01 univariate time series regression

September 29, 2021

1 Recurrent Neural Networks

1.1 Univariate Time Series Regression

This notebook demonstrates how to forecast the S&P 500 index using a Recurrent Neural Network.

1.2 Imports & Settings

```
[1]: import warnings
     warnings.filterwarnings('ignore')
[2]: %matplotlib inline
     from pathlib import Path
     import numpy as np
     import pandas as pd
     import pandas_datareader.data as web
     from scipy.stats import spearmanr
     from sklearn.metrics import mean_squared_error
     from sklearn.preprocessing import MinMaxScaler
     import tensorflow as tf
     from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping
     from tensorflow.keras.models import Sequential
     from tensorflow.keras.layers import Dense, LSTM
     from tensorflow import keras
     import matplotlib.pyplot as plt
     import seaborn as sns
```

```
[3]: gpu_devices = tf.config.experimental.list_physical_devices('GPU')
if gpu_devices:
    print('Using GPU')
    tf.config.experimental.set_memory_growth(gpu_devices[0], True)
else:
    print('Using CPU')
```

Using CPU

```
[4]: sns.set_style('whitegrid')
np.random.seed(42)
```

```
[5]: results_path = Path('results', 'univariate_time_series')
if not results_path.exists():
    results_path.mkdir(parents=True)
```

1.3 Get Data

We obtain data for 2010-2018 from the Federal Reserve Bank's Data Service FRED using the pandas_datareader library in introduced in Chapter 2 on Market and Fundamental Data.



1.4 Preprocessing

```
[12]: scaler = MinMaxScaler()
```

```
[13]: count 2229.000000
mean 0.451605
std 0.254561
min 0.000000
25% 0.238076
```

50% 0.447456 75% 0.659023 max 1.000000

dtype: float64

1.5 Generating recurrent sequences from our time series

Our time series is a sequence of numbers indexed by time:

$$x_0, x_1, x_2, ..., x_T$$

where $\{x_t\}$ is the numerical value in period t and T is the total length of the series.

To apply a RNN for regression of classification, we use a sliding window to construct a rolling set of input/output pairs for our model to learn from as animated below.

We will generate sequences of 63 trading days, approximately three months, and use a single LSTM layer with 20 hidden units to predict the index value one timestep ahead. The input to every LSTM layer must have three dimensions, namely: - **Samples**: One sequence is one sample. A batch contains one or more samples. - **Time Steps**: One time step is one point of observation in the sample. - **Features**: One feature is one observation at a time step.

Our S&P 500 sample has 2,264 observations or time steps. We will create overlapping sequences using a window of 63 observations each. For a simpler window of size T = 5, we obtain input-output pairs as shown in the following table:

Input	Output
$\langle x_1, x_2, x_3, x_4, x_5 \rangle$	x_6
$\langle x_2, x_3, x_4, x_5, x_6 \rangle$	x_7
<u>:</u>	:
$\langle x_{T-5}, x_{T-4}, x_{T-3}, x_{T-2}, x_{T-1} \rangle$	x_T

Generally speaking, for window size S, the relationship takes the form

$$x_t = f(x_{t-1}, x_{t-2}, \dots, x_{t-S}) \quad \forall t = S, S+1, \dots, T$$

Each of the T-S lagged input sequence or vector is of length S with a corresponding scalar output.

We can use the function create_univariate_rnn_data() to stack sequences selected using a rolling windows:

```
[14]: def create_univariate_rnn_data(data, window_size):
    n = len(data)
    y = data[window_size:]
    data = data.values.reshape(-1, 1) # make 2D
    X = np.hstack(tuple([data[i: n-j, :] for i, j in_u
    →enumerate(range(window_size, 0, -1))]))
    return pd.DataFrame(X, index=y.index), y
```

