Week 2: Predicting time series

Welcome! In the previous assignment you got some exposure to working with time series data, but you didn't use machine learning techniques for your forecasts. This week you will be using a deep neural network to create forecasts to see how this technique compares with the ones you already tried out. Once again all of the data is going to be generated.

Let's get started!

NOTE: *To prevent errors from the autograder, you are not allowed to edit or delete some of the cells in this notebook . Please only put your solutions in between the* `### START CODE HERE` *and* `### END CODE HERE` *code comments, and also refrain from adding any new cells.* ***Once you have passed this assignment*** *and want to experiment with any of the locked cells, you may follow the instructions at the bottom of this notebook.*

```
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
from dataclasses import dataclass
```

Generating the data

The next cell includes a bunch of helper functions to generate and plot the time series:

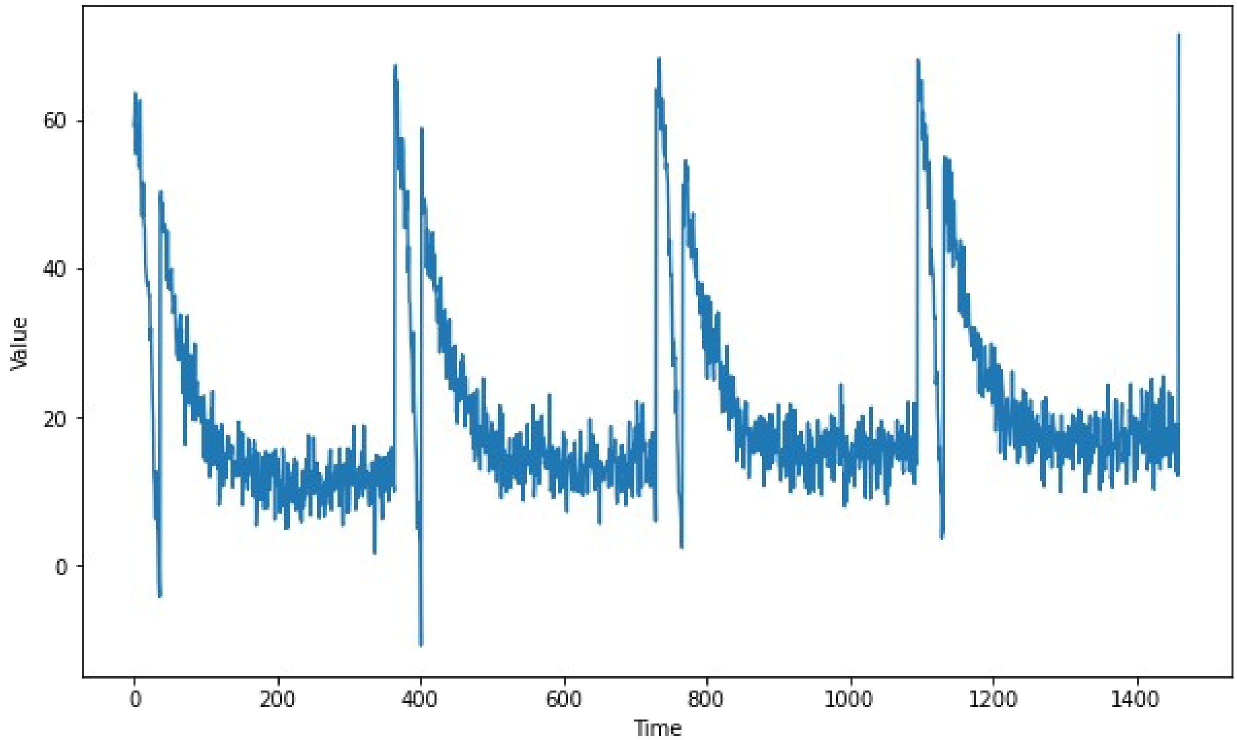
```
def plot_series(time, series, format="-", start=0, end=None):
    plt.plot(time[start:end], series[start:end], format)
    plt.xlabel("Time")
    plt.ylabel("Value")
    plt.grid(False)

def trend(time, slope=0):
    return slope * time

def seasonal_pattern(season_time):
    """An arbitrary pattern"""
    return np.where(season_time < 0.1,
                    np.cos(season_time * 6 * np.pi),
                    2 / np.exp(9 * season_time))

def seasonality(time, period, amplitude=1, phase=0):
    """Repeats the same pattern at each period"""
    season_time = ((time + phase) % period) / period
    return amplitude * seasonal_pattern(season_time)

def noise(time, noise_level=1, seed=None):
    rnd = np.random.RandomState(seed)
    return rnd.randn(len(time)) * noise_level
```

You will be generating time series data that greatly resembles the one from last week but with some differences.

