# C4W2_Assignment

October 23, 2022

## 1 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!

[1]:
```
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
from dataclasses import dataclass
```

### 1.1 Generating the data

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

[2]:
```
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):
    """Just an arbitrary pattern, you can change it if you wish"""
    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):
```

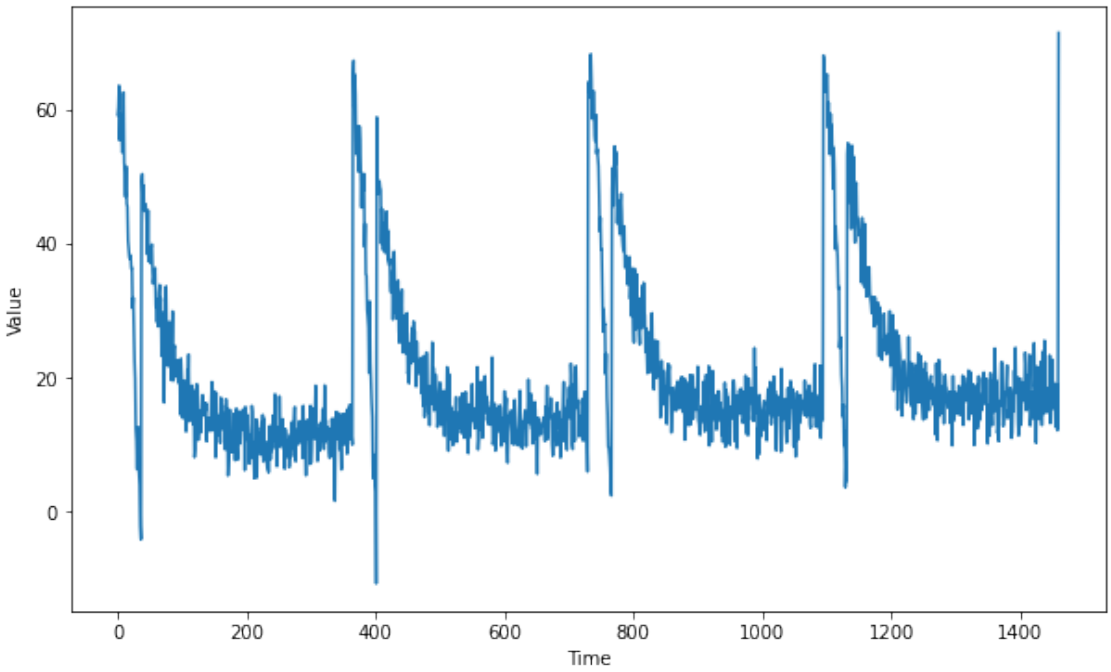
```
    rnd = np.random.RandomState(seed)
    return rnd.randn(len(time)) * noise_level
```

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.

[3]:
```
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()
```




### 1.2 Splitting the data

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

[4]:
```
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)
```

### 1.3 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.

[5]:
```
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`.

[6]:
```
# 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
```

### 1.4 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. - 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.

[7]:
```
def create_model(window_size=G.WINDOW_SIZE):

    ### START CODE HERE

    model = tf.keras.models.Sequential([ tf.keras.layers.Dense(100,␣
 ↪input_shape=[window_size], activation="relu"),
```

```
tf.keras.layers.Dense(10, activation="relu"),
tf.keras.layers.Dense(1)

    ])

    model.compile(loss="mse",
                  optimizer=tf.keras.optimizers.SGD(learning_rate=1e-6,
momentum=0.9))

