Downloading the Data

```
from google.colab import drive
drive.mount('/content/gdrive')
!unzip -qq /content/gdrive/MyDrive/jena_climate_2009_2016.zip
```

```
Mounted at /content/gdrive
```

Basic machine learning model example

Inspecting the dataset

```
import os
fname = os.path.join("jena_climate_2009_2016.csv")

with open(fname) as f:
    data = f.read()

lines = data.split("\n")
header = lines[0].split(",")
lines = lines[1:]
print(header)
print(len(lines))
```

```
['"Date Time"', '"p (mbar)"', '"T (degC)"', '"Tpot (K)"', '"Tdew (degC)"', '"rh (%)"', '"VPmax (mbar)"', '"VPact (mbar)"', '"VPdef (mbar)"', '"sh (g/kg)"', '"H2OC (mmol/mol)"', '"rho
420551
```

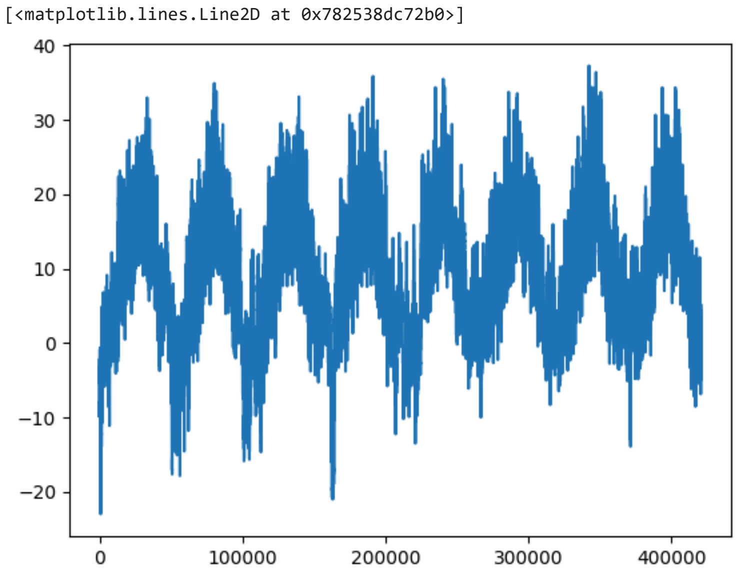
Parsing the dataset

```
import numpy as np
temperature = np.zeros((len(lines),))
raw_data = np.zeros((len(lines), len(header) - 1))
for i, line in enumerate(lines):
    values = [float(x) for x in line.split(",")[1:]]
    temperature[i] = values[1]
    raw_data[i, :] = values[:]
```

Plotting the temperature timeseries

```
from matplotlib import pyplot as plt
plt.plot(range(len(temperature)), temperature)
```

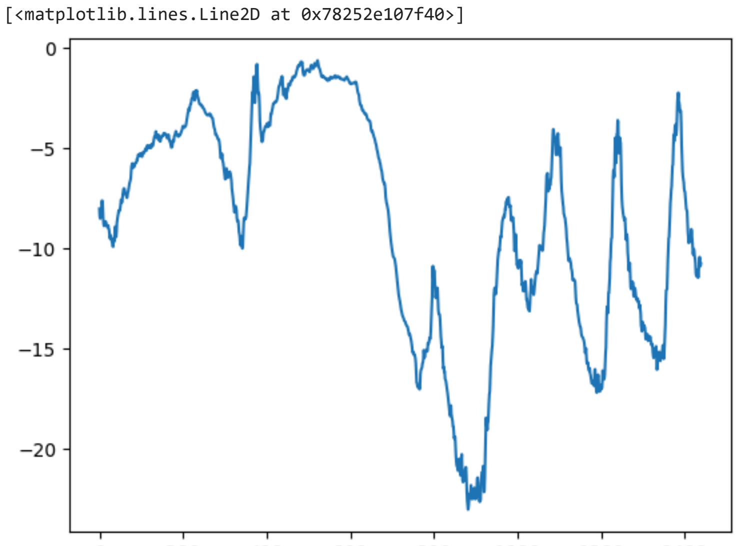
```
[<matplotlib.lines.Line2D at 0x782538dc72b0>]
```