Notice that this time all the generation is done within a function and global variables are saved within a dataclass. This is done to avoid using global scope as it was done in during the previous week.

If you haven't used dataclasses before, they are just Python classes that provide a convenient syntax for storing data. You can read more about them in the docs.

```
def generate_time_series():
    # The time dimension or the x-coordinate of the time series
    time = np.arange(4 * 365 + 1, dtype="float32")

    # Initial series is just a straight line with a y-intercept
    y_intercept = 10
    slope = 0.005
    series = trend(time, slope) + y_intercept

    # Adding seasonality
    amplitude = 50
    series += seasonality(time, period=365, amplitude=amplitude)

    # Adding some noise
    noise_level = 3
    series += noise(time, noise_level, seed=51)

    return time, series


# Save all "global" variables within the G class (G stands for global)
@dataclass
class G:
    TIME, SERIES = generate_time_series()
    SPLIT_TIME = 1100
    WINDOW_SIZE = 20
    BATCH_SIZE = 32
    SHUFFLE_BUFFER_SIZE = 1000


# Plot the generated series
plt.figure(figsize=(10, 6))
plot_series(G.TIME, G.SERIES)
plt.show()
```



Splitting the data

Since you already coded the `train_val_split` function during last week's assignment, this time it is provided for you:

```
def train_val_split(time, series, time_step=G.SPLIT_TIME):

    time_train = time[:time_step]
    series_train = series[:time_step]
    time_valid = time[time_step:]
    series_valid = series[time_step:]

    return time_train, series_train, time_valid, series_valid


# Split the dataset
time_train, series_train, time_valid, series_valid =
train_val_split(G.TIME, G.SERIES)
```

Processing the data

As you saw on the lectures you can feed the data for training by creating a dataset with the appropiate processing steps such as `windowing`, `flattening`, `batching` and `shuffling`. To do so complete the `windowed_dataset` function below.

Notice that this function receives a `series`, `window_size`, `batch_size` and `shuffle_buffer` and the last three of these default to the "global" values defined earlier.

Be sure to check out the docs about `TF Datasets` if you need any help.

```
def windowed_dataset(series, window_size=G.WINDOW_SIZE,
batch_size=G.BATCH_SIZE, shuffle_buffer=G.SHUFFLE_BUFFER_SIZE):

    ### START CODE HERE

    # Create dataset from the series
    dataset = tf.data.Dataset.from_tensor_slices(series)

    # Slice the dataset into the appropriate windows
    dataset = dataset.window(window_size + 1, shift=1,
drop_remainder=True)

    # Flatten the dataset
    dataset = dataset.flat_map(lambda window: window.batch(window_size
+ 1))

    # Shuffle it
    dataset = dataset.shuffle(shuffle_buffer)

    # Split it into the features and labels
    dataset = dataset.map(lambda window: (window[:-1], window[-1]))

    # Batch it
    dataset = dataset.batch(batch_size).prefetch(1)

    ### END CODE HERE

    return dataset
```

To test your function you will be using a `window_size` of 1 which means that you will use each value to predict the next one. This for 5 elements since a `batch_size` of 5 is used and no shuffle since `shuffle_buffer` is set to 1.

Given this, the batch of features should be identical to the first 5 elements of the `series_train` and the batch of labels should be equal to elements 2 through 6 of the `series_train`.

```
# Test your function with windows size of 1 and no shuffling
test_dataset = windowed_dataset(series_train, window_size=1,
batch_size=5, shuffle_buffer=1)

# Get the first batch of the test dataset
batch_of_features, batch_of_labels = next((iter(test_dataset)))

print(f"batch_of_features has type: {type(batch_of_features)}\n")
```

```
print(f"batch_of_labels has type: {type(batch_of_labels)}\n")
print(f"batch_of_features has shape: {batch_of_features.shape}\n")
print(f"batch_of_labels has shape: {batch_of_labels.shape}\n")
print(f"batch_of_features is equal to first five elements in the
series: {np.allclose(batch_of_features.numpy().flatten(),
series_train[:5])}\n")
print(f"batch_of_labels is equal to first five labels:
{np.allclose(batch_of_labels.numpy(), series_train[1:6])}")

batch_of_features has type: <class
'tensorflow.python.framework.ops.EagerTensor'>

batch_of_labels has type: <class
'tensorflow.python.framework.ops.EagerTensor'>

batch_of_features has shape: (5, 1)

batch_of_labels has shape: (5,)

batch_of_features is equal to first five elements in the series: True

batch_of_labels is equal to first five labels: True
```

