582
Epoch 275/500
mse: 532.3442
Epoch 276/500
mse: 532.1300
Epoch 277/500
mse: 531.9156
Epoch 278/500
mse: 531.7007
Epoch 279/500
mse: 531.4855
Epoch 280/500
mse: 531.2701
Epoch 281/500
```

```
mse: 531.0543
Epoch 282/500
mse: 530.8385
Epoch 283/500
mse: 530.6222
Epoch 284/500
mse: 530.4056
Epoch 285/500
mse: 530.1886
Epoch 286/500
mse: 529.9715
Epoch 287/500
mse: 529.7540
Epoch 288/500
mse: 529.5363
Epoch 289/500
mse: 529.3184
Epoch 290/500
mse: 529.0999
Epoch 291/500
mse: 528.8815
Epoch 292/500
mse: 528.6625
Epoch 293/500
mse: 528.4435
Epoch 294/500
mse: 528.2240
Epoch 295/500
mse: 528.0045
Epoch 296/500
527.784 - Os 8ms/step - loss: 527.7843 - mse: 527.7843
Epoch 297/500
mse: 527.5641
Epoch 298/500
```

```
mse: 527.3434
Epoch 299/500
mse: 527.1227
Epoch 300/500
mse: 526.9016
Epoch 301/500
mse: 526.6801
Epoch 302/500
mse: 526.4584
Epoch 303/500
mse: 526.2365
Epoch 304/500
mse: 526.0141
Epoch 305/500
mse: 525.7916
Epoch 306/500
mse: 525.5688
Epoch 307/500
mse: 525.3459
Epoch 308/500
mse: 525.1224
Epoch 309/500
mse: 524.8987
Epoch 310/500
mse: 524.6750
Epoch 311/500
mse: 524.4508
Epoch 312/500
mse: 524.2264
Epoch 313/500
mse: 524.0016
Epoch 314/500
mse: 523.7766
```

```
Epoch 315/500
mse: 523.5515
Epoch 316/500
mse: 523.3260
Epoch 317/500
mse: 523.1002
Epoch 318/500
mse: 522.8739
Epoch 319/500
mse: 522.6476
Epoch 320/500
mse: 522.4209
Epoch 321/500
1/1 [============== ] - Os 15ms/step - loss: 522.1940 -
mse: 522.1940
Epoch 322/500
mse: 521.9670
Epoch 323/500
mse: 521.7394
Epoch 324/500
    1/1 [=======
mse: 521.5117
Epoch 325/500
mse: 521.2838
Epoch 326/500
mse: 521.0553
Epoch 327/500
mse: 520.8270
Epoch 328/500
mse: 520.5981
Epoch 329/500
mse: 520.3694
Epoch 330/500
mse: 520.1397
Epoch 331/500
```

mse: 519.9103 Epoch 332/500

```
mse: 519.6802
Epoch 333/500
mse: 519.4501
Epoch 334/500
mse: 519.2196
Epoch 335/500
mse: 518.9891
Epoch 336/500
mse: 518.7582
Epoch 337/500
1/1 [============= ] - Os 8ms/step - loss: 518.5270 -
mse: 518.5270
Epoch 338/500
mse: 518.2955
Epoch 339/500
mse: 518.0638
Epoch 340/500
mse: 517.8318
Epoch 341/500
mse: 517.5997
Epoch 342/500
mse: 517.3668
Epoch 343/500
mse: 517.1343
Epoch 344/500
mse: 516.9012
Epoch 345/500
mse: 516.6679
Epoch 346/500
mse: 516.4342
Epoch 347/500
mse: 516.2006
```

```
Epoch 348/500
mse: 515.9664
Epoch 349/500
mse: 515.7321
Epoch 350/500
mse: 515.4972
Epoch 351/500
mse: 515.2626
Epoch 352/500
mse: 515.0271
Epoch 353/500
mse: 514.7918
Epoch 354/500
1/1 [============= ] - Os 18ms/step - loss: 514.5562 -
mse: 514.5562
Epoch 355/500
mse: 514.3202
Epoch 356/500
mse: 514.0839
Epoch 357/500
mse: 513.8475
Epoch 358/500
mse: 513.6110
Epoch 359/500
mse: 513.3738
Epoch 360/500
mse: 513.1366
Epoch 361/500
mse: 512.8989
Epoch 362/500
mse: 512.6611
Epoch 363/500
mse: 512.4233
Epoch 364/500
```