We apply this function to the rescaled stock index for a window_size=63 to obtain a two-dimensional dataset of shape number of samples x number of timesteps:

```
[15]:
     window_size = 63
[16]: | X, y = create_univariate_rnn_data(sp500_scaled, window_size=window_size)
[17]:
     X.head()
[17]:
                        0
                                   1
                                             2
                                                       3
                                                                  4
                                                                            5
                                                                                \
      DATE
                            0.096633
                                       0.103069
                                                 0.106498
                                                           0.096740
      2011-05-24
                  0.097240
                                                                     0.097726
                                                 0.096740
                                                           0.097726
      2011-05-25
                  0.096633
                            0.103069
                                       0.106498
                                                                      0.108250
      2011-05-26
                  0.103069
                            0.106498
                                       0.096740
                                                 0.097726
                                                            0.108250
                                                                      0.103663
      2011-05-27
                  0.106498
                            0.096740
                                       0.097726
                                                 0.108250
                                                           0.103663
                                                                      0.098515
      2011-05-31 0.096740
                            0.097726
                                       0.108250
                                                 0.103663
                                                           0.098515
                                                                      0.103976
                                   7
                        6
                                             8
                                                       9
                                                                     53
                                                                               54
      DATE
                                       0.098515
      2011-05-24
                  0.108250
                            0.103663
                                                 0.103976
                                                               0.120484
                                                                         0.113439
      2011-05-25
                  0.103663
                            0.098515
                                       0.103976
                                                 0.103135
                                                               0.113439
                                                                         0.116508
                            0.103976
                                                               0.116508
      2011-05-26
                  0.098515
                                       0.103135
                                                 0.091499
                                                                         0.111426
      2011-05-27
                  0.103976
                            0.103135
                                       0.091499
                                                 0.095782
                                                               0.111426
                                                                         0.107549
      2011-05-31 0.103135
                            0.091499
                                       0.095782
                                                 0.092097
                                                               0.107549
                                                                         0.107320
                        55
                                   56
                                             57
                                                       58
                                                                  59
                                                                            60
                                                                               \
     DATE
      2011-05-24
                  0.116508
                            0.111426
                                       0.107549
                                                 0.107320
                                                           0.112785
                                                                      0.114149
                  0.111426
                            0.107549
                                       0.107320
                                                 0.112785
                                                           0.114149
      2011-05-25
                                                                      0.109324
      2011-05-26
                  0.107549
                            0.107320
                                       0.112785
                                                 0.114149
                                                           0.109324
                                                                      0.101897
      2011-05-27
                  0.107320
                            0.112785
                                       0.114149
                                                 0.109324
                                                            0.101897
                                                                      0.101388
      2011-05-31
                  0.112785
                            0.114149
                                       0.109324
                                                 0.101897
                                                           0.101388
                                                                      0.103345
                        61
                                   62
     DATE
      2011-05-24
                  0.109324
                            0.101897
      2011-05-25
                  0.101897
                            0.101388
      2011-05-26
                  0.101388
                            0.103345
      2011-05-27
                  0.103345
                            0.105783
      2011-05-31 0.105783
                           0.108310
      [5 rows x 63 columns]
[18]:
      y.head()
[18]: DATE
```

2011-05-24

0.101388

```
2011-05-25
              0.103345
2011-05-26
               0.105783
2011-05-27
               0.108310
2011-05-31
               0.114897
```

dtype: float64

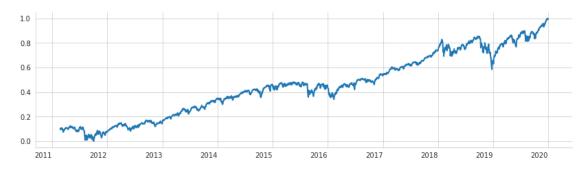
```
[19]: X.shape
```

[19]: (2166, 63)

1.6 Train-test split

To respect the time series nature of the data, we set aside the data at the end of the sample as hold-out or test set. More specifically, we'll use the data for 2018.

```
[20]: ax = sp500_scaled.plot(lw=2, figsize=(14, 4), rot=0)
      ax.set_xlabel('')
      sns.despine()
```



```
[21]: X_train = X[:'2018'].values.reshape(-1, window_size, 1)
      y_train = y[:'2018']
      # keep the last year for testing
      X_test = X['2019'].values.reshape(-1, window_size, 1)
      y_{test} = y['2019']
     n_obs, window_size, n_features = X_train.shape
[22]:
     y_train.shape
[23]: (1914,)
```

Keras LSTM Layer

Keras has several built-in RNN layers with various configuration options described in detail in the documentation.

```
LSTM(units,
     activation='tanh',
     recurrent_activation='hard_sigmoid',
     use bias=True,
     kernel initializer='glorot uniform',
     recurrent initializer='orthogonal',
     bias initializer='zeros',
     unit_forget_bias=True,
     kernel_regularizer=None,
     recurrent_regularizer=None,
     bias_regularizer=None,
     activity_regularizer=None,
     kernel_constraint=None,
     recurrent_constraint=None,
     bias_constraint=None,
     dropout=0.0,
     recurrent_dropout=0.0,
     implementation=1,
     return_sequences=False,
     return state=False,
     go backwards=False,
     stateful=False,
     unroll=False)
```

1.8 Define the Model Architecture

Having created input/output pairs out of our time series and cut this into training/testing sets, we can now begin setting up our RNN. We use Keras to quickly build a two hidden layer RNN of the following specifications

