2020_1124_ANN_Modeling

November 25, 2020

1 Predicting Concrete Compressive Strength - Artificial Neural Network (ANN) Modeling in TensorFlow 2.0

In this code notebook, we will import the data, scale it, perform a train-test split, and run it through various artificial neural network (ANN) configurations in TensorFlow 2.0 using Keras.

1.1 Dataset Citation

This dataset was retrieved from the UC Irvine Machine Learning Repository from the following URL: https://archive.ics.uci.edu/ml/datasets/Concrete+Compressive+Strength.

The dataset was donated to the UCI Repository by Prof. I-Cheng Yeh of Chung-Huah University, who retains copyright for the following published paper: I-Cheng Yeh, "Modeling of strength of high performance concrete using artificial neural networks," Cement and Concrete Research, Vol. 28, No. 12, pp. 1797-1808 (1998). Additional papers citing this dataset are listed at the reference link above.

1.2 Import the Relevant Libraries

```
[2]: # Data Manipulation
     import numpy as np
     import pandas as pd
     # Data Visualization
     import matplotlib.pyplot as plt
     import seaborn as sns
     %matplotlib inline
     sns.set()
     # Data Preprocessing
     from sklearn.model_selection import train_test_split
     from sklearn.preprocessing import MinMaxScaler
     # ANN Modeling in TensorFlow & Keras
     import tensorflow as tf
     from tensorflow.keras.models import Sequential
     from tensorflow.keras.layers import Dense, Activation
     from tensorflow.keras.optimizers import Adam
```

```
from tensorflow.keras.layers import Dropout

# Model Evaluation
from sklearn.metrics import

→mean_squared_error,mean_absolute_error,explained_variance_score
```

1.3 Data Preprocessing

1.3.1 Import & Check the Data

```
[3]: df = pd.read_csv('2020_1124_Modeling_Data.csv')
concrete_data = df.copy()
```

```
[4]: concrete_data.head()
```

```
[4]:
              Blast_Furnace_Slag Fly_Ash Water Superplasticizer \
       Cement
        540.0
                            0.0
                                     0.0 162.0
                                                            2.5
    1 540.0
                            0.0
                                     0.0 162.0
                                                            2.5
    2 332.5
                                     0.0 228.0
                                                            0.0
                          142.5
      332.5
                           142.5
                                     0.0 228.0
                                                            0.0
    4 198.6
                          132.4
                                     0.0 192.0
                                                            0.0
```

	Coarse_Aggregate	Fine_Aggregate	Age	Compressive_Strength
0	1040.0	676.0	28	79.99
1	1055.0	676.0	28	61.89
2	932.0	594.0	270	40.27
3	932.0	594.0	365	41.05
4	978.4	825.5	360	44.30

1.3.2 Train Test Split

```
[12]: X = concrete_data.drop('Compressive_Strength',axis=1)
y = concrete_data['Compressive_Strength']
```

```
[15]: X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.

→2,random_state=42)
```

1.3.3 Scale the Data

```
[16]: scaler = MinMaxScaler()
    X_train= scaler.fit_transform(X_train)
    X_test = scaler.transform(X_test)
```

1.4 Model 1 - ANN with 3 Hidden Layers

1.4.1 Construct the Artificial Neural Network

1.4.2 Train the Model on the Test Data

```
Epoch 1/400
val_loss: 1508.6826
Epoch 2/400
1501.8268
Epoch 3/400
1493.7604
Epoch 4/400
1484.2760
Epoch 5/400
1472.9838
Epoch 6/400
1459.6383
Epoch 7/400
1443.7256
```

```
Epoch 8/400
1424.5239
Epoch 9/400
1401.2220
Epoch 10/400
1372.9393
Epoch 11/400
1338.7654
Epoch 12/400
1296.9757
Epoch 13/400
1246.1107
Epoch 14/400
1185.3334
Epoch 15/400
1113.8789
Epoch 16/400
7/7 [============ ] - Os 4ms/step - loss: 1126.9540 - val_loss:
1031.0339
Epoch 17/400
937.4698
Epoch 18/400
835.0931
Epoch 19/400
725.8336
Epoch 20/400
612.7827
Epoch 21/400
503.3185
Epoch 22/400
403.9704
Epoch 23/400
322.6028
```

```
Epoch 24/400
262.1744
Epoch 25/400
226.4852
Epoch 26/400
210.8604
Epoch 27/400
206.9225
Epoch 28/400
206.7929
Epoch 29/400
206.4270
Epoch 30/400
205.2440
Epoch 31/400
203.5482
Epoch 32/400
201.9958
Epoch 33/400
200.7279
Epoch 34/400
199.5953
Epoch 35/400
198.4823
Epoch 36/400
197.3176
Epoch 37/400
196.0406
Epoch 38/400
194.6746
Epoch 39/400
193.1156
```

```
Epoch 40/400
191.6171
Epoch 41/400
190.0426
Epoch 42/400
188.3955
Epoch 43/400
186.6427
Epoch 44/400
184.7481
Epoch 45/400
182.7501
Epoch 46/400
180.7329
Epoch 47/400
178.7834
Epoch 48/400
176.7494
Epoch 49/400
174.7260
Epoch 50/400
172.7047
Epoch 51/400
170.5597
Epoch 52/400
168.4945
Epoch 53/400
166.5248
Epoch 54/400
164.6324
Epoch 55/400
162.7273
```

```
Epoch 56/400
160.8628
Epoch 57/400
159.0369
Epoch 58/400
157.2498
Epoch 59/400
155.5041
Epoch 60/400
153.7421
Epoch 61/400
152.0627
Epoch 62/400
150.3155
Epoch 63/400
148.6808
Epoch 64/400
147.0856
Epoch 65/400
145.4756
Epoch 66/400
143.9728
Epoch 67/400
142.4589
Epoch 68/400
140.8352
Epoch 69/400
139.3645
Epoch 70/400
137.9483
Epoch 71/400
136.5761
```

```
Epoch 72/400
135,2605
Epoch 73/400
133.8310
Epoch 74/400
132.4466
Epoch 75/400
131.0476
Epoch 76/400
129.8538
Epoch 77/400
128.7971
Epoch 78/400
127.6248
Epoch 79/400
126.4846
Epoch 80/400
125.4859
Epoch 81/400
124.4943
Epoch 82/400
123.4807
Epoch 83/400
122.5207
Epoch 84/400
121.5736
Epoch 85/400
120.5496
Epoch 86/400
119.7033
Epoch 87/400
118.9468
```

```
Epoch 88/400
118.1959
Epoch 89/400
117.3846
Epoch 90/400
116.7002
Epoch 91/400
115.9953
Epoch 92/400
115.3246
Epoch 93/400
114.6734
Epoch 94/400
114.1880
Epoch 95/400
113.6182
Epoch 96/400
113.0719
Epoch 97/400
112.5926
Epoch 98/400
112.0374
Epoch 99/400
111.4540
Epoch 100/400
110.8500
Epoch 101/400
110.2828
Epoch 102/400
109.6675
Epoch 103/400
109.4194
```

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Epoch 104/400
108.9294
Epoch 105/400
108.4607
Epoch 106/400
108.2157
Epoch 107/400
107.7845
Epoch 108/400
107.5061
Epoch 109/400
107.5294
Epoch 110/400
106.9276
Epoch 111/400
106.6234
Epoch 112/400
7/7 [============ - Os 2ms/step - loss: 119.2699 - val_loss:
106.4045
Epoch 113/400
106.0583
Epoch 114/400
105.8091
Epoch 115/400
105.7206
Epoch 116/400
105.4559
Epoch 117/400
105.1202
Epoch 118/400
105.0538
Epoch 119/400
104.7872
```

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Epoch 120/400
104.4889
Epoch 121/400
104.3915
Epoch 122/400
104.2911
Epoch 123/400
7/7 [============ - Os 3ms/step - loss: 117.6229 - val_loss:
104.1105
Epoch 124/400
103.8971
Epoch 125/400
103.6479
Epoch 126/400
103.5283
Epoch 127/400
103.2489
Epoch 128/400
103.2201
Epoch 129/400
103.0281
Epoch 130/400
102.7095
Epoch 131/400
102.4815
Epoch 132/400
102.3902
Epoch 133/400
102.3043
Epoch 134/400
102.0774
Epoch 135/400
102.0317
```

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Epoch 136/400
101.7057
Epoch 137/400
101.5516
Epoch 138/400
101.4446
Epoch 139/400
101.3583
Epoch 140/400
101.2495
Epoch 141/400
101.0847
Epoch 142/400
100.8888
Epoch 143/400
100.9646
Epoch 144/400
100.5726
Epoch 145/400
100.4375
Epoch 146/400
100.2814
Epoch 147/400
100.1199
Epoch 148/400
99.9466
Epoch 149/400
99.8897
Epoch 150/400
99.5975
Epoch 151/400
99.6393
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Epoch 152/400
99.4136
Epoch 153/400
99.4498
Epoch 154/400
99.4863
Epoch 155/400
99.2457
Epoch 156/400
99.2494
Epoch 157/400
99.3139
Epoch 158/400
99.0747
Epoch 159/400
98.8667
Epoch 160/400
98.7255
Epoch 161/400
98.5213
Epoch 162/400
98.2507
Epoch 163/400
98.2880
Epoch 164/400
98.1634
Epoch 165/400
98.1876
Epoch 166/400
98.4476
Epoch 167/400
98.2130
```

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Epoch 168/400
98.1459
Epoch 169/400
97.9401
Epoch 170/400
97.8144
Epoch 171/400
97.7775
Epoch 172/400
97.5302
Epoch 173/400
97.4162
Epoch 174/400
97.3550
Epoch 175/400
97.2983
Epoch 176/400
97.1980
Epoch 177/400
97.0607
Epoch 178/400
96.9607
Epoch 179/400
96.7968
Epoch 180/400
96.7701
Epoch 181/400
96.8539
Epoch 182/400
96.8780
Epoch 183/400
96.7547
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Epoch 184/400
96.7415
Epoch 185/400
96.6603
Epoch 186/400
96.6543
Epoch 187/400
96.5197
Epoch 188/400
96.4028
Epoch 189/400
96.2907
Epoch 190/400
96.3617
Epoch 191/400
96.3378
Epoch 192/400
96.2949
Epoch 193/400
96.2246
Epoch 194/400
96.2053
Epoch 195/400
95.9865
Epoch 196/400
95.8391
Epoch 197/400
95.6005
Epoch 198/400
95.5975
Epoch 199/400
95.6367
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Epoch 200/400
95.4210
Epoch 201/400
95.3763
Epoch 202/400
95.1209
Epoch 203/400
95.2011
Epoch 204/400
95.1269
Epoch 205/400
95.2117
Epoch 206/400
94.9300
Epoch 207/400
94.9835
Epoch 208/400
95.0819
Epoch 209/400
95.1838
Epoch 210/400
95.0918
Epoch 211/400
95.0891
Epoch 212/400
95.0525
Epoch 213/400
94.9858
Epoch 214/400
94.8959
Epoch 215/400
94.8457
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Epoch 216/400
94.7538
Epoch 217/400
94.5517
Epoch 218/400
94.4669
Epoch 219/400
94.1132
Epoch 220/400
94.0750
Epoch 221/400
93.9292
Epoch 222/400
93.9226
Epoch 223/400
93.9984
Epoch 224/400
93.8837
Epoch 225/400
93.8100
Epoch 226/400
93.9296
Epoch 227/400
94.0417
Epoch 228/400
94.0717
Epoch 229/400
94.3192
Epoch 230/400
94.1431
Epoch 231/400
94.0879
```

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Epoch 232/400
94.1189
Epoch 233/400
93.9283
Epoch 234/400
93.8547
Epoch 235/400
93.7979
Epoch 236/400
93.4986
Epoch 237/400
93.4712
Epoch 238/400
93.3166
Epoch 239/400
93.4064
Epoch 240/400
93.2833
Epoch 241/400
93.2078
Epoch 242/400
93.1459
Epoch 243/400
92.9707
Epoch 244/400
92.9697
Epoch 245/400
93.0496
Epoch 246/400
93.0352
Epoch 247/400
92.9395
```

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Epoch 248/400
92.9257
Epoch 249/400
92.9616
Epoch 250/400
92.9895
Epoch 251/400
92.9627
Epoch 252/400
92.7725
Epoch 253/400
92.7595
Epoch 254/400
92.5952
Epoch 255/400
92.6251
Epoch 256/400
92.4450
Epoch 257/400
92.5104
Epoch 258/400
92.4864
Epoch 259/400
92.4304
Epoch 260/400
92.2525
Epoch 261/400
92.1486
Epoch 262/400
92.1146
Epoch 263/400
92.0382
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Epoch 264/400
92.0382
Epoch 265/400
91.8925
Epoch 266/400
91.8409
Epoch 267/400
91.8852
Epoch 268/400
91.9477
Epoch 269/400
91.9490
Epoch 270/400
91.9526
Epoch 271/400
91.9918
Epoch 272/400
91.9117
Epoch 273/400
92.0425
Epoch 274/400
91.7895
Epoch 275/400
91.7594
Epoch 276/400
91.9985
Epoch 277/400
91.5295
Epoch 278/400
91.4496
Epoch 279/400
91.4282
```

