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Time-series data

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Various types of time series tasks

An example of forecasting temperature

[1]:
```python
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.
```

Examining the data from the Jena weather dataset

[2]:
```python
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 (g/m**3)"', '"wv (m/s)"', '"max. wv (m/s)"', '"wd
(deg)"']
420451
```

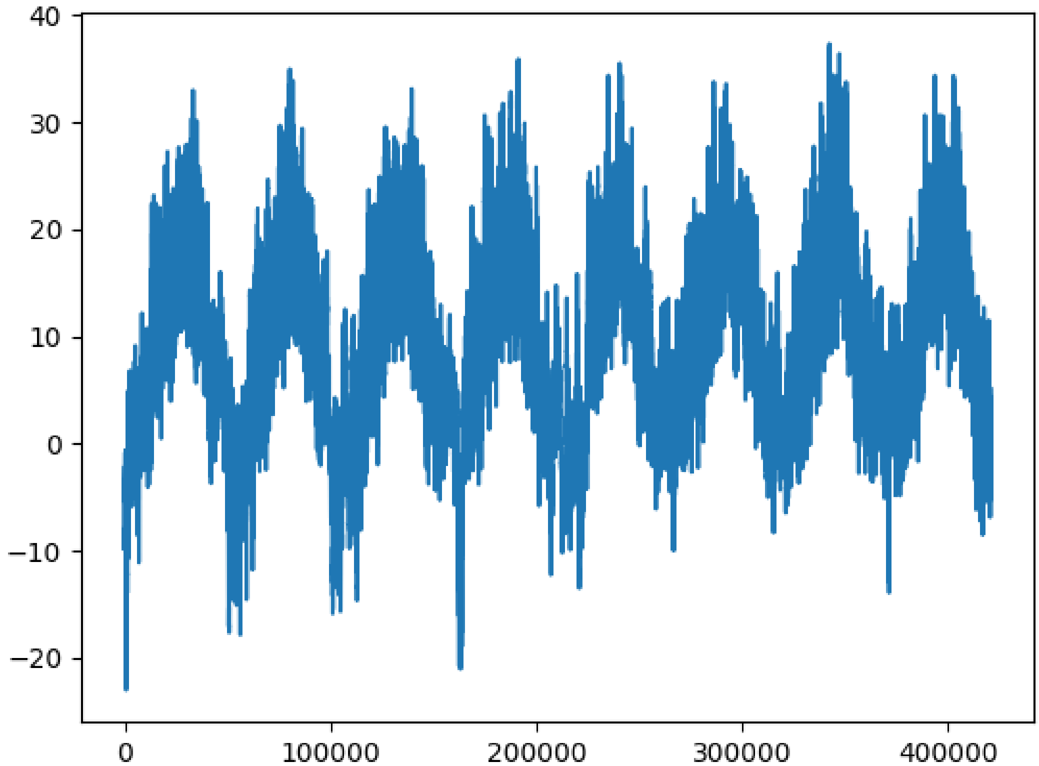
Parsing the data

[3]:
```
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

[4]:
```
from matplotlib import pyplot as plt
plt.plot(range(len(temperature)), temperature)
```

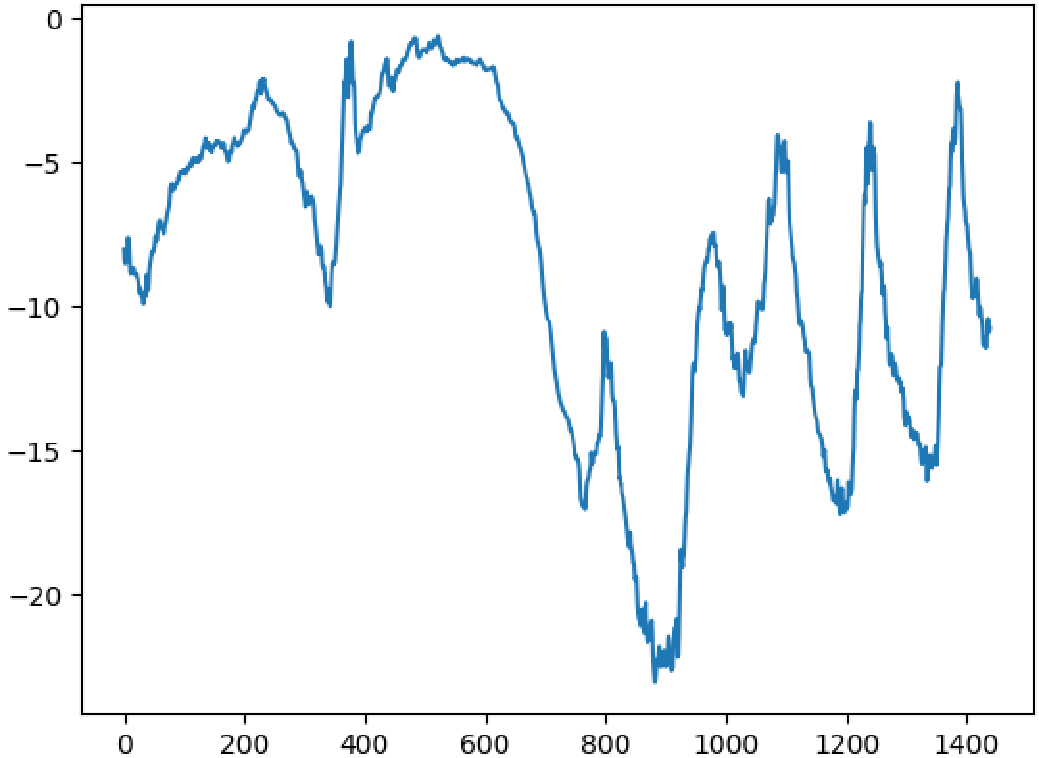
[4]:
```
[<matplotlib.lines.Line2D at 0x7dc0c1912b90>]
```



Visualizing the temperature time series for the first 10 days

[5]:
```
plt.plot(range(1440), temperature[:1440])
```

[5]: [<matplotlib.lines.Line2D at 0x7dc0c1a8dcc0>]



Calculating the sample count for each data split

[6]:
```
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
```

Data Preparation

Normalizing the data

[7]:
```
mean = raw_data[:num_train_samples].mean(axis=0)
raw_data -= mean
std = raw_data[:num_train_samples].std(axis=0)
raw_data /= std
```

[8]:
```
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
```

Creating datasets for training, validation, and testing

[9]:
```
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