- layer 1 uses an LSTM module with 20 hidden units (note here the input_shape = (window_size,1))
- layer 2 uses a fully connected module with one unit
- the 'mean_squared_error' loss should be used (remember: we are performing regression here)

This can be constructed using just a few lines - see e.g., the general Keras documentation and the LSTM documentation in particular for examples of how to quickly use Keras to build neural network models. Make sure you are initializing your optimizer given the keras-recommended approach for RNNs

The summary shows that the model has 1,781 parameters:

```
[25]: rnn.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
LSTM (LSTM)	(None, 10)	480
Output (Dense)	(None, 1)	11
Total params: 491 Trainable params: 491 Non-trainable params: 0		

1.9 Train the Model

We train the model using the RMSProp optimizer recommended for RNN with default settings and compile the model with mean squared error for this regression problem:

We define an EarlyStopping callback and train the model for up to 100 episodes.

Epoch 1/150

```
Epoch 00001: val_loss improved from inf to 0.00766, saving model to
results/univariate_time_series/rnn.h5
0.0077
Epoch 2/150
Epoch 00002: val_loss improved from 0.00766 to 0.00135, saving model to
results/univariate_time_series/rnn.h5
96/96 [============== ] - 1s 9ms/step - loss: 5.0613e-04 -
val_loss: 0.0014
Epoch 3/150
Epoch 00003: val_loss did not improve from 0.00135
96/96 [============= ] - 1s 9ms/step - loss: 4.2515e-04 -
val_loss: 0.0033
Epoch 4/150
Epoch 00004: val_loss did not improve from 0.00135
val loss: 0.0022
Epoch 5/150
Epoch 00005: val_loss did not improve from 0.00135
val_loss: 0.0033
Epoch 6/150
96/96 [========== ] - ETA: Os - loss: 3.4672e-04
Epoch 00006: val_loss improved from 0.00135 to 0.00068, saving model to
results/univariate_time_series/rnn.h5
val_loss: 6.7836e-04
Epoch 7/150
Epoch 00007: val loss did not improve from 0.00068
96/96 [============= ] - 1s 9ms/step - loss: 3.1417e-04 -
val_loss: 0.0047
Epoch 8/150
Epoch 00008: val_loss did not improve from 0.00068
96/96 [============ ] - 1s 9ms/step - loss: 3.1923e-04 -
val_loss: 0.0014
Epoch 9/150
Epoch 00009: val_loss improved from 0.00068 to 0.00043, saving model to
results/univariate_time_series/rnn.h5
val_loss: 4.3396e-04
```

```
Epoch 10/150
Epoch 00010: val_loss did not improve from 0.00043
96/96 [============= ] - 1s 9ms/step - loss: 2.8585e-04 -
val loss: 0.0016
Epoch 11/150
Epoch 00011: val_loss improved from 0.00043 to 0.00032, saving model to
results/univariate_time_series/rnn.h5
96/96 [============= ] - 1s 9ms/step - loss: 2.6074e-04 -
val_loss: 3.1798e-04
Epoch 12/150
Epoch 00012: val_loss did not improve from 0.00032
96/96 [============= ] - 1s 9ms/step - loss: 2.5868e-04 -
val_loss: 4.8836e-04
Epoch 13/150
96/96 [=========== ] - ETA: Os - loss: 2.5184e-04
Epoch 00013: val_loss did not improve from 0.00032
val_loss: 4.2231e-04
Epoch 14/150
Epoch 00014: val_loss did not improve from 0.00032
val_loss: 4.4436e-04
Epoch 15/150
Epoch 00015: val_loss did not improve from 0.00032
val_loss: 4.7206e-04
Epoch 16/150
Epoch 00016: val_loss did not improve from 0.00032
val_loss: 3.2628e-04
Epoch 17/150
Epoch 00017: val_loss did not improve from 0.00032
96/96 [=========== ] - 1s 10ms/step - loss: 2.2815e-04 -
val_loss: 0.0013
Epoch 18/150
96/96 [============= ] - ETA: Os - loss: 2.1929e-04
Epoch 00018: val_loss did not improve from 0.00032
96/96 [============ ] - 1s 9ms/step - loss: 2.1929e-04 -
val_loss: 0.0022
Epoch 19/150
```