Plotting the first 10 days of the temperature timeseries

```
plt.plot(range(1440), temperature[:1440])
```

```
[<matplotlib.lines.Line2D at 0x78252e107f40>]
```



Computing the number of samples we'll use for each data split

```
num_train_samples = int(0.5 * len(raw_data))
num_val_samples = int(0.25 * len(raw_data))
num_test_samples = len(raw_data) - num_train_samples - num_val_samples
print("num_train_samples:", num_train_samples)
print("num_val_samples:", num_val_samples)
print("num_test_samples:", num_test_samples)
```

```
num_train_samples: 210275
num_val_samples: 105137
num_test_samples: 105139
```

Preparing the data

Normalizing the data

```
mean = raw_data[:num_train_samples].mean(axis=0)
raw_data -= mean
std = raw_data[:num_train_samples].std(axis=0)
raw_data /= std
```

```
import numpy as np
from tensorflow import keras
int_sequence = np.arange(10)
dummy_dataset = keras.utils.timeseries_dataset_from_array(
    data=int_sequence[:-3],
    targets=int_sequence[3:],
    sequence_length=3,
    batch_size=2,
)

for inputs, targets in dummy_dataset:
    for i in range(inputs.shape[0]):
        print([int(x) for x in inputs[i]], int(targets[i]))
```

```
[0, 1, 2] 3
[1, 2, 3] 4
[2, 3, 4] 5
[3, 4, 5] 6
[4, 5, 6] 7
```

Instantiating datasets for training, validation, and testing

```
sampling_rate = 6
sequence_length = 120
delay = sampling_rate * (sequence_length + 24 - 1)
batch_size = 256

train_dataset = keras.utils.timeseries_dataset_from_array(
    raw_data[:-delay],
    targets=temperature[delay:],
    sampling_rate=sampling_rate,
    sequence_length=sequence_length,
    shuffle=True,
    batch_size=batch_size,
    start_index=0,
    end_index=num_train_samples)

val_dataset = keras.utils.timeseries_dataset_from_array(
    raw_data[:-delay],
    targets=temperature[delay:],
    sampling_rate=sampling_rate,
    sequence_length=sequence_length,
    shuffle=True,
    batch_size=batch_size,
    start_index=num_train_samples,
    end_index=num_train_samples + num_val_samples)

test_dataset = keras.utils.timeseries_dataset_from_array(
    raw_data[:-delay],
    targets=temperature[delay:],
    sampling_rate=sampling_rate,
    sequence_length=sequence_length,
    shuffle=True,
    batch_size=batch_size,
    start_index=num_train_samples + num_val_samples)
```

Inspecting the output of one of our datasets

```
for samples, targets in train_dataset:
    print("samples shape:", samples.shape)
    print("targets shape:", targets.shape)
    break
```

```
samples shape: (256, 120, 14)
targets shape: (256,)
```

Computing the common-sense baseline MAE

```
def evaluate_naive_method(dataset):
    total_abs_err = 0.
    samples_seen = 0
    for samples, targets in dataset:
        preds = samples[:, -1, 1] * std[1] + mean[1]
        total_abs_err += np.sum(np.abs(preds - targets))
        samples_seen += samples.shape[0]
    return total_abs_err / samples_seen

print(f"Validation MAE: {evaluate_naive_method(val_dataset):.2f}")
print(f"Test MAE: {evaluate_naive_method(test_dataset):.2f}")
```

```
Validation MAE: 2.44
Test MAE: 2.62
```