    ### END CODE HERE

    return model
```

[8]:
```
# 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 7ms/step - loss: 120.1829
Epoch 2/100
34/34 [==============================] - 0s 804us/step - loss: 76.2828
Epoch 3/100
34/34 [==============================] - 0s 848us/step - loss: 64.5907
Epoch 4/100
34/34 [==============================] - 0s 791us/step - loss: 57.7709
Epoch 5/100
34/34 [==============================] - 0s 1ms/step - loss: 53.3116
Epoch 6/100
34/34 [==============================] - 0s 873us/step - loss: 50.2806
Epoch 7/100
34/34 [==============================] - 0s 906us/step - loss: 47.7008
Epoch 8/100
34/34 [==============================] - 0s 841us/step - loss: 45.4832
Epoch 9/100
34/34 [==============================] - 0s 880us/step - loss: 43.9600
Epoch 10/100
34/34 [==============================] - 0s 836us/step - loss: 41.9016
Epoch 11/100
34/34 [==============================] - 0s 791us/step - loss: 40.6865
Epoch 12/100
34/34 [==============================] - 0s 835us/step - loss: 39.4291
Epoch 13/100
```

```
34/34 [==============================] - 0s 860us/step - loss: 38.4974
Epoch 14/100
34/34 [==============================] - 0s 1ms/step - loss: 37.8693
Epoch 15/100
34/34 [==============================] - 0s 958us/step - loss: 36.8478
Epoch 16/100
34/34 [==============================] - 0s 838us/step - loss: 36.0570
Epoch 17/100
34/34 [==============================] - 0s 796us/step - loss: 35.3595
Epoch 18/100
34/34 [==============================] - 0s 847us/step - loss: 34.8536
Epoch 19/100
34/34 [==============================] - 0s 796us/step - loss: 34.3162
Epoch 20/100
34/34 [==============================] - 0s 845us/step - loss: 33.8984
Epoch 21/100
34/34 [==============================] - 0s 1ms/step - loss: 33.4063
Epoch 22/100
34/34 [==============================] - 0s 894us/step - loss: 33.0303
Epoch 23/100
34/34 [==============================] - 0s 978us/step - loss: 32.5229
Epoch 24/100
34/34 [==============================] - 0s 869us/step - loss: 32.3022
Epoch 25/100
34/34 [==============================] - 0s 812us/step - loss: 31.8114
Epoch 26/100
34/34 [==============================] - 0s 817us/step - loss: 31.5501
Epoch 27/100
34/34 [==============================] - 0s 1ms/step - loss: 31.2946
Epoch 28/100
34/34 [==============================] - 0s 837us/step - loss: 31.0775
Epoch 29/100
34/34 [==============================] - 0s 909us/step - loss: 30.7840
Epoch 30/100
34/34 [==============================] - 0s 1ms/step - loss: 30.5323
Epoch 31/100
34/34 [==============================] - 0s 864us/step - loss: 30.4255
Epoch 32/100
34/34 [==============================] - 0s 860us/step - loss: 30.0674
Epoch 33/100
34/34 [==============================] - 0s 1ms/step - loss: 29.8421
Epoch 34/100
34/34 [==============================] - 0s 860us/step - loss: 29.6429
Epoch 35/100
34/34 [==============================] - 0s 918us/step - loss: 29.5681
Epoch 36/100
34/34 [==============================] - 0s 868us/step - loss: 29.2979
Epoch 37/100
```