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Epoch 280/400
91.2104
Epoch 281/400
91.0164
Epoch 282/400
91.0050
Epoch 283/400
7/7 [============ ] - Os 2ms/step - loss: 107.3894 - val_loss:
90.9654
Epoch 284/400
91.0169
Epoch 285/400
90.9688
Epoch 286/400
91.2028
Epoch 287/400
90.8020
Epoch 288/400
90.9637
Epoch 289/400
90.9879
Epoch 290/400
90.9335
Epoch 291/400
90.7432
Epoch 292/400
90.7107
Epoch 293/400
90.7736
Epoch 294/400
90.6068
Epoch 295/400
90.7362
```

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Epoch 296/400
90.6128
Epoch 297/400
90.6022
Epoch 298/400
90.5048
Epoch 299/400
90.5234
Epoch 300/400
90.5646
Epoch 301/400
90.4839
Epoch 302/400
90.4033
Epoch 303/400
90.1220
Epoch 304/400
89.9594
Epoch 305/400
89.9063
Epoch 306/400
90.2001
Epoch 307/400
90.3720
Epoch 308/400
90.2488
Epoch 309/400
90.1371
Epoch 310/400
89.9433
Epoch 311/400
89.9835
```

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Epoch 312/400
89.7816
Epoch 313/400
89.8127
Epoch 314/400
89.4398
Epoch 315/400
89.4602
Epoch 316/400
89.3163
Epoch 317/400
89.3851
Epoch 318/400
89.4258
Epoch 319/400
89.2462
Epoch 320/400
89.3276
Epoch 321/400
89.0243
Epoch 322/400
89.0964
Epoch 323/400
89.1280
Epoch 324/400
89.0750
Epoch 325/400
89.1161
Epoch 326/400
89.2524
Epoch 327/400
89.0969
```

```
Epoch 328/400
89.0379
Epoch 329/400
89.0415
Epoch 330/400
89.0840
Epoch 331/400
89.0393
Epoch 332/400
89.0318
Epoch 333/400
89.0396
Epoch 334/400
88.9609
Epoch 335/400
88.9875
Epoch 336/400
88.8372
Epoch 337/400
88.9570
Epoch 338/400
88.6934
Epoch 339/400
89.0202
Epoch 340/400
88.5338
Epoch 341/400
88.5323
Epoch 342/400
88.8141
Epoch 343/400
88.6516
```

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Epoch 344/400
88.5214
Epoch 345/400
88.3561
Epoch 346/400
88.3316
Epoch 347/400
88.3274
Epoch 348/400
88.1759
Epoch 349/400
88.1366
Epoch 350/400
87.9984
Epoch 351/400
88.0809
Epoch 352/400
88.1317
Epoch 353/400
87.8934
Epoch 354/400
87.8308
Epoch 355/400
87.5595
Epoch 356/400
87.4594
Epoch 357/400
87.6549
Epoch 358/400
87.5449
Epoch 359/400
87.4992
```

```
Epoch 360/400
87.4828
Epoch 361/400
87.5637
Epoch 362/400
87.5539
Epoch 363/400
87.3636
Epoch 364/400
87.2162
Epoch 365/400
87.0727
Epoch 366/400
87.0907
Epoch 367/400
86.9665
Epoch 368/400
87.1883
Epoch 369/400
86.9121
Epoch 370/400
87.0738
Epoch 371/400
86.9626
Epoch 372/400
86.8144
Epoch 373/400
86.7200
Epoch 374/400
86.6844
Epoch 375/400
86.4586
```

```
Epoch 376/400
86.4156
Epoch 377/400
86.3482
Epoch 378/400
86.4119
Epoch 379/400
86.3798
Epoch 380/400
86.3118
Epoch 381/400
86.5173
Epoch 382/400
86.5278
Epoch 383/400
86.5065
Epoch 384/400
86.5765
Epoch 385/400
86.5478
Epoch 386/400
86.2819
Epoch 387/400
86.4750
Epoch 388/400
86.4303
Epoch 389/400
86.0567
Epoch 390/400
85.9176
Epoch 391/400
85.8059
```

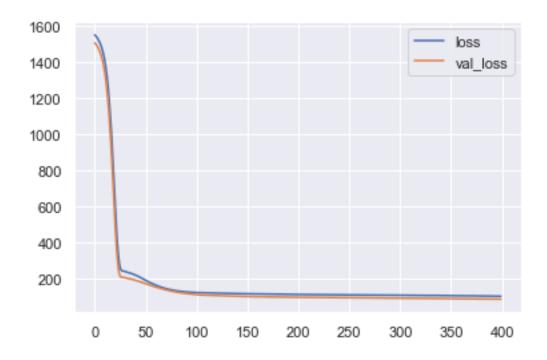
```
Epoch 392/400
85.8079
Epoch 393/400
85.6956
Epoch 394/400
85.4088
Epoch 395/400
85.8008
Epoch 396/400
85.7080
Epoch 397/400
7/7 [=========== ] - Os 2ms/step - loss: 101.4922 - val_loss:
85.5263
Epoch 398/400
85.3534
Epoch 399/400
85.2148
Epoch 400/400
85.2549
```

[21]: <tensorflow.python.keras.callbacks.History at 0x7fe7422d1d60>

1.4.3 Visualize the Loss Function

```
[22]: losses = pd.DataFrame(model.history.history)
losses.plot()
```

[22]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe742ba8b20>



Since the validation loss stays below the actual loss and continues to delcine with it, we observe that overfitting is minimal.

1.4.4 Test the Model

```
[23]: predictions = model.predict(X_test)
```

1.4.5 Model Evaluation

EVALUATION METRICS

 Mean Absolute Error (MAE):
 7.23883411296363

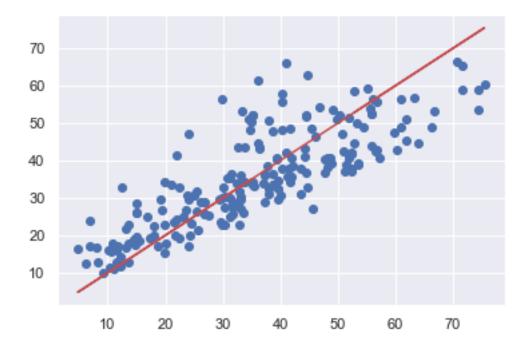
 Root Mean Squared Error (RMSE):
 9.233359748913385

 Explained Variance Score:
 0.6691982422589368

```
[28]: # Plot Model Predictions (Scatter)
plt.scatter(y_test,predictions)

# Plot Perfect predictions (Line)
plt.plot(y_test,y_test,'r')
```

[28]: [<matplotlib.lines.Line2D at 0x7fe742f6b070>]



There is clearly a wide spread of predicted values away from the perfect values. Let us experiment with adding more hidden nodes in the next section to try to increase the performance of our model.

1.5 Model 2 - ANN with 10 Hidden Layers

1.5.1 Construct the Artificial Neural Network

```
model_2.add(Dense(8,activation='relu'))
model_2.add(Dense(8,activation='relu'))
model_2.add(Dense(4,activation='relu')) # Experiment with number of nodes
model_2.add(Dense(2,activation='relu'))
model_2.add(Dense(1))

model_2.compile(optimizer='adam',loss='mse') # Use the adam optimization
→ algorithm
```