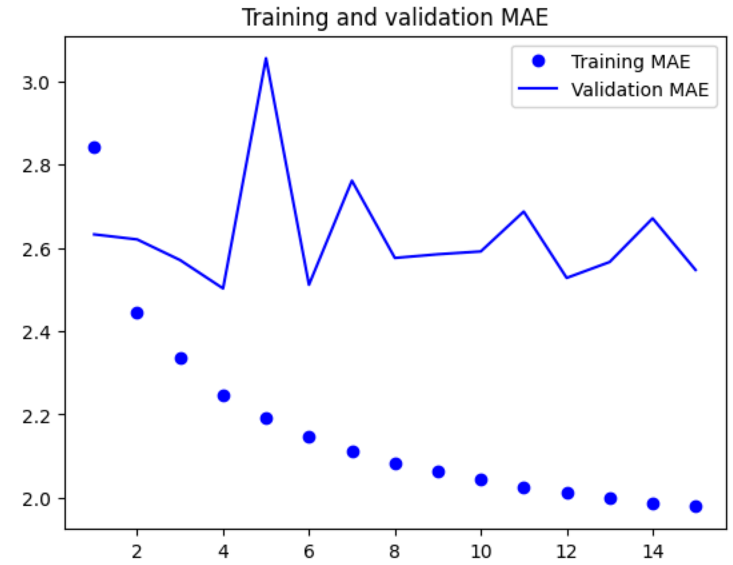
Training and evaluating a densely connected model

```
from tensorflow import keras
from tensorflow.keras import layers

inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.Flatten()(inputs)
x = layers.Dense(16, activation="relu")(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_dense.keras",
                                    save_best_only=True)
]
model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history = model.fit(train_dataset,
                    epochs=15,
                    validation_data=val_dataset,
                    callbacks=callbacks)

model = keras.models.load_model("jena_dense.keras")
print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

```
Epoch 1/15
819/819 [==============================] - 12s 13ms/step - loss: 13.5277 - mae: 2.8421 - val_loss: 11.0558 - val_mae: 2.6321
Epoch 2/15
819/819 [==============================] - 11s 13ms/step - loss: 9.6886 - mae: 2.4453 - val_loss: 10.9619 - val_mae: 2.6200
Epoch 3/15
819/819 [==============================] - 11s 13ms/step - loss: 8.8170 - mae: 2.3346 - val_loss: 10.5536 - val_mae: 2.5705
Epoch 4/15
819/819 [==============================] - 11s 13ms/step - loss: 8.1475 - mae: 2.2455 - val_loss: 10.0161 - val_mae: 2.5024
Epoch 5/15
819/819 [==============================] - 11s 13ms/step - loss: 7.7479 - mae: 2.1916 - val_loss: 14.7316 - val_mae: 3.0549
Epoch 6/15
819/819 [==============================] - 11s 13ms/step - loss: 7.4201 - mae: 2.1455 - val_loss: 10.1386 - val_mae: 2.5113
Epoch 7/15
819/819 [==============================] - 11s 13ms/step - loss: 7.1709 - mae: 2.1114 - val_loss: 12.1913 - val_mae: 2.7610
Epoch 8/15
819/819 [==============================] - 11s 13ms/step - loss: 7.0034 - mae: 2.0837 - val_loss: 10.6919 - val_mae: 2.5756
Epoch 9/15
819/819 [==============================] - 11s 13ms/step - loss: 6.8587 - mae: 2.0629 - val_loss: 10.7387 - val_mae: 2.5844
Epoch 10/15
819/819 [==============================] - 11s 13ms/step - loss: 6.7270 - mae: 2.0438 - val_loss: 10.7917 - val_mae: 2.5912
Epoch 11/15
819/819 [==============================] - 11s 13ms/step - loss: 6.6105 - mae: 2.0261 - val_loss: 11.4807 - val_mae: 2.6869
Epoch 12/15
819/819 [==============================] - 11s 13ms/step - loss: 6.5237 - mae: 2.0119 - val_loss: 10.3063 - val_mae: 2.5277
Epoch 13/15
819/819 [==============================] - 11s 13ms/step - loss: 6.4498 - mae: 2.0012 - val_loss: 10.6630 - val_mae: 2.5658
Epoch 14/15
819/819 [==============================] - 10s 13ms/step - loss: 6.3570 - mae: 1.9857 - val_loss: 11.3801 - val_mae: 2.6706
Epoch 15/15
819/819 [==============================] - 11s 13ms/step - loss: 6.3073 - mae: 1.9790 - val_loss: 10.4757 - val_mae: 2.5468
405/405 [==============================] - 4s 9ms/step - loss: 7479.3208 - mae: 8.8518
Test MAE: 8.85
```

Plotting the results

```python
import matplotlib.pyplot as plt
loss = history.history["mae"]
val_loss = history.history["val_mae"]
epochs = range(1, len(loss) + 1)
plt.figure()
plt.plot(epochs, loss, "bo", label="Training MAE")
plt.plot(epochs, val_loss, "b", label="Validation MAE")
plt.title("Training and validation MAE")
plt.legend()
plt.show()
```



Trying timeseries data with LSTM layering

