TimeSeries_Forecasting

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1 Climate Data Time-Series

You are again moving to another role, not at *The Weather Channel*, where you are ask to create a Weather Forecasting Model.

For that, you will be using *Jena Climate* dataset recorded by the *Max Planck Institute for Biogeochemistry*.

The dataset consists of 14 features such as temperature, pressure, humidity etc, recorded **once per 10 minutes**.

Location: Weather Station, Max Planck Institute for Biogeochemistry in Jena, Germany

Time-frame Considered: **Jan 10, 2009 - December 31, 2012**

Library Imports

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import keras
```

```
c:\Users\Rodolfo\AppData\Local\Programs\Python\Python310\lib\site-
packages\scipy\__init__.py:146: UserWarning: A NumPy version >=1.17.3 and
<1.25.0 is required for this version of SciPy (detected version 1.26.4
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

1.0.1 1) Load your data

Your data can be found on the Deep Learning Module under a file named: climate_data_2009_2012.csv

[2]:
```
df = pd.read_csv("climate_data_2009_2012.csv")
```

1.0.2 2) Data engineering

You are given 3 lists: - titles: Display names of your columns - feature_keys: Names of the columns used as features - colors: The color to use when ploting that column's value

[3]:
```python
titles = [
    "Pressure",
    "Temperature",
    "Temperature in Kelvin",
    "Temperature (dew point)",
    "Relative Humidity",
    "Saturation vapor pressure",
    "Vapor pressure",
    "Vapor pressure deficit",
    "Specific humidity",
    "Water vapor concentration",
    "Airtight",
    "Wind speed",
    "Maximum wind speed",
    "Wind direction in degrees",
]

feature_keys = [
    "p (mbar)",
    "T (degC)",
    "Tpot (K)",
    "Tdew (degC)",
    "rh (%)",
    "VPmax (mbar)",
    "VPact (mbar)",
    "VPdef (mbar)",
    "sh (g/kg)",
    "H2OC (mmol/mol)",
    "rho (g/m**3)",
    "wv (m/s)",
    "max. wv (m/s)",
    "wd (deg)",
]

colors = [
    "blue",
    "orange",
    "green",
    "red",
    "purple",
    "brown",
    "pink",
    "gray",
    "olive",
    "cyan",
]
```

Let’s look at the climate data:

[4]:
```
df.head()
```

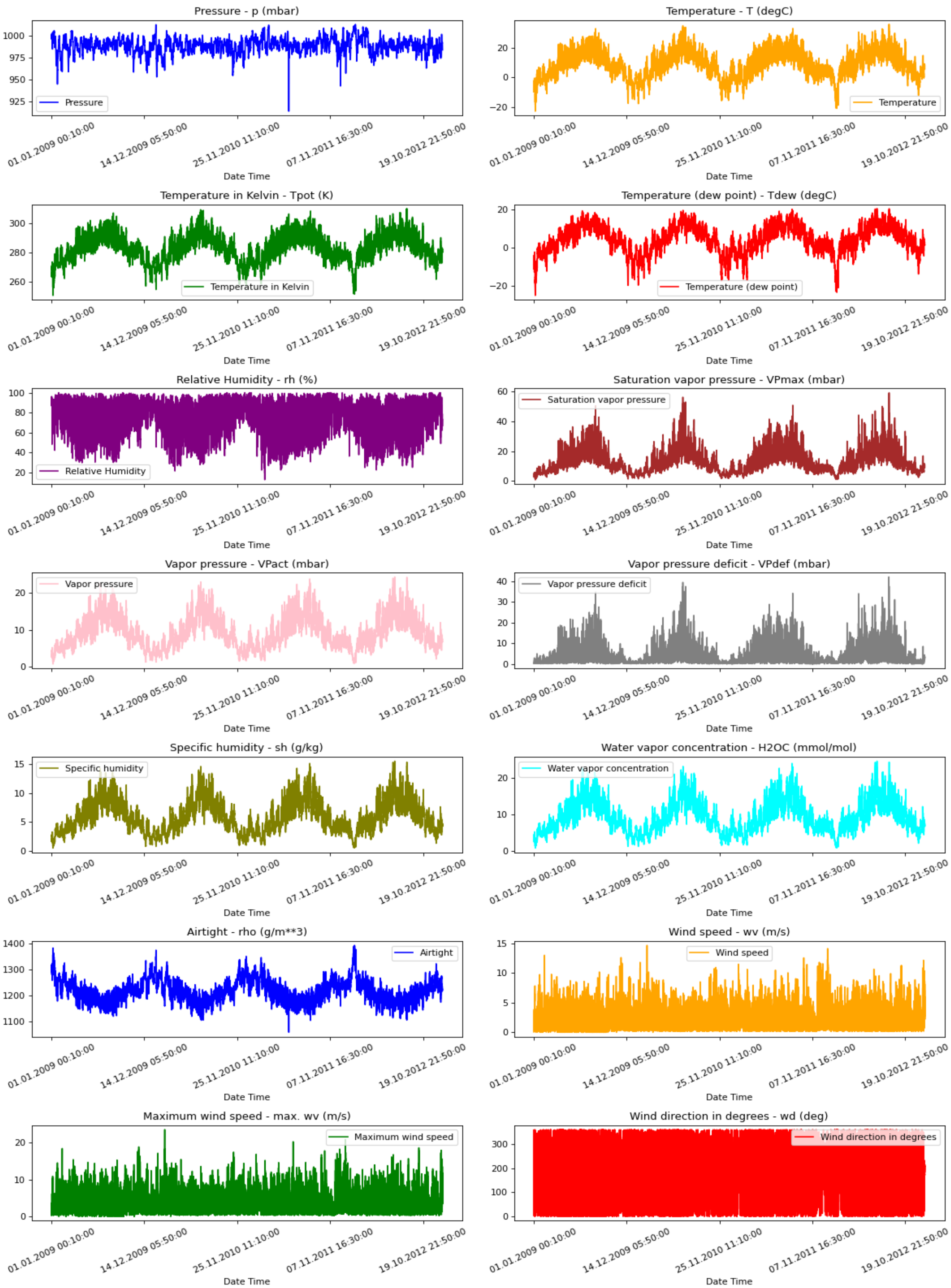
[4]:
```
             Date Time  p (mbar)  T (degC)  Tpot (K)  Tdew (degC)  rh (%)  \
0  01.01.2009 00:10:00    996.52     -8.02    265.40        -8.90    93.3
1  01.01.2009 00:20:00    996.57     -8.41    265.01        -9.28    93.4
2  01.01.2009 00:30:00    996.53     -8.51    264.91        -9.31    93.9
3  01.01.2009 00:40:00    996.51     -8.31    265.12        -9.07    94.2
4  01.01.2009 00:50:00    996.51     -8.27    265.15        -9.04    94.1

   VPmax (mbar)  VPact (mbar)  VPdef (mbar)  sh (g/kg)  H2OC (mmol/mol)  \
0          3.33          3.11          0.22       1.94             3.12
1          3.23          3.02          0.21       1.89             3.03
2          3.21          3.01          0.20       1.88             3.02
3          3.26          3.07          0.19       1.92             3.08
4          3.27          3.08          0.19       1.92             3.09

   rho (g/m**3)  wv (m/s)  max. wv (m/s)  wd (deg)
0       1307.75      1.03           1.75     152.3
1       1309.80      0.72           1.50     136.1
2       1310.24      0.19           0.63     171.6
3       1309.19      0.34           0.50     198.0
4       1309.00      0.32           0.63     214.3
```

Define a function to show a plot of each column (using the respective color)

[5]:
```
def show_raw_visualization(data, date_time_key):
    time_data = data[date_time_key]
    fig, axes = plt.subplots(
        nrows=7, ncols=2, figsize=(15, 20), dpi=80, facecolor="w", edgecolor="k"
    )
    for i in range(len(feature_keys)):
        key = feature_keys[i]
        c = colors[i % (len(colors))]
        t_data = data[key]
        t_data.index = time_data
        t_data.head()
        ax = t_data.plot(
            ax=axes[i // 2, i % 2],
            color=c,
            title="{} - {}".format(titles[i], key),
            rot=25,
        )
        ax.legend([titles[i]])
    plt.tight_layout()
```

Display each column in a plot using above funciton:

[6]:
```
show_raw_visualization(df, "Date Time")
```



As you can see we have lots of data, this can be a challenge when we train our model, to resolve that we will reduce the resolution of our data, instead of having a climate signal each 10 minutes, we will have it each hour