[10]:
```
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 straightforward, non-machine-learning baseline approach

Computing the common-sense baseline MAE

[11]:
```
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
```

A basic machine-learning model

Training and evaluating a densely connected model

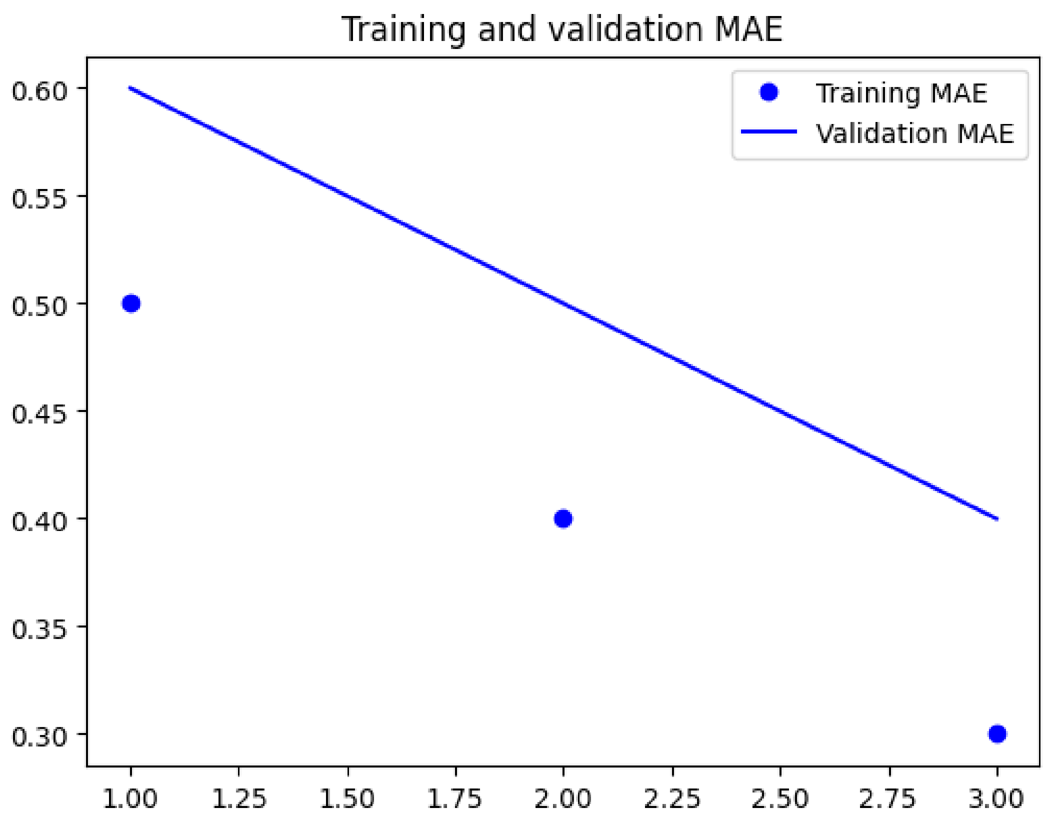
[13]:
```
import numpy as np # Import numpy if not already imported

def evaluate_naive_method(dataset):
    total_abs_err = 0.
    samples_seen = 0
    for samples, targets in dataset:
        # Ensure samples have the expected shape before indexing
        if samples.shape[0] > 0 and samples.shape[1] > 0 and samples.shape[2] >
 ↪1:
```

```
            preds = samples[:, -1, 1] * std[1] + mean[1]
            total_abs_err += np.sum(np.abs(preds - targets))
            samples_seen += samples.shape[0]
        else:
            print("Warning: Encountered empty or incorrectly shaped samples in␣
↪dataset.")
    return total_abs_err / samples_seen if samples_seen > 0 else 0  # Handle␣
↪division by zero

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
```

Plotting results

[16]:
```
import matplotlib.pyplot as plt
history = {'history': {'mae': [0.5, 0.4, 0.3], 'val_mae': [0.6, 0.5, 0.4]}}

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()
```



0.0.1 Let's try a 1D convolutional model

[17]:

