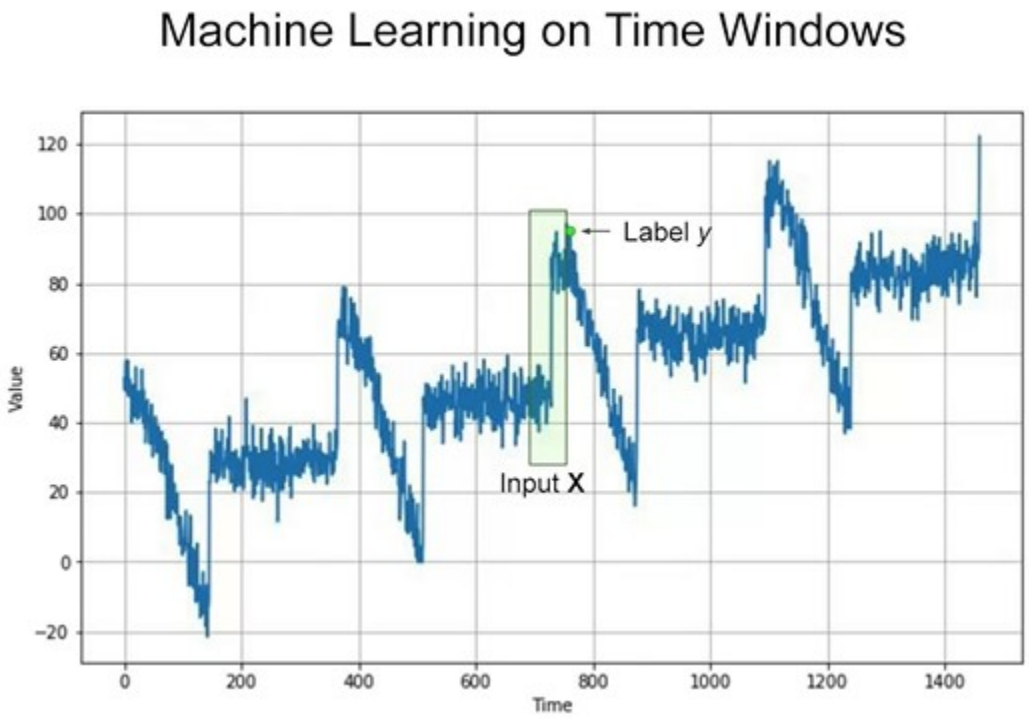
Deep Neural Networks for Time Series

Goal: Teach neural networks to recognize and predict on time series! & Tune the learning rate on of the optimizer. We're going to build a very simple DNN just like a three-layer DNN. Here we can able to tune the learning rate of the optimizer.

- Preparing features and labels
- Feeding windowed dataset into neural network
- Single layer neural network
- Machine learning on time windows
- Prediction
- More on single layer neural network
- Deep neural network training, tuning and prediction
- Deep neural network
- Preparing features and labels notebook
- Sequence bias

Preparing features and labels:

First of all, as with any other ML problem, **we have to divide our data into features and labels**. In this case our feature is effectively a number of values in the series, with our label being the next value. We'll call that number of values that will treat as our feature, the **window size**, where we're taking a window of the data and training an ML model to predict the next value.



For example, if we take our time series data, say, 30 days at a time, we'll use 30 values as the feature and the next value is the label. Then over time, we'll train a neural network to match the 30 features to the single label.

So let's, for example, Use the **tf.data.Dataset** class to create some data for us, we'll make a range of 10 values. When we print them we'll see a series of data from 0 to 9.

```
dataset = tf.data.Dataset.range(10)
for val in dataset:
  print(val.numpy())
```

012345689

So now let's make it a little bit more interesting.

```
dataset = tf.data.Dataset.range(10)
dataset = dataset.window(5, shift=1)
for window_dataset in dataset:
  for val in window_dataset:
    print(val.numpy(), end=" ")
  print()
```

We'll use the **dataset.window** to expand our data set using windowing. Its parameters are the size of the window and how much we want to shift by each time. So if we set a window size of 5 with a shift of 1 when we print it we'll see something like this, 01234, which just stops there because it's five values, then we see 12345 etc, etc,. Once we get towards the end of the data set we'll have less values because they just don't exist. So we'll get 6789, and then 789, etc, etc,.

```
0 1 2 3 4
1 2 3 4 5
2 3 4 5 6
3 4 5 6 7
4 5 6 7 8
5 6 7 8 9
6 7 8 9
7 8 9
8 9
9
```

```
dataset = tf.data.Dataset.range(10)
dataset = dataset.window(5, shift=1, drop_remainder=True)
for window_dataset in dataset:
  for val in window_dataset:
    print(val.numpy(), end=" ")
  print()
```

```
0 1 2 3 4
1 2 3 4 5
2 3 4 5 6
3 4 5 6 7
4 5 6 7 8
5 6 7 8 9
```

So let's edit our window a little bit, so that we have regularly sized data. We can do that with an additional parameter on the window called drop_remainder. And if we set this to true, it will truncate the data by dropping all of the remainders. Namely, this means it will only give us windows of five items. So when we print it, it will now look like this, starting at 01234 and ending at 56789.

```
dataset = tf.data.Dataset.range(10)
dataset = dataset.window(5, shift=1, drop_remainder=True)
dataset = dataset.flat_map(lambda window: window.batch(5))
for window in dataset:
  print(window.numpy())
```

```
[0 1 2 3 4]
[1 2 3 4 5]
[2 3 4 5 6]
[3 4 5 6 7]
[4 5 6 7 8]
[5 6 7 8 9]
```

Great, now let's put these into numpy lists so that we can start using them with machine learning. Good news is, is that this is super easy, we just call the .numpy method on each item in the data set, and when we print we now see that we have a numpy list.

Okay, next up is to split the data into features and labels. For each item in the list it kind of makes sense to have all of the values but the last one to be the feature, and then the last one can be the label. And this can be achieved with mapping, like this, where we split into everything but the last one with :-1, and then just the last one itself with -1: Which gives us this output when we print, which now looks like a nice set of features and labels.

```
dataset = tf.data.Dataset.range(10)
dataset = dataset.window(5, shift=1, drop_remainder=True)
dataset = dataset.flat_map(lambda window: window.batch(5))
dataset = dataset.map(lambda window: (window[:-1], window[-1:]))
for x,y in dataset:
  print(x.numpy(), y.numpy())
```

```
[0 1 2 3] [4]
[1 2 3 4] [5]
[2 3 4 5] [6]
[3 4 5 6] [7]
[4 5 6 7] [8]
[5 6 7 8] [9]
```

Typically, you would shuffle their data before training. And this is possible using the shuffle method. We call it with the buffer size of ten, because that's the amount of data items that we have. And when we print the results, we'll see our features and label sets have been shuffled.

```
dataset = tf.data.Dataset.range(10)
dataset = dataset.window(5, shift=1, drop_remainder=True)
dataset = dataset.flat_map(lambda window: window.batch(5))
dataset = dataset.map(lambda window: (window[:-1], window[-1:]))
dataset = dataset.shuffle(buffer_size=10)
for x,y in dataset:
  print(x.numpy(), y.numpy())
```

```
[3 4 5 6] [7]
[4 5 6 7] [8]
[1 2 3 4] [5]
[2 3 4 5] [6]
[5 6 7 8] [9]
[0 1 2 3] [4]
```

```
dataset = tf.data.Dataset.range(10)
dataset = dataset.window(5, shift=1, drop_remainder=True)
dataset = dataset.flat_map(lambda window: window.batch(5))
dataset = dataset.map(lambda window: (window[:-1], window[-1:]))
dataset = dataset.shuffle(buffer_size=10)
dataset = dataset.batch(2).prefetch(1)
for x,y in dataset:
  print("x = ", x.numpy())
  print("y = ", y.numpy())
```

```
x =  [[4 5 6 7] [1 2 3 4]]
y =  [[8] [5]]
x =  [[3 4 5 6] [2 3 4 5]]
y =  [[7] [6]]
x =  [[5 6 7 8] [0 1 2 3]]
y =  [[9] [4]]
```

```
x =  [[4 5 6 7] [1 2 3 4]]
y =  [[8] [5]]
x =  [[3 4 5 6] [2 3 4 5]]
y =  [[7] [6]]
x =  [[5 6 7 8] [0 1 2 3]]
y =  [[9] [4]]
```

Finally, we can look at batching the data, and this is done with the batch method. It'll take a size parameter, and in this case it's 2. So what we'll do is we'll batch the data into sets of two, and if we print them out, we'll see this. We now have three batches of two data items each. And if you look at the first set, you'll see the corresponding x and y.

```
x =  [[4 5 6 7] [1 2 3 4]]
y =  [[8] [5]]
x =  [[3 4 5 6] [2 3 4 5]]
y =  [[7] [6]]
x =  [[5 6 7 8] [0 1 2 3]]
y =  [[9] [4]]
```

So when x is four, five, six and seven, our y is eight, or when x is zero, one, two, three, and you'll see our y is four. Okay, now that you've seen the tools that let us create a series of x and y's, or features and labels, you have everything you need to work on a data set in order to get predictions from it. We'll take a look at a screen cast of this code next, before moving on to creating our first neural networks to run predictions on this data.

```
dataset = tf.data.Dataset.range(10)
dataset = dataset.window(5, shift=1, drop_remainder=True)
dataset = dataset.flat_map(lambda window: window.batch(5))
dataset = dataset.map(lambda window: (window[:-1], window[-1:]))
dataset = dataset.shuffle(buffer_size=10)
dataset = dataset.batch(2).prefetch(1)
for x,y in dataset:
  print("x = ", x.numpy())
  print("y = ", y.numpy())
```

```
x =  [[0 1 2 3]
 [4 5 6 7]]
y =  [[4]
 [8]]
x =  [[2 3 4 5]
 [3 4 5 6]]
y =  [[6]
 [7]]
x =  [[5 6 7 8]
 [1 2 3 4]]
y =  [[9]
 [5]]
```

Coming up next! We move to the seasonal dataset that you've been using two dates, and with this windowing technique, you'll see how to set up x's and y's that can be fed into a neural network to see how it performs with predicting values.

Sequence bias

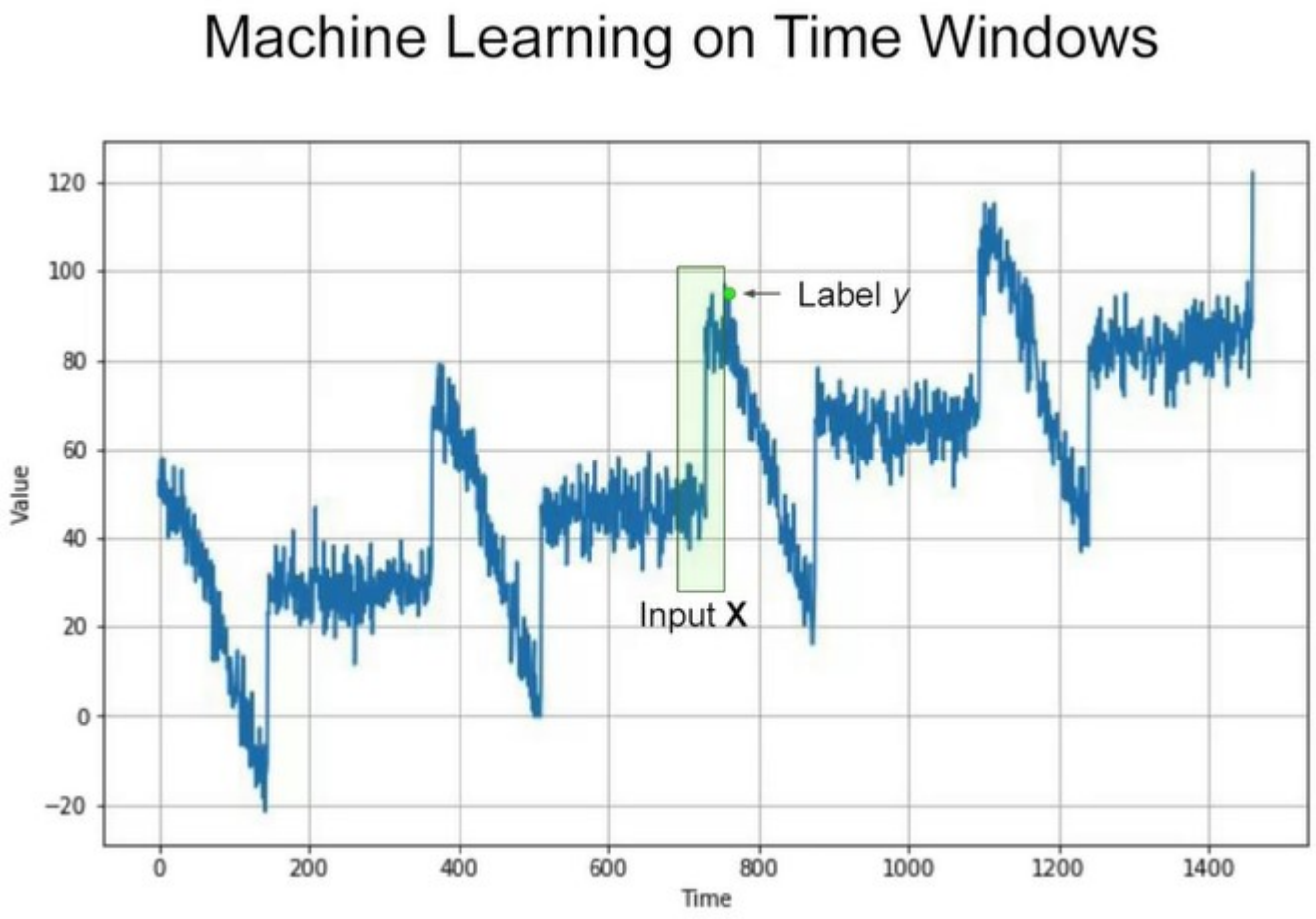
Sequence bias is when the order of things can impact the selection of things.

For example, if I were to ask you your favorite TV show, and listed "Game of Thrones", "Killing Eve", "Travellers" and "Doctor Who" in that order, you're probably more likely to select 'Game of Thrones' as you are familiar with it, and it's the first thing you see. Even if it is equal to the other TV shows.

So, when training data in a dataset, we don't want the sequence to impact the training in a similar way, so it's good to shuffle them up.

Feeding windowed dataset into neural network:

How to prepare time series data for machine learning: By creating a window dataset where the previous n values could be seen as the input features are x. And the current value with any time stamp is the output label or the y. It would then look a little bit like this. With a number of input values on x, typically called a window on the data.



Now adapt the previous code to feed a neural network and then train it on the data.

- So let's start with this function that will call a windows dataset. It will take in a data series along with the parameters for the size of the window that we want. The size of the batches to use when training, and the size of the shuffle buffer, which determines how the data will be shuffled.

```
def windowed_dataset(series, window_size, batch_size, shuffle_buffer):
  dataset = tf.data.Dataset.from_tensor_slices(series)
  dataset = dataset.window(window_size + 1, shift=1, drop_remainder=True)
  dataset = dataset.flat_map(lambda window: window.batch(window_size + 1))
  dataset = dataset.shuffle(shuffle_buffer)
                   .map(lambda window: (window[:-1], window[-1]))
  dataset = dataset.batch(batch_size).prefetch(1)
  return dataset
```

- The first step will be to create a dataset from the series using a tf.data dataset. And we'll pass the series to it using its from_tensor_slices method.

```
def windowed_dataset(series, window_size, batch_size, shuffle_buffer):
  dataset = tf.data.Dataset.from_tensor_slices(series)
  dataset = dataset.window(window_size + 1, shift=1, drop_remainder=True)
  dataset = dataset.flat_map(lambda window: window.batch(window_size + 1))
  dataset = dataset.shuffle(shuffle_buffer)
                   .map(lambda window: (window[:-1], window[-1]))
  dataset = dataset.batch(batch_size).prefetch(1)
  return dataset
```

- We will then use the window method of the dataset based on our window_size to slice the data up into the appropriate windows. Each one being shifted by one time set. We'll keep them all the same size by setting drop remainder to true.

```
def windowed_dataset(series, window_size, batch_size, shuffle_buffer):
  dataset = tf.data.Dataset.from_tensor_slices(series)
  dataset = dataset.window(window_size + 1, shift=1, drop_remainder=True)
  dataset = dataset.flat_map(lambda window: window.batch(window_size + 1))
  dataset = dataset.shuffle(shuffle_buffer)
                   .map(lambda window: (window[:-1], window[-1]))
  dataset = dataset.batch(batch_size).prefetch(1)
  return dataset
```

- We then flatten the data out to make it easier to work with. And it will be flattened into chunks in the size of our window_size + 1.

```
def windowed_dataset(series, window_size, batch_size, shuffle_buffer):
  dataset = tf.data.Dataset.from_tensor_slices(series)
  dataset = dataset.window(window_size + 1, shift=1, drop_remainder=True)
  dataset = dataset.flat_map(lambda window: window.batch(window_size + 1))
  dataset = dataset.shuffle(shuffle_buffer)
                   .map(lambda window: (window[:-1], window[-1]))
  dataset = dataset.batch(batch_size).prefetch(1)
  return dataset
```

- Once it's flattened, it's easy to shuffle it. You call a shuffle and you pass it the shuffle buffer. Using a shuffle buffer speeds things up a bit.
- For example, if you have 100,000 items in your dataset, but you set the buffer to a thousand. It will just fill the buffer with the first thousand elements; pick one of them at random. And then it will replace that with the 1,000 and first element before randomly picking again, and so on.
- This way with super large datasets, the random element choosing can choose from a smaller number which effectively speeds things up.

```
def windowed_dataset(series, window_size, batch_size, shuffle_buffer):
  dataset = tf.data.Dataset.from_tensor_slices(series)
  dataset = dataset.window(window_size + 1, shift=1, drop_remainder=True)
  dataset = dataset.flat_map(lambda window: window.batch(window_size + 1))
  dataset = dataset.shuffle(shuffle_buffer)
                   .map(lambda window: (window[:-1], window[-1]))
  dataset = dataset.batch(batch_size).prefetch(1)
  return dataset
```

- The shuffled dataset is then split into the x's, which is all of the elements except the last, and the y which is the last element. It's then batched into the selected batch size and returned.

Single layer neural network:

- Now we can start training neural networks with window datasets. Let's start with a super simple one that's effectively a linear regression. We'll measure its accuracy, and then we'll work from there to improve that. Before we can do training, we have to split our dataset into training and validation sets. Here's the code to do that at time step 1000.

```
split_time = 1000
time_train = time[:split_time]
x_train = series[:split_time]
time_valid = time[split_time:]
x_valid = series[split_time:]
```


```
split_time = 1000
time_train = time[:split_time]
x_train = series[:split_time]
time_valid = time[split_time:]
x_valid = series[split_time:]
```


- We can see that the training data is the subset of the series called x train up to the split time.

Here's the code to do a simple linear regression.

```
window_size = 20
batch_size = 32
shuffle_buffer_size = 1000

dataset = windowed_dataset(series, window_size, batch_size, shuffle_buffer_size)
l0 = tf.keras.layers.Dense(1, input_shape=[window_size])
model = tf.keras.models.Sequential([l0])
```


```
window_size = 20
batch_size = 32
shuffle_buffer_size = 1000
```


We'll start by setting up all the constants that we want to pass to the window dataset function. These include the window size on the data, the batch size that we want for training, and the size of the shuffled buffer as we've just discussed.


```
dataset = windowed_dataset(series, window_size, batch_size, shuffle_buffer_size)
l0 = tf.keras.layers.Dense(1, input_shape=[window_size])
model = tf.keras.models.Sequential([l0])
```


Then we'll create our dataset. We'll do this by taking our series, and in the notebook that you'll go through later, you'll create the same synthetic series as you did in week one. You'll pass it your series along what your desired window size, batch size, and shuffled buffer size, and it will give you back a formatted datasets that you could use for training for linear regression, that's all you need.


```
dataset = windowed_dataset(series, window_size, batch_size, shuffle_buffer_size)
l0 = tf.keras.layers.Dense(1, input_shape=[window_size])
model = tf.keras.models.Sequential([l0])
```


And then going to create a single dense layer with its input shape being the window size, using this approach. By passing the layer to a variable called L0, because later I want to print out its learned weights, and it's a lot easier for me to do that if I have a variable to refer to the layer for that. Then I simply define my model as a sequential containing the sole layer just like this.

Now compile and fit my model with this code.

```
model.compile(loss="mse", optimizer=tf.keras.optimizers.SGD(lr=1e-6, momentum=0.9))
model.fit(dataset,epochs=100,verbose=0)
```

Use the mean squared error loss function by setting loss to MSE, and my optimizer will use Stochastic Gradient Descent. I'd use this methodology instead of the raw string, so I can set parameters on it to initialize it such as the learning rate or LR and the momentum. Experiment with different values here to see if you can get your model to converge more quickly or more accurately.

```
model.compile(loss="mse", optimizer=tf.keras.optimizers.SGD(lr=1e-6, momentum=0.9))
model.fit(dataset,epochs=100,verbose=0)
```

Next you can fit your model by just passing it the dataset, which has already been preformatted with the x and y values. Just going to run for a 100 epochs here. Ignoring the epoch but epoch output by setting verbose to zero. Once it's done training, you can actually inspect the different weights with this code.

```
print("Layer weights {}".format(l0.get_weights()))
```

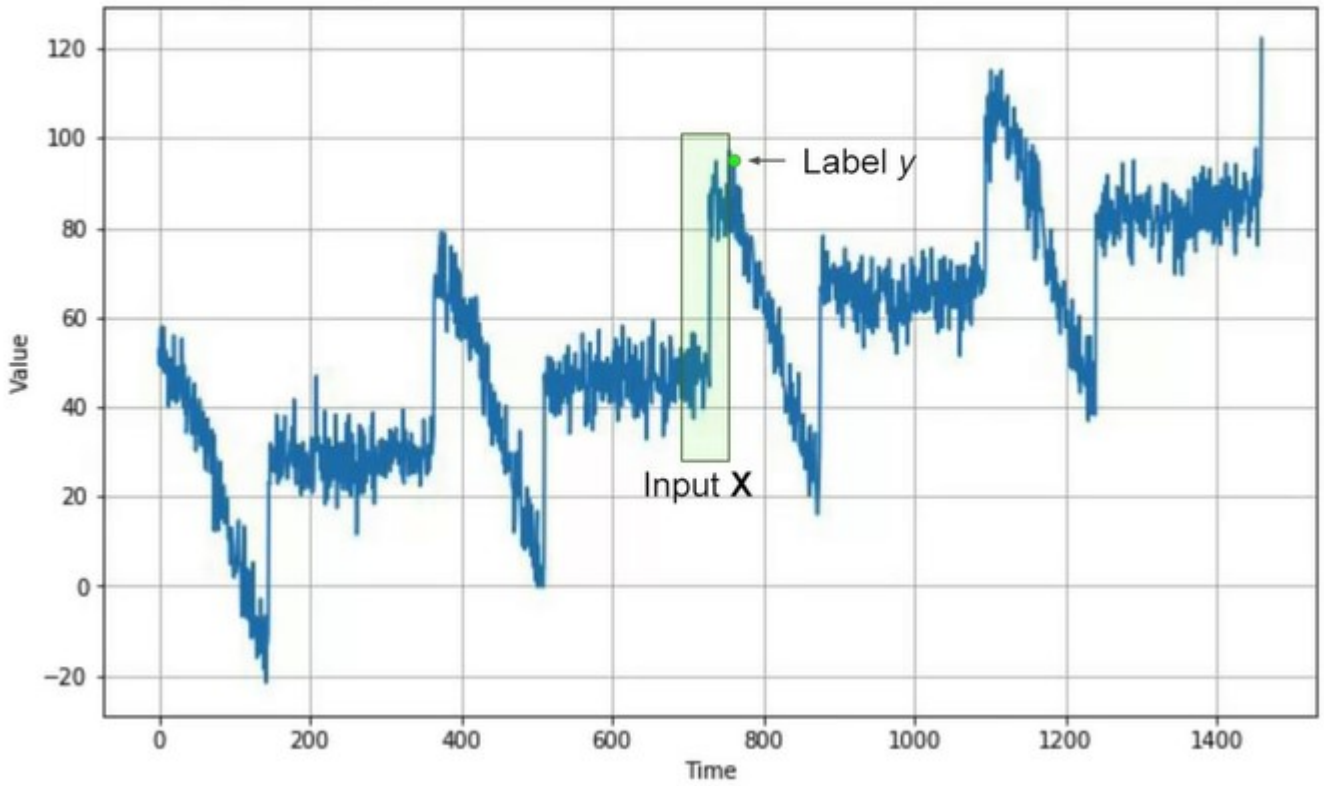
Remember earlier when we referred to the layer with a variable called L 0? Well, here's where that's useful. The output will look like this.

```
print("Layer weights {}".format(l0.get_weights()))

Layer weights [array([[ 0.01633573],
       [-0.02911791],
       [ 0.00845617],
       [-0.02175158],
       [ 0.04962169],
       [-0.03212642],
       [-0.02596855],
       [-0.00689476],
       [ 0.0616533 ],
       [-0.00668752],
       [-0.02735964],
       [ 0.0377918 ],
       [-0.02855931],
       [ 0.05299238],
       [-0.0121608 ],
       [ 0.00138755],
       [ 0.0905595 ],
       [ 0.19994621],
       [ 0.2556632 ],
       [ 0.41660047]], dtype=float32), array([0.01430958], dtype=float32)]
```


If you inspect it closely, you will see that the first array has 20 values in it, and the secondary has only one value. This is because the network has learned a linear regression to fit the values as best as they can. So each of the values in the first array can be seen as the weights for the 20 values in x, and the value for the second array is the b value.

Machine Learning on Time Windows



So if you think back to this diagram and you consider the input window to be 20 values wide, and then let's call them x0, x1, x2, etc, all the way up to x19. But let's be clear. That's not the value on the horizontal axis which is commonly called the x-axis; it's the value of the time series at that point on the horizontal axis. So the value at time t0, which is 20 steps before the current value is called x0, and t1 is called x1, etc. Similarly, for the output, which we would then consider to be the value at the current time to be the y.

```
print("Layer weights {}".format(l0.get_weights()))

Layer weights [array([[ 0.01633573],
       [-0.02911791],
       [ 0.00845617],
       [-0.02175158],
       [ 0.04962169],
       [-0.03212642],
       [-0.02596855],
       [-0.00689476],
       [ 0.0616533 ],
       [-0.00668752],
       [-0.02735964],
       [ 0.0377918 ],
       [-0.02855931],
       [ 0.05299238],
       [-0.0121608 ],
       [ 0.00138755],
       [ 0.0905595 ],
       [ 0.19994621],
       [ 0.2556632 ],
       [ 0.41660047]], dtype=float32), array([0.01430958], dtype=float32)]
```

W_{t0} W_{t1} W_{t2} W_{t3} b

- So now, if we look at the values again and see that these are the weights for the values at that particular timestamp and b is the bias or the slope.

$$Y = W_{t0}X_0 + W_{t1}X_1 + W_{t2}X_2 + \ldots\ldots + W_{t19}X_{19} + b$$

- We can do a standard linear regression like this to predict the value of y at any step by multiplying out the x values by the weights and then adding the bias.

```
print(series[1:21])
model.predict(series[1:21][np.newaxis])
```

- For example, if I take 20 items in my series and print them out, I can see the 20x values.

```
print(series[1:21])
model.predict(series[1:21][np.newaxis])
```

- If I want to predict them, I can pass that series into my model to get a prediction.

- The NumPy new axis then just reshapes it to the input dimension that's used by the model.
- The output will look like this. The top array is the 20 values that provide the input to our model and the bottom is the predicted value back from the model.
- So we've trained our model to say that when it sees 20 values like this, the predicted next value is 49.08478.

```
print(series[1:21])
model.predict(series[1:21][np.newaxis])

[49.35275  53.314735 57.711823 48.934444 48.931244 57.982895 53.897125
 47.67393  52.68371  47.591717 47.506374 50.959415 40.086178 40.919415
 46.612473 44.228207 50.720642 44.454983 41.76799  55.980938]

array([[49.08478]], dtype=float32)
```

If we want to plot our forecasts for every point on the time-series relative to the 20 points before it where our window size was 20, we can write code like this.

```
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]
```

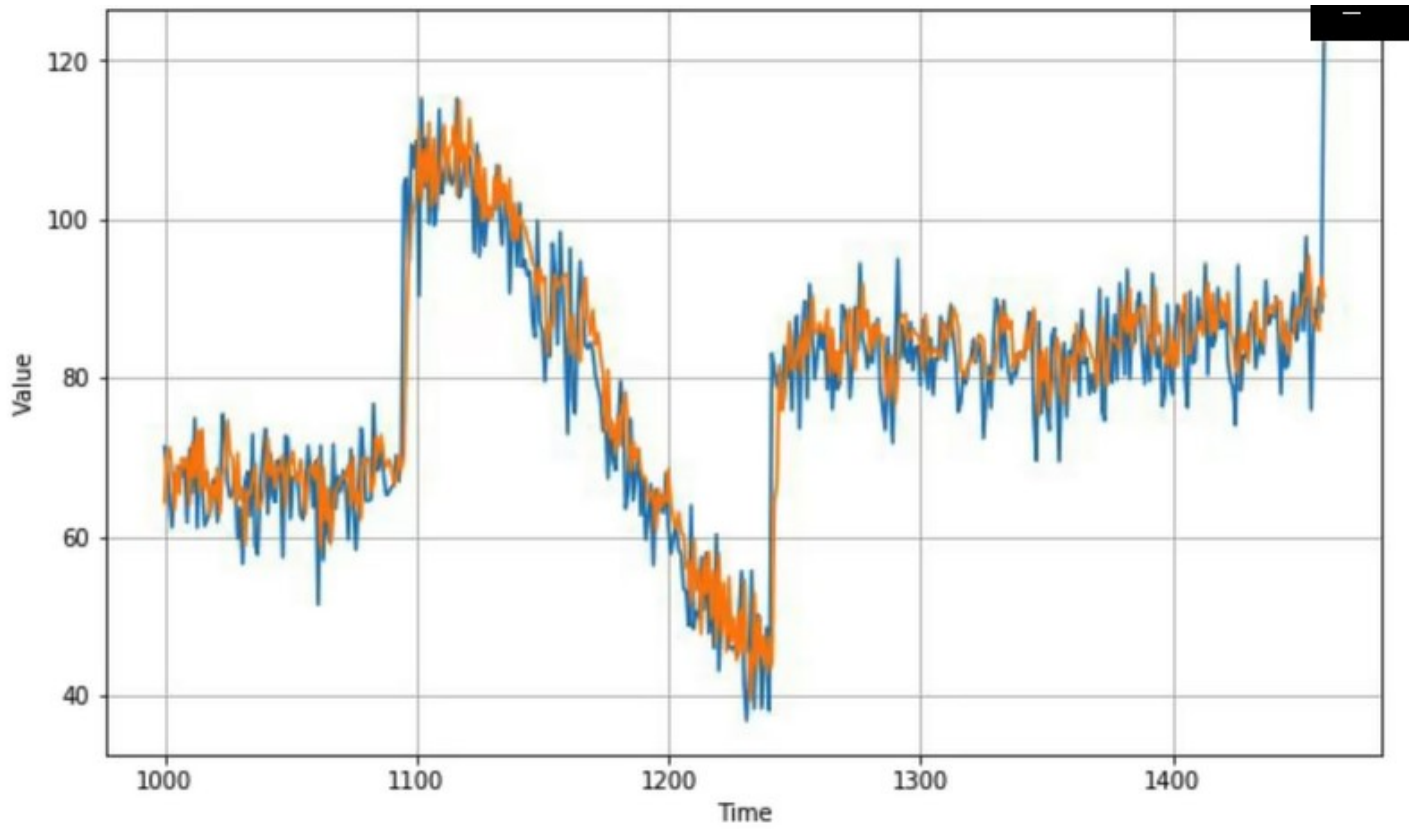
```
forecast = []
for time in range(len(series) - window_size):
  forecast.append(model.predict(series[time:time + window_size][np.newaxis]))

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

We create an empty list of forecasts & **then iterate over the series taking slices and window size, predicting them**, & **adding the results to the forecast list**. **We had split our time series into training and testing sense taking everything before a certain time is training and the rest is validation.**

So we'll just take the **forecasts** after the split time and load them into a NumPy array for charting.

That chart looks like this with the actual values in blue and the predicted ones in orange.



You can see that our predictions look pretty good and getting them was relatively simple in comparison with all the statistical gymnastics that we had to do earlier. So let's measure the mean absolute error as we've done before,

```
tf.keras.metrics.mean_absolute_error(x_valid, results).numpy()

4.9526777
```

And we can see that we're in a similar ballpark to where we were with a complex analysis that we did previously.

```
tf.keras.metrics.mean_absolute_error(x_valid, results).numpy()

5.111128
```

(Practical) Finally, we can measure the mean absolute error between the valid data and the predicted results. Do note that you might see different values here, and in particular as you swap between notebooks, they might change drastically. Remember that the series has a random elements in it with the noise and as such measuring error in one notebook against another may not be the most accurate way because the noise will change. So don't worry if sometimes you see slightly larger values if you were expecting smaller ones.

Now that's just using a single layer in a neural network to calculate a linear regression.

Let's see if we could do better with a fully-connected DNN next.
