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 one step 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.

TIPS FOR SUCCESSFUL GRADING OF YOUR ASSIGNMENT:

- All cells are frozen except for the ones where you need to submit your solutions or when explicitly mentioned you can interact with it.
- You can add new cells to experiment but these will be omitted by the grader, so don't rely on newly created cells to host your solution code, use the provided places for this.
- You can add the comment # grade-up-to-here in any graded cell to signal the grader that it must only evaluate up to that point. This is helpful if you want to check if you are on the right track even if you are not done with the whole assignment. Be sure to remember to delete the comment afterwards!
- Avoid using global variables unless you absolutely have to. The grader tests your code in an isolated environment without running all cells from the top. As a result, global variables may be unavailable when scoring your submission. Global variables that are meant to be used will be defined in UPPERCASE.
- To submit your notebook, save it and then click on the blue submit button at the beginning of the page.

Let's get started!

In [1]:
```
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
```

In [2]:
```
import unittests
```

Generating the data

First things first, you will need to generate your time series data.

The next cell includes a bunch of helper functions to generate and plot the time series. These are very similar to those you saw on Week 1.

In [3]:
```
def plot_series(time, series, format="-", start=0, end=None):
    """Plot the series"""
    plt.plot(time[start:end], series[start:end], format)
    plt.xlabel("Time")
    plt.ylabel("Value")
    plt.grid(False)

def trend(time, slope=0):
    """A trend over time"""
    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):
    """Adds noise to the series"""
    rnd = np.random.RandomState(seed)
    return rnd.randn(len(time)) * noise_level
```

Now, define a function to generate the time series, using the functions from the previous cell. This function should return a time series that has trend, seasonality and noise.

In [4]:
```
def generate_time_series():
    """ Creates timestamps and values of the 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
```

Defining some useful global variables

Next, you will define some global variables that will be used throughout the assignment. Feel free to reference them in the upcoming exercises:

`SPLIT_TIME` : time index to split between train and validation sets

`WINDOW_SIZE` : length of the window to use for smoothing the series

`BATCH_SIZE` : batch size for training the model

`SHUFFLE_BUFFER_SIZE` : number of elements from the dataset used to sample for a new shuffle of the dataset. For more information about the use of this variable you can take a look at the docs.

A note about grading:

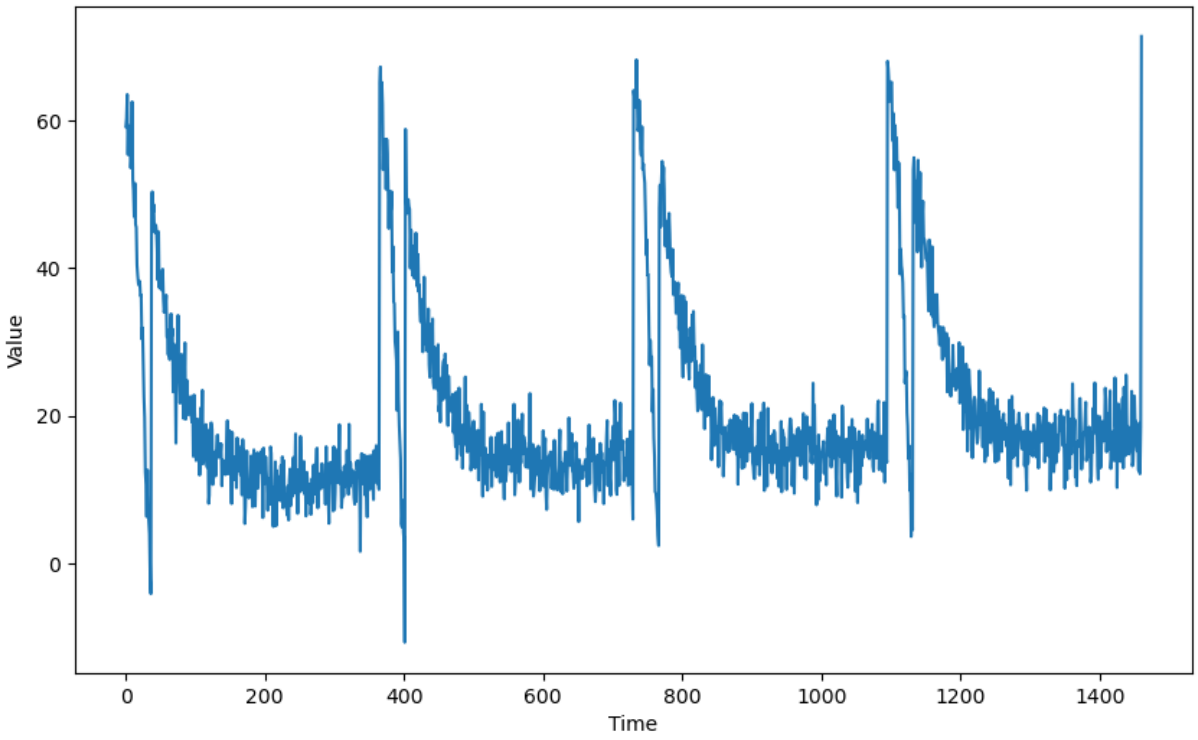
When you submit this assignment for grading these same values for these globals will be used so make sure that all your code works well with these values. After submitting and passing this assignment, you are encouraged to come back here and play with these parameters to see the impact they have in the classification process. Since this next cell is frozen, you will need to copy the contents into a new cell and run it to overwrite the values for these globals.

