Assignment 3 Timeseries

Different kinds of timeseries tasks

A temperature-forecasting example

In [9]:

```
import os
import zipfile
import urllib.request


url = "https://s3.amazonaws.com/keras-datasets/jena_climate_2009_2016.csv.zip"
filename = "jena_climate_2009_2016.csv.zip"
unzipped_filename = "jena_climate_2009_2016.csv"


if not os.path.exists(filename):
    # File doesn't exist, download it
    urllib.request.urlretrieve(url, filename)

if os.path.exists(filename):
    with zipfile.ZipFile(filename, 'r') as zip_ref:
        zip_ref.extractall()
        print(f"{filename} unzipped successfully.")
else:
    print("File not found and could not be downloaded.")
```

```
jena_climate_2009_2016.csv.zip unzipped successfully.
```

Inspecting the data of the Jena weather dataset

In [10]:

```
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/mo
l)"', '"rho (g/m**3)"', '"wv (m/s)"', '"max. wv (m/s)"', '"wd (deg)"']
420451
```

Parsing the data

In [11]:

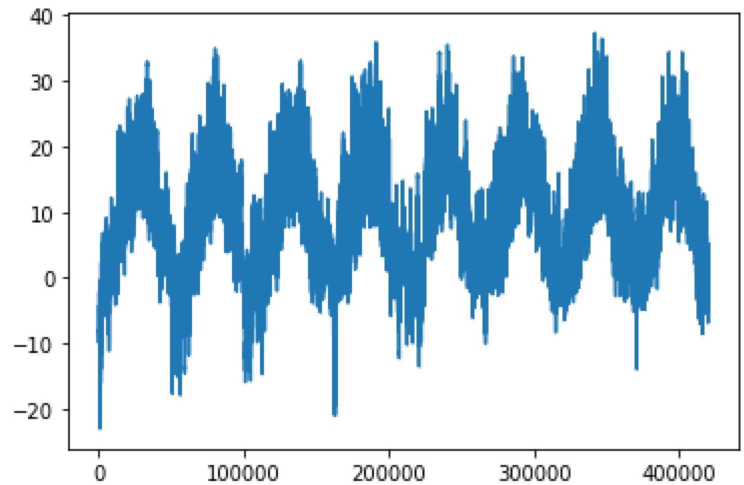
```
import numpy as np
temperature = np.zeros((len(lines),))
raw_data = np.zeros((len(lines), len(header) - 1))
for i, line in enumerate(lines):
```

```
    values = [float(x) for x in line.split(",")[1:]]
    temperature[i] = values[1]
    raw_data[i, :] = values[:]
```

Plotting the temperature timeseries

In [12]:
```
from matplotlib import pyplot as plt
plt.plot(range(len(temperature)), temperature)
```

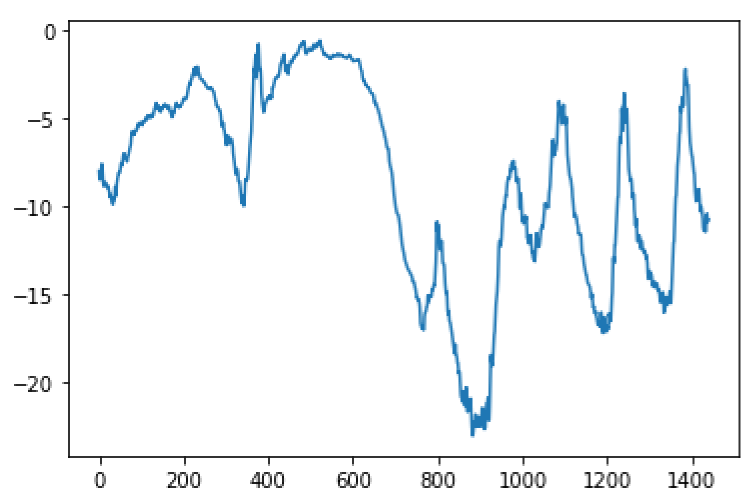
Out[12]: [<matplotlib.lines.Line2D at 0x7f71a2c5bcf8>]



Plotting the first 10 days of the temperature timeseries

In [13]:
```
plt.plot(range(1440), temperature[:1440])
```

Out[13]: [<matplotlib.lines.Line2D at 0x7f7404644128>]



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

In [14]:
```
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: 210225
num_val_samples: 105112
num_test_samples: 105114
```