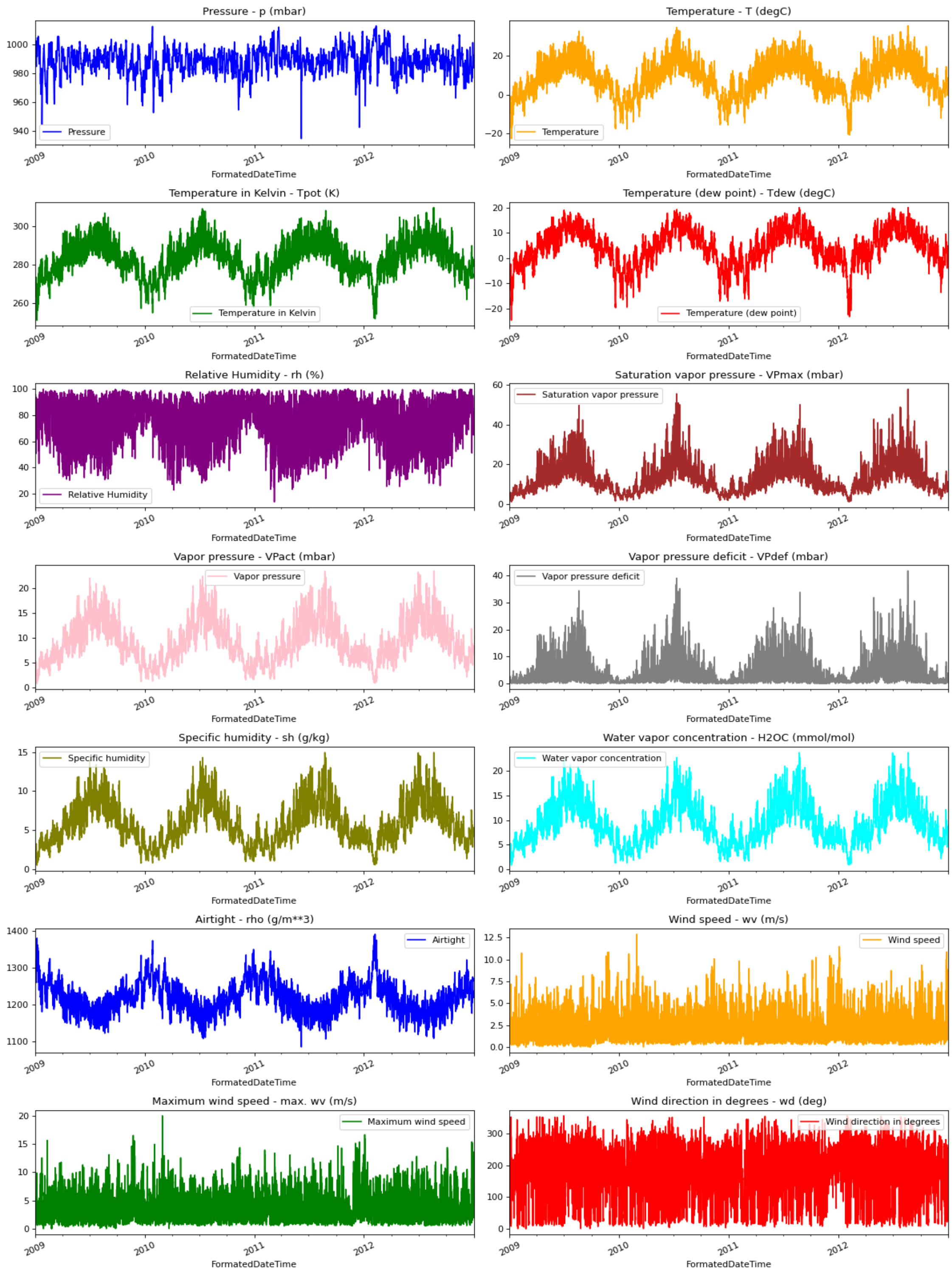
- Add a new column to your dataframe with the Date Time information
- Name that column FormatedDateTime
- Convert that column into date time data type
- Set that column as the dataframe index
- Regroup data to be each 1 hour instead of each 10 minutes
- Save the grouped data into a dataframe called df_resampled
- Remove the FormatedDateTime as the index.
- Show the top 5 rows of df_resampled

[7]:
```
df['FormatedDateTime'] = pd.to_datetime(df['Date Time'], format='%d.%m.%Y %H:%M:
↪%S')
df = df.set_index('FormatedDateTime')
df_resampled = df[feature_keys].resample('H').mean()
df_resampled = df_resampled.reset_index()

df_resampled.head()
```

[7]:
```
     FormatedDateTime    p (mbar)  T (degC)    Tpot (K)  Tdew (degC)  \
0 2009-01-01 00:00:00  996.528000 -8.304000  265.118000    -9.120000
1 2009-01-01 01:00:00  996.525000 -8.065000  265.361667    -8.861667
2 2009-01-01 02:00:00  996.745000 -8.763333  264.645000    -9.610000
3 2009-01-01 03:00:00  996.986667 -8.896667  264.491667    -9.786667
4 2009-01-01 04:00:00  997.158333 -9.348333  264.026667   -10.345000

      rh (%)  VPmax (mbar)  VPact (mbar)  VPdef (mbar)  sh (g/kg)  \
0  93.780000      3.260000      3.058000      0.202000   1.910000
1  93.933333      3.323333      3.121667      0.201667   1.951667
2  93.533333      3.145000      2.940000      0.201667   1.836667
3  93.200000      3.111667      2.898333      0.210000   1.811667
4  92.383333      3.001667      2.775000      0.231667   1.733333

   H2OC (mmol/mol)  rho (g/m**3)  wv (m/s)  max. wv (m/s)    wd (deg)
0         3.068000   1309.196000  0.520000       1.002000  174.460000
1         3.133333   1307.981667  0.316667       0.711667  172.416667
2         2.950000   1311.816667  0.248333       0.606667  196.816667
3         2.906667   1312.813333  0.176667       0.606667  157.083333
4         2.780000   1315.355000  0.290000       0.670000  150.093333
```

Let's look at our fields again

[8]:
```
show_raw_visualization(df_resampled, "FormatedDateTime")
```



1.0.3 3) Data Split: Train and Evaluation datasets.

- We are tracking data from past 120 timestamps (120 hours = 5 days).

- This data will be used to predict the temperature after 12 timestamps (12 hours).
- Since every feature has values with varying ranges, we do normalization to confine feature values to a range of [0, 1] before training a neural network.
- We do this by subtracting the mean and dividing by the standard deviation of each feature in the *normalize* function
- The model is shown data for first 5 days i.e. 120 observations, that are sampled every hour.
- The temperature after 12 hours observation will be used as a label.

[9]:
```
# 70% of the data will be used for training, the rest for testing
split_fraction = 0.7
# The number of samples is the number of rows in the data
number_of_samples = df_resampled.shape[0]
# The size in rows of the split dataset
train_split = int(split_fraction * int(number_of_samples))

# Number of samples in the past used to predict the future
past = 120
# Number of samples in the future to predict (the value in the 72nd hour is our␣
 ↪label)
future = 12
# Learning rate parameter for the Adam optimizer
learning_rate = 0.001
# Batch size for the model training
batch_size = 256
# Number of epochs for the model training
epochs = 10

# Another way to normalize the data (all columns in the same range)
def normalize(data, train_split):
    data_mean = data[:train_split].mean(axis=0)
    data_std = data[:train_split].std(axis=0)
    return (data - data_mean) / data_std
```

- Let's select the following parameters as our features:
  - Pressure, Temperature, Saturation vapor pressure, Vapor pressure deficit, Specific humidity, Airtight, Wind speed
- Set the column FormatedDateTime as the index of our dataframe.
  - This is important since now, FormatedDateTime is used as our datetime field and not as a Feature field
- Normalize all fields
- Generate two datasets:
  - train_data: Train dataset with our normalized fields
  - val_data: Validation dataset