```
mse: 512.1846
Epoch 365/500
mse: 511.9461
Epoch 366/500
mse: 511.7075
Epoch 367/500
mse: 511.4681
Epoch 368/500
mse: 511.2289
Epoch 369/500
mse: 510.9893
Epoch 370/500
1/1 [============= ] - Os 9ms/step - loss: 510.7494 -
mse: 510.7494
Epoch 371/500
mse: 510.5092
Epoch 372/500
mse: 510.2689
Epoch 373/500
mse: 510.0284
Epoch 374/500
mse: 509.7872
Epoch 375/500
mse: 509.5459
Epoch 376/500
mse: 509.3046
Epoch 377/500
mse: 509.0629
Epoch 378/500
mse: 508.8209
Epoch 379/500
mse: 508.5786
Epoch 380/500
mse: 508.3359
Epoch 381/500
```

```
mse: 508.0934
Epoch 382/500
mse: 507.8503
Epoch 383/500
mse: 507.6071
Epoch 384/500
mse: 507.3634
Epoch 385/500
mse: 507.1197
Epoch 386/500
mse: 506.8756
Epoch 387/500
mse: 506.6314
Epoch 388/500
506.386 - 0s 6ms/step - loss: 506.3868 - mse: 506.3868
Epoch 389/500
mse: 506.1419
Epoch 390/500
mse: 505.8970
Epoch 391/500
mse: 505.6516
Epoch 392/500
mse: 505.4059
Epoch 393/500
505.159 - 0s 7ms/step - loss: 505.1599 - mse: 505.1599
Epoch 394/500
mse: 504.9138
Epoch 395/500
mse: 504.6672
Epoch 396/500
mse: 504.4205
Epoch 397/500
mse: 504.1738
```

```
Epoch 398/500
mse: 503.9267
Epoch 399/500
1/1 [============ ] - Os 6ms/step - loss: 503.6790 -
mse: 503.6790
Epoch 400/500
mse: 503.4312
Epoch 401/500
mse: 503.1833
Epoch 402/500
mse: 502.9351
Epoch 403/500
mse: 502.6867
Epoch 404/500
mse: 502.4378
Epoch 405/500
mse: 502.1887
Epoch 406/500
mse: 501.9394
Epoch 407/500
mse: 501.6901
Epoch 408/500
mse: 501.4400
Epoch 409/500
mse: 501.1901
Epoch 410/500
1/1 [============ ] - Os 8ms/step - loss: 500.9397 -
mse: 500.9397
Epoch 411/500
mse: 500.6891
Epoch 412/500
mse: 500.4384
Epoch 413/500
mse: 500.1872
Epoch 414/500
```

```
mse: 499.9357
Epoch 415/500
mse: 499.6840
Epoch 416/500
mse: 499.4322
Epoch 417/500
mse: 499.1800
Epoch 418/500
1/1 [============= ] - 0s 8ms/step - loss: 498.9274 -
mse: 498.9274
Epoch 419/500
mse: 498.6749
Epoch 420/500
mse: 498.4217
Epoch 421/500
mse: 498.1685
Epoch 422/500
mse: 497.9150
Epoch 423/500
mse: 497.6613
Epoch 424/500
mse: 497.4070
Epoch 425/500
mse: 497.1528
Epoch 426/500
mse: 496.8984
Epoch 427/500
mse: 496.6435
Epoch 428/500
mse: 496.3883
Epoch 429/500
mse: 496.1329
Epoch 430/500
mse: 495.8774
```

```
Epoch 431/500
mse: 495.6213
Epoch 432/500
mse: 495.3651
Epoch 433/500
mse: 495.1087
Epoch 434/500
mse: 494.8521
Epoch 435/500
mse: 494.5953
Epoch 436/500
mse: 494.3379
Epoch 437/500
mse: 494.0803
Epoch 438/500
mse: 493.8224
Epoch 439/500
mse: 493.5645
Epoch 440/500
mse: 493.3062
Epoch 441/500
mse: 493.0478
Epoch 442/500
mse: 492.7886
Epoch 443/500
mse: 492.5294
Epoch 444/500
mse: 492.2701
Epoch 445/500
mse: 492.0104
Epoch 446/500
mse: 491.7506
Epoch 447/500
```

