

```
In [1]: !jt -t oceans16 -N -T -cellw 1200 -ofs 14 -dfs 12 -tfs 14 -tf code -nfs 14 -fs 14 -f
```

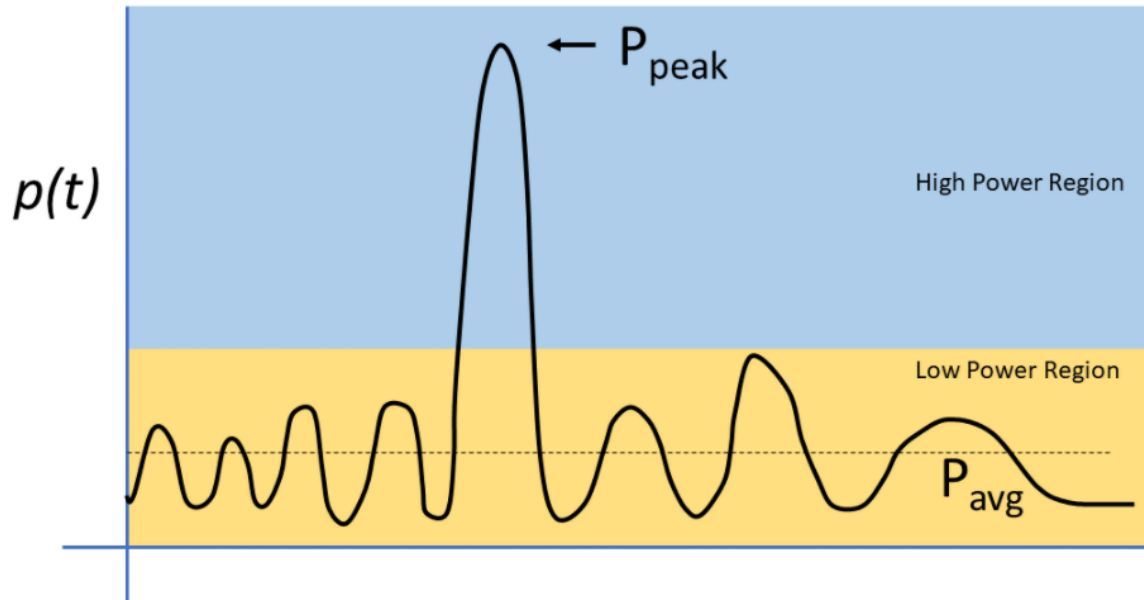
```
In [282... !jt -r
```

Reset css and font defaults in:

C:\Users\kuzne\.jupyter\custom &

C:\Users\kuzne\AppData\Roaming\jupyter\nbextensions

Signal amplification



- B. E. Watkins, R. North and M. Tummala, "Neural network based adaptive predistortion for the linearization of nonlinear RF amplifiers", Proc. MILCOM, pp. 145-149, Nov. 1995.
- T. Liu, S. Boumaiza and F. M. Ghannouchi, "Dynamic behavioral modeling of 3G power amplifiers using real-valued time-delay neural networks", IEEE Trans. Microw. Theory Techn., vol. 52, no. 3, pp. 1025-1033, Mar. 2004.
- M. Rawat, K. Rawat and F. M. Ghannouchi, "Adaptive digital predistortion of wireless power amplifiers/transmitters using dynamic real-valued focused time-delay line neural networks", IEEE Trans. Microw. Theory Techn., vol. 58, no. 1, pp. 95-104, Jan. 2010.

$$\begin{aligned}
 & [x_1^{(1)}, x_2^{(1)}, \dots, x_M^{(1)}] \\
 & = [s_I(n), s_I(n-1), \dots, s_I(n-M+1)] \\
 & [x_{M+1}^{(1)}, x_{M+2}^{(1)}, \dots, x_{2M}^{(1)}] \\
 & = [s_Q(n), s_Q(n-1), \dots, s_Q(n-M+1)].
 \end{aligned}$$

Input layer:

$$x_i^{(l)} = f \left(\sum_{j=1}^D w_{i,j}^{(l)} x_j^{(l-1)} + b_i^{(l)} \right).$$

Hidden layers:

$$y_I(n) = x_1^{(L)} = \sum_{j=1}^D w_{1,j}^{(L)} x_j^{(L-1)} + b_1^{(L)}$$
$$y_Q(n) = x_2^{(L)} = \sum_{j=1}^D w_{2,j}^{(L)} x_j^{(L-1)} + b_2^{(L)}$$

Output layer:

In [173...

```
import pandas as pd
```

In [174...

```
df = pd.read_csv('SOP.csv', delimiter='\t')
df
```

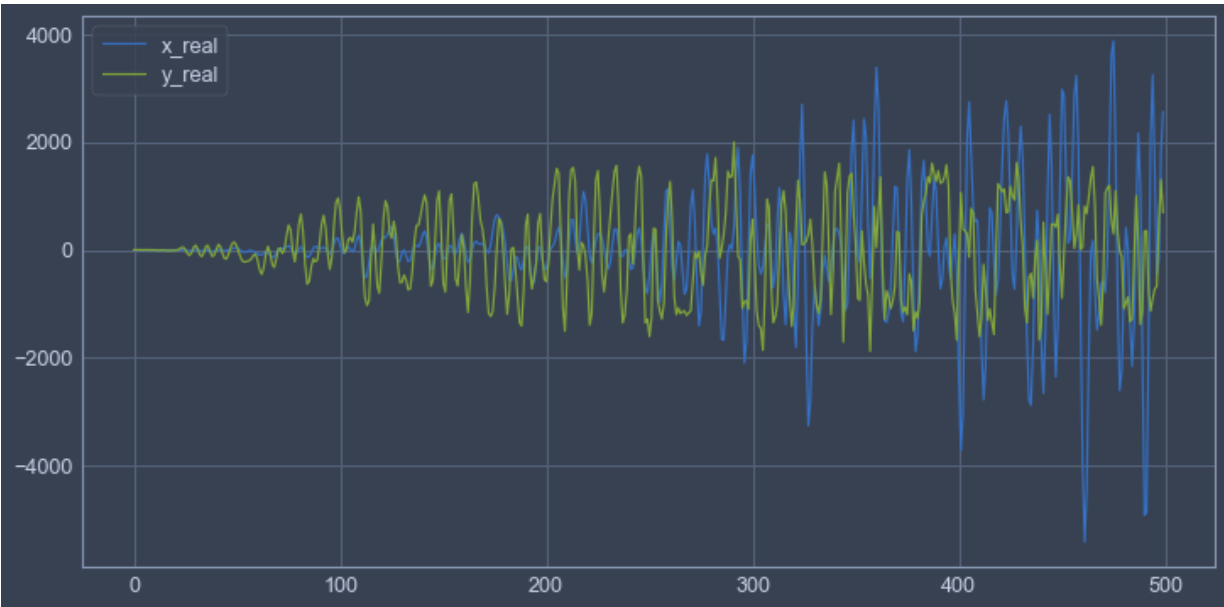
Out[174...

	x_real	x_imag	y_real	y_imag
0	0.0	0.0	1.038738	-4.530646
1	0.0	0.0	1.820132	-6.513940
2	0.0	0.0	1.729341	-1.936011
3	0.0	-0.0	1.851527	2.599776
4	0.0	-0.0	0.448547	6.800751
...
245755	-0.0	0.0	-5.496251	-7.106726
245756	-0.0	0.0	2.497821	1.009522
245757	-0.0	0.0	3.501016	6.063902
245758	-0.0	0.0	0.531160	1.366976
245759	-0.0	0.0	3.339302	-0.865433

245760 rows × 4 columns

In [289...

```
plt.plot(df.x_real[:500], label='x_real')
plt.plot(df.y_real[:500], label='y_real')
plt.legend();
```



```
In [175... df.describe()
```

Out[175...

	x_real	x_imag	y_real	y_imag
count	245760.000000	245760.000000	245760.000000	245760.000000
mean	0.005941	-0.007239	0.326069	-2.405308
std	5216.300247	5170.374673	1278.094777	1288.629409
min	-19135.000000	-19127.000000	-7956.600662	-8184.016771
25%	-3525.000000	-3496.000000	-731.032297	-736.804373
50%	1.000000	-2.000000	-0.043048	-0.088496
75%	3520.000000	3497.000000	732.448839	730.797447
max	19599.000000	19177.000000	7452.054802	7375.195878

```
In [176... df.corr()
```

Out[176...

	x_real	x_imag	y_real	y_imag
x_real	1.000000	-0.001733	0.118638	0.663647
x_imag	-0.001733	1.000000	-0.657381	0.111573
y_real	0.118638	-0.657381	1.000000	0.004954
y_imag	0.663647	0.111573	0.004954	1.000000

```
In [284... df.iloc[100:110, :]
```

Out[284...

	x_real	x_imag	y_real	y_imag
100	82.0	182.0	733.382436	244.160161
101	-44.0	120.0	264.156079	409.143404
102	-62.0	17.0	-50.702194	219.713299
103	11.0	-35.0	0.845572	-77.987027

	x_real	x_imag	y_real	y_imag
104	58.0	14.0	197.166574	-66.922559
105	15.0	103.0	230.747570	267.508468
106	-39.0	131.0	145.535289	504.076440
107	21.0	80.0	324.361002	342.306596
108	185.0	44.0	693.306437	-95.002543
109	270.0	92.0	982.094993	-303.495963

In [181...
`df_np = df.to_numpy()`
`df_np`

Out[181...
`array([[0., 0., 1.03873787, -4.53064645],`
 `[0., 0., 1.82013213, -6.51394005],`
 `[0., 0., 1.72934089, -1.93601107],`
 `...,`
 `[-0., 0., 3.50101648, 6.06390201],`
 `[-0., 0., 0.53116015, 1.36697645],`
 `[-0., 0., 3.33930177, -0.8654325]])`