[10]:
```python
print(
    "The selected parameters are:",
    ", ".join([titles[i] for i in [0, 1, 5, 7, 8, 10, 11]]),
)
selected_features = [feature_keys[i] for i in [0, 1, 5, 7, 8, 10, 11]]
features = df_resampled[selected_features]
features.index = df_resampled["FormatedDateTime"]
print(features.head())

features = normalize(features.values, train_split)
features = pd.DataFrame(features)
print(features.head())

train_data = features.loc[0 : train_split - 1]
val_data = features.loc[train_split:]
```

```
The selected parameters are: Pressure, Temperature, Saturation vapor pressure,
Vapor pressure deficit, Specific humidity, Airtight, Wind speed
                      p (mbar)  T (degC)  VPmax (mbar)  VPdef (mbar)  \
FormatedDateTime
2009-01-01 00:00:00  996.528000 -8.304000      3.260000      0.202000
2009-01-01 01:00:00  996.525000 -8.065000      3.323333      0.201667
2009-01-01 02:00:00  996.745000 -8.763333      3.145000      0.201667
2009-01-01 03:00:00  996.986667 -8.896667      3.111667      0.210000
2009-01-01 04:00:00  997.158333 -9.348333      3.001667      0.231667

                     sh (g/kg)  rho (g/m**3)  wv (m/s)
FormatedDateTime
2009-01-01 00:00:00   1.910000   1309.196000  0.520000
2009-01-01 01:00:00   1.951667   1307.981667  0.316667
2009-01-01 02:00:00   1.836667   1311.816667  0.248333
2009-01-01 03:00:00   1.811667   1312.813333  0.176667
2009-01-01 04:00:00   1.733333   1315.355000  0.290000
          0         1         2         3         4         5         6
0  0.988366 -1.936957 -1.314750 -0.797292 -1.472751  2.198783 -1.116409
1  0.988002 -1.909978 -1.306369 -0.797363 -1.457136  2.169559 -1.256715
2  1.014643 -1.988807 -1.329968 -0.797363 -1.500234  2.261854 -1.303867
3  1.043907 -2.003858 -1.334379 -0.795594 -1.509604  2.285840 -1.353320
4  1.064694 -2.054843 -1.348935 -0.790994 -1.538961  2.347009 -1.275116
```

Now, here we need to set our Label Dataset.

- We want to use the last 5 days of data, to predict the next 12 hours
- This means that our label starts at the 12th hour after the history data.
  - […………………….. .]
  - ——Start——>
- And it will end at the end of our train dataset size.
  - <——— Train ———> <— Test —>
  - […………………………………………|……….]

– ———-End———->

[11]:
```
start = past + future
end = start + train_split

x_train = train_data[[i for i in range(7)]].values
y_train = features.iloc[start:end][[1]]

step = 1
sequence_length = past
```

The *timeseries_dataset_from_array* function takes in a sequence of data-points gathered at equal intervals, along with time series parameters such as length of the sequences/windows, spacing between two sequence/windows, etc., to produce batches of sub-timeseries inputs and targets sampled from the main timeseries.

- Input data (hour features) = x_train
- The **corresponding** value of the temperature 12 hours into the future = y_train
- Since we want to use 5 days of data to predict the future temperature then: sequence_length = 120
- Since we want to sample every hour then: sampling_rate = 1
- Let's use a common batch size of 256 (variable above)

[12]:
```
dataset_train = keras.preprocessing.timeseries_dataset_from_array(
    x_train,
    y_train,
    sequence_length=sequence_length,
    sampling_rate=step,
    batch_size=batch_size,
)
```

Now let's prepare our validation dataset:

- The validation dataset must not contain the last 120+12 rows as we won't have label data for those records, hence these rows must be subtracted from the end of the data.
- The validation label dataset must start from 120+12 after train_split, hence we must add past + future to label_start.

[15]:
```
x_end = len(val_data) - past - future

label_start = train_split + past + future

x_val = val_data.iloc[:x_end][[i for i in range(7)]].values
y_val = features.iloc[label_start:][[1]]

dataset_val = keras.preprocessing.timeseries_dataset_from_array(
    x_val,
    y_val,
    sequence_length=sequence_length,
```

```
    sampling_rate=step,
    batch_size=batch_size,
)


for batch in dataset_train.take(1):
    inputs, targets = batch

print("Input shape:", inputs.numpy().shape)
print("Target shape:", targets.numpy().shape)
```

```
Input shape: (256, 120, 7)
Target shape: (256, 1)
```

1.0.4 4) Define and Compile your model:

- An input layer
- A Long Short-Term Memory Hidden Layer with 32 units. LSTM is a type of recurrent neural network layer that is well-suited for time series data.
- An output Dense Layer (Linear Activation function)

[16]:
```
inputs = keras.layers.Input(shape=(inputs.shape[1], inputs.shape[2]))
lstm_out = keras.layers.LSTM(32)(inputs)
outputs = keras.layers.Dense(1)(lstm_out)

model = keras.Model(inputs=inputs, outputs=outputs)
model.compile(optimizer=keras.optimizers.Adam(learning_rate=learning_rate),
 ↪loss="mse")
model.summary()
```

Model: "functional"

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 120, 7)	0
lstm (LSTM)	(None, 32)	5,120
dense (Dense)	(None, 1)	33

Total params: 5,153 (20.13 KB)

Trainable params: 5,153 (20.13 KB)

```
Non-trainable params: 0 (0.00 B)
```

1.0.5 5) Train your model:

Specify the file path where the model's weights will be saved with: `path_checkpoint = "model_checkpoint.weights.h5"`

We want to add a callback to stop training when a monitored metric stops improving: `es_callback = keras.callbacks.EarlyStopping(monitor="val_loss", min_delta=0, patience=5)`

Train the model using Fit

[17]:
```python
path_checkpoint = "model_checkpoint.weights.h5"
es_callback = keras.callbacks.EarlyStopping(monitor="val_loss", min_delta=0,␣
 ↪patience=5)

modelckpt_callback = keras.callbacks.ModelCheckpoint(
    monitor="val_loss",
    filepath=path_checkpoint,
    verbose=1,
    save_weights_only=True,
    save_best_only=True,
)

history = model.fit(
    dataset_train,
    epochs=epochs,
    validation_data=dataset_val,
    callbacks=[es_callback, modelckpt_callback],
)
```

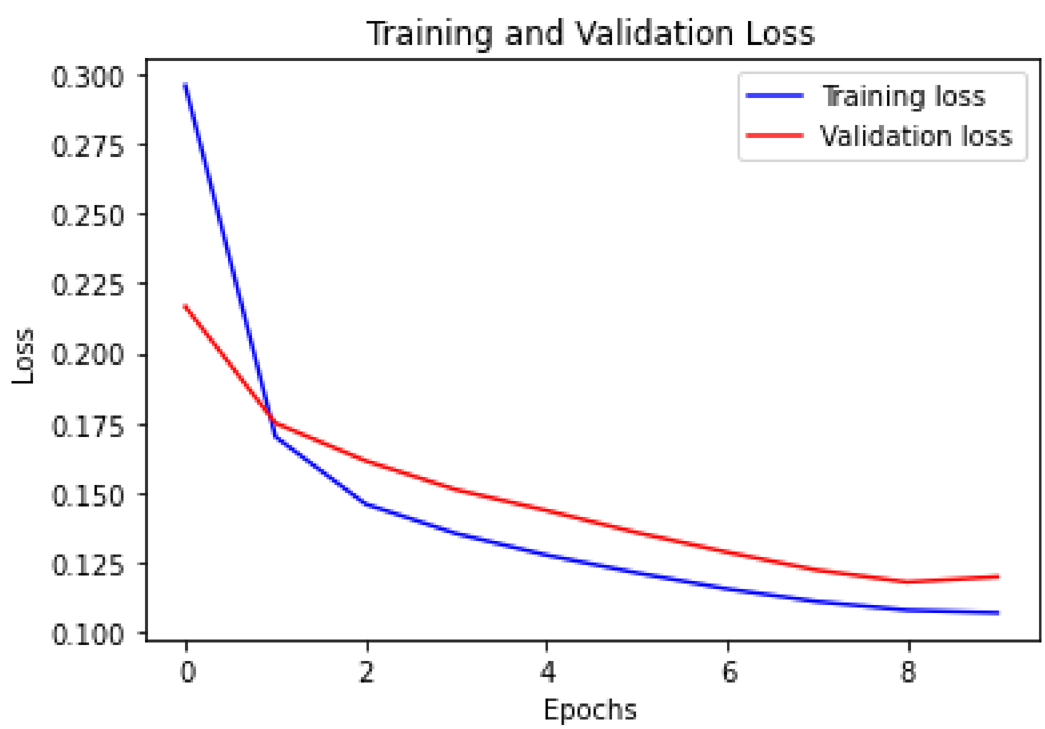
```
Epoch 1/10
96/96              0s 114ms/step -
loss: 0.4509
Epoch 1: val_loss improved from inf to 0.21675, saving model to
model_checkpoint.weights.h5
96/96              14s 133ms/step -
loss: 0.4493 - val_loss: 0.2167
Epoch 2/10
96/96              0s 117ms/step -
loss: 0.1752
Epoch 2: val_loss improved from 0.21675 to 0.17507, saving model to
model_checkpoint.weights.h5
96/96              13s 134ms/step -
loss: 0.1752 - val_loss: 0.1751
Epoch 3/10
96/96              0s 115ms/step -
loss: 0.1533
```

```
Epoch 3: val_loss improved from 0.17507 to 0.16154, saving model to
model_checkpoint.weights.h5
96/96            13s 132ms/step -
loss: 0.1532 - val_loss: 0.1615
Epoch 4/10
96/96            0s 114ms/step -
loss: 0.1411
Epoch 4: val_loss improved from 0.16154 to 0.15121, saving model to
model_checkpoint.weights.h5
96/96            13s 131ms/step -
loss: 0.1410 - val_loss: 0.1512
Epoch 5/10
96/96            0s 117ms/step -
loss: 0.1318
Epoch 5: val_loss improved from 0.15121 to 0.14380, saving model to
model_checkpoint.weights.h5
96/96            13s 134ms/step -
loss: 0.1318 - val_loss: 0.1438
Epoch 6/10
96/96            0s 114ms/step -
loss: 0.1254
Epoch 6: val_loss improved from 0.14380 to 0.13588, saving model to
model_checkpoint.weights.h5
96/96            13s 131ms/step -
loss: 0.1254 - val_loss: 0.1359
Epoch 7/10
96/96            0s 114ms/step -
loss: 0.1196
Epoch 7: val_loss improved from 0.13588 to 0.12885, saving model to
model_checkpoint.weights.h5
96/96            13s 131ms/step -
loss: 0.1195 - val_loss: 0.1288
Epoch 8/10
96/96            0s 114ms/step -
loss: 0.1141
Epoch 8: val_loss improved from 0.12885 to 0.12241, saving model to
model_checkpoint.weights.h5
96/96            13s 131ms/step -
loss: 0.1140 - val_loss: 0.1224
Epoch 9/10
96/96            0s 112ms/step -
loss: 0.1103
Epoch 9: val_loss improved from 0.12241 to 0.11812, saving model to
model_checkpoint.weights.h5
96/96            12s 129ms/step -
loss: 0.1103 - val_loss: 0.1181
Epoch 10/10
96/96            0s 110ms/step -
```

```
loss: 0.1085
Epoch 10: val_loss did not improve from 0.11812
96/96             12s 127ms/step -
loss: 0.1085 - val_loss: 0.1200
```