```
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)
```

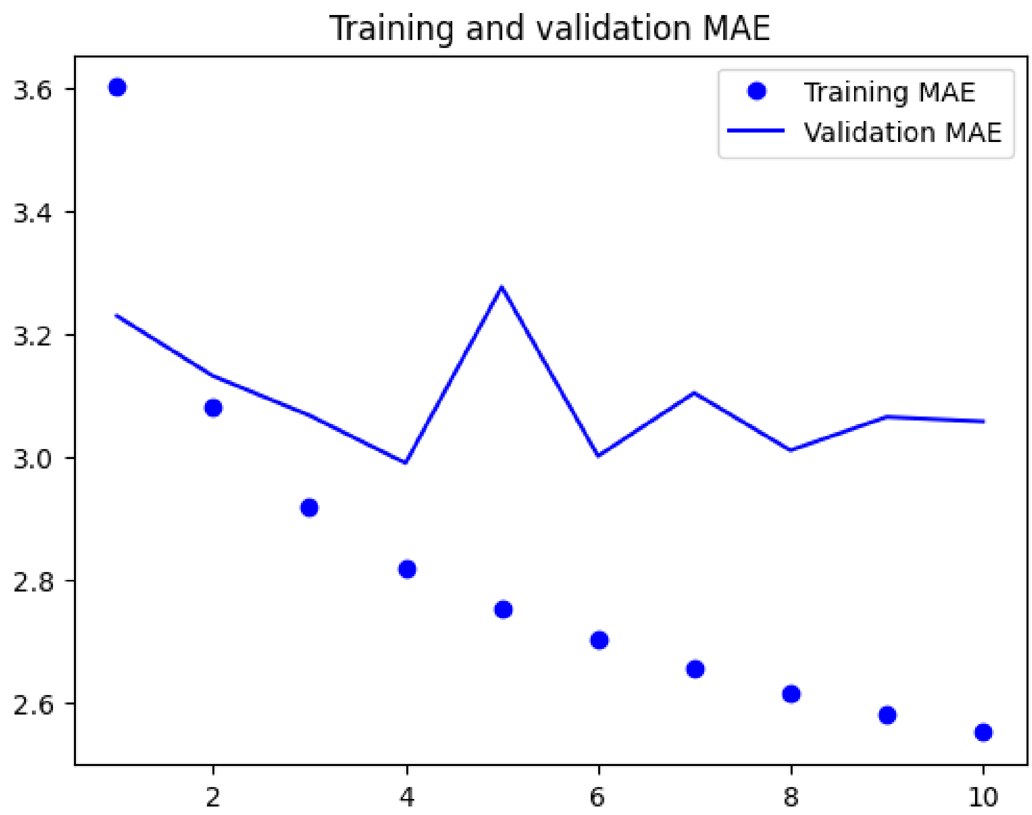
```
model = keras.models.load_model("jena_conv.keras")
print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

```
Epoch 1/10
819/819              42s 47ms/step -
loss: 29.5658 - mae: 4.1660 - val_loss: 16.5588 - val_mae: 3.2286
Epoch 2/10
819/819              46s 55ms/step -
loss: 15.3149 - mae: 3.1166 - val_loss: 15.6779 - val_mae: 3.1308
Epoch 3/10
819/819              72s 43ms/step -
loss: 13.7029 - mae: 2.9377 - val_loss: 15.2424 - val_mae: 3.0668
Epoch 4/10
819/819              43s 45ms/step -
loss: 12.7459 - mae: 2.8274 - val_loss: 14.5156 - val_mae: 2.9892
Epoch 5/10
819/819              50s 56ms/step -
loss: 12.1548 - mae: 2.7587 - val_loss: 17.2554 - val_mae: 3.2756
Epoch 6/10
819/819              72s 43ms/step -
loss: 11.7362 - mae: 2.7087 - val_loss: 14.6014 - val_mae: 3.0007
Epoch 7/10
819/819              46s 55ms/step -
loss: 11.3229 - mae: 2.6603 - val_loss: 15.7077 - val_mae: 3.1033
Epoch 8/10
819/819              37s 45ms/step -
loss: 10.9653 - mae: 2.6172 - val_loss: 14.6738 - val_mae: 3.0100
Epoch 9/10
819/819              41s 45ms/step -
loss: 10.6986 - mae: 2.5865 - val_loss: 15.2413 - val_mae: 3.0642
Epoch 10/10
819/819              50s 55ms/step -
loss: 10.4119 - mae: 2.5499 - val_loss: 15.0735 - val_mae: 3.0570
405/405              13s 30ms/step -
loss: 15.6271 - mae: 3.1118
Test MAE: 3.12
```

