HI3_modeling

November 8, 2017

1 Hand-in 3, Part 2: Data Modeling

In this part you will take the csv file "reduced_field_data.csv" from Part 1, and use it to estimate the line criticality indices.

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt

        %matplotlib inline
```

1.1 Score function

Below is a scoring function we have written for you. The output of this function is a score of how well your procedure is doing. Higher scores are worse!

As you can see, it penalizes heavily when you don't predict accurately values when they are being overloaded, i.e. false negatives.

```
In [2]: def score_func(y_est, y_real):
            """
                This function takes your estimates y_est and
                scores them against the real data y_real.
                You should use this function to show how good your estimation method is.
            """
            # Square deviation
            sqr_err = np.sum(((y_est - y_real)**2).sum())
            # Penalty for not estimating a critical value above 0.95 when it occurs.
            false_negative = np.sum(np.where(np.logical_and(y_est < 0.95, y_real > 0.95), 10*np
            return sqr_err + false_negative
```

1.2 Load and clean data

Load your data from the previous exercise as well as the criticality data.

```
In [3]: # Data is loaded here
        field_data = pd.read_csv("reduced_field_data.csv", index_col=0)
        crit_data = pd.read_csv("flow_criticality_data.csv", index_col=0)
```

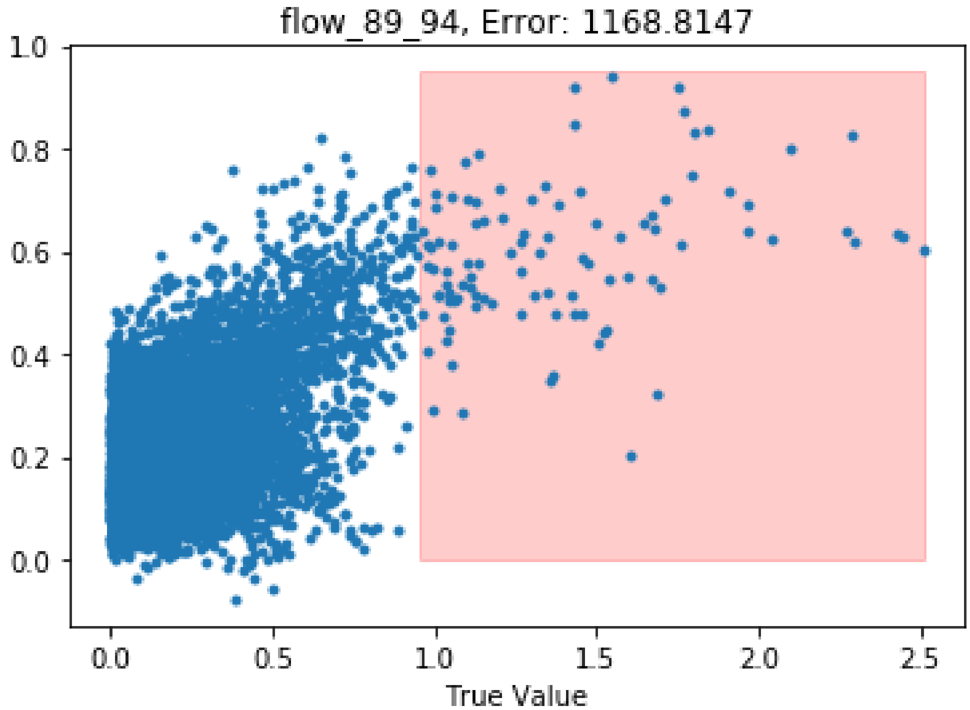
1.3 Linear regression

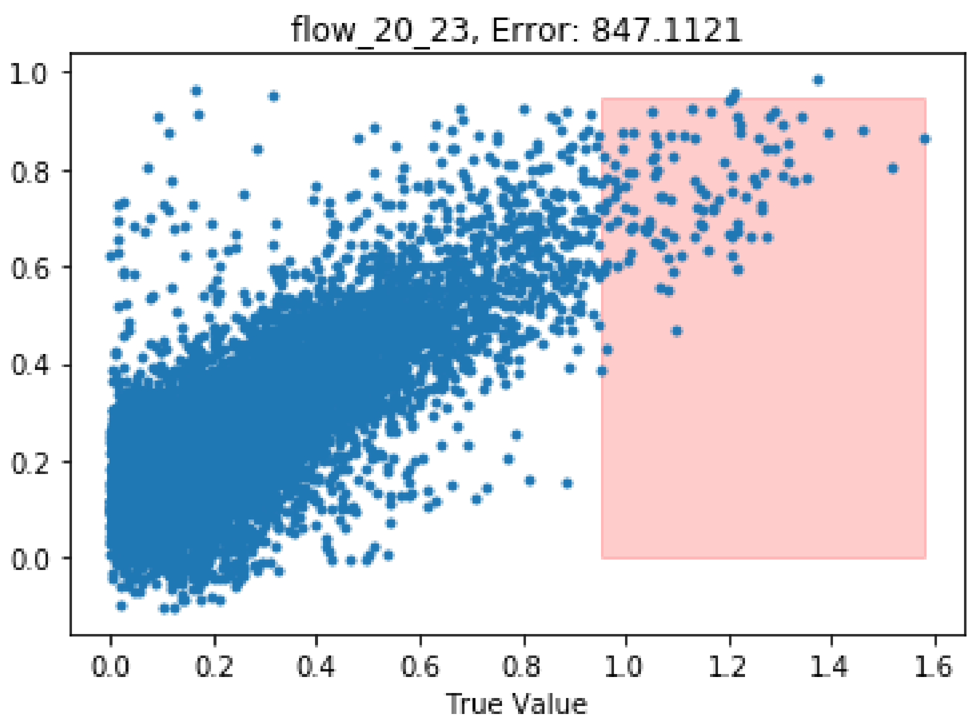
We have implemented a simple linear regression to apply to your data. You should use this as a benchmark for your neural network below.

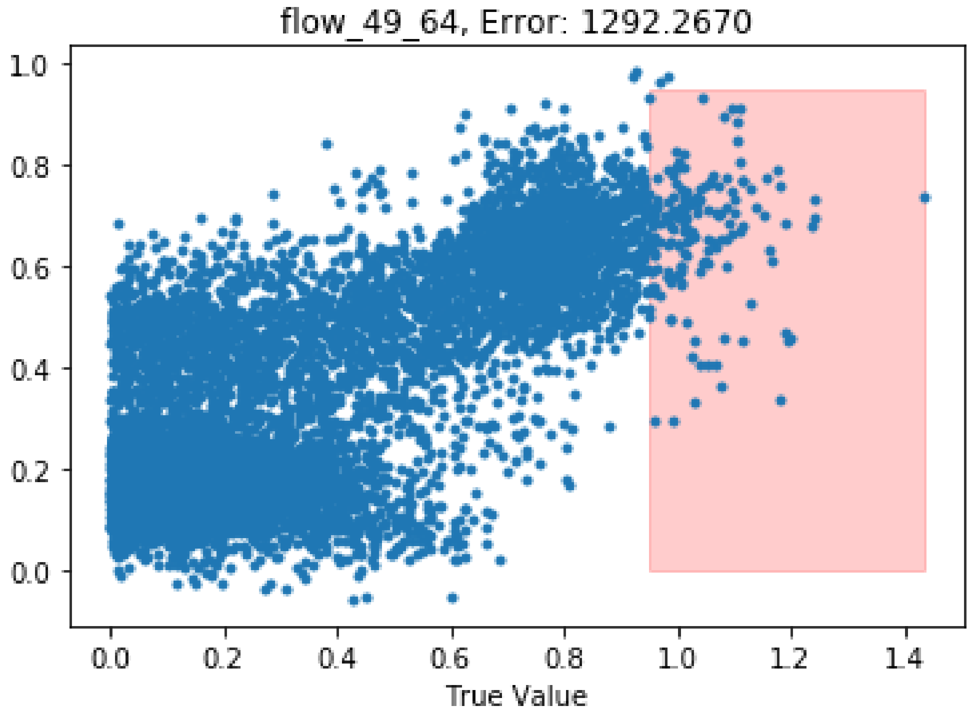
```
In [4]: # Slicing the data, because we have removed the NaN's of the field_data, which is ther
        # Using the time column, from field_data
        crit_data = crit_data[crit_data.index.isin(field_data['time'])].dropna(axis=0)
        # We no longer need the time column, therefore we remove it
        field_data = field_data.drop('time',1)
```

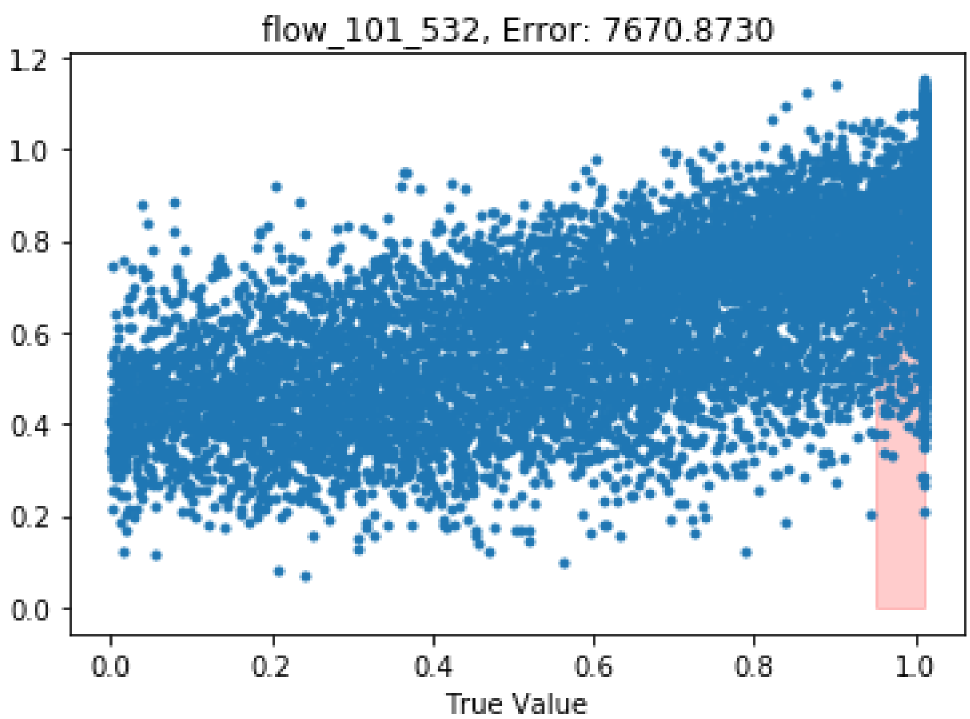
```
In [5]: # The code below implements a linear regression on your data and compares predicted an
        # On the plots there is a red square indicating the areas corresponding to false negat
        from sklearn.linear_model import LinearRegression
        lm = LinearRegression()
        lm.fit(field_data,crit_data)