```python
from tensorflow.keras.layers import LSTM, Dropout
```

Defining the model architecture with LSTM and dropout

```python
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = LSTM(64, return_sequences=True)(inputs)
x = Dropout(0.2)(x)
x = LSTM(64)(x)
x = Dropout(0.2)(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)
```

Create and trian the model

```python
model.compile(optimizer="adam", loss="mse", metrics=["mae"])
history = model.fit(train_dataset,
                    epochs=15,
                    validation_data=val_dataset,
                    callbacks=callbacks)
```

```
Epoch 1/15
819/819 [==============================] - 19s 18ms/step - loss: 17.5695 - mae: 3.0553 - val_loss: 10.8218 - val_mae: 2.5801
Epoch 2/15
819/819 [==============================] - 15s 19ms/step - loss: 7.4791 - mae: 2.1204 - val_loss: 12.1848 - val_mae: 2.7319
Epoch 3/15
819/819 [==============================] - 16s 19ms/step - loss: 5.0866 - mae: 1.7405 - val_loss: 12.9395 - val_mae: 2.8063
Epoch 4/15
819/819 [==============================] - 15s 18ms/step - loss: 3.8539 - mae: 1.5149 - val_loss: 13.8466 - val_mae: 2.9255
Epoch 5/15
819/819 [==============================] - 15s 18ms/step - loss: 3.2509 - mae: 1.3883 - val_loss: 13.8450 - val_mae: 2.9176
Epoch 6/15
819/819 [==============================] - 15s 18ms/step - loss: 2.8574 - mae: 1.2993 - val_loss: 13.7963 - val_mae: 2.9036
Epoch 7/15
819/819 [==============================] - 15s 18ms/step - loss: 2.6615 - mae: 1.2513 - val_loss: 13.9856 - val_mae: 2.9303
Epoch 8/15
819/819 [==============================] - 15s 18ms/step - loss: 2.4173 - mae: 1.1935 - val_loss: 13.9180 - val_mae: 2.9340
Epoch 9/15
819/819 [==============================] - 15s 18ms/step - loss: 2.3643 - mae: 1.1732 - val_loss: 14.3050 - val_mae: 2.9594
Epoch 10/15
819/819 [==============================] - 15s 18ms/step - loss: 2.1190 - mae: 1.1153 - val_loss: 14.4225 - val_mae: 2.9889
Epoch 11/15
819/819 [==============================] - 15s 18ms/step - loss: 2.0193 - mae: 1.0883 - val_loss: 14.5751 - val_mae: 3.0018
Epoch 12/15
819/819 [==============================] - 15s 18ms/step - loss: 1.9743 - mae: 1.0726 - val_loss: 14.2994 - val_mae: 2.9643
Epoch 13/15
819/819 [==============================] - 15s 18ms/step - loss: 1.8471 - mae: 1.0372 - val_loss: 14.4284 - val_mae: 2.9955
Epoch 14/15
819/819 [==============================] - 15s 19ms/step - loss: 1.7707 - mae: 1.0153 - val_loss: 14.3098 - val_mae: 2.9705
```

```
Epoch 15/15
819/819 [==============================] - 15s 18ms/step - loss: 1.7452 - mae: 1.0063 - val_loss: 14.6636 - val_mae: 3.0011
```

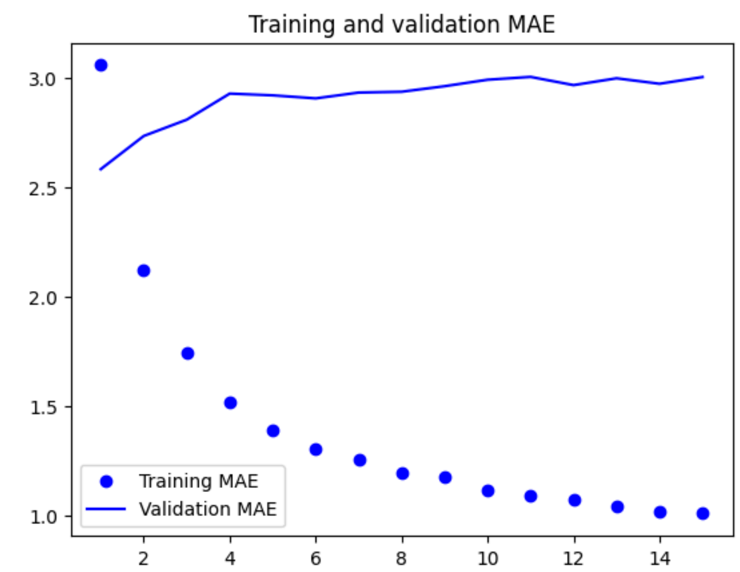
Evaluating the model