Plot the results of your training:

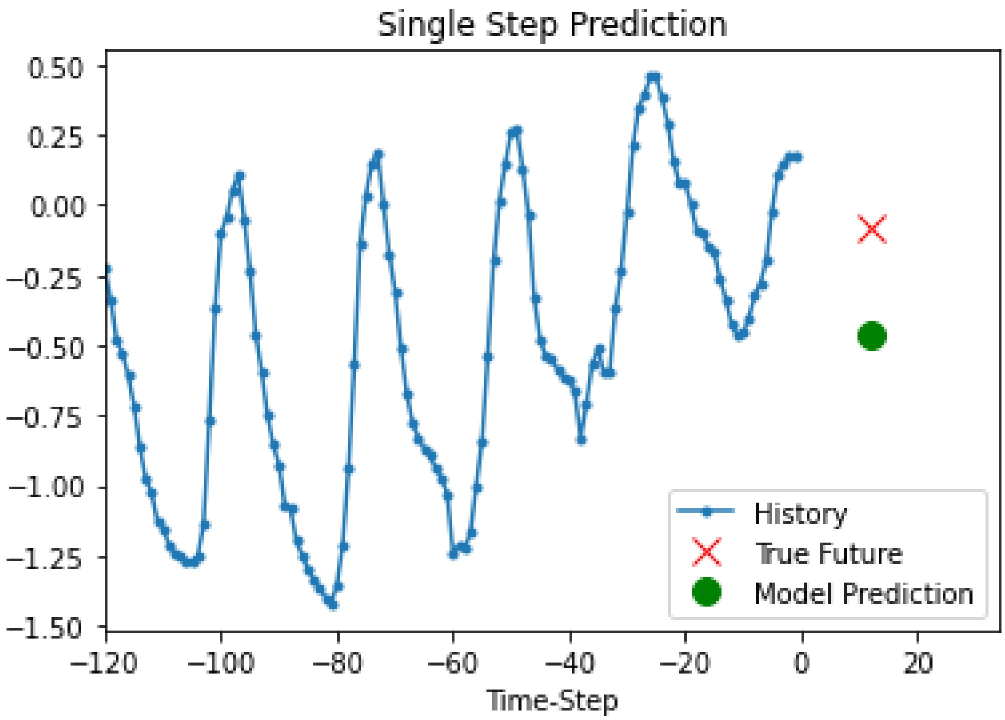
[18]:
```python
def visualize_loss(history, title):
    loss = history.history["loss"]
    val_loss = history.history["val_loss"]
    epochs = range(len(loss))
    plt.figure()
    plt.plot(epochs, loss, "b", label="Training loss")
    plt.plot(epochs, val_loss, "r", label="Validation loss")
    plt.title(title)
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.legend()
    plt.show()


visualize_loss(history, "Training and Validation Loss")
```



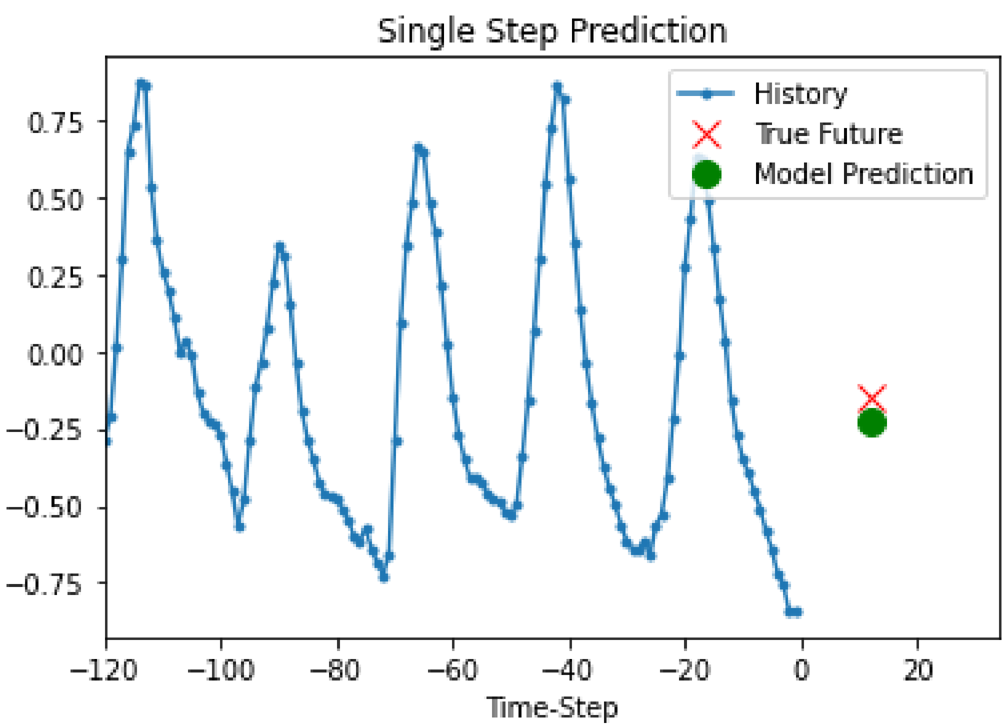
Make 5 predictions and display the predicted value

[19]:
```
def show_plot(plot_data, delta, title):
    labels = ["History", "True Future", "Model Prediction"]
    marker = [".-", "rx", "go"]
    time_steps = list(range(-(plot_data[0].shape[0]), 0))
    if delta:
        future = delta
    else:
        future = 0

    plt.title(title)
    for i, val in enumerate(plot_data):
        if i:
            plt.plot(future, plot_data[i], marker[i], markersize=10,␣
 ↪label=labels[i])
        else:
            plt.plot(time_steps, plot_data[i].flatten(), marker[i],␣
 ↪label=labels[i])
    plt.legend()
    plt.xlim([time_steps[0], (future + 5) * 2])
    plt.xlabel("Time-Step")
    plt.show()
    return


for x, y in dataset_val.take(5):
    show_plot(
        [x[0][:, 1].numpy(), y[0].numpy(), model.predict(x)[0]],
        12,
        "Single Step Prediction",
    )
```