Preparing the data

Normalizing the data

In [15]:

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

In [16]:

```
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

In [17]:

```
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

In [18]:
```
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,)
```

A common-sense, non-machine-learning baseline

Computing the common-sense baseline MAE

In [19]:
```
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
```

Let's try a basic machine-learning model

Training and evaluating a densely connected model

In [20]:
```
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"])
```

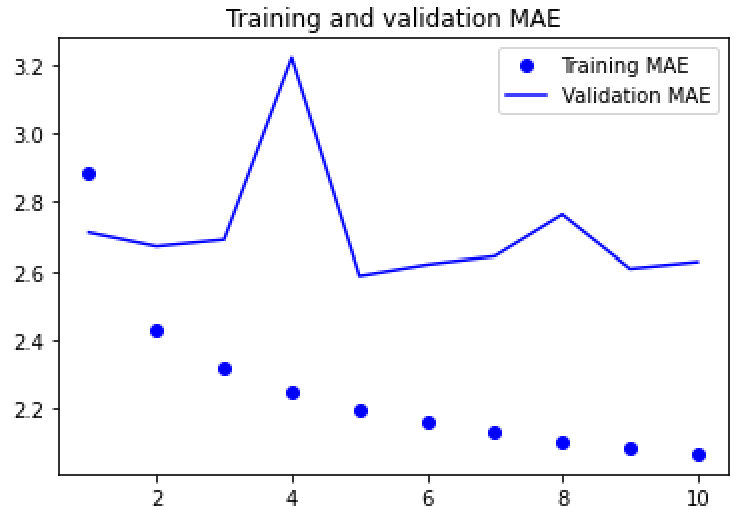
```
history = model.fit(train_dataset,
                    epochs=10,
                    validation_data=val_dataset,
                    callbacks=callbacks)

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

```
Epoch 1/10
819/819 [==============================] - 11s 13ms/step - loss: 13.9448 - mae: 2.8816 -
val_loss: 11.8385 - val_mae: 2.7109
Epoch 2/10
819/819 [==============================] - 10s 12ms/step - loss: 9.5494 - mae: 2.4295 -
val_loss: 11.5174 - val_mae: 2.6705
Epoch 3/10
819/819 [==============================] - 10s 12ms/step - loss: 8.6813 - mae: 2.3187 -
val_loss: 11.5283 - val_mae: 2.6902
Epoch 4/10
819/819 [==============================] - 10s 12ms/step - loss: 8.1316 - mae: 2.2452 -
val_loss: 16.1120 - val_mae: 3.2210
Epoch 5/10
819/819 [==============================] - 9s 11ms/step - loss: 7.7607 - mae: 2.1966 - v
al_loss: 10.6873 - val_mae: 2.5861
Epoch 6/10
819/819 [==============================] - 9s 11ms/step - loss: 7.4997 - mae: 2.1618 - v
al_loss: 10.9699 - val_mae: 2.6185
Epoch 7/10
819/819 [==============================] - 10s 12ms/step - loss: 7.2822 - mae: 2.1314 -
val_loss: 11.2178 - val_mae: 2.6426
Epoch 8/10
819/819 [==============================] - 9s 11ms/step - loss: 7.1027 - mae: 2.1038 - v
al_loss: 12.2452 - val_mae: 2.7633
Epoch 9/10
819/819 [==============================] - 10s 12ms/step - loss: 6.9750 - mae: 2.0853 -
val_loss: 10.9512 - val_mae: 2.6068
Epoch 10/10
819/819 [==============================] - 10s 12ms/step - loss: 6.8521 - mae: 2.0676 -
val_loss: 11.0920 - val_mae: 2.6263
405/405 [==============================] - 3s 7ms/step - loss: 11.6638 - mae: 2.7036
Test MAE: 2.70
```

Plotting results

In [21]:

```
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()
```



Let's try a 1D convolutional model

In [ ]:

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.Conv1D(8, 24, activation="relu")(inputs)
x = layers.MaxPooling1D(2)(x)
x = layers.Conv1D(8, 12, activation="relu")(x)
x = layers.MaxPooling1D(2)(x)
x = layers.Conv1D(8, 6, activation="relu")(x)
x = layers.GlobalAveragePooling1D()(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_conv.keras",
                                    save_best_only=True)
]
model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history = model.fit(train_dataset,
                    epochs=10,
                    validation_data=val_dataset,
                    callbacks=callbacks)

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

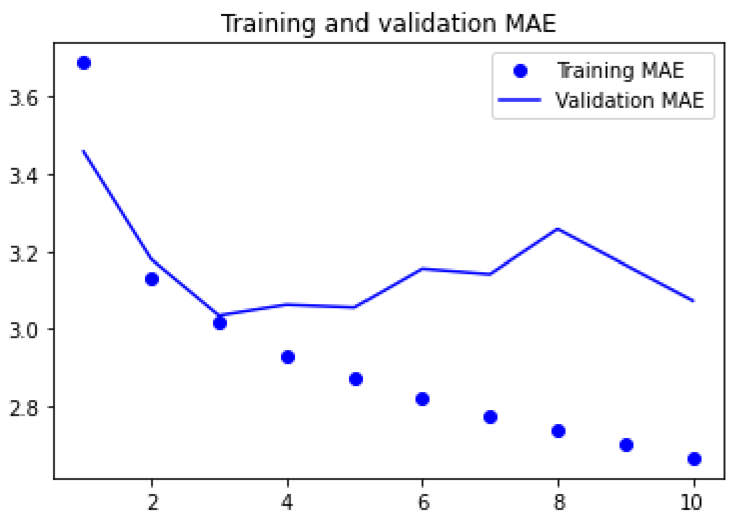
```
Epoch 1/10
819/819 [==============================] - 26s 31ms/step - loss: 22.2297 - mae: 3.6879 -
val_loss: 18.5067 - val_mae: 3.4575
Epoch 2/10
819/819 [==============================] - 26s 32ms/step - loss: 15.5387 - mae: 3.1292 -
val_loss: 15.9798 - val_mae: 3.1802
Epoch 3/10
819/819 [==============================] - 24s 30ms/step - loss: 14.5538 - mae: 3.0169 -
val_loss: 14.8220 - val_mae: 3.0354
Epoch 4/10
819/819 [==============================] - 25s 31ms/step - loss: 13.8255 - mae: 2.9324 -
val_loss: 15.1413 - val_mae: 3.0631
Epoch 5/10
819/819 [==============================] - 25s 30ms/step - loss: 13.3088 - mae: 2.8745 -
val_loss: 15.0597 - val_mae: 3.0559
Epoch 6/10
819/819 [==============================] - 25s 30ms/step - loss: 12.8408 - mae: 2.8238 -
val_loss: 16.0358 - val_mae: 3.1556
```

```
Epoch 7/10
819/819 [==============================] - 25s 31ms/step - loss: 12.4231 - mae: 2.7772 -
val_loss: 16.1009 - val_mae: 3.1414
Epoch 8/10
819/819 [==============================] - 25s 31ms/step - loss: 12.0914 - mae: 2.7400 -
val_loss: 17.2836 - val_mae: 3.2577
Epoch 9/10
819/819 [==============================] - 25s 30ms/step - loss: 11.7430 - mae: 2.7013 -
val_loss: 16.3665 - val_mae: 3.1654
Epoch 10/10
819/819 [==============================] - 25s 30ms/step - loss: 11.4317 - mae: 2.6671 -
val_loss: 15.3121 - val_mae: 3.0734
405/405 [==============================] - 4s 10ms/step - loss: 16.6760 - mae: 3.2124
Test MAE: 3.21
```

Plotting results

In [23]:

```
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()
```



A first recurrent baseline

A simple LSTM-based model with Dense 16

In [24]:

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.LSTM(16)(inputs)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_lstm.keras",
                                    save_best_only=True)
]
model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history = model.fit(train_dataset,
```

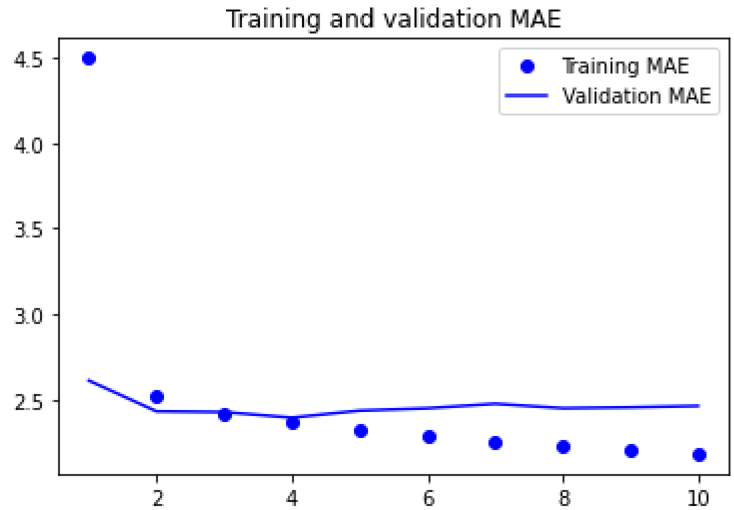
```
                     epochs=10,
                     validation_data=val_dataset,
                     callbacks=callbacks)

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