```
test_mae = model.evaluate(test_dataset)[1]
print(f"Test MAE: {test_mae:.2f}")
```

```
405/405 [==============================] - 4s 9ms/step - loss: 15.4686 - mae: 3.1200
Test MAE: 3.12
```

Plotting the results

```
import matplotlib.pyplot as plt
loss = history.history["mae"]
val_loss = history.history["val_mae"]
epochs = range(1, len(loss) + 1)
plt.figure()
plt.plot(epochs, loss, "bo", label="Training MAE")
plt.plot(epochs, val_loss, "b", label="Validation MAE")
plt.title("Training and validation MAE")
plt.legend()
plt.show()
```



Using a combination of 1d_convnets & RNN

```
from tensorflow.keras.layers import Conv1D, LSTM, Dropout, Dense
from tensorflow.keras.models import Sequential
```

Defining the model architecture with 1D convnets

```
model = Sequential()
model.add(Conv1D(32, 5, activation='relu', input_shape=(sequence_length, raw_data.shape[-1])))
model.add(Conv1D(64, 5, activation='relu'))
model.add(LSTM(64, dropout=0.2, recurrent_dropout=0.2))
model.add(Dense(1))
```

```
WARNING:tensorflow:Layer lstm_2 will not use cuDNN kernels since it doesn't meet the criteria. It will use a generic GPU kernel as fallback when running on GPU.
```

Compile the model

```
model.compile(optimizer='adam', loss='mse', metrics=['mae'])
```

Train the model

```
history = model.fit(train_dataset,
                    epochs=15,
                    validation_data=val_dataset,
                    callbacks=callbacks)
```