In [182...
`from sklearn.preprocessing import MinMaxScaler`

In [183...
`scalerX, scalerY = MinMaxScaler(), MinMaxScaler()`
`X = scalerX.fit_transform(df_np[:, :2])`
`Y = scalerY.fit_transform(df_np[:, 2:])`

In [184...
`X.shape, Y.shape`

Out[184...
`((245760, 2), (245760, 2))`

In [185...
`X[:10, :]`

Out[185...
`array([[0.49401043, 0.49934733],`
 `[0.49401043, 0.49934733],`
 `[0.49401043, 0.49934733],`
 `[0.49401043, 0.49934733],`
 `[0.49401043, 0.49934733],`
 `[0.49401043, 0.49934733],`
 `[0.49401043, 0.49934733],`
 `[0.49401043, 0.49934733],`
 `[0.49401043, 0.49934733],`
 `[0.49403625, 0.49934733]])`

In [186...
`Y[:10, :]`

Out[186...
`array([[0.51643957, 0.52570052],`
 `[0.51649028, 0.52557305],`
 `[0.51648439, 0.52586728],`
 `[0.51649232, 0.52615879],`
 `[0.51640127, 0.52642879],`
 `[0.51634513, 0.52632594],`
 `[0.5165893 , 0.52624054],`
 `[0.51636472, 0.52585947],`

```
[0.51631966, 0.52578413],
[0.5164496 , 0.52631833]])
```

```
In [187... data_scaled = np.concatenate((X, Y), axis=1)
data_scaled.shape
```

```
Out[187... (245760, 4)
```

```
In [188... from sklearn.model_selection import train_test_split
```

```
In [ ]:
```

```
In [189... train, test = train_test_split(
    data_scaled,
    train_size=.75,
    shuffle=False,
)
```

```
In [190... train.shape, test.shape
```

```
Out[190... ((184320, 4), (61440, 4))
```

```
In [191... import numpy as np
```

```
In [192... from tensorflow.keras.backend import clear_session
from tensorflow.keras.models import Sequential
from tensorflow.keras import layers
```

```
In [193... from tensorflow.keras.optimizers import Adam
```

```
In [194... import matplotlib.pyplot as plt
```

```
In [222... # Convert an array of values into a dataset matrix.
def createDataset(dataset, lookBack):
    dataX, dataY = [], []
    for i in range(len(dataset) - lookBack - 1):
        a = dataset[i:(i + lookBack), :]
        dataX.append(a)
        dataY.append(dataset[i + lookBack, 2:])
    return np.array(dataX), np.array(dataY)

def runModel(train, test, lookBack=10, activation='relu', learningRate=1e-3):
    numFeatures = 4
    X_train, Y_train = createDataset(train, lookBack=lookBack)
    X_test, Y_test = createDataset(test, lookBack=lookBack)

    model = Sequential()
    model.add(layers.LSTM(lookBack, input_shape=(lookBack, numFeatures), activation=
    model.add(layers.Dense(2))

    model.compile(
```

```

        loss='mean_squared_error',
        optimizer=Adam(learning_rate=learningRate),
        metrics=['accuracy'],
    )

    history = model.fit(
        x=X_train,
        y=Y_train,
        epochs=5,
        verbose=1,
        shuffle=False,
    )

    Y_pred = model.predict(X_test)
    np.save(
        'grid_search_results\\' + f'look_back_{lookBack}_activation_{activation}_lea
        Y_pred,
    )
    return Y_test, Y_pred

def mse(y1, y2):
    return np.linalg.norm(y1 - y2, 'fro')

def rmse(Y_true, Y_pred):
    return mse(Y_true, Y_pred) / mse(Y_true, np.mean(Y_true) * np.ones_like(Y_true))

def optimalParams(errs, gridParams):
    indmin = np.unravel_index(errs.argmin(), errs.shape)
    bestErr = errs[indmin]
    return {
        'lookBack': list(gridParams['lookBack'])[indmin[0]],
        'activation': list(gridParams['activation'])[indmin[1]],
        'learningRate': list(gridParams['learningRate'])[indmin[2]],
    }, bestErr

def gridSearch(gridParams, train, test):
    errs = []
    for lookBack in gridParams['lookBack']:
        for activation in gridParams['activation']:
            for learningRate in gridParams['learningRate']:
                Y_test, Y_pred = runModel(train, test, lookBack, activation, learnin
                err = rmse(Y_test, Y_pred)
                errs.append(err)
    errs = np.array(errs).reshape((
        len(gridParams['lookBack']),
        len(gridParams['activation']),
        len(gridParams['learningRate']),
    ))

    return *optimalParams(), errs

```

In [172...

```

optimalParams, bestErr, errs = gridSearch({
    'lookBack': np.arange(3, 100, 5),
    'activation': ['relu', 'tanh', 'sigmoid'],
    'learningRate': [1e-3, 1e-2, 1e-1],
}, train, test)

```

Epoch 1/5

5760/5760 [=====] - 7s 1ms/step - loss: 0.0108 - accuracy:

```
0.5456
Epoch 2/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0049 - accuracy:
0.5906
Epoch 3/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0038 - accuracy:
0.6587
Epoch 4/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0031 - accuracy:
0.7048
Epoch 5/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0029 - accuracy:
0.7258
Epoch 1/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0060 - accuracy:
0.5779
Epoch 2/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0049 - accuracy:
0.5891
Epoch 3/5
5760/5760 [=====] - 6s 1ms/step - loss: 0.0049 - accuracy:
0.5876
Epoch 4/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0049 - accuracy:
0.5834: 0s - loss: 0.0049 - accu
Epoch 5/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0049 - accuracy:
0.5777
Epoch 1/5
5760/5760 [=====] - 8s 1ms/step - loss: 0.0057 - accuracy:
0.5943
Epoch 2/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0055 - accuracy:
0.6087
Epoch 3/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0055 - accuracy:
0.6060
Epoch 4/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0055 - accuracy:
0.6017
Epoch 5/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0054 - accuracy:
0.5930
Epoch 1/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0075 - accuracy:
0.6013
Epoch 2/5
5760/5760 [=====] - 9s 2ms/step - loss: 0.0034 - accuracy:
0.6910
Epoch 3/5
5760/5760 [=====] - 9s 2ms/step - loss: 0.0029 - accuracy:
0.7158
Epoch 4/5
5760/5760 [=====] - 9s 2ms/step - loss: 0.0027 - accuracy:
0.7252
Epoch 5/5
5760/5760 [=====] - 9s 2ms/step - loss: 0.0027 - accuracy:
0.7268
Epoch 1/5
5760/5760 [=====] - 11s 2ms/step - loss: 0.0035 - accuracy:
0.7084
Epoch 2/5
5760/5760 [=====] - 9s 2ms/step - loss: 0.0028 - accuracy:
0.7253
Epoch 3/5
```

5760/5760 [=====] - 8s 1ms/step - loss: 0.0028 - accuracy: 0.7240
Epoch 4/5
5760/5760 [=====] - 9s 1ms/step - loss: 0.0028 - accuracy: 0.7244
Epoch 5/5
5760/5760 [=====] - 9s 2ms/step - loss: 0.0028 - accuracy: 0.7259
Epoch 1/5
5760/5760 [=====] - 10s 1ms/step - loss: 0.0039 - accuracy: 0.6898
Epoch 2/5
5760/5760 [=====] - 8s 1ms/step - loss: 0.0033 - accuracy: 0.7129
Epoch 3/5
5760/5760 [=====] - 8s 1ms/step - loss: 0.0033 - accuracy: 0.7118: 0s -
Epoch 4/5
5760/5760 [=====] - 9s 1ms/step - loss: 0.0033 - accuracy: 0.7126
Epoch 5/5
5760/5760 [=====] - 9s 1ms/step - loss: 0.0033 - accuracy: 0.7128
Epoch 1/5
5760/5760 [=====] - 8s 1ms/step - loss: 0.0101 - accuracy: 0.6472
Epoch 2/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0039 - accuracy: 0.7023
Epoch 3/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0033 - accuracy: 0.7183
Epoch 4/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0030 - accuracy: 0.7283
Epoch 5/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0028 - accuracy: 0.7282
Epoch 1/5
5760/5760 [=====] - 9s 1ms/step - loss: 0.0051 - accuracy: 0.6314
Epoch 2/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0028 - accuracy: 0.7252
Epoch 3/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0028 - accuracy: 0.7269
Epoch 4/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0028 - accuracy: 0.7276
Epoch 5/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0028 - accuracy: 0.7280
Epoch 1/5
5760/5760 [=====] - 8s 1ms/step - loss: 0.0042 - accuracy: 0.6728
Epoch 2/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0034 - accuracy: 0.6960
Epoch 3/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0034 - accuracy: 0.6959
Epoch 4/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0033 - accuracy: 0.6977


```
Epoch 5/5
5760/5760 [=====] - 7s 1ms/step - loss: 0.0033 - accuracy:
0.6988
Epoch 1/5
5760/5760 [=====] - 11s 2ms/step - loss: 0.0065 - accuracy:
0.6981
Epoch 2/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0022 - accuracy:
0.7670
Epoch 3/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0019 - accuracy:
0.7779
Epoch 4/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0019 - accuracy:
0.7803
Epoch 5/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0019 - accuracy:
0.7813
Epoch 1/5
5760/5760 [=====] - 12s 2ms/step - loss: 0.0029 - accuracy:
0.7319
Epoch 2/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0022 - accuracy:
0.7640
Epoch 3/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0022 - accuracy:
0.7651
Epoch 4/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0021 - accuracy:
0.7661
Epoch 5/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0021 - accuracy:
0.7673
Epoch 1/5
5760/5760 [=====] - 11s 2ms/step - loss: 0.0076 - accuracy:
0.5066
Epoch 2/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0075 - accuracy:
0.5059
Epoch 3/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0075 - accuracy:
0.5059
Epoch 4/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0075 - accuracy:
0.5059
Epoch 5/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0075 - accuracy:
0.5059
Epoch 1/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0039 - accuracy:
0.6764
Epoch 2/5
5760/5760 [=====] - 18s 3ms/step - loss: 0.0023 - accuracy:
0.7764
Epoch 3/5
5760/5760 [=====] - 17s 3ms/step - loss: 0.0019 - accuracy:
0.7798
Epoch 4/5
5760/5760 [=====] - 17s 3ms/step - loss: 0.0019 - accuracy:
0.7804
Epoch 5/5
5760/5760 [=====] - 17s 3ms/step - loss: 0.0018 - accuracy:
0.7818
Epoch 1/5
5760/5760 [=====] - 18s 3ms/step - loss: 0.0025 - accuracy:
```