```
Epoch 00019: val_loss improved from 0.00032 to 0.00024, saving model to
results/univariate_time_series/rnn.h5
96/96 [=========== ] - 1s 9ms/step - loss: 2.1470e-04 -
val_loss: 2.4200e-04
Epoch 20/150
96/96 [========== ] - ETA: Os - loss: 2.1644e-04
Epoch 00020: val_loss improved from 0.00024 to 0.00023, saving model to
results/univariate_time_series/rnn.h5
val_loss: 2.3101e-04
Epoch 21/150
96/96 [============= ] - ETA: Os - loss: 2.0451e-04
Epoch 00021: val_loss improved from 0.00023 to 0.00021, saving model to
results/univariate_time_series/rnn.h5
96/96 [============= ] - 1s 9ms/step - loss: 2.0451e-04 -
val_loss: 2.1255e-04
Epoch 22/150
Epoch 00022: val_loss did not improve from 0.00021
96/96 [=========== ] - 1s 9ms/step - loss: 2.0179e-04 -
val loss: 2.2027e-04
Epoch 23/150
96/96 [============== ] - ETA: Os - loss: 1.9941e-04
Epoch 00023: val_loss did not improve from 0.00021
96/96 [=========== ] - 1s 9ms/step - loss: 1.9941e-04 -
val_loss: 4.4025e-04
Epoch 24/150
Epoch 00024: val_loss did not improve from 0.00021
96/96 [============= ] - 1s 9ms/step - loss: 1.9096e-04 -
val_loss: 5.4885e-04
Epoch 25/150
96/96 [=========== ] - ETA: Os - loss: 1.8358e-04
Epoch 00025: val_loss did not improve from 0.00021
val_loss: 2.4444e-04
Epoch 26/150
Epoch 00026: val_loss did not improve from 0.00021
96/96 [=========== ] - 1s 10ms/step - loss: 1.8471e-04 -
val_loss: 4.2620e-04
Epoch 27/150
Epoch 00027: val_loss did not improve from 0.00021
96/96 [============ ] - 1s 9ms/step - loss: 1.7350e-04 -
val_loss: 4.0677e-04
Epoch 28/150
```

```
Epoch 00028: val_loss did not improve from 0.00021
val_loss: 3.8056e-04
Epoch 29/150
Epoch 00029: val_loss did not improve from 0.00021
val_loss: 3.5113e-04
Epoch 30/150
Epoch 00030: val_loss improved from 0.00021 to 0.00018, saving model to
results/univariate_time_series/rnn.h5
val_loss: 1.7758e-04
Epoch 31/150
Epoch 00031: val_loss improved from 0.00018 to 0.00016, saving model to
results/univariate_time_series/rnn.h5
val loss: 1.5858e-04
Epoch 32/150
Epoch 00032: val_loss improved from 0.00016 to 0.00016, saving model to
results/univariate_time_series/rnn.h5
val_loss: 1.5702e-04
Epoch 33/150
Epoch 00033: val_loss did not improve from 0.00016
96/96 [============ ] - 1s 10ms/step - loss: 1.5528e-04 -
val_loss: 3.3243e-04
Epoch 34/150
Epoch 00034: val_loss improved from 0.00016 to 0.00014, saving model to
results/univariate time series/rnn.h5
val_loss: 1.4220e-04
Epoch 35/150
Epoch 00035: val_loss did not improve from 0.00014
96/96 [============ ] - 1s 9ms/step - loss: 1.4350e-04 -
val_loss: 8.7128e-04
Epoch 36/150
Epoch 00036: val_loss did not improve from 0.00014
val_loss: 2.2118e-04
Epoch 37/150
```

```
Epoch 00037: val_loss did not improve from 0.00014
96/96 [============ ] - 1s 9ms/step - loss: 1.4475e-04 -
val_loss: 5.7758e-04
Epoch 38/150
Epoch 00038: val_loss did not improve from 0.00014
val_loss: 5.5123e-04
Epoch 39/150
96/96 [=========== ] - ETA: Os - loss: 1.3512e-04
Epoch 00039: val_loss did not improve from 0.00014
96/96 [============= ] - 1s 9ms/step - loss: 1.3512e-04 -
val_loss: 2.0821e-04
Epoch 40/150
Epoch 00040: val_loss did not improve from 0.00014
96/96 [============ ] - 1s 10ms/step - loss: 1.3073e-04 -
val_loss: 6.1821e-04
Epoch 41/150
Epoch 00041: val loss did not improve from 0.00014
val_loss: 5.5452e-04
Epoch 42/150
Epoch 00042: val_loss did not improve from 0.00014
96/96 [=========== ] - 1s 10ms/step - loss: 1.2543e-04 -
val_loss: 3.1468e-04
Epoch 43/150
Epoch 00043: val_loss did not improve from 0.00014
96/96 [============ ] - 1s 12ms/step - loss: 1.2745e-04 -
val_loss: 2.5483e-04
Epoch 44/150
96/96 [========== ] - ETA: Os - loss: 1.3116e-04
Epoch 00044: val loss did not improve from 0.00014
val_loss: 2.0916e-04
Epoch 45/150
Epoch 00045: val_loss did not improve from 0.00014
96/96 [=========== ] - 1s 12ms/step - loss: 1.2624e-04 -
val_loss: 1.5523e-04
Epoch 46/150
Epoch 00046: val_loss did not improve from 0.00014
```