```
mse: 491.4903
Epoch 448/500
mse: 491.2298
Epoch 449/500
mse: 490.9691
Epoch 450/500
mse: 490.7080
Epoch 451/500
mse: 490.4467
Epoch 452/500
mse: 490.1852
Epoch 453/500
mse: 489.9232
Epoch 454/500
mse: 489.6611
Epoch 455/500
mse: 489.3987
Epoch 456/500
mse: 489.1361
Epoch 457/500
mse: 488.8732
Epoch 458/500
mse: 488.6100
Epoch 459/500
mse: 488.3464
Epoch 460/500
mse: 488.0825
Epoch 461/500
mse: 487.8185
Epoch 462/500
mse: 487.5541
Epoch 463/500
mse: 487.2896
Epoch 464/500
```

```
mse: 487.0247
Epoch 465/500
mse: 486.7593
Epoch 466/500
mse: 486.4940
Epoch 467/500
mse: 486.2282
Epoch 468/500
mse: 485.9622
Epoch 469/500
mse: 485.6961
Epoch 470/500
mse: 485.4294
Epoch 471/500
mse: 485.1627
Epoch 472/500
mse: 484.8956
Epoch 473/500
mse: 484.6279
Epoch 474/500
mse: 484.3603
Epoch 475/500
mse: 484.0925
Epoch 476/500
mse: 483.8242
Epoch 477/500
mse: 483.5554
Epoch 478/500
mse: 483.2867
Epoch 479/500
mse: 483.0177
Epoch 480/500
mse: 482.7483
```

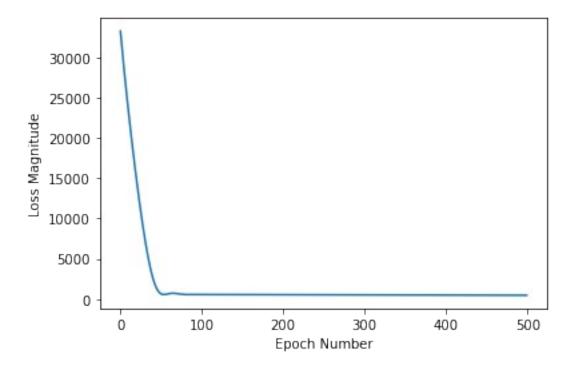
```
Epoch 481/500
mse: 482.4786
Epoch 482/500
mse: 482.2084
Epoch 483/500
mse: 481.9384
Epoch 484/500
mse: 481.6676
Epoch 485/500
mse: 481.3970
Epoch 486/500
mse: 481.1258
Epoch 487/500
mse: 480.8544
Epoch 488/500
mse: 480.5826
Epoch 489/500
mse: 480.3108
Epoch 490/500
mse: 480.0384
Epoch 491/500
mse: 479.7659
Epoch 492/500
mse: 479.4932
Epoch 493/500
1/1 [============= ] - Os 8ms/step - loss: 479.2199 -
mse: 479.2199
Epoch 494/500
mse: 478.9465
Epoch 495/500
mse: 478.6726
Epoch 496/500
mse: 478.3985
Epoch 497/500
```

```
mse: 478.1244
Epoch 498/500
mse: 477.8499
Epoch 499/500
mse: 477.5749
Epoch 500/500
mse: 477.2995
Done with model training
Step 10: Test the performance of the model using the testing dataset
y pred = model.predict(X test)
print('Actual Values\tPredicted Values')
print(y_test,' ',y_pred.reshape(1,-1))
score=r2_score(y_test,y_pred)
print("Overall R squared score: {}".format(score*100))
Actual Values
          Predicted Values
[200. 100. 170.]
             [[196.75392
                       52.905807 148.80455 ]]
Overall R squared score: 49.158599619316
```

1. Analyze training statistics

Other things we can do:

```
plt.xlabel('Epoch Number')
plt.ylabel("Loss Magnitude")
plt.plot(trained_model.history['loss'])
[<matplotlib.lines.Line2D at 0x1eca6a22370>]
```



1. Test NN performance using validation dataset

```
#Array of test values
print("Marketing Budget Values:",X test.reshape(1,-1))
y pred = model.predict(X_test)
print('Actual Values\tPredicted Values')
print(y_test.reshape(1,-1),' ',y_pred.reshape(1,-1))
Marketing Budget Values: [[80. 20. 60.]]
Actual Values Predicted Values
[[200. 100. 170.]]
                      [[196.75392
                                    52.905807 148.80455 ]]
#Single data test value
budget = float(input("Enter Amount for Marketing Budget: "))
predicted Cust Gain = model.predict([budget])
print("Estimated number of customer gain is ",predicted_Cust Gain)
Enter Amount for Marketing Budget: 80
Estimated number of customer gain is [[196.75392]]
```