```
Epoch 1/10
819/819 [==============================] - 39s 46ms/step - loss: 38.2989 - mae: 4.4968 -
val_loss: 11.7446 - val_mae: 2.6135
Epoch 2/10
819/819 [==============================] - 38s 47ms/step - loss: 10.6044 - mae: 2.5282 -
val_loss: 9.7137 - val_mae: 2.4335
Epoch 3/10
819/819 [==============================] - 42s 51ms/step - loss: 9.6890 - mae: 2.4220 -
val_loss: 9.6833 - val_mae: 2.4291
Epoch 4/10
819/819 [==============================] - 40s 49ms/step - loss: 9.3044 - mae: 2.3709 -
val_loss: 9.4734 - val_mae: 2.3966
Epoch 5/10
819/819 [==============================] - 35s 43ms/step - loss: 8.9471 - mae: 2.3250 -
val_loss: 9.7920 - val_mae: 2.4375
Epoch 6/10
819/819 [==============================] - 33s 40ms/step - loss: 8.6403 - mae: 2.2875 -
val_loss: 9.9809 - val_mae: 2.4515
Epoch 7/10
819/819 [==============================] - 38s 46ms/step - loss: 8.3882 - mae: 2.2524 -
val_loss: 10.1379 - val_mae: 2.4777
Epoch 8/10
819/819 [==============================] - 36s 43ms/step - loss: 8.2070 - mae: 2.2273 -
val_loss: 9.8899 - val_mae: 2.4517
Epoch 9/10
819/819 [==============================] - 34s 42ms/step - loss: 8.0527 - mae: 2.2051 -
val_loss: 9.9484 - val_mae: 2.4567
Epoch 10/10
819/819 [==============================] - 39s 47ms/step - loss: 7.9103 - mae: 2.1849 -
val_loss: 9.9955 - val_mae: 2.4651
405/405 [==============================] - 6s 14ms/step - loss: 10.7220 - mae: 2.5758
Test MAE: 2.58
```

Plotting results

In [25]:

```
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()
```



A simple LSTM-based model with Dense 32

In [26]:

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.LSTM(32)(inputs)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_lstm.keras",
                                    save_best_only=True)
]
model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history = model.fit(train_dataset,
                    epochs=10,
                    validation_data=val_dataset,
                    callbacks=callbacks)

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

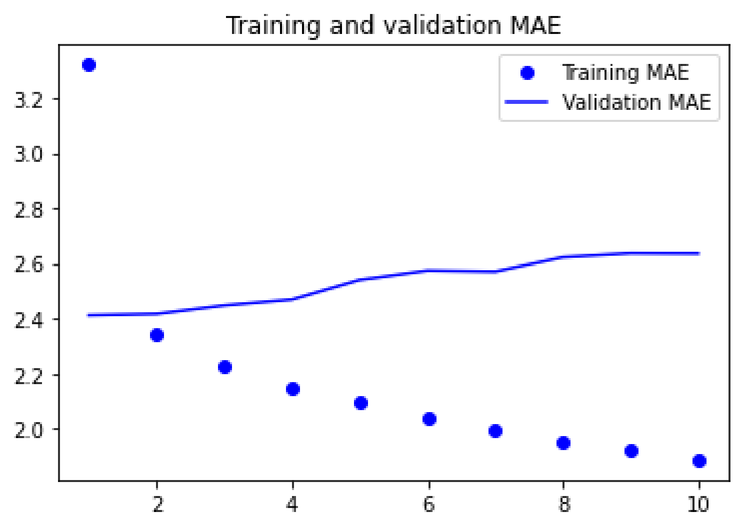
```
Epoch 1/10
819/819 [==============================] - 53s 63ms/step - loss: 21.3527 - mae: 3.3218 -
val_loss: 9.8108 - val_mae: 2.4120
Epoch 2/10
819/819 [==============================] - 49s 60ms/step - loss: 8.9880 - mae: 2.3441 -
val_loss: 9.7837 - val_mae: 2.4170
Epoch 3/10
819/819 [==============================] - 52s 63ms/step - loss: 8.1463 - mae: 2.2268 -
val_loss: 10.0707 - val_mae: 2.4476
Epoch 4/10
819/819 [==============================] - 49s 59ms/step - loss: 7.6097 - mae: 2.1503 -
val_loss: 10.1339 - val_mae: 2.4689
Epoch 5/10
819/819 [==============================] - 45s 55ms/step - loss: 7.2168 - mae: 2.0931 -
val_loss: 10.6482 - val_mae: 2.5399
Epoch 6/10
819/819 [==============================] - 50s 61ms/step - loss: 6.8485 - mae: 2.0384 -
val_loss: 10.9769 - val_mae: 2.5736
Epoch 7/10
819/819 [==============================] - 51s 62ms/step - loss: 6.5607 - mae: 1.9946 -
val_loss: 10.9052 - val_mae: 2.5698
Epoch 8/10
819/819 [==============================] - 53s 64ms/step - loss: 6.2840 - mae: 1.9494 -
val_loss: 11.3172 - val_mae: 2.6218
```