1.5.2 Train the Model on the Test Data

```
Epoch 1/400
val loss: 1527.6510
Epoch 2/400
1525.9512
Epoch 3/400
1524.0394
Epoch 4/400
1521.6041
Epoch 5/400
1518.4763
Epoch 6/400
1514.2502
Epoch 7/400
1508.2246
Epoch 8/400
1499.2045
Epoch 9/400
1485.1907
Epoch 10/400
1462.8864
Epoch 11/400
```

```
1426.7305
Epoch 12/400
1368.1099
Epoch 13/400
1273.9249
Epoch 14/400
1126.3063
Epoch 15/400
907.5222
Epoch 16/400
618.4327
Epoch 17/400
330.0607
Epoch 18/400
237.3927
Epoch 19/400
267.9193
Epoch 20/400
230.1266
Epoch 21/400
232.7351
Epoch 22/400
231.9311
Epoch 23/400
224.0883
Epoch 24/400
222.0743
Epoch 25/400
220.2853
Epoch 26/400
218.4978
Epoch 27/400
```

```
217.2043
Epoch 28/400
215.9870
Epoch 29/400
214.0839
Epoch 30/400
212.6586
Epoch 31/400
211.2211
Epoch 32/400
209.9449
Epoch 33/400
208.6227
Epoch 34/400
207.1406
Epoch 35/400
205.9869
Epoch 36/400
204.4895
Epoch 37/400
203.1762
Epoch 38/400
201.7755
Epoch 39/400
200.6095
Epoch 40/400
199.2050
Epoch 41/400
197.7919
Epoch 42/400
196.4147
Epoch 43/400
```

```
195.3155
Epoch 44/400
193.7910
Epoch 45/400
192.2980
Epoch 46/400
190.9313
Epoch 47/400
189.6548
Epoch 48/400
188.0996
Epoch 49/400
186.7313
Epoch 50/400
185.1171
Epoch 51/400
183.8886
Epoch 52/400
182.1450
Epoch 53/400
180.8331
Epoch 54/400
179.3352
Epoch 55/400
177.8587
Epoch 56/400
176.2689
Epoch 57/400
174.9903
Epoch 58/400
173.0806
Epoch 59/400
```

```
171.5199
Epoch 60/400
169.9536
Epoch 61/400
168.8353
Epoch 62/400
167.0987
Epoch 63/400
165.1435
Epoch 64/400
163.3499
Epoch 65/400
161.7340
Epoch 66/400
160.1569
Epoch 67/400
158, 2611
Epoch 68/400
156.6418
Epoch 69/400
155.1568
Epoch 70/400
153.3897
Epoch 71/400
151.6374
Epoch 72/400
149.9951
Epoch 73/400
148.2305
Epoch 74/400
146.5357
Epoch 75/400
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144.9496
Epoch 76/400
143.6634
Epoch 77/400
141.5844
Epoch 78/400
139.8398
Epoch 79/400
138.6937
Epoch 80/400
136.7506
Epoch 81/400
135.3559
Epoch 82/400
133.6914
Epoch 83/400
132,2848
Epoch 84/400
131.0391
Epoch 85/400
129.7908
Epoch 86/400
128.1191
Epoch 87/400
127.0783
Epoch 88/400
125.9190
Epoch 89/400
124.2839
Epoch 90/400
123.1145
Epoch 91/400
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122.0843
Epoch 92/400
120.9054
Epoch 93/400
119.7059
Epoch 94/400
118.7402
Epoch 95/400
117.9389
Epoch 96/400
117,4998
Epoch 97/400
116.8827
Epoch 98/400
115.4900
Epoch 99/400
114.6794
Epoch 100/400
113.9424
Epoch 101/400
113.1563
Epoch 102/400
112.4010
Epoch 103/400
112.4061
Epoch 104/400
111.0439
Epoch 105/400
110.3191
Epoch 106/400
110.0899
Epoch 107/400
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109.3381
Epoch 108/400
109.0333
Epoch 109/400
108.8180
Epoch 110/400
108.3338
Epoch 111/400
107.6260
Epoch 112/400
107.5217
Epoch 113/400
107.0661
Epoch 114/400
106.6599
Epoch 115/400
106.3395
Epoch 116/400
106.4488
Epoch 117/400
105.8435
Epoch 118/400
105.5976
Epoch 119/400
105.3705
Epoch 120/400
105.0931
Epoch 121/400
105.1560
Epoch 122/400
104.8355
Epoch 123/400
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104.3817
Epoch 124/400
103.9947
Epoch 125/400
103.6998
Epoch 126/400
103.7300
Epoch 127/400
103.6048
Epoch 128/400
103.5013
Epoch 129/400
103.2005
Epoch 130/400
102.9897
Epoch 131/400
102.7991
Epoch 132/400
102.6226
Epoch 133/400
102,6056
Epoch 134/400
102.6805
Epoch 135/400
102.4441
Epoch 136/400
102.1181
Epoch 137/400
102.0209
Epoch 138/400
102.5767
Epoch 139/400
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101.7306
Epoch 140/400
101.7354
Epoch 141/400
101.7845
Epoch 142/400
101.8476
Epoch 143/400
101.8054
Epoch 144/400
101.9466
Epoch 145/400
101.7458
Epoch 146/400
101.6547
Epoch 147/400
101.7018
Epoch 148/400
101.1999
Epoch 149/400
101.0689
Epoch 150/400
100.8821
Epoch 151/400
100.9799
Epoch 152/400
100.7143
Epoch 153/400
100.5467
Epoch 154/400
loss: 116.5486 - val_loss: 100.8119
Epoch 155/400
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100.8745
Epoch 156/400
100.6898
Epoch 157/400
100.6511
Epoch 158/400
100.8680
Epoch 159/400
100.6376
Epoch 160/400
100.5243
Epoch 161/400
100.7051
Epoch 162/400
7/7 [============ - Os 3ms/step - loss: 115.6984 - val_loss:
100.3033
Epoch 163/400
100.0319
Epoch 164/400
99.9591
Epoch 165/400
100.1740
Epoch 166/400
100.0317
Epoch 167/400
99.8893
Epoch 168/400
99.5363
Epoch 169/400
99.1881
Epoch 170/400
99.0408
Epoch 171/400
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98.9944
Epoch 172/400
99.0044
Epoch 173/400
99.0950
Epoch 174/400
99.2414
Epoch 175/400
99.3604
Epoch 176/400
98.7656
Epoch 177/400
98.9037
Epoch 178/400
99.1300
Epoch 179/400
98.8580
Epoch 180/400
98.8848
Epoch 181/400
99.0092
Epoch 182/400
98.8508
Epoch 183/400
98.9210
Epoch 184/400
98.8254
Epoch 185/400
98.7566
Epoch 186/400
98.6985
Epoch 187/400
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98.3156
Epoch 188/400
98.0315
Epoch 189/400
98.0323
Epoch 190/400
97.7953
Epoch 191/400
98.2911
Epoch 192/400
97.8559
Epoch 193/400
97.2654
Epoch 194/400
97.1679
Epoch 195/400
97.1494
Epoch 196/400
96.9499
Epoch 197/400
96.9438
Epoch 198/400
97.0808
Epoch 199/400
7/7 [============ - Os 3ms/step - loss: 111.3231 - val_loss:
96.9861
Epoch 200/400
97.1802
Epoch 201/400
97.2308
Epoch 202/400
97.1553
Epoch 203/400
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96.6995
Epoch 204/400
96.5446
Epoch 205/400
96.7957
Epoch 206/400
96.8204
Epoch 207/400
97.0094
Epoch 208/400
96.7574
Epoch 209/400
96.2462
Epoch 210/400
96.2214
Epoch 211/400
96.3184
Epoch 212/400
loss: 109.9854 - val_loss: 97.1622
Epoch 213/400
96.3277
Epoch 214/400
96.1389
Epoch 215/400
7/7 [============ - Os 3ms/step - loss: 109.2931 - val_loss:
96.5535
Epoch 216/400
96.1302
Epoch 217/400
95.9751
Epoch 218/400
96.0104
Epoch 219/400
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95.4818
Epoch 220/400
95.6029
Epoch 221/400
95.5804
Epoch 222/400
95.4244
Epoch 223/400
95.3040
Epoch 224/400
95.3229
Epoch 225/400
95.0458
Epoch 226/400
94.7947
Epoch 227/400
94.5866
Epoch 228/400
94.0403
Epoch 229/400
93.8158
Epoch 230/400
94.0409
Epoch 231/400
93.3555
Epoch 232/400
93.1946
Epoch 233/400
92.9262
Epoch 234/400
92.7968
Epoch 235/400
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91.4747
Epoch 236/400
90.6055
Epoch 237/400
91.0568
Epoch 238/400
91.4832
Epoch 239/400
91.5883
Epoch 240/400
91.4006
Epoch 241/400
91.2071
Epoch 242/400
90.9679
Epoch 243/400
90.7689
Epoch 244/400
90.6407
Epoch 245/400
90.5584
Epoch 246/400
90.4132
Epoch 247/400
7/7 [============ - Os 3ms/step - loss: 101.1852 - val_loss:
89.9878
Epoch 248/400
89.3499
Epoch 249/400
89.6475
Epoch 250/400
89.9984
Epoch 251/400
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89.3147
Epoch 252/400
89.4396
Epoch 253/400
88.9826
Epoch 254/400
88.4046
Epoch 255/400
87.5854
Epoch 256/400
87.3010
Epoch 257/400
86.7970
Epoch 258/400
86.3914
Epoch 259/400
86.9061
Epoch 260/400
86.1778
Epoch 261/400
86.2878
Epoch 262/400
86.2120
Epoch 263/400
85.5708
Epoch 264/400
85.8767
Epoch 265/400
86.0480
Epoch 266/400
85.2037
Epoch 267/400
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84.9366
Epoch 268/400
84.4750
Epoch 269/400
84.0281
Epoch 270/400
84.7426
Epoch 271/400
83.8004
Epoch 272/400
83.4313
Epoch 273/400
83.3858
Epoch 274/400
83.4775
Epoch 275/400
82.8408
Epoch 276/400
82.1613
Epoch 277/400
82.5789
Epoch 278/400
81.6165
Epoch 279/400
81.6645
Epoch 280/400
80.9041
Epoch 281/400
81.2830
Epoch 282/400
81.2959
Epoch 283/400
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81.0828
Epoch 284/400
80.6168
Epoch 285/400
80.3645
Epoch 286/400
79.8036
Epoch 287/400
79.4174
Epoch 288/400
79.1473
Epoch 289/400
79.0514
Epoch 290/400
79.1159
Epoch 291/400
78.6595
Epoch 292/400
78.0151
Epoch 293/400
77.5639
Epoch 294/400
76.9743
Epoch 295/400
76.7162
Epoch 296/400
76.3669
Epoch 297/400
76.3285
Epoch 298/400
76.0369
Epoch 299/400
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75.7335
Epoch 300/400
75.6888
Epoch 301/400
75.3675
Epoch 302/400
75.0921
Epoch 303/400
74.4261
Epoch 304/400
73,6808
Epoch 305/400
73.9546
Epoch 306/400
7/7 [============ ] - Os 2ms/step - loss: 77.9506 - val_loss:
73.0352
Epoch 307/400
72.9317
Epoch 308/400
72.2192
Epoch 309/400
71.8651
Epoch 310/400
72.1807
Epoch 311/400
71.4056
Epoch 312/400
71.7850
Epoch 313/400
70.8786
Epoch 314/400
70.0609
Epoch 315/400
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69.9456
Epoch 316/400
70.0702
Epoch 317/400
69.4949
Epoch 318/400
69.2193
Epoch 319/400
69.1130
Epoch 320/400
68.2046
Epoch 321/400
68.5353
Epoch 322/400
7/7 [============ ] - Os 3ms/step - loss: 73.3735 - val_loss:
68.3543
Epoch 323/400
67.4873
Epoch 324/400
67.5768
Epoch 325/400
67.1207
Epoch 326/400
66.4007
Epoch 327/400
66.4246
Epoch 328/400
65.8972
Epoch 329/400
65.7042
Epoch 330/400
65.8074
Epoch 331/400
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64.9941
Epoch 332/400
65.9617
Epoch 333/400
65.5244
Epoch 334/400
64.2894
Epoch 335/400
64.0239
Epoch 336/400
63.5303
Epoch 337/400
63.5394
Epoch 338/400
63.7776
Epoch 339/400
63.3850
Epoch 340/400
63.4518
Epoch 341/400
62.3969
Epoch 342/400
62.8076
Epoch 343/400
62.3426
Epoch 344/400
62.6853
Epoch 345/400
61.7281
Epoch 346/400
62.2139
Epoch 347/400
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61.0520
Epoch 348/400
61.4158
Epoch 349/400
61.2798
Epoch 350/400
60.6162
Epoch 351/400
61.8541
Epoch 352/400
60.1766
Epoch 353/400
61.4714
Epoch 354/400
60.4233
Epoch 355/400
60.1702
Epoch 356/400
59.5345
Epoch 357/400
59.7943
Epoch 358/400
59.1220
Epoch 359/400
60.1070
Epoch 360/400
58.9367
Epoch 361/400
7/7 [============ ] - Os 3ms/step - loss: 63.3421 - val_loss:
58.4465
Epoch 362/400
58.2490
Epoch 363/400
```

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58.1622
Epoch 364/400
58.4535
Epoch 365/400
58.1950
Epoch 366/400
57.7896
Epoch 367/400
58.0087
Epoch 368/400
57.1784
Epoch 369/400
57.9913
Epoch 370/400
56.9082
Epoch 371/400
57.4152
Epoch 372/400
57.2272
Epoch 373/400
56.7262
Epoch 374/400
56.9816
Epoch 375/400
7/7 [=========== ] - Os 3ms/step - loss: 60.6217 - val_loss:
56.0683
Epoch 376/400
56.4318
Epoch 377/400
55.8165
Epoch 378/400
55.7089
Epoch 379/400
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55.9656
Epoch 380/400
56.4681
Epoch 381/400
54.9711
Epoch 382/400
55.9956
Epoch 383/400
55.0499
Epoch 384/400
55.0686
Epoch 385/400
55.0170
Epoch 386/400
55.0272
Epoch 387/400
53.9469
Epoch 388/400
55.8160
Epoch 389/400
53.3077
Epoch 390/400
55.2850
Epoch 391/400
7/7 [============ ] - Os 3ms/step - loss: 58.8730 - val_loss:
53.3048
Epoch 392/400
54.2142
Epoch 393/400
55.2248
Epoch 394/400
53.3521
Epoch 395/400
```

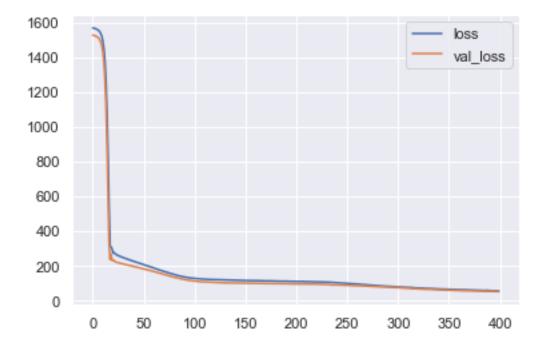
```
54.1252
Epoch 396/400
52.8127
Epoch 397/400
7/7 [=======
          =========] - Os 3ms/step - loss: 56.8663 - val_loss:
53.9135
Epoch 398/400
7/7 [======
            =======] - Os 3ms/step - loss: 56.6674 - val_loss:
53.1033
Epoch 399/400
52.3293
Epoch 400/400
52.8077
```

[35]: <tensorflow.python.keras.callbacks.History at 0x7fe74326d970>

1.5.3 Visualize the Loss Function

```
[36]: losses = pd.DataFrame(model_2.history.history) losses.plot()
```

[36]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe743a04820>



Again, we do not observe overfitting on the training data.

1.5.4 Test the Model

```
[40]: predictions_2 = model_2.predict(X_test)
```

1.5.5 Model Evaluation

EVALUATION METRICS

 Mean Absolute Error (MAE):
 5.738010522323906

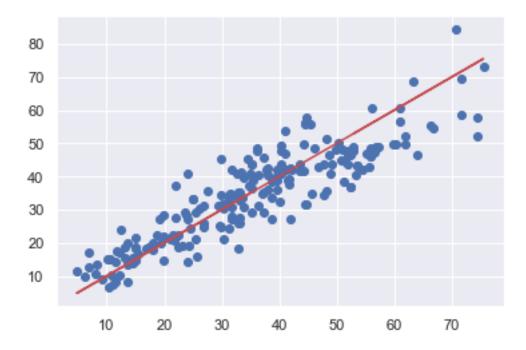
 Root Mean Squared Error (RMSE):
 7.266889552774522

 Explained Variance Score:
 0.797885663610966

```
[42]: # Plot Model Predictions (Scatter)
plt.scatter(y_test,predictions_2)

# Plot Perfect predictions (Line)
plt.plot(y_test,y_test,'r')
```

[42]: [<matplotlib.lines.Line2D at 0x7fe743c7ed90>]



The variance of our predicted values has been decreased, and our explained variance score has increased significantly. Let us continue with an even deeper neural network below to see if it will increase performance.

1.6 Model 3 - ANN with 20 Hidden Layers

1.6.1 Construct the Artificial Neural Network

```
[43]: model_3 = Sequential()
      # Experiment with 20 hidden layers
      model_3.add(Dense(8,activation='relu')) # All layers utilize rectified linear_
      \rightarrowunits (relu)
      model_3.add(Dense(8,activation='relu'))
      model_3.add(Dense(8,activation='relu'))
      model_3.add(Dense(8,activation='relu'))
      model_3.add(Dense(8,activation='relu'))
      model 3.add(Dense(8,activation='relu'))
      model 3.add(Dense(8,activation='relu'))
      model_3.add(Dense(8,activation='relu'))
      model_3.add(Dense(8,activation='relu'))
      model_3.add(Dense(8,activation='relu'))
      model_3.add(Dense(8,activation='relu'))
      model_3.add(Dense(8,activation='relu'))
      model_3.add(Dense(8,activation='relu'))
      model_3.add(Dense(8,activation='relu'))
```

1.6.2 Train the Model on the Test Data