```
Epoch 1/15
819/819 [==============================] - 235s 281ms/step - loss: 16.2991 - mae: 2.9564 - val_loss: 9.6344 - val_mae: 2.3955
Epoch 2/15
819/819 [==============================] - 228s 279ms/step - loss: 7.9609 - mae: 2.1966 - val_loss: 9.8910 - val_mae: 2.4515
Epoch 3/15
819/819 [==============================] - 226s 275ms/step - loss: 6.1291 - mae: 1.9162 - val_loss: 10.9939 - val_mae: 2.5868
Epoch 4/15
819/819 [==============================] - 227s 277ms/step - loss: 4.8233 - mae: 1.6906 - val_loss: 11.8565 - val_mae: 2.7088
Epoch 5/15
819/819 [==============================] - 229s 279ms/step - loss: 3.8821 - mae: 1.5127 - val_loss: 12.4706 - val_mae: 2.7789
Epoch 6/15
819/819 [==============================] - 228s 278ms/step - loss: 3.2702 - mae: 1.3900 - val_loss: 12.9060 - val_mae: 2.8217
Epoch 7/15
819/819 [==============================] - 231s 281ms/step - loss: 2.9037 - mae: 1.3090 - val_loss: 13.2490 - val_mae: 2.8575
Epoch 8/15
819/819 [==============================] - 228s 278ms/step - loss: 2.5829 - mae: 1.2348 - val_loss: 13.9775 - val_mae: 2.9485
Epoch 9/15
819/819 [==============================] - 226s 276ms/step - loss: 2.4004 - mae: 1.1912 - val_loss: 13.9824 - val_mae: 2.9421
Epoch 10/15
819/819 [==============================] - 227s 277ms/step - loss: 2.1636 - mae: 1.1309 - val_loss: 14.4340 - val_mae: 2.9861
Epoch 11/15
819/819 [==============================] - 227s 277ms/step - loss: 2.1111 - mae: 1.1152 - val_loss: 14.5109 - val_mae: 3.0039
Epoch 12/15
819/819 [==============================] - 227s 277ms/step - loss: 1.9013 - mae: 1.0625 - val_loss: 14.5462 - val_mae: 3.0026
Epoch 13/15
819/819 [==============================] - 226s 276ms/step - loss: 1.8228 - mae: 1.0403 - val_loss: 14.6122 - val_mae: 3.0168
Epoch 14/15
819/819 [==============================] - 229s 279ms/step - loss: 1.7491 - mae: 1.0196 - val_loss: 14.7248 - val_mae: 3.0125
Epoch 15/15
819/819 [==============================] - 229s 279ms/step - loss: 1.6612 - mae: 0.9922 - val_loss: 14.7367 - val_mae: 3.0165
```

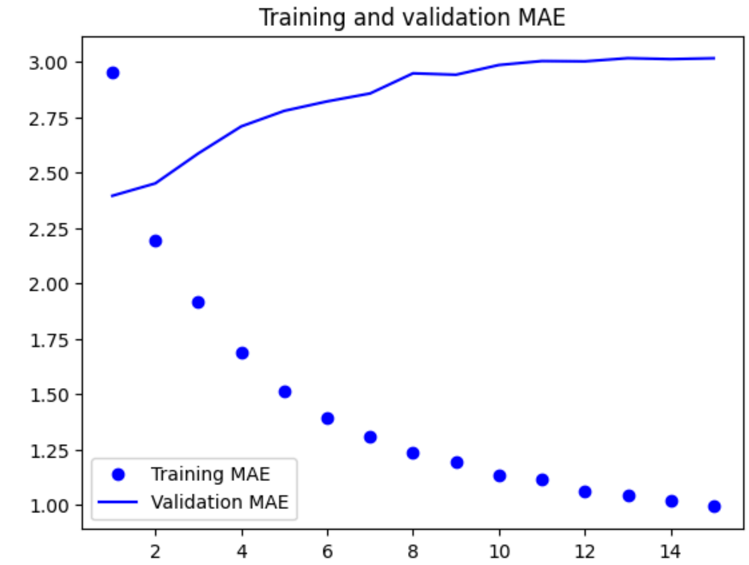
Evaluating the model

```
test_mae = model.evaluate(test_dataset)[1]
print(f"Test MAE: {test_mae:.2f}")
```

```
405/405 [==============================] - 14s 34ms/step - loss: 15.3737 - mae: 3.1133
Test MAE: 3.11
```

Plotting the results

```
import matplotlib.pyplot as plt
loss = history.history["mae"]
val_loss = history.history["val_mae"]
epochs = range(1, len(loss) + 1)
plt.figure()
plt.plot(epochs, loss, "bo", label="Training MAE")
plt.plot(epochs, val_loss, "b", label="Validation MAE")
plt.title("Training and validation MAE")
plt.legend()
plt.show()
```



Adjusting the number of units in each recurrent layer

```
from tensorflow.keras.layers import LSTM, Dropout, Dense
from tensorflow.keras.models import Sequential
```

Define model architecture

```
model = Sequential()
model.add(LSTM(64, return_sequences=True, input_shape=(sequence_length, raw_data.shape[-1])))
model.add(Dropout(0.2))
model.add(LSTM(128))
model.add(Dropout(0.2))
model.add(Dense(1))
```

Compile the model

```
model.compile(optimizer='adam', loss='mse', metrics=['mae'])
```

Train the model

```
history = model.fit(train_dataset,
                    epochs=15,
                    validation_data=val_dataset,
                    callbacks=callbacks)
```