0.7488
Epoch 2/5
5760/5760 [=====] - 17s 3ms/step - loss: 0.0019 - accuracy:
0.7780
Epoch 3/5
5760/5760 [=====] - 17s 3ms/step - loss: 0.0019 - accuracy:
0.7795
Epoch 4/5
5760/5760 [=====] - 17s 3ms/step - loss: 0.0019 - accuracy:
0.7808
Epoch 5/5
5760/5760 [=====] - 17s 3ms/step - loss: 0.0019 - accuracy:
0.7817
Epoch 1/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0028 - accuracy:
0.7346
Epoch 2/5
5760/5760 [=====] - 18s 3ms/step - loss: 0.0024 - accuracy:
0.7521
Epoch 3/5
5760/5760 [=====] - 18s 3ms/step - loss: 0.0023 - accuracy:
0.7595
Epoch 4/5
5760/5760 [=====] - 18s 3ms/step - loss: 0.0025 - accuracy:
0.7590
Epoch 5/5
5760/5760 [=====] - 18s 3ms/step - loss: 0.0022 - accuracy:
0.7618
Epoch 1/5
5760/5760 [=====] - 11s 2ms/step - loss: 0.0088 - accuracy:
0.5930
Epoch 2/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0034 - accuracy:
0.7169
Epoch 3/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0025 - accuracy:
0.7599
Epoch 4/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0021 - accuracy:
0.7758
Epoch 5/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0020 - accuracy:
0.7791
Epoch 1/5
5760/5760 [=====] - 12s 2ms/step - loss: 0.0028 - accuracy:
0.7355
Epoch 2/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0021 - accuracy:
0.7723
Epoch 3/5
5760/5760 [=====] - 11s 2ms/step - loss: 0.0020 - accuracy:
0.7750
Epoch 4/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0020 - accuracy:
0.7762
Epoch 5/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0019 - accuracy:
0.7772
Epoch 1/5
5760/5760 [=====] - 11s 2ms/step - loss: 0.0036 - accuracy:
0.7245
Epoch 2/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0026 - accuracy:
0.7467
Epoch 3/5

5760/5760 [=====] - 10s 2ms/step - loss: 0.0025 - accuracy: 0.7468
Epoch 4/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0025 - accuracy: 0.7453
Epoch 5/5
5760/5760 [=====] - 10s 2ms/step - loss: 0.0025 - accuracy: 0.7496
Epoch 1/5
5760/5760 [=====] - 20s 3ms/step - loss: 0.0037 - accuracy: 0.6985
Epoch 2/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0017 - accuracy: 0.7912
Epoch 3/5
5760/5760 [=====] - 20s 3ms/step - loss: 0.0015 - accuracy: 0.8085
Epoch 4/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0015 - accuracy: 0.8113
Epoch 5/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0015 - accuracy: 0.8125
Epoch 1/5
5760/5760 [=====] - 21s 3ms/step - loss: 0.0029 - accuracy: 0.7288
Epoch 2/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0017 - accuracy: 0.7987
Epoch 3/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0016 - accuracy: 0.8050
Epoch 4/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0015 - accuracy: 0.8068
Epoch 5/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0015 - accuracy: 0.8080
Epoch 1/5
5760/5760 [=====] - 20s 3ms/step - loss: 0.0076 - accuracy: 0.5060
Epoch 2/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0075 - accuracy: 0.5044
Epoch 3/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0075 - accuracy: 0.5044
Epoch 4/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0075 - accuracy: 0.5044
Epoch 5/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0075 - accuracy: 0.5044
Epoch 1/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0066 - accuracy: 0.6373
Epoch 2/5
5760/5760 [=====] - 22s 4ms/step - loss: 0.0026 - accuracy: 0.7454
Epoch 3/5
5760/5760 [=====] - 22s 4ms/step - loss: 0.0017 - accuracy: 0.8054
Epoch 4/5
5760/5760 [=====] - 22s 4ms/step - loss: 0.0015 - accuracy: 0.8144

```
Epoch 5/5
5760/5760 [=====] - 22s 4ms/step - loss: 0.0014 - accuracy:
0.8155
Epoch 1/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0021 - accuracy:
0.7777
Epoch 2/5
5760/5760 [=====] - 22s 4ms/step - loss: 0.0015 - accuracy:
0.8076
Epoch 3/5
5760/5760 [=====] - 22s 4ms/step - loss: 0.0015 - accuracy:
0.8099
Epoch 4/5
5760/5760 [=====] - 22s 4ms/step - loss: 0.0014 - accuracy:
0.8117
Epoch 5/5
5760/5760 [=====] - 22s 4ms/step - loss: 0.0014 - accuracy:
0.8129
Epoch 1/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0033 - accuracy:
0.7407
Epoch 2/5
5760/5760 [=====] - 22s 4ms/step - loss: 0.0021 - accuracy:
0.7785
Epoch 3/5
5760/5760 [=====] - 22s 4ms/step - loss: 0.0030 - accuracy:
0.7510
Epoch 4/5
5760/5760 [=====] - 23s 4ms/step - loss: 0.0043 - accuracy:
0.6694
Epoch 5/5
5760/5760 [=====] - 23s 4ms/step - loss: 0.0031 - accuracy:
0.7209
Epoch 1/5
5760/5760 [=====] - 20s 3ms/step - loss: 0.0105 - accuracy:
0.5815
Epoch 2/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0031 - accuracy:
0.7070
Epoch 3/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0022 - accuracy:
0.7664
Epoch 4/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0018 - accuracy:
0.7945
Epoch 5/5
5760/5760 [=====] - 20s 3ms/step - loss: 0.0016 - accuracy:
0.8053
Epoch 1/5
5760/5760 [=====] - 21s 3ms/step - loss: 0.0028 - accuracy:
0.7378
Epoch 2/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0015 - accuracy:
0.8077
Epoch 3/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0015 - accuracy:
0.8093
Epoch 4/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0015 - accuracy:
0.8105
Epoch 5/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0015 - accuracy:
0.8110
Epoch 1/5
5760/5760 [=====] - 21s 3ms/step - loss: 0.0030 - accuracy:
```

0.7393
Epoch 2/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0021 - accuracy:
0.7715
Epoch 3/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0021 - accuracy:
0.7717
Epoch 4/5
5760/5760 [=====] - 20s 3ms/step - loss: 0.0020 - accuracy:
0.7753
Epoch 5/5
5760/5760 [=====] - 19s 3ms/step - loss: 0.0036 - accuracy:
0.7132
Epoch 1/5
5760/5760 [=====] - 25s 4ms/step - loss: 0.0031 - accuracy:
0.7611
Epoch 2/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0013 - accuracy:
0.8226
Epoch 3/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0012 - accuracy:
0.8291
Epoch 4/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0012 - accuracy:
0.8329
Epoch 5/5
5760/5760 [=====] - 25s 4ms/step - loss: 0.0012 - accuracy:
0.8350
Epoch 1/5
5760/5760 [=====] - 26s 4ms/step - loss: 0.0025 - accuracy:
0.7682
Epoch 2/5
5760/5760 [=====] - 25s 4ms/step - loss: 0.0014 - accuracy:
0.8202
Epoch 3/5
5760/5760 [=====] - 25s 4ms/step - loss: 0.0013 - accuracy:
0.8248
Epoch 4/5
5760/5760 [=====] - 25s 4ms/step - loss: 0.0013 - accuracy:
0.8266
Epoch 5/5
5760/5760 [=====] - 25s 4ms/step - loss: 0.0012 - accuracy:
0.8274
Epoch 1/5
5760/5760 [=====] - 26s 4ms/step - loss: 12259.0332 - accuracy: 0.5170
Epoch 2/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0061 - accuracy:
0.5088
Epoch 3/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0103 - accuracy:
0.5214
Epoch 4/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0064 - accuracy:
0.5548
Epoch 5/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0055 - accuracy:
0.5807
Epoch 1/5
5760/5760 [=====] - 31s 5ms/step - loss: 0.0027 - accuracy:
0.7505
Epoch 2/5
5760/5760 [=====] - 29s 5ms/step - loss: 0.0012 - accuracy:
0.8331
Epoch 3/5