```
Epoch 1/400
val loss: 1526.5952
Epoch 2/400
1523.2644
Epoch 3/400
1519.1927
Epoch 4/400
1514.1138
Epoch 5/400
1507.4445
Epoch 6/400
1498.2806
Epoch 7/400
1484.8186
Epoch 8/400
1463.7943
Epoch 9/400
1428.6099
Epoch 10/400
1365.9451
```

```
Epoch 11/400
1249.4637
Epoch 12/400
1031.9731
Epoch 13/400
658.5852
Epoch 14/400
259.2043
Epoch 15/400
325.0247
Epoch 16/400
233.2467
Epoch 17/400
243.8734
Epoch 18/400
226.5544
Epoch 19/400
225.4052
Epoch 20/400
220.4627
Epoch 21/400
214.3152
Epoch 22/400
210.5043
Epoch 23/400
208.3407
Epoch 24/400
204.9592
Epoch 25/400
202.7213
Epoch 26/400
198.8309
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Epoch 27/400
195.8791
Epoch 28/400
193.4241
Epoch 29/400
192.0114
Epoch 30/400
188.5977
Epoch 31/400
185.3792
Epoch 32/400
183.9854
Epoch 33/400
180.5126
Epoch 34/400
177.9056
Epoch 35/400
175.5407
Epoch 36/400
173.8006
Epoch 37/400
170.2955
Epoch 38/400
168.0126
Epoch 39/400
166.8676
Epoch 40/400
163.7196
Epoch 41/400
161.8724
Epoch 42/400
160.6930
```

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Epoch 43/400
157.5111
Epoch 44/400
155.9300
Epoch 45/400
155.1297
Epoch 46/400
151.6433
Epoch 47/400
149.9436
Epoch 48/400
150.5521
Epoch 49/400
146.5264
Epoch 50/400
145.1618
Epoch 51/400
143.7139
Epoch 52/400
142.3002
Epoch 53/400
140.7299
Epoch 54/400
142.5496
Epoch 55/400
138.5043
Epoch 56/400
137.4242
Epoch 57/400
136.9520
Epoch 58/400
134.6312
```

```
Epoch 59/400
133.9775
Epoch 60/400
133.6870
Epoch 61/400
131.3601
Epoch 62/400
131.2758
Epoch 63/400
129.3985
Epoch 64/400
128.8615
Epoch 65/400
127.6312
Epoch 66/400
126.7778
Epoch 67/400
7/7 [============ - Os 3ms/step - loss: 133.5844 - val_loss:
128.2025
Epoch 68/400
125.6385
Epoch 69/400
124.6122
Epoch 70/400
125.0412
Epoch 71/400
122.9496
Epoch 72/400
122.2687
Epoch 73/400
121.2751
Epoch 74/400
121.1824
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Epoch 75/400
119.9016
Epoch 76/400
119.9744
Epoch 77/400
118.8452
Epoch 78/400
118.5415
Epoch 79/400
117.7335
Epoch 80/400
118.0002
Epoch 81/400
116.6069
Epoch 82/400
116.8624
Epoch 83/400
115.6338
Epoch 84/400
115.3544
Epoch 85/400
114.3140
Epoch 86/400
113.9245
Epoch 87/400
113.5773
Epoch 88/400
113.8418
Epoch 89/400
112.5991
Epoch 90/400
112.2939
```

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Epoch 91/400
111.9269
Epoch 92/400
111.5698
Epoch 93/400
111.7115
Epoch 94/400
110.9570
Epoch 95/400
110.4606
Epoch 96/400
110.9633
Epoch 97/400
109.9210
Epoch 98/400
109.4623
Epoch 99/400
109.8661
Epoch 100/400
109.0219
Epoch 101/400
108.8991
Epoch 102/400
108.4894
Epoch 103/400
108.3575
Epoch 104/400
108.7604
Epoch 105/400
108.0519
Epoch 106/400
107.8850
```

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Epoch 107/400
107.0381
Epoch 108/400
106.8268
Epoch 109/400
106.6754
Epoch 110/400
106.4168
Epoch 111/400
105.9872
Epoch 112/400
105.8090
Epoch 113/400
105.9745
Epoch 114/400
106.0590
Epoch 115/400
7/7 [============ - Os 3ms/step - loss: 118.1858 - val_loss:
105.0715
Epoch 116/400
104.8135
Epoch 117/400
104.6433
Epoch 118/400
104.4528
Epoch 119/400
104.0713
Epoch 120/400
103.9863
Epoch 121/400
104.1757
Epoch 122/400
7/7 [============ - Os 3ms/step - loss: 116.9883 - val_loss:
103.6448
```

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Epoch 123/400
103.8672
Epoch 124/400
103.4464
Epoch 125/400
103.1211
Epoch 126/400
103.0830
Epoch 127/400
102.8191
Epoch 128/400
7/7 [============ - Os 3ms/step - loss: 116.1806 - val_loss:
102.8078
Epoch 129/400
102.5905
Epoch 130/400
102.4652
Epoch 131/400
102.2805
Epoch 132/400
102.6015
Epoch 133/400
102.8718
Epoch 134/400
102.4702
Epoch 135/400
101.8374
Epoch 136/400
101.7645
Epoch 137/400
101.9071
Epoch 138/400
101.4058
```

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Epoch 139/400
101.8231
Epoch 140/400
101.2218
Epoch 141/400
101.7328
Epoch 142/400
7/7 [============ - Os 3ms/step - loss: 115.9969 - val_loss:
102.2211
Epoch 143/400
101.5687
Epoch 144/400
101.0305
Epoch 145/400
101.1117
Epoch 146/400
100.7643
Epoch 147/400
100.3499
Epoch 148/400
100.3305
Epoch 149/400
100.3868
Epoch 150/400
100.1590
Epoch 151/400
100.4196
Epoch 152/400
100.3145
Epoch 153/400
100.1319
Epoch 154/400
99.9895
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Epoch 155/400
99.8626
Epoch 156/400
99.9121
Epoch 157/400
99.7955
Epoch 158/400
99.9919
Epoch 159/400
100.0878
Epoch 160/400
99.8900
Epoch 161/400
99.7452
Epoch 162/400
99.4975
Epoch 163/400
7/7 [============ - Os 3ms/step - loss: 113.5492 - val_loss:
99.4377
Epoch 164/400
99.6511
Epoch 165/400
99.7146
Epoch 166/400
100.0259
Epoch 167/400
99.4759
Epoch 168/400
99.4911
Epoch 169/400
99.3961
Epoch 170/400
99.3446
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Epoch 171/400
99.3381
Epoch 172/400
99.2032
Epoch 173/400
99.2418
Epoch 174/400
99.9449
Epoch 175/400
99.5375
Epoch 176/400
98.4372
Epoch 177/400
98.0723
Epoch 178/400
97.9838
Epoch 179/400
97.8686
Epoch 180/400
97.9603
Epoch 181/400
97.7442
Epoch 182/400
97.9899
Epoch 183/400
97.8528
Epoch 184/400
97.9222
Epoch 185/400
97.8222
Epoch 186/400
98.0757
```

```
Epoch 187/400
98.4589
Epoch 188/400
98.1157
Epoch 189/400
98.3865
Epoch 190/400
98.0528
Epoch 191/400
97.8639
Epoch 192/400
98.4503
Epoch 193/400
98.6284
Epoch 194/400
97.3569
Epoch 195/400
97.2861
Epoch 196/400
97.3085
Epoch 197/400
97.3930
Epoch 198/400
97.4272
Epoch 199/400
97.3585
Epoch 200/400
97.1109
Epoch 201/400
97.1849
Epoch 202/400
7/7 [============ - Os 3ms/step - loss: 111.2603 - val_loss:
97.7187
```

```
Epoch 203/400
97.2351
Epoch 204/400
97.6931
Epoch 205/400
97.4509
Epoch 206/400
97.6902
Epoch 207/400
97.4598
Epoch 208/400
97.2155
Epoch 209/400
97.6105
Epoch 210/400
97.2435
Epoch 211/400
97.9373
Epoch 212/400
97.4237
Epoch 213/400
97.0906
Epoch 214/400
97.3506
Epoch 215/400
96.8717
Epoch 216/400
96.6118
Epoch 217/400
96.5921
Epoch 218/400
96.7165
```

```
Epoch 219/400
96.9227
Epoch 220/400
96.5391
Epoch 221/400
96.5592
Epoch 222/400
96.6689
Epoch 223/400
96.6428
Epoch 224/400
96.8996
Epoch 225/400
96.8857
Epoch 226/400
96.9159
Epoch 227/400
96.2893
Epoch 228/400
96.5012
Epoch 229/400
96.1209
Epoch 230/400
96.2599
Epoch 231/400
96.8142
Epoch 232/400
96.0079
Epoch 233/400
95.8849
Epoch 234/400
95.8701
```

```
Epoch 235/400
95.9728
Epoch 236/400
96.1136
Epoch 237/400
95.8316
Epoch 238/400
7/7 [============ - Os 3ms/step - loss: 110.4189 - val_loss:
96.2819
Epoch 239/400
96.0669
Epoch 240/400
7/7 [============ - Os 3ms/step - loss: 110.0097 - val_loss:
96.5358
Epoch 241/400
95.8543
Epoch 242/400
96.0032
Epoch 243/400
96.0135
Epoch 244/400
96.0098
Epoch 245/400
96.0178
Epoch 246/400
95.9050
Epoch 247/400
95.9541
Epoch 248/400
96.6794
Epoch 249/400
96.5646
Epoch 250/400
7/7 [============ - Os 3ms/step - loss: 110.0963 - val_loss:
96.8593
```

```
Epoch 251/400
96.5974
Epoch 252/400
96.1968
Epoch 253/400
96.3868
Epoch 254/400
7/7 [============ - Os 3ms/step - loss: 109.9681 - val_loss:
96.1871
Epoch 255/400
96.0086
Epoch 256/400
95.8872
Epoch 257/400
96.1096
Epoch 258/400
96.0336
Epoch 259/400
96.0999
Epoch 260/400
95.6770
Epoch 261/400
95.8632
Epoch 262/400
96.1489
Epoch 263/400
95.9381
Epoch 264/400
96.1383
Epoch 265/400
96.1010
Epoch 266/400
96.3845
```

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Epoch 267/400
96.4098
Epoch 268/400
95.9215
Epoch 269/400
95.8596
Epoch 270/400
7/7 [============ - Os 3ms/step - loss: 111.4030 - val_loss:
95.8012
Epoch 271/400
95.8907
Epoch 272/400
7/7 [============ - Os 3ms/step - loss: 109.9682 - val_loss:
95.6458
Epoch 273/400
96.2471
Epoch 274/400
95.8605
Epoch 275/400
95.9027
Epoch 276/400
96.6512
Epoch 277/400
95.7557
Epoch 278/400
96.0911
Epoch 279/400
95.6884
Epoch 280/400
95.8226
Epoch 281/400
95.8467
Epoch 282/400
96.5099
```

```
Epoch 283/400
95.5789
Epoch 284/400
96.3463
Epoch 285/400
95.4780
Epoch 286/400
95.8002
Epoch 287/400
95.8917
Epoch 288/400
7/7 [============ - Os 3ms/step - loss: 109.6347 - val_loss:
95.6814
Epoch 289/400
7/7 [============ - Os 3ms/step - loss: 110.1753 - val_loss:
95.6961
Epoch 290/400
95.4657
Epoch 291/400
95.4014
Epoch 292/400
95.3176
Epoch 293/400
95.3693
Epoch 294/400
95.3634
Epoch 295/400
95.6352
Epoch 296/400
95.2616
Epoch 297/400
95.5369
Epoch 298/400
7/7 [============ - Os 3ms/step - loss: 110.4367 - val_loss:
95.5090
```

```
Epoch 299/400
95.6734
Epoch 300/400
97.5196
Epoch 301/400
97.2529
Epoch 302/400
7/7 [============ - Os 3ms/step - loss: 110.6143 - val_loss:
95.7763
Epoch 303/400
96.0338
Epoch 304/400
95.6884
Epoch 305/400
95.6209
Epoch 306/400
95.2451
Epoch 307/400
95.2852
Epoch 308/400
95.7279
Epoch 309/400
95.7950
Epoch 310/400
95.5303
Epoch 311/400
95.2600
Epoch 312/400
95.3225
Epoch 313/400
95.9079
Epoch 314/400
7/7 [============ - Os 3ms/step - loss: 109.0372 - val_loss:
95.5264
```