Expected Output:

```
batch_of_features has type: <class
'tensorflow.python.framework.ops.EagerTensor'>

batch_of_labels has type: <class
'tensorflow.python.framework.ops.EagerTensor'>

batch_of_features has shape: (5, 1)

batch_of_labels has shape: (5,)

batch_of_features is equal to first five elements in the series: True

batch_of_labels is equal to first five labels: True
```

Defining the model architecture

Now that you have a function that will process the data before it is fed into your neural network for training, it is time to define you layer architecture.

Complete the `create_model` function below. Notice that this function receives the `window_size` since this will be an important parameter for the first layer of your network.

Hint:

- You will only need `Dense` layers.

- Do not include `Lambda` layers. These are not required and are incompatible with the `HDF5` format which will be used to save your model for grading.
- The training should be really quick so if you notice that each epoch is taking more than a few seconds, consider trying a different architecture.

```
def create_model(window_size=G.WINDOW_SIZE):

    ### START CODE HERE

    model = tf.keras.models.Sequential([
        tf.keras.layers.Dense(10,input_shape=[window_size],
activation="relu"),
        tf.keras.layers.Dense(30, activation="relu"),
        tf.keras.layers.Dense(15, activation="relu"),
        tf.keras.layers.Dense(5, activation="relu"),
        tf.keras.layers.Dense(1)
    ])

    lr_schedule = tf.keras.callbacks.LearningRateScheduler(
    lambda epoch: 1e-5 * 10**(epoch / 20))

    model.compile(loss="mse",
                  optimizer=tf.keras.optimizers.SGD(lr=1e-5,
momentum=0.9))

    ### END CODE HERE

    return model

# Apply the processing to the whole training series
dataset = windowed_dataset(series_train)

# Save an instance of the model
model = create_model()

# Train it
model.fit(dataset, epochs=100)

Epoch 1/100
34/34 [==============================] - 1s 9ms/step - loss: 242.2547
Epoch 2/100
34/34 [==============================] - 0s 892us/step - loss: 76.7907
Epoch 3/100
34/34 [==============================] - 0s 1ms/step - loss: 52.7299
Epoch 4/100
34/34 [==============================] - 0s 1ms/step - loss: 46.4451
Epoch 5/100
34/34 [==============================] - 0s 855us/step - loss: 43.2436
Epoch 6/100
34/34 [==============================] - 0s 832us/step - loss: 41.2536
Epoch 7/100
```

```
34/34 [==============================] - 0s 2ms/step - loss: 39.6960
Epoch 8/100
34/34 [==============================] - 0s 1ms/step - loss: 37.9905
Epoch 9/100
34/34 [==============================] - 0s 859us/step - loss: 37.6853
Epoch 10/100
34/34 [==============================] - 0s 1ms/step - loss: 35.4736
Epoch 11/100
34/34 [==============================] - 0s 1ms/step - loss: 34.1327
Epoch 12/100
34/34 [==============================] - 0s 947us/step - loss: 33.0367
Epoch 13/100
34/34 [==============================] - 0s 1ms/step - loss: 32.2980
Epoch 14/100
34/34 [==============================] - 0s 1ms/step - loss: 31.9324
Epoch 15/100
34/34 [==============================] - 0s 1ms/step - loss: 31.5280
Epoch 16/100
34/34 [==============================] - 0s 891us/step - loss: 31.2512
Epoch 17/100
34/34 [==============================] - 0s 1ms/step - loss: 29.9280
Epoch 18/100
34/34 [==============================] - 0s 1ms/step - loss: 30.7458
Epoch 19/100