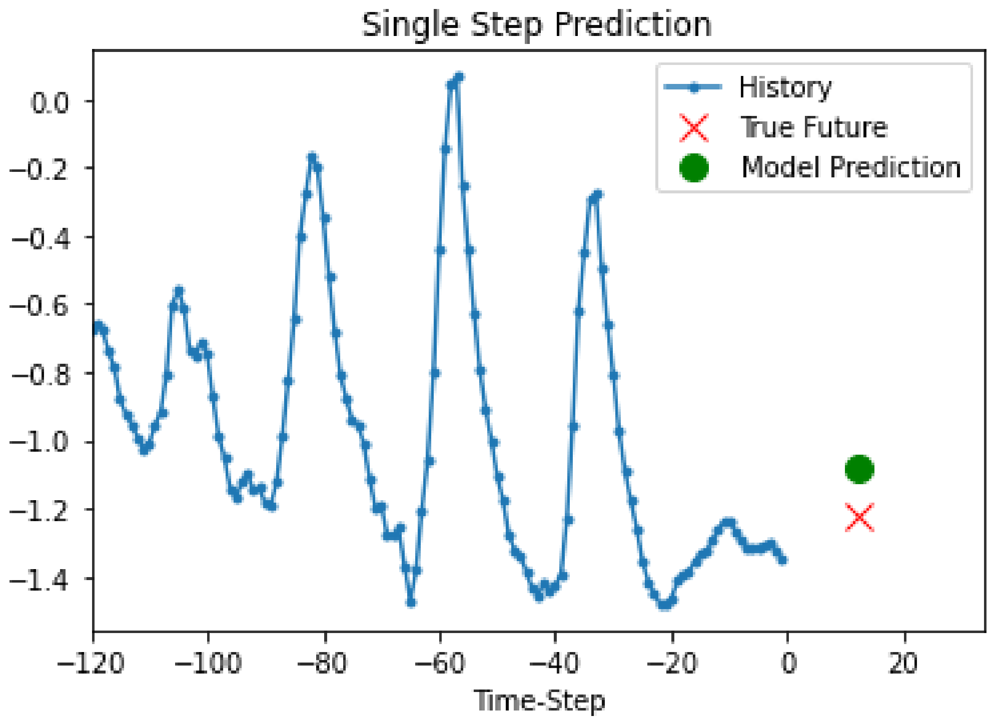
```
8/8                0s 17ms/step
```



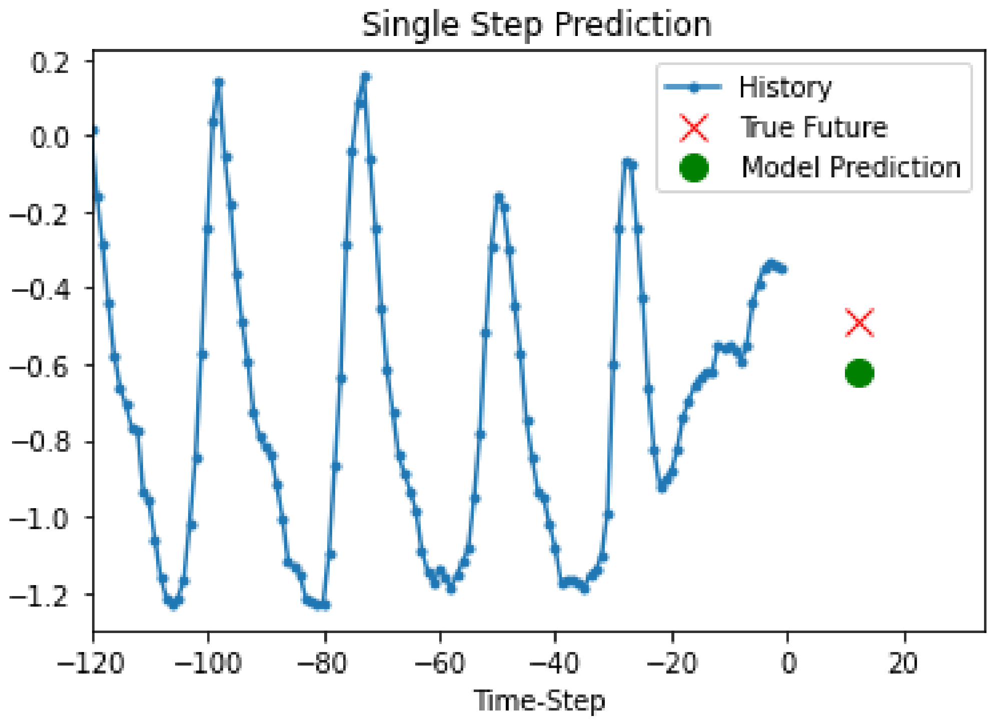

```
8/8                  0s 15ms/step
```



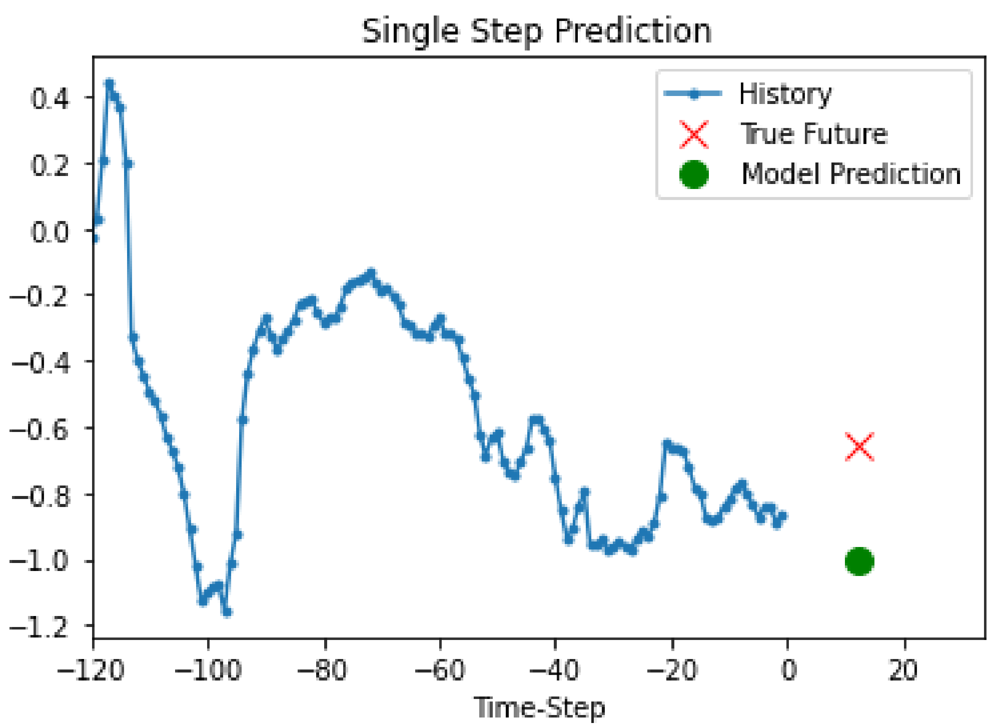
```
8/8                    0s 14ms/step
```




```
8/8                    0s 19ms/step
```




```
8/8                    0s 18ms/step
```



Now make a Time Series Forecasting where using the last 3 days you will predict the weather in the next 3 hours.

[20]:
```
# Establecer que se tomarán los registros de las últimas 72 horas para realizar␣
↪el pronóstico del clima

past = 72

# Establecer que se pronosticará el clima en las siguientes 3 horas

future = 3
```

Dado que se quiere pronosticar el clima en las próximas 3 horas en base a datos de las últimas 72 horas (3 días), eso implica que el label comenzará en la 3er hora después de los datos históricos y finalizará cuando se alcanze el tamaño establecido para el dataset de entrenamiento.