```
Epoch 315/400
95,4280
Epoch 316/400
95.7286
Epoch 317/400
95.3349
Epoch 318/400
95.7625
Epoch 319/400
94.9487
Epoch 320/400
95.0502
Epoch 321/400
95.1230
Epoch 322/400
95.2453
Epoch 323/400
95.2177
Epoch 324/400
94.8899
Epoch 325/400
94.7188
Epoch 326/400
94.6036
Epoch 327/400
94.7908
Epoch 328/400
95.2060
Epoch 329/400
95.1535
Epoch 330/400
95.1778
```

```
Epoch 331/400
94.9863
Epoch 332/400
94.9732
Epoch 333/400
94.7596
Epoch 334/400
94.6337
Epoch 335/400
94.5630
Epoch 336/400
95.0573
Epoch 337/400
95.1235
Epoch 338/400
95.2804
Epoch 339/400
95.3463
Epoch 340/400
95.6430
Epoch 341/400
94.4793
Epoch 342/400
95.6188
Epoch 343/400
94.9766
Epoch 344/400
95.4528
Epoch 345/400
94.9270
Epoch 346/400
94.8311
```

```
Epoch 347/400
95.2963
Epoch 348/400
94.7394
Epoch 349/400
94.9320
Epoch 350/400
94.5451
Epoch 351/400
94.4001
Epoch 352/400
94.3887
Epoch 353/400
94.1661
Epoch 354/400
94.3902
Epoch 355/400
7/7 [============ - Os 3ms/step - loss: 108.2493 - val_loss:
94.1639
Epoch 356/400
94.3452
Epoch 357/400
94.3426
Epoch 358/400
94.7075
Epoch 359/400
94.1667
Epoch 360/400
93.9132
Epoch 361/400
94.3511
Epoch 362/400
94.0218
```

```
Epoch 363/400
94.4790
Epoch 364/400
94.3014
Epoch 365/400
93.9753
Epoch 366/400
93.7848
Epoch 367/400
93.6093
Epoch 368/400
7/7 [============ - Os 3ms/step - loss: 109.4378 - val_loss:
94.1859
Epoch 369/400
94.0445
Epoch 370/400
94.4229
Epoch 371/400
94.0270
Epoch 372/400
94.3858
Epoch 373/400
94.8304
Epoch 374/400
94.6525
Epoch 375/400
94.9383
Epoch 376/400
95.1534
Epoch 377/400
94.3007
Epoch 378/400
94.2014
```

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Epoch 379/400
93.8799
Epoch 380/400
93.7775
Epoch 381/400
94.2975
Epoch 382/400
93.9851
Epoch 383/400
93.9258
Epoch 384/400
94.1631
Epoch 385/400
94.2064
Epoch 386/400
94.1071
Epoch 387/400
94.0848
Epoch 388/400
93.8705
Epoch 389/400
93.7152
Epoch 390/400
93.6017
Epoch 391/400
93.5495
Epoch 392/400
93.6386
Epoch 393/400
92.9440
Epoch 394/400
93.4834
```

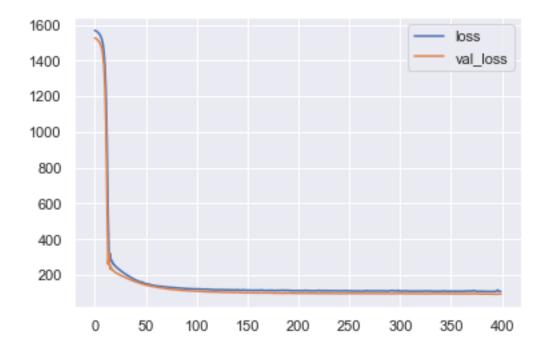
```
Epoch 395/400
7/7 [=========== ] - Os 3ms/step - loss: 108.0449 - val_loss:
92.6760
Epoch 396/400
7/7 [=========== - Os 3ms/step - loss: 112.1823 - val_loss:
92.2604
Epoch 397/400
92.2536
Epoch 398/400
92.9420
Epoch 399/400
7/7 [=========== ] - Os 3ms/step - loss: 108.0355 - val_loss:
93.8703
Epoch 400/400
92.5438
```

[44]: <tensorflow.python.keras.callbacks.History at 0x7fe743c45220>

1.6.3 Visualize the Loss Function

```
[45]: losses = pd.DataFrame(model_3.history.history)
losses.plot()
```

[45]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe7445635e0>



1.6.4 Test the Model

```
[46]: predictions_3 = model_3.predict(X_test)
```

1.6.5 Model Evaluation

EVALUATION METRICS

 Mean Absolute Error (MAE):
 7.611444954733247

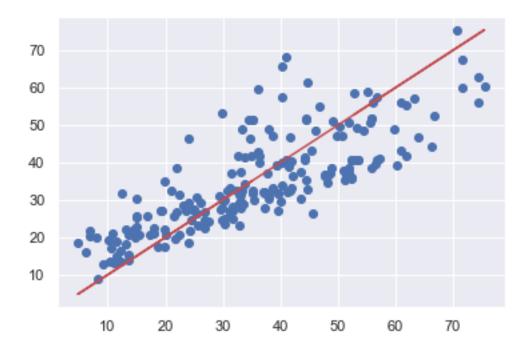
 Root Mean Squared Error (RMSE):
 9.619967686192227

 Explained Variance Score:
 0.6426482928244076

```
[51]: # Plot Model Predictions (Scatter)
plt.scatter(y_test,predictions_3)

# Plot Perfect predictions (Line)
plt.plot(y_test,y_test,'r')
```

[51]: [<matplotlib.lines.Line2D at 0x7fe745807820>]



Interesting - we would expect from the loss function that the data was not overfitted. But Our model evaluation metrics are worse with the deeper neural network. It appears that Model 3 has overfitted to the training data.

1.7 Model 4 - ANN with 15 Hidden Layers

1.7.1 Construct the Artificial Neural Network

```
[52]: model_4 = Sequential()
      # Experiment with 15 hidden layers
      model_4.add(Dense(8,activation='relu')) # All layers utilize rectified linear_
      \rightarrow units (relu)
      model_4.add(Dense(8,activation='relu'))
      model_4.add(Dense(8,activation='relu'))
      model_4.add(Dense(8,activation='relu'))
      model_4.add(Dense(8,activation='relu'))
      model 4.add(Dense(8,activation='relu'))
      model 4.add(Dense(8,activation='relu'))
      model_4.add(Dense(8,activation='relu'))
      model_4.add(Dense(8,activation='relu'))
      model_4.add(Dense(8,activation='relu'))
      model_4.add(Dense(8,activation='relu'))
      model_4.add(Dense(8,activation='relu'))
      model_4.add(Dense(8,activation='relu'))
      model_4.add(Dense(4,activation='relu')) # Experiment with number of nodes
```

```
model_4.add(Dense(2,activation='relu'))
model_4.add(Dense(1))

model_4.compile(optimizer='adam',loss='mse') # Use the adam optimization

→algorithm
```

1.7.2 Train the Model on the Test Data

```
Epoch 1/400
val_loss: 1528.5724
Epoch 2/400
1527.8374
Epoch 3/400
1527.0037
Epoch 4/400
1526.0594
Epoch 5/400
1524.9404
Epoch 6/400
1523.5724
Epoch 7/400
1521.8213
Epoch 8/400
1519.4446
Epoch 9/400
1516.0094
Epoch 10/400
1510.6748
Epoch 11/400
1501.3348
Epoch 12/400
```

```
1483.3419
Epoch 13/400
1446.5977
Epoch 14/400
1369.2535
Epoch 15/400
1209.3948
Epoch 16/400
902.4726
Epoch 17/400
447.1139
Epoch 18/400
290.0338
Epoch 19/400
282.7052
Epoch 20/400
253.0698
Epoch 21/400
252.3701
Epoch 22/400
233.1269
Epoch 23/400
232.0586
Epoch 24/400
223.9356
Epoch 25/400
219.6889
Epoch 26/400
214.9944
Epoch 27/400
211.0973
Epoch 28/400
```

```
206.8980
Epoch 29/400
203.0097
Epoch 30/400
199.3719
Epoch 31/400
195.8316
Epoch 32/400
192.2419
Epoch 33/400
188.8632
Epoch 34/400
184.6434
Epoch 35/400
180.8664
Epoch 36/400
176,9061
Epoch 37/400
172.6709
Epoch 38/400
168.4651
Epoch 39/400
163.8840
Epoch 40/400
158.8861
Epoch 41/400
153.9319
Epoch 42/400
148.6303
Epoch 43/400
142.8735
Epoch 44/400
```

```
136.8508
Epoch 45/400
132.4601
Epoch 46/400
126.6207
Epoch 47/400
122.8430
Epoch 48/400
118.8344
Epoch 49/400
115.7323
Epoch 50/400
113.1091
Epoch 51/400
110.4724
Epoch 52/400
108.6249
Epoch 53/400
106.6511
Epoch 54/400
105,4246
Epoch 55/400
104.0983
Epoch 56/400
103.5813
Epoch 57/400
102.2931
Epoch 58/400
102.1570
Epoch 59/400
100.9484
Epoch 60/400
```

```
100.1003
Epoch 61/400
99.3473
Epoch 62/400
98.5844
Epoch 63/400
98.6674
Epoch 64/400
97.6782
Epoch 65/400
97.6411
Epoch 66/400
97.3358
Epoch 67/400
7/7 [=========== - Os 3ms/step - loss: 112.6499 - val_loss:
96.3799
Epoch 68/400
96.1720
Epoch 69/400
95.7298
Epoch 70/400
95.3371
Epoch 71/400
95.0931
Epoch 72/400
94.3576
Epoch 73/400
94.9939
Epoch 74/400
93.7686
Epoch 75/400
93.1857
Epoch 76/400
```

```
92.9079
Epoch 77/400
92.2739
Epoch 78/400
91.9535
Epoch 79/400
91.3619
Epoch 80/400
91.8785
Epoch 81/400
91.3594
Epoch 82/400
90.8102
Epoch 83/400
90.4847
Epoch 84/400
89.8474
Epoch 85/400
89.3449
Epoch 86/400
88.9763
Epoch 87/400
88.4824
Epoch 88/400
88.0458
Epoch 89/400
87.8621
Epoch 90/400
87.3873
Epoch 91/400
86.3990
Epoch 92/400
```

```
85.7669
Epoch 93/400
85.3662
Epoch 94/400
85.0207
Epoch 95/400
84.5055
Epoch 96/400
83.9207
Epoch 97/400
83.2244
Epoch 98/400
82.9134
Epoch 99/400
82.7603
Epoch 100/400
81.6754
Epoch 101/400
81.3458
Epoch 102/400
80.7655
Epoch 103/400
79.9830
Epoch 104/400
79.1865
Epoch 105/400
77.9169
Epoch 106/400
76.6562
Epoch 107/400
75.1235
Epoch 108/400
```

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74.0828
Epoch 109/400
72.5612
Epoch 110/400
72.2569
Epoch 111/400
71.2570
Epoch 112/400
70.4560
Epoch 113/400
69.4554
Epoch 114/400
69.0550
Epoch 115/400
68.9941
Epoch 116/400
67.8163
Epoch 117/400
67.4640
Epoch 118/400
66.4543
Epoch 119/400
65.7818
Epoch 120/400
65.8063
Epoch 121/400
64.8729
Epoch 122/400
65.5652
Epoch 123/400
64.6070
Epoch 124/400
```

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63.8343
Epoch 125/400
64.1022
Epoch 126/400
63.5339
Epoch 127/400
64.0992
Epoch 128/400
63.1678
Epoch 129/400
63.0343
Epoch 130/400
62.3366
Epoch 131/400
61.9465
Epoch 132/400
62, 1998
Epoch 133/400
61.6267
Epoch 134/400
61.7030
Epoch 135/400
61.2276
Epoch 136/400
7/7 [=========== ] - Os 3ms/step - loss: 71.3225 - val_loss:
61.0671
Epoch 137/400
60.6831
Epoch 138/400
60.4708
Epoch 139/400
60.0813
Epoch 140/400
```

```
59.6526
Epoch 141/400
59.1673
Epoch 142/400
60.0246
Epoch 143/400
58.6059
Epoch 144/400
58.7058
Epoch 145/400
59.0404
Epoch 146/400
57.9866
Epoch 147/400
58.0702
Epoch 148/400
57.9181
Epoch 149/400
57.5075
Epoch 150/400
57.3234
Epoch 151/400
56.5315
Epoch 152/400
7/7 [=========== ] - Os 3ms/step - loss: 62.5580 - val_loss:
56.6052
Epoch 153/400
55.9849
Epoch 154/400
55.4379
Epoch 155/400
55.8411
Epoch 156/400
```

```
54.8196
Epoch 157/400
56.8759
Epoch 158/400
53.9383
Epoch 159/400
54.3141
Epoch 160/400
53.2708
Epoch 161/400
54.9199
Epoch 162/400
52.9028
Epoch 163/400
53.2608
Epoch 164/400
52.1335
Epoch 165/400
51.9141
Epoch 166/400
51.6541
Epoch 167/400
51.7029
Epoch 168/400
7/7 [=========== ] - Os 3ms/step - loss: 56.8169 - val_loss:
51.6462
Epoch 169/400
51.1733
Epoch 170/400
50.6746
Epoch 171/400
51.4101
Epoch 172/400
```

```
50.4976
Epoch 173/400
50.0213
Epoch 174/400
50.6922
Epoch 175/400
49.3613
Epoch 176/400
50.0147
Epoch 177/400
49.8415
Epoch 178/400
48.9431
Epoch 179/400
7/7 [============ ] - Os 3ms/step - loss: 53.1128 - val_loss:
51.2482
Epoch 180/400
48.3569
Epoch 181/400
49.2123
Epoch 182/400
49.0435
Epoch 183/400
48.5132
Epoch 184/400
47.6919
Epoch 185/400
48.7518
Epoch 186/400
47.4757
Epoch 187/400
48.6520
Epoch 188/400
```

```
47.2217
Epoch 189/400
48.4986
Epoch 190/400
loss: 50.1144 - val loss: 47.1089
Epoch 191/400
48.7421
Epoch 192/400
47.2399
Epoch 193/400
47.7874
Epoch 194/400
47.4867
Epoch 195/400
7/7 [============ ] - Os 3ms/step - loss: 48.5485 - val_loss:
47.3379
Epoch 196/400
47.0699
Epoch 197/400
47.7425
Epoch 198/400
46.3859
Epoch 199/400
47.3561
Epoch 200/400
7/7 [=========== ] - Os 3ms/step - loss: 47.9093 - val_loss:
46.6186
Epoch 201/400
46.8720
Epoch 202/400
46.9844
Epoch 203/400
46.3417
Epoch 204/400
```