```
34/34 [==============================] - 0s 901us/step - loss: 29.1888
Epoch 38/100
34/34 [==============================] - 0s 786us/step - loss: 28.9549
Epoch 39/100
34/34 [==============================] - 0s 778us/step - loss: 29.0213
Epoch 40/100
34/34 [==============================] - 0s 1ms/step - loss: 28.6393
Epoch 41/100
34/34 [==============================] - 0s 892us/step - loss: 28.5642
Epoch 42/100
34/34 [==============================] - 0s 776us/step - loss: 28.5843
Epoch 43/100
34/34 [==============================] - 0s 947us/step - loss: 28.4059
Epoch 44/100
34/34 [==============================] - 0s 878us/step - loss: 28.1876
Epoch 45/100
34/34 [==============================] - 0s 829us/step - loss: 28.1692
Epoch 46/100
34/34 [==============================] - 0s 830us/step - loss: 27.9583
Epoch 47/100
34/34 [==============================] - 0s 827us/step - loss: 27.8896
Epoch 48/100
34/34 [==============================] - 0s 1ms/step - loss: 27.8599
Epoch 49/100
34/34 [==============================] - 0s 908us/step - loss: 27.6626
Epoch 50/100
34/34 [==============================] - 0s 931us/step - loss: 27.6002
Epoch 51/100
34/34 [==============================] - 0s 929us/step - loss: 27.5101
Epoch 52/100
34/34 [==============================] - 0s 829us/step - loss: 27.6784
Epoch 53/100
34/34 [==============================] - 0s 864us/step - loss: 27.4408
Epoch 54/100
34/34 [==============================] - 0s 828us/step - loss: 27.3425
Epoch 55/100
34/34 [==============================] - 0s 828us/step - loss: 27.2652
Epoch 56/100
34/34 [==============================] - 0s 921us/step - loss: 27.1923
Epoch 57/100
34/34 [==============================] - 0s 870us/step - loss: 27.1801
Epoch 58/100
34/34 [==============================] - 0s 870us/step - loss: 27.2079
Epoch 59/100
34/34 [==============================] - 0s 880us/step - loss: 27.1267
Epoch 60/100
34/34 [==============================] - 0s 820us/step - loss: 26.8986
Epoch 61/100
```

```
34/34 [==============================] - 0s 812us/step - loss: 26.9265
Epoch 62/100
34/34 [==============================] - 0s 829us/step - loss: 26.8846
Epoch 63/100
34/34 [==============================] - 0s 831us/step - loss: 26.7125
Epoch 64/100
34/34 [==============================] - 0s 796us/step - loss: 26.8197
Epoch 65/100
34/34 [==============================] - 0s 982us/step - loss: 26.6189
Epoch 66/100
34/34 [==============================] - 0s 848us/step - loss: 26.8172
Epoch 67/100
34/34 [==============================] - 0s 790us/step - loss: 26.5124
Epoch 68/100
34/34 [==============================] - 0s 809us/step - loss: 26.4838
Epoch 69/100
34/34 [==============================] - 0s 888us/step - loss: 26.5528
Epoch 70/100
34/34 [==============================] - 0s 830us/step - loss: 26.3504
Epoch 71/100
34/34 [==============================] - 0s 951us/step - loss: 26.4786
Epoch 72/100
34/34 [==============================] - 0s 894us/step - loss: 26.3071
Epoch 73/100
34/34 [==============================] - 0s 856us/step - loss: 26.2906
Epoch 74/100
34/34 [==============================] - 0s 880us/step - loss: 26.2584
Epoch 75/100
34/34 [==============================] - 0s 828us/step - loss: 26.1402
Epoch 76/100
34/34 [==============================] - 0s 796us/step - loss: 26.1994
Epoch 77/100
34/34 [==============================] - 0s 836us/step - loss: 26.2379
Epoch 78/100
34/34 [==============================] - 0s 1ms/step - loss: 26.0105
Epoch 79/100
34/34 [==============================] - 0s 860us/step - loss: 26.0383
Epoch 80/100
34/34 [==============================] - 0s 832us/step - loss: 26.0306
Epoch 81/100
34/34 [==============================] - 0s 830us/step - loss: 25.9096
Epoch 82/100
34/34 [==============================] - 0s 852us/step - loss: 25.8330
Epoch 83/100
34/34 [==============================] - 0s 822us/step - loss: 26.0146
Epoch 84/100
34/34 [==============================] - 0s 847us/step - loss: 25.9435
Epoch 85/100
```

```
34/34 [==============================] - 0s 1ms/step - loss: 25.7528
Epoch 86/100
34/34 [==============================] - 0s 994us/step - loss: 25.8282
Epoch 87/100
34/34 [==============================] - 0s 817us/step - loss: 25.7657
Epoch 88/100
34/34 [==============================] - 0s 863us/step - loss: 25.6701
Epoch 89/100
34/34 [==============================] - 0s 795us/step - loss: 25.7647
Epoch 90/100
34/34 [==============================] - 0s 796us/step - loss: 25.8900
Epoch 91/100
34/34 [==============================] - 0s 1ms/step - loss: 25.5903
Epoch 92/100
34/34 [==============================] - 0s 785us/step - loss: 25.6400
Epoch 93/100
34/34 [==============================] - 0s 1ms/step - loss: 25.6683
Epoch 94/100
34/34 [==============================] - 0s 796us/step - loss: 25.5138
Epoch 95/100
34/34 [==============================] - 0s 809us/step - loss: 25.4487
Epoch 96/100
34/34 [==============================] - 0s 909us/step - loss: 25.5930
Epoch 97/100
34/34 [==============================] - 0s 892us/step - loss: 25.6188
Epoch 98/100
34/34 [==============================] - 0s 814us/step - loss: 25.3471
Epoch 99/100
34/34 [==============================] - 0s 947us/step - loss: 25.5315
Epoch 100/100
34/34 [==============================] - 0s 934us/step - loss: 25.4125
```

[8]: `<keras.callbacks.History at 0x7f4978742af0>`

### 1.5 Evaluating the forecast

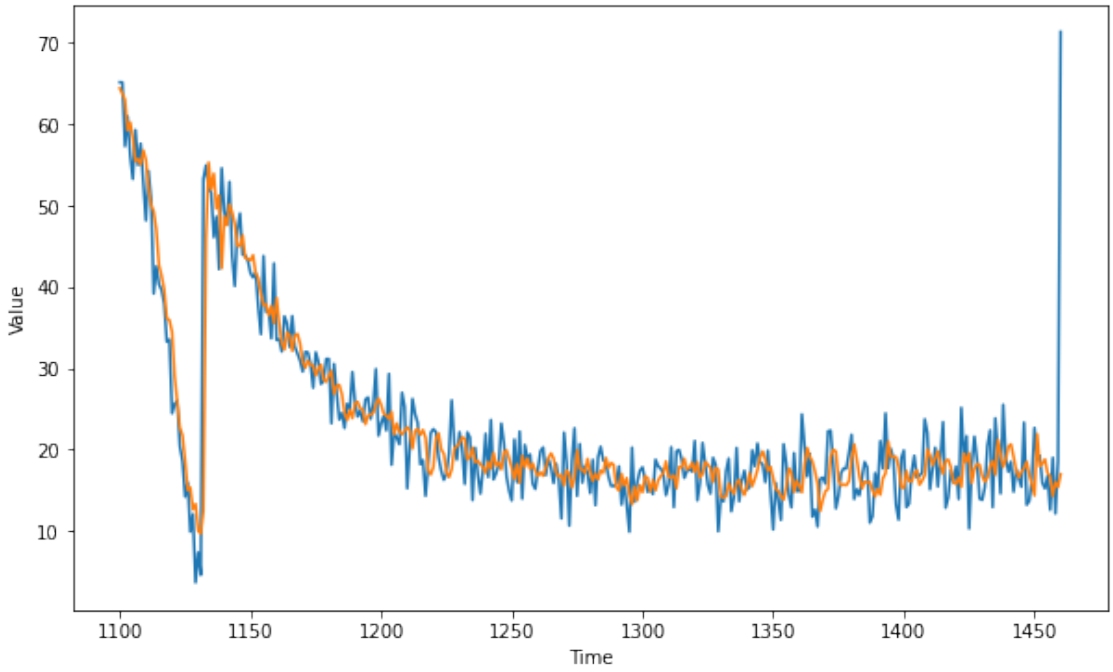
Now it is time to evaluate the performance of the forecast. For this you can use the `compute_metrics` function that you coded in the previous assignment:

[9]:
```python
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.

[10]:
```
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:

[11]:
```
mse, mae = compute_metrics(series_valid, dnn_forecast)

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

```
mse: 26.88, mae: 3.25 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.
- 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.**

[12]:
```
# 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!**