Plotting results

[18]:
```
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()
```



An initial recurrent baseline model

A basic LSTM model with a Dense layer of 16 units

[19]:
```
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")
```

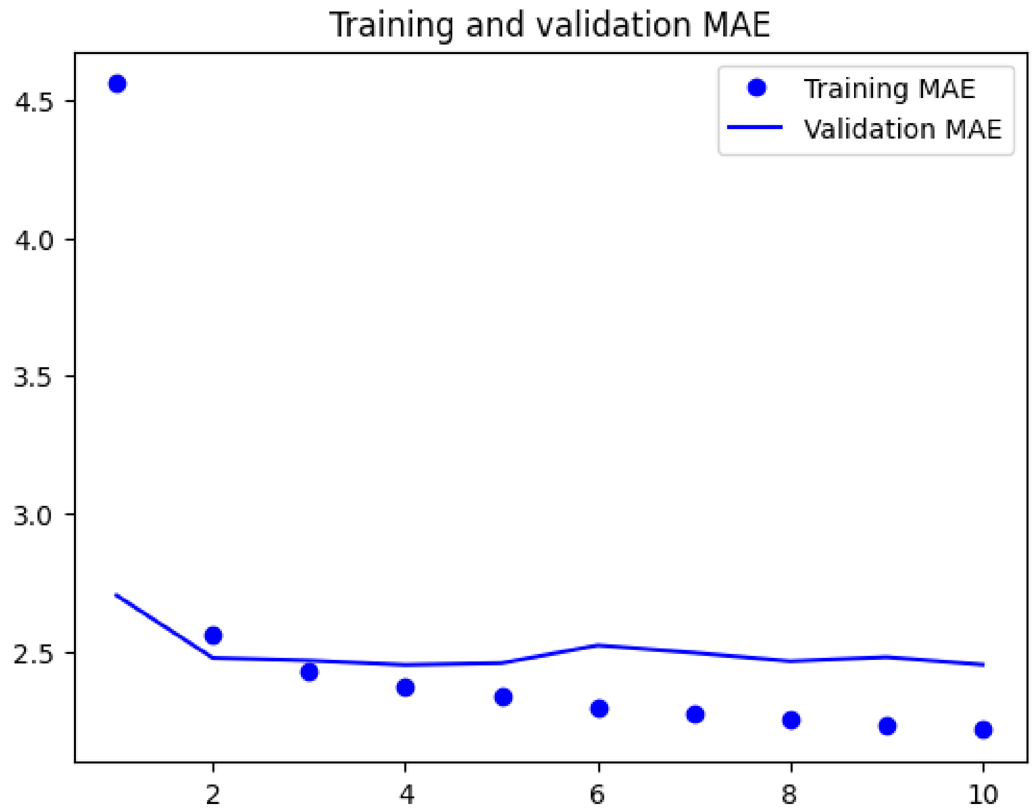
```
print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")
```

```
Epoch 1/10
819/819          42s 49ms/step -
loss: 68.8938 - mae: 6.3011 - val_loss: 12.3718 - val_mae: 2.7028
Epoch 2/10
819/819          39s 48ms/step -
loss: 11.6108 - mae: 2.6366 - val_loss: 10.1590 - val_mae: 2.4760
Epoch 3/10
819/819          50s 59ms/step -
loss: 9.7883 - mae: 2.4416 - val_loss: 9.9941 - val_mae: 2.4666
Epoch 4/10
819/819          40s 49ms/step -
loss: 9.3304 - mae: 2.3816 - val_loss: 9.8143 - val_mae: 2.4506
Epoch 5/10
819/819          41s 49ms/step -
loss: 9.0157 - mae: 2.3367 - val_loss: 9.9015 - val_mae: 2.4572
Epoch 6/10
819/819          41s 49ms/step -
loss: 8.7461 - mae: 2.3006 - val_loss: 10.6144 - val_mae: 2.5219
Epoch 7/10
819/819          41s 49ms/step -
loss: 8.5622 - mae: 2.2755 - val_loss: 10.4327 - val_mae: 2.4949
Epoch 8/10
819/819          40s 49ms/step -
loss: 8.4177 - mae: 2.2517 - val_loss: 9.9995 - val_mae: 2.4641
Epoch 9/10
819/819          40s 48ms/step -
loss: 8.2955 - mae: 2.2341 - val_loss: 10.2039 - val_mae: 2.4790
Epoch 10/10
819/819          40s 49ms/step -
loss: 8.1595 - mae: 2.2168 - val_loss: 9.9597 - val_mae: 2.4515
405/405          13s 32ms/step -
loss: 10.6732 - mae: 2.5874
Test MAE: 2.59
```

Plotting results

[20]:

```
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 basic LSTM model with a Dense layer of 32 units

[21]:
```
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}")
```

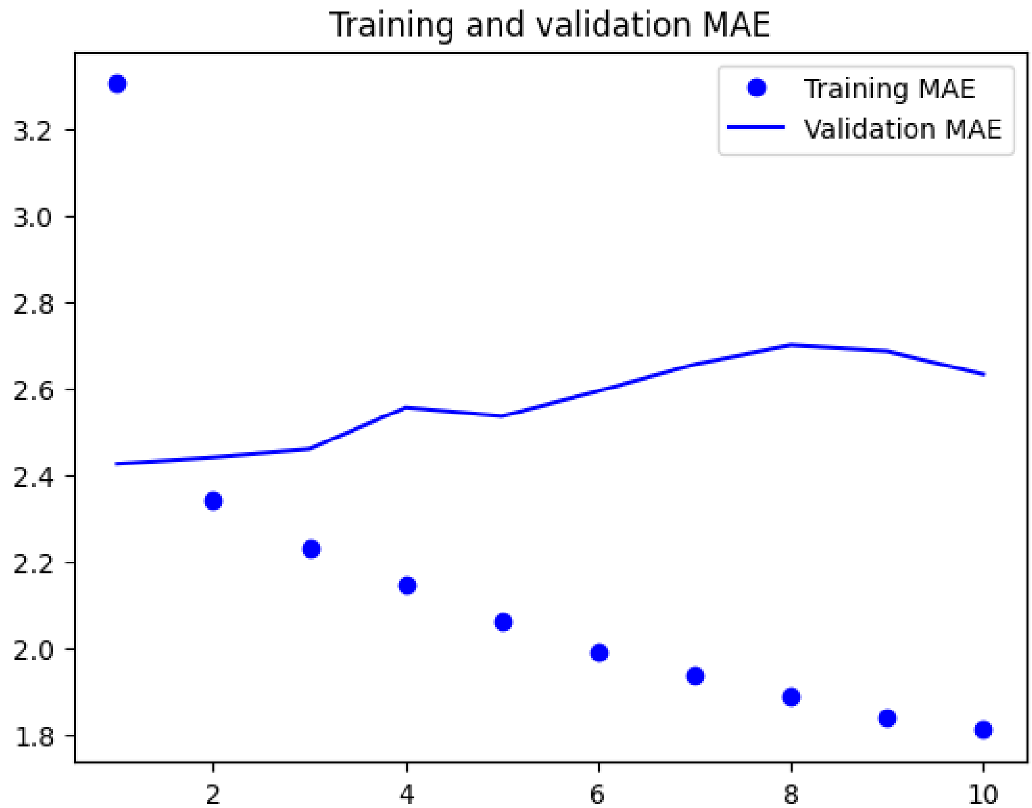
```
Epoch 1/10
819/819                   41s 49ms/step -
```