```
Epoch 1/15
819/819 [==============================] - 19s 19ms/step - loss: 16.1775 - mae: 3.0249 - val_loss: 9.8786 - val_mae: 2.4347
Epoch 2/15
819/819 [==============================] - 15s 19ms/step - loss: 8.1679 - mae: 2.2380 - val_loss: 11.7606 - val_mae: 2.6885
Epoch 3/15
819/819 [==============================] - 16s 19ms/step - loss: 5.6320 - mae: 1.8400 - val_loss: 13.4830 - val_mae: 2.9098
Epoch 4/15
819/819 [==============================] - 15s 19ms/step - loss: 3.7851 - mae: 1.5008 - val_loss: 14.2912 - val_mae: 3.0024
Epoch 5/15
819/819 [==============================] - 16s 19ms/step - loss: 2.8523 - mae: 1.2974 - val_loss: 14.3236 - val_mae: 2.9916
Epoch 6/15
819/819 [==============================] - 16s 19ms/step - loss: 2.4165 - mae: 1.1903 - val_loss: 14.5370 - val_mae: 3.0084
Epoch 7/15
819/819 [==============================] - 16s 19ms/step - loss: 2.1698 - mae: 1.1228 - val_loss: 14.2328 - val_mae: 2.9680
Epoch 8/15
819/819 [==============================] - 16s 19ms/step - loss: 2.0719 - mae: 1.0864 - val_loss: 13.3831 - val_mae: 2.8790
Epoch 9/15
819/819 [==============================] - 16s 19ms/step - loss: 2.0437 - mae: 1.0767 - val_loss: 14.3813 - val_mae: 2.9925
Epoch 10/15
819/819 [==============================] - 16s 19ms/step - loss: 1.6431 - mae: 0.9808 - val_loss: 14.2290 - val_mae: 2.9686
Epoch 11/15
819/819 [==============================] - 16s 19ms/step - loss: 1.5004 - mae: 0.9352 - val_loss: 13.9478 - val_mae: 2.9314
Epoch 12/15
819/819 [==============================] - 16s 19ms/step - loss: 1.4446 - mae: 0.9171 - val_loss: 13.9055 - val_mae: 2.9364
Epoch 13/15
819/819 [==============================] - 15s 19ms/step - loss: 1.3379 - mae: 0.8826 - val_loss: 13.7740 - val_mae: 2.9203
Epoch 14/15
819/819 [==============================] - 15s 19ms/step - loss: 1.2853 - mae: 0.8633 - val_loss: 13.9135 - val_mae: 2.9347
Epoch 15/15
819/819 [==============================] - 16s 19ms/step - loss: 1.2340 - mae: 0.8450 - val_loss: 13.8518 - val_mae: 2.9374
```

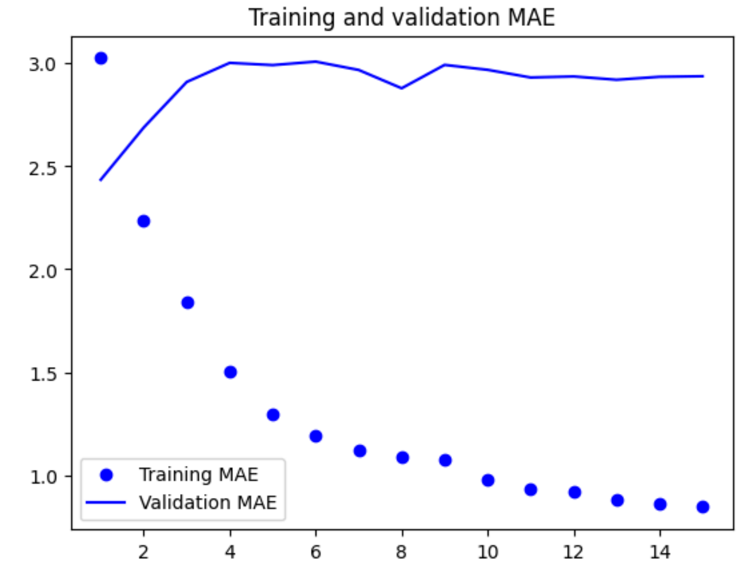
Evaluate the model

```
test_mae = model.evaluate(test_dataset)[1]
print(f"Test MAE: {test_mae:.2f}")
```

```
405/405 [==============================] - 4s 9ms/step - loss: 15.0211 - mae: 3.0818
Test MAE: 3.08
```

Plot the results

```
import matplotlib.pyplot as plt
loss = history.history["mae"]
val_loss = history.history["val_mae"]
epochs = range(1, len(loss) + 1)
plt.figure()
plt.plot(epochs, loss, "bo", label="Training MAE")
plt.plot(epochs, val_loss, "b", label="Validation MAE")
plt.title("Training and validation MAE")
plt.legend()
plt.show()
```


Training and validation MAE
3.0
2.5
2.0
1.5
1.0
2
4
6
8
10
12
14
Training MAE
Validation MAE