[21]:
```
# Calcular en qué número de fila comenzar a realizar los pronósticos

start = past + future

# Calcular dónde terminar de pronosticar

end = start + train_split
```

[22]:
```
# Obtener los valores de las 7 columnas del dataframe de datos de entrenamiento

x_train2 = train_data[[i for i in range(7)]].values

# Obtener los datos cotemplados desde el inicio hasta el fin de los datos␣
↪previamente establecidos

y_train2 = features.iloc[start:end][[1]]

# Establecer un incremento unitario

step = 1

# Establecer la longitud o número de elementos de la secuencia de datos en␣
↪cuestión

sequence_length = past
```

[23]:
```
# Usar la función timeseries_dataset_from_array() para generar una muestra de␣
↪datos del tamaño establecido en sequence_length

dataset_train2 = keras.preprocessing.timeseries_dataset_from_array(
```

```
    x_train2,
    y_train2,
    sequence_length = sequence_length,
    sampling_rate=step,
    batch_size=batch_size,
)
```

Una vez establecido el dataset de entrenamiento para el nuevo modelo predictivo, ahora se procederá a generar el datset para la validación de dicho modelo, mediante los pasos a continuación:

[24]:
```
# Calcular el valor en el que terminarán los datos de x de validación restando␣
↪cantidad de datos históricos recopilados y
# cantidad de periodos futuros para los que se desea pronosticar el clima, del␣
↪número de elementos de los datos originales de validación

fin_x = len(val_data) - past - future

# Definir el label de inicio sumando el tamaño del dataset de entrenamiento más␣
↪la cantidad de datos históricos recopilados más
# la cantidad de periodos de tiempo a futuro para la cual se desea pronosticar␣
↪el clima

label_start = train_split + past + future

# Definir el conjunto de datos en x y y para validación

x_val = val_data.iloc[:fin_x][[i for i in range(7)]].values
y_val = features.iloc[label_start:][[1]]
```

[25]:
```
# Definir el dataset general para la validación del posterior modelo

dataset_val2 = keras.preprocessing.timeseries_dataset_from_array(
    x_val,
    y_val,
    sequence_length=sequence_length,
    sampling_rate=step,
    batch_size=batch_size,
)

# Asignar un batch a cada par de entradas (inputs) y salidas (targets)

for batch in dataset_train2.take(1):
    inputs, targets = batch

# Mostrar cantidad de filas y columnas de las entradas o inputs y de los␣
↪objetivos (targets)
```

```
print("Input shape:", inputs.numpy().shape)
print("Target shape:", targets.numpy().shape)
```

```
Input shape: (256, 72, 7)
Target shape: (256, 1)
```

Ahora se procede a definir y compilar el modelo de red Neuronal para realizar el posterior pronóstico del clima:

[26]:
```
# Crear capa de inputs de la red neuronal con dimensiones 120 x 7

inputs = keras.layers.Input(shape=(inputs.shape[1], inputs.shape[2]))

# Definir capa de salida de tipo LSTM con 32 unidades

lstm_out = keras.layers.LSTM(32)(inputs)

# Definir capa de salida de la red neuronal con 1 unidad y sin función de␣
↪activación especificada para que sea lineal por defecto

outputs = keras.layers.Dense(1)(lstm_out)

# Crear el modelo de red neuronal con los inputs y salidas (outputs)␣
↪especificados previamente

modelo2 = keras.Model(inputs=inputs, outputs=outputs)

# Compilar el modelo generado con optimizador Adam y MSE como función de pérdida

modelo2.compile(optimizer=keras.optimizers.Adam(learning_rate=learning_rate),␣
↪loss="mse")

# Mostrar un resumen de los atributos del modelo

modelo2.summary()
```

Model: "functional_1"

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 72, 7)	0
lstm_1 (LSTM)	(None, 32)	5,120
dense_1 (Dense)	(None, 1)	33

Total params: 5,153 (20.13 KB)

Trainable params: 5,153 (20.13 KB)

Non-trainable params: 0 (0.00 B)

[27]:
```
# Definir nombre del espacio en el que se guardarán los pesos del modelo␣
↪predictivo generado

path_checkpoint2 = "modelo2_pesos.weights.h5"

# Especificar que el entrenamiento del modelo se detenga cuando pasen 10␣
↪iteraciones sin que mejore el valor de la función de
# pérdida en el conjunto de datos de validación (val_loss)

es_callback2 = keras.callbacks.EarlyStopping(monitor="val_loss", min_delta=0,␣
↪patience=10)

# Función para guardar únicamente los pesos del modelo y de dichso pesos,␣
↪quedarse sólo con el mejor de ellos

modelckpt_callback = keras.callbacks.ModelCheckpoint(
    monitor="val_loss",
    filepath=path_checkpoint2,
    verbose=1,
    save_weights_only=True,
    save_best_only=True,
)

# Guardar en la variable history, los resultados del entrenamiento del modelo

history_modelo2 = modelo2.fit(
    dataset_train,
    epochs=epochs,
    validation_data=dataset_val,
    callbacks=[es_callback2, modelckpt_callback],
)
```

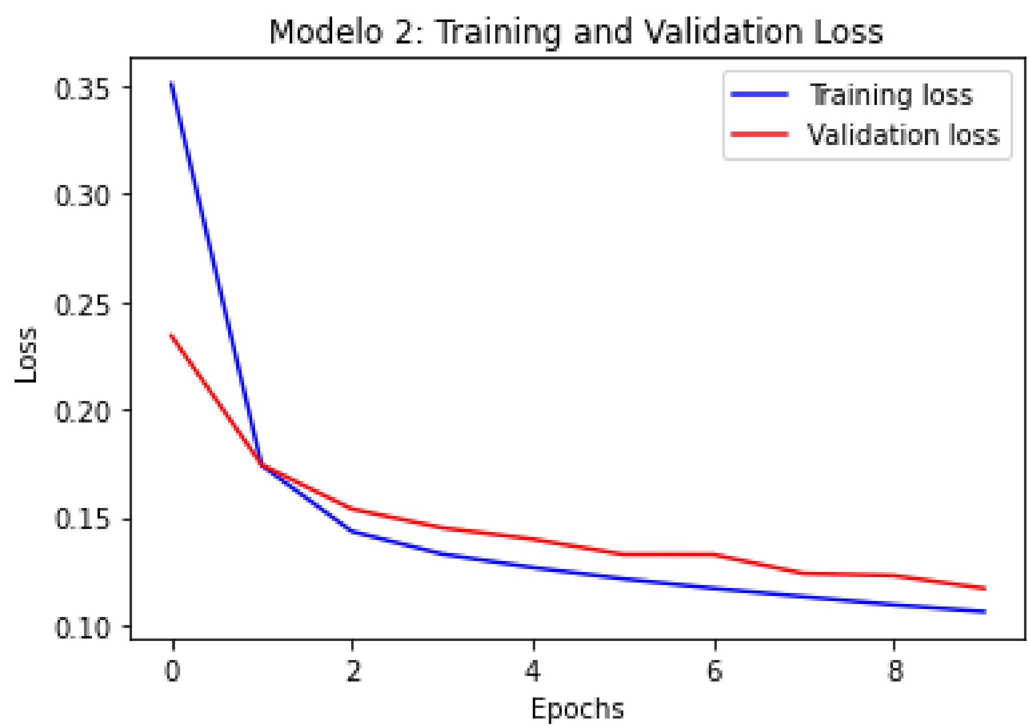
```
Epoch 1/10
96/96            0s 121ms/step -
loss: 0.6133
Epoch 1: val_loss improved from inf to 0.23418, saving model to
modelo2_pesos.weights.h5
96/96            15s 140ms/step -
loss: 0.6106 - val_loss: 0.2342
Epoch 2/10
```

```
96/96            0s 114ms/step -
loss: 0.1865
Epoch 2: val_loss improved from 0.23418 to 0.17447, saving model to
modelo2_pesos.weights.h5
96/96            13s 131ms/step -
loss: 0.1864 - val_loss: 0.1745
Epoch 3/10
96/96            0s 115ms/step -
loss: 0.1463
Epoch 3: val_loss improved from 0.17447 to 0.15396, saving model to
modelo2_pesos.weights.h5
96/96            13s 132ms/step -
loss: 0.1463 - val_loss: 0.1540
Epoch 4/10
96/96            0s 117ms/step -
loss: 0.1348
Epoch 4: val_loss improved from 0.15396 to 0.14523, saving model to
modelo2_pesos.weights.h5
96/96            13s 134ms/step -
loss: 0.1348 - val_loss: 0.1452
Epoch 5/10
96/96            0s 114ms/step -
loss: 0.1288
Epoch 5: val_loss improved from 0.14523 to 0.13999, saving model to
modelo2_pesos.weights.h5
96/96            13s 130ms/step -
loss: 0.1288 - val_loss: 0.1400
Epoch 6/10
96/96            0s 115ms/step -
loss: 0.1239
Epoch 6: val_loss improved from 0.13999 to 0.13291, saving model to
modelo2_pesos.weights.h5
96/96            13s 131ms/step -
loss: 0.1238 - val_loss: 0.1329
Epoch 7/10
96/96            0s 114ms/step -
loss: 0.1190
Epoch 7: val_loss improved from 0.13291 to 0.13286, saving model to
modelo2_pesos.weights.h5
96/96            13s 130ms/step -
loss: 0.1190 - val_loss: 0.1329
Epoch 8/10
96/96            0s 117ms/step -
loss: 0.1162
Epoch 8: val_loss improved from 0.13286 to 0.12410, saving model to
modelo2_pesos.weights.h5
96/96            13s 133ms/step -
loss: 0.1161 - val_loss: 0.1241
```

```
Epoch 9/10
96/96              0s 114ms/step -
loss: 0.1118
Epoch 9: val_loss improved from 0.12410 to 0.12310, saving model to
modelo2_pesos.weights.h5
96/96              13s 131ms/step -
loss: 0.1118 - val_loss: 0.1231
Epoch 10/10
96/96              0s 114ms/step -
loss: 0.1093
Epoch 10: val_loss improved from 0.12310 to 0.11718, saving model to
modelo2_pesos.weights.h5
96/96              13s 131ms/step -
loss: 0.1093 - val_loss: 0.1172
```

[28]:

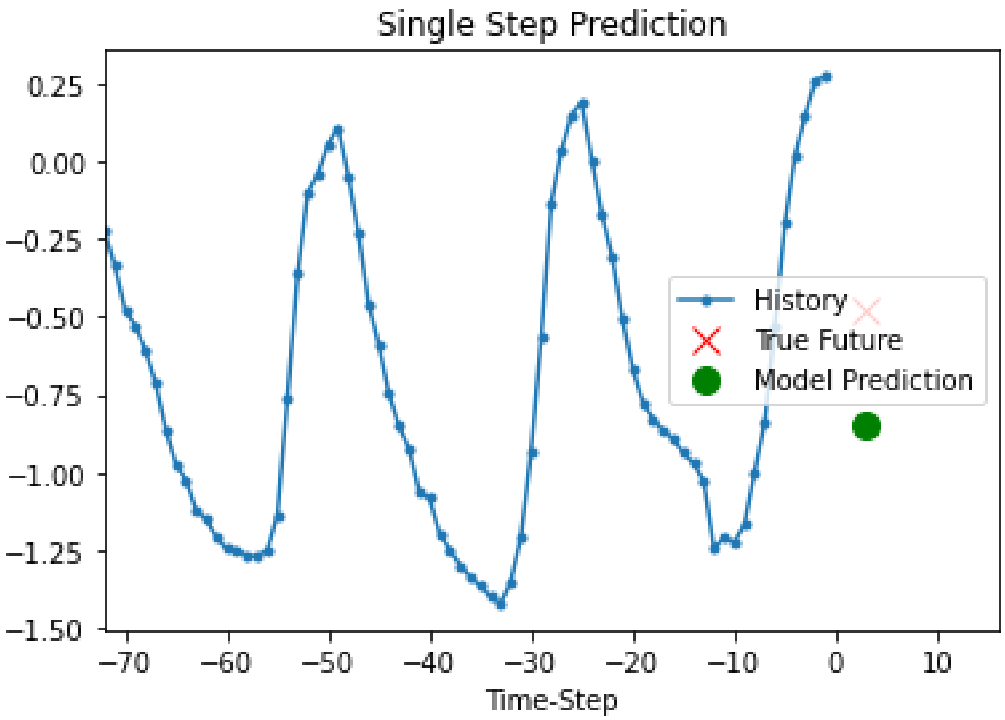
```
# Visualizar en un gráfico los cambios en la función de pérdida a medida que
↪avanza el entrenaminto del modelo

visualize_loss(history_modelo2, "Modelo 2: Training and Validation Loss")
```



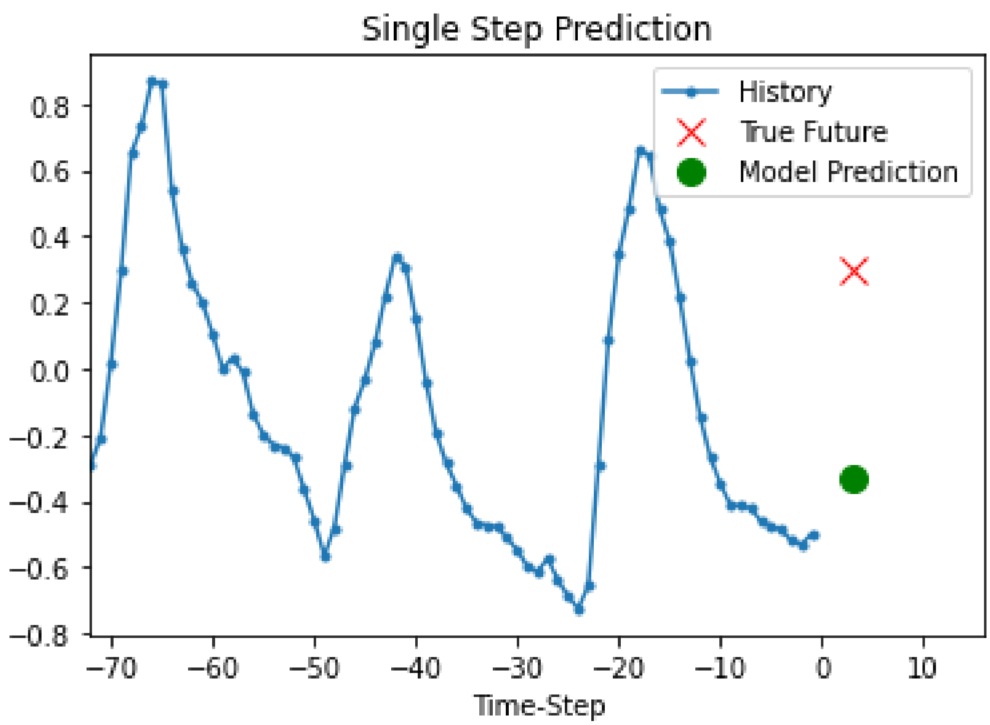
A continuación se procederá a realizar 5 pronósticos para poner a prueba el modelo anteriormente generado y entrenado y además para cada una de las predicciones realizadas, se desplgará un gráfico para mostrar cada una:

[29]:
```
# Para cada uno de los 5 pronósticos de clima realizados, desplegar el gráfico␣
↪mostrando el histórico de datos de las 72 horas previas,
# además de el valor real a futuro y el valor pronosticado igualmente a futuro

for x2, y2 in dataset_val2.take(5):
    show_plot(
        [x2[0][:, 1].numpy(), y2[0].numpy(), modelo2.predict(x2)[0]],
        3,
        "Single Step Prediction",
    )
```

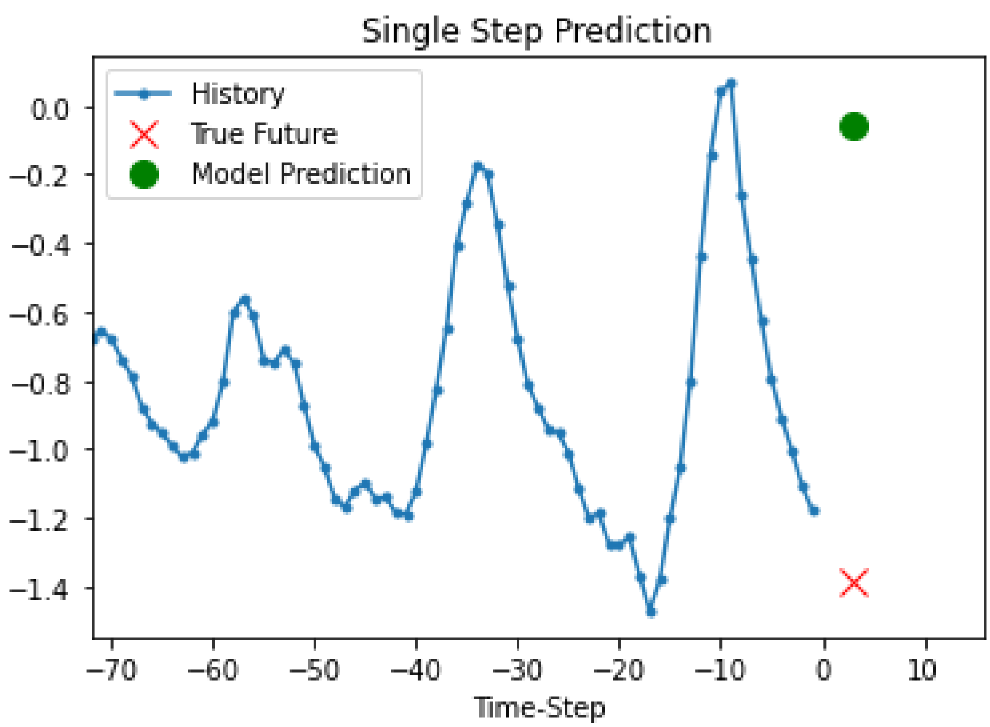
```
8/8                0s 10ms/step
```



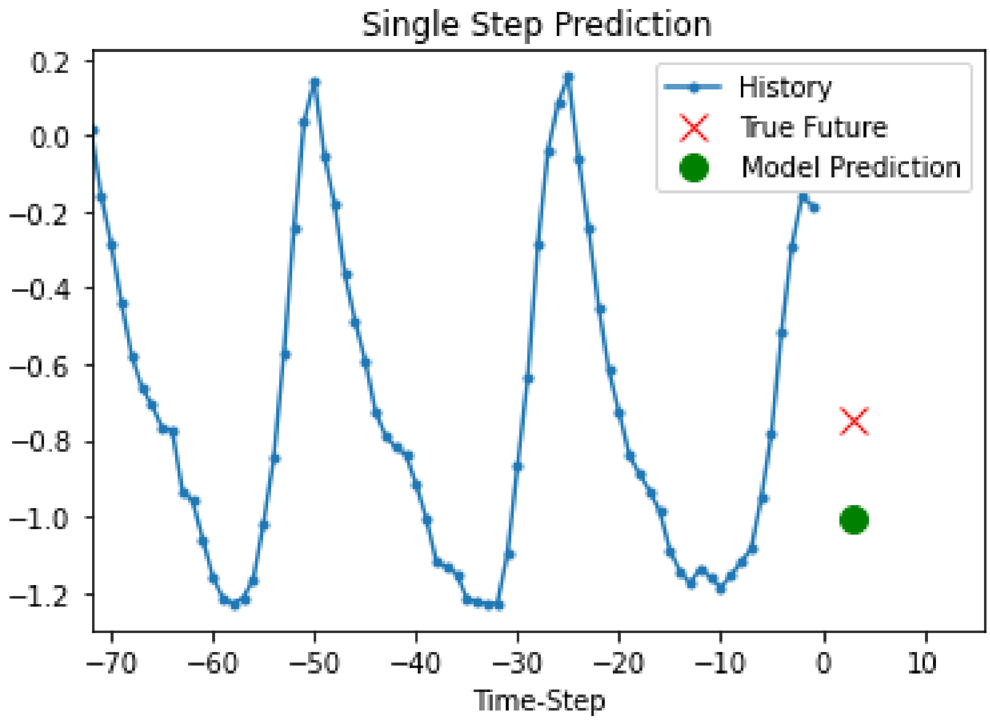

```
8/8                0s 9ms/step
```



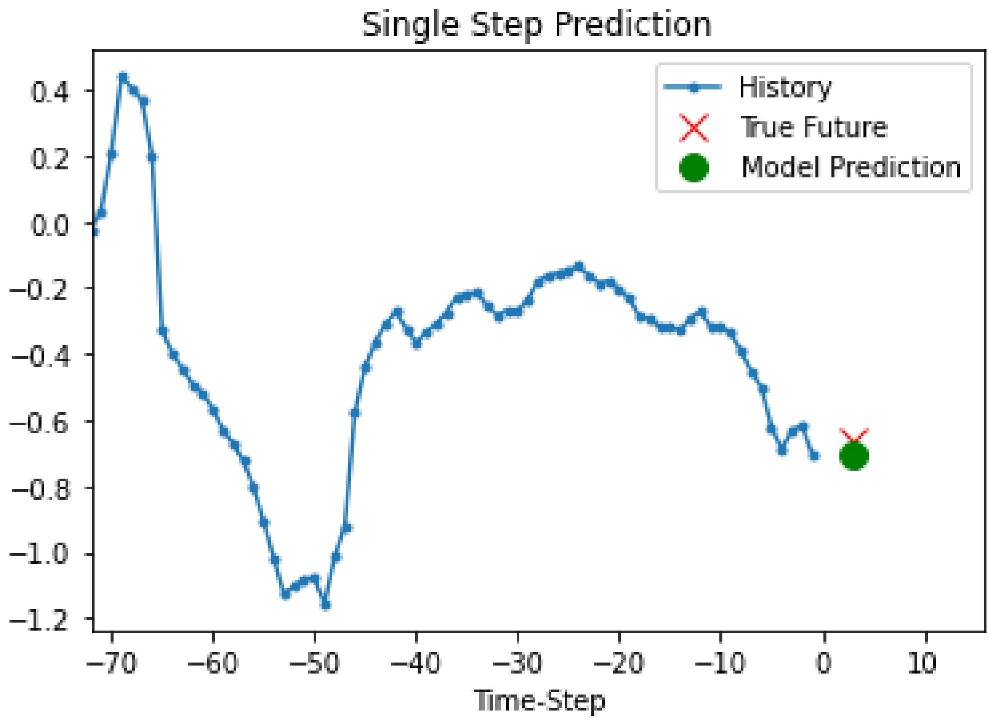

```
8/8                0s 9ms/step
```



8/8 0s 11ms/step



8/8 0s 10ms/step



1.0.6 Tabla comparativa de MSE por modelo

[37]:
```
# Obtener el mejor valor de pérdida MSE en training para el modelo 1

MSE_best_M1_train = history.history["loss"][len(history.history["loss"]) - 1]

# Mejor MSE en validación del modelo 1

MSE_best_M1_val = history.history["val_loss"][len(history.history["val_loss"])␣
↪- 1]

# Mejor MSE en training del modelo 2

MSE_best_M2_train = history_modelo2.history["loss"][len(history_modelo2.
↪history["loss"]) - 1]

# Mejor MSE en validación del modelo 2

MSE_best_M2_val = history_modelo2.history["val_loss"][len(history_modelo2.
↪history["val_loss"]) - 1]
```

[39]:
```
# Generar dataframe con los mejores valores de MSE en entrenamiento y␣
↪validación para ambos modelos generados
```

```
models_MSE = pd.DataFrame({"Best_MSE_train": [MSE_best_M1_train,␣
 ↪MSE_best_M2_train], "Best_MSE_validation": [MSE_best_M1_val,␣
 ↪MSE_best_M2_val]},
                          index = ["Modelo 1", "Modelo 2"])

# Nombrar el index del dataframe

models_MSE.index.name = "Modelo"

# Mostrar el dataframe con los mejores valores de MSE

models_MSE
```

[39]:

Modelo	Best_MSE_train	Best_MSE_validation
Modelo 1	0.107121	0.120026
Modelo 2	0.106396	0.117184

Nota: Los valores en el dataframe anterior son cada uno el último valor registrado del MSE en la lista de valores MSE de entrenamiento (ubicada en el atributo "loss" de la variable history de ambos modelos) y en la lista de valores MSE de prueba (ubicada en el atributo "val_loss" de la variable history de ambos modelos), dado que el úlimo valor de MSE representa la menor pérdida posible para cada modelo tanto en la etapa de entrenamiento como en la de prueba.

1.0.7 Conclusión final

En base a los resultados anteriores, es posible observar que el mejor MSE en training para el modelo 1 fue de 0.1071, mientras que el del modelo 2 fue de 0.1063, mientras que de forma similar, el mejor MSE en validación para el modelo 1 es de 0.12 y para el modelo 2 es de 0.1171, con lo cual, se aprecia que el modelo 2 posee el menor MSE tanto en entrenamiento como en validación, lo cual indica que el modelo 2 es ligeramente mejor que el modelo 1 para predecir las condiciones climáticas, en base a las variables meteorológicas que se tienen, lo cual además sugiere que el modelo 2 logró tener un aprendizaje ligeramente mejor que el del modelo 1 al tener el MSE en training más bajo, mientras que el modelo 2 también logró tener una precisión ligeramente más alta para predecir el clima que el segundo modelo al tener también el menor MSE en validación, por lo cual, además de lo anterior, también es posible concluir que los pronósticos del clima de las siguientes 3 horas realizados a partir de datos históricos de las últimas 72 horas (3 días) son ligeramente más precisos que aquellos pronósticos de las siguientes 12 horas realizados en base a los datos históricos de las últimas 120 horas, por lo cual, se concluye que al pronosticar el clima en base a datos históricos, los pronósticos más precisos serán aquellos que correspondan a los pocos días más próximos a la última fecha registrada en los datos históricos, por lo que a medida que transcurra una mayor cantidad de días después de esa última fecha, los pronósticos serán menos precisos y por tanto también perderán confiabilidad.