5760/5760 [=====] - 29s 5ms/step - loss: 0.0012 - accuracy: 0.8356
Epoch 4/5
5760/5760 [=====] - 29s 5ms/step - loss: 0.0011 - accuracy: 0.8365
Epoch 5/5
5760/5760 [=====] - 29s 5ms/step - loss: 0.0011 - accuracy: 0.8372
Epoch 1/5
5760/5760 [=====] - 30s 5ms/step - loss: 0.0020 - accuracy: 0.7871
Epoch 2/5
5760/5760 [=====] - 29s 5ms/step - loss: 0.0012 - accuracy: 0.8276
Epoch 3/5
5760/5760 [=====] - 29s 5ms/step - loss: 0.0012 - accuracy: 0.8304
Epoch 4/5
5760/5760 [=====] - 29s 5ms/step - loss: 0.0012 - accuracy: 0.8322
Epoch 5/5
5760/5760 [=====] - 29s 5ms/step - loss: 0.0012 - accuracy: 0.8336
Epoch 1/5
5760/5760 [=====] - 31s 5ms/step - loss: 0.0030 - accuracy: 0.7428
Epoch 2/5
5760/5760 [=====] - 29s 5ms/step - loss: 0.0033 - accuracy: 0.6992
Epoch 3/5
5760/5760 [=====] - 29s 5ms/step - loss: 0.0030 - accuracy: 0.7263
Epoch 4/5
5760/5760 [=====] - 29s 5ms/step - loss: 0.0031 - accuracy: 0.7241
Epoch 5/5
5760/5760 [=====] - 29s 5ms/step - loss: 0.0031 - accuracy: 0.7370
Epoch 1/5
5760/5760 [=====] - 25s 4ms/step - loss: 0.0048 - accuracy: 0.6554
Epoch 2/5
5760/5760 [=====] - 25s 4ms/step - loss: 0.0026 - accuracy: 0.7446
Epoch 3/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0019 - accuracy: 0.7836
Epoch 4/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0017 - accuracy: 0.7974
Epoch 5/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0015 - accuracy: 0.8097
Epoch 1/5
5760/5760 [=====] - 25s 4ms/step - loss: 0.0034 - accuracy: 0.7223
Epoch 2/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0014 - accuracy: 0.8180
Epoch 3/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0013 - accuracy: 0.8236
Epoch 4/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0012 - accuracy: 0.8272

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Epoch 5/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0012 - accuracy:
0.8282
Epoch 1/5
5760/5760 [=====] - 25s 4ms/step - loss: 0.0031 - accuracy:
0.7369
Epoch 2/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0024 - accuracy:
0.7644
Epoch 3/5
5760/5760 [=====] - 24s 4ms/step - loss: 0.0025 - accuracy:
0.7601
Epoch 4/5
5760/5760 [=====] - 25s 4ms/step - loss: 0.0028 - accuracy:
0.7406
Epoch 5/5
5760/5760 [=====] - 25s 4ms/step - loss: 0.0044 - accuracy:
0.6168
Epoch 1/5
5760/5760 [=====] - 31s 5ms/step - loss: 0.0049 - accuracy:
0.7322
Epoch 2/5
5760/5760 [=====] - 30s 5ms/step - loss: 0.0012 - accuracy:
0.8283
Epoch 3/5
5760/5760 [=====] - 30s 5ms/step - loss: 0.0010 - accuracy:
0.8434
Epoch 4/5
5760/5760 [=====] - 30s 5ms/step - loss: 9.8547e-04 - accur
acy: 0.8465
Epoch 5/5
5760/5760 [=====] - 30s 5ms/step - loss: 9.6797e-04 - accur
acy: 0.8487
Epoch 1/5
5760/5760 [=====] - 31s 5ms/step - loss: 0.0023 - accuracy:
0.7788
Epoch 2/5
5760/5760 [=====] - 30s 5ms/step - loss: 0.0014 - accuracy:
0.8288
Epoch 3/5
5760/5760 [=====] - 30s 5ms/step - loss: 0.0013 - accuracy:
0.8325
Epoch 4/5
5760/5760 [=====] - 30s 5ms/step - loss: 0.0012 - accuracy:
0.8352
Epoch 5/5
5760/5760 [=====] - 30s 5ms/step - loss: 0.0012 - accuracy:
0.8362
Epoch 1/5
5760/5760 [=====] - 31s 5ms/step - loss: 44389.4180 - accur
acy: 0.6307
Epoch 2/5
5760/5760 [=====] - 30s 5ms/step - loss: 0.0030 - accuracy:
0.7358
Epoch 3/5
5760/5760 [=====] - 30s 5ms/step - loss: 0.0049 - accuracy:
0.6596
Epoch 4/5
5760/5760 [=====] - 31s 5ms/step - loss: 0.0037 - accuracy:
0.6744
Epoch 5/5
5760/5760 [=====] - 30s 5ms/step - loss: 0.0025 - accuracy:
0.7575
Epoch 1/5
5760/5760 [=====] - 37s 6ms/step - loss: 0.0035 - accuracy:
```

0.7158
Epoch 2/5
5760/5760 [=====] - 35s 6ms/step - loss: 0.0012 - accuracy:
0.8353
Epoch 3/5
5760/5760 [=====] - 35s 6ms/step - loss: 0.0010 - accuracy:
0.8466
Epoch 4/5
5760/5760 [=====] - 36s 6ms/step - loss: 9.7387e-04 - accur
acy: 0.8486
Epoch 5/5
5760/5760 [=====] - 36s 6ms/step - loss: 9.5705e-04 - accur
acy: 0.8496
Epoch 1/5
5760/5760 [=====] - 37s 6ms/step - loss: 0.0020 - accuracy:
0.7912
Epoch 2/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0011 - accuracy:
0.8392
Epoch 3/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0010 - accuracy:
0.8420
Epoch 4/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0010 - accuracy:
0.8445
Epoch 5/5
5760/5760 [=====] - 35s 6ms/step - loss: 9.9596e-04 - accur
acy: 0.8460
Epoch 1/5
5760/5760 [=====] - 37s 6ms/step - loss: 0.0039 - accuracy:
0.7381
Epoch 2/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0045 - accuracy:
0.6855
Epoch 3/5
5760/5760 [=====] - 37s 6ms/step - loss: 0.0067 - accuracy:
0.6075
Epoch 4/5
5760/5760 [=====] - 37s 6ms/step - loss: 0.0061 - accuracy:
0.5912
Epoch 5/5
5760/5760 [=====] - 37s 6ms/step - loss: 0.0033 - accuracy:
0.7168
Epoch 1/5
5760/5760 [=====] - 32s 5ms/step - loss: 0.0064 - accuracy:
0.6121
Epoch 2/5
5760/5760 [=====] - 31s 5ms/step - loss: 0.0028 - accuracy:
0.7243
Epoch 3/5
5760/5760 [=====] - 31s 5ms/step - loss: 0.0020 - accuracy:
0.7688
Epoch 4/5
5760/5760 [=====] - 30s 5ms/step - loss: 0.0017 - accuracy:
0.7969
Epoch 5/5
5760/5760 [=====] - 30s 5ms/step - loss: 0.0014 - accuracy:
0.8070
Epoch 1/5
5760/5760 [=====] - 30s 5ms/step - loss: 0.0022 - accuracy:
0.7682
Epoch 2/5
5760/5760 [=====] - 30s 5ms/step - loss: 0.0012 - accuracy:
0.8328
Epoch 3/5

5760/5760 [=====] - 31s 5ms/step - loss: 0.0011 - accuracy: 0.8375
Epoch 4/5
5760/5760 [=====] - 31s 5ms/step - loss: 0.0011 - accuracy: 0.8397
Epoch 5/5
5760/5760 [=====] - 30s 5ms/step - loss: 0.0010 - accuracy: 0.8408
Epoch 1/5
5760/5760 [=====] - 31s 5ms/step - loss: 0.0034 - accuracy: 0.7444
Epoch 2/5
5760/5760 [=====] - 31s 5ms/step - loss: 0.0029 - accuracy: 0.7404
Epoch 3/5
5760/5760 [=====] - 31s 5ms/step - loss: 0.0023 - accuracy: 0.7552
Epoch 4/5
5760/5760 [=====] - 31s 5ms/step - loss: 0.0022 - accuracy: 0.7602
Epoch 5/5
5760/5760 [=====] - 31s 5ms/step - loss: 0.0022 - accuracy: 0.7617
Epoch 1/5
5760/5760 [=====] - 37s 6ms/step - loss: 0.0039 - accuracy: 0.7213
Epoch 2/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0011 - accuracy: 0.8361
Epoch 3/5
5760/5760 [=====] - 36s 6ms/step - loss: 9.5560e-04 - accuracy: 0.8486
Epoch 4/5
5760/5760 [=====] - 36s 6ms/step - loss: 8.9956e-04 - accuracy: 0.8533
Epoch 5/5
5760/5760 [=====] - 36s 6ms/step - loss: 8.7631e-04 - accuracy: 0.8549
Epoch 1/5
5760/5760 [=====] - 37s 6ms/step - loss: 0.0026 - accuracy: 0.7574
Epoch 2/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0013 - accuracy: 0.8193
Epoch 3/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0013 - accuracy: 0.8275
Epoch 4/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0011 - accuracy: 0.8399
Epoch 5/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0010 - accuracy: 0.8451
Epoch 1/5
5760/5760 [=====] - 37s 6ms/step - loss: 0.0547 - accuracy: 0.6379
Epoch 2/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0037 - accuracy: 0.7021
Epoch 3/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0047 - accuracy: 0.6488
Epoch 4/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0059 - accuracy: 0.6113

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Epoch 5/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0062 - accuracy:
0.6219
Epoch 1/5
5760/5760 [=====] - 43s 7ms/step - loss: 0.0046 - accuracy:
0.7184
Epoch 2/5
5760/5760 [=====] - 41s 7ms/step - loss: 0.0011 - accuracy:
0.8383
Epoch 3/5
5760/5760 [=====] - 41s 7ms/step - loss: 8.9557e-04 - accur
acy: 0.8529
Epoch 4/5
5760/5760 [=====] - 42s 7ms/step - loss: 8.6172e-04 - accur
acy: 0.8561
Epoch 5/5
5760/5760 [=====] - 42s 7ms/step - loss: 8.4398e-04 - accur
acy: 0.8581
Epoch 1/5
5760/5760 [=====] - 44s 7ms/step - loss: 0.0018 - accuracy:
0.8054
Epoch 2/5
5760/5760 [=====] - 42s 7ms/step - loss: 0.0010 - accuracy:
0.8440
Epoch 3/5
5760/5760 [=====] - 43s 7ms/step - loss: 9.7320e-04 - accur
acy: 0.8473
Epoch 4/5
5760/5760 [=====] - 42s 7ms/step - loss: 9.3167e-04 - accur
acy: 0.8500
Epoch 5/5
5760/5760 [=====] - 42s 7ms/step - loss: 8.9987e-04 - accur
acy: 0.8521
Epoch 1/5
5760/5760 [=====] - 44s 7ms/step - loss: 0.0041 - accuracy:
0.7044
Epoch 2/5
5760/5760 [=====] - 42s 7ms/step - loss: 0.0030 - accuracy:
0.7228
Epoch 3/5
5760/5760 [=====] - 42s 7ms/step - loss: 0.0032 - accuracy:
0.7152
Epoch 4/5
5760/5760 [=====] - 42s 7ms/step - loss: 0.0049 - accuracy:
0.6991
Epoch 5/5
5760/5760 [=====] - 42s 7ms/step - loss: 0.0202 - accuracy:
0.6471
Epoch 1/5
5760/5760 [=====] - 37s 6ms/step - loss: 0.0048 - accuracy:
0.6683
Epoch 2/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0020 - accuracy:
0.7858
Epoch 3/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0016 - accuracy:
0.8090
Epoch 4/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0013 - accuracy:
0.8314
Epoch 5/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0011 - accuracy:
0.8439
Epoch 1/5
5760/5760 [=====] - 37s 6ms/step - loss: 0.0024 - accuracy:
```