        y_pred = lm.predict(field_data)
        for index in range(10):
            plt.figure()
            plt.fill_between([0.95, crit_data.iloc[:,index].max()], [0.95, 0.95], color='r', a
            plt.plot(crit_data.iloc[:,index],y_pred[:,index],'.')
            error = score_func(y_pred[:,index],crit_data.iloc[:,index])
            plt.title('{0}, Error: {1:.04f}'.format(crit_data.columns[index], error))
            plt.xlabel('True Value')

        plt.ylabel('Predicted Value')
        print('Overall error: {0:.04f}'.format(score_func(y_pred, crit_data)))
```

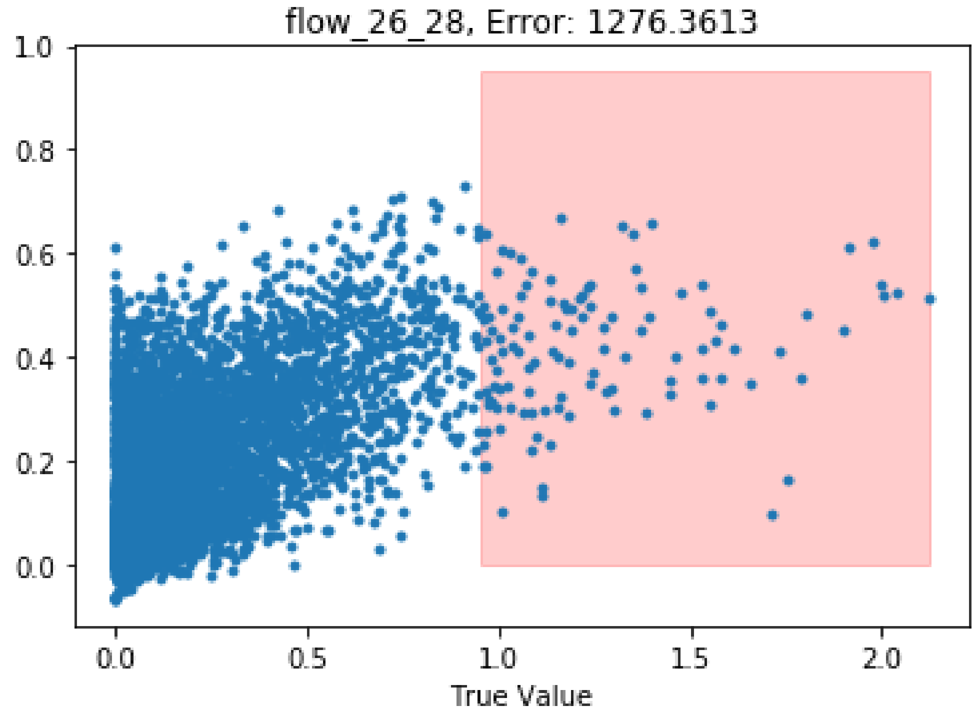
```
Overall error: 21640.1275
```

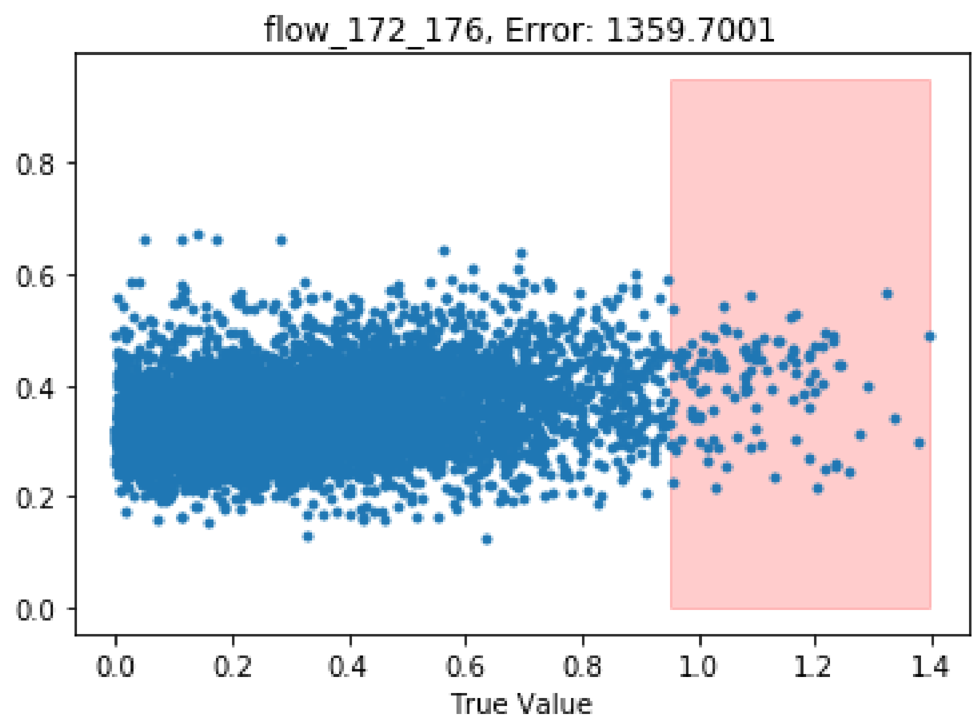

flow_89_94, Error: 1168.8147
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.5
1.0
1.5
2.0
2.5
True Value

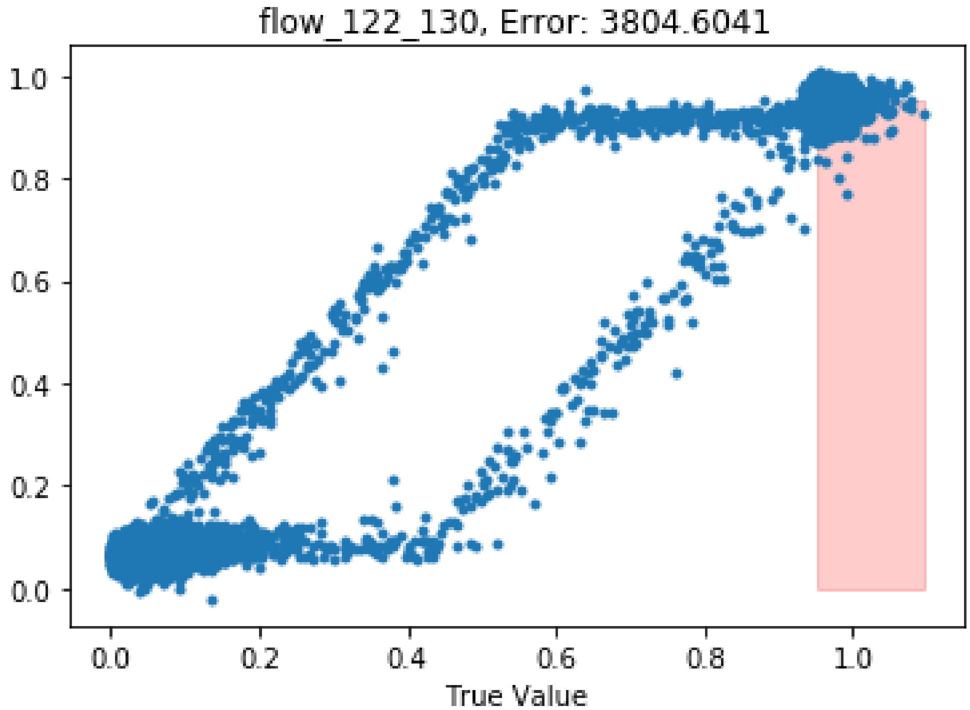

flow_20_23, Error: 847.1121
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
True Value

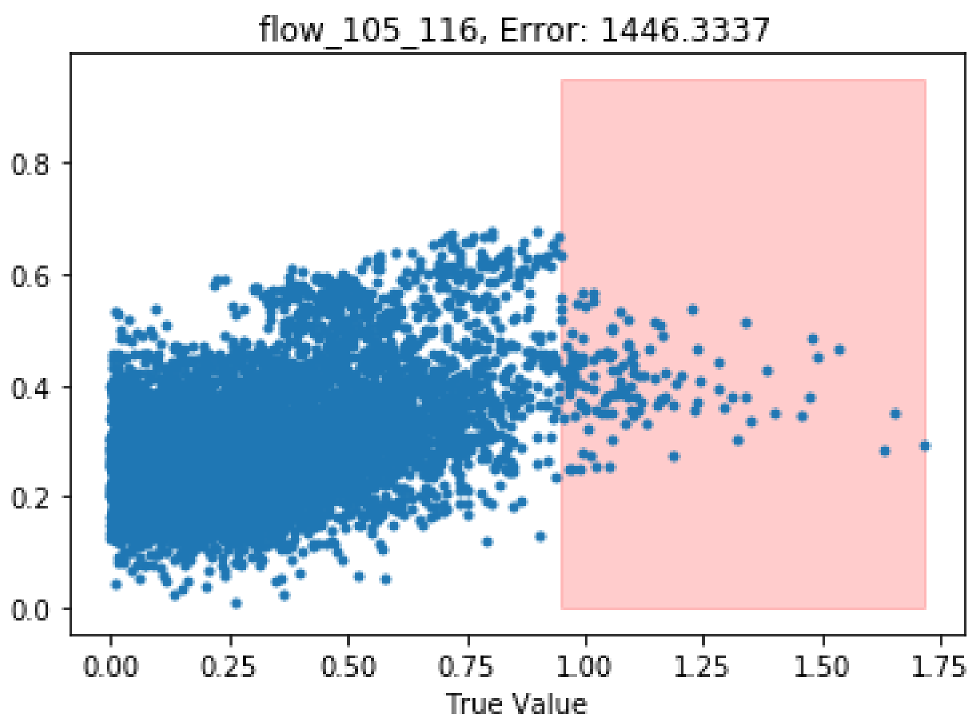

flow_49_64, Error: 1292.2670
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
True Value

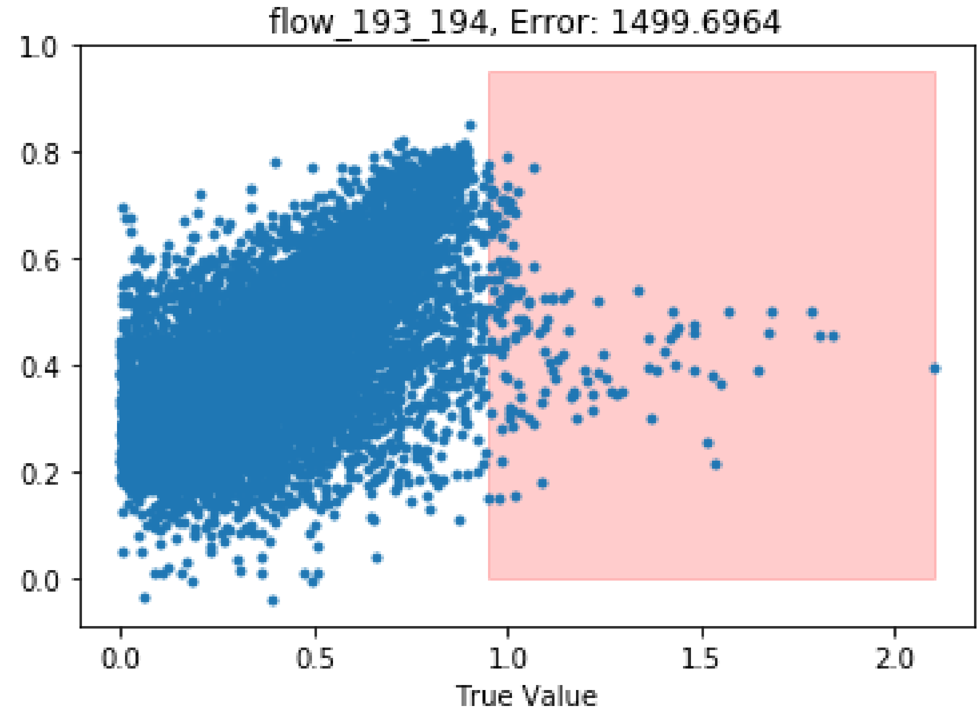

flow_101_532, Error: 7670.8730
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
True Value

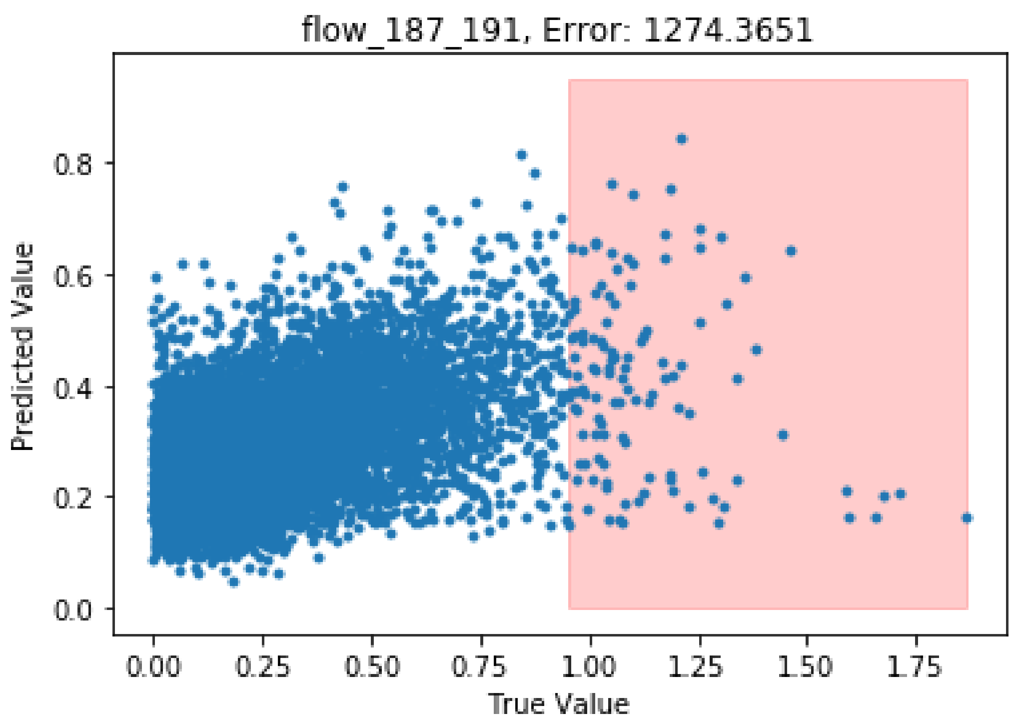

flow_26_28, Error: 1276.3613
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.5
1.0
1.5
2.0
True Value


flow_172_176, Error: 1359.7001
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
True Value


flow_122_130, Error: 3804.6041
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
True Value


flow_105_116, Error: 1446.3337
0.8
0.6
0.4
0.2
0.0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
True Value


flow_193_194, Error: 1499.6964
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.5
1.0
1.5
2.0
True Value


flow_187_191, Error: 1274.3651
Predicted Value
0.8
0.6
0.4
0.2
0.0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
True Value

Q#6 Would you recommend using Linear Regression for estimating line criticality indices? Why/why not?

Using linear regression is a good idea, if the data you're working with contains a linear relationship. Otherwise the approximation you make, will not be usefull when predicting from a dataset

2 Neural Network

You should now produce a neural network that can estimate criticality indices. Split your data into a training and test set, build your neural network below, and use the score_func defined above to estimate your model quality.

Q#7 Explain why you chose the layers, nodes and activation functions you did. (No wrong answers, we want to know your thought process!) What is the best score you can get with a single layer?

For the NN Linear regression We tried using the linear activation function. This gives a slow estimation, but gives a very good approximation. We ended up using the rectified linear activation function "relu", this gives a really quick and consistent estimation, but appears limited in the precission it can reach

We use the optimizer adam, as it is a memory light, computationally efficient algorithm From reading, the standard parameters of tensorflow, should be pretty good. However we tweaked hte learning rate, to be slightly faster 0.001 -> 0.05. As this gave quick results, but still seem to narrow in on the same result quickly.

We made the neural network, with a single layer, using 10 nodes. We try to keepit simple with small amount of layers. and we get a pretty good approximation using just one layer

using linear, the best score was(however it was very inconsistent) Epoch 50/50 6648/6648 [==============================] - 0s - loss: 0.1149
Score: 5144.7368582568579

Using relu, the best score was Epoch 3/3 6648/6648 [==============================] - 0s - loss: 0.2178
Score: 16170.9507471

Both results are better than the linear regression function