```
val_loss: 1.4887e-04
Epoch 47/150
Epoch 00047: val_loss did not improve from 0.00014
val_loss: 3.1503e-04
Epoch 48/150
Epoch 00048: val_loss did not improve from 0.00014
96/96 [=========== ] - 1s 10ms/step - loss: 1.2169e-04 -
val_loss: 3.1043e-04
Epoch 49/150
Epoch 00049: val_loss did not improve from 0.00014
val_loss: 3.6431e-04
Epoch 50/150
Epoch 00050: val_loss did not improve from 0.00014
val_loss: 2.0745e-04
Epoch 51/150
96/96 [============== ] - ETA: Os - loss: 1.1787e-04
Epoch 00051: val_loss did not improve from 0.00014
val_loss: 3.8254e-04
Epoch 52/150
Epoch 00052: val_loss improved from 0.00014 to 0.00013, saving model to
results/univariate_time_series/rnn.h5
val_loss: 1.3098e-04
Epoch 53/150
Epoch 00053: val loss did not improve from 0.00013
96/96 [============= ] - 1s 8ms/step - loss: 1.1118e-04 -
val_loss: 3.5197e-04
Epoch 54/150
Epoch 00054: val_loss did not improve from 0.00013
96/96 [=========== ] - 1s 9ms/step - loss: 1.1724e-04 -
val_loss: 1.9148e-04
Epoch 55/150
Epoch 00055: val_loss did not improve from 0.00013
val_loss: 2.7836e-04
Epoch 56/150
```

```
Epoch 00056: val_loss did not improve from 0.00013
96/96 [============= ] - 1s 9ms/step - loss: 1.0802e-04 -
val_loss: 1.3425e-04
Epoch 57/150
Epoch 00057: val_loss improved from 0.00013 to 0.00012, saving model to
results/univariate_time_series/rnn.h5
val_loss: 1.1734e-04
Epoch 58/150
Epoch 00058: val_loss did not improve from 0.00012
val_loss: 2.0888e-04
Epoch 59/150
Epoch 00059: val_loss did not improve from 0.00012
96/96 [============= ] - 1s 9ms/step - loss: 1.0444e-04 -
val loss: 1.2834e-04
Epoch 60/150
96/96 [=========== ] - ETA: Os - loss: 1.0868e-04
Epoch 00060: val_loss did not improve from 0.00012
val_loss: 1.7766e-04
Epoch 61/150
Epoch 00061: val_loss did not improve from 0.00012
val_loss: 2.2622e-04
Epoch 62/150
Epoch 00062: val_loss did not improve from 0.00012
96/96 [============ ] - 1s 9ms/step - loss: 1.0332e-04 -
val loss: 1.1764e-04
Epoch 63/150
Epoch 00063: val_loss did not improve from 0.00012
val_loss: 1.7721e-04
Epoch 64/150
Epoch 00064: val_loss did not improve from 0.00012
96/96 [============= ] - 1s 9ms/step - loss: 1.0589e-04 -
val_loss: 2.7786e-04
Epoch 65/150
Epoch 00065: val_loss did not improve from 0.00012
```

```
val_loss: 2.5257e-04
Epoch 66/150
Epoch 00066: val loss did not improve from 0.00012
val loss: 1.2785e-04
Epoch 67/150
Epoch 00067: val_loss did not improve from 0.00012
val_loss: 1.5218e-04
Epoch 68/150
96/96 [============= ] - ETA: Os - loss: 9.5239e-05
Epoch 00068: val_loss improved from 0.00012 to 0.00011, saving model to
results/univariate_time_series/rnn.h5
96/96 [=========== ] - 1s 9ms/step - loss: 9.5239e-05 -
val_loss: 1.0982e-04
Epoch 69/150
Epoch 00069: val_loss did not improve from 0.00011
val_loss: 1.3820e-04
Epoch 70/150
Epoch 00070: val_loss did not improve from 0.00011
96/96 [============= ] - 1s 9ms/step - loss: 1.0096e-04 -
val_loss: 2.6083e-04
Epoch 71/150
Epoch 00071: val_loss did not improve from 0.00011
96/96 [============= ] - 1s 9ms/step - loss: 9.8619e-05 -
val_loss: 1.4675e-04
Epoch 72/150
Epoch 00072: val_loss did not improve from 0.00011
96/96 [============ ] - 1s 9ms/step - loss: 9.7614e-05 -
val_loss: 1.7677e-04
Epoch 73/150
Epoch 00073: val_loss did not improve from 0.00011
96/96 [============== ] - 1s 9ms/step - loss: 9.5436e-05 -
val_loss: 2.8398e-04
Epoch 74/150
Epoch 00074: val_loss did not improve from 0.00011
96/96 [============ ] - 1s 9ms/step - loss: 9.7079e-05 -
val_loss: 1.4352e-04
```

```
Epoch 75/150
Epoch 00075: val_loss did not improve from 0.00011
val loss: 1.2011e-04
Epoch 76/150
Epoch 00076: val_loss did not improve from 0.00011
val_loss: 1.7817e-04
Epoch 77/150
96/96 [========== ] - ETA: Os - loss: 9.1118e-05
Epoch 00077: val_loss did not improve from 0.00011
96/96 [============ ] - 1s 9ms/step - loss: 9.1118e-05 -
val_loss: 1.1157e-04
Epoch 78/150
Epoch 00078: val_loss did not improve from 0.00011
96/96 [============== ] - 1s 9ms/step - loss: 9.5155e-05 -
val loss: 1.5538e-04
Epoch 79/150
96/96 [============== ] - ETA: Os - loss: 9.4418e-05
Epoch 00079: val_loss did not improve from 0.00011
96/96 [============ ] - 1s 9ms/step - loss: 9.4418e-05 -
val_loss: 1.4241e-04
Epoch 80/150
Epoch 00080: val_loss improved from 0.00011 to 0.00011, saving model to
results/univariate_time_series/rnn.h5
val_loss: 1.0896e-04
Epoch 81/150
Epoch 00081: val_loss did not improve from 0.00011
val_loss: 1.3463e-04
Epoch 82/150
Epoch 00082: val_loss did not improve from 0.00011
96/96 [============ ] - 1s 9ms/step - loss: 9.4321e-05 -
val_loss: 1.4250e-04
Epoch 83/150
Epoch 00083: val_loss did not improve from 0.00011
96/96 [============ ] - 1s 9ms/step - loss: 9.6019e-05 -
val_loss: 1.1075e-04
Epoch 84/150
```

```
Epoch 00084: val_loss did not improve from 0.00011
val_loss: 2.0834e-04
Epoch 85/150
Epoch 00085: val_loss did not improve from 0.00011
96/96 [============= ] - 1s 9ms/step - loss: 8.7901e-05 -
val_loss: 1.2320e-04
Epoch 86/150
Epoch 00086: val_loss did not improve from 0.00011
val_loss: 1.1778e-04
Epoch 87/150
Epoch 00087: val_loss did not improve from 0.00011
val_loss: 1.8410e-04
Epoch 88/150
Epoch 00088: val_loss did not improve from 0.00011
96/96 [============== ] - 1s 9ms/step - loss: 9.1169e-05 -
val_loss: 1.5173e-04
Epoch 89/150
Epoch 00089: val_loss did not improve from 0.00011
96/96 [============= ] - 1s 9ms/step - loss: 9.0969e-05 -
val_loss: 2.6647e-04
Epoch 90/150
Epoch 00090: val_loss did not improve from 0.00011
val_loss: 2.2579e-04
Epoch 91/150
Epoch 00091: val_loss did not improve from 0.00011
val_loss: 1.4102e-04
Epoch 92/150
Epoch 00092: val_loss did not improve from 0.00011
val_loss: 1.5866e-04
Epoch 93/150
Epoch 00093: val_loss did not improve from 0.00011
val_loss: 2.2237e-04
```

```
Epoch 94/150
Epoch 00094: val_loss did not improve from 0.00011
val loss: 2.0188e-04
Epoch 95/150
Epoch 00095: val_loss did not improve from 0.00011
val_loss: 1.1806e-04
Epoch 96/150
Epoch 00096: val_loss did not improve from 0.00011
96/96 [============ ] - 1s 9ms/step - loss: 9.1519e-05 -
val_loss: 1.1541e-04
Epoch 97/150
Epoch 00097: val_loss improved from 0.00011 to 0.00011, saving model to
results/univariate_time_series/rnn.h5
val loss: 1.0814e-04
Epoch 98/150
Epoch 00098: val_loss did not improve from 0.00011
val_loss: 1.1347e-04
Epoch 99/150
Epoch 00099: val_loss did not improve from 0.00011
val_loss: 1.3592e-04
Epoch 100/150
96/96 [=========== ] - ETA: Os - loss: 8.6722e-05
Epoch 00100: val_loss did not improve from 0.00011
val_loss: 7.0361e-04
Epoch 101/150
Epoch 00101: val_loss did not improve from 0.00011
96/96 [=========== ] - 1s 9ms/step - loss: 8.9286e-05 -
val_loss: 1.1654e-04
Epoch 102/150
Epoch 00102: val_loss did not improve from 0.00011
96/96 [============= ] - 1s 9ms/step - loss: 8.6557e-05 -
val_loss: 1.1325e-04
Epoch 103/150
```

```
Epoch 00103: val_loss did not improve from 0.00011
val_loss: 2.9964e-04
Epoch 104/150
Epoch 00104: val_loss improved from 0.00011 to 0.00011, saving model to
results/univariate_time_series/rnn.h5
val_loss: 1.0701e-04
Epoch 105/150
Epoch 00105: val_loss did not improve from 0.00011
96/96 [============== ] - 1s 9ms/step - loss: 8.5441e-05 -
val_loss: 2.6547e-04
Epoch 106/150
Epoch 00106: val_loss did not improve from 0.00011
96/96 [============== ] - 1s 9ms/step - loss: 8.6718e-05 -
val_loss: 1.4452e-04
Epoch 107/150
Epoch 00107: val_loss did not improve from 0.00011
96/96 [============== ] - 1s 9ms/step - loss: 8.8267e-05 -
val_loss: 1.1976e-04
Epoch 108/150
Epoch 00108: val_loss did not improve from 0.00011
val_loss: 1.0868e-04
Epoch 109/150
96/96 [=========== ] - ETA: Os - loss: 9.0933e-05
Epoch 00109: val_loss did not improve from 0.00011
96/96 [============ ] - 1s 9ms/step - loss: 9.0933e-05 -
val_loss: 1.1853e-04
Epoch 110/150
Epoch 00110: val loss did not improve from 0.00011
val_loss: 1.0818e-04
Epoch 111/150
Epoch 00111: val_loss did not improve from 0.00011
96/96 [============== ] - 1s 9ms/step - loss: 8.8124e-05 -
val_loss: 2.3456e-04
Epoch 112/150
Epoch 00112: val_loss did not improve from 0.00011
96/96 [============ ] - 1s 9ms/step - loss: 8.6186e-05 -
```

```
val_loss: 1.1133e-04
Epoch 113/150
96/96 [======== ] - ETA: Os - loss: 9.0423e-05
Epoch 00113: val_loss did not improve from 0.00011
val_loss: 1.3993e-04
Epoch 114/150
Epoch 00114: val_loss did not improve from 0.00011
96/96 [============ ] - 1s 9ms/step - loss: 8.9644e-05 -
val_loss: 1.1688e-04
Epoch 115/150
Epoch 00115: val_loss did not improve from 0.00011
val_loss: 1.3260e-04
Epoch 116/150
Epoch 00116: val_loss did not improve from 0.00011
val loss: 1.0909e-04
Epoch 117/150
Epoch 00117: val_loss did not improve from 0.00011
val_loss: 1.5286e-04
Epoch 118/150
Epoch 00118: val_loss did not improve from 0.00011
val_loss: 1.6449e-04
Epoch 119/150
Epoch 00119: val_loss did not improve from 0.00011
96/96 [=========== ] - 1s 9ms/step - loss: 8.6209e-05 -
val_loss: 3.1345e-04
Epoch 120/150
Epoch 00120: val_loss did not improve from 0.00011
96/96 [=========== ] - 1s 9ms/step - loss: 8.5270e-05 -
val_loss: 1.1120e-04
Epoch 121/150
Epoch 00121: val_loss did not improve from 0.00011
96/96 [============ ] - 1s 9ms/step - loss: 8.6331e-05 -
val_loss: 1.0745e-04
Epoch 122/150
```

Training stops after 51 epochs; the early_stopping callback restores the weights for the best model (after 41 epochs)

1.10 Evaluate model performance

```
[31]: fig, ax = plt.subplots(figsize=(12, 4))

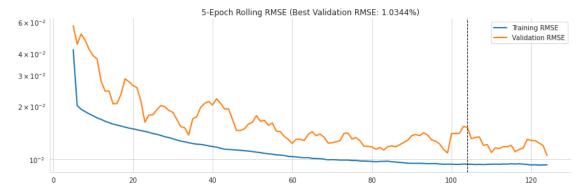
loss_history = pd.DataFrame(lstm_training.history).pow(.5)
loss_history.index += 1
best_rmse = loss_history.val_loss.min()

best_epoch = loss_history.val_loss.idxmin()

title = f'5-Epoch Rolling RMSE (Best Validation RMSE: {best_rmse:.4%})'
loss_history.columns=['Training RMSE', 'Validation RMSE']
loss_history.rolling(5).mean().plot(logy=True, lw=2, title=title, ax=ax)

ax.axvline(best_epoch, ls='--', lw=1, c='k')

sns.despine()
fig.tight_layout()
fig.savefig(results_path / 'rnn_sp500_error', dpi=300);
```

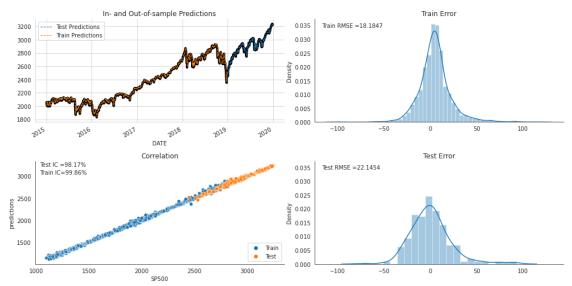


```
[32]: train_rmse_scaled = np.sqrt(rnn.evaluate(X_train, y_train, verbose=0))
     test_rmse_scaled = np.sqrt(rnn.evaluate(X_test, y_test, verbose=0))
     print(f'Train RMSE: {train_rmse_scaled:.4f} | Test RMSE: {test_rmse_scaled:.
      →4f}')
     Train RMSE: 0.0085 | Test RMSE: 0.0103
[33]: train_predict_scaled = rnn.predict(X_train)
     test_predict_scaled = rnn.predict(X_test)
[34]: train_ic = spearmanr(y_train, train_predict_scaled)[0]
     test_ic = spearmanr(y_test, test_predict_scaled)[0]
     print(f'Train IC: {train_ic:.4f} | Test IC: {test_ic:.4f}')
     Train IC: 0.9986 | Test IC: 0.9817
     1.10.1 Rescale predictions
[35]: train predict = pd.Series(scaler.inverse transform(train predict scaled).
      test_predict = (pd.Series(scaler.inverse_transform(test_predict_scaled))
                               .squeeze(),
                               index=y_test.index))
[36]: y_train_rescaled = scaler.inverse_transform(y_train.to_frame()).squeeze()
     y_test_rescaled = scaler.inverse_transform(y_test.to_frame()).squeeze()
[37]: train_rmse = np.sqrt(mean_squared_error(train_predict, y_train_rescaled))
     test_rmse = np.sqrt(mean_squared_error(test_predict, y_test_rescaled))
     f'Train RMSE: {train_rmse:.2f} | Test RMSE: {test_rmse:.2f}'
[37]: 'Train RMSE: 18.18 | Test RMSE: 22.15'
[38]: sp500['Train Predictions'] = train_predict
     sp500['Test Predictions'] = test_predict
     sp500 = sp500.join(train_predict.to_frame('predictions').assign(data='Train')
                             .append(test_predict.to_frame('predictions').
      →assign(data='Test')))
```

1.10.2 Plot Results

```
[39]: fig=plt.figure(figsize=(14,7))
      ax1 = plt.subplot(221)
      sp500.loc['2015':, 'SP500'].plot(lw=4, ax=ax1, c='k')
```

```
sp500.loc['2015':, ['Test Predictions', 'Train Predictions']].plot(lw=1,_
\rightarrowax=ax1, ls='--')
ax1.set_title('In- and Out-of-sample Predictions')
with sns.axes style("white"):
    ax3 = plt.subplot(223)
    sns.scatterplot(x='SP500', y='predictions', data=sp500, hue='data', ax=ax3)
    ax3.text(x=.02, y=.95, s=f'Test IC ={test_ic:.2%}', transform=ax3.transAxes)
    ax3.text(x=.02, y=.87, s=f'Train IC={train_ic:.2%}', transform=ax3.
→transAxes)
    ax3.set title('Correlation')
    ax3.legend(loc='lower right')
    ax2 = plt.subplot(222)
    ax4 = plt.subplot(224, sharex = ax2, sharey=ax2)
    sns.distplot(train_predict.squeeze()- y_train_rescaled, ax=ax2)
    ax2.set_title('Train Error')
    ax2.text(x=.03, y=.92, s=f'Train RMSE ={train rmse:.4f}', transform=ax2.
 →transAxes)
    sns.distplot(test_predict.squeeze()-y_test_rescaled, ax=ax4)
    ax4.set_title('Test Error')
    ax4.text(x=.03, y=.92, s=f'Test RMSE ={test rmse:.4f}', transform=ax4.
 →transAxes)
sns.despine()
fig.tight_layout()
fig.savefig(results_path / 'rnn_sp500_regression', dpi=300);
```



[]:[