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0.7564
Epoch 2/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0012 - accuracy:
0.8348
Epoch 3/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0010 - accuracy:
0.8421
Epoch 4/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0010 - accuracy:
0.8462
Epoch 5/5
5760/5760 [=====] - 36s 6ms/step - loss: 9.7203e-04 - accur
acy: 0.8481
Epoch 1/5
5760/5760 [=====] - 37s 6ms/step - loss: 0.0038 - accuracy:
0.7292
Epoch 2/5
5760/5760 [=====] - 36s 6ms/step - loss: 0.0027 - accuracy:
0.7407
Epoch 3/5
5760/5760 [=====] - 39s 7ms/step - loss: 0.0024 - accuracy:
0.7636
Epoch 4/5
5760/5760 [=====] - 40s 7ms/step - loss: 0.0031 - accuracy:
0.7409
Epoch 5/5
5760/5760 [=====] - 40s 7ms/step - loss: 0.0030 - accuracy:
0.7394
Epoch 1/5
5759/5759 [=====] - 53s 9ms/step - loss: 0.0037 - accuracy:
0.7025
Epoch 2/5
5759/5759 [=====] - 54s 9ms/step - loss: 0.0010 - accuracy:
0.8401
Epoch 3/5
5759/5759 [=====] - 54s 9ms/step - loss: 9.9147e-04 - accur
acy: 0.8531
Epoch 4/5
5759/5759 [=====] - 53s 9ms/step - loss: 8.1772e-04 - accur
acy: 0.8637
Epoch 5/5
5759/5759 [=====] - 53s 9ms/step - loss: 7.7658e-04 - accur
acy: 0.8664
Epoch 1/5
5759/5759 [=====] - 53s 9ms/step - loss: 0.0022 - accuracy:
0.7652
Epoch 2/5
5759/5759 [=====] - 53s 9ms/step - loss: 0.0013 - accuracy:
0.8227
Epoch 3/5
5759/5759 [=====] - 53s 9ms/step - loss: 0.0012 - accuracy:
0.8326
Epoch 4/5
5759/5759 [=====] - 53s 9ms/step - loss: 0.0012 - accuracy:
0.8354
Epoch 5/5
5759/5759 [=====] - 53s 9ms/step - loss: 0.0011 - accuracy:
0.8445
Epoch 1/5
5759/5759 [=====] - 57s 10ms/step - loss: nan - accuracy:
0.4620
Epoch 2/5
5759/5759 [=====] - 56s 10ms/step - loss: nan - accuracy:
0.4620
Epoch 3/5
```

5759/5759 [=====] - 56s 10ms/step - loss: nan - accuracy:
0.4620
Epoch 4/5
5759/5759 [=====] - 56s 10ms/step - loss: nan - accuracy:
0.4620 0s - loss: nan -
Epoch 5/5
5759/5759 [=====] - 56s 10ms/step - loss: nan - accuracy:
0.4620
Epoch 1/5
5759/5759 [=====] - 61s 10ms/step - loss: 0.0029 - accurac
y: 0.7537
Epoch 2/5
5759/5759 [=====] - 59s 10ms/step - loss: 9.8820e-04 - accu
racy: 0.8489
Epoch 3/5
5759/5759 [=====] - 59s 10ms/step - loss: 8.4299e-04 - accu
racy: 0.8596
Epoch 4/5
5759/5759 [=====] - 59s 10ms/step - loss: 7.9616e-04 - accu
racy: 0.8634
Epoch 5/5
5759/5759 [=====] - 59s 10ms/step - loss: 7.7712e-04 - accu
racy: 0.8657
Epoch 1/5
5759/5759 [=====] - 58s 10ms/step - loss: 0.0018 - accurac
y: 0.8035
Epoch 2/5
5759/5759 [=====] - 57s 10ms/step - loss: 0.0010 - accurac
y: 0.8445
Epoch 3/5
5759/5759 [=====] - 57s 10ms/step - loss: 9.5477e-04 - accu
racy: 0.8509
Epoch 4/5
5759/5759 [=====] - 57s 10ms/step - loss: 9.0382e-04 - accu
racy: 0.8549
Epoch 5/5
5759/5759 [=====] - 57s 10ms/step - loss: 8.8557e-04 - accu
racy: 0.8560
Epoch 1/5
5759/5759 [=====] - 57s 10ms/step - loss: 0.0043 - accurac
y: 0.7311
Epoch 2/5
5759/5759 [=====] - 55s 10ms/step - loss: 0.0040 - accurac
y: 0.7236
Epoch 3/5
5759/5759 [=====] - 55s 10ms/step - loss: 0.0044 - accurac
y: 0.7151
Epoch 4/5
5759/5759 [=====] - 57s 10ms/step - loss: 0.0034 - accurac
y: 0.7115
Epoch 5/5
5759/5759 [=====] - 57s 10ms/step - loss: 0.0034 - accurac
y: 0.7106
Epoch 1/5
5759/5759 [=====] - 55s 9ms/step - loss: 0.0042 - accuracy:
0.6623
Epoch 2/5
5759/5759 [=====] - 53s 9ms/step - loss: 0.0022 - accuracy:
0.7641
Epoch 3/5
5759/5759 [=====] - 54s 9ms/step - loss: 0.0017 - accuracy:
0.7946
Epoch 4/5
5759/5759 [=====] - 54s 9ms/step - loss: 0.0014 - accuracy:
0.8147

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Epoch 5/5
5759/5759 [=====] - 54s 9ms/step - loss: 0.0011 - accuracy:
0.8373
Epoch 1/5
5759/5759 [=====] - 54s 9ms/step - loss: 0.0024 - accuracy:
0.7600
Epoch 2/5
5759/5759 [=====] - 53s 9ms/step - loss: 0.0012 - accuracy:
0.8312
Epoch 3/5
5759/5759 [=====] - 53s 9ms/step - loss: 0.0010 - accuracy:
0.8439
Epoch 4/5
5759/5759 [=====] - 53s 9ms/step - loss: 9.8313e-04 - accur
acy: 0.8488
Epoch 5/5
5759/5759 [=====] - 53s 9ms/step - loss: 9.5151e-04 - accur
acy: 0.8510
Epoch 1/5
5759/5759 [=====] - 54s 9ms/step - loss: 0.0057 - accuracy:
0.7326
Epoch 2/5
5759/5759 [=====] - 55s 10ms/step - loss: 0.0022 - accurac
y: 0.7732
Epoch 3/5
5759/5759 [=====] - 56s 10ms/step - loss: 0.0024 - accurac
y: 0.7718
Epoch 4/5
5759/5759 [=====] - 57s 10ms/step - loss: 0.0042 - accurac
y: 0.7082
Epoch 5/5
5759/5759 [=====] - 57s 10ms/step - loss: 0.0042 - accurac
y: 0.6919
Epoch 1/5
5759/5759 [=====] - 62s 11ms/step - loss: 0.0037 - accurac
y: 0.7458
Epoch 2/5
5759/5759 [=====] - 61s 11ms/step - loss: 0.0011 - accurac
y: 0.8416
Epoch 3/5
5759/5759 [=====] - 60s 10ms/step - loss: 9.1574e-04 - accu
racy: 0.8552
Epoch 4/5
5759/5759 [=====] - 60s 10ms/step - loss: 8.3954e-04 - accu
racy: 0.8592
Epoch 5/5
5759/5759 [=====] - 60s 10ms/step - loss: 8.1003e-04 - accu
racy: 0.8623
Epoch 1/5
5759/5759 [=====] - 65s 11ms/step - loss: 0.0045 - accurac
y: 0.6899
Epoch 2/5
5759/5759 [=====] - 64s 11ms/step - loss: 0.0021 - accurac
y: 0.7670
Epoch 3/5
5759/5759 [=====] - 64s 11ms/step - loss: 0.0016 - accurac
y: 0.8004
Epoch 4/5
5759/5759 [=====] - 64s 11ms/step - loss: 0.0015 - accurac
y: 0.8067
Epoch 5/5
5759/5759 [=====] - 66s 11ms/step - loss: 0.0012 - accurac
y: 0.8303
Epoch 1/5
5759/5759 [=====] - 67s 11ms/step - loss: nan - accuracy:
```

```
0.4622
Epoch 2/5
5759/5759 [=====] - 65s 11ms/step - loss: nan - accuracy:
0.4620
Epoch 3/5
5759/5759 [=====] - 65s 11ms/step - loss: nan - accuracy:
0.4620
Epoch 4/5
5759/5759 [=====] - 66s 11ms/step - loss: nan - accuracy:
0.4620
Epoch 5/5
5759/5759 [=====] - 65s 11ms/step - loss: nan - accuracy:
0.4620
Epoch 1/5
5759/5759 [=====] - 66s 11ms/step - loss: 0.0031 - accurac
y: 0.7300
Epoch 2/5
5759/5759 [=====] - 65s 11ms/step - loss: 9.2361e-04 - accu
racy: 0.8509
Epoch 3/5
5759/5759 [=====] - 65s 11ms/step - loss: 8.2980e-04 - accu
racy: 0.8595
Epoch 4/5
5759/5759 [=====] - 66s 11ms/step - loss: 7.8920e-04 - accu
racy: 0.8637
Epoch 5/5
5759/5759 [=====] - 65s 11ms/step - loss: 7.6429e-04 - accu
racy: 0.8663
Epoch 1/5
5759/5759 [=====] - 66s 11ms/step - loss: 0.0019 - accurac
y: 0.7988
Epoch 2/5
5759/5759 [=====] - 65s 11ms/step - loss: 0.0011 - accurac
y: 0.8400
Epoch 3/5
5759/5759 [=====] - 65s 11ms/step - loss: 9.7589e-04 - accu
racy: 0.8495
Epoch 4/5
5759/5759 [=====] - 65s 11ms/step - loss: 9.1398e-04 - accu
racy: 0.8548
Epoch 5/5
5759/5759 [=====] - 65s 11ms/step - loss: 8.8543e-04 - accu
racy: 0.8570
Epoch 1/5
5759/5759 [=====] - 66s 11ms/step - loss: 0.0052 - accurac
y: 0.6991
Epoch 2/5
5759/5759 [=====] - 63s 11ms/step - loss: 0.0038 - accurac
y: 0.7227
Epoch 3/5
5759/5759 [=====] - 66s 12ms/step - loss: 0.0058 - accurac
y: 0.6209
Epoch 4/5
5759/5759 [=====] - 68s 12ms/step - loss: 0.0075 - accurac
y: 0.6143
Epoch 5/5
5759/5759 [=====] - 66s 12ms/step - loss: 0.0085 - accurac
y: 0.5138
Epoch 1/5
5759/5759 [=====] - 64s 11ms/step - loss: 0.0041 - accurac
y: 0.6560
Epoch 2/5
5759/5759 [=====] - 62s 11ms/step - loss: 0.0023 - accurac
y: 0.7516
Epoch 3/5
```

```

5759/5759 [=====] - 62s 11ms/step - loss: 0.0017 - accurac
y: 0.7910
Epoch 4/5
5759/5759 [=====] - 63s 11ms/step - loss: 0.0013 - accurac
y: 0.8118
Epoch 5/5
5759/5759 [=====] - 62s 11ms/step - loss: 0.0011 - accurac
y: 0.8359
Epoch 1/5
5759/5759 [=====] - 63s 11ms/step - loss: 0.0023 - accurac
y: 0.7685
Epoch 2/5
5759/5759 [=====] - 62s 11ms/step - loss: 0.0014 - accurac
y: 0.8199
Epoch 3/5
5759/5759 [=====] - 62s 11ms/step - loss: 0.0012 - accurac
y: 0.8340
Epoch 4/5
5759/5759 [=====] - 62s 11ms/step - loss: 9.9525e-04 - accu
racy: 0.8478
Epoch 5/5
5759/5759 [=====] - 62s 11ms/step - loss: 9.6426e-04 - accu
racy: 0.8498
Epoch 1/5
5759/5759 [=====] - 63s 11ms/step - loss: 0.0044 - accurac
y: 0.7242
Epoch 2/5
5759/5759 [=====] - 66s 11ms/step - loss: 0.0028 - accurac
y: 0.7333
Epoch 3/5
5759/5759 [=====] - 68s 12ms/step - loss: 0.0038 - accurac
y: 0.7115
Epoch 4/5
5759/5759 [=====] - 68s 12ms/step - loss: 0.0030 - accurac
y: 0.7355
Epoch 5/5
5759/5759 [=====] - 68s 12ms/step - loss: 0.0023 - accurac
y: 0.7661
Epoch 1/5
301/5759 [>.....] - ETA: 1:06 - loss: 0.0155 - accuracy: 0.
5366