```
In [6]: # Split data into training and test

        # Using the sklearn's builtin function, we split the data, so that 1/5 will be used fo
        # Given a random_state, to make the data reproducable
        from sklearn.model_selection import train_test_split

        x_train, x_test, y_train, y_test = train_test_split(field_data, crit_data, test_size=0
```

```
In [7]: #INSERT Neural Network Code here for a linear regression.
        random_state=100
        from keras.models import Sequential
        from keras.layers import Dense, Activation
        from keras import optimizers

        model = Sequential()
        model.add(Dense(10, input_shape=(20,)))
        model.add(Activation('relu'))
```

```
adam = optimizers.Adam(lr=0.05, beta_1=0.95,
beta_2=0.999, epsilon=1e-08, decay=0.0)
model.compile(loss='mean_squared_error', optimizer=adam)
model.fit(x_train.values,y_train.values,
epochs = 3, batch_size=250, shuffle=False)
y_pred = model.predict(x_test.values, batch_size = 1000)

print("Score: ", score_func(y_pred, y_test))
```

```
Using TensorFlow backend.


Epoch 1/3
7027/7027 [==============================] - 0s - loss: 18560.5444
Epoch 2/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 3/3
7027/7027 [==============================] - 0s - loss: 0.2187
Score:  16170.9507471
```

3 K-fold cross validation

To ensure that your neural network actually works when presented with new data, take the neural network you defined above, and perform a k-fold cross validation on it.

Q#8 Using a test window size of one tenth of your data (ten-fold cross validation), plot a histogram of the output of score_func for the validation. Tweak your neural network to achieve the lowest mean score.H

We have done K-fold for both the relu and linear activation. it clearly shows that relu gives consistent results fast, however this is probably due to relu being undifferentiable in zero. Which leads to bad learning when values are zero

The linear activation can get better scores, however needs more epochs to reach them, and is not very consistent in the k-fold. However this can probably be fixed by more finetuning optimizer.

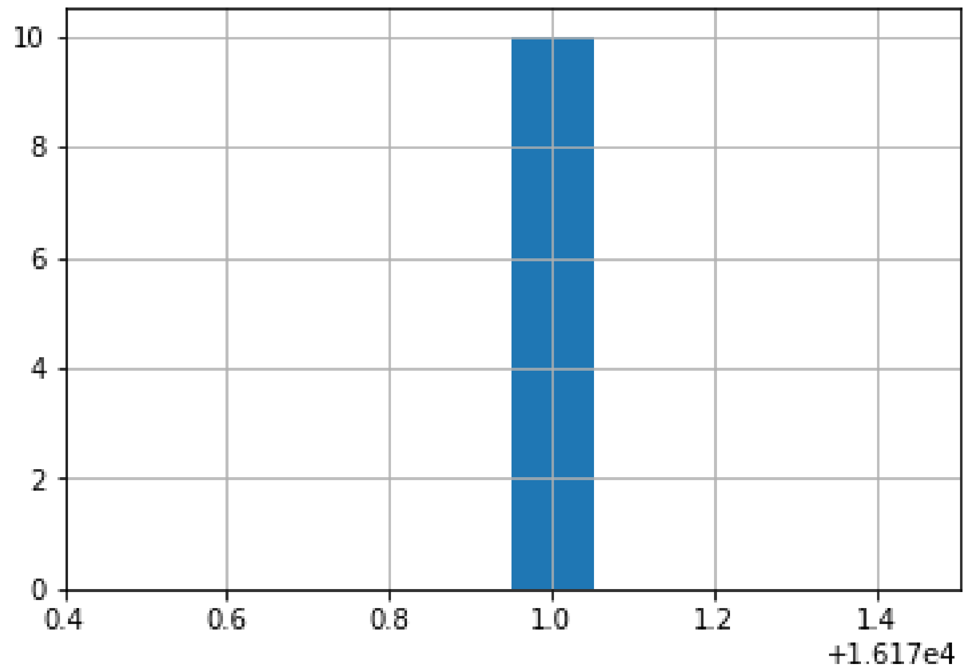
```
In [8]: # Your k-fold code goes here.