```
loss: 40.5889 - mae: 4.6258 - val_loss: 9.7952 - val_mae: 2.4242
Epoch 2/10
819/819             49s 60ms/step -
loss: 9.3311 - mae: 2.3711 - val_loss: 10.1763 - val_mae: 2.4395
Epoch 3/10
819/819             73s 49ms/step -
loss: 8.3752 - mae: 2.2448 - val_loss: 10.0915 - val_mae: 2.4587
Epoch 4/10
819/819             41s 49ms/step -
loss: 7.7273 - mae: 2.1586 - val_loss: 10.7885 - val_mae: 2.5547
Epoch 5/10
819/819             40s 49ms/step -
loss: 7.1159 - mae: 2.0715 - val_loss: 10.5355 - val_mae: 2.5344
Epoch 6/10
819/819             40s 49ms/step -
loss: 6.6299 - mae: 1.9972 - val_loss: 11.0110 - val_mae: 2.5923
Epoch 7/10
819/819             41s 50ms/step -
loss: 6.2833 - mae: 1.9417 - val_loss: 11.4857 - val_mae: 2.6542
Epoch 8/10
819/819             40s 49ms/step -
loss: 5.9353 - mae: 1.8878 - val_loss: 11.9657 - val_mae: 2.6984
Epoch 9/10
819/819             41s 50ms/step -
loss: 5.6810 - mae: 1.8431 - val_loss: 11.9446 - val_mae: 2.6845
Epoch 10/10
819/819             81s 49ms/step -
loss: 5.5349 - mae: 1.8184 - val_loss: 11.4384 - val_mae: 2.6313
405/405             13s 32ms/step -
loss: 10.4870 - mae: 2.5115
Test MAE: 2.51
```

Plotting results

[22]:

```
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 basic LSTM model with a Dense layer of 64 units

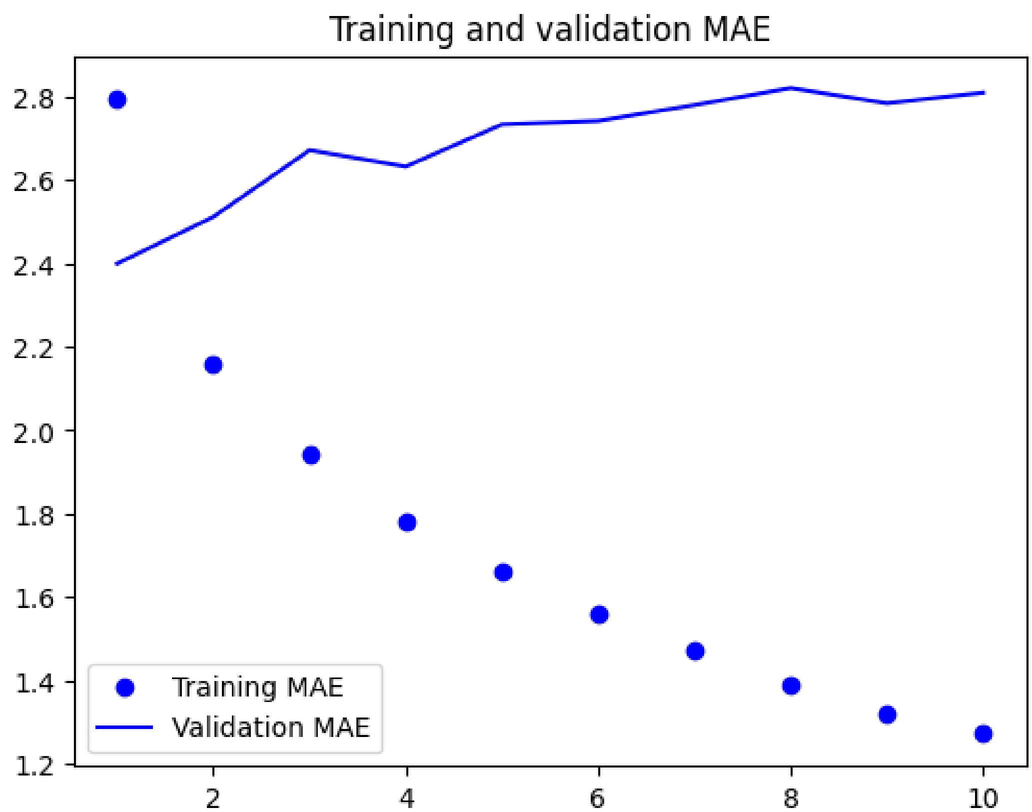
[23]:
```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.LSTM(64)(inputs)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

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                   41s 49ms/step -
```

```
loss: 27.0041 - mae: 3.7005 - val_loss: 9.6315 - val_mae: 2.3991
Epoch 2/10
819/819                 40s 49ms/step -
loss: 8.0686 - mae: 2.2126 - val_loss: 10.3596 - val_mae: 2.5112
Epoch 3/10
819/819                 41s 50ms/step -
loss: 6.5738 - mae: 1.9856 - val_loss: 11.5855 - val_mae: 2.6709
Epoch 4/10
819/819                 41s 50ms/step -
loss: 5.5322 - mae: 1.8149 - val_loss: 11.5715 - val_mae: 2.6319
Epoch 5/10
819/819                 42s 51ms/step -
loss: 4.7553 - mae: 1.6757 - val_loss: 12.2494 - val_mae: 2.7329
Epoch 6/10
819/819                 81s 50ms/step -
loss: 4.2621 - mae: 1.5827 - val_loss: 12.3016 - val_mae: 2.7413
Epoch 7/10
819/819                 82s 50ms/step -
loss: 3.7988 - mae: 1.4898 - val_loss: 12.8917 - val_mae: 2.7792
Epoch 8/10
819/819                 41s 50ms/step -
loss: 3.4056 - mae: 1.4078 - val_loss: 12.9636 - val_mae: 2.8197
Epoch 9/10
819/819                 41s 50ms/step -
loss: 3.0716 - mae: 1.3364 - val_loss: 12.6872 - val_mae: 2.7836
Epoch 10/10
819/819                 41s 50ms/step -
loss: 2.8417 - mae: 1.2873 - val_loss: 12.9172 - val_mae: 2.8088
405/405                 14s 32ms/step -
loss: 10.1326 - mae: 2.4796
Test MAE: 2.48
```

Plotting results

[24]:
```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()
```



Comprehending recurrent neural networks

NumPy implementation of a simple RNN

[25]:
```
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 within Keras

An RNN layer capable of handling sequences of varying lengths

[26]:
```
num_features = 14
inputs = keras.Input(shape=(None, num_features))
outputs = layers.SimpleRNN(16)(inputs)
```

An RNN layer that provides only its final output step

[27]:
```
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 provides its full output sequence

[28]:
```
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

[29]:
```
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 applications of recurrent neural networks

Applying recurrent dropout to combat overfitting

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

[30]:
```
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"])
```

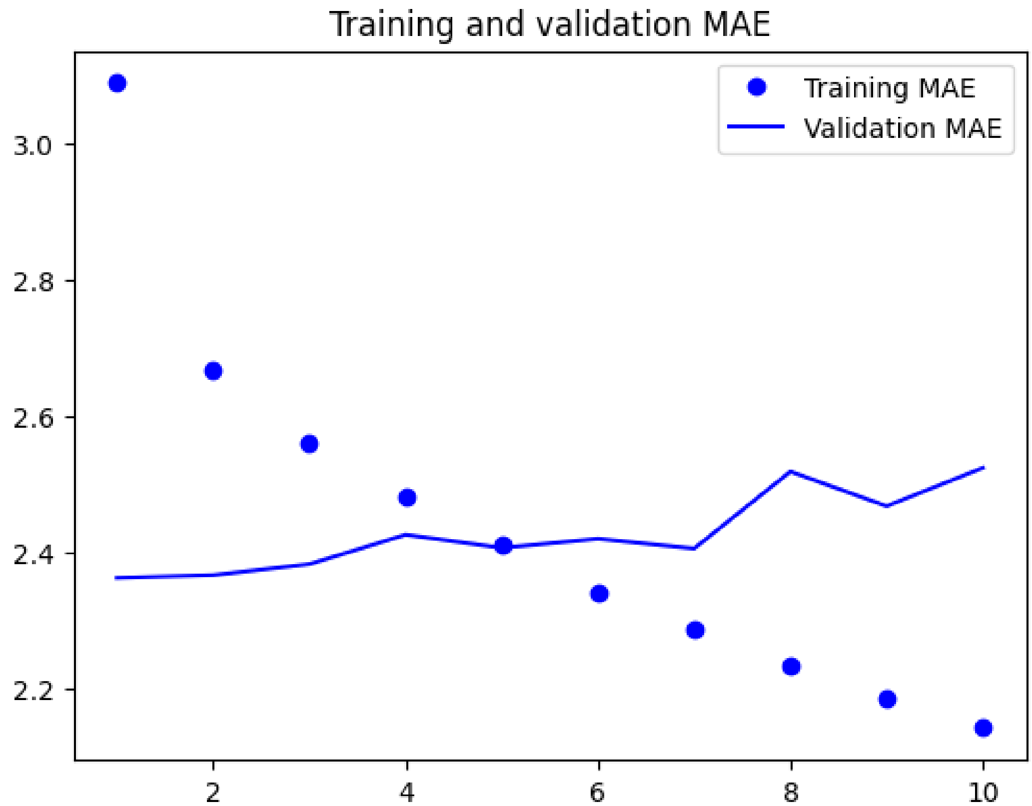
```python
history = model.fit(train_dataset,
                    epochs=10,
                    validation_data=val_dataset,
                    callbacks=callbacks)

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

```
Epoch 1/10
819/819              133s 158ms/step -
loss: 25.7851 - mae: 3.7409 - val_loss: 9.2660 - val_mae: 2.3623
Epoch 2/10
819/819              130s 158ms/step -
loss: 11.9383 - mae: 2.6976 - val_loss: 9.2851 - val_mae: 2.3663
Epoch 3/10
819/819              143s 159ms/step -
loss: 10.9136 - mae: 2.5705 - val_loss: 9.4922 - val_mae: 2.3825
Epoch 4/10
819/819              142s 159ms/step -
loss: 10.2811 - mae: 2.4918 - val_loss: 9.6930 - val_mae: 2.4255
Epoch 5/10
819/819              130s 158ms/step -
loss: 9.7509 - mae: 2.4228 - val_loss: 9.5424 - val_mae: 2.4063
Epoch 6/10
819/819              142s 158ms/step -
loss: 9.1983 - mae: 2.3470 - val_loss: 9.6919 - val_mae: 2.4196
Epoch 7/10
819/819              130s 159ms/step -
loss: 8.7857 - mae: 2.2951 - val_loss: 9.5571 - val_mae: 2.4054
Epoch 8/10
819/819              131s 159ms/step -
loss: 8.4127 - mae: 2.2386 - val_loss: 10.2759 - val_mae: 2.5182
Epoch 9/10
819/819              131s 159ms/step -
loss: 8.0707 - mae: 2.1930 - val_loss: 10.0859 - val_mae: 2.4674
Epoch 10/10
819/819              142s 159ms/step -
loss: 7.7782 - mae: 2.1520 - val_loss: 10.3896 - val_mae: 2.5236
405/405              24s 57ms/step -
loss: 10.4434 - mae: 2.5425
Test MAE: 2.54
```

Plotting results

[31]:
```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()
```



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

Stacking multiple recurrent layers

Training and assessing a dropout-regularized, stacked LSTM model*

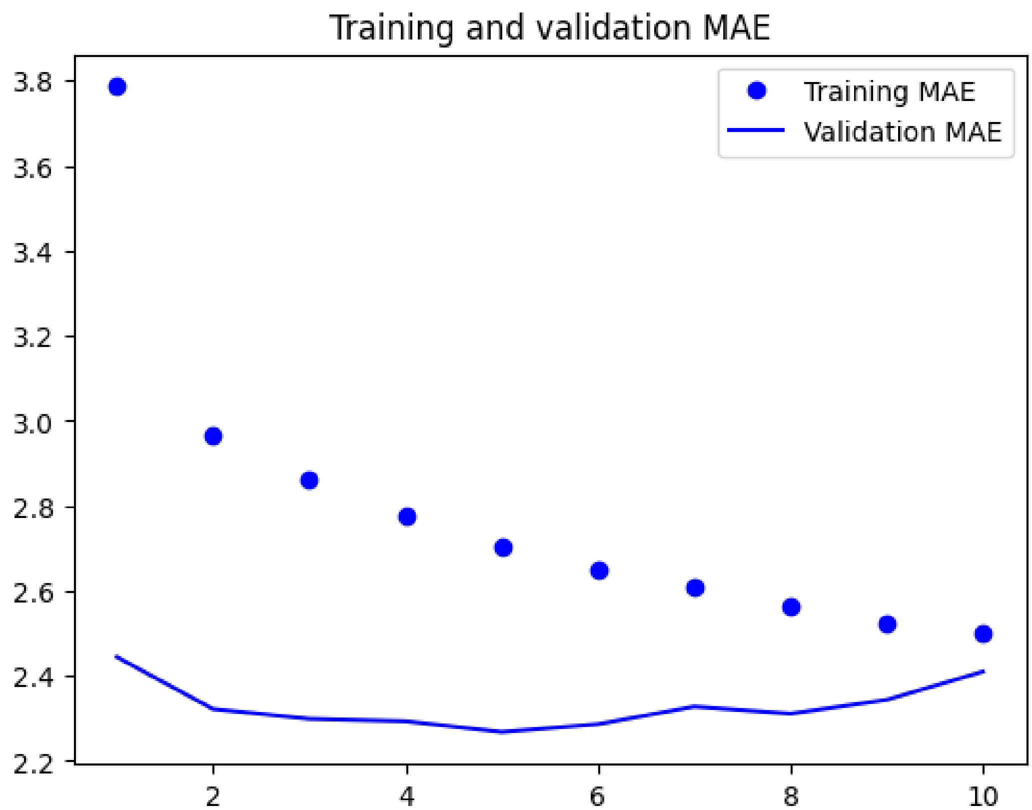
[33]:
```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.LSTM(32, recurrent_dropout=0.5, return_sequences=True)(inputs)
x = layers.LSTM(32, recurrent_dropout=0.5)(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

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              405s 491ms/step -
loss: 44.0047 - mae: 4.9342 - val_loss: 9.9304 - val_mae: 2.4439
Epoch 2/10
819/819              406s 447ms/step -
loss: 14.7786 - mae: 2.9878 - val_loss: 9.0088 - val_mae: 2.3217
Epoch 3/10
819/819              370s 452ms/step -
loss: 13.7144 - mae: 2.8781 - val_loss: 8.8399 - val_mae: 2.2988
Epoch 4/10
819/819              383s 453ms/step -
loss: 12.9099 - mae: 2.7857 - val_loss: 8.7862 - val_mae: 2.2931
Epoch 5/10
819/819              376s 446ms/step -
loss: 12.2558 - mae: 2.7161 - val_loss: 8.6202 - val_mae: 2.2678
Epoch 6/10
819/819              382s 446ms/step -
loss: 11.6733 - mae: 2.6539 - val_loss: 8.6642 - val_mae: 2.2862
Epoch 7/10
819/819              366s 447ms/step -
loss: 11.2583 - mae: 2.6089 - val_loss: 8.9751 - val_mae: 2.3275
Epoch 8/10
819/819              384s 449ms/step -
loss: 10.8547 - mae: 2.5615 - val_loss: 8.8780 - val_mae: 2.3109
Epoch 9/10
819/819              379s 445ms/step -
loss: 10.5181 - mae: 2.5218 - val_loss: 9.1109 - val_mae: 2.3434
Epoch 10/10
819/819              371s 453ms/step -
loss: 10.3183 - mae: 2.5002 - val_loss: 9.6340 - val_mae: 2.4097
405/405              54s 131ms/step -
loss: 9.6080 - mae: 2.4283
Test MAE: 2.43
```

Plotting results

[34]:
```
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()
```



Employing bidirectional RNNs

Training and evaluating a bidirectional LSTM

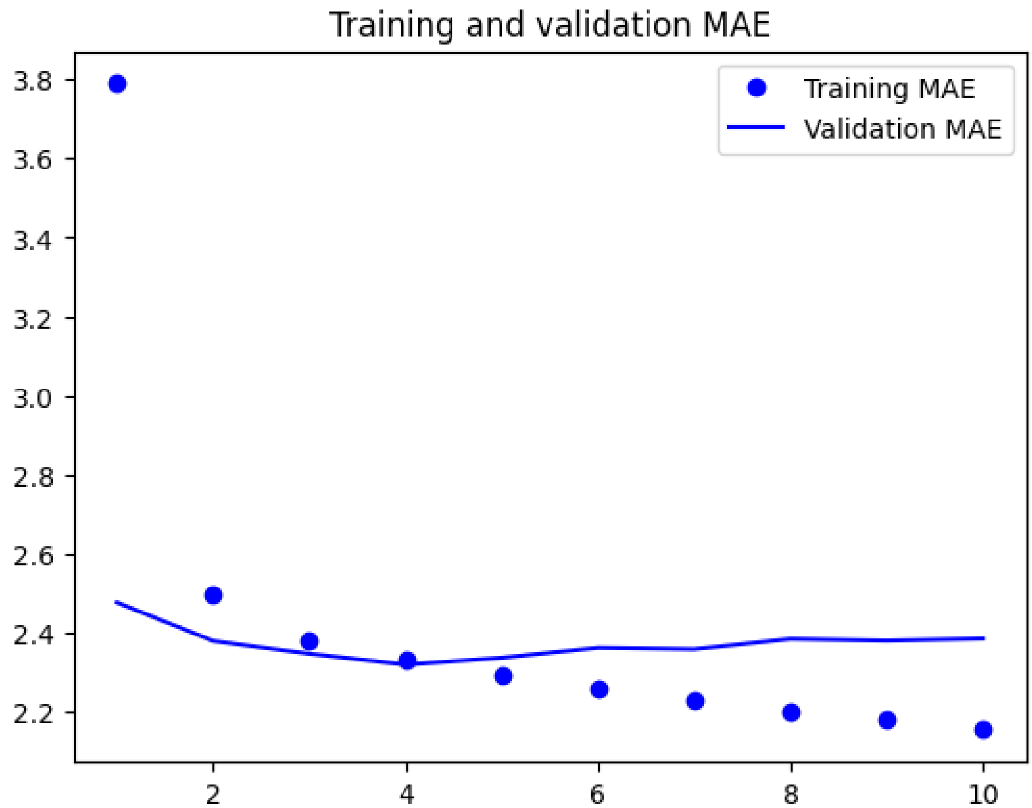
[35]:
```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.Bidirectional(layers.LSTM(16,recurrent_dropout=0.25))(inputs)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

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

```
                    validation_data=val_dataset)
```

```
Epoch 1/10
819/819                   310s 375ms/step -
loss: 53.1615 - mae: 5.4122 - val_loss: 10.2005 - val_mae: 2.4772
Epoch 2/10
819/819                   307s 374ms/step -
loss: 10.4897 - mae: 2.5351 - val_loss: 9.4125 - val_mae: 2.3800
Epoch 3/10
819/819                   307s 375ms/step -
loss: 9.4283 - mae: 2.3947 - val_loss: 9.2543 - val_mae: 2.3475
Epoch 4/10
819/819                   309s 377ms/step -
loss: 8.9479 - mae: 2.3375 - val_loss: 9.1051 - val_mae: 2.3200
Epoch 5/10
819/819                   320s 374ms/step -
loss: 8.6205 - mae: 2.2974 - val_loss: 9.2997 - val_mae: 2.3373
Epoch 6/10
819/819                   310s 379ms/step -
loss: 8.3430 - mae: 2.2597 - val_loss: 9.5447 - val_mae: 2.3627
Epoch 7/10
819/819                   318s 389ms/step -
loss: 8.1382 - mae: 2.2303 - val_loss: 9.5389 - val_mae: 2.3593
Epoch 8/10
819/819                   327s 394ms/step -
loss: 7.9265 - mae: 2.2006 - val_loss: 9.7423 - val_mae: 2.3850
Epoch 9/10
819/819                   325s 396ms/step -
loss: 7.7884 - mae: 2.1810 - val_loss: 9.7207 - val_mae: 2.3807
Epoch 10/10
819/819                   322s 392ms/step -
loss: 7.5975 - mae: 2.1543 - val_loss: 9.7520 - val_mae: 2.3859
```

Plotting results

[36]:
```
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
Training MAE
Validation MAE
3.8
3.6
3.4
3.2
3.0
2.8
2.6
2.4
2.2
2
4
6
8
10

```
[ ]:
```