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46.3237
Epoch 205/400
46.3023
Epoch 206/400
46.6334
Epoch 207/400
45.8680
Epoch 208/400
46.5239
Epoch 209/400
47.5345
Epoch 210/400
45.4544
Epoch 211/400
7/7 [============ ] - Os 3ms/step - loss: 46.2953 - val_loss:
49.3516
Epoch 212/400
46.0816
Epoch 213/400
48.5340
Epoch 214/400
45.8613
Epoch 215/400
45.4549
Epoch 216/400
48.2548
Epoch 217/400
45.4943
Epoch 218/400
46.0363
Epoch 219/400
47.0925
Epoch 220/400
```

```
45.0404
Epoch 221/400
46.3280
Epoch 222/400
46.1049
Epoch 223/400
45.3858
Epoch 224/400
47.8457
Epoch 225/400
45.2590
Epoch 226/400
48.2978
Epoch 227/400
44.8772
Epoch 228/400
48.0400
Epoch 229/400
44.7687
Epoch 230/400
46.7971
Epoch 231/400
44.8473
Epoch 232/400
46.7624
Epoch 233/400
44.5385
Epoch 234/400
47.0116
Epoch 235/400
44.6429
Epoch 236/400
```

```
45.7402
Epoch 237/400
44.8927
Epoch 238/400
45.0137
Epoch 239/400
45.4418
Epoch 240/400
47.2283
Epoch 241/400
44.5021
Epoch 242/400
46.7107
Epoch 243/400
7/7 [============ ] - Os 3ms/step - loss: 43.9508 - val_loss:
44.4866
Epoch 244/400
7/7 [=========== ] - Os 3ms/step - loss: 43.5043 - val_loss:
45.8101
Epoch 245/400
45.8260
Epoch 246/400
44.3676
Epoch 247/400
47.4438
Epoch 248/400
7/7 [============ ] - Os 3ms/step - loss: 43.9401 - val_loss:
44.5632
Epoch 249/400
47.5237
Epoch 250/400
45.1721
Epoch 251/400
45.2212
Epoch 252/400
```

```
44.0301
Epoch 253/400
44.4261
Epoch 254/400
44.2183
Epoch 255/400
46.8413
Epoch 256/400
44.4353
Epoch 257/400
45.9353
Epoch 258/400
44.1830
Epoch 259/400
7/7 [============ ] - Os 3ms/step - loss: 43.3043 - val_loss:
49.0198
Epoch 260/400
44.3749
Epoch 261/400
49.5640
Epoch 262/400
44.5551
Epoch 263/400
46.5772
Epoch 264/400
44.0145
Epoch 265/400
44.4700
Epoch 266/400
44.4905
Epoch 267/400
44.9180
Epoch 268/400
```

```
44.8002
Epoch 269/400
45.2533
Epoch 270/400
43.9054
Epoch 271/400
45.5893
Epoch 272/400
44.0076
Epoch 273/400
43.7751
Epoch 274/400
45.2819
Epoch 275/400
7/7 [============ ] - Os 3ms/step - loss: 42.8406 - val_loss:
43.8690
Epoch 276/400
45,1805
Epoch 277/400
45.0542
Epoch 278/400
44.4262
Epoch 279/400
44.5195
Epoch 280/400
44.9827
Epoch 281/400
44.1199
Epoch 282/400
7/7 [=========== ] - Os 3ms/step - loss: 42.4251 - val_loss:
44.7838
Epoch 283/400
44.0997
Epoch 284/400
```

```
44.4429
Epoch 285/400
44.1800
Epoch 286/400
43.5746
Epoch 287/400
44.9791
Epoch 288/400
43.9570
Epoch 289/400
50.7917
Epoch 290/400
43.4779
Epoch 291/400
7/7 [============ ] - Os 3ms/step - loss: 42.2928 - val_loss:
43.7405
Epoch 292/400
44.5014
Epoch 293/400
43.5162
Epoch 294/400
43.7064
Epoch 295/400
44.5826
Epoch 296/400
42.6400
Epoch 297/400
43.9823
Epoch 298/400
7/7 [=========== ] - Os 3ms/step - loss: 41.5820 - val_loss:
42.8088
Epoch 299/400
44.5335
Epoch 300/400
```

```
43.2071
Epoch 301/400
44.1535
Epoch 302/400
44.0678
Epoch 303/400
44.0236
Epoch 304/400
43.5975
Epoch 305/400
44.8474
Epoch 306/400
43.1534
Epoch 307/400
7/7 [============ ] - Os 3ms/step - loss: 41.5303 - val_loss:
42.7298
Epoch 308/400
45.9504
Epoch 309/400
42.7341
Epoch 310/400
44.6117
Epoch 311/400
43.7957
Epoch 312/400
7/7 [=========== ] - Os 3ms/step - loss: 42.0897 - val_loss:
42.8131
Epoch 313/400
42.9411
Epoch 314/400
7/7 [============ ] - Os 3ms/step - loss: 41.2538 - val_loss:
43.0138
Epoch 315/400
43.7077
Epoch 316/400
```

```
42.4518
Epoch 317/400
44.1773
Epoch 318/400
42.5356
Epoch 319/400
42.9135
Epoch 320/400
44.1604
Epoch 321/400
42.5750
Epoch 322/400
43.3573
Epoch 323/400
7/7 [============ ] - Os 3ms/step - loss: 40.8294 - val_loss:
42.2866
Epoch 324/400
42.9576
Epoch 325/400
46.4091
Epoch 326/400
42.5587
Epoch 327/400
44.3349
Epoch 328/400
7/7 [=========== ] - Os 3ms/step - loss: 41.3114 - val_loss:
43.2276
Epoch 329/400
41.8275
Epoch 330/400
46.5434
Epoch 331/400
41.9355
Epoch 332/400
```

```
42.6079
Epoch 333/400
44.5767
Epoch 334/400
41.7780
Epoch 335/400
42.6180
Epoch 336/400
44.3947
Epoch 337/400
41.7205
Epoch 338/400
46.5346
Epoch 339/400
7/7 [============ ] - Os 3ms/step - loss: 42.6630 - val_loss:
42.1233
Epoch 340/400
43,6290
Epoch 341/400
43.0989
Epoch 342/400
42.1824
Epoch 343/400
42.1762
Epoch 344/400
41.6763
Epoch 345/400
41.8872
Epoch 346/400
41.3554
Epoch 347/400
41.9624
Epoch 348/400
```

```
41.5849
Epoch 349/400
41.0906
Epoch 350/400
41.5787
Epoch 351/400
41.3447
Epoch 352/400
43.3074
Epoch 353/400
41.0987
Epoch 354/400
42.4865
Epoch 355/400
41.0014
Epoch 356/400
7/7 [============ ] - Os 3ms/step - loss: 39.3482 - val_loss:
42.1550
Epoch 357/400
41.8452
Epoch 358/400
41.1494
Epoch 359/400
41.2416
Epoch 360/400
7/7 [=========== ] - Os 3ms/step - loss: 39.0588 - val_loss:
41.8345
Epoch 361/400
40.2576
Epoch 362/400
7/7 [============ ] - Os 3ms/step - loss: 39.8652 - val_loss:
40.7502
Epoch 363/400
41.4834
Epoch 364/400
```

```
42.8860
Epoch 365/400
40.1426
Epoch 366/400
45.3333
Epoch 367/400
40.4457
Epoch 368/400
43.1630
Epoch 369/400
39.8676
Epoch 370/400
40.8587
Epoch 371/400
42.6925
Epoch 372/400
39.8806
Epoch 373/400
42.2835
Epoch 374/400
39.6683
Epoch 375/400
40.8396
Epoch 376/400
43.8077
Epoch 377/400
40.4930
Epoch 378/400
40.4233
Epoch 379/400
41.7753
Epoch 380/400
```

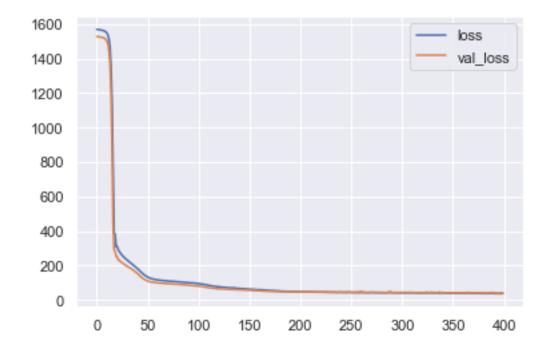
```
39.6325
Epoch 381/400
43.0120
Epoch 382/400
39.9728
Epoch 383/400
40.2657
Epoch 384/400
41.3274
Epoch 385/400
40.3087
Epoch 386/400
42.6194
Epoch 387/400
7/7 [============ ] - Os 3ms/step - loss: 38.4573 - val_loss:
40.3869
Epoch 388/400
39.5894
Epoch 389/400
44.1040
Epoch 390/400
39.5866
Epoch 391/400
41.0239
Epoch 392/400
39.3443
Epoch 393/400
40.8900
Epoch 394/400
7/7 [=========== ] - Os 3ms/step - loss: 37.4189 - val_loss:
39.6160
Epoch 395/400
40.6460
Epoch 396/400
```

[53]: <tensorflow.python.keras.callbacks.History at 0x7fe7458b6cd0>

1.7.3 Visualize the Loss Function

```
[54]: losses = pd.DataFrame(model_4.history.history)
losses.plot()
```

[54]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe7458c7100>



1.7.4 Test the Model

```
[55]: predictions_4 = model_4.predict(X_test)
```

1.7.5 Model Evaluation

EVALUATION METRICS

 Mean Absolute Error (MAE):
 4.913074249712009

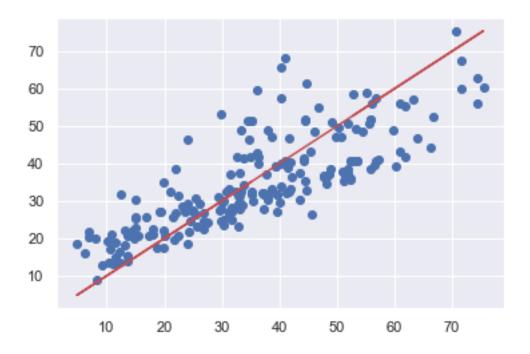
 Root Mean Squared Error (RMSE):
 6.255377818962742

 Explained Variance Score:
 0.8488666652349717

```
[58]: # Plot Model Predictions (Scatter)
plt.scatter(y_test,predictions_3)

# Plot Perfect predictions (Line)
plt.plot(y_test,y_test,'r')
```

[58]: [<matplotlib.lines.Line2D at 0x7fe7422f7ca0>]



1.7.6 Model Comparison

Let us compare the evaluation metrics between models 1, 2, 3, and 4:

```
[75]: print('EVALUATION METRICS, MODEL 1')
   print('----')
   print(f"Mean Absolute Error (MAE):\t\t{MAE}\nRoot Mean Squared Error (RMSE):
    →\t\t{RMSE}\nExplained Variance Score:\t\t{EVS}")
   print('----\n\n')
   print('EVALUATION METRICS, MODEL 2')
   print('----')
   print(f"Mean Absolute Error (MAE):\t\t{MAE_2}\nRoot Mean Squared Error (RMSE):
    print('----\n\n')
   print('EVALUATION METRICS, MODEL 3')
   print('----')
   print(f"Mean Absolute Error (MAE):\t\t{MAE_3}\nRoot Mean Squared Error (RMSE):
    print('----\n\n')
   print('EVALUATION METRICS, MODEL 4')
   print('----')
   print(f"Mean Absolute Error (MAE):\t\t{MAE_4}\nRoot Mean Squared Error (RMSE):
```

EVALUATION METRICS, MODEL 1

```
Mean Absolute Error (MAE):
                                   7.23883411296363
Root Mean Squared Error (RMSE):
                                   9.233359748913385
Explained Variance Score:
                                   0.6691982422589368
EVALUATION METRICS, MODEL 2
_____
                                   5.738010522323906
Mean Absolute Error (MAE):
Root Mean Squared Error (RMSE):
                                   7.266889552774522
Explained Variance Score:
                                   0.797885663610966
_____
EVALUATION METRICS, MODEL 3
_____
Mean Absolute Error (MAE):
                                   7.611444954733247
Root Mean Squared Error (RMSE):
                                   9.619967686192227
Explained Variance Score:
                                   0.6426482928244076
-----
EVALUATION METRICS, MODEL 4
Mean Absolute Error (MAE):
                                   4.913074249712009
Root Mean Squared Error (RMSE):
                                   6.255377818962742
Explained Variance Score:
                                   0.8488666652349717
```

1.8 Determining Optimal Number of Hidden Layers

1.8.1 Iterating Through 2-50 Hidden Layers

We now know that 15 hidden layers is more effective than 20. Let us iterate from 2 to 50 to explore the other possible number of layers, assuming each deep layer contains 8 nodes. Once we find the optimal number of nodes in that range, we can further experiment to optimize the ANN architecture. The for loop below will print out the evaluation metrics for each iteration in real time. Please note that it may take several minutes to run the following code.

```
[138]: results = []
for i in range(2,51):
    model_loop = Sequential()
    for j in range(0,(i+1)):
        model_loop.add(Dense(8,activation='relu'))
    model_loop.add(Dense(1))

    model_loop.compile(optimizer='adam',loss='mse')

# We will reduce epochs to 200 to reduce run time.
```

```
# 200 was chosen based on previous loss function visualizations.
    model_loop.fit(x=X_train,y=y_train.values,
         validation_data=(X_test,y_test.values),
         batch_size=128,epochs=200,verbose=0)
    # Model evaluation
    predictions_loop = model_loop.predict(X_test)
    MAE_loop = mean_absolute_error(y_test,predictions_loop)
    RMSE_loop = np.sqrt(mean_squared_error(y_test,predictions_loop))
    EVS_loop = explained_variance_score(y_test,predictions_loop)
    results.append([i, MAE_loop,RMSE_loop,EVS_loop])
    print(f"EVALUATION METRICS, HIDDEN LAYERS = {i}")
    print('----')
    print(f"Mean Absolute Error (MAE):\t\t{MAE loop}\nRoot Mean Squared Error ⊔
 → (RMSE):\t\t{RMSE_loop}\nExplained Variance Score:\t\t{EVS_loop}")
    print('----\n\n')
EVALUATION METRICS, HIDDEN LAYERS = 2
_____
Mean Absolute Error (MAE):
                                  8.120154531719615
Root Mean Squared Error (RMSE):
                                10.110879538827527
Explained Variance Score:
                                  0.603573240618023
_____
EVALUATION METRICS, HIDDEN LAYERS = 3
-----
                                  6.316067462847071
Mean Absolute Error (MAE):
Root Mean Squared Error (RMSE):
                                 8.01847651997628
Explained Variance Score:
                                  0.7504890012616049
_____
EVALUATION METRICS, HIDDEN LAYERS = 4
                                 6.733620031967904
Mean Absolute Error (MAE):
Root Mean Squared Error (RMSE):
                                 8.728310582799304
                                 0.7044559113122469
Explained Variance Score:
EVALUATION METRICS, HIDDEN LAYERS = 5
_____
                                  5.57671700866477
Mean Absolute Error (MAE):
```

6.996037765940304 Root Mean Squared Error (RMSE): Explained Variance Score: 0.8191998499945969 EVALUATION METRICS, HIDDEN LAYERS = 6 6.711770730250091 Mean Absolute Error (MAE): 8.615350695520469 Root Mean Squared Error (RMSE): Explained Variance Score: 0.7119503067668893 _____ EVALUATION METRICS, HIDDEN LAYERS = 7 -----Mean Absolute Error (MAE): 5.984079652064056 Root Mean Squared Error (RMSE): 7.614730395172845 0.7755222006242926 Explained Variance Score: EVALUATION METRICS, HIDDEN LAYERS = 8 _____ Mean Absolute Error (MAE): 5.735270093158611 7.086722805080626 Root Mean Squared Error (RMSE): Explained Variance Score: 0.8053037696318728 -----EVALUATION METRICS, HIDDEN LAYERS = 9 -----Mean Absolute Error (MAE): 5.478865822542061 6.867825825775559 Root Mean Squared Error (RMSE): Explained Variance Score: 0.819553935582044 _____ EVALUATION METRICS, HIDDEN LAYERS = 10 _____ Mean Absolute Error (MAE): 7.823388269294812 Root Mean Squared Error (RMSE): 9.795787697246654 Explained Variance Score: 0.6284665360679961 _____ EVALUATION METRICS, HIDDEN LAYERS = 11

Mean Absolute Error (MAE):

5.583180159041025

EVALUATION METRICS, HIDDEN LAYERS = 12

 Mean Absolute Error (MAE):
 5.378429776812063

 Root Mean Squared Error (RMSE):
 6.801692005893954

 Explained Variance Score:
 0.8254431803201379

EVALUATION METRICS, HIDDEN LAYERS = 13

 Mean Absolute Error (MAE):
 6.112327872248529

 Root Mean Squared Error (RMSE):
 7.62031079259648

 Explained Variance Score:
 0.7747771892371211

EVALUATION METRICS, HIDDEN LAYERS = 14

 Mean Absolute Error (MAE):
 5.5185722788097795

 Root Mean Squared Error (RMSE):
 6.858810612151086

 Explained Variance Score:
 0.8183444896012475

EVALUATION METRICS, HIDDEN LAYERS = 15

 Mean Absolute Error (MAE):
 5.938035524886789

 Root Mean Squared Error (RMSE):
 7.459843610366862

 Explained Variance Score:
 0.7858784431548431

EVALUATION METRICS, HIDDEN LAYERS = 16

 Mean Absolute Error (MAE):
 6.821452794676844

 Root Mean Squared Error (RMSE):
 8.900650789849243

 Explained Variance Score:
 0.6936457735710044

EVALUATION METRICS, HIDDEN LAYERS = 17

Mean Absolute Error (MAE): 5.533272227500248

 Root Mean Squared Error (RMSE):
 6.793224274989845

 Explained Variance Score:
 0.8209112610561281

EVALUATION METRICS, HIDDEN LAYERS = 18

 Mean Absolute Error (MAE):
 5.663948101302954

 Root Mean Squared Error (RMSE):
 7.359722788575843

 Explained Variance Score:
 0.8015666267805353

EVALUATION METRICS, HIDDEN LAYERS = 19

 Mean Absolute Error (MAE):
 7.126552193095383

 Root Mean Squared Error (RMSE):
 9.161850954927273

 Explained Variance Score:
 0.6752519590130766

EVALUATION METRICS, HIDDEN LAYERS = 20

 Mean Absolute Error (MAE):
 5.533255350612902

 Root Mean Squared Error (RMSE):
 7.090032891571433

 Explained Variance Score:
 0.8052541645002692

EVALUATION METRICS, HIDDEN LAYERS = 21

 Mean Absolute Error (MAE):
 6.057331670001872

 Root Mean Squared Error (RMSE):
 7.735291412130756

 Explained Variance Score:
 0.7771645158797513

EVALUATION METRICS, HIDDEN LAYERS = 22

Mean Absolute Error (MAE): 13.053801832476866 Root Mean Squared Error (RMSE): 16.054067583075092

Explained Variance Score: 0.0

EVALUATION METRICS, HIDDEN LAYERS = 23

Mean Absolute Error (MAE): 13.063179582021768

Root Mean Squared Error (RMSE): 16.141319898403207

Explained Variance Score: 0.0

EVALUATION METRICS, HIDDEN LAYERS = 24

 Mean Absolute Error (MAE):
 6.0291853160302615

 Root Mean Squared Error (RMSE):
 7.523479760077879

 Explained Variance Score:
 0.7818280460200446

EVALUATION METRICS, HIDDEN LAYERS = 25

 Mean Absolute Error (MAE):
 5.45227837257015

 Root Mean Squared Error (RMSE):
 6.848838990375106

 Explained Variance Score:
 0.8230922728390744

EVALUATION METRICS, HIDDEN LAYERS = 26

Mean Absolute Error (MAE): 13.04146576816596 Root Mean Squared Error (RMSE): 16.05251979248055

Explained Variance Score: 0.0

EVALUATION METRICS, HIDDEN LAYERS = 27

 Mean Absolute Error (MAE):
 5.105980217294786

 Root Mean Squared Error (RMSE):
 6.488557487152753

 Explained Variance Score:
 0.8366699650916528

EVALUATION METRICS, HIDDEN LAYERS = 28

 Mean Absolute Error (MAE):
 5.71979399412581

 Root Mean Squared Error (RMSE):
 7.53736009502298

 Explained Variance Score:
 0.7796426678238857

EVALUATION METRICS, HIDDEN LAYERS = 29

Mean Absolute Error (MAE): 5.488801206570227

Root Mean Squared Error (RMSE): 6.935423136007702 Explained Variance Score: 0.8177958145966675

EVALUATION METRICS, HIDDEN LAYERS = 30

 Mean Absolute Error (MAE):
 5.059363350451572

 Root Mean Squared Error (RMSE):
 6.513469468892874

 Explained Variance Score:
 0.8402378858490599

EVALUATION METRICS, HIDDEN LAYERS = 31

 Mean Absolute Error (MAE):
 7.2751414971212744

 Root Mean Squared Error (RMSE):
 9.238453187252782

 Explained Variance Score:
 0.6689495050997574

EVALUATION METRICS, HIDDEN LAYERS = 32

Mean Absolute Error (MAE): 13.047311662099894 Root Mean Squared Error (RMSE): 16.05246971586041

Explained Variance Score: 0.0

EVALUATION METRICS, HIDDEN LAYERS = 33

 Mean Absolute Error (MAE):
 34.27170157488111

 Root Mean Squared Error (RMSE):
 37.844767448102836

Explained Variance Score: 0.0

EVALUATION METRICS, HIDDEN LAYERS = 34

 Mean Absolute Error (MAE):
 13.059186999867263

 Root Mean Squared Error (RMSE):
 16.05671375701027

Explained Variance Score: 0.0

EVALUATION METRICS, HIDDEN LAYERS = 35

Mean Absolute Error (MAE): 5.1497897412938975

 Root Mean Squared Error (RMSE):
 6.419044845657203

 Explained Variance Score:
 0.8438115650510409

EVALUATION METRICS, HIDDEN LAYERS = 36

Mean Absolute Error (MAE): 13.034295915029581 Root Mean Squared Error (RMSE): 16.054508710066703

Explained Variance Score: -2.5621756938321028e-08

EVALUATION METRICS, HIDDEN LAYERS = 37

 Mean Absolute Error (MAE):
 13.054120193037015

 Root Mean Squared Error (RMSE):
 16.0541907207132

Explained Variance Score: 0.0

EVALUATION METRICS, HIDDEN LAYERS = 38

 Mean Absolute Error (MAE):
 34.27141976412061

 Root Mean Squared Error (RMSE):
 37.844512244337785

Explained Variance Score: 0.0

EVALUATION METRICS, HIDDEN LAYERS = 39

 Mean Absolute Error (MAE):
 5.128188093240979

 Root Mean Squared Error (RMSE):
 6.508868622553171

 Explained Variance Score:
 0.8360870774081537

EVALUATION METRICS, HIDDEN LAYERS = 40

 Mean Absolute Error (MAE):
 5.668614755463832

 Root Mean Squared Error (RMSE):
 7.202048651134695

 Explained Variance Score:
 0.8214597430602204

EVALUATION METRICS, HIDDEN LAYERS = 41

Mean Absolute Error (MAE): 13.052142031771465

Root Mean Squared Error (RMSE): 16.053493385733766

Explained Variance Score: 0.0

EVALUATION METRICS, HIDDEN LAYERS = 42

 Mean Absolute Error (MAE):
 6.285670373231463

 Root Mean Squared Error (RMSE):
 7.894684085869782

 Explained Variance Score:
 0.758491275678627

EVALUATION METRICS, HIDDEN LAYERS = 43

 Mean Absolute Error (MAE):
 4.913707746672399

 Root Mean Squared Error (RMSE):
 6.690457709869514

 Explained Variance Score:
 0.8339618633118577

EVALUATION METRICS, HIDDEN LAYERS = 44

 Mean Absolute Error (MAE):
 4.953942543418663

 Root Mean Squared Error (RMSE):
 6.234954243834083

 Explained Variance Score:
 0.850606045042105

EVALUATION METRICS, HIDDEN LAYERS = 45

 Mean Absolute Error (MAE):
 4.879614045226458

 Root Mean Squared Error (RMSE):
 6.422680429911674

 Explained Variance Score:
 0.8417760419622913

EVALUATION METRICS, HIDDEN LAYERS = 46

 Mean Absolute Error (MAE):
 34.27101039942029

 Root Mean Squared Error (RMSE):
 37.8441415302349

Explained Variance Score: 0.0

EVALUATION METRICS, HIDDEN LAYERS = 47

Mean Absolute Error (MAE): 13.048629991846177

Root Mean Squared Error (RMSE): 16.05265348522672

Explained Variance Score: 0.0

EVALUATION METRICS, HIDDEN LAYERS = 48

Mean Absolute Error (MAE): 34.270735979635745 Root Mean Squared Error (RMSE): 37.84389302052811

Explained Variance Score: 0.0

EVALUATION METRICS, HIDDEN LAYERS = 49

 Mean Absolute Error (MAE):
 13.055442670803625

 Root Mean Squared Error (RMSE):
 16.054747037532167

Explained Variance Score: 0.0

EVALUATION METRICS, HIDDEN LAYERS = 50

 Mean Absolute Error (MAE):
 5.8415424287666395

 Root Mean Squared Error (RMSE):
 7.226975235195714

 Explained Variance Score:
 0.7981404573686495

1.8.2 Layer Optimization Analysis

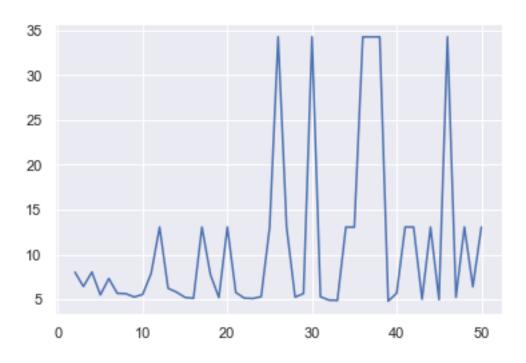
```
[144]: # Convert the results into a numpy array
results_np = np.array(results)