        from sklearn.model_selection import KFold
        import matplotlib.pyplot as plt
        import numpy as np
        from keras.models import Sequential
        from keras.layers import Dense, Activation
        from keras import optimizers

        ErrorList = list()

        kf1 = KFold(n_splits=10,shuffle=True)

        for train_index, test_index in kf1.split(field_data):
```

```
        X_train, X_test = field_data.iloc[train_index], field_data.iloc[test_index]
        Y_train, Y_test = crit_data.iloc[train_index], crit_data.iloc[test_index]
        model = Sequential()
        model.add(Dense(10, input_shape=(20,)))
        model.add(Activation('relu'))

        adam = optimizers.Adam(lr=0.05, beta_1=0.95,
                                beta_2=0.999, epsilon=1e-08, decay=0.0)
        model.compile(loss='mean_squared_error', optimizer=adam)
        model.fit(x_train.values,y_train.values,
                            epochs=3, batch_size=250, shuffle=True)
        y_pred = model.predict(x_test.values, batch_size=1000)


        ErrorList.append(score_func(y_pred, y_test))
```

```
Epoch 1/3
7027/7027 [==============================] - 0s - loss: 24883.4991
Epoch 2/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 3/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 1/3
7027/7027 [==============================] - 0s - loss: 10146.9320
Epoch 2/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 3/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 1/3
7027/7027 [==============================] - 0s - loss: 14243.2632
Epoch 2/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 3/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 1/3
7027/7027 [==============================] - 0s - loss: 2355.7900
Epoch 2/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 3/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 1/3
7027/7027 [==============================] - 0s - loss: 8136.5870
Epoch 2/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 3/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 1/3
7027/7027 [==============================] - 0s - loss: 26687.7506
```

```
Epoch 2/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 3/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 1/3
7027/7027 [==============================] - 0s - loss: 24136.2189
Epoch 2/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 3/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 1/3
7027/7027 [==============================] - 0s - loss: 12088.0795
Epoch 2/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 3/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 1/3
7027/7027 [==============================] - 0s - loss: 9964.4092
Epoch 2/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 3/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 1/3
7027/7027 [==============================] - 0s - loss: 8558.6671
Epoch 2/3
7027/7027 [==============================] - 0s - loss: 0.2187
Epoch 3/3
7027/7027 [==============================] - 0s - loss: 0.2187
```

In [9]:
```
plt.hist(ErrorList)
plt.grid(True)
plt.show()

print("Mean score: " , np.mean(ErrorList))
print("KFold scores: ", ErrorList)
```




```
Mean score:  16170.9507471
KFold scores:  [16170.950747078065, 16170.950747078065, 16170.950747078065, 16170.950747078065
```

```
In [10]: # k-fold of the linear version

         from sklearn.model_selection import KFold
         import matplotlib.pyplot as plt
         import numpy as np
         from keras.models import Sequential
         from keras.layers import Dense, Activation
         from keras import optimizers

         ErrorList2 = list()

         kf1 = KFold(n_splits=10,shuffle=True)
         for train_index, test_index in kf1.split(field_data):
             X_train, X_test = field_data.iloc[train_index], field_data.iloc[test_index]
             Y_train, Y_test = crit_data.iloc[train_index], crit_data.iloc[test_index]

             model = Sequential()
             model.add(Dense(10, input_shape=(20,)))
             model.add(Activation('linear'))
             model.add(Dense(10,))
             model.add(Activation('linear'))
```

```
adam = optimizers.Adam(lr=0.0095, beta_1=0.97,
                        beta_2=0.999, epsilon=1e-085, decay=0.0)
model.compile(loss='mean_squared_error', optimizer=adam)
history1 = model.fit(x_train.values,y_train.values,
                     epochs=50, batch_size=100, shuffle=True)
y_pred2 = model.predict(x_test.values, batch_size=1000)
ErrorList2.append(score_func(y_pred2, y_test))
```

```
Epoch 1/50
7027/7027 [==============================] - 0s - loss: 59553.2305
Epoch 2/50
7027/7027 [==============================] - 0s - loss: 3499.1809
Epoch 3/50
7027/7027 [==============================] - 0s - loss: 513.1609
Epoch 4/50
7027/7027 [==============================] - 0s - loss: 150.5774
Epoch 5/50
7027/7027 [==============================] - 0s - loss: 63.0348
Epoch 6/50
7027/7027 [==============================] - ETA: 0s - loss: 38.12 - 0s - loss: 36.5303
Epoch 7/50
7027/7027 [==============================] - 0s - loss: 24.4236
Epoch 8/50
7027/7027 [==============================] - 0s - loss: 17.6141
Epoch 9/50
7027/7027 [==============================] - 0s - loss: 13.2560
Epoch 10/50
7027/7027 [==============================] - 0s - loss: 10.2426
Epoch 11/50
7027/7027 [==============================] - 0s - loss: 8.0990
Epoch 12/50
7027/7027 [==============================] - 0s - loss: 6.4924
Epoch 13/50
7027/7027 [==============================] - 0s - loss: 5.2488
Epoch 14/50
7027/7027 [==============================] - 0s - loss: 4.2998
Epoch 15/50
7027/7027 [==============================] - 0s - loss: 3.5582
Epoch 16/50
7027/7027 [==============================] - 0s - loss: 2.9434
Epoch 17/50
7027/7027 [==============================] - 0s - loss: 2.4544
Epoch 18/50
7027/7027 [==============================] - 0s - loss: 2.0724
Epoch 19/50
7027/7027 [==============================] - 0s - loss: 1.7682
Epoch 20/50
```

```
7027/7027 [==============================] - 0s - loss: 1.5108
Epoch 21/50
7027/7027 [==============================] - 0s - loss: 1.3081
Epoch 22/50
7027/7027 [==============================] - 0s - loss: 1.1432
Epoch 23/50
7027/7027 [==============================] - 0s - loss: 1.0072
Epoch 24/50
7027/7027 [==============================] - 0s - loss: 0.8912
Epoch 25/50
7027/7027 [==============================] - 0s - loss: 0.7984
Epoch 26/50
7027/7027 [==============================] - 0s - loss: 0.7204
Epoch 27/50
7027/7027 [==============================] - 0s - loss: 0.6531
Epoch 28/50
7027/7027 [==============================] - 0s - loss: 0.5988
Epoch 29/50
7027/7027 [==============================] - 0s - loss: 0.5462
Epoch 30/50
7027/7027 [==============================] - 0s - loss: 0.5044
Epoch 31/50
7027/7027 [==============================] - 0s - loss: 0.4653
Epoch 32/50
7027/7027 [==============================] - 0s - loss: 0.4304
Epoch 33/50
7027/7027 [==============================] - 0s - loss: 0.3963
Epoch 34/50
7027/7027 [==============================] - 0s - loss: 0.3671
Epoch 35/50
7027/7027 [==============================] - 0s - loss: 0.3417
Epoch 36/50
7027/7027 [==============================] - 0s - loss: 0.3205
Epoch 37/50
7027/7027 [==============================] - 0s - loss: 0.2976
Epoch 38/50
7027/7027 [==============================] - 0s - loss: 0.2746
Epoch 39/50
7027/7027 [==============================] - 0s - loss: 0.2565
Epoch 40/50
7027/7027 [==============================] - 0s - loss: 0.2410
Epoch 41/50
7027/7027 [==============================] - 0s - loss: 0.2272
Epoch 42/50
7027/7027 [==============================] - 0s - loss: 0.2121
Epoch 43/50
7027/7027 [==============================] - 0s - loss: 0.1972
Epoch 44/50
```

```
7027/7027 [==============================] - 0s - loss: 0.1831
Epoch 45/50
7027/7027 [==============================] - 0s - loss: 0.1719
Epoch 46/50
7027/7027 [==============================] - 0s - loss: 0.1615
Epoch 47/50
7027/7027 [==============================] - 0s - loss: 0.1518
Epoch 48/50
7027/7027 [==============================] - 0s - loss: 0.1442
Epoch 49/50
7027/7027 [==============================] - 0s - loss: 0.1383
Epoch 50/50
7027/7027 [==============================] - 0s - loss: 0.1271
Epoch 1/50
7027/7027 [==============================] - 0s - loss: 114955.2955
Epoch 2/50
7027/7027 [==============================] - 0s - loss: 6746.3088
Epoch 3/50
7027/7027 [==============================] - 0s - loss: 1326.9138
Epoch 4/50
7027/7027 [==============================] - 0s - loss: 531.1920
Epoch 5/50
7027/7027 [==============================] - 0s - loss: 286.9908
Epoch 6/50
7027/7027 [==============================] - 0s - loss: 175.3462
Epoch 7/50
7027/7027 [==============================] - 0s - loss: 113.3401
Epoch 8/50
7027/7027 [==============================] - 0s - loss: 75.9009
Epoch 9/50
7027/7027 [==============================] - 0s - loss: 52.6600
Epoch 10/50
7027/7027 [==============================] - 0s - loss: 37.5715
Epoch 11/50
7027/7027 [==============================] - 0s - loss: 27.5090
Epoch 12/50
7027/7027 [==============================] - 0s - loss: 20.6972
Epoch 13/50
7027/7027 [==============================] - 0s - loss: 15.9652
Epoch 14/50
7027/7027 [==============================] - 0s - loss: 12.6670
Epoch 15/50
7027/7027 [==============================] - 0s - loss: 10.2523
Epoch 16/50
7027/7027 [==============================] - 0s - loss: 8.5075
Epoch 17/50
7027/7027 [==============================] - 0s - loss: 7.2079
Epoch 18/50
```