34/34 [==============================] - 0s 1ms/step - loss: 29.4186
Epoch 20/100
34/34 [==============================] - 0s 906us/step - loss: 29.0030
Epoch 21/100
34/34 [==============================] - 0s 862us/step - loss: 28.9786
Epoch 22/100
34/34 [==============================] - 0s 998us/step - loss: 28.1940
Epoch 23/100
34/34 [==============================] - 0s 1ms/step - loss: 28.2960
Epoch 24/100
34/34 [==============================] - 0s 865us/step - loss: 27.6397
Epoch 25/100
34/34 [==============================] - 0s 827us/step - loss: 27.4588
Epoch 26/100
34/34 [==============================] - 0s 791us/step - loss: 27.0408
Epoch 27/100
34/34 [==============================] - 0s 1ms/step - loss: 26.9104
Epoch 28/100
34/34 [==============================] - 0s 1ms/step - loss: 26.7699
Epoch 29/100
34/34 [==============================] - 0s 1ms/step - loss: 26.8669
Epoch 30/100
34/34 [==============================] - 0s 835us/step - loss: 26.1324
Epoch 31/100
34/34 [==============================] - 0s 849us/step - loss: 26.2956
```

```
Epoch 32/100
34/34 [==============================] - 0s 1ms/step - loss: 25.6753
Epoch 33/100
34/34 [==============================] - 0s 1ms/step - loss: 25.6727
Epoch 34/100
34/34 [==============================] - 0s 996us/step - loss: 25.5431
Epoch 35/100
34/34 [==============================] - 0s 820us/step - loss: 24.9366
Epoch 36/100
34/34 [==============================] - 0s 1ms/step - loss: 25.0606
Epoch 37/100
34/34 [==============================] - 0s 1ms/step - loss: 24.6109
Epoch 38/100
34/34 [==============================] - 0s 852us/step - loss: 24.7024
Epoch 39/100
34/34 [==============================] - 0s 882us/step - loss: 24.2677
Epoch 40/100
34/34 [==============================] - 0s 1ms/step - loss: 24.5185
Epoch 41/100
34/34 [==============================] - 0s 1ms/step - loss: 23.6678
Epoch 42/100
34/34 [==============================] - 0s 796us/step - loss: 23.7184
Epoch 43/100
34/34 [==============================] - 0s 804us/step - loss: 24.0932
Epoch 44/100
34/34 [==============================] - 0s 883us/step - loss: 23.6329
Epoch 45/100
34/34 [==============================] - 0s 963us/step - loss: 23.3627
Epoch 46/100
34/34 [==============================] - 0s 1ms/step - loss: 23.1507
Epoch 47/100
34/34 [==============================] - 0s 849us/step - loss: 22.9230
Epoch 48/100
34/34 [==============================] - 0s 840us/step - loss: 23.1648
Epoch 49/100
34/34 [==============================] - 0s 1ms/step - loss: 22.8226
Epoch 50/100
34/34 [==============================] - 0s 1ms/step - loss: 22.6037
Epoch 51/100
34/34 [==============================] - 0s 889us/step - loss: 22.5609
Epoch 52/100
34/34 [==============================] - 0s 844us/step - loss: 22.1362
Epoch 53/100
34/34 [==============================] - 0s 1ms/step - loss: 22.7152
Epoch 54/100
34/34 [==============================] - 0s 1ms/step - loss: 22.0940
Epoch 55/100
34/34 [==============================] - 0s 866us/step - loss: 22.2330
Epoch 56/100
```

```
34/34 [==============================] - 0s 827us/step - loss: 22.1173
Epoch 57/100
34/34 [==============================] - 0s 818us/step - loss: 21.6122
Epoch 58/100
34/34 [==============================] - 0s 1ms/step - loss: 21.7746
Epoch 59/100
34/34 [==============================] - 0s 1ms/step - loss: 21.6231
Epoch 60/100
34/34 [==============================] - 0s 1ms/step - loss: 21.7472
Epoch 61/100
34/34 [==============================] - 0s 850us/step - loss: 21.5719
Epoch 62/100
34/34 [==============================] - 0s 857us/step - loss: 22.4009
Epoch 63/100
34/34 [==============================] - 0s 1ms/step - loss: 21.9059
Epoch 64/100
34/34 [==============================] - 0s 1ms/step - loss: 21.4833
Epoch 65/100
34/34 [==============================] - 0s 1ms/step - loss: 22.9089
Epoch 66/100
34/34 [==============================] - 0s 844us/step - loss: 21.4882
Epoch 67/100
34/34 [==============================] - 0s 903us/step - loss: 21.5425
Epoch 68/100
34/34 [==============================] - 0s 1ms/step - loss: 20.7567
Epoch 69/100
34/34 [==============================] - 0s 1ms/step - loss: 20.8927
Epoch 70/100
34/34 [==============================] - 0s 1ms/step - loss: 20.6009
Epoch 71/100
34/34 [==============================] - 0s 1ms/step - loss: 20.7228
Epoch 72/100
34/34 [==============================] - 0s 872us/step - loss: 20.3843
Epoch 73/100
34/34 [==============================] - 0s 825us/step - loss: 20.6025
Epoch 74/100
34/34 [==============================] - 0s 1ms/step - loss: 20.6045
Epoch 75/100
34/34 [==============================] - 0s 1ms/step - loss: 22.0301
Epoch 76/100
34/34 [==============================] - 0s 910us/step - loss: 21.3076
Epoch 77/100
34/34 [==============================] - 0s 858us/step - loss: 21.1588
Epoch 78/100
34/34 [==============================] - 0s 1ms/step - loss: 20.9613
Epoch 79/100
34/34 [==============================] - 0s 1ms/step - loss: 21.2362
Epoch 80/100
34/34 [==============================] - 0s 1ms/step - loss: 20.0292
```

```
Epoch 81/100
34/34 [==============================] - 0s 829us/step - loss: 20.4904
Epoch 82/100
34/34 [==============================] - 0s 847us/step - loss: 20.6279
Epoch 83/100
34/34 [==============================] - 0s 1ms/step - loss: 20.3991
Epoch 84/100
34/34 [==============================] - 0s 1ms/step - loss: 19.7374
Epoch 85/100
34/34 [==============================] - 0s 1ms/step - loss: 20.4584
Epoch 86/100
34/34 [==============================] - 0s 854us/step - loss: 20.4089
Epoch 87/100
34/34 [==============================] - 0s 801us/step - loss: 19.7493
Epoch 88/100
34/34 [==============================] - 0s 1ms/step - loss: 20.8852
Epoch 89/100
34/34 [==============================] - 0s 999us/step - loss: 21.1064
Epoch 90/100
34/34 [==============================] - 0s 1ms/step - loss: 20.7245
Epoch 91/100
34/34 [==============================] - 0s 805us/step - loss: 19.8996
Epoch 92/100
34/34 [==============================] - 0s 1ms/step - loss: 20.1420
Epoch 93/100
34/34 [==============================] - 0s 1ms/step - loss: 19.7755
Epoch 94/100
34/34 [==============================] - 0s 1ms/step - loss: 19.4294
Epoch 95/100
34/34 [==============================] - 0s 833us/step - loss: 20.7962
Epoch 96/100
34/34 [==============================] - 0s 831us/step - loss: 21.9586
Epoch 97/100
34/34 [==============================] - 0s 1ms/step - loss: 20.4837
Epoch 98/100
34/34 [==============================] - 0s 1ms/step - loss: 19.6784
Epoch 99/100
34/34 [==============================] - 0s 1ms/step - loss: 20.2837
Epoch 100/100
34/34 [==============================] - 0s 1ms/step - loss: 20.8348

<keras.callbacks.History at 0x7f89d8327be0>
```

Evaluating the forecast

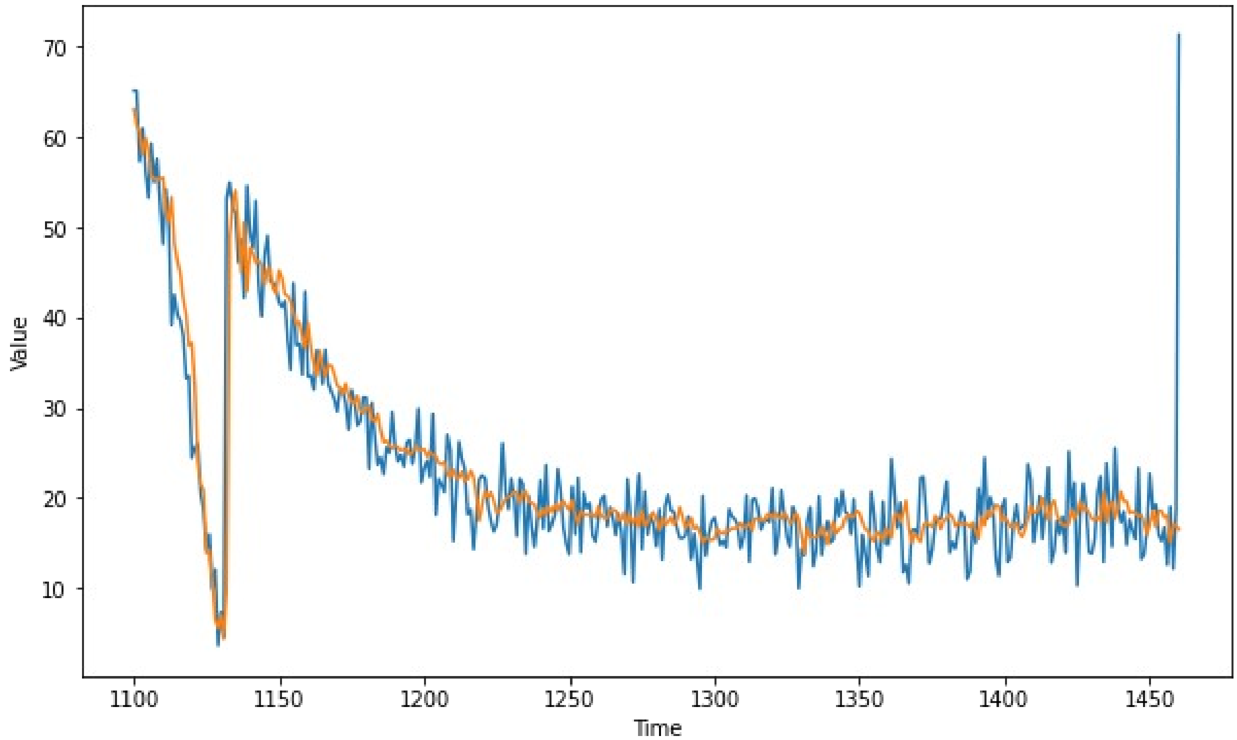
Now it is time to evaluate the performance of the forecast. For this you can use the `compute_metrics` function that you coded in the previous assignment:

```
def compute_metrics(true_series, forecast):

    mse = tf.keras.metrics.mean_squared_error(true_series, 
forecast).numpy()
    mae = tf.keras.metrics.mean_absolute_error(true_series, 
forecast).numpy()

    return mse, mae
```

At this point only the model that will perform the forecast is ready but you still need to compute the actual forecast.

For this, run the cell below which uses the `generate_forecast` function to compute the forecast. This function generates the next value given a set of the previous `window_size` points for every point in the validation set.

```
def generate_forecast(series=G.SERIES, split_time=G.SPLIT_TIME, 
window_size=G.WINDOW_SIZE):
    forecast = []
    for time in range(len(series) - window_size):
        forecast.append(model.predict(series[time:time + window_size]
[np.newaxis]))

    forecast = forecast[split_time-window_size:]
    results = np.array(forecast)[:, 0, 0]
    return results


# Save the forecast
dnn_forecast = generate_forecast()

# Plot it
plt.figure(figsize=(10, 6))
plot_series(time_valid, series_valid)
plot_series(time_valid, dnn_forecast)
```



Expected Output:

A series similar to this one:

```
mse, mae = compute_metrics(series_valid, dnn_forecast)

print(f"mse: {mse:.2f}, mae: {mae:.2f} for forecast")

mse: 27.08, mae: 3.17 for forecast
```

To pass this assignment your forecast should achieve an MSE of 30 or less.

- If your forecast didn't achieve this threshold try re-training your model with a different architecture or tweaking the optimizer's parameters.
- If your forecast did achieve this threshold run the following cell to save your model in a HDF5 file file which will be used for grading and after doing so, submit your assigment for grading.
- Make sure you didn't use `Lambda` layers in your model since these are incompatible with the `HDF5` format which will be used to save your model for grading.
- This environment includes a dummy `my_model.h5` file which is just a dummy model trained for one epoch. **To replace this file with your actual model you need to run the next cell before submitting for grading.**

```python
# Save your model in HDF5 format
model.save('my_model.h5')
```

Congratulations on finishing this week's assignment!

You have successfully implemented a neural network capable of forecasting time series while also learning how to leverage Tensorflow's Dataset class to process time series data!

Keep it up!