```

KeyboardInterrupt

Traceback (most recent call last)

~\AppData\Local\Temp\ipykernel_25360\1785499270.py in <module>

```

----> 1 optimalParams, bestErr, errs = gridSearch({
      2     'lookBack': np.arange(3, 100, 5),
      3     'activation': ['relu', 'tanh', 'sigmoid'],
      4     'learningRate': [1e-3, 1e-2, 1e-1],
      5 }, train, test)

```

~\AppData\Local\Temp\ipykernel_25360\2679425061.py in gridSearch(gridParams, train, test)

```

      53         for activation in gridParams['activation']:
      54             for learningRate in gridParams['learningRate']:
----> 55                 Y_test, Y_pred = runModel(train, test, lookBack, activation,
learningRate)
      56                 err = rmse(Y_test, Y_pred)
      57                 errs.append(err)

```

~\AppData\Local\Temp\ipykernel_25360\2679425061.py in runModel(train, test, lookBack, activation, learningRate)

```

      24     )
      25
----> 26     history = model.fit(
      27         x=X_train,

```

```

28         y=Y_train,

~\anaconda3\envs\tf\lib\site-packages\tensorflow\python\keras\engine\training.py in
fit(self, x, y, batch_size, epochs, verbose, callbacks, validation_split, validation
_data, shuffle, class_weight, sample_weight, initial_epoch, steps_per_epoch, validat
ion_steps, validation_batch_size, validation_freq, max_queue_size, workers, use_mult
iprocessing)
1191         _r=1):
1192             callbacks.on_train_batch_begin(step)
-> 1193             tmp_logs = self.train_function(iterator)
1194             if data_handler.should_sync:
1195                 context.async_wait()

~\anaconda3\envs\tf\lib\site-packages\tensorflow\python\eager\def_function.py in __c
all__(self, *args, **kws)
883
884         with OptionalXlaContext(self._jit_compile):
--> 885             result = self._call(*args, **kws)
886
887             new_tracing_count = self.experimental_get_tracing_count()

~\anaconda3\envs\tf\lib\site-packages\tensorflow\python\eager\def_function.py in _ca
ll(self, *args, **kws)
915         # In this case we have created variables on the first call, so we run
the
916         # defunned version which is guaranteed to never create variables.
--> 917         return self._stateless_fn(*args, **kws) # pylint: disable=not-callab
le
918         elif self._stateful_fn is not None:
919             # Release the lock early so that multiple threads can perform the call

~\anaconda3\envs\tf\lib\site-packages\tensorflow\python\eager\function.py in __call_
__(self, *args, **kwargs)
3037         (graph_function,
3038          filtered_flat_args) = self._maybe_define_function(args, kwargs)
-> 3039         return graph_function._call_flat(
3040             filtered_flat_args, captured_inputs=graph_function.captured_inputs)
# pylint: disable=protected-access
3041

~\anaconda3\envs\tf\lib\site-packages\tensorflow\python\eager\function.py in _call_f
lat(self, args, captured_inputs, cancellation_manager)
1961         and executing_eagerly):
1962             # No tape is watching; skip to running the function.
-> 1963             return self._build_call_outputs(self._inference_function.call(
1964                 ctx, args, cancellation_manager=cancellation_manager))
1965             forward_backward = self._select_forward_and_backward_functions(

~\anaconda3\envs\tf\lib\site-packages\tensorflow\python\eager\function.py in call(se
lf, ctx, args, cancellation_manager)
589         with _InterpolateFunctionError(self):
590             if cancellation_manager is None:
--> 591                 outputs = execute.execute(
592                     str(self.signature.name),
593                     num_outputs=self._num_outputs,

~\anaconda3\envs\tf\lib\site-packages\tensorflow\python\eager\execute.py in quick_ex
ecute(op_name, num_outputs, inputs, attrs, ctx, name)
57         try:
58             ctx.ensure_initialized()
---> 59             tensors = pywrap_tfe.TFE_Py_Execute(ctx._handle, device_name, op_name,
60                                                         inputs, attrs, num_outputs)
61         except core._NotOkStatusException as e:

```

KeyboardInterrupt:

In []:

In [218...

```

gridParams = {
    'lookBack': np.arange(3, 40, 5),
    'activation': ['relu', 'tanh', 'sigmoid'],
    'learningRate': [1e-3, 1e-2, 1e-1],
}
errs = []
for lookBack in gridParams['lookBack']:
    for activation in gridParams['activation']:
        for learningRate in gridParams['learningRate']:
            _, Y_test = createDataset(test, lookBack=lookBack)
            Y_pred = np.load(
                'grid_search_results\\' + f'look_back_{lookBack}_activation_{activation}'
            )
            err = rmse(Y_test, Y_pred)
            errs.append(err)
errs = np.array(errs).reshape((
    len(gridParams['lookBack']),
    len(gridParams['activation']),
    len(gridParams['learningRate']),
))