```
7027/7027 [==============================] - 0s - loss: 6.2056
Epoch 19/50
7027/7027 [==============================] - 0s - loss: 5.4271
Epoch 20/50
7027/7027 [==============================] - 0s - loss: 4.7594
Epoch 21/50
7027/7027 [==============================] - 0s - loss: 4.2474
Epoch 22/50
7027/7027 [==============================] - 0s - loss: 3.8238
Epoch 23/50
7027/7027 [==============================] - 0s - loss: 3.4047
Epoch 24/50
7027/7027 [==============================] - 0s - loss: 3.0649
Epoch 25/50
7027/7027 [==============================] - 0s - loss: 2.7782
Epoch 26/50
7027/7027 [==============================] - 0s - loss: 2.5250
Epoch 27/50
7027/7027 [==============================] - 0s - loss: 2.2978
Epoch 28/50
7027/7027 [==============================] - 0s - loss: 2.0829
Epoch 29/50
7027/7027 [==============================] - 0s - loss: 1.8851
Epoch 30/50
7027/7027 [==============================] - 0s - loss: 1.7167
Epoch 31/50
7027/7027 [==============================] - 0s - loss: 1.5692
Epoch 32/50
7027/7027 [==============================] - 0s - loss: 1.4344
Epoch 33/50
7027/7027 [==============================] - 0s - loss: 1.3090
Epoch 34/50
7027/7027 [==============================] - 0s - loss: 1.1958
Epoch 35/50
7027/7027 [==============================] - 0s - loss: 1.1037
Epoch 36/50
7027/7027 [==============================] - 0s - loss: 1.0204
Epoch 37/50
7027/7027 [==============================] - 0s - loss: 0.9270
Epoch 38/50
7027/7027 [==============================] - 0s - loss: 0.8570
Epoch 39/50
7027/7027 [==============================] - 0s - loss: 0.8055
Epoch 40/50
7027/7027 [==============================] - 0s - loss: 0.7372
Epoch 41/50
7027/7027 [==============================] - 0s - loss: 0.6818
Epoch 42/50
```

```
7027/7027 [==============================] - 0s - loss: 0.6349
Epoch 43/50
7027/7027 [==============================] - 0s - loss: 0.5954
Epoch 44/50
7027/7027 [==============================] - 0s - loss: 0.5557
Epoch 45/50
7027/7027 [==============================] - 0s - loss: 0.5190
Epoch 46/50
7027/7027 [==============================] - 0s - loss: 0.4871
Epoch 47/50
7027/7027 [==============================] - 0s - loss: 0.4591
Epoch 48/50
7027/7027 [==============================] - 0s - loss: 0.4395
Epoch 49/50
7027/7027 [==============================] - 0s - loss: 0.4238
Epoch 50/50
7027/7027 [==============================] - 0s - loss: 0.3988
Epoch 1/50
7027/7027 [==============================] - 0s - loss: 14633.5355
Epoch 2/50
7027/7027 [==============================] - 0s - loss: 759.5428
Epoch 3/50
7027/7027 [==============================] - 0s - loss: 115.1763
Epoch 4/50
7027/7027 [==============================] - 0s - loss: 31.4628
Epoch 5/50
7027/7027 [==============================] - 0s - loss: 14.8466
Epoch 6/50
7027/7027 [==============================] - 0s - loss: 9.3822
Epoch 7/50
7027/7027 [==============================] - 0s - loss: 6.6308
Epoch 8/50
7027/7027 [==============================] - 0s - loss: 4.9603
Epoch 9/50
7027/7027 [==============================] - 0s - loss: 3.8402
Epoch 10/50
7027/7027 [==============================] - 0s - loss: 3.0552
Epoch 11/50
7027/7027 [==============================] - 0s - loss: 2.4643
Epoch 12/50
7027/7027 [==============================] - 0s - loss: 2.0370
Epoch 13/50
7027/7027 [==============================] - 0s - loss: 1.6949
Epoch 14/50
7027/7027 [==============================] - 0s - loss: 1.4420
Epoch 15/50
7027/7027 [==============================] - 0s - loss: 1.2264
Epoch 16/50
```

```
7027/7027 [==============================] - 0s - loss: 1.0574
Epoch 17/50
7027/7027 [==============================] - 0s - loss: 0.9226
Epoch 18/50
7027/7027 [==============================] - 0s - loss: 0.8056
Epoch 19/50
7027/7027 [==============================] - 0s - loss: 0.7108
Epoch 20/50
7027/7027 [==============================] - 0s - loss: 0.6320
Epoch 21/50
7027/7027 [==============================] - 0s - loss: 0.5657
Epoch 22/50
7027/7027 [==============================] - 0s - loss: 0.5091
Epoch 23/50
7027/7027 [==============================] - 0s - loss: 0.4580
Epoch 24/50
7027/7027 [==============================] - 0s - loss: 0.4159
Epoch 25/50
7027/7027 [==============================] - 0s - loss: 0.3817
Epoch 26/50
7027/7027 [==============================] - 0s - loss: 0.3513
Epoch 27/50
7027/7027 [==============================] - 0s - loss: 0.3209
Epoch 28/50
7027/7027 [==============================] - 0s - loss: 0.2944
Epoch 29/50
7027/7027 [==============================] - 0s - loss: 0.2726
Epoch 30/50
7027/7027 [==============================] - 0s - loss: 0.2526
Epoch 31/50
7027/7027 [==============================] - 0s - loss: 0.2347
Epoch 32/50
7027/7027 [==============================] - 0s - loss: 0.2168
Epoch 33/50
7027/7027 [==============================] - 0s - loss: 0.2026
Epoch 34/50
7027/7027 [==============================] - 0s - loss: 0.1894
Epoch 35/50
7027/7027 [==============================] - 0s - loss: 0.1779
Epoch 36/50
7027/7027 [==============================] - 0s - loss: 0.1678
Epoch 37/50
7027/7027 [==============================] - 0s - loss: 0.1585
Epoch 38/50
7027/7027 [==============================] - 0s - loss: 0.1489
Epoch 39/50
7027/7027 [==============================] - 0s - loss: 0.1404
Epoch 40/50
```

```
7027/7027 [==============================] - 0s - loss: 0.1326
Epoch 41/50
7027/7027 [==============================] - 0s - loss: 0.1290
Epoch 42/50
7027/7027 [==============================] - 0s - loss: 0.1220
Epoch 43/50
7027/7027 [==============================] - 0s - loss: 0.1135
Epoch 44/50
7027/7027 [==============================] - 0s - loss: 0.1099
Epoch 45/50
7027/7027 [==============================] - 0s - loss: 0.1051
Epoch 46/50
7027/7027 [==============================] - 0s - loss: 0.1022
Epoch 47/50
7027/7027 [==============================] - 0s - loss: 0.0964
Epoch 48/50
7027/7027 [==============================] - 0s - loss: 0.0934
Epoch 49/50
7027/7027 [==============================] - 0s - loss: 0.0951
Epoch 50/50
7027/7027 [==============================] - 0s - loss: 0.0897
Epoch 1/50
7027/7027 [==============================] - 0s - loss: 62513.0449
Epoch 2/50
7027/7027 [==============================] - 0s - loss: 3883.9933
Epoch 3/50
7027/7027 [==============================] - 0s - loss: 609.3667
Epoch 4/50
7027/7027 [==============================] - 0s - loss: 206.1883
Epoch 5/50
7027/7027 [==============================] - 0s - loss: 102.7927
Epoch 6/50
7027/7027 [==============================] - 0s - loss: 64.1737
Epoch 7/50
7027/7027 [==============================] - 0s - loss: 43.9821
Epoch 8/50
7027/7027 [==============================] - 0s - loss: 31.3364
Epoch 9/50
7027/7027 [==============================] - 0s - loss: 22.8291
Epoch 10/50
7027/7027 [==============================] - 0s - loss: 16.9493
Epoch 11/50
7027/7027 [==============================] - 0s - loss: 12.7220
Epoch 12/50
7027/7027 [==============================] - 0s - loss: 9.7045
Epoch 13/50
7027/7027 [==============================] - 0s - loss: 7.5177
Epoch 14/50
```

```
7027/7027 [==============================] - 0s - loss: 5.9181
Epoch 15/50
7027/7027 [==============================] - 0s - loss: 4.7316
Epoch 16/50
7027/7027 [==============================] - 0s - loss: 3.8380
Epoch 17/50
7027/7027 [==============================] - 0s - loss: 3.1585
Epoch 18/50
7027/7027 [==============================] - 0s - loss: 2.6363
Epoch 19/50
7027/7027 [==============================] - 0s - loss: 2.2275
Epoch 20/50
7027/7027 [==============================] - 0s - loss: 1.9024
Epoch 21/50
7027/7027 [==============================] - 0s - loss: 1.6456
Epoch 22/50
7027/7027 [==============================] - 0s - loss: 1.4412
Epoch 23/50
7027/7027 [==============================] - 0s - loss: 1.2676
Epoch 24/50
7027/7027 [==============================] - 0s - loss: 1.1242
Epoch 25/50
7027/7027 [==============================] - 0s - loss: 1.0074
Epoch 26/50
7027/7027 [==============================] - 0s - loss: 0.9022
Epoch 27/50
7027/7027 [==============================] - 0s - loss: 0.8119
Epoch 28/50
7027/7027 [==============================] - 0s - loss: 0.7394
Epoch 29/50
7027/7027 [==============================] - 0s - loss: 0.6740
Epoch 30/50
7027/7027 [==============================] - 0s - loss: 0.6162
Epoch 31/50
7027/7027 [==============================] - 0s - loss: 0.5645
Epoch 32/50
7027/7027 [==============================] - 0s - loss: 0.5203
Epoch 33/50
7027/7027 [==============================] - 0s - loss: 0.4781
Epoch 34/50
7027/7027 [==============================] - 0s - loss: 0.4430
Epoch 35/50
7027/7027 [==============================] - 0s - loss: 0.4148
Epoch 36/50
7027/7027 [==============================] - 0s - loss: 0.3851
Epoch 37/50
7027/7027 [==============================] - 0s - loss: 0.3619
Epoch 38/50
```