# Store the np array in a pandas dataframe
results_df = pd.

→DataFrame(columns=['Hidden_Layers', 'MAE', 'RMSE', 'EVS'], data=results_np)
```

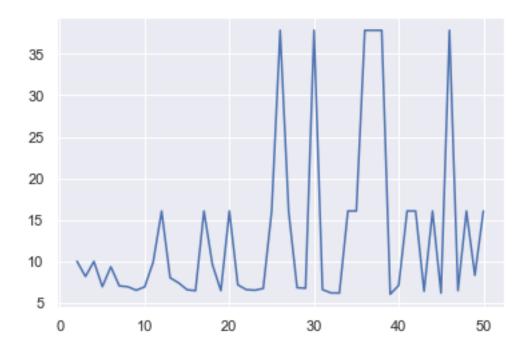
```
[114]: # Plot the mean absolute error for each iteration
X_plot = results_df['Hidden_Layers']
y_MAE = results_df['MAE']
plt.plot(X_plot,y_MAE)
```

[114]: [<matplotlib.lines.Line2D at 0x7fe72411ba30>]



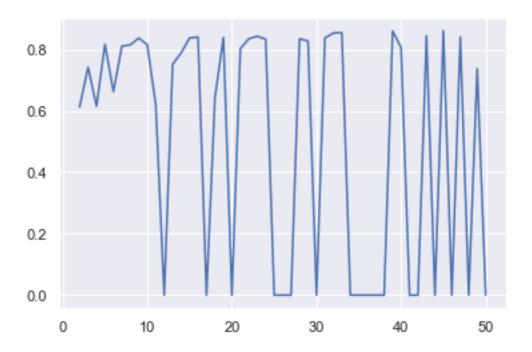
[115]: # Plot the root mean squared error for each iteration
y_RMSE = results_df['RMSE']
plt.plot(X_plot,y_RMSE)

[115]: [<matplotlib.lines.Line2D at 0x7fe725091400>]



```
[116]: # Plot the explained variance score for each iteration
y_EVS = results_df['EVS']
plt.plot(X_plot,y_EVS)
```

[116]: [<matplotlib.lines.Line2D at 0x7fe725171550>]



```
[140]: # Determine the minimum MAE, RMSE, and maximum EVS results_df.describe()
```

```
[140]:
              Hidden_Layers
                                    MAE
                                              RMSE
                                                             EVS
                   49.00000
                                         49.000000
                             49.000000
       count
                                                    4.900000e+01
       mean
                   26.00000
                              9.679436
                                         11.720185
                                                    5.581656e-01
                   14.28869
                              7.974965
                                          8.633592
                                                    3.607205e-01
       std
      min
                    2.00000
                              4.879614
                                          6.234954 -2.562176e-08
       25%
                   14.00000
                              5.533255
                                          6.935423
                                                   0.000000e+00
       50%
                   26.00000
                              6.057332
                                          7.620311
                                                    7.755222e-01
       75%
                   38.00000
                             13.041466
                                         16.052520
                                                   8.195539e-01
                   50.00000
                             34.271702
      max
                                         37.844767 8.506060e-01
```

```
[141]: # Iteration with the lowest MAE results_df[results_df['MAE']<4.88]
```

[141]: Hidden_Layers MAE RMSE EVS 43 45.0 4.879614 6.42268 0.841776

```
[142]: # Iteration with the lowest RMSE
       results_df[results_df['RMSE']<6.24]
[142]:
           Hidden_Layers
                                                    EVS
                               MAE
                                        RMSE
       42
                    44.0 4.953943 6.234954
                                              0.850606
[143]: # Iteration with the largest EVS
       results_df[results_df['EVS']>0.85]
[143]:
           Hidden_Layers
                               MAE
                                        RMSF.
                                                    EVS
       42
                    44.0
                         4.953943 6.234954 0.850606
```

We see that the minimum MAE is from 45 hidden layers, and the lowest RMSE and highest EVS are from 42 hidden layers. We will continue to work with the 44 hidden layer architecture.

1.9 Experimenting with the 44 Hidden Layer Model

There is an infinite number of possible configurations for a neural network. We will explore three below, keeping the 44 total hidden layers.

1.9.1 The Flat Model

```
[162]: optimization_results = []
       model_flat = Sequential()
       for i in range (45):
           model_flat.add(Dense(8,activation='relu'))
       model flat.add(Dense(1))
       model_flat.compile(optimizer='adam',loss='mse')
       # We will reset epochs to 200.
       model_flat.fit(x=X_train,y=y_train.values,
             validation_data=(X_test,y_test.values),
             batch_size=128,epochs=200,verbose=0)
       # Model evaluation
       predictions_flat = model_flat.predict(X_test)
       MAE_flat = mean_absolute_error(y_test,predictions_flat)
       RMSE flat = np.sqrt(mean squared error(y test,predictions flat))
       EVS_flat = explained_variance_score(y_test,predictions_flat)
       optimization_results.append(['Flat', MAE_flat,RMSE_flat,EVS_flat])
       print(f"EVALUATION METRICS, HIDDEN LAYERS = 44")
```

```
EVALUATION METRICS, HIDDEN LAYERS = 44
```

 Mean Absolute Error (MAE):
 5.08355243840264

 Root Mean Squared Error (RMSE):
 6.466492906453852

 Explained Variance Score:
 0.8383600376691335

1.9.2 The Descending Model

```
[180]: model_desc = Sequential()
      for i in range(39):
          model_desc.add(Dense(8,activation='relu'))
      model_desc.add(Dense(7,activation='relu'))
      model_desc.add(Dense(6,activation='relu'))
      model_desc.add(Dense(5,activation='relu'))
      model_desc.add(Dense(4,activation='relu'))
      model_desc.add(Dense(3,activation='relu'))
      model_desc.add(Dense(2,activation='relu'))
      model_desc.add(Dense(1))
      model_desc.compile(optimizer='adam',loss='mse')
      model_desc.fit(x=X_train,y=y_train.values,
            validation_data=(X_test,y_test.values),
            batch_size=128,epochs=200,verbose=0)
      predictions_desc = model_desc.predict(X_test)
      MAE_desc = mean_absolute_error(y_test,predictions_desc)
      RMSE_desc = np.sqrt(mean_squared_error(y_test,predictions_desc))
      EVS_desc = explained_variance_score(y_test,predictions_desc)
      optimization_results.append(['Desc', MAE_desc,RMSE_desc,EVS_desc])
      print(f"EVALUATION METRICS, HIDDEN LAYERS = 44, DESCENDING")
      print('----')
      print(f"Mean Absolute Error (MAE):\t\t{MAE_desc}\nRoot Mean Squared Error ∪
       → (RMSE):\t\t{RMSE_desc}\nExplained Variance Score:\t\t{EVS_desc}")
      print('----\n\n')
```

EVALUATION METRICS, HIDDEN LAYERS = 44, DESCENDING

 Mean Absolute Error (MAE):
 5.313633555532659

 Root Mean Squared Error (RMSE):
 6.834572877180595

 Explained Variance Score:
 0.8265445916481245

```
[191]: # We can see that the descencing model performed worse than the flat model

optimization_df = pd.DataFrame(columns=['Model','MAE','RMSE','EVS'],data=np.

array(optimization_results))
optimization_df
```

[191]: Model MAE RMSE EVS
0 Flat 5.08355243840264 6.466492906453852 0.8383600376691335
1 Desc 5.313633555532659 6.834572877180595 0.8265445916481245

1.9.3 The Flat Dropout Model

```
[202]: model_flat_drop = Sequential()
       # Input layer
       model_flat_drop.add(Dense(8,activation='relu'))
       # Hidden Layers
       for i in range(22): # Let's make half of the layers in the network dropout □
       → layers at a 50% dropout rate
           model_flat_drop.add(Dense(8,activation='relu'))
           model_flat_drop.add(Dense(8,activation='relu'))
           model_flat_drop.add(Dropout(0.5))
       # Output layer
       model_flat_drop.add(Dense(1))
       model_flat_drop.compile(optimizer='adam',loss='mse')
       model_flat_drop.fit(x=X_train,y=y_train.values,
             validation_data=(X_test,y_test.values),
             batch_size=128,epochs=200,verbose=0)
       # Model evaluation
       predictions_flat_drop = model_flat_drop.predict(X_test)
       MAE_flat_drop = mean_absolute_error(y_test,predictions_flat_drop)
       RMSE_flat_drop = np.sqrt(mean_squared_error(y_test,predictions_flat_drop))
```

EVALUATION METRICS, ACTIVE HIDDEN LAYERS = 22, DROPOUT HIDDEN LAYERS = 22

Mean Absolute Error (MAE): 18.2897413887098 Root Mean Squared Error (RMSE): 22.422906635113907

Explained Variance Score: 0.0

1.10 Conclusions & Recommendations

We conclude that the "flat model" deep neural network containing 44 hidden layers of 8 nodes each, with no dropout nodes, is the optimal model from all the models tested in this project.

Additional models with different numbers of hidden layers and different architectures of the node networks could be subject to further experimentation and optimization. All three models containing the 44 hidden layers studied in this project are saved in the Keras ANN Models folder.

As discussed in the Exploratory Data Analysis code notebook, the compressive strength of concrete inreases rapidly from 0 to 28 days, then more much more stably from 28 days onward. A more intuitive and practical engineering model for predicting the compressive strength of concrete would rely on a given dataset containing only data of a certain curing time. Common testing times are at 3, 7, 14, 28, 60, 90, 128, and 365 days, with the 28 day mark being the industry standard. We analyze linear models at 28 days cure time in the Comparison with Linear Models notebook.

This dataset presented a unique challenge of predicting compressive strength not only as a function of its constituents, but also of time. The model in this project is able to predict the compressive strength of concrete to within a mean absolute error of 5.08 Megapascals (MPa), a root mean square error of 6.47 MPa, and an explained variance score of 0.838. The actual standard deviation for compressive strength in the dataset is 16.71 MPa. Therefore, the MAE is approximately 0.30, and The RMSE is approximately 0.39.

Given the high variance of the data, particularly in the 0 to 28 day range, these errors are reasonable. We recommend performing additional studies on larger datasets that represent a constant curing time, particularly the standard 28-day curing time, for the most practical engineering applications. Additional analysis comparing the ANN model with linear models is presented in the Model Analysis folder.