```

In [226...

errs

Out[226...

```

array([[0.6414269 , 0.83603474, 0.85826896],
       [0.62607609, 0.63024976, 0.63787453],
       [0.63879832, 0.64057386, 0.65165237]],

       [[0.51196927, 0.55213708, 1.01947071],
       [0.51120873, 0.51703726, 0.53209992],
       [0.53684744, 0.53839308, 0.59609721]],

       [[0.45262104, 0.48162762, 1.00781651],
       [0.4515218 , 0.44993459, 0.58011941],
       [0.47501522, 0.46524087, 0.63843059]],

       [[0.40681028, 0.41532148, 0.86891362],
       [0.39862751, 0.40349585, 0.65236153],
       [0.43636565, 0.41282277, 0.71989363]],

       [[0.36959019, 0.44483344, 0.58547245],
       [0.37299922, 0.38219771, 0.84569208],
       [0.43502095, 0.41048232, 0.80821859]],

       [[0.36333964, 0.38886573, 0.98191604],
       [0.35115707, 0.35059232, 0.88705153],
       [0.42260604, 0.39652337, 0.66386524]],

       [[0.33520708, 0.3468475 ,          nan],
       [0.33877559, 0.3384003 , 0.61274334],
       [0.38368197, 0.35446079, 0.6780404 ]],

       [[0.33547904, 0.39381983,          nan],
       [0.32414165, 0.3619262 , 1.03652624],
       [0.39219947, 0.37187296, 0.77961029]]])

```

In [229...

```

errs[np.isnan(errs)] = 1.
errs

```

```
Out[229...] array([[0.6414269 , 0.83603474, 0.85826896],
 [0.62607609, 0.63024976, 0.63787453],
 [0.63879832, 0.64057386, 0.65165237]],

 [[0.51196927, 0.55213708, 1.01947071],
 [0.51120873, 0.51703726, 0.53209992],
 [0.53684744, 0.53839308, 0.59609721]],

 [[0.45262104, 0.48162762, 1.00781651],
 [0.4515218 , 0.44993459, 0.58011941],
 [0.47501522, 0.46524087, 0.63843059]],

 [[0.40681028, 0.41532148, 0.86891362],
 [0.39862751, 0.40349585, 0.65236153],
 [0.43636565, 0.41282277, 0.71989363]],

 [[0.36959019, 0.44483344, 0.58547245],
 [0.37299922, 0.38219771, 0.84569208],
 [0.43502095, 0.41048232, 0.80821859]],

 [[0.36333964, 0.38886573, 0.98191604],
 [0.35115707, 0.35059232, 0.88705153],
 [0.42260604, 0.39652337, 0.66386524]],

 [[0.33520708, 0.3468475 , 1.          ],
 [0.33877559, 0.3384003 , 0.61274334],
 [0.38368197, 0.35446079, 0.6780404 ]],

 [[0.33547904, 0.39381983, 1.          ],
 [0.32414165, 0.3619262 , 1.03652624],
 [0.39219947, 0.37187296, 0.77961029]]])
```

```
In [219...] errs.shape
```

```
Out[219...] (8, 3, 3)
```

```
In [230...] bestParams, bestErr = optimalParams(errs, gridParams)
```

```
In [231...] bestParams
```

```
Out[231...] {'lookBack': 38, 'activation': 'tanh', 'learningRate': 0.001}
```

```
In [247...] bestErr, errs.mean(), errs.max()
```

```
Out[247...] (0.3241416533103591, 0.5560737886800533, 1.0365262373786537)
```

```
In [233...] Y_test, Y_pred = runModel(train, test, **bestParams)
```

Epoch 1/5

5759/5759 [=====] - 66s 11ms/step - loss: 0.0025 - accuracy: 0.7749

Epoch 2/5

5759/5759 [=====] - 66s 11ms/step - loss: 9.1548e-04 - accuracy: 0.8538

Epoch 3/5

5759/5759 [=====] - 65s 11ms/step - loss: 8.2328e-04 - accuracy: 0.8619

Epoch 4/5

```
5759/5759 [=====] - 65s 11ms/step - loss: 7.7972e-04 - accu  
racy: 0.8654  
Epoch 5/5  
5759/5759 [=====] - 65s 11ms/step - loss: 7.5123e-04 - accu  
racy: 0.8673
```

```
In [234... rmse(Y_test, Y_pred)
```

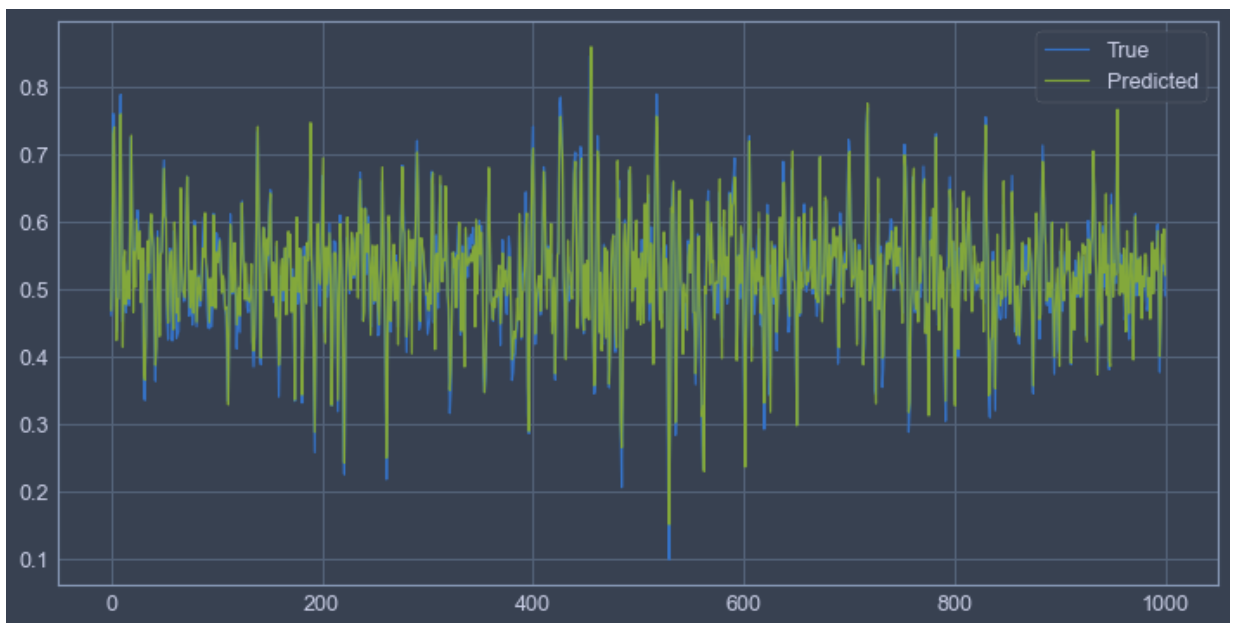
```
Out[234... 0.3284646982588869
```

```
In [237... from jupyterthemes import jtplot
```

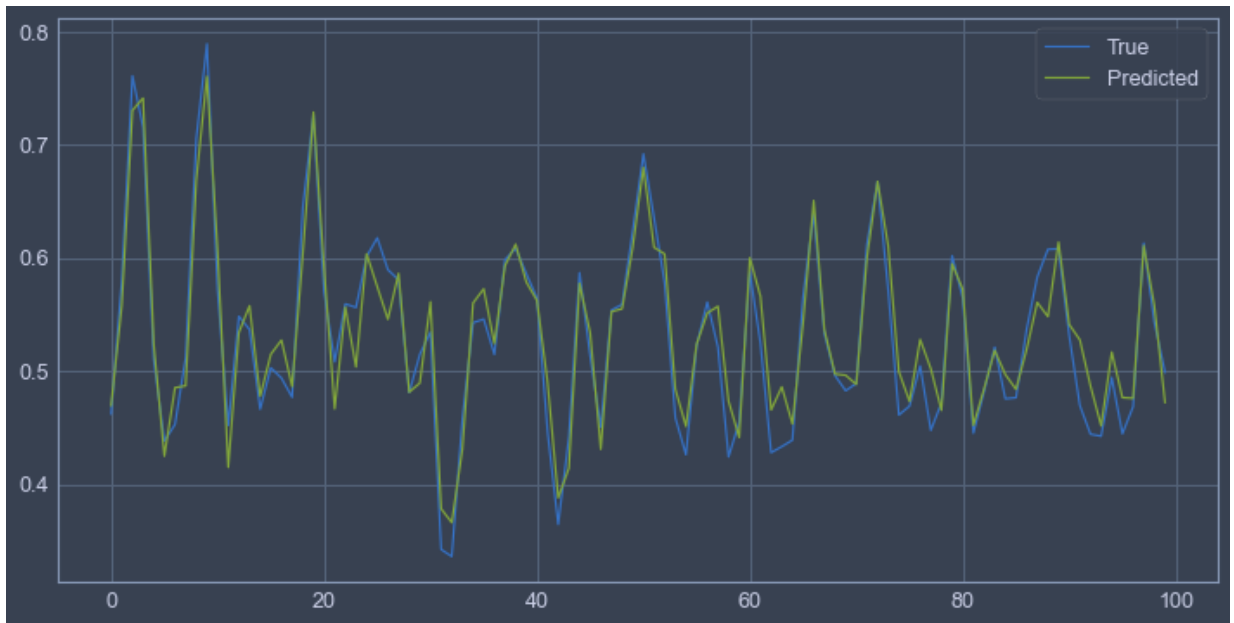
```
In [238... jtplot.style()
```

```
In [260... plt.rcParams['figure.figsize'] = 12, 6
```

```
In [291... plt.plot(Y_test[:1000, 0], label='True')  
plt.plot(Y_pred[:1000, 0], label='Predicted')  
plt.legend();
```