```
7027/7027 [==============================] - 0s - loss: 0.3382
Epoch 39/50
7027/7027 [==============================] - 0s - loss: 0.3158
Epoch 40/50
7027/7027 [==============================] - 0s - loss: 0.2977
Epoch 41/50
7027/7027 [==============================] - 0s - loss: 0.2813
Epoch 42/50
7027/7027 [==============================] - 0s - loss: 0.2659
Epoch 43/50
7027/7027 [==============================] - 0s - loss: 0.2531
Epoch 44/50
7027/7027 [==============================] - 0s - loss: 0.2400
Epoch 45/50
7027/7027 [==============================] - 0s - loss: 0.2274
Epoch 46/50
7027/7027 [==============================] - 0s - loss: 0.2172
Epoch 47/50
7027/7027 [==============================] - 0s - loss: 0.2077
Epoch 48/50
7027/7027 [==============================] - 0s - loss: 0.2012
Epoch 49/50
7027/7027 [==============================] - 0s - loss: 0.1922
Epoch 50/50
7027/7027 [==============================] - 0s - loss: 0.1835
Epoch 1/50
7027/7027 [==============================] - 0s - loss: 82867.0885
Epoch 2/50
7027/7027 [==============================] - 0s - loss: 3519.6751
Epoch 3/50
7027/7027 [==============================] - 0s - loss: 978.8057
Epoch 4/50
7027/7027 [==============================] - 0s - loss: 372.2967
Epoch 5/50
7027/7027 [==============================] - 0s - loss: 219.4658
Epoch 6/50
7027/7027 [==============================] - 0s - loss: 153.7309
Epoch 7/50
7027/7027 [==============================] - 0s - loss: 115.8111
Epoch 8/50
7027/7027 [==============================] - 0s - loss: 90.0539
Epoch 9/50
7027/7027 [==============================] - 0s - loss: 72.2049
Epoch 10/50
7027/7027 [==============================] - 0s - loss: 58.8328
Epoch 11/50
7027/7027 [==============================] - 0s - loss: 48.5932
Epoch 12/50
```

```
7027/7027 [==============================] - 0s - loss: 40.3580
Epoch 13/50
7027/7027 [==============================] - 0s - loss: 34.0186
Epoch 14/50
7027/7027 [==============================] - 0s - loss: 28.9015
Epoch 15/50
7027/7027 [==============================] - 0s - loss: 24.6934
Epoch 16/50
7027/7027 [==============================] - 0s - loss: 21.2386
Epoch 17/50
7027/7027 [==============================] - 0s - loss: 18.3301
Epoch 18/50
7027/7027 [==============================] - 0s - loss: 15.8260
Epoch 19/50
7027/7027 [==============================] - 0s - loss: 13.8053
Epoch 20/50
7027/7027 [==============================] - 0s - loss: 12.0239
Epoch 21/50
7027/7027 [==============================] - 0s - loss: 10.4770
Epoch 22/50
7027/7027 [==============================] - 0s - loss: 9.1666
Epoch 23/50
7027/7027 [==============================] - 0s - loss: 8.0175
Epoch 24/50
7027/7027 [==============================] - 0s - loss: 7.0209
Epoch 25/50
7027/7027 [==============================] - 0s - loss: 6.1532
Epoch 26/50
7027/7027 [==============================] - 0s - loss: 5.4090
Epoch 27/50
7027/7027 [==============================] - 0s - loss: 4.7617
Epoch 28/50
7027/7027 [==============================] - 0s - loss: 4.1610
Epoch 29/50
7027/7027 [==============================] - 0s - loss: 3.6409
Epoch 30/50
7027/7027 [==============================] - 0s - loss: 3.1869
Epoch 31/50
7027/7027 [==============================] - 0s - loss: 2.7721
Epoch 32/50
7027/7027 [==============================] - 0s - loss: 2.4189
Epoch 33/50
7027/7027 [==============================] - 0s - loss: 2.1144
Epoch 34/50
7027/7027 [==============================] - 0s - loss: 1.8439
Epoch 35/50
7027/7027 [==============================] - 0s - loss: 1.5981
Epoch 36/50
```

```
7027/7027 [==============================] - 0s - loss: 1.3899
Epoch 37/50
7027/7027 [==============================] - 0s - loss: 1.2124
Epoch 38/50
7027/7027 [==============================] - 0s - loss: 1.0510
Epoch 39/50
7027/7027 [==============================] - 0s - loss: 0.9111
Epoch 40/50
7027/7027 [==============================] - 0s - loss: 0.7902
Epoch 41/50
7027/7027 [==============================] - 0s - loss: 0.6897
Epoch 42/50
7027/7027 [==============================] - 0s - loss: 0.5977
Epoch 43/50
7027/7027 [==============================] - 0s - loss: 0.5253
Epoch 44/50
7027/7027 [==============================] - 0s - loss: 0.4615
Epoch 45/50
7027/7027 [==============================] - 0s - loss: 0.4047
Epoch 46/50
7027/7027 [==============================] - 0s - loss: 0.3594
Epoch 47/50
7027/7027 [==============================] - 0s - loss: 0.3207
Epoch 48/50
7027/7027 [==============================] - 0s - loss: 0.2904
Epoch 49/50
7027/7027 [==============================] - 0s - loss: 0.2611
Epoch 50/50
7027/7027 [==============================] - 0s - loss: 0.2366
Epoch 1/50
7027/7027 [==============================] - 0s - loss: 38124.8953
Epoch 2/50
7027/7027 [==============================] - 0s - loss: 2301.3722
Epoch 3/50
7027/7027 [==============================] - 0s - loss: 385.1148
Epoch 4/50
7027/7027 [==============================] - 0s - loss: 103.9710
Epoch 5/50
7027/7027 [==============================] - 0s - loss: 48.3758
Epoch 6/50
7027/7027 [==============================] - 0s - loss: 28.6718
Epoch 7/50
7027/7027 [==============================] - 0s - loss: 18.7931
Epoch 8/50
7027/7027 [==============================] - 0s - loss: 12.8911
Epoch 9/50
7027/7027 [==============================] - 0s - loss: 9.2374
Epoch 10/50
```

```
7027/7027 [==============================] - 0s - loss: 6.8224
Epoch 11/50
7027/7027 [==============================] - 0s - loss: 5.1958
Epoch 12/50
7027/7027 [==============================] - ETA: 0s - loss: 4.175 - 0s - loss: 4.0797
Epoch 13/50
7027/7027 [==============================] - 0s - loss: 3.3059
Epoch 14/50
7027/7027 [==============================] - 0s - loss: 2.7158
Epoch 15/50
7027/7027 [==============================] - 0s - loss: 2.2927
Epoch 16/50
7027/7027 [==============================] - 0s - loss: 1.9754
Epoch 17/50
7027/7027 [==============================] - 0s - loss: 1.7172
Epoch 18/50
7027/7027 [==============================] - 0s - loss: 1.5129
Epoch 19/50
7027/7027 [==============================] - 0s - loss: 1.3584
Epoch 20/50
7027/7027 [==============================] - 0s - loss: 1.2121
Epoch 21/50
7027/7027 [==============================] - 0s - loss: 1.0890
Epoch 22/50
7027/7027 [==============================] - 0s - loss: 0.9772
Epoch 23/50
7027/7027 [==============================] - 0s - loss: 0.8825
Epoch 24/50
7027/7027 [==============================] - 0s - loss: 0.8107
Epoch 25/50
7027/7027 [==============================] - 0s - loss: 0.7378
Epoch 26/50
7027/7027 [==============================] - 0s - loss: 0.6599
Epoch 27/50
7027/7027 [==============================] - 0s - loss: 0.5857
Epoch 28/50
7027/7027 [==============================] - 0s - loss: 0.5392
Epoch 29/50
7027/7027 [==============================] - 0s - loss: 0.4767
Epoch 30/50
7027/7027 [==============================] - 0s - loss: 0.4259
Epoch 31/50
7027/7027 [==============================] - 0s - loss: 0.3864
Epoch 32/50
7027/7027 [==============================] - 0s - loss: 0.3475
Epoch 33/50
7027/7027 [==============================] - 0s - loss: 0.3157
Epoch 34/50
```

```
7027/7027 [==============================] - 0s - loss: 0.2808
Epoch 35/50
7027/7027 [==============================] - 0s - loss: 0.2586
Epoch 36/50
7027/7027 [==============================] - 0s - loss: 0.2307
Epoch 37/50
7027/7027 [==============================] - 0s - loss: 0.2168
Epoch 38/50
7027/7027 [==============================] - 0s - loss: 0.1974
Epoch 39/50
7027/7027 [==============================] - 0s - loss: 0.1825
Epoch 40/50
7027/7027 [==============================] - 0s - loss: 0.1680
Epoch 41/50
7027/7027 [==============================] - 0s - loss: 0.1610
Epoch 42/50
7027/7027 [==============================] - 0s - loss: 0.1474
Epoch 43/50
7027/7027 [==============================] - 0s - loss: 0.1378
Epoch 44/50
7027/7027 [==============================] - 0s - loss: 0.1332
Epoch 45/50
7027/7027 [==============================] - 0s - loss: 0.1243
Epoch 46/50
7027/7027 [==============================] - 0s - loss: 0.1178
Epoch 47/50
7027/7027 [==============================] - 0s - loss: 0.1149
Epoch 48/50
7027/7027 [==============================] - 0s - loss: 0.1112
Epoch 49/50
7027/7027 [==============================] - 0s - loss: 0.1052
Epoch 50/50
7027/7027 [==============================] - 0s - loss: 0.1048
Epoch 1/50
7027/7027 [==============================] - 0s - loss: 21925.3169
Epoch 2/50
7027/7027 [==============================] - 0s - loss: 1259.6024
Epoch 3/50
7027/7027 [==============================] - 0s - loss: 211.1487
Epoch 4/50
7027/7027 [==============================] - 0s - loss: 56.7484
Epoch 5/50
7027/7027 [==============================] - 0s - loss: 27.5073
Epoch 6/50
7027/7027 [==============================] - 0s - loss: 16.8844
Epoch 7/50
7027/7027 [==============================] - 0s - loss: 12.0700
Epoch 8/50
```