```
Epoch 9/10
819/819 [==============================] - 48s 58ms/step - loss: 6.1162 - mae: 1.9204 -
val_loss: 11.4476 - val_mae: 2.6360
Epoch 10/10
819/819 [==============================] - 52s 64ms/step - loss: 5.8782 - mae: 1.8862 -
val_loss: 11.5579 - val_mae: 2.6349
405/405 [==============================] - 9s 21ms/step - loss: 10.8352 - mae: 2.5802
Test MAE: 2.58
```

Plotting results

In [27]:

```
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()
```



A simple LSTM-based model with Dense 64

In [36]:

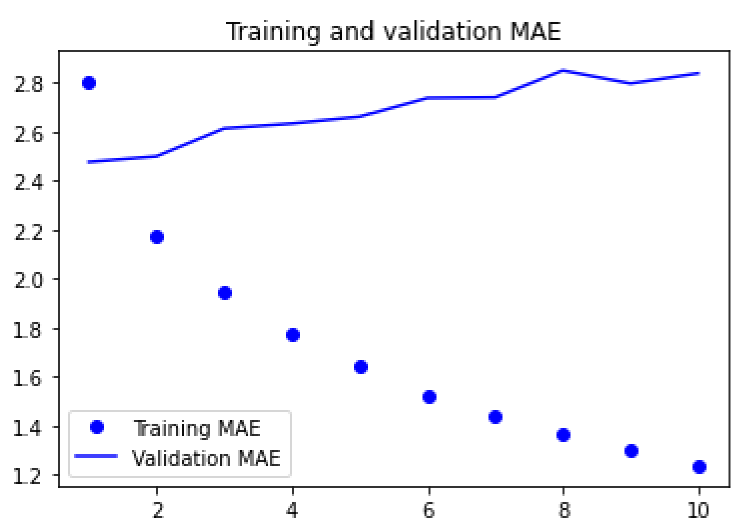
```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.LSTM(64)(inputs)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_lstm.keras",
                                    save_best_only=True)
]
model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history = model.fit(train_dataset,
                    epochs=10,
                    validation_data=val_dataset,
                    callbacks=callbacks)

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

```
Epoch 1/10
819/819 [==============================] - 93s 112ms/step - loss: 14.5536 - mae: 2.8049
- val_loss: 9.9137 - val_mae: 2.4759
Epoch 2/10
819/819 [==============================] - 89s 108ms/step - loss: 7.7493 - mae: 2.1727 -
val_loss: 10.1414 - val_mae: 2.4989
Epoch 3/10
819/819 [==============================] - 88s 108ms/step - loss: 6.2542 - mae: 1.9440 -
val_loss: 10.9031 - val_mae: 2.6124
Epoch 4/10
819/819 [==============================] - 90s 110ms/step - loss: 5.2248 - mae: 1.7715 -
val_loss: 11.1763 - val_mae: 2.6323
Epoch 5/10
819/819 [==============================] - 90s 110ms/step - loss: 4.5190 - mae: 1.6425 -
val_loss: 11.4128 - val_mae: 2.6603
Epoch 6/10
819/819 [==============================] - 89s 108ms/step - loss: 3.9307 - mae: 1.5256 -
val_loss: 12.1055 - val_mae: 2.7367
Epoch 7/10
819/819 [==============================] - 88s 108ms/step - loss: 3.4888 - mae: 1.4369 -
val_loss: 12.0399 - val_mae: 2.7393
Epoch 8/10
819/819 [==============================] - 90s 110ms/step - loss: 3.1740 - mae: 1.3663 -
val_loss: 13.1740 - val_mae: 2.8487
Epoch 9/10
819/819 [==============================] - 89s 108ms/step - loss: 2.8710 - mae: 1.3008 -
val_loss: 12.6051 - val_mae: 2.7958
Epoch 10/10
819/819 [==============================] - 90s 110ms/step - loss: 2.6069 - mae: 1.2370 -
val_loss: 12.9789 - val_mae: 2.8371
405/405 [==============================] - 17s 40ms/step - loss: 12.7425 - mae: 2.7018
Test MAE: 2.70
```

Plotting results

In [37]:

```python
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()
```



Understanding recurrent neural networks

NumPy implementation of a simple RNN

In [38]:

```
import numpy as np
timesteps = 100
input_features = 32
output_features = 64
inputs = np.random.random((timesteps, input_features))
state_t = np.zeros((output_features,))
W = np.random.random((output_features, input_features))
U = np.random.random((output_features, output_features))
b = np.random.random((output_features,))
successive_outputs = []
for input_t in inputs:
    output_t = np.tanh(np.dot(W, input_t) + np.dot(U, state_t) + b)
    successive_outputs.append(output_t)
    state_t = output_t
final_output_sequence = np.stack(successive_outputs, axis=0)
```

A recurrent layer in Keras

An RNN layer that can process sequences of any length

In [39]:

```
num_features = 14
inputs = keras.Input(shape=(None, num_features))
outputs = layers.SimpleRNN(16)(inputs)
```

An RNN layer that returns only its last output step

In [40]:

```
num_features = 14
steps = 120
inputs = keras.Input(shape=(steps, num_features))
outputs = layers.SimpleRNN(16, return_sequences=False)(inputs)
print(outputs.shape)
```

```
(None, 16)
```

An RNN layer that returns its full output sequence

In [41]:

```
num_features = 14
steps = 120
inputs = keras.Input(shape=(steps, num_features))
outputs = layers.SimpleRNN(16, return_sequences=True)(inputs)
print(outputs.shape)
```

```
(None, 120, 16)
```

Stacking RNN layers

In [42]:

```
inputs = keras.Input(shape=(steps, num_features))
x = layers.SimpleRNN(16, return_sequences=True)(inputs)
x = layers.SimpleRNN(16, return_sequences=True)(x)
outputs = layers.SimpleRNN(16)(x)
```

Advanced use of recurrent neural networks

Using recurrent dropout to fight overfitting

Training and evaluating a combination of 1d_Convnet and dropout-regularized LSTM

In [43]:

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.Conv1D(32, 5, activation="relu", padding="same")(inputs)
x = layers.MaxPooling1D(2)(x)
x = layers.LSTM(64, recurrent_dropout=0.25)(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_lstm_dropout.keras",
                                    save_best_only=True)
]
model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history = model.fit(train_dataset,
                    epochs=10,
                    validation_data=val_dataset,
                    callbacks=callbacks)

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

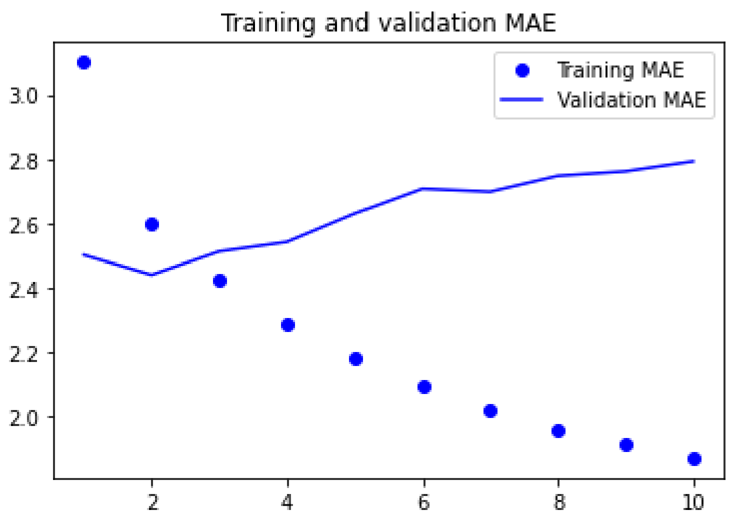
```
Epoch 1/10
819/819 [==============================] - 63s 74ms/step - loss: 16.9194 - mae: 3.1015 -
val_loss: 10.3037 - val_mae: 2.5020
Epoch 2/10
819/819 [==============================] - 60s 73ms/step - loss: 11.1376 - mae: 2.5988 -
val_loss: 9.8968 - val_mae: 2.4397
Epoch 3/10
819/819 [==============================] - 61s 74ms/step - loss: 9.7803 - mae: 2.4274 -
val_loss: 10.2925 - val_mae: 2.5130
Epoch 4/10
819/819 [==============================] - 61s 75ms/step - loss: 8.7840 - mae: 2.2882 -
val_loss: 10.6391 - val_mae: 2.5420
Epoch 5/10
819/819 [==============================] - 61s 75ms/step - loss: 8.0154 - mae: 2.1805 -
val_loss: 11.1962 - val_mae: 2.6297
Epoch 6/10
819/819 [==============================] - 61s 74ms/step - loss: 7.4194 - mae: 2.0917 -
val_loss: 11.8224 - val_mae: 2.7070
Epoch 7/10
819/819 [==============================] - 61s 74ms/step - loss: 6.9193 - mae: 2.0193 -
val_loss: 11.8553 - val_mae: 2.6978
Epoch 8/10
819/819 [==============================] - 60s 73ms/step - loss: 6.5114 - mae: 1.9565 -
val_loss: 12.2576 - val_mae: 2.7472
Epoch 9/10
819/819 [==============================] - 60s 74ms/step - loss: 6.2315 - mae: 1.9127 -
```

```
val_loss: 12.2997 - val_mae: 2.7612
Epoch 10/10
819/819 [==============================] - 61s 74ms/step - loss: 5.9731 - mae: 1.8713 -
val_loss: 12.8547 - val_mae: 2.7922
405/405 [==============================] - 8s 19ms/step - loss: 10.9916 - mae: 2.6172
Test MAE: 2.62
```

Plotting results

In [44]:

```
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()
```



In [45]:

```
inputs = keras.Input(shape=(sequence_length, num_features))
x = layers.LSTM(32, recurrent_dropout=0.2, unroll=True)(inputs)
```

Stacking recurrent layers

Training and evaluating a dropout-regularized, stacked LSTM model

In [46]:

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.LSTM(32, recurrent_dropout=0.5, return_sequences=True)(inputs)
x = layers.LSTM(32, recurrent_dropout=0.5)(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_stacked_gru_dropout.keras",
                                    save_best_only=True)
]
model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history = model.fit(train_dataset,
                    epochs=10,
```

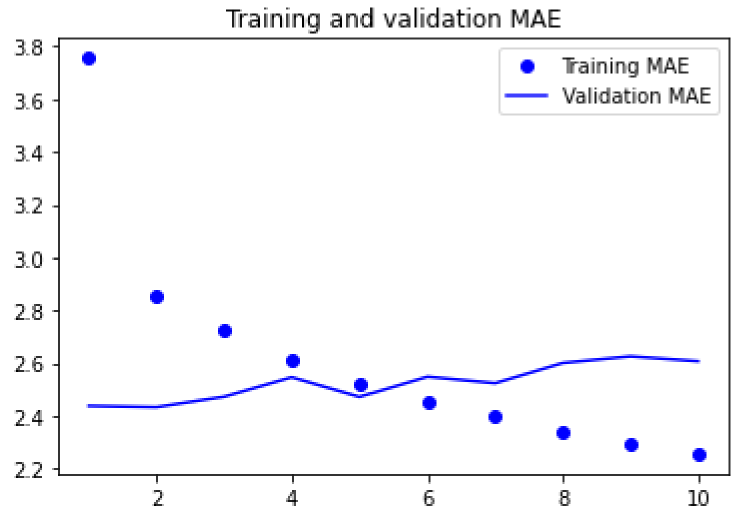
```
                      validation_data=val_dataset,
                      callbacks=callbacks)
model = keras.models.load_model("jena_stacked_gru_dropout.keras")
print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

```
Epoch 1/10
819/819 [==============================] - 149s 178ms/step - loss: 25.7697 - mae: 3.7564
- val_loss: 9.9786 - val_mae: 2.4382
Epoch 2/10
819/819 [==============================] - 146s 178ms/step - loss: 13.6101 - mae: 2.8564
- val_loss: 9.7934 - val_mae: 2.4336
Epoch 3/10
819/819 [==============================] - 148s 180ms/step - loss: 12.3832 - mae: 2.7229
- val_loss: 9.9396 - val_mae: 2.4732
Epoch 4/10
819/819 [==============================] - 147s 180ms/step - loss: 11.4439 - mae: 2.6125
- val_loss: 10.4649 - val_mae: 2.5469
Epoch 5/10
819/819 [==============================] - 148s 181ms/step - loss: 10.7232 - mae: 2.5242
- val_loss: 9.9930 - val_mae: 2.4727
Epoch 6/10
819/819 [==============================] - 145s 178ms/step - loss: 10.1543 - mae: 2.4539
- val_loss: 10.6136 - val_mae: 2.5489
Epoch 7/10
819/819 [==============================] - 147s 179ms/step - loss: 9.7073 - mae: 2.4005
- val_loss: 10.4126 - val_mae: 2.5244
Epoch 8/10
819/819 [==============================] - 147s 180ms/step - loss: 9.2331 - mae: 2.3386
- val_loss: 11.1224 - val_mae: 2.6011
Epoch 9/10
819/819 [==============================] - 146s 178ms/step - loss: 8.8723 - mae: 2.2950
- val_loss: 11.2667 - val_mae: 2.6262
Epoch 10/10
819/819 [==============================] - 147s 179ms/step - loss: 8.6032 - mae: 2.2564
- val_loss: 11.0992 - val_mae: 2.6078
405/405 [==============================] - 12s 29ms/step - loss: 10.4945 - mae: 2.5256
Test MAE: 2.53
```

Plotting results

In [47]:

```
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 bidirectional RNNs

Training and evaluating a bidirectional LSTM

In [48]:

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.Bidirectional(layers.LSTM(16,recurrent_dropout=0.25))(inputs)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history = model.fit(train_dataset,
                    epochs=10,
                    validation_data=val_dataset)
```

```
Epoch 1/10
819/819 [==============================] - 90s 105ms/step - loss: 26.5152 - mae: 3.7255
- val_loss: 10.8732 - val_mae: 2.5499
Epoch 2/10
819/819 [==============================] - 85s 104ms/step - loss: 9.8607 - mae: 2.4536 -
val_loss: 9.9145 - val_mae: 2.4398
Epoch 3/10
819/819 [==============================] - 85s 104ms/step - loss: 8.9717 - mae: 2.3360 -
val_loss: 9.8620 - val_mae: 2.4366
Epoch 4/10
819/819 [==============================] - 86s 105ms/step - loss: 8.4879 - mae: 2.2764 -
val_loss: 9.9146 - val_mae: 2.4437
Epoch 5/10
819/819 [==============================] - 86s 105ms/step - loss: 8.1358 - mae: 2.2290 -
val_loss: 9.9742 - val_mae: 2.4491
Epoch 6/10
819/819 [==============================] - 86s 104ms/step - loss: 7.8347 - mae: 2.1853 -
val_loss: 10.2091 - val_mae: 2.4724
Epoch 7/10
819/819 [==============================] - 85s 103ms/step - loss: 7.5430 - mae: 2.1452 -
val_loss: 10.4170 - val_mae: 2.5077
Epoch 8/10
819/819 [==============================] - 85s 104ms/step - loss: 7.3490 - mae: 2.1196 -
val_loss: 11.1986 - val_mae: 2.5836
Epoch 9/10
819/819 [==============================] - 85s 104ms/step - loss: 7.1447 - mae: 2.0909 -
val_loss: 11.0339 - val_mae: 2.5573
Epoch 10/10
819/819 [==============================] - 86s 105ms/step - loss: 6.9454 - mae: 2.0603 -
val_loss: 10.4320 - val_mae: 2.5108
```

Plotting results

In [49]:

```python
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()
```