In [5]:
```
# Save all global variables
SPLIT_TIME = 1100
WINDOW_SIZE = 20
BATCH_SIZE = 32
SHUFFLE_BUFFER_SIZE = 1000
```

Finally, put everything together and create the times series you will use for this assignment.

In [6]:
```
# Create the time series
TIME, SERIES = generate_time_series()
```

In [7]:
```
# Plot the generated series
plt.figure(figsize=(10, 6))
plot_series(TIME, SERIES)
plt.show()
```



Splitting the data

As usual, you will need a function to split the data between train and validation sets. Since you already coded the `train_val_split` function during last week's assignment, this time it is provided for you:

In [8]:
```
def train_val_split(time, series):

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

    return time_train, series_train, time_valid, series_valid


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

Processing the data

Exercise 1: windowed_dataset

As you saw on the lectures, you can feed the data for training by creating a TF Dataset with the appropriate processing steps such as `windowing`, `flattening`, `batching` and `shuffling`. Remember you can do all these using the different methods of the `tf.data.Dataset` object. Next, complete the `windowed_dataset` function below that effectively pre-processes your time series and returns a TF Dataset.

This function receives a `series` and a `window_size`, and returns a TF Dataset. You should already be familiar with `tf.data.Dataset` objects from the this week's lectures, but be sure to check out the docs if you need any help.

In [9]:
```
# GRADED FUNCTION: windowed_dataset
def windowed_dataset(series, window_size, shuffle=True):
    """Create a windowed dataset

    Args:
        series (np.ndarray): time series
        window_size (int): length of window to use for prediction
        shuffle (bool): (For testing purposes) Indicates whether to shuffle data before batching or not. Defaults to True

    Returns:
```

```
        td.data.Dataset: windowed dataset
    """

    ### START CODE HERE ###
    # Create dataset from the series.
    # HINT: use an appropriate method from the tf.data.Dataset object
    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
    if shuffle:  # For testing purposes
        dataset = dataset.shuffle(SHUFFLE_BUFFER_SIZE)

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

    # Batch it
    dataset = dataset.batch(BATCH_SIZE)

    ### END CODE HERE ###

    return dataset
```

To test your function you will be using a `window_size` of 10 which means that you will use 10 consecutive values to predict the next one. You will also set the parameter `shuffle=False`. Given this, the first element of the batch of features should be identical to the first 15 elements of the `series_train`, and the batch of labels should be equal to elements 10 through 42 of the `series_train`.

In [10]:
```
# Try out your function with windows size of 1 and no shuffling
test_dataset = windowed_dataset(series_train, window_size=10,shuffle= False)

# 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"First element in batch_of_features is equal to first 10 elements in the series: {np.allclose(batch_of_features.num
print(f"batch_of_labels is equal to the first 32 values after the window_lenght of 10): {np.allclose(batch_of_labels.numpy
```

```
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: (32, 10)

batch_of_labels has shape: (32,)

First element in batch_of_features is equal to first 10 elements in the series: True

batch_of_labels is equal to the first 32 values after the window_lenght of 10): True
```

Expected Output:

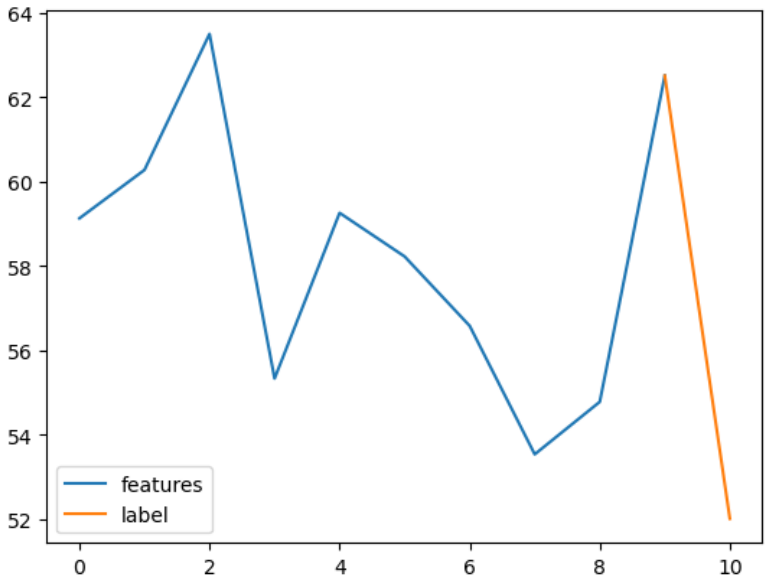
```
batch_of_features has type: <class 'tensorflow.python.framework.ops.EagerTensor'>

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

batch_of_features has shape: (32, 10)

batch_of_labels has shape: (32,)

First element in batch_of_features is equal to first 10 elements in the series: True

batch_of_labels is equal to the first 32 values after the window_lenght of 10): True
```

Now plot the first item in the batch. You will be displayng the 20 features, followed by the label, which is the value you want to predict.

In [11]:
```
plt.plot(np.arange(10), batch_of_features[0].numpy(), label='features')
plt.plot(np.arange(9,11), [batch_of_features[0].numpy()[-1], batch_of_labels[0].numpy()], label='label');
```

```
plt.legend()
```

Out[11]: <matplotlib.legend.Legend at 0x7c34dc43ba90>



Now that you have tested your `windowed_dataset` function, use it to create your train dataset. For that, just run the cell below

In [12]:
```
# Apply the processing to the whole training series
train_dataset = windowed_dataset(series_train, WINDOW_SIZE)
```

In [13]:
```
# Test your code!
unittests.test_windowed_dataset(windowed_dataset)
```

```
All tests passed!
```

Defining the model architecture

Exercise 2: create_model

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 model 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.

Remember that this time you are predicting the values of a time series, so use an appropriate loss for this task. There are many you can choose for, but for grading purposes, please stick to 'mse'.

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.

In [28]:
```
# GRADED FUNCTION: create_model
def create_model(window_size):
    """Create model for predictions
    Args:
        window_size (int): length of window to use for prediction

    Returns:
        tf.keras.Model: model
    """
    ### START CODE HERE ###

    model = tf.keras.models.Sequential([
        tf.keras.Input(shape=(window_size,)),
        tf.keras.layers.Dense(units=16, activation='relu'),
        tf.keras.layers.Dense(units=32, activation='relu'),
        tf.keras.layers.Dense(units=64, 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
```

The next cell allows you to check the number of total and trainable parameters of your model and prompts a warning in case these exceeds those of a reference solution, this serves the following 3 purposes listed in order of priority:

- Helps you prevent crashing the kernel during training.
- Helps you avoid longer-than-necessary training times.
- Provides a reasonable estimate of the size of your model. In general you will usually prefer smaller models given that they accomplish their goal successfully.

Notice that this is just informative and may be very well below the actual limit for size of the model necessary to crash the kernel. So even if you exceed this reference you are probably fine. However, **if the kernel crashes during training or it is taking a very long time and your model is larger than the reference, come back here and try to get the number of parameters closer to the reference.**

In [29]:
```
# Get the untrained model
model = create_model(WINDOW_SIZE)

# Check the parameter count against a reference solution
unittests.parameter_count(model)
```

```
Your model has 3,057 total parameters and the reference is 3,200. You are good to go!

Your model has 3,057 trainable parameters and the reference is 3,200. You are good to go!
```

In [30]:
```
example_batch = train_dataset.take(1)

try:
        model.evaluate(example_batch, verbose=False)
except:
        print("Your model is not compatible with the dataset you defined earlier. Check that the loss function and last lay
else:
        predictions = model.predict(example_batch, verbose=False)
        print(f"predictions have shape: {predictions.shape}")
```

```
predictions have shape: (32, 1)
```

Expected output:

```
predictions have shape: (NUM_BATCHES, 1)

Where NUM_BATCHES is the number of batches you have set to your dataset.
```

Before going any further, check that the input and output dimensions of your model are correct. Do this by running the cell below:

In [31]:
```
print(f'Model input shape: {model.input_shape}')
print(f'Model output shape: {model.output_shape}')
```

```
Model input shape: (None, 20)
Model output shape: (None, 1)
```

You can also print a summary of your model to see what the architecture looks like.

In [32]:
```
model.summary()
```

```
Model: "sequential_2"
```

Layer (type)	Output Shape	Param #
dense_6 (Dense)	(None, 16)	336
dense_7 (Dense)	(None, 32)	544
dense_8 (Dense)	(None, 64)	2,112
dense_9 (Dense)	(None, 1)	65

Total params: 3,057 (11.94 KB)

Trainable params: 3,057 (11.94 KB)

Non-trainable params: 0 (0.00 B)

In [33]:
```
# Test your code!
unittests.test_create_model(create_model, windowed_dataset)
```

```
All tests passed!
```

In [34]:
```
# Train it
history = model.fit(train_dataset, epochs=100)
```

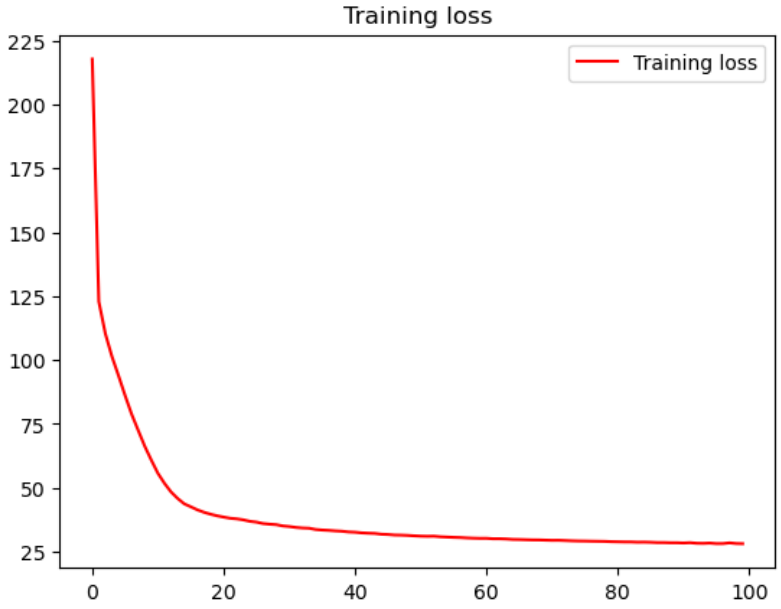
```
Epoch 1/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 1s 987us/step - loss: 330.6848
Epoch 2/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 902us/step - loss: 125.1342
Epoch 3/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 875us/step - loss: 109.7952
Epoch 4/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 934us/step - loss: 118.3786
Epoch 5/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 96.3389
Epoch 6/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 987us/step - loss: 90.3084
Epoch 7/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 821us/step - loss: 69.6821
Epoch 8/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 899us/step - loss: 68.3521
Epoch 9/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 69.6749
Epoch 10/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 56.4207
Epoch 11/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 863us/step - loss: 55.4504
Epoch 12/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 847us/step - loss: 54.8006
Epoch 13/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 862us/step - loss: 47.5435
Epoch 14/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 903us/step - loss: 43.8758
Epoch 15/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 39.3059
Epoch 16/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 871us/step - loss: 54.5468
Epoch 17/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 992us/step - loss: 40.5868
Epoch 18/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 892us/step - loss: 39.4869
Epoch 19/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 995us/step - loss: 41.4328
Epoch 20/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 34.9667
Epoch 21/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 860us/step - loss: 35.2932
Epoch 22/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 848us/step - loss: 35.8099
Epoch 23/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 32.3010
Epoch 24/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 836us/step - loss: 31.1981
Epoch 25/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 852us/step - loss: 40.0193
Epoch 26/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 863us/step - loss: 36.2322
Epoch 27/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 859us/step - loss: 32.5275
Epoch 28/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 883us/step - loss: 33.5674
Epoch 29/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 845us/step - loss: 38.4821
Epoch 30/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 803us/step - loss: 35.1489
Epoch 31/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 32.0206
Epoch 32/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 823us/step - loss: 35.2734
Epoch 33/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 46.2891
Epoch 34/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 30.5523
Epoch 35/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 34.3804
Epoch 36/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 30.2991
Epoch 37/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 902us/step - loss: 31.4225
Epoch 38/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 860us/step - loss: 32.0017
Epoch 39/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 914us/step - loss: 28.0312
```

```
Epoch 40/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 23.4507
Epoch 41/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 859us/step - loss: 29.2156
Epoch 42/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 864us/step - loss: 38.5143
Epoch 43/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 865us/step - loss: 29.0720
Epoch 44/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 835us/step - loss: 26.6091
Epoch 45/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 872us/step - loss: 31.8444
Epoch 46/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 917us/step - loss: 29.5505
Epoch 47/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 868us/step - loss: 27.0909
Epoch 48/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 858us/step - loss: 28.4657
Epoch 49/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 900us/step - loss: 33.8525
Epoch 50/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 869us/step - loss: 35.0817
Epoch 51/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 990us/step - loss: 31.6955
Epoch 52/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 955us/step - loss: 32.9612
Epoch 53/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 906us/step - loss: 30.4218
Epoch 54/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 878us/step - loss: 33.7822
Epoch 55/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 867us/step - loss: 27.5352
Epoch 56/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 898us/step - loss: 41.1749
Epoch 57/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 879us/step - loss: 32.1078
Epoch 58/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 893us/step - loss: 24.8504
Epoch 59/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 920us/step - loss: 26.9685
Epoch 60/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 883us/step - loss: 26.6330
Epoch 61/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 22.8206
Epoch 62/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 940us/step - loss: 28.5139
Epoch 63/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 894us/step - loss: 47.9168
Epoch 64/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 869us/step - loss: 32.5685
Epoch 65/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 900us/step - loss: 37.2277
Epoch 66/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 27.8210
Epoch 67/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 842us/step - loss: 25.5074
Epoch 68/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 831us/step - loss: 35.8869
Epoch 69/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 831us/step - loss: 33.5623
Epoch 70/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 870us/step - loss: 28.5514
Epoch 71/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 30.1085
Epoch 72/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 867us/step - loss: 22.8574
Epoch 73/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 888us/step - loss: 25.7162
Epoch 74/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 905us/step - loss: 29.1571
Epoch 75/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 955us/step - loss: 27.8788
Epoch 76/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 802us/step - loss: 24.9063
Epoch 77/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 873us/step - loss: 29.9035
Epoch 78/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 34.3940
```

```
Epoch 79/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 803us/step - loss: 34.6120
Epoch 80/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 845us/step - loss: 37.2098
Epoch 81/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 882us/step - loss: 37.1309
Epoch 82/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 27.5679
Epoch 83/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 24.2526
Epoch 84/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 841us/step - loss: 27.5600
Epoch 85/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 829us/step - loss: 35.3796
Epoch 86/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 24.3209
Epoch 87/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 967us/step - loss: 33.9620
Epoch 88/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 951us/step - loss: 29.5991
Epoch 89/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 827us/step - loss: 28.1807
Epoch 90/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 885us/step - loss: 30.5368
Epoch 91/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 31.2260
Epoch 92/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 807us/step - loss: 20.9763
Epoch 93/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 855us/step - loss: 20.6778
Epoch 94/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 825us/step - loss: 25.4348
Epoch 95/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 882us/step - loss: 30.8395
Epoch 96/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 865us/step - loss: 27.4862
Epoch 97/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 857us/step - loss: 30.1068
Epoch 98/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 837us/step - loss: 29.5180
Epoch 99/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 823us/step - loss: 42.8613
Epoch 100/100
34/34 ━━━━━━━━━━━━━━━━━━━━ 0s 860us/step - loss: 26.5334
```

Now go ahead and plot the training loss so you can monitor the learning process.

In [35]:
```
# Plot the training loss for each epoch

loss = history.history['loss']

epochs = range(len(loss))

plt.plot(epochs, loss, 'r', label='Training loss')
plt.title('Training loss')
plt.legend(loc=0)
plt.show()
```



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:

In [36]:
```
def compute_metrics(true_series, forecast):
    mse = tf.keras.losses.MSE(true_series, forecast)
    mae = tf.keras.losses.MAE(true_series, forecast)
    return mse, mae
```

You will also be generating `predict_forecast` function, that simply computes predictions for all values in the validation data.

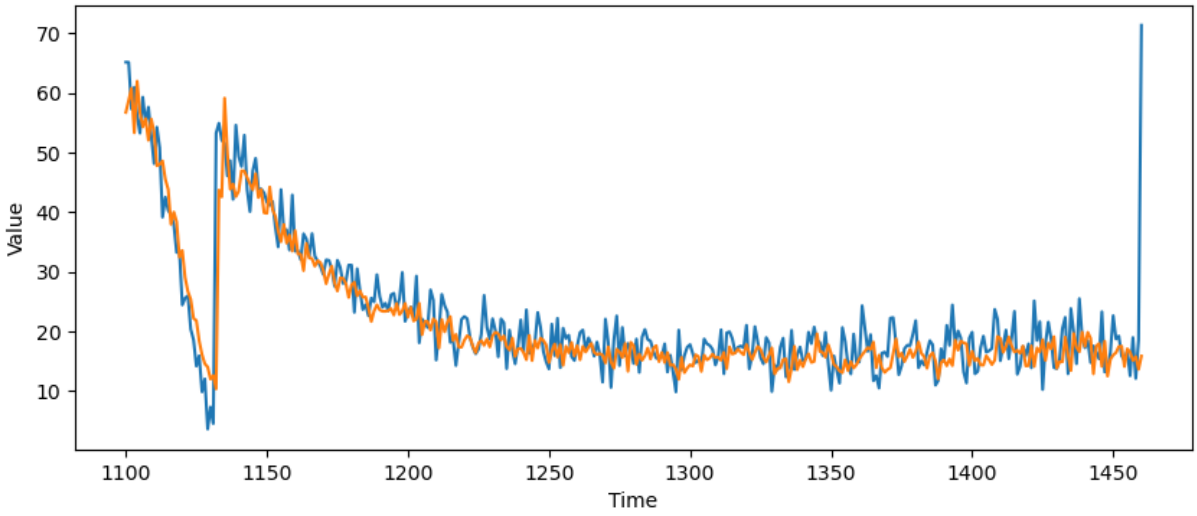
In [37]:
```
def generate_forecast(model, series, window_size):
    forecast = []
    for time in range(SPLIT_TIME, len(series)):
        pred = model.predict(series[time-window_size:time][np.newaxis], verbose=0)
        forecast.append(pred[0][0])
    return forecast
```

Now, go ahead and make the predictions. This run should take no more time than the actual training.

In [38]:
```
# Save the forecast
dnn_forecast = generate_forecast(model, SERIES, WINDOW_SIZE)
```

You can now plot the true series, and the predicted series in order to get a visual estimate of how good your model is doing.

In [39]:
```
# Plot it
plt.figure(figsize=(10, 4))
plot_series(time_valid, series_valid)
plot_series(time_valid, dnn_forecast)
```



Expected Output:

A series similar to this one:

No description has been provided for this image

Finally, go ahead and compute the MSE and MAE metrics using the `compute_metrics` function you defined earlier.

In [40]:
```
mse, mae = compute_metrics(series_valid, dnn_forecast)

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

```
mse: 29.40, mae: 3.40 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 the MSE in a binary file which will be used for grading and after doing so, submit your assigment for grading.

In [41]:
```
# ONLY RUN THIS CELL IF YOUR MSE ACHIEVED THE DESIRED MSE LEVEL
# Save your model
model.save('trained_model.keras')
```

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!