```
7027/7027 [==============================] - 0s - loss: 9.0264
Epoch 9/50
7027/7027 [==============================] - 0s - loss: 7.0763
Epoch 10/50
7027/7027 [==============================] - 0s - loss: 5.7144
Epoch 11/50
7027/7027 [==============================] - 0s - loss: 4.7647
Epoch 12/50
7027/7027 [==============================] - 0s - loss: 3.9578
Epoch 13/50
7027/7027 [==============================] - 0s - loss: 3.3449
Epoch 14/50
7027/7027 [==============================] - 0s - loss: 2.8441
Epoch 15/50
7027/7027 [==============================] - 0s - loss: 2.4435
Epoch 16/50
7027/7027 [==============================] - 0s - loss: 2.1064
Epoch 17/50
7027/7027 [==============================] - 0s - loss: 1.8319
Epoch 18/50
7027/7027 [==============================] - 0s - loss: 1.6120
Epoch 19/50
7027/7027 [==============================] - 0s - loss: 1.4162
Epoch 20/50
7027/7027 [==============================] - 0s - loss: 1.2358
Epoch 21/50
7027/7027 [==============================] - 0s - loss: 1.0989
Epoch 22/50
7027/7027 [==============================] - 0s - loss: 0.9792
Epoch 23/50
7027/7027 [==============================] - 0s - loss: 0.8929
Epoch 24/50
7027/7027 [==============================] - 0s - loss: 0.7790
Epoch 25/50
7027/7027 [==============================] - 0s - loss: 0.7111
Epoch 26/50
7027/7027 [==============================] - 0s - loss: 0.6535
Epoch 27/50
7027/7027 [==============================] - 0s - loss: 0.6222
Epoch 28/50
7027/7027 [==============================] - 0s - loss: 0.5533
Epoch 29/50
7027/7027 [==============================] - 0s - loss: 0.5180
Epoch 30/50
7027/7027 [==============================] - 0s - loss: 0.4836
Epoch 31/50
7027/7027 [==============================] - 0s - loss: 0.4477
Epoch 32/50
```

```
7027/7027 [==============================] - 0s - loss: 0.4262
Epoch 33/50
7027/7027 [==============================] - 0s - loss: 0.4001
Epoch 34/50
7027/7027 [==============================] - 0s - loss: 0.3815
Epoch 35/50
7027/7027 [==============================] - 0s - loss: 0.3605
Epoch 36/50
7027/7027 [==============================] - 0s - loss: 0.3448
Epoch 37/50
7027/7027 [==============================] - 0s - loss: 0.3309
Epoch 38/50
7027/7027 [==============================] - 0s - loss: 0.3225
Epoch 39/50
7027/7027 [==============================] - 0s - loss: 0.3072
Epoch 40/50
7027/7027 [==============================] - 0s - loss: 0.2917
Epoch 41/50
7027/7027 [==============================] - 0s - loss: 0.2794
Epoch 42/50
7027/7027 [==============================] - 0s - loss: 0.2647
Epoch 43/50
7027/7027 [==============================] - 0s - loss: 0.2560
Epoch 44/50
7027/7027 [==============================] - 0s - loss: 0.2525
Epoch 45/50
7027/7027 [==============================] - 0s - loss: 0.2392
Epoch 46/50
7027/7027 [==============================] - 0s - loss: 0.2290
Epoch 47/50
7027/7027 [==============================] - 0s - loss: 0.2275
Epoch 48/50
7027/7027 [==============================] - 0s - loss: 0.2251
Epoch 49/50
7027/7027 [==============================] - 0s - loss: 0.2142
Epoch 50/50
7027/7027 [==============================] - 0s - loss: 0.2068
Epoch 1/50
7027/7027 [==============================] - 0s - loss: 48919.0338
Epoch 2/50
7027/7027 [==============================] - 0s - loss: 2378.2040
Epoch 3/50
7027/7027 [==============================] - 0s - loss: 478.6720
Epoch 4/50
7027/7027 [==============================] - 0s - loss: 149.4937
Epoch 5/50
7027/7027 [==============================] - 0s - loss: 72.6565
Epoch 6/50
```

```
7027/7027 [==============================] - 0s - loss: 44.9915
Epoch 7/50
7027/7027 [==============================] - 0s - loss: 30.9168
Epoch 8/50
7027/7027 [==============================] - 0s - loss: 22.2313
Epoch 9/50
7027/7027 [==============================] - 0s - loss: 16.6117
Epoch 10/50
7027/7027 [==============================] - 0s - loss: 12.7463
Epoch 11/50
7027/7027 [==============================] - 0s - loss: 10.0836
Epoch 12/50
7027/7027 [==============================] - 0s - loss: 8.0286
Epoch 13/50
7027/7027 [==============================] - 0s - loss: 6.5582
Epoch 14/50
7027/7027 [==============================] - 0s - loss: 5.4408
Epoch 15/50
7027/7027 [==============================] - 0s - loss: 4.5977
Epoch 16/50
7027/7027 [==============================] - 0s - loss: 3.9313
Epoch 17/50
7027/7027 [==============================] - 0s - loss: 3.4259
Epoch 18/50
7027/7027 [==============================] - 0s - loss: 3.0385
Epoch 19/50
7027/7027 [==============================] - 0s - loss: 2.7215
Epoch 20/50
7027/7027 [==============================] - 0s - loss: 2.3462
Epoch 21/50
7027/7027 [==============================] - 0s - loss: 2.1108
Epoch 22/50
7027/7027 [==============================] - 0s - loss: 1.8886
Epoch 23/50
7027/7027 [==============================] - 0s - loss: 1.7075
Epoch 24/50
7027/7027 [==============================] - 0s - loss: 1.5542
Epoch 25/50
7027/7027 [==============================] - 0s - loss: 1.4160
Epoch 26/50
7027/7027 [==============================] - 0s - loss: 1.2897
Epoch 27/50
7027/7027 [==============================] - 0s - loss: 1.1836
Epoch 28/50
7027/7027 [==============================] - 0s - loss: 1.0844
Epoch 29/50
7027/7027 [==============================] - 0s - loss: 1.0015
Epoch 30/50
```

```
7027/7027 [==============================] - 0s - loss: 0.9263
Epoch 31/50
7027/7027 [==============================] - 0s - loss: 0.8362
Epoch 32/50
7027/7027 [==============================] - 0s - loss: 0.7781
Epoch 33/50
7027/7027 [==============================] - 0s - loss: 0.7164
Epoch 34/50
7027/7027 [==============================] - 0s - loss: 0.6605
Epoch 35/50
7027/7027 [==============================] - 0s - loss: 0.6151
Epoch 36/50
7027/7027 [==============================] - 0s - loss: 0.5676
Epoch 37/50
7027/7027 [==============================] - 0s - loss: 0.5379
Epoch 38/50
7027/7027 [==============================] - 0s - loss: 0.5009
Epoch 39/50
7027/7027 [==============================] - 0s - loss: 0.4588
Epoch 40/50
7027/7027 [==============================] - 0s - loss: 0.4293
Epoch 41/50
7027/7027 [==============================] - 0s - loss: 0.4087
Epoch 42/50
7027/7027 [==============================] - 0s - loss: 0.3784
Epoch 43/50
7027/7027 [==============================] - 0s - loss: 0.3642
Epoch 44/50
7027/7027 [==============================] - 0s - loss: 0.3558
Epoch 45/50
7027/7027 [==============================] - 0s - loss: 0.3335
Epoch 46/50
7027/7027 [==============================] - 0s - loss: 0.3071
Epoch 47/50
7027/7027 [==============================] - 0s - loss: 0.2925
Epoch 48/50
7027/7027 [==============================] - 0s - loss: 0.2814
Epoch 49/50
7027/7027 [==============================] - 0s - loss: 0.2546
Epoch 50/50
7027/7027 [==============================] - 0s - loss: 0.2386
Epoch 1/50
7027/7027 [==============================] - 0s - loss: 88443.6111
Epoch 2/50
7027/7027 [==============================] - 0s - loss: 6038.8679
Epoch 3/50
7027/7027 [==============================] - 0s - loss: 845.5214
Epoch 4/50
```

```
7027/7027 [==============================] - 0s - loss: 243.1316
Epoch 5/50
7027/7027 [==============================] - 0s - loss: 94.6150
Epoch 6/50
7027/7027 [==============================] - 0s - loss: 51.1874
Epoch 7/50
7027/7027 [==============================] - 0s - loss: 33.3559
Epoch 8/50
7027/7027 [==============================] - 0s - loss: 24.0410
Epoch 9/50
7027/7027 [==============================] - 0s - loss: 18.3223
Epoch 10/50
7027/7027 [==============================] - 0s - loss: 14.4744
Epoch 11/50
7027/7027 [==============================] - 0s - loss: 11.7450
Epoch 12/50
7027/7027 [==============================] - 0s - loss: 9.7126
Epoch 13/50
7027/7027 [==============================] - 0s - loss: 8.1937
Epoch 14/50
7027/7027 [==============================] - 0s - loss: 6.9875
Epoch 15/50
7027/7027 [==============================] - 0s - loss: 6.0222
Epoch 16/50
7027/7027 [==============================] - 0s - loss: 5.2383
Epoch 17/50
7027/7027 [==============================] - 0s - loss: 4.5889
Epoch 18/50
7027/7027 [==============================] - 0s - loss: 4.0395
Epoch 19/50
7027/7027 [==============================] - 0s - loss: 3.5694
Epoch 20/50
7027/7027 [==============================] - 0s - loss: 3.1746
Epoch 21/50
7027/7027 [==============================] - 0s - loss: 2.8249
Epoch 22/50
7027/7027 [==============================] - 0s - loss: 2.5219
Epoch 23/50
7027/7027 [==============================] - 0s - loss: 2.2595
Epoch 24/50
7027/7027 [==============================] - 0s - loss: 2.0325
Epoch 25/50
7027/7027 [==============================] - 0s - loss: 1.8273
Epoch 26/50
7027/7027 [==============================] - 0s - loss: 1.6457
Epoch 27/50
7027/7027 [==============================] - 0s - loss: 1.4866
Epoch 28/50
```

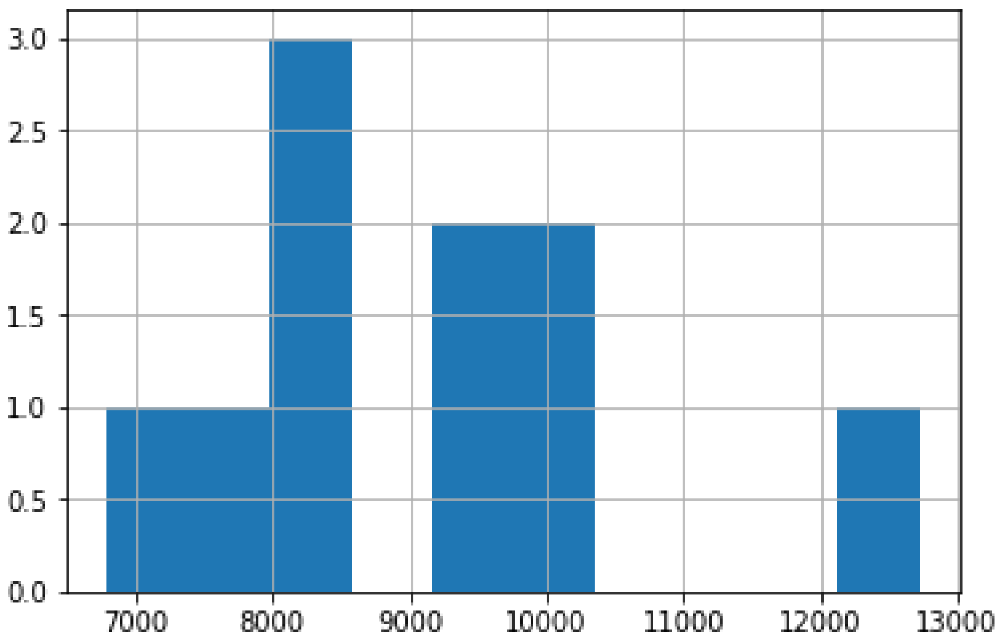
```
7027/7027 [==============================] - 0s - loss: 1.3449
Epoch 29/50
7027/7027 [==============================] - 0s - loss: 1.2196
Epoch 30/50
7027/7027 [==============================] - 0s - loss: 1.1131
Epoch 31/50
7027/7027 [==============================] - 0s - loss: 1.0083
Epoch 32/50
7027/7027 [==============================] - 0s - loss: 0.9187
Epoch 33/50
7027/7027 [==============================] - 0s - loss: 0.8413
Epoch 34/50
7027/7027 [==============================] - 0s - loss: 0.7695
Epoch 35/50
7027/7027 [==============================] - 0s - loss: 0.7082
Epoch 36/50
7027/7027 [==============================] - 0s - loss: 0.6506
Epoch 37/50
7027/7027 [==============================] - 0s - loss: 0.5962
Epoch 38/50
7027/7027 [==============================] - 0s - loss: 0.5538
Epoch 39/50
7027/7027 [==============================] - 0s - loss: 0.5156
Epoch 40/50
7027/7027 [==============================] - 0s - loss: 0.4795
Epoch 41/50
7027/7027 [==============================] - 0s - loss: 0.4422
Epoch 42/50
7027/7027 [==============================] - 0s - loss: 0.4139
Epoch 43/50
7027/7027 [==============================] - 0s - loss: 0.3899
Epoch 44/50
7027/7027 [==============================] - 0s - loss: 0.3648
Epoch 45/50
7027/7027 [==============================] - 0s - loss: 0.3470
Epoch 46/50
7027/7027 [==============================] - 0s - loss: 0.3274
Epoch 47/50
7027/7027 [==============================] - 0s - loss: 0.3093
Epoch 48/50
7027/7027 [==============================] - 0s - loss: 0.2921
Epoch 49/50
7027/7027 [==============================] - 0s - loss: 0.2769
Epoch 50/50
7027/7027 [==============================] - 0s - loss: 0.2656
Epoch 1/50
7027/7027 [==============================] - 0s - loss: 56935.1965
Epoch 2/50
```

```
7027/7027 [==============================] - 0s - loss: 2951.4610
Epoch 3/50
7027/7027 [==============================] - 0s - loss: 491.0214
Epoch 4/50
7027/7027 [==============================] - 0s - loss: 96.9649
Epoch 5/50
7027/7027 [==============================] - 0s - loss: 38.6569
Epoch 6/50
7027/7027 [==============================] - 0s - loss: 22.9288
Epoch 7/50
7027/7027 [==============================] - 0s - loss: 15.8603
Epoch 8/50
7027/7027 [==============================] - 0s - loss: 11.4632
Epoch 9/50
7027/7027 [==============================] - 0s - loss: 8.5629
Epoch 10/50
7027/7027 [==============================] - 0s - loss: 6.5824
Epoch 11/50
7027/7027 [==============================] - 0s - loss: 5.1541
Epoch 12/50
7027/7027 [==============================] - 0s - loss: 4.1076
Epoch 13/50
7027/7027 [==============================] - 0s - loss: 3.3331
Epoch 14/50
7027/7027 [==============================] - 0s - loss: 2.7271
Epoch 15/50
7027/7027 [==============================] - 0s - loss: 2.2673
Epoch 16/50
7027/7027 [==============================] - 0s - loss: 1.9096
Epoch 17/50
7027/7027 [==============================] - 0s - loss: 1.6215
Epoch 18/50
7027/7027 [==============================] - 0s - loss: 1.3901
Epoch 19/50
7027/7027 [==============================] - 0s - loss: 1.2071
Epoch 20/50
7027/7027 [==============================] - 0s - loss: 1.0602
Epoch 21/50
7027/7027 [==============================] - 0s - loss: 0.9390
Epoch 22/50
7027/7027 [==============================] - 0s - loss: 0.8389
Epoch 23/50
7027/7027 [==============================] - 0s - loss: 0.7574
Epoch 24/50
7027/7027 [==============================] - 0s - loss: 0.6904
Epoch 25/50
7027/7027 [==============================] - 0s - loss: 0.6390
Epoch 26/50
```

```
7027/7027 [==============================] - 0s - loss: 0.5941
Epoch 27/50
7027/7027 [==============================] - 0s - loss: 0.5473
Epoch 28/50
7027/7027 [==============================] - 0s - loss: 0.5145
Epoch 29/50
7027/7027 [==============================] - 0s - loss: 0.4837
Epoch 30/50
7027/7027 [==============================] - 0s - loss: 0.4606
Epoch 31/50
7027/7027 [==============================] - 0s - loss: 0.4355
Epoch 32/50
7027/7027 [==============================] - 0s - loss: 0.4151
Epoch 33/50
7027/7027 [==============================] - 0s - loss: 0.3928
Epoch 34/50
7027/7027 [==============================] - 0s - loss: 0.3758
Epoch 35/50
7027/7027 [==============================] - 0s - loss: 0.3597
Epoch 36/50
7027/7027 [==============================] - 0s - loss: 0.3410
Epoch 37/50
7027/7027 [==============================] - 0s - loss: 0.3294
Epoch 38/50
7027/7027 [==============================] - 0s - loss: 0.3215
Epoch 39/50
7027/7027 [==============================] - 0s - loss: 0.3065
Epoch 40/50
7027/7027 [==============================] - 0s - loss: 0.2897
Epoch 41/50
7027/7027 [==============================] - 0s - loss: 0.2778
Epoch 42/50
7027/7027 [==============================] - 0s - loss: 0.2686
Epoch 43/50
7027/7027 [==============================] - 0s - loss: 0.2567
Epoch 44/50
7027/7027 [==============================] - 0s - loss: 0.2463
Epoch 45/50
7027/7027 [==============================] - 0s - loss: 0.2371
Epoch 46/50
7027/7027 [==============================] - 0s - loss: 0.2324
Epoch 47/50
7027/7027 [==============================] - 0s - loss: 0.2201
Epoch 48/50
7027/7027 [==============================] - 0s - loss: 0.2145
Epoch 49/50
7027/7027 [==============================] - 0s - loss: 0.2021
Epoch 50/50
```

```
7027/7027 [==============================] - 0s - loss: 0.1911
```

In [11]:
```
plt.hist(ErrorList2)
plt.grid(True)
plt.show()

print("Mean score: " , np.mean(ErrorList2))
print("KFold scores: ", ErrorList2)
```




```
Mean score:  9118.54580197
KFold scores:  [7831.9183049607018, 12724.78799175028, 6793.6098976185131, 8365.2591229723002,
```

Q#9 Are you satisfied with the quality of the final estimator? What would be your recommendation for your boss on this issue?

Using the relu activation function, gives fast and consisten estimations, though they are limited in their precision.

However the linear activation function gives great precision, but requires many iterations, and therefore a lot more time, and is not very consistent. Possible you can tune the values, and get some consistent high-precision results.

The problem using relu, is that it is not differentiable in zero, and this data has a lot of zero's therefore it will not learn well.

We would definitely recommend using the linear neural network over both the relu and the linear regression algorithm. as it gives good precision, and it a better estimate, even when it doesn't give the best results

4 Extra task for 3-person groups

Q#10 Repeat the process, once reducing to 15 sensors, and once reducing to 25 sensors. The costs to keep these sensors running is directly proportional to the number of sensors used. Does changing the number of sensors used change your conclusion in Q#9?

Not required
We are only 2 people