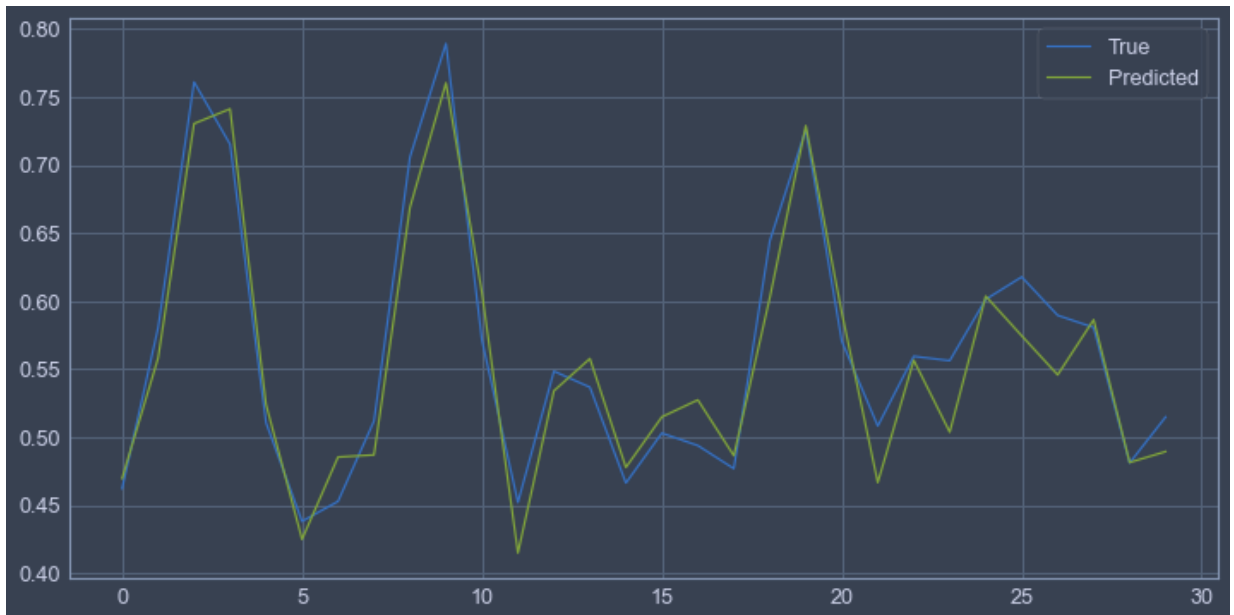


```
In [292... plt.plot(Y_test[:100, 0], label='True')  
plt.plot(Y_pred[:100, 0], label='Predicted')  
plt.legend();
```



In [293...

```
plt.plot(Y_test[:30, 0], label='True')
plt.plot(Y_pred[:30, 0], label='Predicted')
plt.legend();
```

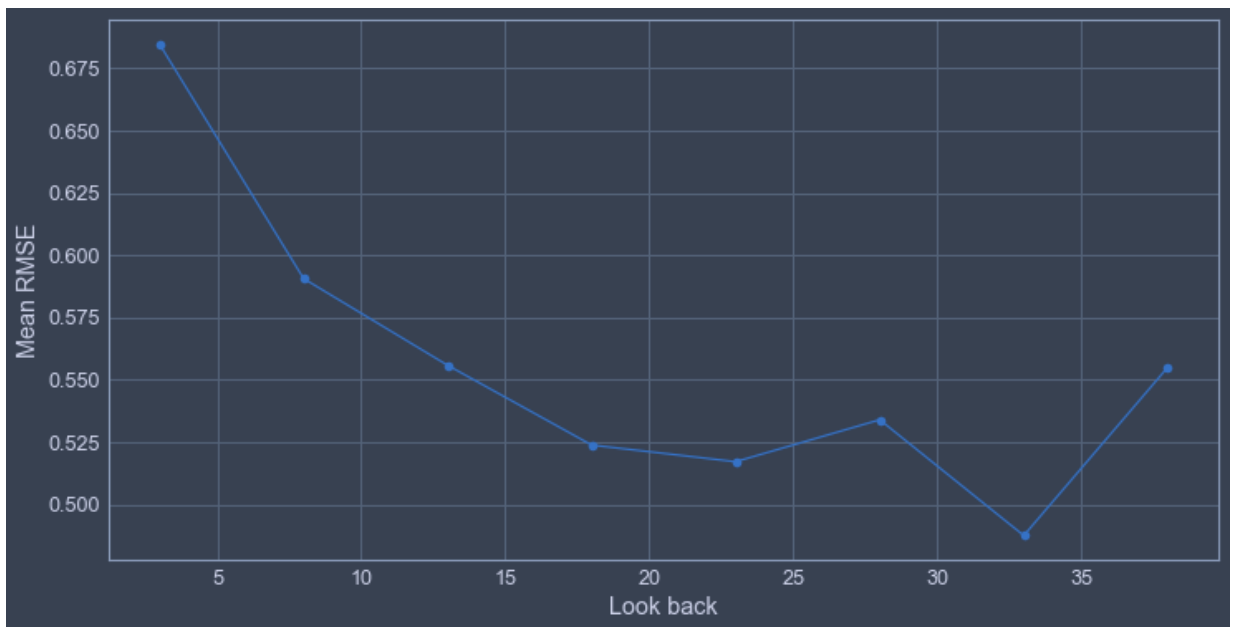


In [268...

```
# RMSE vs. Look back.
plt.plot(gridParams['lookBack'], errs.mean(axis=(1, 2)), 'o-')
plt.xlabel('Look back')
plt.ylabel('Mean RMSE')
print(f'Optimal look back value from the simulations: {bestParams["lookBack"]}')

```

Optimal look back value from the simulations: 38



In [270...

```
# RMSE vs. Learning rate.
plt.semilogx(gridParams['learningRate'], errs.mean(axis=(0, 1)), 'o-')
plt.xlabel('Learning rate')
plt.ylabel('Mean RMSE')
print(f'Optimal learning rate value from the simulations: {bestParams["learningRate"]}
```

Optimal learning rate value from the simulations: 0.001



In [271...

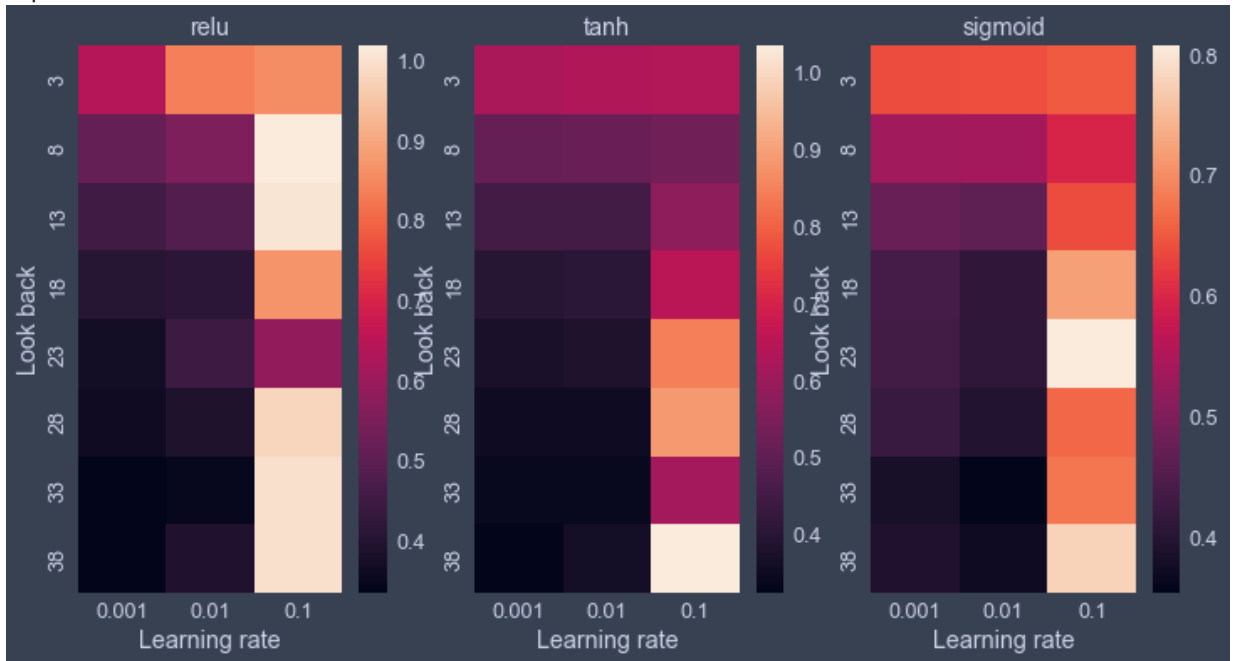
```
import seaborn as sns
```

In [277...

```
# RMSE vs. activation.
for i in range(3):
    plt.subplot(1, 3, i + 1)
    sns.heatmap(
        errs[:, i, :],
        xticklabels=gridParams['learningRate'],
        yticklabels=gridParams['lookBack'],
    )
    plt.xlabel('Learning rate')
    plt.ylabel('Look back')
```

```
plt.title(gridParams['activation'][i])  
print(f'Optimal activation function from the simulations: {bestParams["activation"]})
```

Optimal activation function from the simulations: tanh



In [278...

bestParams

Out[278...

```
{'lookBack': 38, 'activation': 'tanh', 'learningRate': 0.001}
```

In [279...

bestErr

Out[279...

```
0.3241416533103591
```

In []: